Effects of the Paycheck Protection Program on Small Businesses' Financial Health and Real Activity

Olga Gorbachev
University of Delaware

Maria Luengo-Prado
ICAE

J. Christina Wang
Federal Reserve Bank of Boston

March 28, 2024

Abstract

Using data on firms' real performance and financial well-being, this study explores the likely mechanism through which the Paycheck Protection Program (PPP) affected small businesses' recovery in the aftermath of COVID-19. Our results reveal a positive, significant, and enduring resurgence in the activity and financial health of PPP recipients relative to closely matched non-recipient peers. Early recovery in real activity predicts modest subsequent improvement in PPP firms' financial health relative to peers, but not vice versa. This suggests the PPP aided small businesses' recovery more by facilitating continued operations than by providing liquidity reserves to finance expanded production later on.

1 Introduction

In response to the COVID-19 outbreak, Congress passed the CARES Act on March 27, 2020. Together with subsequent legislation, a total of $525 billion was appropriated in 2020 to fund the Paycheck Protection Program (PPP). The goal of the PPP was to provide small businesses with the much needed liquidity to weather the widespread disruptions wrought by the pandemic. Small businesses, broadly defined as those with no more than 500 employees, were eligible for PPP funding, primarily to either maintain employment despite the loss of income due to initial lockdown orders, or to hire back laid-off employees as the economy reopened. In addition, the funds could also be used to pay for eligible expenses, such as rent, utilities, and interest payments on mortgages and other debts.

We examine the impact of PPP funding on businesses' recovery from the pandemic's effects, concurrently exploring the relationship between the PPP, economic activity (as measured by foot traffic), and financial well-being (as measured by credit scores). Our results indicate a positive correlation between PPP funds receipt and business metrics of real activity and financial health. Specifically, businesses that received PPP funds exhibited a substantial and enduring resurgence in business activity and financial health relative to closely matched (nearest-neighbors) non-recipient counterparts, as well as a reduction in closures. These effects were particularly notable in industries heavily impacted by the pandemic. In terms of the timing of the recovery in financial condition versus real activity, we find that the enhancement in PPP recipients' finances did not precede the upturn in their real activity. Instead, foot traffic to PPP firms and their financial conditions improved largely in tandem. Outside the very small firms, we demonstrate that the timing of PPP receipt was not as crucial as the actual receipt of funds. Firms that received PPP early in the pandemic displayed statistically similar trends to those receiving funds at a later stage. We also document that an early rebound in economic activity predicts subsequent modest enhancements in the financial health of PPP firms relative to their peers, as indicated by credit scores. However, early relative improvements in credit scores do not necessarily lead to significantly larger disparities in economic activity later on. This suggests the PPP aided small businesses' recovery more by facilitating their continued operations than by providing liquidity reserves to finance expanded productions later on.

Research on the impact of the PPP consistently suggests that the program mitigated the employment losses caused by the pandemic, yet at a high cost. Various studies, including those by Gorbachev, Luengo-Prado, and Wang (2024), Granja et al. (2022), Autor et al. (2022), Doniger and Kay (2023), Balyuk, Prabhala, and Puri (2021), and Li and Strahan (2021), support this conclusion. Cole (2022), a study closely aligned with ours, utilizes private payroll data from very small firms (with a median of 5 employees) in the Southwest of the US and reports a 7.5 percent increase in average employment at PPP firms compared to their peers in the five months following loan approval. In contrast, our study covers a broader geographic scope (the entire US) and includes businesses of all sizes, with our control group of peers being more precisely matched to PPP borrowers. Nevertheless, our findings align with those of Cole (2022): a substantial and enduring rise in visits and visitors, and a notable reduction in business closures for PPP recipients compared to their peers. Moreover, we find that these effects persist irrespective of the timing of loan receipt. It is crucial to highlight that, beyond the dimensions investigated in earlier papers, our study provides additional evidence on the influence of PPP on firms' financial well-being.

The remainder of this study is organized as follows: Section 2 describes our main empirical specification and discusses the effect of the PPP on recipient firms' foot traffic, input spending, and credit scores. Section 3 focuses on the timing of the PPP effects on foot traffic versus credit scores, and Section 4 concludes.

2 The Impact of the PPP on Firms' Economic Activity and Financial Health

To gauge economic activity at the firm level, we utilize Advan data, which captures foot traffic based on mobile devices utilizing GPS location for tracking movements to and from points of interest (POIs). In examining the impact of PPP funding on the economic recovery, we first identify PPP recipients in the Advan data. Subsequently, we create observationally equivalent (nearest-neighbor) pairs by matching each PPP recipient with a business operating pre-pandemic in the same Census Block Group (CBG) and in the same industry, according to the the 6-digit North American Industry Classification System (NAICS-6).[1]

To understand the impact of PPP funding on business' financial health, we match Advan pairs to Cortera data. Cortera is a major US business credit registry, providing

[1]When multiple non-PPP businesses satisfy the location-industry matching condition vis-à-vis a given PPP recipient, we choose the one with the most similar number of visits just before the pandemic started (average weekly visits over December 2019 to February 2020).

data on businesses' payment records, credit risk scores and spending on materials and supplies. This matched sample will be referred to as the Cortera sub-sample in subsequent analyses.[2] Among both PPP recipients and their counterparts within our Cortera sub-sample, log visits are highly correlated with log spending, both before and after the onset of COVID-19 (see Appendix Figure A.1).[3] This high cross-sectional correlation corroborates that visits serve as an informative proxy for the level of a business' real commercial activity. Summary statistics for the full Advan sample and the Cortera sub-sample are presented in Tables A.1 and A.2 in the Appendix.

We study the effects of PPP receipt within each pair over time at a monthly frequency. With our matched-pair sample, we first estimate the PPP's effect using the following specification:

$$Y_{ijt} = \alpha_i + \delta_{jt} + \beta_t \, \mathrm{PPP}_i + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is the outcome variable of interest for firm i within the matched pair j in month t, α_i denote firm fixed effects, δ_{jt} are pair-by-time fixed effects, and PPP_i is a dummy variable equal to one if firm i received PPP funding and zero otherwise. β_t measures the effect of PPP in month t. Standard errors are clustered at the pair-id level.

We also apply the Sun and Abraham (2021) estimator, which yields consistent estimates of staggered heterogeneous treatment effects relative to timing of receipt:

$$Y_{ijt} = \alpha_i + \delta_{jt} + \sum_{l=-T+1}^{-2} \mu_l D_{ijt}^l + \sum_{l=0}^{T} \mu_l D_{ijt}^l + \epsilon_{ijt}, \tag{2}$$

where $D_{ijt}^l = \mathbb{I}\{t - K_i = l\}$, and K_i is the month when firm i received a PPP loan.

Note that by including δ_{jt}, the pair-by-time fixed effects, we simultaneously control for time-varying location and industry-specific factors, including industry and location

[2] We are not able to match all firms in the Advan data to Cortera records, so the resulting Cortera-Advan matched sample is a strict sub-sample, and it contains firms that are on average slightly larger than the full Advan sample.

[3] Appendix A contains details on the datasets used, along with the sample and variable construction.

fixed effects. That is, our analysis accounts for common changes in local-industry conditions over time, such as local COVID-19 impact intensity or adopted measures, local receipt of stimulus funds and unemployment insurance extensions, information on the overall amount of funding received or the number of jobs saved in a given area and industry, and other such controls. Firm fixed effects, α_i, remove time-invariant, firm-specific effects.

The PPP effect on foot traffic

We first examine the impact of PPP receipt on the number of visits to a business establishment and the likelihood of having zero visits as our proxy for business closure, which might be temporary or permanent. We computed Log Visits as the log of number of visits plus one; and Zero Visits as an indicator equal to one when visits are recorded as zero in the Advan data, or when a firm is not observed in a given month.[4]

Figure 1 clearly shows that PPP recipients experienced a significant increase in visits relative to their non-recipient peers. This impact was substantial, marked by a noteworthy 10 percent increase relative to pre-pandemic levels by the end of 2020. Notably, the PPP funding allowed recipients to weather the storm without immediately reopening during the peak of the first COVID-19 wave. Instead, their visits (relative to peers) temporarily dropped during that period but more than recovered as the economy accelerated in Fall 2020. This trend is depicted in the left-hand side (LHS) panel of Figure 1, based on the regressions in calendar time. The temporary reduction in operations for PPP recipients did not result in permanent damage, as the number of closures or zero visits significantly decreased over time for these firms compared to their non-PPP peers. Importantly, these effects likely represent a lower bound of the actual impact of PPP funds because we could not match 30 percent of PPP recipients to

[4]Our sample is initially constructed based on PPP receipt. Therefore, it includes only firms that were operational at the time of PPP receipt/match. However, peer firms are identified from the set of firms that were already operating prior to the pandemic (specifically from December 2019 to February 2020). When Advan reports no traffic to a specific firm in the match, we fill its monthly observations with zero visits. This approach ensures the continued inclusion of all firms in our regression sample, maintaining the balance of our panel dataset.

