The Real Effects of Liquidity Relief:

Commercial Rent Forbearance in the Covid-19 Recession

Angela Ma[1]
Boston College

Abstract

This paper assesses a key trade-off when providing widespread liquidity relief to businesses during an economic crisis: the benefit of saving solvent businesses versus the cost of prolonging survival of insolvent businesses. Using data on establishments and commercial rent forbearance policies during the Covid-19 recession, I employ a difference-in-differences strategy that compares businesses along the border of adjacent cities that differ in liquidity relief. In the longer run, liquidity relief reduces closure only for liquidity-constrained but solvent businesses. In the shorter run, liquidity relief prolongs survival of less solvent businesses. However the opportunity cost of doing so appears low because new businesses are unlikely during this time to replace closed ones. Along the pecking order of business financing, liquidity relief leads businesses to reduce usage of more costly loans but does not affect usage of grants.

Keywords: Business, closure, liquidity, solvency, government, intervention, Covid-19
JEL Codes: G30, G32, G33, G38

[1]Email: angela.ma@bc.edu. Boston College, Carroll School of Management. I am grateful to my PhD advisors Edward Glaeser, Robin Greenwood, Jeremy Stein, Adi Sunderam, and Emily Williams for invaluable guidance and support throughout this project. I am also grateful to Hyuntae Choi for excellent research assistance, SafeGraph, Dewey (Evan Barry) and Homebase (Joey Nedland) for generously making data available and providing support. For helpful comments, I thank Jessica Bai, Alex Chan, Varanya Chaubey, Slava Fos, Claudia Goldin, Sam Hanson, Sam Hartzmark, Sebastian Hillenbrand, Victoria Ivashina, Elisabeth Kempf, Nadya Malenko, Erica Moszkowski, Dominic Russel, Marco Sammon, Jesse Shapiro, Claire Shi, Andrei Shleifer, Emil Siriwardane, Luis Viceira, Jennifer Walsh, Sasha Watkins, Miles Zheng, and participants in the Harvard doctoral seminars in finance, contracts, and economic history. I gratefully acknowledge support from the Paul & Daisy Soros Fellowship and the NSF Graduate Research Fellowship. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE1745303. All errors are my own.

1 Introduction

With the onset of the Covid-19 pandemic, many businesses experienced a sudden decline in revenue due to transmission of the disease and due to government policies aimed at reducing transmission. This liquidity shock was thought to be largely divorced from underlying business fundamentals and therefore posed the threat of shuttering businesses that were solvent but temporarily illiquid. In response, policymakers enacted a series of unprecedented programs to administer rapid and direct aid to businesses. In the U.S. at the national level, the Federal Reserve authorized the Main Street Lending Program and the Primary and Secondary Market Corporate Credit Facilities, while the Small Business Administration administered the Paycheck Protection Program (PPP) and the Economic Injury Disaster Loan (EIDL) program. At the regional level, local governments funded business grants and loans and enacted additional forms of liquidity relief such as commercial rent forbearance.

Theoretically, the overall effectiveness of widespread liquidity relief in a crisis is ambiguous. On one hand, liquidity relief may have permanent real effects by preventing solvent businesses from closing due to liquidity constraints. Excessive liquidation of businesses is of particular concern during an economic crisis when credit markets may not be functioning normally and therefore when credit market frictions are more severe. Under these circumstances, private credit markets do not extend sufficient liquidity to solvent businesses, which creates a role for policymakers to extend additional liquidity in order to preserve businesses. On the other hand, however, widespread liquidity relief may also prolong business survival regardless of solvency. This phenomenon is socially costly if it prevents reallocation of resources to more productive businesses. Specifically, generous liquidity relief may prop up existing businesses and discourage new entrants, which hampers overall economic growth. Ultimately, empirical study is required to understand the strength of these effects and to characterize this key trade-off in providing widespread liquidity relief to businesses in a crisis.

In this paper, I ask the following research questions about liquidity relief to businesses during an economic crisis. What is the impact of liquidity relief on business closure? More specifically, which types of businesses does liquidity relief tend to aid in the shorter run and in the longer run? To answer these questions, I hand-collect enactments of commer-

cial rent forbearance policies for all 482 cities and 58 counties in California during the Covid-19 recession.[1] To identify the causal effect of this liquidity relief, I employ a geographic border-based difference-in-differences strategy that compares businesses along the border of neighboring cities with differing liquidity relief policy. The identifying assumption is that these treated and control businesses would have followed parallel trends of closure in the absence of the liquidity relief policy. Businesses along the border of the neighboring cities lie in a similar local economic environment, which makes this assumption more likely to be hold.Hi

My main findings are as follows. In liquidity-constrained industries, the forbearance liqudity relief reduces business closure significantly by approximately 6 basis points per quarter, or 1.1 percentage points in total over the treatment period of 2020-2024. For my sample of Claifornia, this equals approximately 61,700 business establishments. Moreover, the liquidity relief is more effective in reducing closure for businesses that are more solvent coming into the pandemic. For example, the liquidity relief reduces closure for food services businesses by 19 basis points per quarter, or 3.6 percentage points, but has no significant effects on business closure for retail businesses. Turning to the shorter run, I do find evidence that liquidity relief temporarily prolongs the survival of less solvent businesses. However, the fact that new businesses do not tend to open to replace closing businesses suggests that the resource opportunity cost of prolonging business survival is low during this recession. Finally, along the pecking order of business financing, I observe that the liquidity relief reduces business take-up of costly loans but does not affect take-up of grants.

The challenge of identifying the causal impact of commercial rent forbearance liquidity relief on business closure stems from the fact that there is reverse causality from business closure to the liquidity relief policy. Because the purpose of enacting liquidity relief is to prevent business closure, local policymakers gather information about business closure likelihood by monitoring local economic conditions and hearing directly from small business owners. This reverse causality results in selection bias where a place with more business closure selects into enacting longer liquidity relief policies. Indeed, the data

[1]California serves as an ideal laboratory because of its decentralized implementation of commercial rent forbearance. Governor Gavin Newsom gave cities and counties the legal option to enact the policy if they so choose. This feature creates variation in the policy across space and time that I exploit in the empirical analysis. Another advantage of studying California is that it contains a significant share of U.S. businesses, accounting for 13% of the number of small businesses and 12% of the small business employment.

shows that longer commercial rent forbearance policies is correlated with higher rates of business closure during the pandemic. However, the causal effect of liquidity relief remains unclear because, even if its true effect is to reduce business closure, the selection bias may result in the observed, positive relationship between liquidity relief policies and business closure.

To overcome this selection bias, I set up a geographic border difference-in-differences strategy that compares businesses along the border of neighboring cities that differ in commercial rent forbearance policy. The motivation for the geographic border approach is that businesses on either side of the border likely face similar economic conditions but then different liquidity relief policies. The liquidity relief policy is arguably as-if randomly assigned and less endogenous to business closure likelihood because these businesses lie on the outskirts of the city. The identifying assumption for the difference-in-differences strategy is then that these treated and control businesses would have followed parallel trends in business closure in the absence of the liquidity relief. In the data, I observe evidence of parallel trends in business closure prior to the liquidity relief period.

Using the geographic border difference-in-differences strategy, I go on to estimate the effect of liquidity relief on business closure. Turning first to more liquidity-constrained industries, I find that liquidity relief reduces business closure by 6 basis points per quarter, or 1.1 percentage points in total over the treatment period of 2020-2024. In my sample of California, I estimate that this liquidity relief prevents the liquidation of 61,700 business establishments across liquidity-constrained industries. By contrast, I find that the liquidity relief has no effect on business closure for less liquidity-constrained industries. These results are consistent with the commercial rent forbearance being demanded primarily by liquidity-constrained businesses and therefore making a material difference on their business survival only.

To investigate the "efficiency" of these business closure effects, I next examine how the effectiveness of liquidity relief varies with business solvency. Using the 10-year pre-pandemic employment growth rate as an industry-level proxy for business solvency, I find that liquidity relief is more effective in reducing business closure in industries that are more solvent coming into the pandemic. For example, a natural juxtaposition arises between retail trade and food services, two industries that are both liquidity-constrained during the Covid-19 recession but that differed substantially in terms of their funda-

mentals coming into the recession. Prior to the pandemic, food services was among the fastest-growing industries, while retail trade was in the midst of a decade-long "retail apocalypse." I find that the liquidity relief reduces business closure for food services by 19 basis points per quarter, or 3.6 percentage points in total, but has no significant effect on business closure for retail.

I then turn to the effect of liquidity relief on takeup of other sources of financing. According to the 2021 Small Business Credit Survey, the top sources of pandemic-related financial assistance that businesses sought out were: Economic Injury Disaster Loan (EIDL) program (63% of respondents), Paycheck Protection Program (PPP) (51% of respondents), state and local government grants (48% of respondents), and EIDL advance grant (36%). I begin by gathering granular data on three of these top four sources of business financing during Covid-19: EIDL Advance grants, PPP forgivable loans, and EIDL loans. Then I place them along a pecking order of business financing opportunities during Covid-19 based on the cost of financing.

Broadly, there are two types of financing available to businesses during the Covid-19 pandemic. First, there is loan financing that must be repaid, such as the EIDL loan program. There is likely to be substitution towards commercial rent forbearance usage and away from loan financing because the loan is more costly than the zero-interest liquidity relief of commercial rent forbearance. Second, there is grant financing that does not need to be repaid, such as the EIDL advance program. There is unlikely to be substitution between commercial rent forbearance and grants because grants improve business solvency. The Paycheck Protection Program forgivable loan is a sort of hybrid between a grant and a loan since it is originally framed as a loan but then has very reasonable terms for forgiveness. Turning first to the EIDL Advance grant, I find that the liquidity relief does not affect business take-up of these grants, consistent with businesses being equally incentivized to seek out grants irrespective of liquidity relief. Turning next to PPP, I observe somme modest crowd-out of PPP forgivable loan usage. Finally turning to the EIDL loans, which are a more costly source of liquidity relief (with an interest rate of 3.75%) than the commercial rent forbearance (with an interest rate of zero), I observe that the liquidity relief makes businesses take out an EIDL with a lower likelihood and in a lower amount by 10%.

I next consider whether the liquidity relief prolongs the survival of less solvent busi-

nesses. First I show that the short-run effects of liquidity relief are less aligned with business solvency than the total effects are. Specifically, the liquidity relief has similar effects on business closure in the short run regardless of business solvency, consistent with some prolonging of the survival of less solvent businesses. To understand the opportunity cost of prolonging the survival of businesses in the short run, I then consider business openings effects. I do not find that new businesses tend to take the place of closed businesses, which points to a low resource opportunity cost of prolonging business survival.

Related Literature.

This paper connects to the literature on the real effects of credit market frictions. For example, Chodorow-Reich (2014) show that firms with less financially healthy lenders face more severe credit constraints and cut employment more severely during the Great Recession. Giroud and Mueller (2017) show that, in response to declines in local consumer demand, establishments of more levered firms cut employment more severely during the Great Recession. Turning to the Covid-19 recession, I examine a policy that temporarily strengthens firm balance sheets and find that the liquidity relief has real effects in terms of permanently preventing closure for liquidity-constrained, solvent firms.

Second, this paper connects to the literature on how firms weathered the Covid-19 recession. One pod of this literature aims to understand the liquidity and solvency of firms preceding and during the recession. For example, Ding et al. (2021) and Fahlenbrach et al. (2021) show that corporate firms with stronger financial positions (in terms of liquidity and solvency) and greater financial flexibility and experience less severe stock price drops during the Covid-19 recession. Bartik et al. (2020a) and Bartik et al. (2020b) examine business establishments at the onset of the pandemic and find that small businesses had very limited cash on hand and that "firms that were already unhealthy were more likely to close and less likely to reopen." Relative to this body of work, I focus on business establishments and follow their fate through a longer run. Additionally, I examine the interaction between liquidity relief and firm solvency, and show that liquidity relief was more effective in reducing closure for more solvent firms.

Another pod of this literature focuses on the rationale behind and the effectiveness of government intervention to aid businesses during the Covid-19 crisis. Several studies have examined the design and effect of federal business aid programs, including PPP

(Autor et al., 2022; Bartik et al., 2023; Chetty et al., Forthcoming; Granja et al., 2022), Main Street Lending Program (Hanson et al., 2020; English et al., 2020; Arseneau et al., 2022), and COVID-19 EIDL (Fairlie and Fossen, 2022; Li, 2021). This paper evaluates the effects of a widely enacted local policy that provides liquidity relief to businesses, and shows that this liquidity relief policy was able to generate effects of a similar magnitude to solvency relief programs. This paper shows that liquidity relief was effective in saving solvent, liquidity-constrained businesses and had modest costs in terms of prolonging less solvent businesses' survival. Moreover, this paper makes the point that the prolonging of less solvent businesses was less concerning because there were few business entrants waiting to take the spot, i.e. reallocation was paused.

