

NBER WORKING PAPER SERIES

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

Working Paper 27623
<http://www.nber.org/papers/w27623>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2020, Revised June 2021

We thank Karen Mills for connecting us to Alignable and Alignable's founders for providing data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at <http://www.nber.org/papers/w27623.ack>

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2020 by Alexander W. Bartik, Zoe B. Cullen, Edward L. Glaeser, Michael Luca, Christopher T. Stanton, and Adi Sunderam. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

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,
and Adi Sunderam

NBER Working Paper No. 27623

July 2020, Revised June 2021

JEL No. D22,G01,G2,L26,M13

ABSTRACT

What happens when public resources are allocated by private actors, whose objectives may be imperfectly aligned with public goals? We study this question in the context of the Paycheck Protection Program (PPP), which relied on private banks to rapidly disburse aid to small businesses. We present a model suggesting that such delegation is optimal if delay is very costly, the variance of the impact of funds across firms is small, and the correlation between public and private objectives is high. We then use firm-level data to measure heterogeneity in the impact of PPP and to assess whether banks targeted loans to high-impact firms. Using an instrumental variables approach, we find that PPP loans increased business's expected survival rates by 9 to 22 percentage points and modestly boosted employment. While banks did target loans to their pre-existing customers, treatment effect heterogeneity is sufficiently modest and the correlation between bank and public objectives seems sufficiently strong that delegation could still have been optimal given the high costs of delay.

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

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

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

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

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

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

I. Introduction

When should private entities, like banks, allocate public resources, like subsidized loans? Private entities, including both banks and hospitals, often have more capacity than the public sector to quickly deliver services, such as loans and vaccines. But their allocation choices may diverge from public objectives. In this paper, we examine the distance between the revealed preferences of the banking sector and the stated public goals of the Paycheck Protection Program (PPP), which has now swelled to almost \$1 trillion.

Small businesses were hit hard by the COVID-19 crisis (Bartik et al 2020a), with employment declining by more than 18 percent at firms with under 50 employees by April 2020. In anticipation of the economic impact of COVID-19, Congress created PPP as part of the March 27, 2020 CARES Act. PPP allowed small and medium sized firms that certified that their businesses were “substantially affected by COVID-19” to take out uncollateralized, low-interest rate loans for up to 2.5 times their monthly pre-COVID payroll – with the potential for these loans to be forgiven altogether.

A key design element of the PPP program was that the loans were guaranteed by the federal government’s Small Business Administration (SBA) but were administered by banks. This program design was meant to expedite delivery of funds, but the decision to delegate delivery also reduced the government’s ability to target the funds to businesses most in need, or to businesses where the funds would have the largest impact. Instead, program take-up was determined by bank decisions, especially in the program’s first tranche when there was considerable excess demand for funding.

After describing the PPP program in Section II, Section III presents a model that highlights the key tradeoffs between delegated delivery and direct public provision of aid. Our model is motivated by the PPP, but similar tradeoffs exist when private hospitals or pharmacies administer publicly provided vaccines or when FEMA provides insurance payments directly after a natural disaster rather than relying on local entities.

The primary advantage of delegation in our model is speed. Private entities have existing relationships with clients or patients; any public effort to duplicate those relationships is assumed to entail delay. The cost of delegation is that funds get misallocated from the perspective of the government. Three variables determine whether delegation is optimal: the cost of delay,

heterogeneity across recipients in the social benefit of aid, and the correlation between the preferences of the government and private entities. If either private entities have similar preferences to the government, or if a dollar spent one place is as good as a dollar spent elsewhere, then delegation has limited costs.

In this paper, we provide evidence on these three variables—costs of delay, heterogeneity of aid treatment effects, and the correlation between public and private objectives—in the PPP setting. The first tranche of PPP loans included funds for \$349 billion of loans. Applications started on April 3, 2020, and that tranche was exhausted by April 16, 2020. This shortfall was largely eliminated by the second PPP tranche, which was approved on April 24 and included over \$300 billion in additional funding.² Consequently, bank discretion was far more important in the first tranche, and banks' decisions for that tranche reveal the most about their preferences. The limited supply of loans during that period also enables us to estimate treatment effects for the loans, and particularly whether those treatment effects differ substantially across firms.

We investigate the administration and impact of first-tranche PPP loans using surveys of small businesses conducted through the Alignable small business network between April 25 and April 27, 2020. Ninety percent of our 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 due to supply caps.

We first examine the businesses' decisions to apply for loans, which seem to largely reflect COVID-related dislocation. Firms with less cash on hand and those in more affected industries were more likely to apply for PPP loans. Unsurprisingly, businesses reporting more distress due to the COVID-19 crisis were particularly likely to ask for a PPP loan.

Our first test of the match between bank preferences and public objectives is to assess whether loan applications from these COVID-distressed businesses are more likely to be approved. They are not. Approval rates for loans, conditional upon applying, are lower among firms that report distress. Moreover, banks were particularly likely to channel loans to businesses with more, rather than less, cash on hand. They were also more likely to direct loans to businesses with which they had long-standing relationships, particularly if those businesses had outstanding loans with

² A third tranche of \$284 billion, with somewhat different eligibility rules, was approved on December 27, 2020 and began distributing loans on January 11, 2021. This third tranche allowed firms that had already received a loan during the first two PPP tranches to, under some additional conditions, receive a second PPP loan.

the bank. These facts support the hypothesis that banks were pursuing their private business objectives but do not demonstrate a meaningful gap between public and private objectives.

To quantify this gap, we assume that the larger public purposes of the program were to boost employment and firm survival rates. Our approach is to estimate the heterogeneity in the treatment effect of loans on survival and employment based on observable firm characteristics. We then test whether banks disproportionately favored businesses with characteristics associated with high treatment effects. This procedure allows us to quantify two central parameters of the model: the overall degree of impact heterogeneity and the correlation between bank preferences and public objectives.

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 businesses' pre-existing banking relationships. We use the fact that individual banks varied in their approval rates, with the largest banks having lower approval rates.

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 banks. These differences in approval rates likely reflect operational challenges in administering the program as borrowers rushed to apply. 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.

We then instrument for whether a firm was approved for a PPP loan in the first tranche with dummies for the firm's primary bank, estimated using Limited Information Maximum Likelihood (LIML) to reduce the finite-sample bias of overidentified instrumental variable models. Our results are similar for the entire sample and when we split the sample based on whether the firm banks with a top 20 bank or not. In our specifications that split the sample, the exclusion restriction boils down to the assumption that firms using a particular bank type are similar except for their individual bank's handling of PPP.

Using 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 probabilities ranging from 9 to 23 percentage points. PPP approval does appear to increase employment, but the confidence intervals around our estimates are wide, ranging from under 1 job saved per firm to over 10 jobs saved. To corroborate our main results and shed light on realized closure rates, we

conducted a phone survey in July 2020, calling businesses to see if they were open. The results are consistent with our main analysis on survival expectations, suggesting that PPP funding ultimately led to fewer small businesses closing.

We then estimate the heterogeneity in treatment effects by different firm characteristics, including those that appear to correlate with bank funding allocation and approval rates. Along some dimensions, banks appear to preferentially disburse funds to firms with low treatment effects. For instance, banks are more likely to approve PPP loans for firms that have high cash-on-hand, while treatment effects are larger for low cash-on-hand firms. Along other dimensions, most notably payroll size, the businesses approved for funding have higher estimated treatment effects.

Overall, we find that loans were well-targeted on some but not all dimensions. On balance, banks' targeting appears to do better than a random allocation of the loans; treatment effects on firm expected survival and employment were, respectively, four and 25 percent higher than they would have been under random loan allocation. This targeting improvement was driven by banks being significantly less likely to approve loans for the lowest treatment effect firms.

Moreover, we estimate the variance of treatment effects to be modest. Of course, the true treatment heterogeneity may have been larger than our estimates, but we have no reason to think that a government agency would have been better at targeting than our model, especially since we are basing our heterogeneity estimates on ex post outcomes that would not have been observable to the government ex ante.

While we cannot provide a complete welfare analysis, these results suggest that the cost of delegating administration may have been relatively low in this case. The benefits of speed may also have been quite high since many firms at the time had little cash on hand. In related work Bartik et al. (2020) found that in the early stages of the COVID-19 pandemic many firms expected to close permanently if the crisis lasted even a few months. Given that our analysis essentially compares firms that got PPP money in the first tranche to firms that got it in the second tranche, our estimates suggest that getting loans to firms quickly increased program efficacy. Designing a program with rules for better targeting may have resulted in further delay in getting funds to needy businesses with only modest benefits in terms of employment and survival effects.

This paper contributes to a growing literature studying the effects of the CARES Act. Recent research has studied the effects of PPP loans, exploiting variation in PPP loan receipt intensity between firms above and below the 500 employee PPP eligibility threshold for most

industries (Chetty et al. 2020, Autor et al. 2020, and Hubbard and Strain 2020), locations (Granja et al. 2020, Faulkender, Jackman, and Miran 2020, Bartik et al. 2020c, Doniger and Kay 2021), and firms with similar characteristics who differed in PPP receipt (Humphries, Neilsen, and Ulyssea 2020, Granja et al. 2020, Joaquim and Netto 2021, Elenev, Landvoigt and Van Nieuwerburgh 2020, Barrios, Minnis, Minnis and Sijthoff 2020, Cororaton and Rosen 2020). Estimated employment effects are generally positive in these other papers, but the magnitude varies with the empirical approach. Papers exploiting the 500 employee PPP eligibility threshold for most industries tend to find more modest effects, possibly reflecting greater access to alternative sources of capital among the largest firms eligible for PPP. Work exploiting firm level variation in PPP exposure tends to find significantly larger effects on firm shut-downs and employment, while work exploiting geographic variation in exposure finds a wider range of effects. One of the first papers on PPP, Granja et al. 2020 also study the targeting of the program. They exploit variation in bank geographical footprints, showing that PPP funds did not flow to areas disproportionately affected by Covid-19 and had modest average effects on employment.

Unlike most of the existing literature, our paper leverages individual firm-bank relationships to focus on the distribution of PPP loans, rather than evaluating the program overall. 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 the established literature on financial constraints (Myers and Majluf 1984, Holmstrom and Tirole 1997, Fazzari et al. 1988, Kaplan and Zingales 1997). We are also able to quantify how the program affected firms' expectations about survival and resilience, providing important context for the long-run effects of PPP if improved balance sheets allowed 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 for public crisis-lending that highlights the tradeoffs the government faces in deciding whether to delegate loan delivery. The fourth section describes the survey data we use from Alignable. In Section 5, we present results on the characteristics of firms that applied for and received PPP loans. Section 6 then presents estimates of the causal effect of PPP loans on firm reported survival probabilities and employment and investigates how heterogeneity in treatment effects was correlated with lending decisions. Section 7 concludes.

II. The Paycheck Protection Program and the CARES Act

The Coronavirus Aid, Relief, and Economic Security Act, or CARES Act, is a unique bill in recent US history due to 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. 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.”⁷

After these early proposals, economic fear continued to spread. Between March 4 and March 23, the Dow Jones Industrial Average dropped by 8,498 points or 31 percent of its March 4 level. 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.

It took until Tuesday, March 24th for the Senate to agree, unanimously, on a stimulus package—the CARES Act—that authorized over \$2 trillion 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 benefits, and tax deferrals. Over \$800 billion

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/>

was allocated for corporate loans, with the \$349 billion Paycheck Protection Program (PPP) targeting smaller businesses.