Advan data, resulting in the possibility that some nearest-neighbor peers were in fact PPP recipients.

The PPP effect on spending and credit scores

Next, we examine whether the PPP had effects on businesses' financial health and their spending on materials and supplies, as it did on visits. The bottom panel of Figure 2 confirms that our Cortera sub-sample shows similar trends in log visits and zero visits as our full Advan data sample analyzed in Figure 1. The magnitude of the effect is smaller (up to 10 percent increase in foot traffic 20 months after loan receipt, versus 20 percent in the full Advan sample). Since the companies in our Cortera sub-sample tend to be larger on average than those in the full Advan sample, this finding suggests that the PPP had a more pronounced beneficial impact on smaller enterprises. The top panel of Figure 2 illustrates that PPP receipt had positive effects beyond simply increasing visits and reducing the likelihood of closure. Given the liquidity injection, PPP borrowers, compared to their non-recipient peers, experienced a noticeable and persistent improvement in their overall creditworthiness—an extra boost to borrowers' credit scores of on average 10 points or more, starting from six months after the loan receipt,[5] and lasting for almost two years after the injection of funding.

In contrast, the increase in spending on intermediate inputs by PPP borrowers relative to their control peers was statistically insignificant. This lack of significant differences in expenditures on business supplies, unlike the significant disparities in the growth in visits, could be attributed to the exclusion of several PPP-eligible major expense categories, such as labor compensation and rent, from Cortera's spending data.[6] Additionally, the inherent noise in Cortera's spending data, which only captures transactions between firms within the Cortera network, may have been exacerbated by the pandemic because of supply chain disruptions and other factors. By comparison, credit

[5] An increase of 10 points is one-fifth of the within-firm standard deviation of the credit score before the pandemic (which averages to 49).

[6] Note also that this insignificant *average relative* difference in spending is not necessarily inconsistent with the high *cross-section* correlation between visits and spending shown earlier in Appendix Figure A.1.

scores provide a more reliable and informative signal because credit scores leverage a broader array of firms' activities, including bill payment records.

Heterogeneity of the PPP's effects by industry and date of loan receipt

The impact of the PPP was heterogeneous across industries, see the top panel of Figure 3. Consistent with our general findings, we observe that companies operating in industries heavily impacted by the pandemic — more affected industries — exhibited a substantial increase in foot traffic relative to their peers and compared to sectors that did not receive funds.[7] This is perhaps not surprising, since these sectors are well measured and represented in Advan data. The recovery of visits for firms within these industries took much longer (at least 4 months post fund receipt) due to delayed re-opening for these industries during the pandemic. However, this delay did not adversely affect the likelihood of survival. In fact, these firms exhibited a notably higher survival probability compared to their non-recipient peers and firms in other sectors.

The receipt of PPP funds could be endogenous, as better-performing firms were likely more inclined to apply for and receive PPP funds and concurrently had a heightened probability of survival. Our Cortera sub-sample supports this hypothesis, revealing that recipient firms had higher credit scores compared to their non-recipient counterparts pre-pandemic, see Figure 5. Furthermore, as Figure 6 shows, mean and median credit scores among the PPP recipients were monotonically higher the earlier a firm was approved for a loan, with the median score uniformly higher than the mean score. In spite of this pattern, the bottom panel of Figure 3 shows that the recovery in visits relative to peers for early PPP recipients (those receiving loans before May 2, 2020) was somewhat slower than that of later recipients.[8] Moreover, late 2020 PPP recipients suffered fewer closures relative to their peers than their early 2020 counterparts.

At first glance, this result may seem surprising, since firms receiving funding later

[7]More affected industries include NAICS 44 *Retail Trade*, 62 *Health Care and Social Assistance*, 71 *Arts, Entertainment, and Recreation*, 72 *Accommodation and Food Services*, and 81 *Other Services*. Less affected industries are all the others.

[8]It's noteworthy that 72 percent of SBA loans were approved before May 2, 2020. In our Cortera sub-sample this share was over 85 percent.

in the pandemic likely had to deal with financial constraints and the effects of the crisis for longer. On the other hand, these firms tend to be smaller and had smaller cash buffers (according to Granja et al. (2022), for example). To the extent they managed to survive until receiving a PPP loan, the funds were likely a larger boost to their liquidity (relative to their peer firms) than for the larger early recipients. It is thus possible that the receipt of PPP funding holds greater significance for recovery and firm survival than the timing of the receipt.[9] However, it is also possible that late recipients' peers had a higher probability of closure. Thus, later recipients might look better than earlier ones relative to their peers for this reason. This pattern is not present in the Cortera sub-sample, though (see Figure 4), as the difference between early and late recipients relative to their peers is insignificant across all outcomes examined, including financial health and spending. Since Advan firms are on average smaller than those in the Cortera sub-sample, our findings suggest that, if anything, only very small firms could have been potentially hurt by loan delays. We do not investigate loan delay effects further in this paper.

3 The Relationship and Timing of the PPP effects on Foot Traffic and Credit Scores

Relative to existing studies, the matched Cortera-Advan data enable us to gain further insight into the likely mechanisms through which the PPP contributed to the economic recovery. Specifically, the timing of the relationship between the PPP's impact on a firm's credit score and its level of real activity can help discern between at least two mechanisms. Did PPP recipients fare better in terms of real activity (foot traffic) because PPP funding improved their credit scores upfront and in turn enabled them to resume or even expand operations? Or did the process work in reverse? Or did the real and financial performance mutually reinforce each other? On one hand, we

[9] We reach a similar conclusion in a companion paper, Gorbachev, Luengo-Prado, and Wang (2024), where we focus on pairs that received funding in a very tight window, right before a 10-day funding delay (April 14th–16th) to those that received it immediately after (April 27th–28th), as studied in Doniger and Kay (2023).

may expect that PPP funding would quickly improve firms' finances, as funds could be used to settle existing bills and repay debt, thus boosting recipients' credit scores. By comparison, the program's positive impact on production and employment could take longer to materialize.[10] On the other hand, borrowers may have been able to remain open or reopen sooner owing to PPP funding, and the resulting increase in revenue could have improved credit scores subsequently, resulting in a virtuous cycle.

Table 1 investigates the timing of the relationship between the PPP's effect on recipients' credit scores and real activity based on the following regression:

$$\Delta Y_{i(j),t_2} - \Delta Y_{i(j),t_1} = \alpha + \beta(\Delta Y_{i(j),t_1} - \Delta Y_{i(j),t_0}) + \gamma(\Delta \mathrm{CS}_{i(j),t_1} - \Delta \mathrm{CS}_{i(j),t_0}) + \epsilon_{i(j),t_1,t_2}, \quad (3)$$

where $\Delta Y_{i(j),s}$ denotes the difference in real outcome variable Y (log visits), between PPP recipient i and its peer in the matched pair j in month s (with $s = t_0, t_1, t_2$). The left hand side thus measures the *relative* growth in visits to PPP firm i relative to its matched peer between periods t_1 and t_2. $\Delta \mathrm{CS}_{i(j),s}$ is likewise defined for credit scores (measured in simple changes instead of growth rates).[11] In all the estimations, t_1 denotes 2020:M6, three months after the outbreak, while t_0 denotes 2020:M2, the last pre-COVID-19 month. We interpret the change/growth rate between these months as the short-term impact of COVID-19. Three values of t_2, 2020:M12, 2021:M6 and 2021:M12 are chosen to correspond to a longer-term recovery over 6-, 12- and 18-month horizons after the initial period. Equation (3) estimates how the *relative* growth rate in visits for PPP recipients' later on in the pandemic relates to the relative change in credit scores immediately following the outbreak, after we control for possible autocorrelation in the relative growth in visits (that is, controlling for relative growth in visits from t_0 to t_1).

Column (1) in Panel A of Table 1 shows that, after the initial outbreak through

[10]During the pandemic, such delays could easily result from delayed recovery of commerce in certain localities due to imposed restrictions or fear of infection.