Finally, this paper connects to the literature on the efficiency of economic recessions. Built on the notion of "creative destruction" raised by Schumpeter (1939), the "cleansing effects" hypothesis proposes that less productive firms close during recessions (e.g., Caballero and Hammour, 1994). Meanwhile, competing hypotheses point to other frictions, importantly credit market frictions, as the driver of firm closure during recessions. The evidence has been mixed across recessions, with the Great Recession exhibiting less efficient reallocation and prior recessions exhibiting more efficient reallocation (Foster et al., 2016, 2008, 2001; Davis et al., 1996). By exploiting a policy that dispensed liquidity relief irregardless of business solvency, I have an opportunity to test both the "credit constraints" hypothesis and the "cleansing effects" hypothesis during the Covid-19 recession. I provide micro-level evidence of illiquidity-induced business closure, which points to the credit constraints hypothesis at play. However, I then find evidence of relatively "efficient" business survival conditional on liquidity relief, which points to the cleansing effects hypothesis. In short, my paper suggests that liquidity relief enables cleansing effects during the Covid-19 recession.

This paper proceeds as follows. Section 2 develops a conceptual framework of commercial rent forbearance in liquidity provision. Section 3 describes the data sources and provides summary statistics. Section 4 develops the geographic border-based difference-differences strategy and estimates the impact of liquidity relief on business closure. Section 5 investigates the impact of liquidity relief on business financing. Finally, Section 6 concludes.

2 A conceptual framework of liquidity provision

In this section, I develop a conceptual framework for the impact of commercial rent forbearance liquidity relief on business closure. Section 2.1 gives background on the commercial rent forbearance policy. Section 2.2 provides illustrative examples of different commercial rent forbearance policies. Section 2.3 introduces the setup of the model of commercial rent forbearance in liquidity provision during the Covid-19 crisis. Section 2.4 analyzes the impact of commercial rent forbearance on business closure and discusses empirical predictions.

2.1 Background on commercial rent forbearance

Enacted during the Covid-19 pandemic to combat business stress, commercial rent forbearance policies legalize non-payment of rent due to Covid-19 pandemic disruptions and prohibit commercial evictions, which are the enforcement mechanism for businesses to pay rent. While such a policy is in effect, a commercial landlord may not evict a business for not paying rent if the business has experienced a substantial decrease in income due to the Covid-19 pandemic or associated government interventions. Evictions may still proceed if the tenant violates its lease in other ways, e.g. by damaging property or committing illegal acts. Enforcement of the policy happens through the judicial courts. If a landlord initiates commercial eviction proceedings, the policy can be cited by the business tenant as a legal defense. The vast majority of policies are not targeted and simply apply to all businesses.

The stated goal of the policy is to prevent business closure by pausing the obligation of rent payments and pausing eviction proceedings. The direct consequence of the policy is liquidity relief. By pausing rent payments, the policy effectively requires a landlord to offer its business tenant zero-interest, non-forgivable credit with face value equal to the amount of rent accrued during the policy period. Therefore, the policy is essentially a credit policy where businesses can borrow from their landlord by delaying rent payment.[2]

Commercial rent forbearance policies are enacted by local governments, rather than the federal government. While the start date of the policy is almost uniformly March

[2]The potential second consequence of the policy is solvency relief by spurring renegotiation between businesses and landlords. However, because renegotiation is not a direct requirement of the policy and is not observed in the data, this paper will only speak to the liquidity relief implication of the policy.

2020, there is substantial variation in the end date. For example, in Massachusetts, the legislature and Governor approved a bill pausing non-essential small business evictions through October 2020. In Texas, multiple county courts paused non-essential commercial eviction hearings for varying amounts of time. In California, the Judicial Council enacted a pause on eviction proceedings through September 2020, while the Governor gave city and county governments the option to enact commercial rent forbearance through September 2021.

2.2 Illustrative examples of commercial rent forbearance policies

Figure 1 provides illustrative examples of the timeline of a commercial rent forbearance policy. Panel A shows that in Oakland, California, the policy is enacted in March 2020, at which point the obligation of rent payment is paused. The policy lasts for 19 months and ends in September 2021, at which point the obligation of rent payment resumes. Additionally, all back rent comes due. To concretely understand how the policy provides liquidity relief, Panel B presents an illustrative example of the effective loan balance that businesses can borrow under the policy in Oakland, California. Businesses can steadily borrow each month by deferring monthly rent until the policy ends, at which point they must repay the loan balance. Specifically, given a restaurant with monthly rent of $5,000, the policy would enable the business to borrow $95,000 (19 * $5,000) over 19 months at zero interest.

2.3 Model setting

To develop a conceptual framework for the impact of commercial rent forbearance on business closure, I extend the model of government intervention in business credit markets during the Covid-19 crisis developed in Hanson et al. (2020). There are two added ingredients to this framework relative to Hanson et al. (2020). First, I introduce the commercial rent forbearance policy into the model and analyze the impact on the market outcome, specifically business closure. Second, I introduce business-level heterogeneity in pre-pandemic solvency and analyze its implications for the effectiveness of the policy in reducing long-run business closure.

The model has three periods. $t = 1$ is the early period of the pandemic, $t = 2$ is the

later period of the pandemic, and $t = \infty$ is the steady state. There is a negative shock that arrives at $t = 1$, and there is a continuum of businesses $f \in [0, 1]$ that have differing exposure to the negative shock. More exposed businesses experience a larger decline in cash flows. At $t = 1$, there is aggregate uncertainty about whether the recession will be mild or severe at $t = 2$. At $t = 2$, it is revealed whether the economy is in a mild or severe recession, which also determines whether the economy will be in the post-mild-recession or post-severe-recession steady state at $t = \infty$. All agents in the economy are risk neutral with constant time discount factor $\delta \in (0, 1)$. F_{S_t} denotes the mass of businesses that are operating in state S_t at time t.

There are two key frictions in the model of Hanson et al. (2020). First, there are credit market frictions parameterized by $\phi > 0$. At $t = 1$, businesses can only borrow against $(1 - \phi)$ of their value in $t = 2$. The limited pledgeability problem is heightened during the Covid-19 crisis because short-run cash flows become less informative about long-run solvency of businesses. Second, there are aggregate demand externalities parameterized by $\gamma > 0$. At $t = 2$, a business experiences positive cash flow of $\gamma \times F_{S_2}$ from F_{S_2} total businesses operating. Intuitively, this captures the fact that a business will experience greater demand when the economy is functioning well and more businesses are open.

At each date t, a business may shut down or continue operating. If a business shuts down, it generates zero cash flow in the current and all future periods. If a business operates, it generates some cash flow. If cash flow is positive, it may go to outside investors. If cash flow is negative, then the business requires investment from investors to continue operating.

If business f operates at $t = 1$, it generates the following cash flow:

$$X_1(f, R_1) = \mu + \gamma - R_1 - \Delta \times f \tag{1}$$

where μ captures baseline cash flow which proxies for business solvency, R_1 is the common impact of the recession on business cash flows at $t = 1$, Δ captures the impact of the recession that scales with business exposure, and f captures business exposure to the recession.

If the business f operates in state S_2 at $t = 2$, it generates the following cash flow:

$$X_2(f, R_{S_2}, F_{S_2}) = \mu + \gamma \times F_{S_2} - R_{S_2} - \Delta \times f \tag{2}$$

where $\gamma \times F_{S_2} \geq 0$ is the aggregate demand externality that exists at $t = 2$ from having F_{S_2} businesses operating.

If the business f operates in state S_∞ at $t = \infty$, it generates the following cash flow:

$$X_\infty(f, R_{S_\infty}) = \mu + \gamma - R_{S_\infty} - \Delta \times f \tag{3}$$

To investigate the impact of commercial rent forbearance on business closure, I augment the model by introducing commercial rent forbearance as mandated zero-interest lending to businesses in amount ρ between $t = 1$ and $t = 2$. Specifically, if commercial rent forbearance is enacted, then businesses are injected with ρ at $t = 1$ and must repay ρ at $t = 2$.

2.4 The impact of commercial rent forbearance on business closure

In the online appendix, I solve the model by backward inducting from $t = \infty$ to $t = 2$ to $t = 1$. I enter each state S_t with all businesses $f \in \left[0, F_{S_{t-1}}\right]$ from the preceding state S_{t-1} at time $t - 1$. The task in each period is to find a cutoff $F_{S_t} \leq F_{S_{t-1}}$ such that all businesses $f \in [0, F_{S_t}]$ survive state S_t at time t.

At $t = \infty$, the private value of business f is:

$$V_\infty(f, S_\infty) = \frac{1}{1 - \delta} \cdot \max\{X_\infty(f, R_{S_\infty}), 0\} \tag{4}$$

At $t = 2$, the private value of business f is:

$$V_2(f, R_{S_2}, F_{S_2}) = \max\{X_2(f, R_{S_2}, F_{S_2}) + \delta \cdot V_\infty(f, R_{s_\infty}), 0\} \tag{5}$$

At $t = 1$, the private value of business f is:

$$V_1(f, F_1) = \max\{X_1(f, R_1) + (1 - \phi) \cdot \delta \cdot [(1 - p) \cdot V_2(f, R_{G_2}, F_{G_2}(F_1)) + p \cdot V_2(f, R_{B_2}, F_{B_2}(F_1))], 0\} \quad (6)$$

Let $F^*_{S_t}$ denote the cutoff in the private market outcome without commercial rent forbearance, and let $F^{c*}_{S_t}$ denote the cutoff in the private market outcome with commercial rent forbearance. The following propositions describe the key properties of the solutions.

Proposition 1

Under the assumptions outlined above, strictly more businesses operate at $t = 1$ with commercial rent forbearance than without commercial rent forbearance.

Specifically, we have: $F^{c*}_1 - F^*_1 > 0$.

By providing financial support to all businesses, liquidity relief enables the survival of some liquidity-constrained businesses that could not procure sufficient financing from private markets alone. There are two reasons that these businesses would be supported by commercial rent forbearance but would not be supported by the private market. The first reason is that credit market frictions prevent these businesses from borrowing against the full value of their future cash flows. The second reason is that these businesses are insolvent with $V_1 < 0$ and private market investors would lose money by investing in these businesses at $t = 1$. Because the commercial rent forbearance policy mandates that commercial landlords provide liquidity relief to their business tenants, these businesses are preserved by the liquidity relief at $t = 1$ when they would not have survived without commercial rent forbearance.

After analyzing the short-run effect of commercial rent forbearance on business closure at $t = 1$, I next explore the long-run effect of commercial rent forbearance on business closure at $t = 2$. I also examine the implications of heterogeneity in business solvency on the effectiveness of the liquidity relief.

Proposition 2

Under the assumptions outlined above, commercial rent forbearance reduces business closure by $t = 2$ if μ is sufficiently high.
Specifically, $F_2^{c*} - F_2^* > 0$ when μ is sufficiently high.

In the model, μ captures business solvency or fundamental health. A higher μ means that a business has higher cash flow in all time periods and states. When we arrive at $t = 2$, more solvent businesses will be more likely to remain open because they have higher cash flows that they can use to repay borrowing and continue operating. By contrast, less solvent businesses will be more likely to shut down at $t = 2$. By accepting the liquidity relief at $t = 1$, they have used up the credit of commercial rent forbearance. As a result, at $t = 2$, they owe back rent ($-\rho$) to their landlords but cannot generate enough cash flow to repay back rent, leading them to close.

The propositions yield the following empirical predictions.

Prediction 1
Under substantial credit market frictions, commercial rent forbearance reduces closure for businesses in the short run.

Prediction 2
Under substantial credit market frictions, commercial rent forbearance is more effective in reducing closure in the long run for more solvent businesses.

3 Data and summary statistics

My sample of study will focus on California, where commercial rent forbearance is enacted by local governments for varying amounts of time during the Covid-19 pandemic. California serves as an ideal laboratory for commercial rent forbearance because of its decentralized implementation which creates variation in commercial rent forbearance across space and time that I exploit in the empirical analysis. Another advantage of studying California is that it contains a significant share of U.S. businesses. According to the Small Business Administration, in 2019, there were 4.0 million small businesses employing 7.1

million individuals in California, which accounts for 13% of the number of small businesses and 12% of the small business employment in the United States.

To evaluate the impact of commercial rent forbearance on business closure and employment, it is necessary to collect the enactments and updates of commercial rent forbearance and to observe the closure and employment behavior of businesses. To do so, I hand-collect commercial rent forbearance policies enacted by state, county, and city governments in California and connect them to business closure data from SafeGraph / Advan and business employment data from Homebase.

3.1 Commercial rent forbearance data

One challenge of assessing the impact of commercial rent forbearance on business closure is data availability. Commercial rent forbearance is a policy enacted by local governing bodies, rather than the federal government. Accordingly, commercial rent forbearance varies across geographies, and information about the policy is scattered across local government documents. Furthermore, commercial rent forbearance is a real-time response to business stress, which makes it necessary to continuously monitor the policy over time for any extension or premature termination.

By parsing City Council and County Board of Supervisors meeting agendas and minutes from March 2020 through May 2023, I collect a novel dataset on commercial rent forbearance enacted throughout California during the Covid-19 pandemic. Specifically, I record the following details about commercial rent forbearance: the geographic level of the policy (state, county, or city), start date, end date, additional repayment time, final due date of back rent, required number of repayment installments, and applicability to businesses (i.e. all businesses or small businesses only).