In most industries, PPP was limited to firms with fewer than 500 employees and loans were capped at \$10,000,000.⁸ Any recipient of a PPP loan had 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 did not 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.⁹

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 Act allowed 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 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.¹⁰

Banks rushed to get applications into the E-TRAN system. Some of the larger banks were able to move quickly; 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 PPP 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

⁸ 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 were eligible for PPP as long as they had fewer than 500 employees at each location. See <https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program>

⁹ <https://www.govinfo.gov/content/pkg/BILLS-116hr748enr/pdf/BILLS-116hr748enr.pdf>

¹⁰ <https://abc7.com/banks-scramble-to-make-small-business-loan-applications-available/6074915/>

¹¹ <https://twitter.com/marcorubio/status/1250516086136754176>

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 a significant 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 \$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 cap of \$10,000,000 remained. 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.

III. A Model of Private Allocation of Public Resources

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 as the Paycheck Protection Program. The PPP put few restrictions on which firms 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.

The PPP program provides an extreme example of a setting where public resources were allocated by private actors, but it is hardly unique. More recently, private hospitals delivering COVID-19 vaccines have been subject to public guidelines but also retain significant discretion. For instance, if the rules restricted vaccines to medical personnel, it was still possible to define back-room administrators working from home as such personnel. Similarly, age-based rules still leave the hospital with discretion about whether to vaccinate their older donors first.

In this section, we present a model where delegation means that the public sector loses some control over the targeting of resources but gains speed. The price of delegated discretion is

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

that the lenders' preferences may be poorly aligned with social welfare. The price of direct government provision is the business failures 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.¹³ We 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. In the context of the PPP, many of these considerations are mitigated by the fact that much of the funds were ultimately grants to firms rather than loans. Our focus is the tradeoff between speed and targeting. The planner has the option to either allocate funds through the banking sector immediately or delay long enough to establish more control over the process. 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.¹⁴

Total funds T must be allocated across a continuum of businesses normalized to have measure one. We 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, or any other positive 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 assume that $v(x, \alpha) = e^\alpha x^\gamma$ and $\gamma < 1$, 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 $T = \int_\alpha x f(\alpha) d\alpha$. If second order conditions hold, then socially 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.

¹³ 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.

¹⁴ This tradeoff could be ameliorated if the planner itself had the ability to directly deliver the funds in a rapid and controlled way. This was likely not possible during the early stages of the COVID crisis, and our approach takes institutions as fixed and characterizes the tradeoffs given these institutional capacity limitations.

We consider two institutional choices: (1) immediate bank lending and (2) delayed public lending. We assume that delay is costly because some firms will die before the delayed payments can be made. If the government delays, then a random fraction of the firms, denoted $1 - \delta$, shut down and cannot be resuscitated with lending. There are no other costs of delay in our model other than the loss of potential borrowers.¹⁵

Immediate Delegation vs. Delayed Control

Our first comparison is between 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, or can delegate to a single bank that allocates T across the entire economy.

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, mean zero independent random variables with variances σ_α^2 and σ_ξ^2 , respectively. These variables are meant to capture the mismatch between public and private objectives.

If the government delays and designs a more targeted allocation mechanism, 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 assume that $1 \geq \theta > \phi$ and $\sigma_\zeta^2 < \sigma_\xi^2$. We assume that delayed targeting increases the correlation of the decision-making with true social value, either because the public sector can set up its own bureaucracy to better target loans or because it can design better rules to improve targeting by the banking sector. We assume that the variance relationship is strict, so that there is some benefit of delay, even if it is small.

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

¹⁵ Although standard intuition would suggest that the first businesses to die are likely the most fragile and hence would have been close to the exit margin absent the pandemic, Bartlett and Morse (2020) indicate that the death process may have looked very different during COVID-19 because extreme demand reductions fall hardest on businesses with high levels of committed capital. Hanson et al (2020) similarly point to a potentially low correlation between firm revenues during the pandemic and long-run viability as an economic rationale for aid to firms.

lending. Targeting provides higher welfare than immediate lending if and only if $\delta > \delta^*$. The value of δ^* is falling with $\gamma, \theta, \sigma_\xi^2$ 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 high (e.g., Bartik et al., 2020a).

This cutoff survival rate depends on the four parameters associated with targeted and non-targeted lending. When the bank's 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 rates. When 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 survival rate is lower. Consequently, it is possible to support immediate lending either because of faith in banks' decision-making or skepticism about the public sector's ability to improve on that decision-making.

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 high, i.e. σ_α^2 is larger, then it is more valuable to delay funding to improve targeting.

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 mean that targeting can lead to larger gains by giving particularly generous loans to high social value borrowers.

In the Appendix, we show that we obtain similar results when we consider slightly more complex model formulations that allow us to capture additional features of the PPP program, including maximum loan sizes.

IV. Data Description

We evaluate the efficacy of the PPP program and the nature of bank delegation through unique survey data on small businesses. 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. There were also 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 operational over the following 8 months. The survey also included a series of retrospective questions covering 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 main 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 5,903 observations—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%.¹⁶

67% of respondents attempted to apply for PPP funding in the first tranche, and among those that attempted application, 24% were approved. The remaining applications were either pending (51%) or had been denied (24%). Our definition of denial includes both applications rejected by the SBA and applicants reporting an inability to submit an application, which picks up rationing. The inability to submit accounts for about two-thirds of the 24% who were denied.

At the time of the survey, the average firm had 5.4 employees, down from an average of 7.6 employees in January 2020. Firms reported \$24,400 in average monthly payroll expenses and \$15,000 in fixed monthly expenditures. These averages are somewhat skewed by the larger firms in our sample. Median employment in January, payroll, and fixed expenses are 3 employees, \$5,000, and \$5,000 respectively (payroll and fixed expense amounts were categorical, and we report midpoints of categories). Firms reported having cash on hand to cover about 5.2 weeks worth of expenses.

Approximately one third of the sample reported having primary banking relationship with one of the top 4 largest banks. Thirteen percent used banks 5-10, while 11% used a credit union, meaning that about 39% of the sample used a small bank that was not a credit union. Among firms, there is significant heterogeneity in interactions with their banks. 40% of firms report having an existing loan with their bank, which includes credit card loans. 24% 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. We first establish some basic facts about the correlates between firm characteristics and both application and approval rates. Figure 2 summarizes how application rates (the left panel)

¹⁶ December 2020 survival probabilities were asked of respondents in two different ways in different questions toward the beginning and end of the survey. The order of questions was randomized between respondents. The first version of the question was worded “What is the likelihood of your business remaining operational by Dec. 31, 2020? Please provide your best guess.” Options included “0% Extremely Unlikely,” “10%,” ..., “90%,” and “100% Extremely Likely.” The second version of the question was worded identically but had response options “Extremely Unlikely,” “Somewhat Unlikely,” “Somewhat Likely,” “Very Likely,” and “Extremely Likely.” We use the question version with 10-point increments unless the response is missing (6% of the sample); for these respondents we fill in the average of the 10-point question for the corresponding qualitative categories.

and approval and denial rates (the right panel) vary with firm characteristics, with different characteristics shown along the vertical axis. We begin by looking at the application and outcome measures captured by different levels of distress, but we emphasize that higher distress may not signify a higher value borrower. We then turn to firm size, age, and industry. After this examination of firm characteristics, we dive deeper into patterns of variation by bank, which forms part of our empirical strategy. 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 also checked for differences among self-reported female, veteran, and minority owned business and find some differences in application and approval rates, as shown in Figure A2 in the Appendix.

Applications, Approvals and Distress

The stated goal of 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 on firms that are somewhat less distressed?

The first section of Figure 2 shows patterns of applications and approvals 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 is "starting to impact my business," and High Impact firms said that it is "really impacting my business."

The application rates rise monotonically with the severity of the crisis for the firm. Over 70 percent of firms that suffered high impact from COVID-19 applied for PPP loans. One-fifth of the firms with the least severe impact applied for the loans. The right panel of Figure 2, however, shows that the most severely impacted firms were most likely to apply, but they were also the most likely to be denied a PPP loan conditional on application.¹⁷ The denial rate rises from 12% in the lowest severity category to 26% in the highest severity category. The approval rate is roughly the

¹⁷ 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 in our data.

same between the least severe and the median severity category, at about 33%, but is lower for the most severely impacted firms, at 23%.

The gap between approval and denial rates reflects the large share of firms whose loan applications were pending when the first tranche of PPP was exhausted. These firms did not receive loans in the first round of the PPP program, so if the program had been more constrained they would have been excluded. In reality, the second tranche of PPP was so generous that a large fraction of these firms ultimately did eventually receive PPP loans. Our focus here, however, is on firm expectations for firms prior to the knowledge there would be a second tranche.

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.

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

Most small firms have relatively little cash on hand, and the second section of Figure 2 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. For firms with three or more months of cash on hand, the application rate then drops from over 65 percent to close to 45 percent.

However, turning to the right panel of Figure 2 we once again see a pattern where loans were most likely to go to firms that had been impacted the least severely. The approval rate for firms with three or 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 would have folded even if they received a loan. However, the higher approval rate for more cash-rich firms could also reflect banks' private incentives.

Firm Size, Age, and Industry

We now turn to differences in applications and approval rates across firm size, age, and industry. The third section of Figure 2 shows patterns in applications and approvals by the number of employees in January of 2020. 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 were clarified in a SBA announcement on April 10, 2020. 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 80 percent among firms with over six employees.

By contrast, the right panel shows that approval rates monotonically increase with firm size and denial 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 fees¹⁸ and because satisfying a larger customer is presumably more valuable in the long run than satisfying a smaller customer. The fourth section of Figure 2 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, measure in terms of fixed expenditure.¹⁹

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 type.

The fifth section of Figure 2 shows the patterns by business age. Older firms are more likely to apply and more likely to be approved. This pattern could mean that the documentation of older firms is in better shape. A less benign view is that older firms have a more established relationship with the lender.

The final section of Figure 2 shows overall patterns by industry. Application rates were particularly high in accommodation and retail, two sectors that were particularly hammered by

¹⁸ 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>

¹⁹ 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.

COVID-19. Construction also saw high application rates. Unlike many of the previous characteristics discussed above, approval rates by industry mostly mirror application rates.

Lenders and Approval Rates

We now turn to understanding how application and approval rates vary by bank and based on the nature of the relationship between the lender and the borrower. We primarily differentiate between the top four banks, banks ranked five to ten, other large banks (ranked eleven to twenty), and smaller banks.²⁰ Appendix Table A1 provides the number of borrowers, average loan sizes, and total lending for these four categories, while further distinguishing other banks as credit unions, small business specialists (defined as banks in the top 20 for small business lending volume but not assets), and other banks. 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 1,900 applications. The top four got about 1,400 applications, and banks 5-20 received about one-half of that number.

Figure 3 shows application and approval rates by bank size. For the application rate, we divide the number of firms in our sample who applied to a lender in that category by the sum of that number and the number 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.

Application rates are roughly equal across size of lender, although the rate falls slightly among firms that banked regularly with smaller banks in the other category. More strikingly, relative to the 10 largest banks, the approval rate is sharply higher for loan applications to banks ranked 11-20 and to smaller banks and credit unions. Thirty-three percent of applications to non-ranked banks were approved, while only thirteen percent of applications to the top four were approved. This heterogeneity in approval rates will lie at the heart of our instrumental variables strategy in the next section.