[11]Since credit scores in Cortera data directly map into default probabilities, we use simple changes to measure changes in default probabilities, see the Appendix for more details.

2020:M6, foot traffic and credit scores improved largely in tandem among PPP recipients relative to their peers.[12] To put the estimate in perspective, the average relative improvement in PPP's firms credit scores of 10 points (as shown in the top left panel of Figure 2) would correspond to 23 basis points faster growth in visits. By comparison, estimates in columns (2) to (7) indicate that in later months, the recipients' relative growth in visits was negatively correlated with the initial relative change in credit scores, although by a smaller magnitude than that shown in column (1).[13] The correlation, however, becomes mostly insignificant once we control for autocorrelation in the growth rate in relative visits. This result is hardly surprising given that the two RHS variables positively co-move (as shown in column 1).[14] The negative correlation with the lagged growth in visits is consistent with the idea that visits to firms hit harder early on in the pandemic ultimately caught up to their counterparts and recovered more vigorously upon reopening of the economy, as well as over the longer-term.[15] These dynamics are investigated further in Appendix Table A.3, which distinguishes the negative impact over the initial acute phase of COVID-19 (change between 2020:M2 and 2020:M4) from the immediate recovery (over 2020:M4 and 2020:M6). Column (3) shows that PPP firms hit harder (relative to their peers) early on recovered more vigorously upon reopening. In fact, even the longer-term recovery after 2020:M6 was stronger for borrowers initially hit harder by the pandemic, as can be seen in columns (5) and (7) of that table. On the other hand, borrowers receiving a larger boost (compared to their peers) to growth from the PPP early on during reopening (2020:M4–M6) showed less relative improvement later on, because their peers' performance caught up.[16]

In Panel B of Table 1, we explore the inverse relationship: to what extent early growth in visits is correlated with later changes in credit scores for PPP recipients

[12] In unreported results, we confirm that the short-term positive contemporaneous correlation reported in column (1) also holds for changes over longer horizons, through 2021:M12.

[13] Specifically, columns (2) and (3) examine the response from 2020:M6 to 2020:M12; columns (4) and (5) from 2020:M6 to 2021:M6; and (6) and (7) from 2020:M6 to 2021:M12.

[14] That is, when the lagged relative visit growth is not accounted for, its highly negative correlation with the later longer-term visit growth loads on the lagged relative change in credit score.

[15] This pattern can be rationalized with a simple AR(1) model of visits growth; see Appendix B for a detailed derivation.

[16] Again see columns (5) and (7) of Table A.3.

relative to their non-recipient peers. These estimates demonstrate that better relative growth in visits early on in the pandemic predicts greater improvement in credit scores in later months, as far as 18 months out, even after we control for the negative autocorrelation in the relative change in credit scores. However, the magnitude of this improvement is fairly modest.[17] The likely explanation for this pattern is that the cash flow from operations is the more enduring source of support for a firm's financial well-being over the longer term. Additionally, it generally takes time for a firm to attain meaningful changes in its credit score, as credit registries accumulate signals from a firm's actual commercial operation.

Collectively, our estimates indicate that the relative operational performance of PPP firms early on led the subsequent modest relative change in credit scores. In contrast, early improvements in the creditworthiness of PPP firms or their early recovery in visits did not necessarily foreshadow superior real performance at a later stage. Therefore, while it is possible that some of the initial increase in credit scores (and visits) resulted from PPP firms' improved ability to pay down existing debt or make timely payments, the initial relative increase in credit scores (visits) did not lead to an accelerated growth in visits over a longer period after the pandemic shock. This is reminiscent of the findings by Hurst and Pugsley (2011) that most small businesses show little desire to grow big. Consequently, additional financial resources from external sources may not necessarily lead to further expansion in operations later on. However, we do not observe whether these business owners used the additional resources to open new establishments in different locations. This is in fact a distinct possibility because, according to the U.S. Census Bureau's Business Formation Statistics, there were 5.4 million small business applications in 2021, an increase of 54 percent relative to 2019 levels. Given the rise of remote work, some small businesses in service industries may have followed the demand and relocated from urban centers to suburban locations, or opened additional locations in these areas.

[17] Holding all else constant, a 100 percent higher growth rate in visits over 2020:M2-M6 corresponds to a 4.5 to 6.4 points relative increase in the credit score six to 18 months after 2020:M6.

4 Summary and Concluding Remarks

Utilizing firm-level data on foot traffic and financial health, we document that businesses that received PPP funds experienced a substantial and lasting recovery in both business activity and financial health compared to narrowly-matched non-recipient counterparts. Business closures were also reduced, especially in industries most vulnerable to pandemic-induced disruptions. The PPP's positive effects were more pronounced for borrowers that were smaller or financially weaker, or both, and thus received PPP loans later.

More importantly, by combining data on firms' real activity and financial conditions, we gain further understanding of the likely mechanism through which the PPP supported the economic recovery. We find that improvements in PPP recipients' financial conditions and real business operations occurred largely simultaneously. Early credit score improvements among PPP firms did not necessarily lead to significant long-term differences in economic activity, whereas faster initial recovery in foot traffic led to subsequently (even if only modestly) better credit scores. This timing pattern suggests that the PPP provided meaningful short-term assistance to the recipients. Nevertheless, the long-term financial health of a firm depends on its business fundamentals, not a one-time modest liquidity injection.

Our analysis suggests that if a similar small-business funding program is needed in the future, prioritizing smaller firms in more affected industries would be more effective. Our findings indicate that PPP recipient firms exhibited limited expansion at existing locations relative to their nearest-neighbor peers. Additionally, there was a notable increase in new business applications following the COVID-19 outbreak. This combination suggests the need for further research into the PPP's effects on the dynamics of re-allocation during the pandemic. In particular, more data should be sought to study if the PPP facilitated the reallocation or opening of additional locations for some small businesses, following the shift of commercial activity from urban central business districts to suburban areas.

References

Autor, David, David Cho, Leland D. Crane, Mita Goldar, Byron Lutz, Joshua Montes, William B. Peterman, David Ratner, Daniel Villar, and Ahu Yildirmaz. 2022. "The $800 Billion Paycheck Protection Program: Where Did the Money Go and Why Did It Go There?" *Journal of Economic Perspectives* 36 (2): 55–80 (May).

Balyuk, Tetyana, Nagpurnanand Prabhala, and Manju Puri. 2021. "Small Bank Financing and Funding Hesitancy in a Crisis: Evidence from the Paycheck Protection Program." Available at SSRN: https://ssrn.com/abstract=3717259.

Cole, Allison. 2022, May 13. "The Impact of the Paycheck Protection Program on (Really) Small Businesses." Available at SSRN: http://dx.doi.org/10.2139/ssrn.3730268.

Doniger, Cynthia L., and Benjamin Kay. 2023. "Long Lived Employment Effects of Delays in Emergency Financing for Small Businesses." *Journal of Monetary Economics* 140:78–91.

Gorbachev, Olga, Maria Luengo-Prado, and J. Christina Wang. 2024. "Cities Disrupted: The Diverse Impact of the PPP and Other Pandemic Support Programs." Working Paper.