Table 1 summarizes the key characteristics of commercial rent forbearance at the state, county, and city level. At the state level, the California Judicial Council enacted a pause on eviction proceedings through September 1, 2020 by stopping all courts from processing commercial evictions. Additionally, Governor Gavin Newsom issued an executive order giving county and city governments the option to enact commercial rent forbearance until September 30, 2021.

28 of the 58 counties in California exercised the option and enacted commercial rent

forbearance. 18 counties enacted commercial rent forbearance over unincorporated areas only, while 10 counties enacted commercial rent forbearance county-wide. County-enacted commercial rent forbearance averaged 0.39 years (4.6 months) in length with an additional 0.08 years (1.0 month) of repayment time. The vast majority of county-enacted commercial rent forbearance policies allow for back rent to be paid in a single installment on the due date. 156 of the 482 cities in California exercised the option and enacted commercial rent forbearance. City-enacted commercial rent forbearance averaged 0.35 years (4.2 months) in length with an additional 0.13 years (1.6 months) of repayment time. The vast majority of city-enacted commercial rent forbearance also allow for back rent to be paid in a single installment on the due date.

When there are multiple policies in effect (e.g. state, county, and city), the binding commercial rent forbearance policy is the one that is most generous to business tenants. At the city level, binding policies averaged 1.02 years (12.2 months) in length with an additional 0.2 years (2.4 months) of repayment time. Once again, the vast majority of binding policies allow for back rent to be paid in a single installment on the due date.

Figure 2 illustrates the length of commercial rent forbearance enacted throughout California. The three categories of forbearance policies correspond intuitively to three categories of local government behavior. The lightest blue category (with forbearance of 6 months) consists of cities and counties that deferred to the state-wide policy enacted by the California Judicial Council. These areas did not enact the policy for any longer than the state policy, although they did have the legal option to do so. The medium blue category (with forbearance of 7 to 19 months) consists of cities and counties that exercised their option to enact forbearance. The dark blue category (with forbearance greater than 19 months) consists of cities and counties that extended their forbearance past the maximum date set by Governor Newsom.

3.2 Business closure data

The business closure data comes from SafeGraph and covers the effective universe of all business establishments. SafeGraph collects business information on a monthly basis from many sources, including first-party data and open-source data. A business is flagged as closed when it consistently disappears from this data collection pipeline. The

strength of this approach is that it can detect business closure in a high-frequency manner – estimated to be within 2 months. There are a few exceptions to the accuracy of the business closure date. Specifically, there are spikes in business closure attributed to March 2022 and April 2022, which actually denote a business closure that happened sometime in 2020-2021 but SafeGraph has not yet determined when. Table 2 provides summary statistics for the SafeGraph business closure data across all industries.

4 The impact of liquidity relief on business closure

In this section, I estimate the causal impact of liquidity relief on business closure. In Section 4.1, I identify the causal impact of liquidity relief on business closure by developing a geographic border-based difference-in-differences strategy. In Section 4.2, I test the relationship between pre-pandemic business solvency and the effectiveness of liquidity relief in reducing business closure.

4.1 Estimating the causal impact of liquidity relief on business closure

In this section, I identify the causal effect of liquidity relief on business closure. The main challenge is the reverse causality from business closure to the liquidity relief policy, which arises from local policymakers enacting the policy precisely to address business closure. For example, in April 2020, the city of San Jose prepared a memo assessing the extent of business financial stress and stating that the aim of the policy is to prevent business closure.[3] Panel A of Figure 3 shows a binned scatter plot of the business closure rate in 2020-2022 vs. the length of the policy (including repayment time) for cities in California. There is a positive relationship between business closure rate and length of the policy. Panel B of Figure 3 shows a binned scatter plot of the length of the policy (including repayment time) vs. change in unemployment rate from 2019 to 2020 for cities in California. There is also a positive relationship between length of the policy and the change in unem-

[3]Specifically, the memo states, "During this rapidly changing environment caused by the COVID-19 pandemic small businesses across the city are experiencing widespread financial injury. The introduction of a temporary moratorium banning the eviction of small business tenants for the nonpayment of rent directly impacted by the COVID-19 pandemic aims to mitigate preventable business failure and support the city's economy." The document can be found at https://sanjose.legistar.com/LegislationDetail.aspx?ID=4400682&GUID=D54AC5C9-09E6-46DD-8338-1FF8E6A05A05.

ployment rate, suggesting that cities that are more economically affected by the pandemic also enact longer policies.[4]

To overcome this selection bias, I set up a geographic border difference-in-differences strategy that compares businesses along the border of neighboring cities that differ in commercial rent forbearance policy. The criteria for identifying these borders is that one city has no liquidity relief policy, while the neighboring city has a substantial rent forbearance policy that lasts through the Newsom-specified date or even longer. For each border, I identify zip codes that lie along the border. I require that the zip code does not dominate the city, otherwise the zip code is effectively equivalent to the city and the rent forbearance policy is less random for the city due to the reverse causality issue discussed earlier. Figure 4 presents an illustrative example two neighboring cities that differ in their liquidity relief and the zip codes along the border that I hone in on to gather treated and control businesses. The motivation for the geographic border approach is that businesses on either side of the border likely face similar economic conditions but then different liquidity relief policies. The liquidity relief policy is arguably as-if randomly assigned and less endogenous to business closure likelihood because these businesses lie on the outskirts of the city.

The identifying assumption for the difference-in-differences strategy is that these treated and control businesses would have followed parallel trends in business closure in the absence of the liquidity relief. Figure 5 plots quarterly coefficients of the difference-in-differences regression of business closure for treated businesses relative to control businesses along a border before versus after the enactment of liquidity relief. I find evidence of parallel trends in business closure prior to the liquidity relief period.

Table 3 presents the quarterly impact of liquidity relief on business closure. More (less) liquidity-constrained industries are defined as those NAICS sectors with with an above-median (below-median) share of temporary closure in the Small Business Pulse Survey at the onset of the pandemic (April 2020).[5] Among more liquidity-constrained industries,

[4] **??** shows a binned scatter plot of business closure rate in 2020-2022 vs. length of the forbearance policy (including repayment time) for unincorporated cities, which are cities that have no municipal government and therefore cannot enact their own policy. For unincorporated cities, the forbearance policy will be determined at the county and state level. The relationship between forbearance and business closure is mitigated for these unincorporated cities that do not set their own forbearance policy. In my main analysis, I exclude unincorporated cities because of lack of voting registration data needed for my instrumental variable strategy.

[5] Using this classification, I identify the more liquidity-constrained NAICS sectors to be NAICS 72: Ac-

liquidity relief reduces business closure by 6 basis points per quarter, or 1.1 percentage points in total over the treatment period of 2020-2024. In my sample of California, I estimate that this liquidity relief prevents the liquidation of 61,700 business establishments across liquidity-constrained industries. By contrast, the liquidity relief has no effect on business closure for less liquidity-constrained industries. These results are consistent with the commercial rent forbearance being demanded by more liquidity-constrained businesses primarily and therefore making a material difference on their business survival only.

4.2 Business solvency & the effectiveness of liquidity relief

In this section, I analyze the relationship between business solvency and the effectiveness of liquidity relief. Using pre-pandemic employment growth rate as an industry-level proxy for business solvency, I examine the relationship between business solvency and the impact of liquidity relief on business closure across industries in Figure 6. A clear pattern emerges, which is that the more solvent industries are the places where liquidity relief had the strongest effect in terms of reducing business closure.

Table 4 highlights this point by juxtaposing retail v.s. food services. Both industries were liquidity-constrained during the pandemic. However, they had very different fundamentals coming into the pandemic. As well documented in the news & literature, there was a retail apocalypse phenomenon already underway prior to the pandemic.[6] By contrast, food services was among the fastest growing industries in the decade before the pandemic. Focusing on the early period of the Covid-19 crisis, Bartik et al. (2020b) find that pre-pandemic firm health predicts a lower likelihood of firm closure and a higher likelihood of firm reopening. I find a similar pattern of pre-pandemic firm health mattering for firm survival that occurs at the industry level and over a longer horizon (2020-

commodation and food services, NAICS 71: Arts, entertainment, and recreation, NAICS 61: Educational services, NAICS 62: Health care and social assistance, NAICS 81: Other services (except public administration), NAICS 44–45: Retail trade, NAICS 48–49: Transportation and warehousing, and NAICS 42: Wholesale trade. I identify the less liquidity-constrained industries to be NAICS 11: Agriculture, forestry, fishing and hunting, NAICS 23: Construction, NAICS 31–33: Manufacturing, NAICS 51: Information, NAICS 53: Real estate and rental and leasing, NAICS 54: Professional, scientific, and technical services, NAICS 55: Management of companies and enterprises, and NAICS 56: Admin. and support and waste management services.

[6]For example, Trepp has reported that the Covid-19 crisis amplified the retail apocalypse phenomenon. The article can be found at https://www.trepp.com/trepptalk/covid-accelerated-the-retail-apocalypse.

2022).

4.3 Shorter-run effects

To investigate whether liquidity relief helped prolong business survival in the short run, I re-estimate the business closure effects over a shorter post-treatment period of 2020-2021. Table 6 presents the quarterly impact of liquidity relief on business closure over the shorter run. For more liquidity-constrained industries, the liquidity relief reduces business closure by 6.0 basis points per quarter, which is slightly larger than the 5.9 basis points per quarter estimated over the full post-period.

Figure 7 presents these shorter-run business closure effects along the axis of business solvency. The relationship between liquidity relief effectiveness v.s. business solvency is less clear than the relationship that we saw in Figure 6 for the full horizon. In other words, the business closure effects of liquidity relief are less "efficient" in the short run, which points to liquidity relief prolonging business survival irrespective of business solvency in the short run. Then in the longer run, the business closure effects of liquidity relief become more aligned with business solvency as businesses are required to repay their delayed rent payments. In sum, I find evidence of the liquidity relief prolonging business survival in the shorter run in a way that is less aligned with business solvency.

4.4 Business openings

To understand the opportunity cost of prolonging business survival, I turn next to business openings. Using the same empirical machinery, I ask: how does the liquidity relief affect business openings? If new businesses replace the businesses that close, then the business opening effect should precisely equal the business closure effect. That is, we observe that the liquidity relief reduces business closure. If there is replacement of these closed businesses, then the liquidity relief should also be found to reduce business opening. However, if new businesses do not open to replace the businesses that close, then the business opening effect will be zero.

Business openings data comes from SafeGraph as well. I caveat however that SafeGraph captures business openings only for "branded" businesses, i.e. businesses with multiple locations under the same brand. Although the business openings data does not

include the full universe of business openings, it is not apparent ex ante that focusing on branded business openings would bias the results one way or the other.

Table 7 shows that there is no significant impact of the liquidity relief on business openings. Given the finding that liquidity relief reduces business closure and holds existing businesses in place, it is striking to observe that there is no crowd-out of business openings. There does not appear to be a supply of business establishments ready to enter and take the space of the businesses that close, which suggests in turn that the opportunity cost is low of prolonging business survival and keeping existing businesses in place.

5 The impact of liquidity relief on other business financing

In this section, I estimate the effect of the liquidity relief on business take-up of other sources of financing.

5.1 Pecking order of business financing during the pandemic

Overall, there are two types of financing available to businesses during the Covid-19 pandemic. First, there is loan financing that must be repaid, such as the EIDL loan program. There is likely to be substitution towards commercial rent forbearance usage and away from loan financing because the loan is more costly than the zero-interest liquidity relief of commercial rent forbearance. Second, there is grant financing that does not need to be repaid, such as the EIDL advance program. There is unlikely to be substitution between commercial rent forbearance and grants because grants improve business solvency. The Paycheck Protection Program forgivable loan is a sort of hybrid between a grant and a loan since it is originally framed as a loan but then has very reasonable terms for forgiveness. I present this pecking order of business financing, including commercial rent forbearance liquidity relief, in Figure 8. It is ordered from from least costly (most desirable) to most costly (least desirable).

The EIDL advance program provides grants of up to $15,000 to businesses that can be used for working capital and operating expenses during the Covid-19 pandemic. EIDL advances do not need to be repaid.[7] I obtain details on grants administered through the

[7]This program consists of two parts. First, the targeted EIDL advance provides grants of up to $10,000 to hard-hit businesses. To be eligible, a business must be located in a low-income community, experience a

EIDL advance program from the public database on federal spending. Throughout the U.S., the EIDL advance program disbursed ∼1 million grants totaling ∼$7.5 billion. In my sample of California, the program disbursed ∼150,000 grants totaling ∼$1 billion. My analysis proceeds at the business level. I compute the average dollars of EIDL advance grants per business by dividing the total dollars of EIDL advances disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore captures the EIDL advance take-up of the average business in the zip code.