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

²⁰ 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).

expeditiously than the large lenders. One explanation for this difference, which is consistent with reporting around the PPP program, is that the large lenders were 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.

Table 2 provides results on PPP outcomes in a multivariate regression format, providing a sense for the association between firm and lender characteristics and borrowing outcomes conditional on other characteristics. The table shows four 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 final column conducts a similar exercise to examine receipt of a PPP loan without conditioning on application.

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 24 percentage points more likely to apply for a loan. Firms with significant cash on hand were 12 percentage points less likely to apply for a loan, holding payroll constant. Firms with a large payroll were 21 percentage points 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 does not significantly impact application rate, but firms that bank with credit unions are 6 percentage points less likely to apply for a loan. The relationship between lender and borrower does matter. Firms that had an existing loan were 5 percentage points more likely to send in an application, although this may mix need and access. Holding fixed having an existing loan, firms that knew a loan officer were 8 percentage points more likely to apply for a loan.

The factors that determine approval are often diametrically opposite to the factors that determine application. Firms that said that COVID-19 impacted them severely more were 4 percentage points less likely to receive a loan relative to a baseline approval rate of 24 percent.

Firms that had high level of cash were 15 percentage points more likely to receive a loan. A large payroll positively predicts both loan application and loan approval. Firms with a large payroll were 13 percentage points more likely to receive a loan.

Bank attributes are far stronger predictors of loan approval than loan application. Firms that have relationships with top four banks are 22 percentage points less likely to be approved for a PPP loan relative to non-credit union banks outside of the 20 largest banks (the excluded category). A relationship with top 5-10 sized bank reduces the probability of loan approval by 15 percentage points relative to the excluded category. Banks 11-20 are indistinguishable from other banks, while credit unions have a strong negative correlation with approval. These bank effects on approval are at the core of our subsequent instrumental variables strategy.

There is mixed evidence in this multivariate analysis around the strength of ties to the bank and approval probabilities. A preexisting loan with the bank is associated with a three percentage point increase in the probability of approval, but the confidence interval includes zero. Firms with a preexisting relationship with a bank loan officer were six percentage points more likely to have their loans approved, and we can reject a null effect. One interpretation of this results is that it reflects 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.²¹ Whether these ties altered the allocation of loans to firms that would have systematically higher or lower benefits from loan receipt is an empirical question that we subsequently address when examining heterogeneous effects.

The next column studies rejections. In some cases, the coefficients in this column are exactly the opposite of the coefficients in column (2). For example, the absolute value of 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. 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 for an immediate infusion of money, were actually less likely

²¹ Consistent with the idea that banks may have steered PPP to firms at high risk of bankruptcy, approval rates are higher for low-cash firms with large existing debts compared to other firms. Appendix Figure A3 shows the impact of having a large loan and low cash on approval rates across bank sizes.

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.

The final column examines receipt without conditioning on application. Despite a below-average approval rate, high COVID impact firms have a higher than average receipt rate because of these firms' 24 percentage point higher likelihood of applying. High cash and high payroll firms also have high receipt rates compared to firms without these features. Firms banking with the top 4 banks, banks ranked 5-10, and credit unions have below average receipt rates. Finally, eventual receipt rates show a positive relationship between having a bank loan and knowing a loan officer and eventual PPP receipt.

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

We now turn to the impact of PPP loans on firms' expected survival and employment. We examine both the ordinary least squares coefficient on receiving a PPP loan among those firms that apply for a loan, controlling for a rich set of firm characteristics, and the IV coefficient where we use bank dummies to instrument for loan approval. We have two different outcome variables that come from our April 25 Alignable survey: (1) respondents' expected probability of being open in December 2020 and (2) employment at the time of the survey. Firms that received a PPP loan should face strong incentives to keep their workforce, in order to be eligible for full loan forgiveness. Many of them may not have received the funding at time of the survey, however, and thus illiquidity may have led them to furlough workers. Thus, the employment measure may not capture the full impact of a PPP loan if those loans work primarily by enabling the firm to survive. The expectations variable captures a longer-term outcome.

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 14 percentage points more likely to remain open in December. The second column includes controls for industry and state fixed effects, and the coefficient changes little. While it is unclear if this result reflects a true treatment effect of the PPP loan, or whether PPP loans flowed to sturdier firms (as suggested by the positive correlation between approval and cash on hand), the estimated coefficients are both large and estimated with reasonably high levels of precision

The third regression controls for whether the business is currently open (business status). The coefficient on receiving a PPP loan drops slightly. The fourth column includes the amount of cash on hand, which reduces the estimated coefficient to .09, 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 cash on hand because firms with more cash were more likely to receive loans and cash on hand is strongly correlated with firms' expectations about their ability to survive. Column 5 reweights the sample to match characteristics of the industry and size composition of the population of firms receiving PPP in tranche 1; we obtain very similar results.²²

It is possible that PPP loans have a real treatment effect on firms' expectations, but that this will not translate into a higher likelihood of actually surviving. The final two columns report validation exercises for these measures where we examine realized outcomes rather than firm expectations. Specifically, we conducted a phone follow up survey in July 2020 to assess whether the firms in the survey were operational at that time. Column 6 restricts the sample to the firms we surveyed by phone and shows that our results on survey expectations are similar to the full sample. Column 7 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.²³ The coefficients in these

²² See Figure A1 for how loan sizes among loan recipients in our sample compares to the loan size distribution of the universe of PPP recipients in the first tranche of the program. For the reweighted estimates, we first match approvals in the survey data to the distribution of loans in the first tranche based on 9 Census regions, 3 terciles of employee proximity (a measure of contagion potential at the 3-digit NAICS level from Mongey, Pilossoph and Weinberg (2021)), and 13 categories of loan sizes. We then form estimation weights that allow us to recover treatment effects matching the SBA distribution by taking the average approval weights within 9 Census regions, 3 proximity terciles, and 10 categorical payroll buckets. Payroll categories are used to get weights for all applicants because PPP loan amounts are based on payroll.

²³ 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

specifications are quite similar, with an eight percentage point increase in survival expectations due to PPP in the survey and a 13 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 survival contain real information about actual firm survival outcomes.

Panel B repeats these specifications, using employment as the outcome. Employment is defined as the level of employment in our April 27 survey, and we control for the level of employment in January. The coefficient in this specification can be interpreted as the extra jobs associated with receiving a PPP loan. We have no way of quantifying how long each of those jobs will last, but matches will of course dissolve if the firm fails.

The first column shows a coefficient of 2.34, indicating that the average loan was associated with over 2 extra jobs relative to a mean for January employment in this sample of firms of 9.4 employees (applicant firms on average larger than the overall sample, where the mean January headcount is 7.6 employees). In the second column, we control for industry and state fixed effects. The estimated coefficient declines to 2.18. In the third specification, we control for business status and the coefficient falls to 1.90. When we also control for cash on hand in the fourth column, the coefficient declines to 1.73. While the controls do lead to an attenuation of the coefficient, it remains highly significant statistically and reasonable in terms of economic magnitude. Column 5 reweights the sample to match the industry and size composition of the population of firms receiving PPP; the coefficient rises to 3.24 in this specification.

Panel C presents similar estimates, but the dependent variable is the inverse hyperbolic sine of employment, which is similar to a logarithmic transformation of employment but allows for zeros. The January employment control is also inverse hyperbolic sine transformed, meaning this specification yields employment growth rates rather than level changes. Estimates of employment growth rate increases due to PPP range from 0.23 with the full suite of controls to 0.31 with no controls.

Overall, the estimates suggest that PPP approval increased employment by between 18 to 25 percent of January employment in levels or increased employment growth by up to 31 percent. As the average PPP loan in our sample is \$195,000, this represents at least \$67,000 dollars per employee. Any cost-benefit analysis, however, must address both the duration of these jobs and

closure, but some non-response is likely due to measurement error that biases the share of operational businesses downward.

whether these payments to firms represent lost resources or simply a transfer. We lack the variation to conduct this full cost-benefit analysis. We are however equipped to understand whether these estimates are causal and to estimate whether different allocations of loans would have materially changed program benefits.

The potential endogeneity of loan approval even after the inclusion of our rich set of controls motivates using an instrumental variable strategy. We instrument PPP approval with dummies for the identity of the bank each respondent reports as their primary banking relationship. We group together banks by type (i.e., small business specialist, other small bank, credit union) if we observe very few responses for a given bank. This leaves us with 61 bank dummies as instruments, and we estimate the model using Limited Information Maximum Likelihood (LIML), which reduces the final sample bias of 2SLS when there are many instruments.²⁴ This strategy exploits variation between banks like JPMorgan Chase, where fewer than 12 percent of applicants were approved, and Citibank, where over 34 percent of applicants received funding. To ameliorate concerns about unobserved firm differences that correlate with bank type, we test for differences in pre-Covid firm characteristics (January employees, payroll, fixed expenses) between different bank groups in Appendix Table A2. The last two columns of Appendix Table A2 also analyze a measure of firm distress that might impact the bank, where the dependent variable is having a large loan and low cash. Among all of these measures, we can never reject equality between top 4 banks, top 5-10 banks, and banks 11-20 among the large bank subsample. We also cannot reject that small business specialist banks equal other non-credit union banks among the small bank subsample. Firms that bank with credit unions are different than other firms in our sample. Consequently, based on these tests we also split the sample to those that use large banks and small banks excluding credit unions.

Table 4, Panel A, shows results for expectations about being open in December and firm operational status in July 2020. The first four regressions show results for the pooled sample. The survival effects remain large and significant, with an estimated coefficient of 0.20 in the first regression, which includes no other controls, and 0.13 in the fourth regression, where we control for industry, state, cash on hand, and business status. The reweighted estimate in the fifth

²⁴ Our estimates are similar when using 2 stage least squares or other estimators like a leave-out-mean instrument by bank group, but Davidson and MacKinnon (2006) argue that LIML estimators with group dummies work well and often outperform jack-knife IV estimators.

regression is 0.24. These estimates are generally slightly larger than the ordinary least squares coefficients, indicating that unobserved firm quality is unlikely to bias the OLS estimates upward. Instead, the IV estimates should be higher than the OLS estimates if loans flowed to firms that would otherwise have a lower probability of survival. Some evidence supports that view. For instance, firms that have existing loans were more likely to receive a loan. Alternatively, the IV estimates may be biased upwards if the exclusion restriction is violated and the identity of a firm's pre-COVID-19 lender is correlated with expected survival probability for other reasons.

To strengthen the plausibility of the exclusion restriction, Columns 6 and 7 split the sample into the large and small bank sample, respectively. In these cases, the exclusion restriction boils down to the assumption that firms using a particular bank type are similar except for their individual bank's handling of PPP. The split sample results in Columns 6 and 7 are similar, at 0.10 and 0.10, but splitting the sample reduces power, especially among the smaller banks subsample. Column 8 shows IV results for the phone survey follow up sample and shows qualitatively similar results.