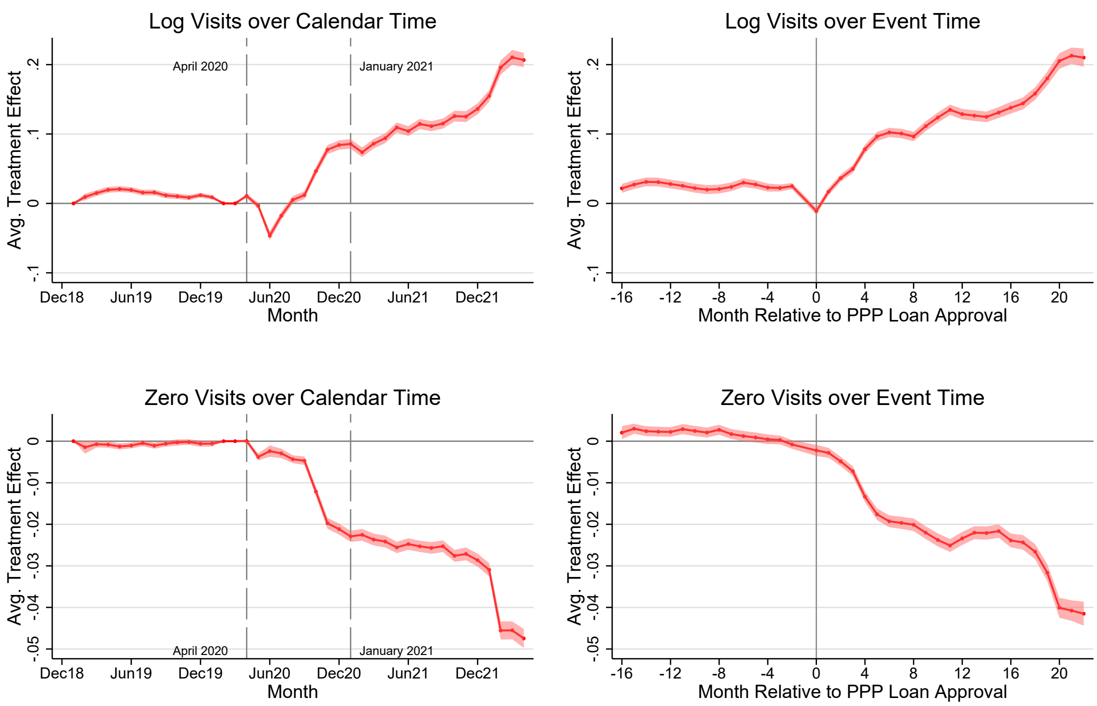
Granja, João, Christos Makridis, Constantine Yannelis, and Eric Zwick. 2022. "Did the Paycheck Protection Program Hit the Target?" *Journal of Financial Economics* 145 (3): 725–761.

Hurst, Erik, and Benjamin Wild Pugsley. 2011, May. "What Do Small Businesses Do?" Working paper 17041, National Bureau of Economic Research.

Li, Lei, and Philip E. Strahan. 2021. "Who Supplies PPP Loans (and Does It Matter)? Banks, Relationships, and the COVID Crisis." *Journal of Financial and Quantitative Analysis* 56 (7): 2411–2438.

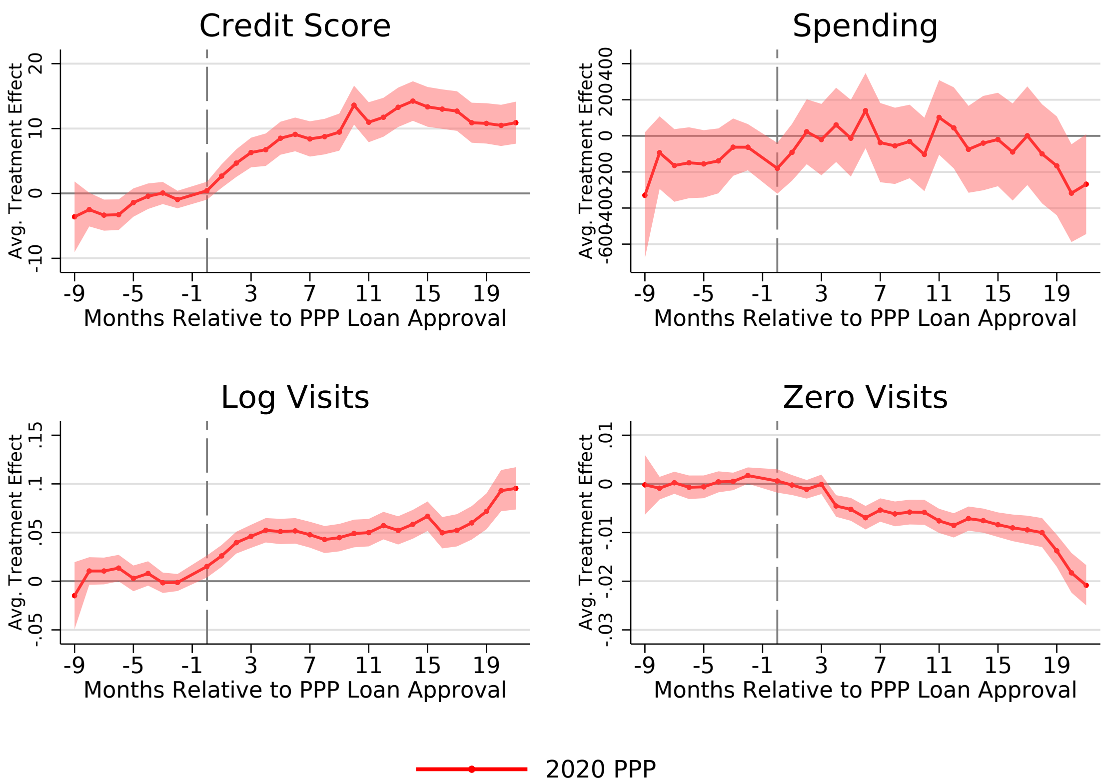
Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2): 175–199. Themed Issue: Treatment Effect 1.

Figure 1: Effect of 2020 PPP Loans: CBG-NAICS6 Advan Firm Pairs



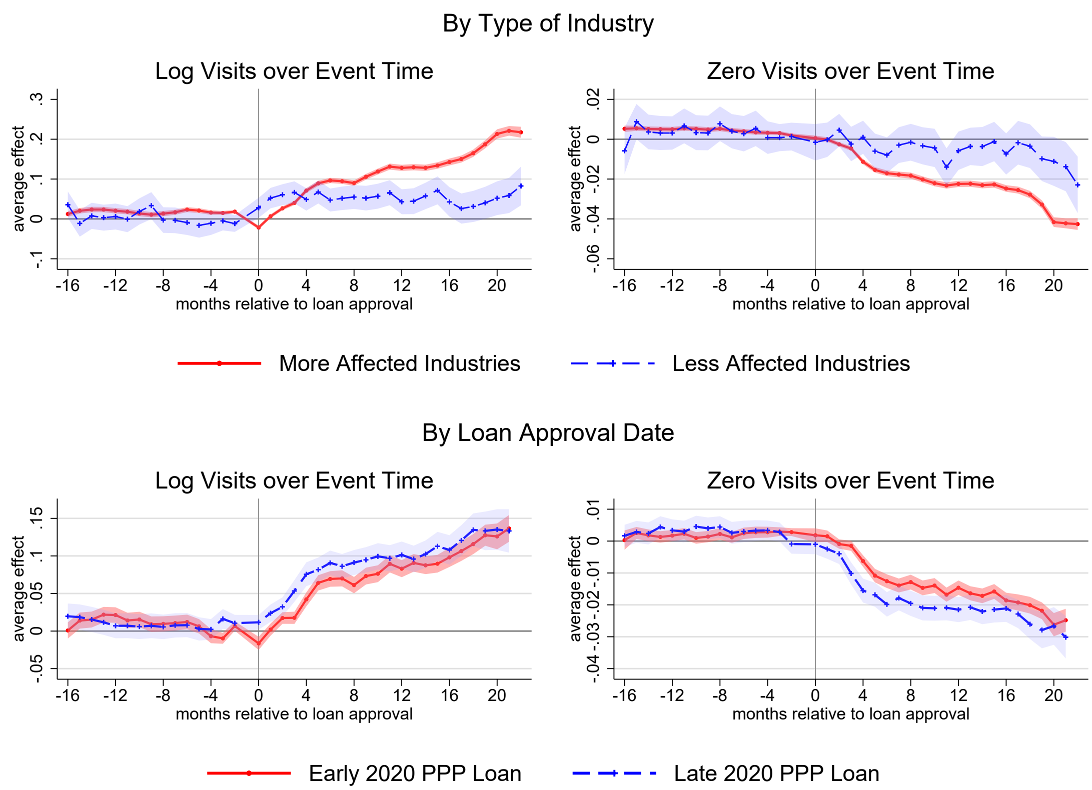
Notes: The left panels plot the β_t coefficients from estimating Equation (1). The right panels plot the μ_l coefficients from estimating Equation (2) using Sun and Abraham (2021). Standard errors are clustered at the pair-ID level. The shaded areas delineate a two-standard-deviation confidence band. Source: PPP data from the Small Business Administration matched via Placekeys with Advan data.