The Paycheck Protection Program provides forgivable loans to small businesses to be used primarily for payroll, rent, utilities, and interest on mortgages.[8] The loan amount is determined as a multiple of a business's monthly payroll cost. Loans are fully forgiven if the business retains employees and uses at least 60% of funds for payroll. In this way, PPP is effectively a business grant, albeit one with conditions attached. I obtain details on forgivable loans administered through PPP from the Small Business Administration website. Throughout the U.S., PPP disbursed ∼11.8 million forgivable loans totaling face value of ∼$800 billion. In my sample of California, the program disbursed ∼1.3 million forgivable loans totaling face value of ∼$100 billion. I compute the average dollars of PPP forgivable loans per business by dividing the total dollars of PPP disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore captures PPP take-up of the average business in the zip code.

The Economic Injury Disaster Loan (EIDL) Program provides low-interest, fixed-rate, long-term loans from the Small Business Administration directly to small businesses that can be used for working capital, operating expenses and debt repayment during the Covid-19 pandemic. To be eligible, a business must have fewer than 500 employees and must not have access to other credit. Under the latest program guidelines, EIDL loans have a maximum amount of $2 million, a term of 30 years, and a fixed interest rate of 3.75%. No payment is required for the first 2 years, and there is no penalty for prepay-

30% or greater economic loss over an 8-week period during the pandemic, and have no more than 300 employees. Second, the supplemental EIDL advance provides additional grants of up to $5,000 for especially hard-hit businesses. To be eligible, a business must experience a 50% or greater economic loss and have no more than 10 employees.

[8]PPP loans are disbursed in three rounds. The first round allocated $349 billion to businesses over the course of two weeks in April 2020. The second round allocated $176 billion to businesses between April and August 2020. The third round allocated $284 billion to businesses between January and June 2021.

ment. The program opened for applications in March 2020 and closed by January 2022. I obtain details on loans administered through this program from the public database on federal spending.[9] Throughout the U.S., the COVID EIDL program disbursed ∼3.9 million loans totaling ∼$380 billion. In my sample of California, the program disbursed ∼600,000 loans totaling ∼$68 billion. My analysis proceeds at the zip code level. After connecting SafeGraph business establishment data and EIDL loan data at the zip code level, I compute the average dollars of borrowing per business by dividing the total dollars of EIDL loans disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore represents the EIDL borrowing behavior of the average business in the zip code.

5.2 Impact of liquidity relief on business financing

While commercial rent forbearance gives businesses more time to pay rent without forgiving rent, grants give businesses funds that do not need to be repaid. Therefore, businesses will seek out grants irrespective of the liquidity relief policy because grants improve business profitability. As a result, there is unlikely to be substitution away from grants toward forbearance liquidity relief, and liquidity relief has no effect on business grant take-up.

Commercial rent forbearance is a lower-cost source of liquidity relief for businesses than EIDL. While EIDL allows businesses to borrow at 3.75%, commercial rent forbearance effectively allows businesses to borrow at 0% interest. Therefore, if businesses are not so constrained that they demand full liquidity relief of both EIDL and commercial rent forbearance, then they will substitute away from the higher-cost EIDL borrowing and towards the lowest-cost forbearance liquidity relief. In this case, rent forbearance will have a negative effect on EIDL borrowing.

Table 5 presents the impact of liquidity relief on business financing take-up from the EIDL Advance grant program, Paycheck Protection forgivable loan program, and the Economic Injury Disaster Loan program. My empirical specification is now a difference between businesses along the border of neighboring cities with differing liquidity relief policy.[10]

[9] Specifically, the data is available at USASpending.gov.

[10] It is no longer possibly to employ a difference-in-differences strategy because the business financing programs only happen in the post treatment period.

In Panel A, I focus on the more liquidity-constrained industries. In the first 2 columns, I estimate the effect of liquidity relief on take-up from the EIDL advance program. In column 1, I find that forbearance has no significant effect on the extensive margin of EIDL advance take-up, which is the likelihood of receiving an EIDL advance. In column 2, I find that liquidity relief has no significant effect on the intensive margin of EIDL advance take-up as captured by the log EIDL advance grant amount. In the next two columns, I estimate the effect of liquidity relief on usage of the PPP forgivable loan program. In column 1, I find that the liquidity relief reduces the likelihood of having PPP by 1.9 percentage points and reduces the amount of PPP by approximately 20 percentage points, likely from receiving fewer rounds of PPP. In the next 2 columns, I estimate the effect of liquidity relief on usage of the EIDL loan program. I find that the liquidity relief reduces the likelihood of having EIDL by 1.0 percentage point and reduces the loan amount by approximately 10%. In sum, I observe liquidity relief crowding out more costly loan financing more than it crowds out pure grant financing. Interestingly, the liquidity relief also partly crowds out PPP forgivable loan financing take-up, which may be attributable to the costs of applying for PPP or uncertainty about whether PPP would function more like a loan or a grant. In Panel B, I turn to the less liquidity-constrained industries and find no effect of the liquidity relief on any of the types of business financing.

6 Conclusion

The Covid-19 pandemic is a sudden shock to businesses, especially small businesses that generate the majority of employment in the U.S. and are an important driver of economic growth. In response to the Covid-19 shock, federal and local governments rapidly enacted aid programs aiming to prevent immediate business closure.

In this paper, I assess the tradeoff that arises when enacting widespread liquidity relief for businesses. A key benefit is the opportunity to save liquidity-constrained but solvent businesses, while a key cost is the possibility of prolonging the survival of less solvent businesses. I find that commercial rent forbearance liquidity relief significantly reduces closure of liquidity-constrained businesses by approximately 6 basis points per quarter, or 1.1 percentage points in total, which equals 61,700 business establishments in my sample of California. The liquidity relief is more effective in reducing business closure for more

solvent businesses, which lends empirical credence to the key benefit of widespread liquidity relief. I find some evidence that liquidity relief is less efficient in the short run and temporarily prolongs the closure of less solvent businesses. However, because new businesses did not tend to open to replace closing businesses during the recession, the opportunity cost of prolonging business survival appears to be low. Along the pecking order of business financing opportunities, I show that the liquidity relief does not affect business take-up of grants and only partly crowds out business take-up of more costly loan financing as credit constraints remain severe during this time.

References

Agarwal, Sumit, Brent W. Ambrose, Luis A. Lopez, and Xue Xiao (Forthcoming), "Did the paycheck protection program help small businesses? evidence from commercial mortgage-backed securities." *American Economic Journal: Economic Policy*.

Allan, Roddy, Ervi Liusman, Teddy Lu, and Desmond Tsang (2021), "The covid-19 pandemic and commercial property rent dynamics." *Journal of Risk and Financial Management*, 14.

An, Xudong, Stuart A. Gabriel, and Nitzan Tzur-Ilan (2022), "More than shelter: The effect of rental eviction moratoria on household well-being." *AEA Papers and Proceedings*, 112.

Arseneau, David, Jose Fillat, Molly Mahar, Donald Morgan, and Skander Van den Heuvel (2022), "The Main Street Lending Program." *Economic Policy Review*, 28.

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.

Baghai, Ramin P. and Bo Becker (2020), "Reputations and credit ratings: Evidence from commercial mortgage-backed securities." *Journal of Financial Economics*, 135.

Bai, Jessica, Angela Ma, and Miles Zheng (2023), "Segmented going-public markets and the demand for SPACs." Working paper.

Barlevy, Gadi (2003), "Credit market frictions and the allocation of resources over the business cycle." *Journal of Monetary Economics*, 50, 1795–1818.

Barnanke, Ben and Mark Gertler (1989), "Agency costs, net worth, and business fluctuations." *American Economic Review*, 79, 14–31.

Barrios, John Manuel, Michael Minnis, William C. Minnis, and Joost Sijthoff (2020), "Assessing the payroll protection program: A framework and preliminary results." Working paper.

Bartik, Alexander W., Marianne Bertrand, Zoe Cullen, Edward L. Glaeser, Michael Luca, and Christopher Stanton (2020a), "The impact of COVID-19 on small business outcomes and expectations." *PNAS*, 117.

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matthew Unrath (2020b), "Measuring the labor market at the onset of the COVID-19 crisis." *Brookings Papers on Economic Activity*, Summer 2020.

Bartik, Alexander W., Zoe Cullen, Edward L. Glaeser, Michael Luca, Christopher Stanton, and Adi Sunderam (2023), "The targeting and impact of Paycheck Protection Program loans to small businesses." Working paper.

Benmelech, Efraim, Jennifer Dlugosz, and Victoria Ivashina (2012), "Securitization without adverse selection: The case of CLOs." *Journal of Financial Economics*, 106.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999), "The financial accelerator in a quantitative business cycle framework." In *Handbook of Macroeconomics* (John Taylor and Michael Woodford, eds.), volume 1, Amsterdam: North-Holland.

Caballero, Ricardo J. and Mohamad L. Hammour (1994), "The cleansing effect of recessions." *American Economic Review*, 84, 1350–1368.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz (2020), "The US labor market during the beginning of the pandemic recession." *Brookings Papers on Economic Activity*, Summer 2020.

Cajner, Tomaz, Laura J. Feiveson, Christopher J. Kurz, and Stacey Telvin (2022), "Lessons learned from the use of nontraditional data during COVID-19." In *Recession Remedies: Lessons Learned from the U.S. Economic Policy Response to COVID-19* (Wendy Edelberg, Louise Sheiner, and David Wessel, eds.), chapter 9, The Hamilton Project and Hutchins Center on Fiscal & Monetary Policy at Brookings.

Canes-Wrone, Brandice, Jonathan T. Rothwell, and Christos Makridis (2022), "Partisanship and policy on an emerging issue: Mass and elite responses to COVID-19 as the pandemic evolved." Working paper.

Cherry, Susan, Erica Jiang, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2021), "Government and private household debt relief during COVID-19." *Brookings Papers on Economic Activity,*, Fall 2021.

Chetty, Raj, John N. Friedman, Michael Stepner, and The Opportunity Insights Team (Forthcoming), "The economic impacts of COVID-19: Evidence from a new public database built using private sector data." *The Quarterly Journal of Economics*.

Chodorow-Reich, Gabriel (2014), "The employment effects of credit market disruptions: Firm-level evidence from the 2008-9 financial crisis." *Quarterly Journal of Economics*, 129, 1–59.

Chodorow-Reich, Gabriel, Ben Iverson, and Adi Sunderam (2022), "Lessons learned from support to business during COVID-19." In *Recession Remedies: Lessons Learned from the U.S. Economic Policy Response to COVID-19* (Wendy Edelberg, Louise Sheiner, and David Wessel, eds.), chapter 4, The Hamilton Project and Hutchins Center on Fiscal & Monetary Policy at Brookings.

Coase, Ronald (1960), "The problem of social cost." *The Journal of Law & Economics*, 3.

Crane, Leland D., Ryan A. Decker, Aaron Flaaen, Adrian Hamins-Puertolas, and Christopher Kurz (2022), "Business exit during the COVID-19 pandemic: Non-traditional measures in historical context." *Journal of Macroeconomics*, 72.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh (1996), *Job creation and destruction*. MIT Press, Cambridge, MA.

de Vaan, Mathijs, Saqib Mumtaz, Abhishek Nagaraj, and Sameer B. Srivastava (2021), "Social learning in the COVID-19 pandemic: Community establishments' closure decisions follow those of nearby chain establishments." *Management Science*, 67.

Di Maggio, Marco, Angela Ma, and Emily Williams (2022), "In the red: Overdrafts, payday lending and the underbanked." Working paper.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie (2021), "Corporate immunity to the COVID-19 pandemic." *Journal of Financial Economics*, 141, 802–830.

English, William B., , and J. Nellie Liang (2020), "Designing the Main Street Lending Program: Challenges and options." Hutchins Center Working Paper 64.

Fahlenbrach, Rüdiger, Kevin Rageth, and René M Stulz (2021), "How valuable is financial flexibility when revenue stops? evidence from the covid-19 crisis." *Review of Financial Studies*, 34, 5474–5521.

Fairlie, Robert (2020), "The impact of COVID-19 on small business owners: Evidence from the first three months after widespread social-distancing restrictions." *Journal of Economics & Management Strategy*, 29.

Fairlie, Robert and Frank M. Fossen (2022), "Did the Paycheck Protection Program and Economic Injury Disaster Loan Program get disbursed to minority communities in the early stages of COVID-19?" *Small Business Economics*, 58.

Fairlie, Robert, Frank M. Fossen, Reid Johnsen, and Gentian Droboniku (2023), "Were small businesses more likely to permanently close in the pandemic?" *Small Business Economics*, 60.

Foster, Lucia, Cheryl Grim, and John Haltiwanger (2016), "Reallocation in the Great Recession: Cleansing or not?" *Journal of Labor Economics*, 34.

Foster, Lucia, John Haltiwanger, and C. J. Krizan (2001), "Aggregate productivity growth: Lessons from microeconomic evidence." In *New developments in productivity analysis* (Charles R. Hulten, Edward R. Dean, and Michael J. Harper, eds.), Chicago: University of Chicago Press for National Bureau of Economic Research.