Table 4, Panel B, shows our results for employment, following the same structure as Panel A. These estimates are significantly larger than the OLS estimates, ranging from 6.09 to 3.83 across columns 1 through 5, but estimate precision falls as we add controls. The reweighted estimates are no longer significant. When splitting the sample in columns 6 and 7, the coefficients is 4.05 for large banks but we lose precision. The estimates are very imprecise for firms using small banks, and the point estimate is actually negative. This appears to arise because the reduced form regression has little predictive power in the small bank subsample, likely because the average approval rate of each small bank is measured error due to small cell sizes. A different possibility is that since the small bank approval rate is double the large bank rate, the marginal approved applicant for small banks has a smaller treatment effect. A similar pattern of results to Panel B is present in Panel C, which looks at employment growth.

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 which firm 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 estimates of survival and interactions with dummies for 7 splits based on median firm characteristics (Z). These interaction terms are instrumented with the bank dummy instruments multiplied by an above median characteristic dummy. The first column splits the sample based on the impact of COVID-19 to the business. The top coefficient in Panel A shows that receiving a PPP loan increased the expected probability of survival by seven percentage points more among those firms that were more impacted by COVID-19 relative to the baseline effect of six percentage points, but the estimated interaction effect is not precise.

In the second column, we show results based on cash on hand. The expected survival impact of a PPP loan is estimated to be 18 percentage points at baseline and declines to six percentage points for firms with more cash on hand. The PPP loans are thus more effective for more cash constrained firms.

The third and fourth regressions interact receiving a PPP loan with the ex-ante relationship between the borrower and the bank. Despite negative coefficients on having a loan or knowing a loan officer, the estimates are not precise. The next two regressions split the sample based on either payroll expenditures or overall fixed expenditures. The effect is stronger for high payroll firms, while there are no significant differences relative to baseline for high fixed expenses firms. The final column tries to evaluate whether some firms would have a larger or smaller effect if they are business-to-business industries (and thus more central industries for other firms). We find that these firms have larger effects, but these estimates are not precise.

Panel B shows results on employment where we split the sample along the same six variables. Only for having an existing loan is the interaction term significant. Panel C looks at employment growth, and having an existing loan remains significant, while high payroll and high fixed expense interactions become significant in this growth specification. Overall, there is some evidence of treatment effect heterogeneity for survival and employment.

Was the Allocation of Loans Efficient?

The model in Section III highlights that the efficiency of delegation depends on both the correlation of the social valuation of loans with the bank's private valuation of the loans and the overall variance in social valuation of loans. In this section, we explore these two factors in detail by estimating firm-level treatment effects and the correlation of these heterogeneous treatment effects with PPP application and approval. Specifically, we estimate Least Absolute Shrinkage and Selection Operator (LASSO) models of firm survival expectations and employment as a function of approval interacted with firm, bank-relationship, and industry characteristics in the sample of PPP applicants. The interactions considered are between PPP approval and COVID impact severity, months of cash available, monthly fixed expenditures pre-COVID, pre-COVID firm size, an indicator for a bank loan, an indicator for a loan officer relationship, and two-digit industry dummies. From these estimates, we also calculate implied treatment effects for non-applicants based on their characteristics. Figures 4 and 5 plot the CDF of the firm level survival expectations and employment percent change treatment effects estimated using this approach (we use employment percent changes to ease interpretation because it means readers do not need to keep track of baseline employment levels). The hollow green circles show the CDF for all firms, the red triangles for PPP applicants, and the blue circles for PPP recipients. Table 6 then reports summary statistics for the individual treatment effect estimates for both survival expectations (Panel A) and employment percent changes (Panel B).

These tables and figures illustrate three broad features of the allocation of loans in the first round of PPP. First, PPP applicants have somewhat larger estimated treatment effects than all firms for both survival expectations (0.074 versus 0.068) and employment percent changes (0.231 versus 0.171), reflected by a general rightward shift of the applicant CDF compared to the all firms CDF.²⁵ Second, PPP recipients have larger estimated treatment effects than PPP applicants for both survival expectations (0.074 versus 0.070) and employment percent changes (0.231 versus 0.185), primarily driven by a much smaller share of PPP recipient firms among the lowest treatment effect categories (only about 35 percent of PPP recipients compared to 50 percent of all firms). Third, there is only moderate treatment effect heterogeneity overall. For both survival expectations and employment percent changes, the estimated treatment effects are substantially positive for all firms, and the standard deviation of treatment effects is less than one third of the

²⁵ These estimates are below the estimates in Table 3 because the LASSO shrinks coefficients toward zero.

mean treatment effect for survival expectations and is about half the mean treatment effect for employment percent changes.

These first two features mean that, despite the difficulties of the PPP application process and the favoritism displayed by banks towards their clients, PPP receipt was still positively correlated with estimated treatment effects. The third finding of moderate treatment effect heterogeneity means that the gains from further improvement in this allocation would likely be modest. Moreover, our evidence indicates loan delay was costly – as it is important to recognize that the substantial treatment effects in our sample likely come from differences between firms that received PPP loans in the first tranche relative to those who in expectation would receive PPP loans in the second tranche. That is, once the program received new funding, all eligible applicants could eventually receive a loan, but with delay. As a consequence, our results suggest that the government’s choice to delegate PPP lending to banks was likely a sensible one, given the goal of maximizing the total impact of the program on firm survival and employment.

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 but 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 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. On net, we find on average banks allocated loans to firms with higher treatment effects, increasing the average treatment effect of recipients by 4 to 25 percent depending on the outcome. Overall heterogeneity in treatment effects was also modest. Furthermore, loan delay was costly, as evidenced by the fact that the treatment effects we estimate reflect the effects of getting PPP loans in the first tranche relative to the second tranche. We develop a model that characterizes the optimality of loan delegation in settings such as PPP and find that these three findings imply that bank delegation was likely optimal in this setting; the cost of delaying loan rollout would have outweighed the benefits of improved targeting.

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 focus on a segment of smaller firms. Using this approach, we arrive at a somewhat different answer regarding the cost of each job saved using PPP. Our estimates range from \$32,000 (using our IV estimates) to \$67,000 per job saved (using our OLS estimates), substantially lower than the figures arrived at by researchers using the 500-employee cutoff to estimate treatment effects, such as the \$224,000 per job saved estimated by Autor, et al (2020) and similar to the findings in Doniger and Kay (2021). Consistent with our findings, Morse and Bartlett (2020) use survey data and find that PPP receipt increases survival probabilities for micro-businesses.

As more data becomes available on outcomes for small businesses over-time, several key questions about the PPP remain unanswered. First, how will the long-run effects of PPP on firm survival and outcomes, and resulting implications for targeting effectiveness, differ from the estimates produced so far using short-run data? Second, how does PPP compare to alternative programs that could have been implemented to assist small businesses. A survey of firms found that that loans with generous terms but no forgiveness may have had similar treatment effects as PPP at much lower cost (Bartik, et al, 2020a), but more work needs to be done to see if these self-reports are borne out in practice. Third, even if PPP targeting was close to the constrained optimum in terms of maximizing the total treatment effect, bank allocation of loans may still have been inequitable. For example, Fairlie and Fossen (2021) find that areas with higher numbers of minority small business owners received PPP loans at a lower rate than other areas. Chodorow-Reich, Darmouni, Luck and Plosser(2020) show that small and medium sized recipients of PPP

reduced their non-PPP borrowing and find that a significant portion of funds was used to strengthen balance sheets.

Beyond the specific context of COVID-19 and PPP, our results illustrate the tradeoff between delay and targeting quality faced by governments when deciding whether to delegate the allocation of time sensitive funds. Guided by a model which characterizes the determinants of optimal delegation, we find that delegation was unlikely to have severely distorted the impact of the PPP program. However, the parameters may differ in other settings, resulting in a different answer on the optimality of delegation.

References

- Autor, D., Cho, D., Crane, L., Goldar, M., Lutz, B., Montes, J., Peterman, W., Ratner, D., Villar, D., Yildirmaz, A., 2020. "An Evaluation of the Paycheck Protection Program Using Administrative Payroll Microdata." MIT Working Paper.
- Balla-Elliott, D., Cullen, Z.B., Glaeser, E.L., Luca, M. and Stanton, C.T., 2020. "Business Reopening Decisions and Demand Forecasts During the COVID-19 Pandemic" (No. w27362). National Bureau of Economic Research.
- Barrios, John, Michael Minnis, William Minnis, and Joost Sijthoff. 2020. "Assessing the Payroll Protection Program: A Framework and Preliminary Results." Working paper.
- Bartik, A.W., Bertrand, M., Cullen, Z., Glaeser, E.L., Luca, M. and Stanton, C., 2020a. "The impact of COVID-19 on small business outcomes and expectations." *Proceedings of the National Academy of Sciences*.
- Bartik, A.W., Cullen, Z.B., Glaeser, E.L., Luca, M. and Stanton, C.T., 2020b. "What Jobs are Being Done at Home During the COVID-19 Crisis? Evidence from Firm-Level Surveys" (No. w27422). National Bureau of Economic Research.
- Bartik, A., Bertrand, M., Lin, F., Rothstein, J., and Unrath, M., 2020c. "Measuring the Labor Market at the Onset of the COVID-19 Crisis," *Brookings Papers on Economic Activity*.
- Bartlett, R., and Morse, A., 2020. "Small Business Survival Capabilities and Policy Effectiveness: Evidence from Oakland" (No. w27629). National Bureau of Economic Research.
- Chetty, R., Friedman, J.N., Hendren, N. and Stepner, M., 2020. "How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data" (No. w27431). National Bureau of Economic Research.
- Chodorow-Reich, Gabriel, Olivier Darmouni, Stephan Luck, and Matthew C. Plosser. 2020. "Bank Liquidity Provision across the Firm Size Distribution."
- Cororaton, Anna, and Samuel Rosen. 2020. "Public Firm Borrowers of the US Paycheck Protection Program." SSRN working paper
- Davidson, Russell, and James G. MacKinnon, 2006. "The case against JIVE." *Journal of Applied Econometrics* 21, no. 6: 827-833.
- Doniger, C. and Kay, B., 2021. "Ten Days Late and Billions of Dollars Short: The Employment Effects of Delays in Paycheck Protection Program Financing." Federal Reserve Working Paper.
- Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh. 2020. "Can the Covid Bailouts Save the Economy?" National Bureau of Economic Research.

Faulkender, R., Jackman, R., and Miran, S., 2020. *The Job Preservation Effects of Paycheck Protection Program Loans*. US Department of the Treasury, Office of Economic Policy. Working Paper 2020-01.

Fairlie, R. and Fossen, F, 2020. “Did the \$660 Billion Paycheck Protection Program and \$220 Billion Economic Injury Disaster Loan Program Get Disbursed to Minority Communities in the Early Stages of COVID-19?” *National Bureau of Economic Research Working Paper 28321*.

Fazzari, S.M., R.G. Hubbard and B.C. Petersen, 1988. “Financing Constraints and Corporate Investment.” *Brookings Papers on Economic Activity*, 141-195.

Granja, J., Makridis, C., Yannelis, C. and Zwick, E., 2020. “Did the Paycheck Protection Program Hit the Target?” (No. w27095). National Bureau of Economic Research.

Hanson, S., Stein, J., Sunderam, A., and Zwick, E. 2020. “Business Credit Programs in the Pandemic Era.” *Brookings Papers on Economic Activity*, Fall 2020.

Holmstrom, B., and J. Tirole, 1997. “Financial intermediation, loanable funds, and the real sector.” *Quarterly Journal of Economics* 112:663–691.

Hubbard, R.G. and Strain, M., 2020. “Has the Paycheck Protection Program Succeeded?” *National Bureau of Economics Working Paper 28032*.