Figure 2: Effect of 2020 PPP Loans on Credit Score, Spending and Visits
Cortera Sub-sample



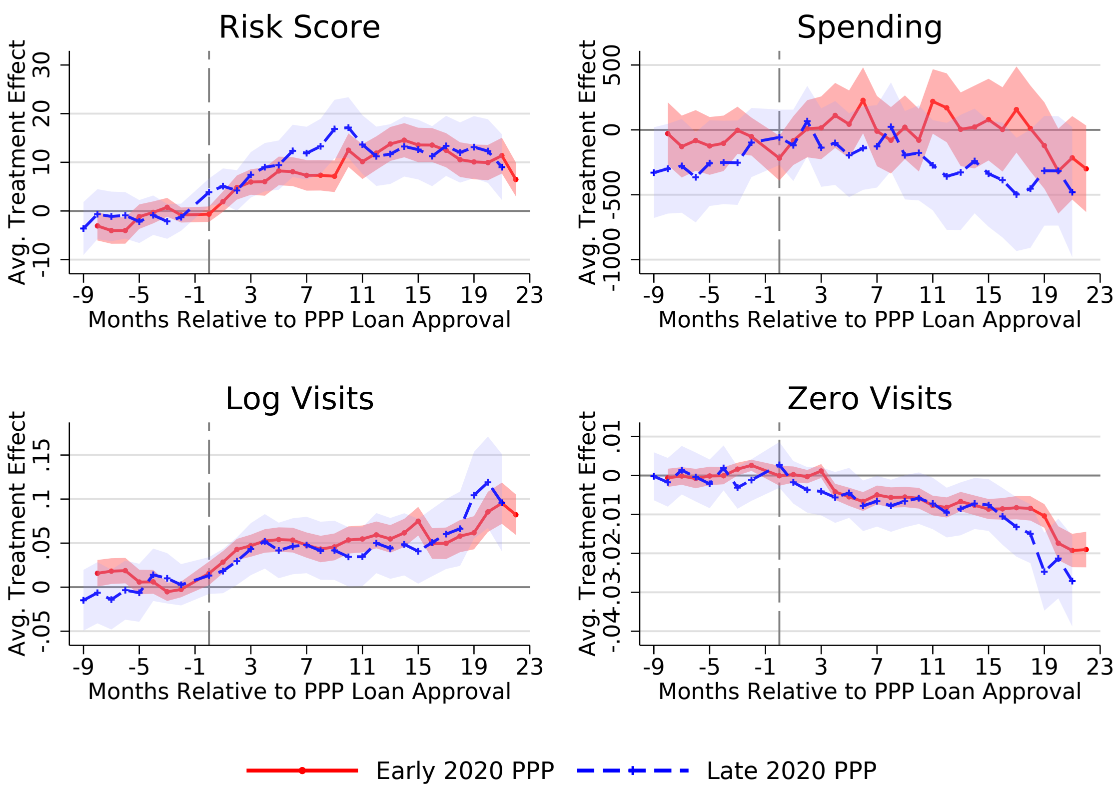
Notes: This figure plots the μ_l coefficients from estimating Equation (2) using Sun and Abraham (2021). The sample includes only those Advan firms that also have spending data from Cortera. A higher credit (risk) score means a firm is more creditworthy. Standard errors are clustered at the pair-ID level. The shaded areas delineate a two-standard-deviation confidence band. Source: Sub-sample of PPP firms from the Small Business Administration matched via Placekeys with Advan data that have spending data in Cortera.

Figure 3: Effect of PPP on Visits over Event Time by Industry and Receipt Date
Advan Sample



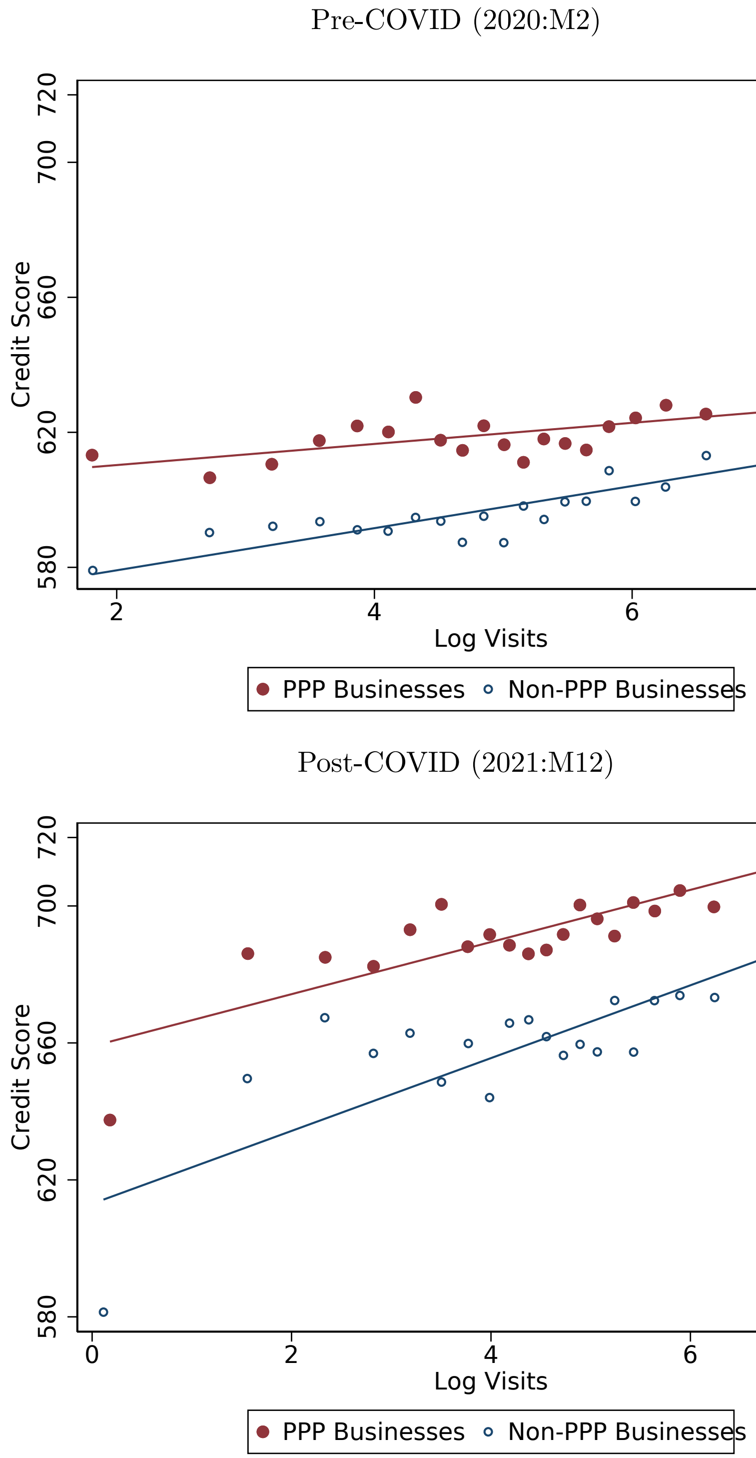
Notes: In these graphs, we compare PPP establishments to their non-PPP pairs allowing for a differential effect based on either the type of industry or the date of their first loan approval. More Affected Industries are those in Retail Trade; Health Care and Social Assistance; Arts, Entertainment, and Recreation; Accommodation and Food Services; and Other Services (except Public Administration)—corresponding NAICS-2 codes 44–45, 62, 71, 72, and 81. Less Affected Industries are all others. Early 2020 PPP firms received loans before May 2, while Late 2020 PPP firms received loans on May 2 or later. The graphs plot the μ_l coefficients from estimating Equation (2) using Sun and Abraham (2021), with separate regressions for each group. Standard errors are clustered at the pair-ID level. The shaded areas delineate a two-standard-deviation confidence band. Source: PPP data from the Small Business Administration matched via Placekeys with Advan data.