Foster, Lucia, John Haltiwanger, and Chad Syverson (2008), "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?" *American Economic Review*, 98, 394–425.

Gahng, Minmo, Jay R. Ritter, and Donghang Zhang (2023), "SPACs." *Review of Financial Studies*.

Giroud, Xavier and Holger M. Mueller (2017), "Firm leverage, consumer demand, and employment losses during the Great Recession." *Quarterly Journal of Economics*, 132, 271–316.

Glancy, David, John Krainer, Robert Kurtzman, and Joseph Nichols (2021), "Intermediary segmentation in the commercial real estate market." *Journal of Money, Credit and Banking*, 54.

Glancy, David, Robert Kurtzman, and Lara Loewenstein (2022), "Loan modifications and the commercial real estate market." Finance and Economics Discussion Series working paper.

Glode, Vincent and Christian C. Opp (Forthcoming), "Private renegotiations and government interventions in credit chains." *Review of Financial Studies*.

Gollwitzer, Anton, Cameron Martel, William J. Brady, Philip Parnamets, Isaac G. Freedman, Eric D. Knowles, and Jay J. Van Bavel (2020), "Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic." *Nature Human Behaviour*, 4.

Granja, Joao, Christos Makridis, Constantine Yannelis, and Eric Zwick (2022), "Did the Paycheck Protection Program hit the target?" *Journal of Financial Economics*, 145.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen (2020), "Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and "normal" economic times." *American Economic Journal: Economic Policy*, 12, 200–225.

Greenwood, Robin, Ben Iverson, and David Thesmar (2020), "Sizing up corporate restructuring in the COVID crisis." *Brookings Papers on Economic Activity*, Fall 2020.

Gromis, Ashley, Ian Fellows, James R. Hendrickson, Lavar Edmonds, Lillian Leung, Adam Porton, and Matthew Desmond (2022), "Estimating eviction prevalance across the United States." *PNAS*, 119.

Gupta, Arpit, Vrinda Mittal, and Stijn Van Nieuwerburgh (2023), "Work from home and the office real estate apocalypse." NBER working paper 30526.

Hamilton, Steve (2020), "From survival to revival: How to help small businesses through the covid-19 crisis." *The Hamilton Project*. Policy proposal.

Hanson, Samuel G., Adi Sunderam, Jeremy C. Stein, and Eric Zwick (2020), "Business credit programs in the pandemic era." *Brookings Papers on Economic Activity*, Fall 2020.

Howell, Sabrina (2017), "Financing innovation: Evidence from R&D grants." *American Economic Review*, 107.

Hubbard, Glenn and Michael R. Strain (2020), "Has the paycheck protection program succeeded?" *Brookings Papers on Economic Activity*, Fall 2020.

Iverson, Ben, Renhao Jiang, Jialan Wang, and Jeyul Yang (2022), "Bankruptcy and the COVID-19 crisis." Working paper.

Jowers, Kay, Christopher Timmins, Nrupen Bhavsar, Qihui Hu, and Julia Marshall (2021), "Housing precarity & the covid-19 pandemic: Impacts of utility disconnection and eviction moratoria on infections and deaths across us counties." NBER working paper 28394.

Kiyotaki, Nobuhiro and John Moore (1997), "Credit cycles." *Journal of Political Economy*, 105, 211–248.

Klausner, Michael, Michael Ohlrogge, and Emily Ruan (2022), "A sober look at SPACs." *Yale Journal on Regulation*.

Kurmann, André, Etienne Lalé, and Lien Ta (2022), "Measuring small business dynamics and employment with private-sector real-time data." Working paper.

Lewis, Verlan (2018), "Party control of government and american party ideology development." *Studies in American Political Development*, 32.

Li, Meng (2021), "Did the small business administration's COVID-19 assistance go to the hard hit firms and bring the desired relief?" *Journal of Economics and Business*, 115.

Liebersohn, Jack, Ricardo Correa, and Martin Sicilian (2022), "Debt overhang and the retail apocalypse." Working paper.

Morse, Adair (2011), "Payday lenders: Heroes or villains?" *Journal of Financial Economics*, 102, 28–44.

Moszkowski, Erica and Daniel Stackman (2023), "Option value and storefront vacancy in New York City." Working paper.

Osotimehin, Sophie and Francesco Pappadà (2015), "Credit frictions and the cleansing effect of recessions." *Economic Journal*, 127, 1153–1187.

Raajkumar, Adithya (2022), "How effective were national, state, and local eviction moratoria?" FEDS Notes.

Rigobon, Daniel E., Thibaut Duprey, Artur Kotlicki, Philip Schnattinger, Soheil Baharian, and Thomas R. Hurd (2022), "Business closures and (re)openings in real-time using Google Places: Proof of concept." *Journal of Risk and Financial Management*, 15.

Sadikin, Natasha, Irmak Turan, and Andrea Chegut (2021), "The financial impact of healthy buildings: Rental prices and market dynamics in commercial office." MIT Center for Real Estate Research Paper No. 21/04.

Schumpeter, Joseph A. (1939), *Business cycles: A theoretical, historical and statistical analysis of the capitalist process*. McGraw Hill, New York.

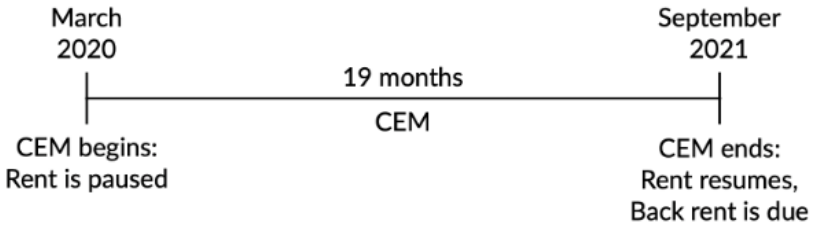
Wang, Gang, Richard A. Devine, and Gonzalo Molina-Sieiro (2021), "Democratic governors quicker to issue stay-at-home orders in response to COVID-19." *The Leadership Quarterly*.

Weiner, Perrie, Aaron Goodman, Kelton Basirico, and Baker McKenzie (2020), "Commercial lease defenses during Covid-19." *Bloomberg Law: Professional Perspective*.

Wong, Maisy (2018), "Cmbs and conflicts of interest: Evidence from ownership changes for servicers." *The Journal of Finance*, 73.

Figure 1: Illustrative example of commercial rent forbearance

This figure presents an illustrative example of the commercial rent forbearance policy for Oakland, CA. Panel A shows the timeline of the policy, while Panel B shows the effective borrowing that businesses can incur under the policy.



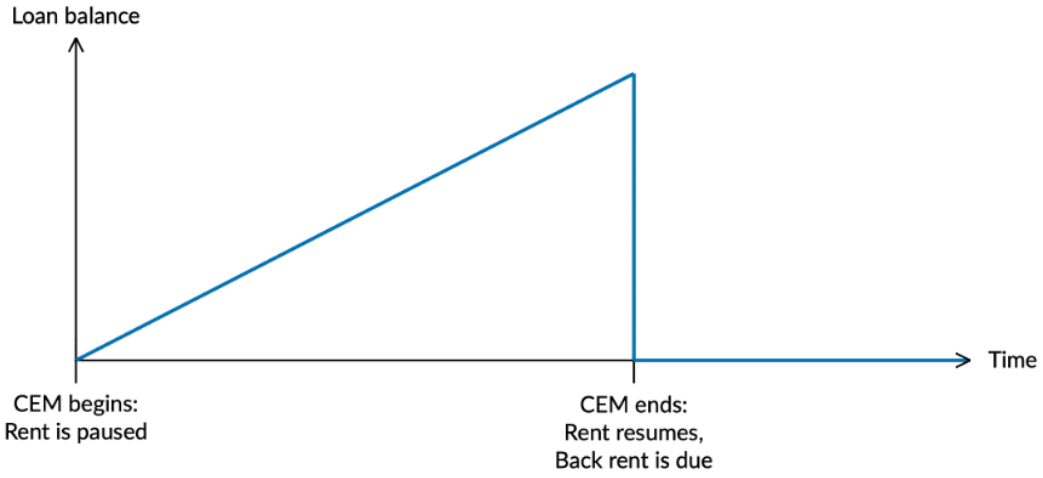
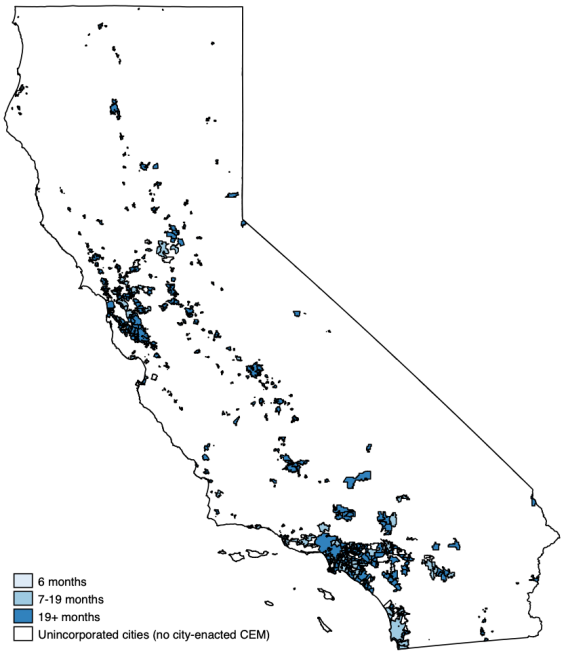


Figure 2: Commercial rent forbearance in California

This figure illustrates the length of commercial rent forbearance policies enacted throughout California. Panel A shows the length of rent forbearance enacted by cities, while Panel B shows the length of rent forbearance enacted by counties. The three categories of length of forbearance correspond intuitively to three categories of local government behavior. The lightest blue category (with forbearance of 6 months) consists of cities and counties that deferred to the state-wide forbearance enacted by the California Judicial Council. The medium blue category (with forbearance of 7 to 19 months) consists of cities and counties that exercised the option given to them by Newsom and enacted forbearance up to the September 30, 2021 maximum date. The dark blue category (with forbearance greater than 19 months) consists of cities and counties that extended their forbearance past the maximum date allowed by Newsom's executive order.

Panel A: City-level commercial rent forbearance



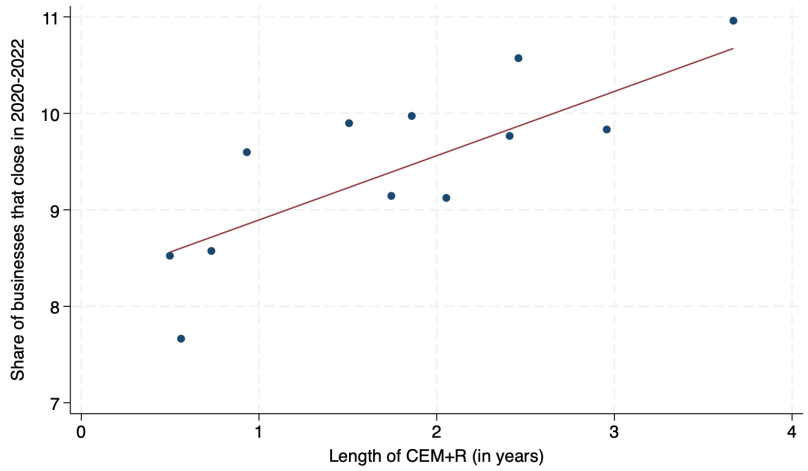
Panel B: County-level commercial rent forbearance



Figure 3: Relationship between commercial rent forbearance policy, business closure, and unemployment

This figure illustrates the binscatter relationship between commercial rent forbearance policy, business closure rate, and unemployment rate for incorporated cities in California. Panel A presents a binscatter of business closure rate in 2020-2022 v.s. length of forbearance (plus repayment time). Panel B presents a binscatter of length of forbearance (plus repayment time) v.s. change in unemployment rate from 2019 to 2020.

Panel A: Relationship between business closure and commercial rent forbearance policy



Panel B: Relationship between commercial rent forbearance policy and unemployment

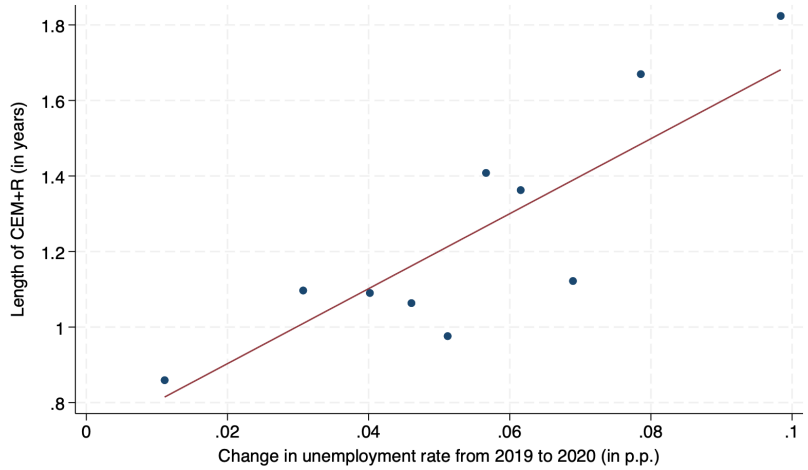


Figure 4: Illustrative example of empirical strategy: Comparing businesses along the border of two cities with differing liquidity relief policy

This figure illustrates the empirical strategy of comparing businesses along the border of two cities with differing commercial rent forbearance liquidity relief policies.