Humphries, J. and Neilsen, C. and Ulyssea, G, 2020. “Information Frictions and Access to the Paycheck Protection Program.” *Journal of Public Economics* 190: October 2020.

Joaquim, G., and Netto, F., 2021. “Bank Incentives and the Effect of the Paycheck Protection Programs.” Federal Reserve Working Paper.

Kaplan, S.N., and L. Zingales (1997), “Do investment-cash flow sensitivities provide useful measures of financing constraints?” *Quarterly Journal of Economics* 112:159–216.

Mongey, S., L. Pilossoph, and A. Weinberg (2021), “Which workers bear the burden of social distancing?” *Journal of Economic Inequality*, forthcoming.

Morse, Adair, and Robert Bartlett. 2020. “Small Business Survival Capabilities and Policy Effectiveness: Evidence from Oakland.” National Bureau of Economic Research.

Myers, S.C., and N.C. Majluf, 1984. “Corporate financing and investment decisions when firms have information that investors do not have.” *Journal of Financial Economics* 13:187–222

Zwick, E., and J. Mahon, 2017. “Tax Policy and Heterogeneous Investment Behavior.” *American Economic Review*, 107(1): 217-48.

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 loan amount buckets for loans over \$150k, which was how these loan amounts were originally published by the SBA.

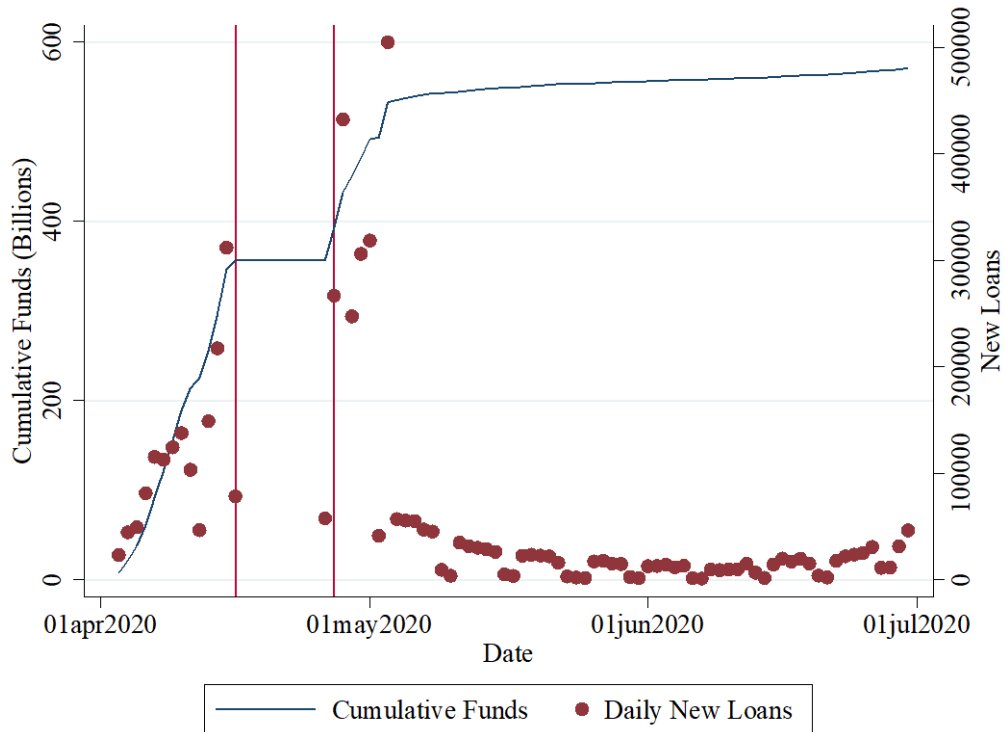


Figure 2. Fraction of respondents applying for PPP and application outcomes by respondent characteristics. Outcomes (approval, pending, and denial rates) are conditional on applications, and the excluded category is a pending outcome. The first set of characteristics is by the stated impact of Covid on the firm as of April 25, 2020. Low impact firms reported that COVID-19 is “not impacting my business.” Medium impact firms said that “It’s starting to impact my business,” and high impact firms said that “it’s really impacting my business.” The second set of characteristics is by cash on hand. 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 third set of characteristics is by the firm’s number of employees in January of 2020. The fourth set of characteristics is 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 fifth set of characteristics is business age. The sixth set of characteristics is industry.

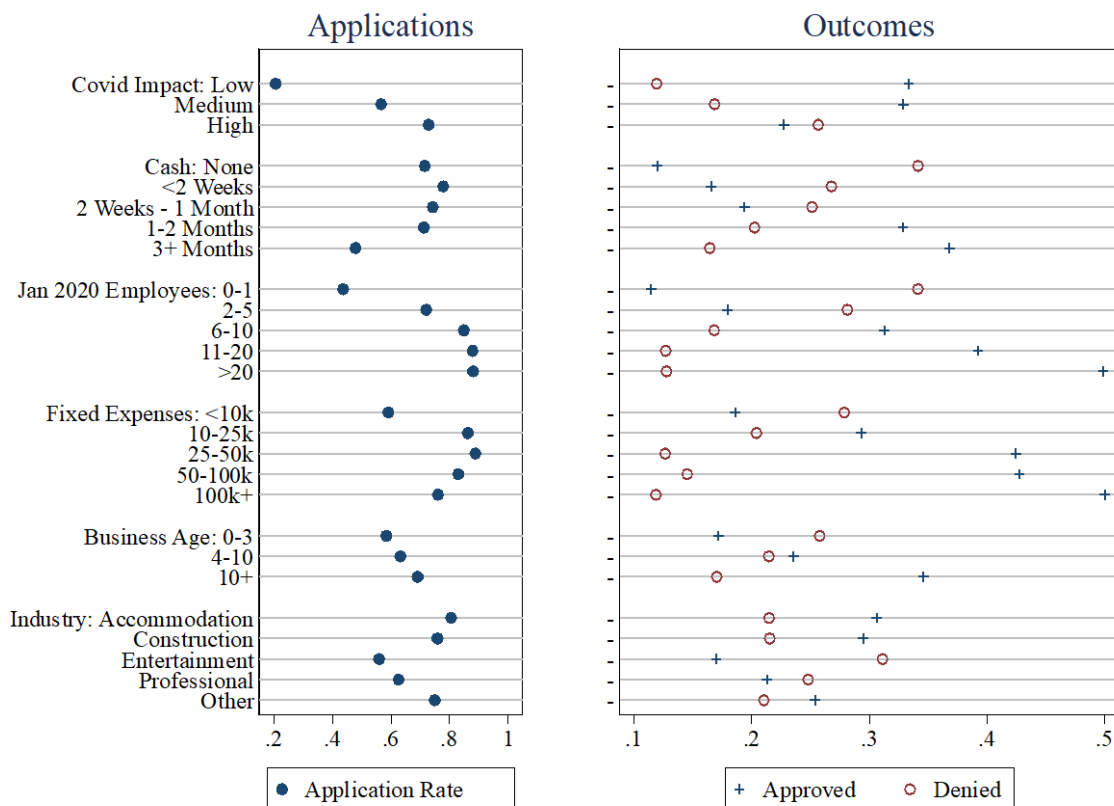


Figure 3. Fraction of respondents applying for PPP and application outcomes as of April 25, 2020 by bank size (x-axis).

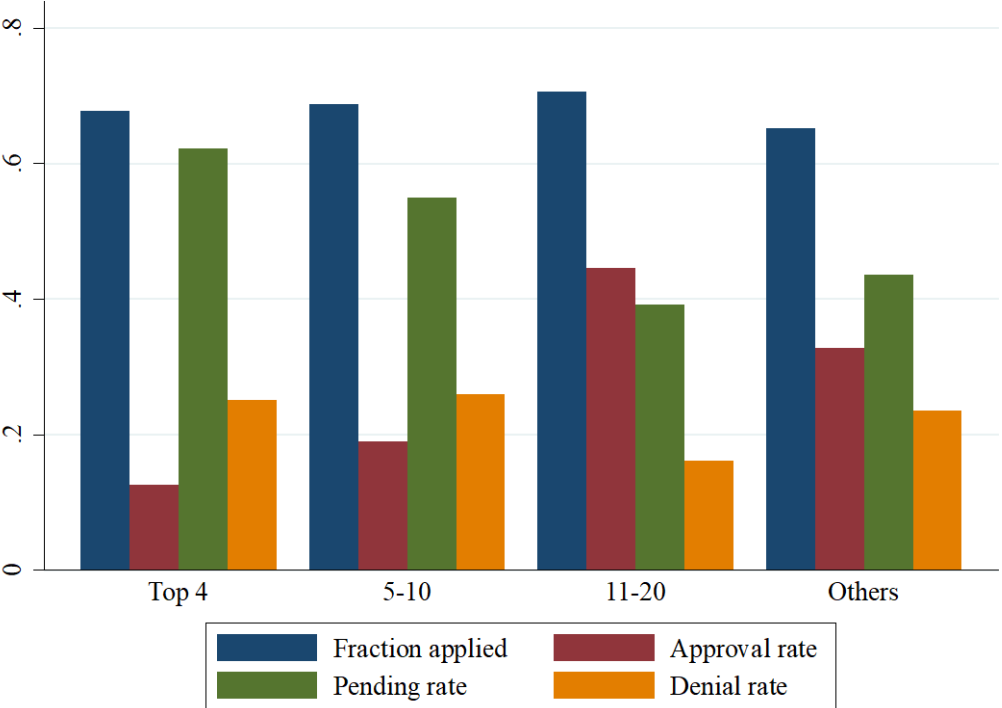


Figure 4. Estimated distributions of heterogeneous treatment effects on firm survival expectations. Treatment effects are estimated among applicants by fitting Lasso models of approval interacted with firm, bank-relationship, and industry characteristics. Specifically, the possible interactions are between PPP approval and COVID severity, months of cash available, monthly fixed expenditures pre-COVID, pre-COVID employment categories, an indicator for a bank loan, an indicator for a loan officer relationship, and 2-digit industry dummies. Treatment effects are projected to non-applicants based on these characteristics.