Figure 4: Effects of PPP on Credit Scores, Spending, and Visits over Event Time: Early versus Late 2020 PPP recipients
Cortera Sub-sample



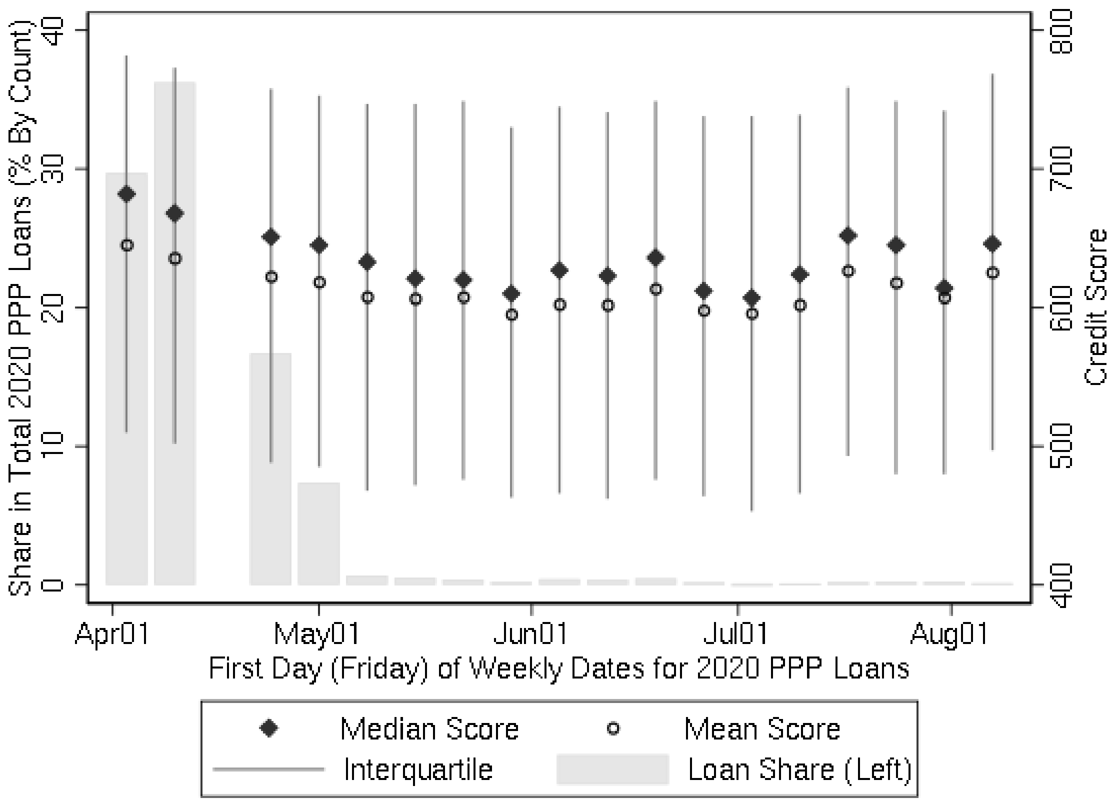
Notes: This figure compares establishments receiving PPP loans Early (that is, before May 2, 2020) versus Late (that is, May 2 through August 8, 2020) both relative to their peers. The graphs plot the μ_l coefficients from estimating Equation (2) using Sun and Abraham (2021), with separate regressions for each group. Standard errors are clustered at the pair-ID level. The shaded areas delineate a two-standard-deviation confidence band. Source: Sub-sample of PPP firms from the Small Business Administration matched via Placekeys with Advan data that also have credit score and spending data in Cortera.

Figure 5: Unobserved Heterogeneity in Financial Health: PPP Recipients Were More Creditworthy



Notes: This figure presents a binscatter plot of the credit score against log visits for 2020 PPP recipient firms versus their matched peer firms in the Cortera–Advan matched sample. The top and bottom panels depict the pattern before (as of 2020:M2) versus after (as of 2021:M12) the initial COVID-19 outbreak. It is clear that at any given level of business activity (as measured by number of visits), the PPP recipients are deemed more creditworthy. Source: Cortera, Advan, and authors' calculations.

Figure 6: Distribution of PPP Recipients Risk Scores and Loan Counts in The Cortera-Advan Matched Sample



Notes: This figure presents the distribution of risk scores (on the right scale) along with the loan counts (left scale) by week of loan approval in the Cortera–Advan matched sample.

Table 1: Temporal Relationship of PPP Treatment Effects on Visits versus Credit Scores

	2020: M2–M6	2020:M6 to 2020:M12		2020:M6 to 2021:M6		2020:M6 to 2021:M12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: GROWTH RATE OF VISITS VERSUS LAGGED CHANGE IN CREDIT SCORE							
ΔScore 2020:M2–M6	2.341***	–0.698	0.294	–1.674***	–0.722*	–1.962***	–0.540
	(0.424)	(0.472)	(0.433)	(0.458)	(0.426)	(0.736)	(0.684)
ΔLog Visits 2020:M2–M6			–0.424***		–0.407***		–0.607***
			(0.010)		(0.011)		(0.015)
Adj. R^2	0.002	0.000	0.151	0.001	0.132	0.000	0.123
Observations	16450	16450	16450	16450	16450	16450	16450
PANEL B: CHANGE IN CREDIT SCORE VERSUS LAGGED GROWTH RATE OF VISITS							
ΔScore 2020:M2–M6			–0.297***		–0.363***		–0.419***
			(0.008)		(0.010)		(0.010)
ΔLog Visits 2020:M2–M6		1.931	4.473***	3.286*	6.393***	1.119	4.699**
		(1.597)	(1.529)	(1.887)	(1.821)	(2.058)	(1.958)
Adj. R^2		0.000	0.081	0.000	0.085	–0.000	0.097
Observations		16450	16450	16450	16450	16450	16450

Notes: Panel A explores the relationship between growth of visits to PPP firms (relative to peers) and contemporaneous as well as lagged relative changes in credit scores, to examine whether financial health changes lead real activity growth at different horizons. Specifically, it reports coefficients from estimating:

$$\Delta Y_{i(j),t_2} - \Delta Y_{i(j),t_1} = \alpha + \beta(\Delta Y_{i(j),t_1} - \Delta Y_{i(j),t_0}) + \gamma(\Delta \mathrm{CS}_{i(j),t_1} - \Delta \mathrm{CS}_{i(j),t_0}) + \epsilon_{i(j),t_1,t_2},$$

where Y is log visits and $\Delta Y_{i(j),s}$ is the difference between the log of visits to PPP firm i and its peer firm in pair j in period s. Thus, the left hand side measures the *relative* growth in visits to PPP firm (i) relative to its matched peer between periods t_1 and t_2. Analogously, $\Delta \mathrm{CS}_{i(j),s}$ denotes the difference between firm $i's$ and firm $j's$ credit scores in period s, and the right hand side includes the relative change in a PPP firm's credit scores between periods t_0 and t_1, as well as lagged relative growth in visits.
As a baseline, in column (1), we estimate the contemporaneous relationship between (relative) visits growth are (relative) credit score changes. Growth rates are measured in percent, while credit scores are divided by 100 to yield more convenient coefficient magnitude. In estimating this equation, t_0 =2020:M2, the month prior to COVID outbreak, while t_1 =2020:M6, the start of the recovery in economic activity after the initial outbreak. The regression is estimated for three t_2, corresponding to 2020:M12, 2021:M6 and 2021:M12, respectively, with the coefficients reported in the last 6 six columns. The lagged growth in visits is included as a control (columns 3, 5 and 7). Robust standard errors in parentheses.
Panel B explores the inverse relationship vis-à-vis that reported in Panel A, that is, between relative changes in credit scores and lagged relative growth in visits, to examine whether financial health recovery follows real activity growth at different horizons. Specifically, it reports coefficients from the following regression:

$$\Delta \mathrm{CS}_{i(j),t_2} - \mathrm{CS}_{i(j),t_1} = \alpha + \beta(\Delta Y_{i(j),t_1} - \Delta Y_{i(j),t_0}) + \gamma(\Delta \mathrm{CS}_{i(j),t_1} - \Delta \mathrm{CS}_{i(j),t_0}) + \epsilon_{i(j),t_1,t_2},$$

where the terms and timing are defined as in Panel A. The growth rate in visits in the RHS is a log difference to obtain a suitable coefficient magnitude. The lagged relative score change is included as a control in columns 2, 4, and 6. Robust standard errors in parentheses.

A Online Appendix: Additional Results

A Sample Construction

To identify PPP recipients, we use data released by the Small Business Administration (SBA) as of August 2021 and available at https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program/ppp-data.

We use the business names and full addresses provided by the borrowers in their PPP applications to obtain unique Placekey identifiers that allow us to find these business in Advan data; see https://docs.placekey.io/ and the corresponding white paper. Advan uses mobile phone pings to track movements to and from points of interest (POIs), which achieves an extensive, although not universal, coverage of businesses with fixed locations of operation. (See https://docs.safegraph.com/docs/places-data-evaluation for coverage rates by industry.) We are able to match about 814,700 or 69.2 percent of PPP recipients to Placekeys in the Advan data.