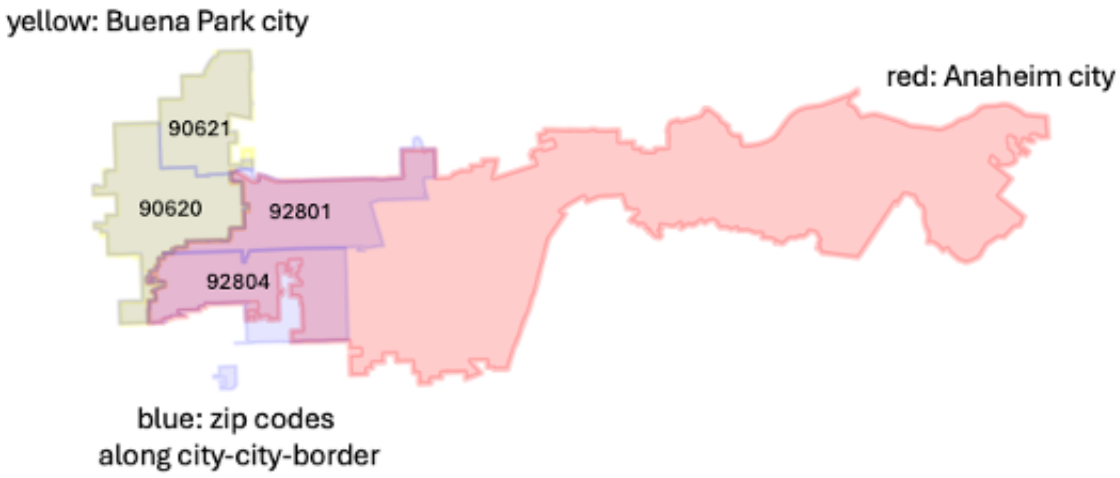


Figure 5: Impact of liquidity relief on business closure:
Liquidity-constrained industries

The figure plots the coefficients of the business × quarter-level difference-in-differences analysis around commercial rent forbearance policies. The outcome variable is business closure measured in basis points. 95% confidence intervals are given based on standard errors clustered at the city-city border level.

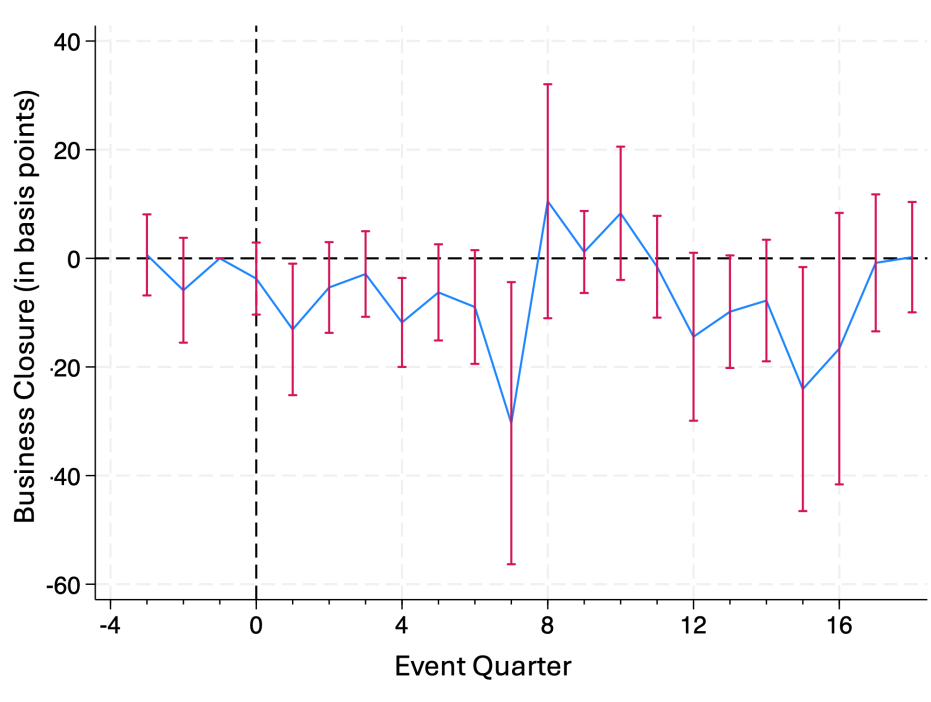


Figure 6: Impact of liquidity relief on business closure: By industry

This figure shows the relationship between the 10-year pre-pandemic employment growth and the business closure effects of liquidity relief for each NAICS sector.

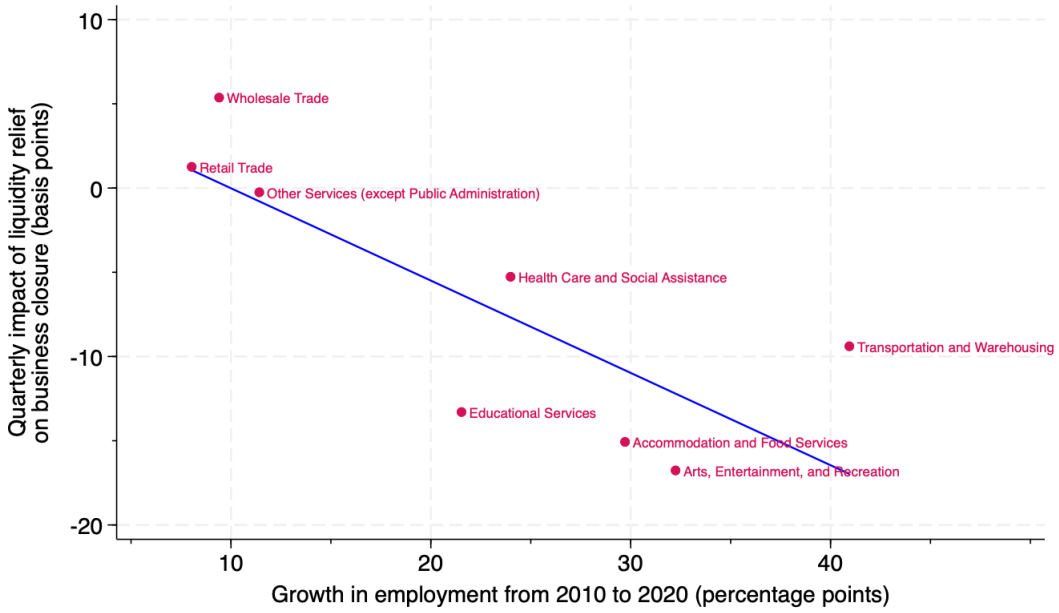


Figure 7: Impact of liquidity relief on business closure: By industry: Shorter-run effects

This figure shows the relationship between the 10-year pre-pandemic employment growth and the short-run business closure effect of liquidity relief for NAICS sectors. Specifically, short-run refers to the post-treatment period being 2020-2021.

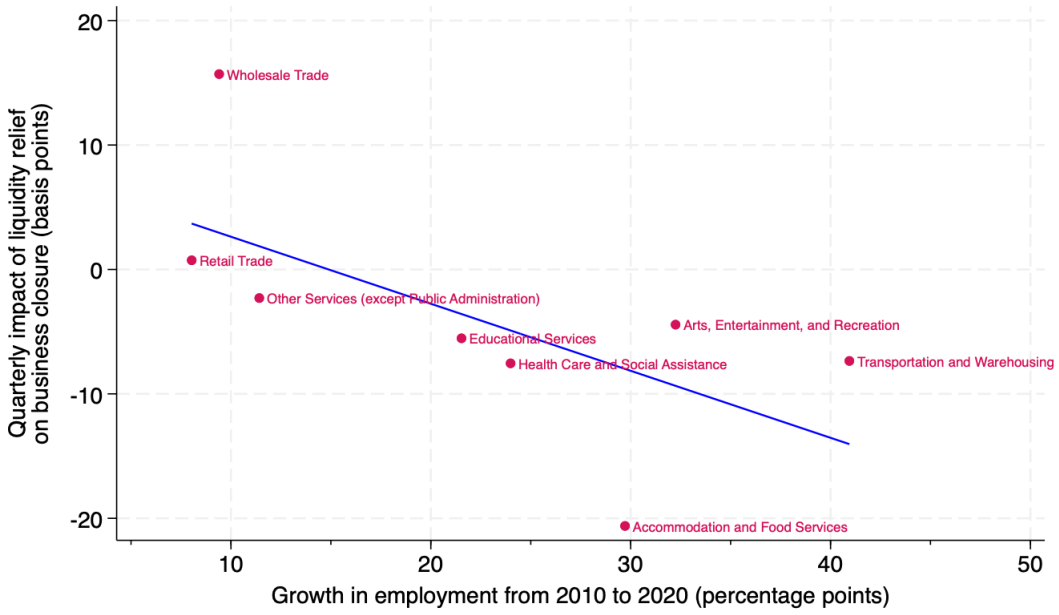


Figure 8: Pecking order of business financing during the Covid-19 recession

This figure presents a pecking order of business financing opportunities during Covid-19, arranged from lower cost of financing (most desirable) to higher cost of financing (least desirable).

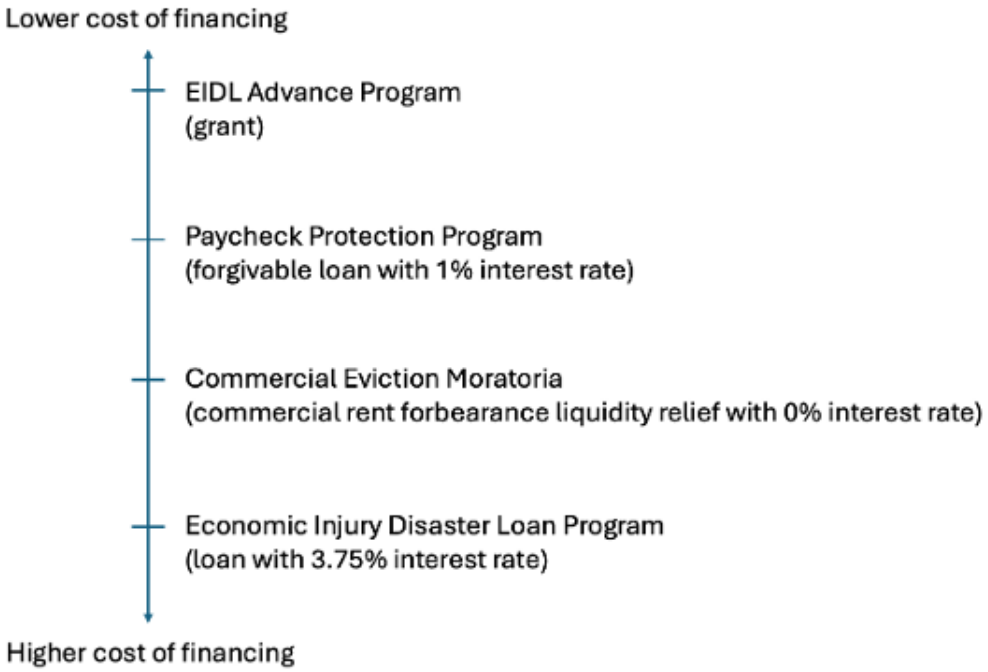


Table 1: Summary statistics for commercial rent forbearance

This table summarizes the key characteristics of commercial rent forbearance policy at the state, county, and incorporated city level.

Panel A: State-level commercial rent forbearance policy

1. California Judicial Council enacts state-wide eviction pause through September 1, 2020

2. Governor Newsom gives county and city governments the option to enact forbearance through September 30, 2021

Panel B: County-level commercial rent forbearance policy

	Obs.	Min.	Median	Max.	Mean	Std dev.
Indicator of forbearance enacted by county	58	0.00	0.00	1.00	0.48	0.50
Indicator of forbearance applying to unincorporated areas only	58	0.00	0.00	1.00	0.31	0.47
Indicator of forbearance applying to entire county	58	0.00	0.00	1.00	0.17	0.38
Forbearance enacted by county:						
Length of forbearance (in years)	58	0.00	0.00	3.24	0.39	0.66
Additional time for repayment (in years)	58	0.00	0.00	1.00	0.08	0.22
Length of forbearance + repayment time (in years)	58	0.00	0.00	3.24	0.47	0.77
Number of required installments for repayment	28	1.00	1.00	2.00	1.04	0.19

Panel C: Incorporated city-level commercial rent forbearance policy

	Obs.	Min.	Median	Max.	Mean	Std dev.
Indicator of forbearance enacted by city	482	0.00	0.00	1.00	0.32	0.47
Forbearance enacted by city:						
Length of forbearance (in years)	482	0.00	0.00	3.18	0.35	0.67
Additional time for repayment (in years)	482	0.00	0.00	2.00	0.13	0.26
Length of forbearance + repayment (in years)	482	0.00	0.00	5.18	0.48	0.86
Number of required installments for repayment	156	1.00	1.00	16	1.53	2.11
Policy that binds:						
Length of forbearance (in years)	482	0.50	0.50	3.24	1.02	0.72
Additional time for repayment (in years)	482	0.00	0.00	2.00	0.20	0.29
Length of forbearance + repayment (in years)	482	0.50	0.50	5.22	1.22	0.92
Number of required installments for repayment	482	1.00	1.00	16.00	1.19	1.21

Table 2: Summary statistics for business closure

This table provides summary statistics for SafeGraph business closure data. Observations are at the business establishment level.