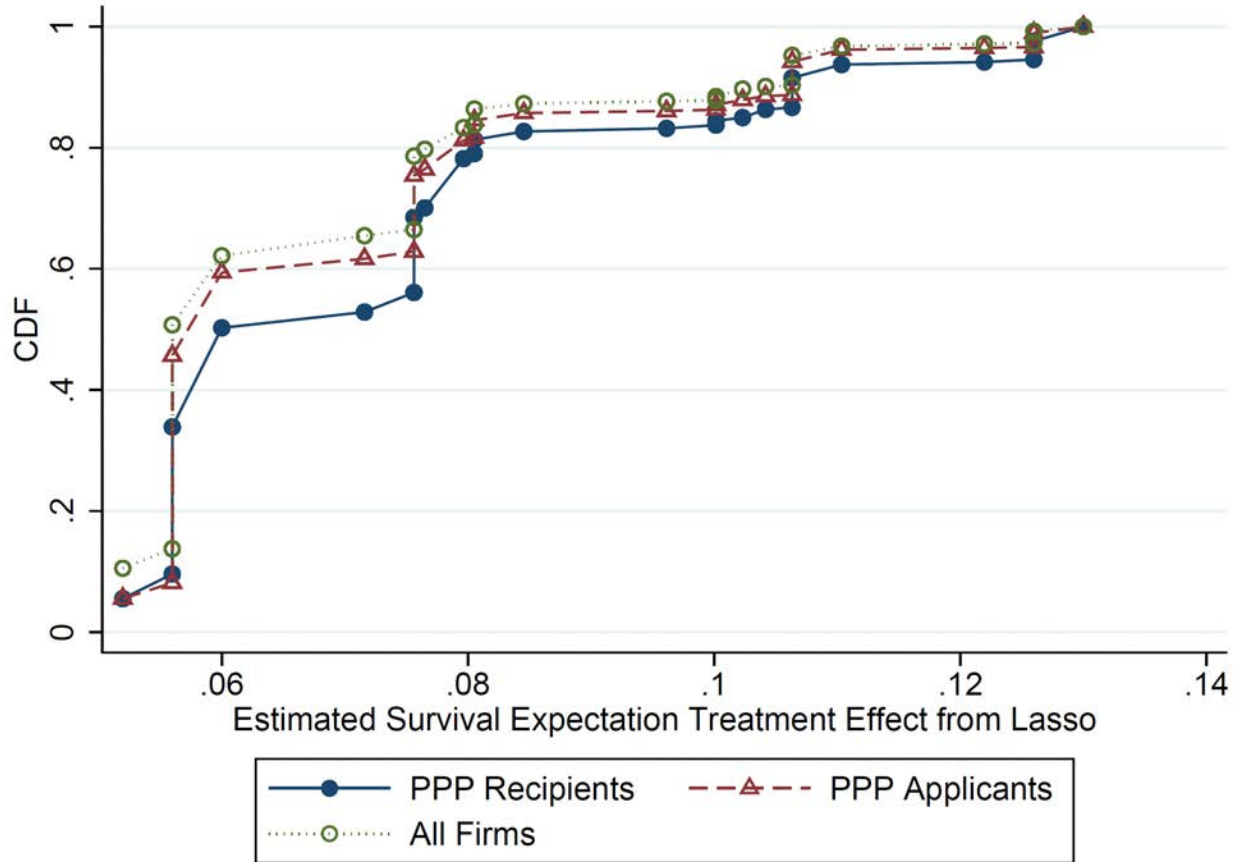


Figure 5. Estimated distributions of heterogeneous treatment effects on firm employment percentage changes. Treatment effects are estimated among applicants by fitting Lasso models of approval interacted with firm, bank-relationship, and industry characteristics. Specifically, the possible interactions are between PPP approval and COVID severity, months of cash available, monthly fixed expenditures pre-COVID, pre-COVID employment categories, an indicator for a bank loan, an indicator for a loan officer relationship, and 2-digit industry dummies. Treatment effects are projected to non-applicants based on these characteristics.

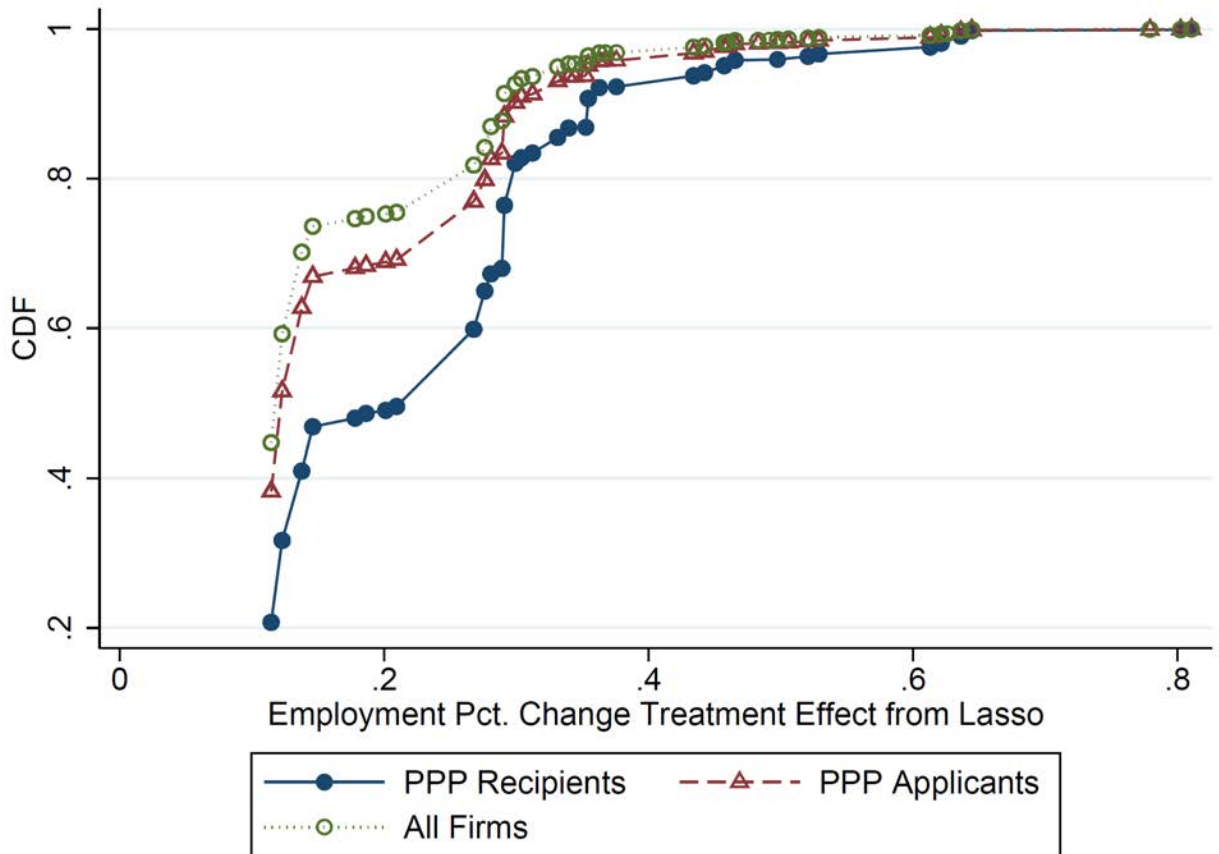


Table 1: Summary Statistics

This table reports summary statistics. Open on 4/25/2020 is an indicator that the firm was open for business at the time of the survey. Survival expectations are the probability a firm expects to be open in December 2020. Applied for PPP is an indicator that the firm applied or intended to apply for PPP in the past, with approval, pending, or denial/unable as outcomes. PPP denied/unable indicates 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 was categorical in the survey instrument and had a maximum value of “3 or more months”. Payroll and fixed expenses are in thousands of dollars for the typical month before Covid-19 disruptions. Top 4, top 5-10, top 11-20, 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
Open on 4/25/2020	5903	0.56	0.50	0	1	1
Survival Expectation	5903	0.73	0.28	0.5	0.8	1
Applied for PPP	5903	0.67	0.47	0	1	1
PPP Approved	3945	0.24	0.43	0	0	0
PPP Pending	3945	0.51	0.50	0	1	1
PPP Denied/Unable	3945	0.24	0.43	0	0	0
4/25 Employees	5903	5.45	17.17	1	2	5
Jan Employees	5903	7.60	21.38	1	3	7
High Covid Impact	5903	0.78	0.42	1	1	1
Cash (weeks)	5903	5.23	4.49	1	6	12
Payroll (\$k)	5903	24.36	75.87	5	5	17.5
Fixed Expenses (\$k)	5903	14.97	39.24	5	5	17.5
Top 4 Bank	5903	0.35	0.48	0	0	1
Top 5-10 Bank	5903	0.13	0.33	0	0	0
Top 11-20 Bank	5903	0.03	0.17	0	0	0
Credit Union	5903	0.11	0.31	0	0	0
Existing Loan	5903	0.40	0.49	0	0	1
Loan Officer	5903	0.24	0.43	0	0	0

Table 2: PPP Applications, Approvals, and Denials.

This table displays regressions of PPP application, approval, and denial indicators as of April 25, 2020 on firm and banking relationship characteristics. In columns 2 and 3, the sample is restricted to firms that applied for PPP. Receipt rate in column 4 does not condition on applying for PPP. The excluded category for banking relationships is non-credit union smaller banks. Absolute values of t-statistics clustered by bank name (or category for sparsely populated banks) are reported in brackets, with 61 clusters represented.

	Application Rate	Approval Rate	Denial Rate	Receipt Rate
High Covid Impact	0.24 [16.36]	-0.04 [1.80]	0.06 [3.06]	0.04 [4.53]
High Cash	-0.12 [10.12]	0.15 [5.59]	-0.07 [4.79]	0.08 [4.84]
High Payroll	0.21 [18.28]	0.13 [3.96]	-0.13 [6.98]	0.14 [4.15]
Top 4 Bank	0.00 [0.15]	-0.22 [9.78]	0.03 [1.04]	-0.15 [-9.96]
Top 5-10 Bank	0.01 [0.59]	-0.15 [5.54]	0.04 [3.63]	-0.10 [5.21]
Top 11-20 Bank	0.02 [1.04]	0.07 [1.19]	-0.04 [1.76]	0.05 [1.06]
Credit Union	-0.06 [5.15]	-0.11 [5.07]	0.10 [7.62]	-0.09 [6.88]
Existing Loan	0.05 [4.59]	0.03 [1.79]	-0.04 [3.47]	0.04 [2.50]
Loan Officer	0.08 [6.54]	0.06 [3.07]	-0.01 [0.78]	0.07 [4.05]
Adj R2	0.18	0.16	0.06	0.15
N	5903	3945	3945	5903

Table 3: OLS Estimates of Survival Expectations, Operational Status, and Employment

This table reports OLS estimates relating whether a firm had been approved for the PPP program as of April 25, 2020 to its expectations of survival at the time of the survey, operational status as-of late July 2020, 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. In Columns 1-6 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 6 of Panel A restricts to the sample in Column 7. Column 7 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 25, 2020, and we control for firm employment in January. In Panel C, the dependent variable is the inverse hyperbolic sine transformation of April 25 employment, and we control for the inverse hyperbolic sine of January employment. In all panels, column 2 controls for industry and state, column 3 for whether the business was open at the time of the survey, column 4 for its remaining cash on hand, column 5 reweights the sample to match the industry and size composition of the population of firms receiving PPP. t-statistics clustered by bank are reported in brackets.