We then construct observationally equivalent peers matching each PPP recipient observed in Advan data to a business operating in the same Census Block Group (CBG) and industry at the six-digit level of the North American Industry Classification System (NAICS-6). When constructing peers in the Advan data, we restrict the matches so that the number of visits to a PPP establishment and its peer over the first two months of 2020 (the omitted time dummy in our regressions) are within 30 percent of each other. We call the match a pair. When multiple matches occur, we keep the match with the closest average number of visits to the PPP recipient during the first two months of 2020. The sample is also restricted to firms that received just one PPP loan, but this restriction does not affect the results in any meaningful way.

Importantly, businesses had to have been in operation pre-pandemic to be matched (PPP and non-PPP recipients alike). If Advan no longer reports traffic to a specific firm, we fill in its monthly observations with zero visits to make sure that firm is still included in our regression sample (making our panel balanced). Zero Visits, our proxy for temporary or permanent closures, is an indicator equal to one when visits are recorded as zero in the Advan data, or when a firm is not observed in a given month.

Advan visits are available at a daily frequency, but we aggregate them to a monthly frequency. The number of unique visitors, in addition to visits, is also available in Advan data. Results are very similar when using visitors instead of visits and thus, for brevity, are not reported.

The Cortera data we use in our analysis was provided to us by Cortera before its acquisition by Moody's analytics. Cortera, a business directory, maintains a comprehensive database of US businesses, including small firms. Firm-level data on the financial position and economic activity of small firms in the US is hard to obtain because American small firms, unlike in other countries, are not subject to periodic fillings regarding their financial health and operations. Cortera data include businesses names and addresses, which we use to assign Placekeys. Part of our analysis matches Advan data to Cortera data using these Placekeys.

Cortera gathers data from many sources, which are not disclosed to us, but are understood to include information from major service providers such as telecom companies, shipping companies, utilities and lenders, government agencies (such as business registrations with state governments), as well as the covered companies that supply intermediate input to other covered companies. Cortera claims to enhance the raw information through artificial intelligence. We received two data feeds: (1) Spending data reported by a set of selected business suppliers to individual businesses (B2B spending); (2) monthly records on payment-behavior ratings and credit scores for these businesses, as constructed by Cortera.

The credit score (referred to as Cortera Score) measures the probability of serious delinquency (90+ days late in paying bills) in the next 12 months; its level directly maps to a probability of default—the higher the score, the lower the risk—but Cortera does not disclose the exact mapping schedule. By comparison, the Payment Rating is a backward-looking metric that measures the speed at which a company paid its bills over the past 3 month. Its level also directly maps into the relative speed of payment. Given that the probability estimate is generated using past data, and that there is typically a high degree of persistence in firm performance, these two indicators are highly correlated. We focus on the more forward-looking measure, Credit Score.

B Dynamic Relationship of Visits over Time

This section develops a simply AR(1) model of the growth in visits to each business that can rationalize the time series pattern documented in Section 3.

Assume (log) visits to each firm i follows a stationary AR(1) process around a deterministic trend:

$$Y_{i,s} = \alpha_i(1-\rho_i)s + \rho_i Y_{i,s-1} + \varepsilon_{i,s},$$

where $Y_{i,s}$ is log visits to firm i in period s, α_i is its growth rate, ρ_i is the autocorrelation coefficient, and $\varepsilon_{i,s}$ is an i.i.d. shock.

Recursive substitution leads to the following expression for $Y_{i,s}$ as a function of $Y_{i,s-\tau}$:

$$Y_{i,s} = \alpha_i(1-\rho_i)\sum_{t=0}^{\tau-1}\rho_i^t(s-t) + \rho_i^\tau Y_{i,s-\tau} + \sum_{t=0}^{\tau-1}\rho_i^t\varepsilon_{i,s-t}.$$

The composite shock term ($\sum_{t=0}^{\tau-1}\rho_i^t\varepsilon_{i,s-t}$) is uncorrelated with the RHS given the i.i.d. assumption.

We can show that the cumulative growth of log visits over $s-\tau$ to s depends negatively on its earlier condition $Y_{i,s-\tau}$:

$$Y_{i,s} - Y_{i,s-\tau} = \alpha_i(1-\rho_i)\sum_{t=0}^{\tau-1}\rho_i^t(s-t) - (1-\rho_i^\tau)Y_{i,s-\tau} + \sum_{t=0}^{\tau-1}\rho_i^t\varepsilon_{i,s-t}.$$

In the COVID-19 episode, $Y_{i,s-\tau}$ can be interpreted as the immediate post-shock value given the normalization that sets the pre-pandemic value to 0.

Given our nearest-neighbor matching process and the lack of pre-trends, we can assume that a PPP borrower i and its peer firm share the same parameters α_i and

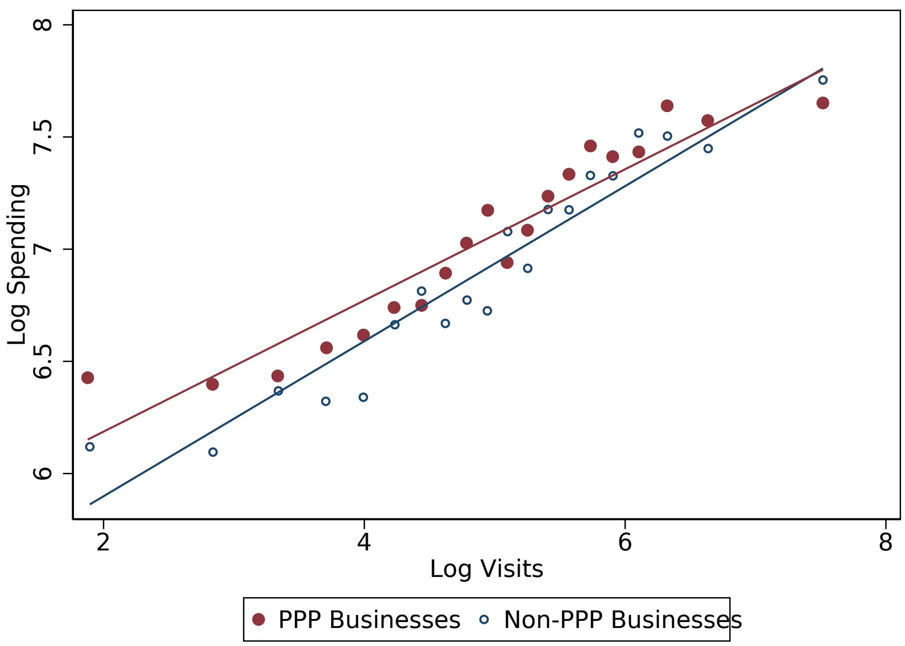
ρ_i, thus the cumulative growth *differential* between them over $s - \tau$ to s is negatively correlated with the *difference* in the initial post-shock value:

$$\Delta Y_{i(j),s} - \Delta Y_{i(j),s-\tau} = -(1 - \rho_i^\tau)\Delta Y_{i(j),s-\tau} + \sum_{t=0}^{\tau-1} \rho_i^t \Delta\varepsilon_{i(j),s-t}.$$

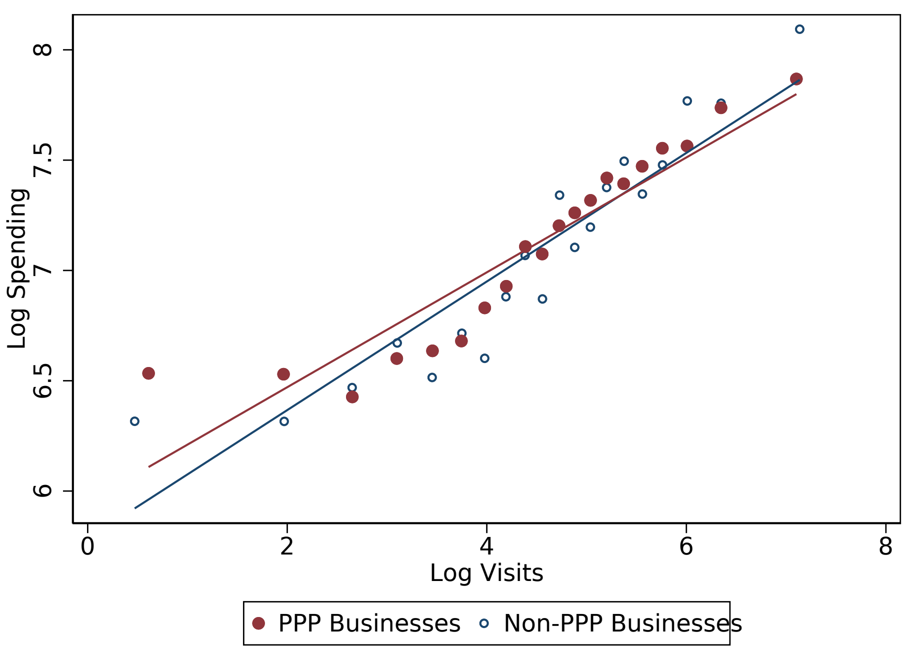
This is consistent with the coefficient pattern reported in Tables 1 and A.3.