Business establishments as of 2019 Q3								
			Closure likehood (p.p.)					
	Observations	2019–2024	2019	2020	2021	2022	2023	2024
NAICS 11: Agriculture, Forestry, Fishing and Hunting	1,435	10.10	0.14	0.28	0.42	0.63	4.25	4.39
NAICS 21: Mining, Quarrying, and Oil and Gas Extraction	25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NAICS 22: Utilities	797	5.40	0.00	0.00	0.00	0.13	1.76	3.51
NAICS 23: Construction	35,760	15.70	0.50	0.76	0.68	4.43	3.56	5.78
NAICS 31–33: Manufacturing	19,421	12.73	0.20	0.66	0.53	4.77	2.55	4.03
NAICS 42: Wholesale Trade	7,559	10.78	0.13	1.48	1.30	3.10	1.93	2.84
NAICS 44–45: Retail Trade	182,123	25.57	0.38	1.82	1.58	10.39	4.43	6.96
NAICS 48–49: Transportation and Warehousing	48,213	4.44	0.14	0.30	0.29	1.34	1.07	1.30
NAICS 51: Information	15,538	23.41	0.19	4.80	1.40	6.62	4.71	5.70
NAICS 52: Finance and Insurance	32,740	18.87	0.25	1.90	2.10	4.32	4.98	5.33
NAICS 53: Real Estate and Rental and Leasing	70,002	9.22	0.18	1.05	0.62	3.01	1.47	2.90
NAICS 54: Professional, Scientific, and Technical Services	62,791	13.43	0.25	0.52	0.52	2.91	2.94	6.29
NAICS 55: Management of Companies and Enterprises	4,118	0.32	0.00	0.05	0.02	0.02	0.07	0.15
NAICS 56: Admin. & Support and Waste Management Services	20,761	12.75	0.55	0.77	0.67	3.25	3.35	4.16
NAICS 61: Educational Services	27,283	10.45	0.28	0.78	0.65	3.00	1.76	3.98
NAICS 62: Health Care and Social Assistance	181,756	10.05	0.15	0.66	0.53	4.22	1.72	2.76
NAICS 71: Arts, Entertainment, and Recreation	50,838	15.70	0.34	1.23	0.90	4.94	2.90	5.38
NAICS 72: Accommodation and Food Services	134,165	27.89	0.51	2.67	2.27	9.81	5.46	7.17
NAICS 81: Other Services (except Public Administration)	159,311	14.84	0.65	1.87	1.26	4.28	2.73	4.07
NAICS 92: Public Administration	6,847	4.37	0.09	0.28	0.28	0.82	1.20	1.71

Table 3: Impact of liquidity relief on business closure:
More v.s. less liquidity-constrained sectors

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. In the first three columns, the sample is restricted to above-median liquidity-constrained industries. In the last three columns, the sample is restricted to below-median liquidity-constrained industries. The outcome variable is business closure measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median household income, log median gross rent, homeownership rate, high school graduation rate, and partisanship spread. Standard errors are clustered at the city-city border level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained industries			Less liquidity-constrained industries		
	Quarterly business closure (basis points)			Quarterly business closure (basis points)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-5.758**	-5.853**	-5.876**	1.382	1.470	1.523
	(2.653)	(2.655)	(2.672)	(4.200)	(4.218)	(4.236)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
City-city border fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector fixed effects	No	Yes	Yes	No	Yes	Yes
Additional controls	No	No	Yes	No	No	Yes
Observations	2,631,469	2,631,469	2,631,469	807,463	807,463	807,463
R-squared	0.001	0.002	0.003	0.001	0.002	0.002

Table 4: Impact of liquidity relief on business closure:
Retail v.s. food services

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. In the first two columns, the sample is restricted to retail trade businesses. In the last two columns, the sample is restricted to accommodation & food services businesses. The outcome variable is business closure measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median household income, log median gross rent, homeownership rate, high school graduation rate, and partisanship spread. Standard errors are clustered at the city-city border level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	NAICS 44–45: Retail trade		NAICS 72: Accommodation & food services	
	Quarterly business closure (basis points)		Quarterly business closure (basis points)	
	(1)	(2)	(3)	(4)
Treated x Post	-0.858	-0.934	-19.11**	-19.05**
	(5.332)	(5.358)	(7.985)	(7.947)
Treated	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes
City-city border fixed effects	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes
Observations	578,444	578,444	395,324	395,324
R-squared	0.001	0.002	0.001	0.002

Table 5: Impact of liquidity relief on usage of other financing

The table presents results of the business-level analysis on how commercial rent forbearance policies affects usage of other financing. In Panel A, the sample is restricted to above-median liquidity-constrained industries. In Panel B, the sample is restricted to below-median liquidity-constrained industries. The outcome variable is an indicator or the log(1+amount) for EIDL Advance grant, PPP forgivable loan, or EIDL loan. A city-city border encapsulates the area along the border of two neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median household income, log median gross rent, homeownership rate, high school graduation rate, and partisanship spread. Standard errors are clustered at the city-city border level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: More liquidity-constrained industries					
	EIDL Advance (grant)		PPP (forgivable loan)		EIDL Loan (loan)	
	Indicator	Ln(1 + Amount)	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)
Treated	-0.0120	-0.0949	-0.0194*	-0.212*	-0.0100**	-0.110*
	(0.00762)	(0.0652)	(0.0110)	(0.123)	(0.00465)	(0.0550)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125,346	125,346	125,346	125,346	125,346	125,346
R-squared	0.029	0.029	0.030	0.029	0.020	0.018
	Panel B: Less liquidity-constrained industries					
	EIDL Advance (grant)		PPP (forgivable loan)		EIDL Loan (loan)	
	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)
Treated	-0.00344	-0.0197	-0.00611	-0.129	-0.000484	-0.0248
	(0.00661)	(0.0591)	(0.0155)	(0.182)	(0.00484)	(0.0537)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,942	37,942	37,942	37,942	37,942	37,942
R-squared	0.022	0.023	0.070	0.075	0.020	0.020

Standard errors are clustered by city-city-border and shown in parentheses.

Table 6: Impact of liquidity relief on business closure: Shorter run effects

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. To examine shorter-run effects, the post-treated period is restricted to 2020-2021. In the first three columns, the sample is restricted to above-median liquidity-constrained industries. In the last three columns, the sample is restricted to below-median liquidity-constrained industries. The outcome variable is business closure measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median household income, log median gross rent, homeownership rate, high school graduation rate, and partisanship spread. Standard errors are clustered at the city-city border level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained industries			Less liquidity-constrained industries		
	Quarterly business closure (basis points)			Quarterly business closure (basis points)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-5.995***	-6.028***	-6.026***	-0.109	-0.0565	-0.0243
	-1.859	-1.863	-1.866	-3.622	-3.636	-3.673
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
City-city border fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector fixed effects	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	1,246,870	1,246,870	1,246,870	377,533	377,533	377,533
R-squared	0.000	0.001	0.001	0.000	0.002	0.006

Table 7: Impact of liquidity relief on business opening

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. In the first three columns, the sample is restricted to above-median liquidity-constrained industries. In the last three columns, the sample is restricted to below-median liquidity-constrained industries. The outcome variable is business opening measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median household income, log median gross rent, homeownership rate, high school graduation rate, and partisanship spread. Standard errors are clustered at the city-city border level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained industries			Less liquidity-constrained industries		
	Quarterly business opening (basis points)			Quarterly business opening (basis points)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-0.785	-0.785	-0.785	2.207	2.207	2.207
	(0.901)	(0.901)	(0.901)	(1.426)	(1.426)	(1.426)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
City-city border fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector fixed effects	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	2,777,852	2,777,852	2,777,852	838,222	838,222	838,222
R-squared	0.000	0.001	0.001	0.000	0.003	0.003

Table 8: Impact of liquidity relief on new lease pricing

Observation level: Lease

	More liquidity-constrained industries			Less liquidity-constrained industries		
	Net effective rent ($)			Net effective rent ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-1.056	0.0219	0.0938	-5.174	-5.854	-4.607
	(2.237)	(2.254)	(2.178)	(4.440)	(4.379)	(4.213)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
City-city border fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector fixed effects	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	1,086	1,086	1,086	739	739	739
R-squared	0.080	0.182	0.213	0.171	0.205	0.261

Standard errors are clustered by city-city-border and shown in parentheses.

Appendix A: Model Solution

1 Baseline model

In this section, I present the solutions of the baseline model in Hanson et al. (2020). Section 1.1 provides the private market outcome without commercial rent forbearance. Section 1.2 provides the social planner's solution. In the next section, I will solve for the private market outcome with commercial rent forbearance.

1.1 Private market outcome

To solve the model, we backwards induct from $t = \infty$.

Steady state: $t = \infty$

We start in state S_∞ at $t = \infty$. Assuming they have survived at both $t = 1$ and $t = 2$, only viable firms with $X_\infty(f, R_{S_\infty}) \geq 0$ (or equivalently $f \leq \bar{F}_{S_\infty} = \frac{\mu + \gamma - R_{S_\infty}}{\delta}$) will continue operating in state S_∞ at $t = \infty$. Thus, if firm f survives until $t = \infty$ in state S_∞, its value to private investors will be:

$$\begin{aligned} V_\infty(f, S_\infty) &= \frac{1}{1-\delta} \cdot \min\{X_\infty(f, R_{S_\infty}), 0\} \\ &= \frac{1}{1-\delta} \cdot [\mu + \gamma - R_{S_\infty} - \Delta \times f] \cdot 1_{\{f \leq \bar{F}_{S_\infty}\}} \end{aligned} \tag{A.1}$$

where $1_{\{f \leq \bar{F}_{S_\infty}\}}$ is a binary indicator that switches on when $f \leq \bar{F}_{S_\infty}$.

Interim date: $t = 2$

We next backwards induct to state S_2 at $t = 2$. Suppose all firms $f \in [0, F_1]$ survived at t = 1. If the mass of firms that continue operating in state S_2 at $t = 2$ is equal to F_{S_2}, the private value of firm f will be:

$$\begin{aligned} V_2(f, R_{S_2}, F_{S_2}) &= \min\{X_2(f, R_{S_2}, F_{S_2}) + \delta \cdot V_\infty(f, R_{S_\infty}), 0\} \\ &= \min\{[\mu + \gamma \times F_{S_2} - R_{S_2} - \Delta \times f] \\ &\quad + \delta \cdot \frac{1}{1-\delta} \cdot [\mu + \gamma - R_{S_\infty} - \Delta \times f] \cdot 1_{\{f \leq \bar{F}_{S_\infty}\}}, 0\} \end{aligned} \tag{A.2}$$

There are two cases.

Case 1: $V_2(F_1, R_{S_2}, F_1) \geq 0$

This is the case where all firms that survive at $t = 1$ are privately valuable in state S_2 at $t = 2$. Then, no additional firms will be shut down in S_2. In sum, we have $F^*_{S_2} = F_1$.