Panel A: Survival Expectations and July Operational Status							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Survival Expectations					Status	
PPP approved	0.14 [21.32]	0.14 [20.18]	0.12 [18.86]	0.09 [14.95]	0.1 [8.79]	0.08 [7.18]	0.13 [4.60]
Adj R2	0.05	0.09	0.14	0.2	0.21	0.18	0.06
N	3945	3945	3945	3945	3945	1938	1938
Panel B: Employment as of April 25, 2020							
PPP approved	2.34 [2.35]	2.18 [2.47]	1.9 [2.17]	1.73 [2.11]	3.24 [2.05]		
Adj R2	0.55	0.55	0.56	0.56	0.48		
N	3945	3945	3945	3945	3945		

Panel C: Employment Pct Changes (Inv. Hyperbolic Sine)

PPP approved	0.31 [9.08]	0.3 [9.56]	0.26 [9.40]	0.23 [9.75]	0.3 [5.59]			
Adj R2	0.5	0.51	0.54	0.55	0.53			
N	3945	3945	3945	3945	3945			
Industry FE	N	Y	Y	Y	Y	Y		Y
State FE	N	Y	Y	Y	Y	Y		Y
Bus Status FE	N	N	Y	Y	N	Y		Y
Cash FE	N	N	N	Y	N	Y		Y
Rewighted	N	N	N	N	Y	N		N

Table 4: IV Estimates of Survival Expectations, Operational Status, and Employment Changes

This table reports LIML regressions relating whether a firm had been approved for the PPP program as of April 25, 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 25, 2020, and we control for employment in January. In Panel C, the dependent variable is the inverse hyperbolic sine transformation of April 25 employment, and we control for the inverse hyperbolic sine of January employment. In all panels, we instrument for PPP approval with the dummies for banking relationships (grouping by bank type if sparse) and estimate the model via LIML, which yields very similar results to improved jack-knife IV. Column 2 adds controls for the firm’s state and industry. Column 3 adds controls for whether the business was open at the time of the survey. Column 4 adds controls for cash on hand. Column 5 reweights the sample to match the industry and size composition of the population of firms receiving PPP. Column 6 restricts the sample to firms that bank with a large (top 20) bank. Column 7 restricts the sample to firms that bank with banks outside the top 20, excluding credit unions. Column 8 in Panel A uses actual survival and has the same controls as Column 4. t-statistics clustered by bank are reported in brackets. The most conservative Montiel-Pflueger effective F statistic for the full sample after clustering by bank is 65.8. It is 54.3 among large banks and 22.3 among small banks excluding credit unions.

Panel A: Survival Expectations and July Operational Status								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Survival Expectations							Status
PPP approved	0.2 [6.63]	0.23 [6.77]	0.2 [5.80]	0.13 [3.88]	0.24 [5.82]	0.1 [2.92]	0.1 [0.27]	0.18 [2.58]
Adj R2	0.04	0.08	0.13	0.19	0.1	0.17	0.22	0.06
N	3945	3945	3945	3945	3945	2045	1556	1938
Panel B: Employment as of April 25, 2020								
PPP approved	6.09 [2.78]	5.17 [2.48]	4.49 [2.24]	4.44 [2.17]	3.83 [1.04]	4.05 [1.45]	-2.79 [0.97]	
Adj R2	0.54	0.55	0.55	0.55	0.48	0.46	0.73	
N	3945	3945	3945	3945	3945	2045	1556	

Panel C: Employment Pct Changes (Inv. Hyperbolic Sine)

PPP approved	0.39 [2.81]	0.35 [2.16]	0.22 [1.47]	0.17 [1.08]	0.16 [0.70]	0.28 [1.10]	-0.15 [0.72]	
Adj R2	0.5	0.51	0.54	0.55	0.54	0.48	0.62	
N	3945	3945	3945	3945	3945	2045	1556	
Industry FE	N	Y	Y	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y	Y	Y
Bus Status FE	N	N	Y	Y	N	Y	Y	Y
Cash FE	N	N	N	Y	N	Y	Y	Y
Reweighted	N	N	N	N	Y	N	N	N

Table 5: Survival Expectations and PPP Approval: Heterogeneous Treatment Effects

This table relates firm outcomes to PPP approval as of April 25, 2020 as a function of firm characteristics (in column headings) denoted Z. “Covid Impact” is the firm’s reported impact from COVID, “Cash” is months of cash on hand at the time of the survey, “Loan” indicates the firm had a bank loan, “Officer” indicates the firm had a relationship with a loan officer, “Payroll” is the firm’s monthly wage bill, “Fixed expenses” are non-variable monthly expenses, and “Industry Cen” is a measure of the network importance to other firms based on the share of business-to-business industry sales. In Panel A, the outcome is the probability a firm expects to be open in December 2020, reported in 10 percentage point increments. In Panel B, the dependent variable is employment as of April 25, 2020, controlling for employment in January. In Panel C, the dependent variable is the inverse hyperbolic sine transformed employment level. We instrument for PPP approval with the firm’s bank dummy and for the interaction of approval and characteristic Z with the firm’s bank dummy interacted with Z. Characteristic Z is also included in the regressions but coefficients are not reported for brevity. All specifications include fixed effects for industry, state, whether the business was open at the time of the survey, and the business’s cash on hand. Panels B and C include controls for January employment in levels or the inverse hyperbolic sine of employment. t-statistics clustered by bank reported in brackets.

Panel A: Survival Expectations							
Z=	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Covid Impact	Cash	Loan	Officer	Payroll	Fixed Expenses	Industry Centrality
PPP approved x high Z	0.07 [1.22]	-0.12 [1.96]	-0.01 [0.07]	-0.06 [1.16]	0.11 [2.11]	-0.04 [1.23]	0.06 [0.91]
PPP approved	0.06 [1.54]	0.18 [2.83]	0.16 [1.96]	0.17 [2.95]	0.02 [0.37]	0.18 [3.39]	0.13 [2.46]
Adj R2	0.05	0.09	0.14	0.2	0.21	0.18	0.06
Panel B: Employment as of April 25, 2020							
PPP approved x high Z	-1.1 [0.51]	-1.06 [0.28]	4.17 [2.05]	-0.64 [0.23]	0.8 [0.25]	2.9 [1.08]	4.38 [1.26]
PPP approved	4.34 [1.93]	5.95 [1.53]	1.2 [0.58]	4.76 [1.66]	2.37 [0.95]	1.61 [0.79]	1.98 [0.71]
Adj R2	0.56	0.55	0.55	0.55	0.59	0.56	0.56

Panel C: Employment Pct Changes (Inv. Hyperbolic Sine)

PPP approved x high Z	-0.28	-0.04	0.42	0.31	0.64	0.46	-0.18
	[1.97]	[0.12]	[2.04]	[1.69]	[3.41]	[2.63]	[1.17]
PPP approved	0.28	0.3	0.02	0.08	-0.39	-0.14	0.4
	[2.74]	[0.91]	[0.09]	[0.37]	[1.67]	[-0.52]	[1.97]
Adj R2	0.54	0.55	0.54	0.55	0.54	0.54	0.54
N	3945	3945	3945	3945	3945	3945	2495

Table 6: Estimates of Treatment Effect Heterogeneity and Bank Bias

This table reports the standard deviation of treatment effects, estimated from Lasso regressions fit on the sample of applicants, where we interact PPP approval with applicant characteristics. The possible interactions are between PPP approval and COVID severity, months of cash available, monthly fixed expenditures pre-COVID, pre-COVID employment (categorical), an indicator for a bank loan, an indicator for a loan officer relationship, and 2-digit industry dummies. Given these characteristics, we project the potential treatment effects on all firms (not just applicants). The last row gives the mean and standard error approval bias relative to random sampling from applicants, computed as the average treatment effect among recipients less the average treatment effect among applicants.

Panel A: Survival Expectations				
<u>Treatment Effect Moments for:</u>	Mean	(Std Error)	Standard Deviation	(Std Error)
Recipients	0.074	0.009	0.022	0.007
Applicants	0.07	0.009	0.02	0.007
All Firms	0.068	0.009	0.019	0.007
Difference Relative to Random Allocation	0.003	0.003		
Difference Relative to Best Possible Allocation	-0.026	0.008		
Panel B: Employment Percent Changes				
<u>Treatment Effect Moments for:</u>	Mean	(Std Error)	Standard Deviation	(Std Error)
Recipients	0.231	0.057	0.124	0.044
Applicants	0.185	0.047	0.105	0.038
All Firms	0.171	0.044	0.096	0.035
Difference Relative to Random Allocation	0.046	0.021		
Difference Relative to Best Possible Allocation	-0.106	0.049		

Internet Appendix for The Targeting and Impact of Paycheck Protection Program Loans to Small Businesses

APPENDIX A: Additional Model Results and Proofs of Propositions

Here we provide additional model results that make the model more comparable to the actual design of the PPP program. This section also provides proofs of all model propositions.

We first compare fixing the loan size at T per firm with allowing bank flexibility. Since we assumed measure 1 of businesses above, we are holding the total amount of funds allocated to the lending program fixed at T . 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 coefficient from a regression of the social welfare of lending on the bank's rule. If that slope is more than one-half, so that on average the bank gets it right, then social welfare benefits by giving the bank discretion. If the slope is smaller than one-half, then higher social surplus is generated by tying the bank's 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 (i.e., a closer alignment of social and bank objectives) 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. There was a cap on loan size, but many loans came in below that cap. We now compare loans that are fixed in size at T , with loans that are fixed in size at $T' > T$. We continue to hold the total amount of funds fixed

at T , so that banks can allocate more financing to the firms that they favor, but these larger loans cannot be distributed to the full measure 1 of firms. This proposition formally analyzes 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 $\phi \leq 0$, it is never optimal to set $T' > T$.

(ii) If $\phi > 0$, 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 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 bank 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, i.e., diminishing returns involved in lending are weaker. 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.

Proof of Proposition 1: If the banks hand out cash $e^{\phi\alpha + \xi}x^{\gamma-1}$ is constant over borrowers or $x = (e^\beta/k_B)^{\frac{1}{1-\gamma}}$, where k_B solves the adding up constraint of $T = \int_\beta (e^\beta/k_B)^{\frac{1}{1-\gamma}}g(\beta)d\alpha$, 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, $x = T e^{\frac{\beta}{1-\gamma} - \frac{\sigma_\beta^2}{2(1-\gamma)^2}}$. Condition upon α , welfare based on bank discretion is

$$\int_{\xi} e^{\alpha} \left(T e^{\frac{\phi\alpha + \xi}{1-\gamma} - \frac{\sigma_\beta^2}{2(1-\gamma)^2}} \right)^{\gamma} h(\xi) d\xi = e^{\frac{(1-\gamma+\phi\gamma)\alpha}{1-\gamma}} T^{\gamma} e^{-\frac{\gamma(\phi^2\sigma_\alpha^2)}{2(1-\gamma)^2} - \frac{\gamma\sigma_\xi^2}{2(1-\gamma)}}. \quad \text{Integrating over } \alpha \text{ then}$$

$$\text{yields total social welfare of } T^{\gamma} e^{\frac{(1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}}.$$

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 $q =$

$$\theta\alpha + \zeta \text{ and } \sigma_q^2 \text{ is the variance of } \beta. \text{ Welfare equals } \int_{\alpha} \delta e^{\alpha} \left(\frac{T}{\delta} e^{\frac{q}{1-\gamma} - \frac{\sigma_q^2}{2(1-\gamma)^2}} \right)^{\gamma} m(q) dq =$$

$$\delta^{1-\gamma} T^{\gamma} e^{\frac{(1-\gamma(1-\theta)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}}.$$

Welfare is higher with delay if and only if $\delta^{1-\gamma} T^{\gamma} e^{\frac{(1-\gamma(1-\theta)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}} > T^{\gamma} e^{\frac{(1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2}{2(1-\gamma)}}$ or

$$\delta > e^{\frac{[(1-\theta)^2 - (1-\phi)^2]\sigma_\alpha^2 + \sigma_\xi^2 - \sigma_\xi^2}{2(1-\gamma)^2}}. \quad \text{This condition clear does not hold when } \delta = 0 \text{ and must hold when}$$