Figure A.1: Relationship between Visits and Spending: PPP Recipients and Peer Firms

Pre-COVID (2020:M2)



Post-COVID (2021:M12)



Notes: This figure presents a binscatter plot of log spending against log visits for 2020 PPP recipient firms versus their matched peer firms in the Cortera–Advan matched sample. This sample is smaller than that underlying Figure 5 because less than 50 percent of the firms in the Cortera sample have spending data. The top and bottom panels depict the pattern before (as of 2020:M2) versus after the COVID-19 outbreak (as of 2021:M12). The linear relationship is nearly identical between the PPP recipients and their matched peer firms. Source: Cortera, Advan, and authors' calculations.

Table A.1: Summary Statistics, Advan Sample

	N	Mean	S.D.	P25	Median	P75
Non-PPP Business						
Pre-COVID Log Visits	104,012	4.54	1.26	3.75	4.66	5.44
PPP Business						
Pre-COVID Log Visits	104,012	4.52	1.26	3.74	4.65	5.42
PPP Loan Size ($1,000)	104,012	130.38	337.53	20.68	49.55	113.43
Differences between each PPP firm and its matched peer in						
ΔLog Visits 2020:M2–2020:M6	104,012	–0.55	87.71	–46.71	-1.40	43.22
ΔLog Visits 2020:M6–2020:M12	104,012	6.73	106.33	–44.24	0.49	47.75
ΔLog Visits 2020:M6–2021:M6	104,012	10.29	114.51	–43.92	2.59	51.41
ΔLog Visits 2020:M6–2021:M12	104,012	18.20	176.20	–60.84	6.36	81.38

Table A.2: Summary Statistics, Cortera-Advan Matched Sample

	N	Mean	S.D.	P25	Median	P75
Non-PPP Business						
Pre-COVID Log Visits	21,593	4.88	1.34	4.07	5.00	5.80
Pre-COVID Spending	21,593	2,979.97	13,905.13	0.00	83.33	1,079.33
Pre-COVID Credit Score	20,996	587.68	146.36	468.83	607.67	717.00
Pre-COVID Payment Rating	13,698	616.48	162.34	526.00	700.00	716.33
PPP Business						
Pre-COVID Log Visits	21,593	4.87	1.34	4.06	5.00	5.79
Pre-COVID Spending	21,593	4,066.04	17,783.55	0.00	167.33	1,604.67
Pre-COVID Credit Score	21,006	610.58	145.19	486.00	646.00	732.67
Pre-COVID Payment Rating	15,367	629.07	155.29	560.00	700.00	720.00
PPP Loan Size ($1,000)	21,593	269.04	529.69	40.10	92.85	245.14
Differences between each PPP firm and its matched peer in						
ΔLog Visits 2020:M2–2020M6	21,593	3.60	88.37	–42.08	2.52	48.36
ΔLog Visits 2020:M6–2020M12	21,593	1.07	96.86	–46.94	-0.79	45.34
ΔLog Visits 2020:M6–2021:M6	21,593	2.23	99.02	–44.63	-0.07	44.20
ΔLog Visits 2020:M6–2021:M12	21,593	5.39	154.45	–63.91	0.38	67.16
ΔCredit Score 2020:M2–2020:M6	21,593	6.10	165.83	–79.00	0.00	94.00
ΔCredit Score 2020:M6–2020:M12	21,593	3.26	173.93	–93.00	0.00	103.00
ΔCredit Score 2020:M6–2021:M6	21,593	8.98	208.30	–116.00	6.00	138.00
ΔCredit Score 2020:M6–2021:M12	21,593	5.81	223.58	–133.00	3.00	146.00

Table A.3: Temporal Relationship of PPP Treatment Effects on Visits versus Credit Scores

	2020: M2–M4	2020: M4–M6		2020: M6–M12		2020:M6 to 2021:M12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: GROWTH RATE OF VISITS VERSUS LAGGED CHANGE IN CREDIT SCORE							
ΔScore 2020:M2–M4	2.013***		–0.062	–0.240	0.108	—1.881*	—1.107
	(0.680)		(0.460)	(0.643)	(0.582)	(1.008)	(0.934)
ΔScore 2020:M4–M6		—1.654***		—1.097*	–0.132	–2.033**	–0.218
		(0.548)		(0.579)	(0.527)	(0.920)	(0.861)
ΔLog Visits 2020:M2–M4			–0.517***		–0.383***		–0.596***
			(0.007)		(0.011)		(0.016)
ΔLog Visits 2020:M4–M6					–0.518***		–0.635***
					(0.012)		(0.018)
Adj. R^2	0.000	0.001	0.369	0.000	0.165	0.000	0.123
Observations	16450	16450	16450	16450	16450	16450	16450
PANEL B: CHANGE IN CREDIT SCORE VERSUS LAGGED GROWTH RATE OF VISITS							
ΔScore 2020:M2–M4			–0.154***	–0.223***	–0.224***	–0.298***	–0.298***
			(0.009)	(0.011)	(0.011)	(0.014)	(0.014)
ΔScore 2020:M4–M6				–0.360***	–0.362***	–0.522***	–0.522***
				(0.011)	(0.011)	(0.013)	(0.013)
ΔLog Visits 2020:M2–M4			7.645***		4.972***		4.037**
			(1.007)		(1.601)		(2.046)
ΔLog Visits 2020:M4–M6					4.308**		7.831***
					(1.859)		(2.351)
Adj. R^2			0.024	0.086	0.087	0.106	0.106
Observations			16450	16450	16450	16450	16450

Notes: Panel A explores the relationship between PPP firms' visits growth relative to peers and contemporaneous as well as lagged relative changes in credit scores, to examine whether financial health changes lead real activity growth at different horizons. Specifically, it reports coefficients from estimating:

$$\Delta Y_{i(j),t_2} - \Delta Y_{i(j),t_1} = \alpha + \beta(\Delta Y_{i(j),t_1} - \Delta Y_{i(j),t_0}) + \gamma(\Delta \mathrm{CS}_{i(j),t_1} - \Delta \mathrm{CS}_{i(j),t_0}) + \epsilon_{i(j),t_1,t_2},$$

where Y is log visits and $\Delta Y_{i(j),s}$ is the difference between the log of visits to PPP firm i and its peer firm j in period s. Thus, the left hand side is the log growth in visits to firm i relative to firm j between periods t_1 and t_2. Analogously, $\Delta \mathrm{CS}_{i(j),s}$ denotes the difference between firm $i's$ and firm $j's$ credit scores in period s, and the right hand side includes the relative change in credit scores for both firms between periods t_0 and t_1, as well as lagged relative growth in visits.

As a baseline, in column (1), we estimate the contemporaneous relationship between (relative) visits growth are (relative) credit score changes. Growth rates are measured in percent, while credit scores are divided by 100 to yield more convenient coefficient magnitude. In estimating this equation, t_0 =2020:M2, the month prior to COVID outbreak, while t_1 =2020:M6, the start of the recovery in economic activity after the initial outbreak. The regression is estimated for three t_2, corresponding to 2020:M12, 2021:M6 and 2021:M12, respectively, with the coefficients reported in the last 6 six columns. The lagged growth in visits is included as a control (columns 3, 5 and 7). Robust standard errors in parentheses.

Panel B explores the inverse relationship vis-à-vis that reported in Panel A, that is, between relative changes in credit scores and lagged relative growth in visits, to examine whether financial health recovery follows real activity growth at different horizons. Specifically, it reports coefficients from the following regression:

$$\Delta \mathrm{CS}_{i(j),t_2} - \mathrm{CS}_{i(j),t_1} = \alpha + \beta(\Delta Y_{i(j),t_1} - \Delta Y_{i(j),t_0}) + \gamma(\Delta \mathrm{CS}_{i(j),t_1} - \Delta \mathrm{CS}_{i(j),t_0}) + \epsilon_{i(j),t_1,t_2},$$

where the terms and timing are defined as in Panel A. The lagged relative score change is included as a control in columns 2, 4 and 6. Robust standard errors in parentheses.