$\delta = 1$ as we have assumed that $[(1-\phi)^2 - (1-\theta)^2]\sigma_\alpha^2 + \sigma_\xi^2 - \sigma_\xi^2 > 0$. 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 than immediate lending if and

only if $\delta > \delta^*$, where $\delta^* = e^{-\frac{[(1-\phi)^2 - (1-\theta)^2]\sigma_\alpha^2 - \sigma_\xi^2 + \sigma_\xi^2}{2(1-\gamma)^2}}$. Differentiation then yields that δ^* is falling with $\gamma, \theta, \sigma_\xi^2$ and σ_α^2 , and rising with ϕ and σ_ξ^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

$$\sigma_\alpha^2(1-\gamma) > (1-\gamma(1-\phi)^2)\sigma_\alpha^2 - \gamma\sigma_\xi^2 \text{ or } \frac{1}{2} > \frac{\phi\sigma_\alpha^2}{\sigma_\xi^2 + \phi^2\sigma_\alpha^2} \text{ or } \frac{\sigma_\xi^2}{\sigma_\alpha^2} > 2\phi - \phi^2.$$

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

$$\left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_\beta^2}} d\beta \right)^{-\gamma} T^\gamma \int_{\beta > \hat{\beta}} E(e^\alpha | \beta) g(\beta) d\beta \text{ where } E(e^\alpha | \beta) = \frac{\int_\alpha e^\alpha h\left(\frac{\beta - \phi\alpha}{\vartheta}\right) f(\alpha) d\alpha}{\int_\alpha h\left(\frac{\beta - \phi\alpha}{\vartheta}\right) f(\alpha) d\alpha} =$$

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

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

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

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

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

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 $x = \beta -$

$$\phi\sigma_\alpha^2, \text{ we have } \int_{\beta > \hat{\beta}} e^{\frac{-(\beta - \phi\sigma_\alpha^2)^2}{2\sigma_\beta^2}} d\beta = \int_{x > \hat{\beta} - \phi\sigma_\alpha^2} e^{\frac{-x^2}{2\sigma_\beta^2}} dx.$$

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

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

If $\phi < 0$, then $\int_{x > \hat{\beta} - \phi\sigma_{\alpha}^2} e^{\frac{-x^2}{2\sigma_{\beta}^2}} dx < \int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta = \frac{T}{T'}$ and so $V(\hat{\beta}; Z) < \left(\frac{T}{T'}\right)^{1-\gamma} \leq 1$, 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:

$$\gamma e^{\frac{-\hat{\beta}^2}{2\sigma_{\beta}^2}} \left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta \right)^{-\gamma-1} \int_{\beta > \hat{\beta} - \phi\sigma_{\alpha}^2} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta - \left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta \right)^{-\gamma} e^{\frac{-(\hat{\beta} - \phi\sigma_{\alpha}^2)^2}{2\sigma_{\beta}^2}}, \text{ which is positive if}$$

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

$$-\left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta \right)^{-\gamma} \int_{\beta > \hat{\beta}} e^{\frac{-(\beta - \phi\sigma_{\alpha}^2)^2}{2\sigma_{\beta}^2}} d\beta \ln \left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta \right) > 0, \text{ and so that if some value of } T' > T$$

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

$$\sigma_{\beta}^2 \text{ constant) is positive, and given by } \sigma_{\alpha}^2 e^{\frac{-\hat{\beta}^2 + 2\phi\sigma_{\alpha}^2\hat{\beta} - \phi^2\sigma_{\alpha}^4}{2(\phi^2\sigma_{\alpha}^2 + \sigma_{\xi}^2)}} \left(\int_{\beta > \hat{\beta}} e^{\frac{-\beta^2}{2\sigma_{\beta}^2}} d\beta \right)^{-\gamma} > 0. \text{ Consequently,}$$

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 B: Survey Instrument

What impact are you currently experiencing from the Coronavirus Outbreak?

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

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

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

- 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

\$10 million - \$20 million

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.

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

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

0% Extremely Unlikely

10%

20%

30%

40%

50%

60%

70%

80%

90%

100% Extremely Likely

Is your business open?

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

- 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

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

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?

Already gone

Less than 2 weeks

2 weeks to 1 months

1 to 2 months

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?

0

1

2

3

4

5

6

7

8

9

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

More than \$10 million

What is your main industry?

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

Other Services (except Public Administration)

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.

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

Appendix C: Additional Figures and Tables

Figure A1. This figure displays the share of loans by loan-size buckets in the SBA administrative data and in the survey. The survey had recipients choose the amount of funding they were approved for out of the following categories: under \$10,000; \$10,000-\$25,000; \$25,000-\$50,000; \$50,000-\$75,000; etc. The SBA data prior to tranche 2 are classified based on the midpoint of these categories, and loan amounts are top-coded at \$2.5 million. Each point thus represents the midpoint of the categories in the Alignable survey. The x-axis is on a log scale in thousands of dollars.



Figure A2. This figure plots PPP application, approval, pending, and denial rates as of April 25, 2020 by firm owner demographics. The sample includes 1628 observations with owner demographics collected from subsequent Alignable surveys and matched to the main survey wave.

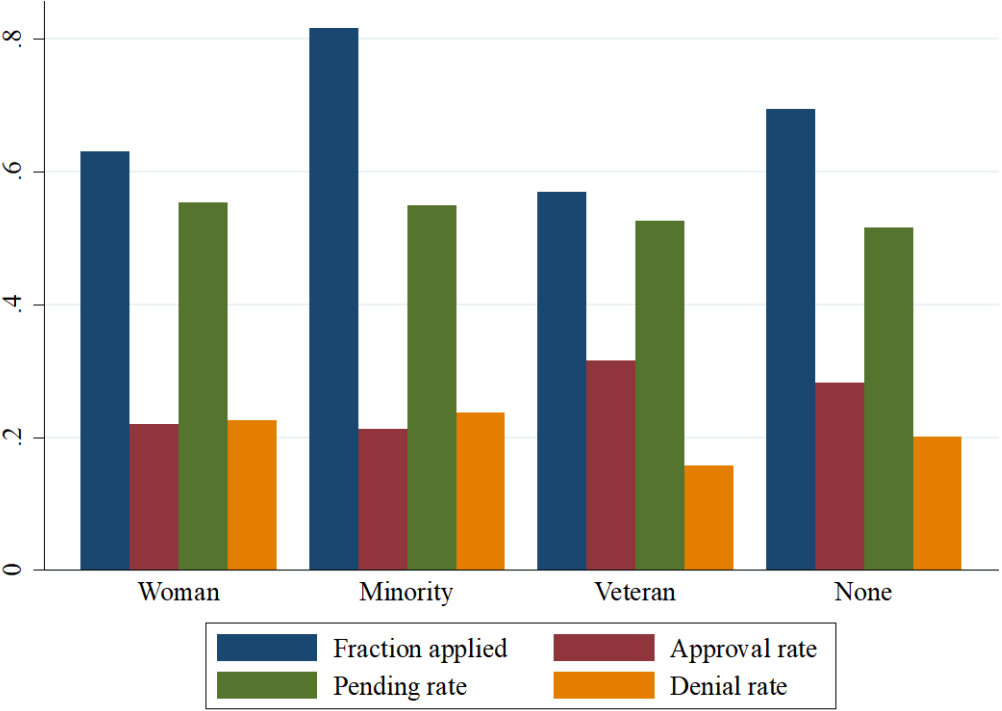


Figure A3. Approval rates by bank size for firms with low cash and large existing loans.

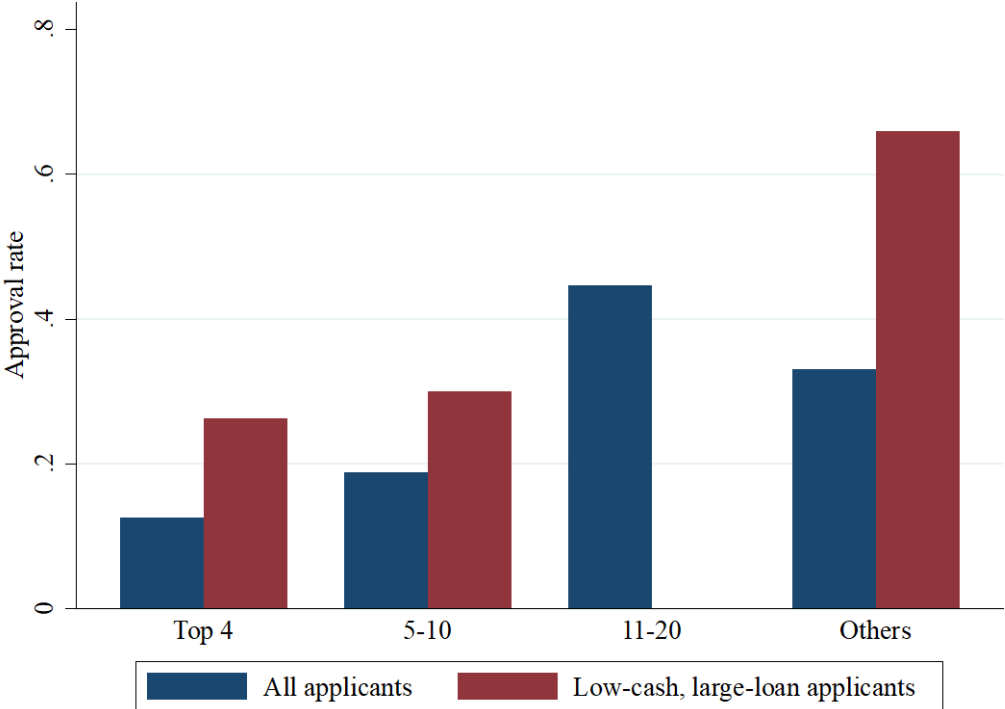


Table A1. Total PPP applications, approvals, and PPP loan amounts by bank size

This table reports aggregate statistics on PPP applications, approvals, and PPP loans amounts by bank size or characteristics. The top banks are ranked by size. Small business specialists are top 20 banks by small business lending volume but not by assets. Others contains all other banks besides credit unions, small business specialists, and the top 20 banks by assets. For total applications and approvals, the sample includes 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 657 out of 964 approved firms that report loan amounts. Therefore, total dollars of loans approved are understated.

	<u>Top 4</u>	<u>Top 5-10</u>	<u>Top 11-20</u>	<u>Small Business Specialists</u>	<u>Credit Unions</u>	<u>Others</u>
Total PPP applications	1401	511	130	197	332	1374
Total approved PPP loans (#)	176	97	58	57	61	510
Total approved PPP loans (\$m)	31.1	9.7	4	6.6	2	73.9
Average PPP loan size (\$000)	338	147	109	190	51	192

P-Value on Joint Test of All Bank Type Coefficients	<.01	<.01	<.01	<.01	<.01	<.01	<.01	<.01
P-Value on Joint Test Excluding Credit Unions	0.105	0.137	0.011	0.004	0.328	0.04	<.01	<.01
P-Value on Top 5-10 = 0 and Top 11-20 = 0	0.577	0.713	0.757	0.151	0.808	0.149	0.282	0.339
P-Value of Specialists = Other	0.179	0.166	0.299	0.35	0.987	0.79	0.462	0.517
Industry FE	N	Y	N	Y	N	Y	N	Y
State FE	N	Y	N	Y	N	Y	N	Y
Bus Status FE	N	Y	N	Y	N	Y	N	Y
Cash FE	N	Y	N	Y	N	Y	N	Y