Case 2: $V_2(F_1, R_{S_2}, F_1) < 0$

This is the case where the marginal firm that survives in $t = 1$ has negative private value

in state S_2 at $t = 2$. This marginal firm will be shut down in S_2. Then $F^*_{S_2} = \hat{F}^*_{S_2} < F_1$ where $F^*_{S_2}$ is the solution to $V_2(\hat{F}^*_{S_2}, R_{S_2}, \hat{F}^*_{S_2}) = 0$. Solving for $\hat{F}^*_{S_2}$, we have:

$$\hat{F}^*_{S_2} = \frac{(1-\delta)\cdot(\mu - R_{S_2}) + \delta\cdot(\mu + \gamma - R_{S_\infty})}{(1-\delta)\cdot(\Delta - \gamma) + \delta\cdot\Delta} \tag{A.3}$$

Combining these two cases, we have:

$$F^*_{S_2}(F_1) = \min\{F_1, \hat{F}^*_{S_2}\} \tag{A.4}$$

Initial date: t = 1

Finally, we consider what happens at t = 1. If the mass of firms that continue operating at $t = 1$ is equal to F_1, then the private value of firm f is given by:

$$\begin{aligned} V_1(f, F_1) = \min\{&X_1(f, R_1) \\ &+ (1-\phi)\cdot\delta\cdot\left[(1-p)\cdot V_2(f, R_{G_2}, F^*_{G_2}(F_1)) + p\cdot V_2(f, R_{B_2}, F^*_{B_2}(F_1))\right], 0\} \end{aligned} \tag{A.5}$$

where $\phi \in (0,1)$ reflects the credit market frictions that exist at $t = 1$ and $F^*_{S_2} = \min\{F_1, \hat{F}^*_{S_2}\}$ is agents' rational expectation of the mass of firms that will continue operating in state S_2 at $t = 2$ if all firms $f \in [0, F_1]$ continue operating at $t = 1$. Thus, the marginal firm who continues operating at $t = 1$ satisfies $0 = V_1(F^*_1, F^*_1)$, or

$$\begin{aligned} 0 = &[\mu + \gamma - R_1 - \Delta \times F^*_1] \\ &+ (1-\phi)(1-p)\delta([\mu + \gamma \times F^*_1 - R_{G_2} - \Delta \times F^*_1] + \frac{\delta}{1-\delta}\cdot[\mu + \gamma - R_{G_\infty} - \Delta \times F^*_1])\cdot 1_{\{F^*_1 \le \hat{F}^*_{G_2}\}} \\ &+ (1-\phi)p\delta([\mu + \gamma \times F^*_1 - R_{B_2} - \Delta \times F^*_1] + \frac{\delta}{1-\delta}[\mu + \gamma - R_{B_\infty} - \Delta \times F^*_1])\cdot 1_{\{F^*_1 \le \hat{F}^*_{B_2}\}} \end{aligned} \tag{A.6}$$

Let $\bar{F}_1 = \dfrac{\mu + \gamma - R_1}{\Delta} < 1$ denote the index of the firm that generates zero free cash flows at $t = 1$. We assume $\bar{F}_1 < \bar{F}^*_{G_2}$. This means that there are firms who require outside investment to survive at $t = 1$, i.e. firms with negative free cash flow that have positive value in state G_2 at $t = 2$. This assumption then implies that the marginal firm who continues operating at $t = 1$ must satisfy $\bar{F}_1 < F^*_1 < \hat{F}^*_{G_2}$.

There are then 2 relevant cases.

Case 1: $\hat{F}^*_{B_2} < F^*_1 < \hat{F}^*_{G_2}$

In other words, the marginal firm who continues operating at $t = 1$ survives in the good state at $t = 2$ but is shut down in the bad state. In this case, the marginal firm that survives at $t = 1$ is given by:

$$F^*_1 = \frac{(1-\delta)\cdot[\mu + \gamma - R_1] + (1-\phi)\cdot(1-p)\cdot\delta\cdot[(1-\delta)\cdot(\mu - R_{G_2}) + \delta\cdot(\mu + \gamma - R_{G_\infty})]}{(1-\delta)\cdot\Delta + (1-\phi)\cdot(1-p)\cdot\delta\,[(1-\delta)\cdot(\Delta - \gamma) + \delta\cdot\Delta]} \tag{A.7}$$

Case 2: $F_1^* \leq \hat{F}_{B_2}^* < \hat{F}_{G_2}^*$
In other words, the marginal firm that continues operating at $t = 1$ survives in both states at $t = 2$. In this case, the marginal firm that survives at $t = 1$ is given by:

$$F_1^* = \frac{(1-\delta)\cdot[\mu+\gamma-R_1]+(1-\phi)\cdot\delta\cdot[(1-\delta)\cdot(\mu-\bar{R}_{S_2})+\delta\cdot(\mu+\gamma-\bar{R}_{S_\infty})]}{(1-\delta)\cdot\Delta+(1-\phi)\cdot\delta\,[(1-\delta)\cdot(\Delta-\gamma)+\delta\cdot\Delta]} \tag{A.8}$$

where $\bar{R}_2 = pR_{B_2} + (1-p)R_{G_2}$ and $\bar{R}_\infty = pR_{B_\infty} + (1-p)R_{G_\infty}$ are the average recession severity at $t = 2$ and $t = \infty$, respectively.

What are the conditions for being in case 1 or case 2? Given that we must have $\bar{F}_1 < F_1^*$, we will be in case 1 (where the marginal firm operating at $t = 1$ fails in state B_2) if $\hat{F}_{B_2}^* < \bar{F}_1$. Otherwise, we will be in case 2 (where the marginal firm operating at $t = 1$ survives in both states at $t = 2$) if $\hat{F}_{B_2}^* > \bar{F}_1$ and $0 < V_1(\hat{F}_{B_2}^{c*}, \hat{F}_{B_2}^{c*})$.

1.2 Social planner's solution

Steady state: $t = \infty$

We start in state S_∞ at $t = \infty$. Since there are no market failures in the long run, the planner places the same value as the private market on firms in the steady state.

$$\begin{aligned} W_\infty(f, S_\infty) &= V_\infty(f, S_\infty) \\ &= \frac{1}{1-\delta}\cdot\min\{X_\infty(f, R_{S_\infty}), 0\} \\ &= \frac{1}{1-\delta}\cdot[\mu+\gamma-R_{S_\infty}-\Delta\times f] \end{aligned} \tag{A.9}$$

Interim date: $t = 2$

We next backwards induct to state S_2 at $t = 2$. Suppose all firms $f \in [0, F_1]$ survived at $t = 1$. If the mass of firms that continue operating in state S_2 at $t = 2$ is equal to F_{S_2}, total social value is given by:

$$\begin{aligned} W_2(R_{S_2}, F_1) &= \max_{F_{S_2}\leq F_1}\{\int_0^{F_{S_2}}(X_2(f, R_{S_2}, F_{S_2}) + \delta\cdot V_\infty(f, R_{S_\infty}))df\} \\ &= \max_{F_{S_2}\leq F_1}\{\int_0^{F_{S_2}}(\mu+\gamma\times F_{S_2} - R_{S_2} - \Delta\times f) \\ &\quad + \delta\cdot\frac{1}{1-\delta}\cdot[\mu+\gamma-R_{S_\infty}-\Delta\times f])df\} \end{aligned} \tag{A.10}$$

There are two cases.

Case 1: $F_{S_2}^{**} = \hat{F}_{S_2}^{**} < F_1$
where $\hat{F}_{S_2}^{**}$ is the unconstrained maximizer of $W_2(R_{S_2}, F_1)$ In other words, some firms that survive at $t = 1$ may be shut down by the planner in state S_2 at $t = 2$

Case 2: $\hat{F}^{**}_{S_2} > F_1$
In other words, no firms are shut down in S_2. Then, the planner sets $F^{**}_{S_2} = F_1$.

Combining the two cases, we have:

$$F^{**}_{S_2}(F_1) = \min\{F_1, \hat{F}^{**}_{S_2}\} \tag{A.11}$$

and the planner's social value function is given by:

$$\begin{aligned} W_2(R_{S_2}, F_1) = \int_0^{F^{**}_{S_2}(F_1)} (\Big[\mu + \gamma \times F^{**}_{S_2} - R_{S_2} - \Delta \times f\Big] \\ + \frac{\delta}{1-\delta} \cdot [\mu + \gamma - R_{S_\infty} - \Delta \times f] \cdot 1_{\{f \leq \bar{F}_{S_\infty}\}}) df \end{aligned} \tag{A.12}$$

Initial date: $t = 1$

Finally, we consider what happens at $t = 1$. If the mas sof firms that continue operating at $t = 1$ is equal to F_1, then total social value is given by:

$$\begin{aligned} W_1(F_1) = \int_0^{F_1} (X_1(f, R_1) \\ + \delta \cdot \Big[(1-p) \cdot W_2(R_{G_2}, F^*_{G_2}(F_1)) + p \cdot W_2(f, R_{B_2}, F^*_{B_2}(F_1))\Big]) df \end{aligned} \tag{A.13}$$

The first-order condition for maximizing total social value is:

$$\begin{aligned} 0 = X_1(F_1, R_1) \\ + \delta \cdot \left[(1-p) \cdot \frac{\partial W_2}{\partial F_{G_2}} \cdot \frac{\partial F^{**}_{G_2}(F_1)}{\partial F_1} + p \cdot \frac{\partial W_s(f, R_{B_2}, F^{**}_{B_2}(F_1))}{\partial F_{B_2}} \cdot \frac{\partial F^{**}_{B_2}(F_1)}{\partial F_1}\right] \end{aligned} \tag{A.14}$$

Writing this out, we obtain:

$$\begin{aligned} 0 = [\mu + \gamma - R_1 - \Delta \times F^{**}_1] \\ + (1-p) \cdot \delta \cdot ([\mu + 2\gamma \times F^{**}_1] + \frac{\delta}{1-\delta} \cdot [\mu + \gamma - R_{G_\infty} - \Delta \times F^{**}_1]) \cdot 1_{\{F^{**}_1 \leq \hat{F}^{**}_{G_2}\}} \\ + p \cdot \delta \cdot ([\mu + 2\gamma \times F^*_1 - R_{B_2} - \Delta \times F^{**}_1] + \frac{\delta}{1-\delta} \cdot [\mu + \gamma - R_{B_\infty} - \Delta \times F^{**}_1]) \cdot 1_{\{F^{**}_1 \leq \hat{F}^{**}_{B_2}\}} \end{aligned} \tag{A.15}$$

There are then two relevant cases.

Case 1: $\hat{F}^{**}_{B_2} < F^{**}_1 < \hat{F}^{**}_{G_2}$
In other words, the marginal firm at $t = 1$ survives in the good state at $t = 2$ but is shut down by the planner in the bad state. In this case, the marginal firm at $t = 1$ is given by:

$$F^{**}_1 = \frac{(1-\delta) \cdot [\mu + \gamma - R_1] + (1-p) \cdot \delta \cdot [(1-\delta) \cdot (\mu - R_{G_2}) + \delta \cdot (\mu + \gamma - R_{G_\infty})]}{(1-\delta) \cdot \Delta + (1-p) \cdot \delta \cdot [(1-\delta) \cdot (\Delta - 2\gamma) + \delta \cdot \Delta]} \tag{A.16}$$

Case 2: $F_1^{**} \leq \hat{F}_{B_2}^{**} < \hat{F}_{G_2}^{**}$
In other words, the marginal firm at $t = 1$ will survive in both states at $t = 2$. In this case, the marginal firm at $t = 1$ is given by:

$$F_1^{**} = \frac{(1-\delta) \cdot [\mu + \gamma - R_1] + \delta \cdot [(1-\delta) \cdot (\mu - \bar{R}_{S_2}) + \delta \cdot (\mu + \gamma - \bar{R}_{S_\infty})]}{(1-\delta) \cdot \Delta + \delta \cdot [(1-\delta) \cdot (\Delta - 2\gamma) + \delta \cdot \Delta]} \tag{A.17}$$

What are the conditions for being in case 1 or case 2? Given that we must have $\bar{F}_1 < F_1^{**}$, we will be in case 1 (where the marginal firm operating at $t = 1$ fails in state B_2) if $\hat{F}_{B_2}^{**} < \bar{F}_1$. Otherwise, we will be in case 2 (where the marginal firm operating at $t = 1$ survives in both states at $t = 2$) if $\hat{F}^{**} > \bar{F}_1$ and $0 < V_1(\hat{F}_{B_2}^{**}, \hat{F}_{B_2}^{**})$

2 Private market outcome with commercial rent forbearance policy

In this section, I solve for the private market outcome with forbearance. Commercial rent forbearance requires landlords to provide liquidity to business tenants by prohibiting evictions and pausing the obligation of rent payments. Because forbearance is a mandated liquidity policy, commercial landlords do not optimize over a lending decision. The policy can be directly incorporated into the model by adjusting the cash flow equations. Let X_t^c denote the cash flow function in a world with forbearance.

At time $t = 1$, all firms receive funds from their landlords. The cash flow of firm f is increased by ρ relative to the world without forbearance:

$$\begin{aligned} X_1^c(f, R_1) &= X_1(f, R_1) + \rho \\ &= \mu + \gamma - R_1 - \Delta \times f + \rho \end{aligned} \tag{A.18}$$

At time $t = 2$, accumulated back rent must be repaid to the landlord. In other words, the zero-interest credit from landlords comes due. The cash flow of firm f is decreased by ρ relative to the world without forbearance.

$$\begin{aligned} X_2^c(f, R_{S_2}, F_{S_2}) &= X_2(f, R_{S_2}, F_{S_2}) - \rho \\ &= \mu + \gamma \times F_{S_2} - R_{S_2} - \Delta \times f - \rho \end{aligned} \tag{A.19}$$

At time $t = \infty$, the cash flow of firm f is the same as in a world without forbearance:

$$\begin{aligned} X_\infty^c(f, R_{S_\infty}) &= X_\infty(f, R_{S_\infty}) \\ &= \mu + \gamma - R_{S_\infty} - \Delta \times f \end{aligned} \tag{A.20}$$

To solve the model, we backwards induct from $t = \infty$.

Steady state: $t = \infty$

We start in state S_∞ at $t = \infty$. Since the forbearance policy does not apply in the steady state, there is no difference between the private market valuation of firms without

v.s. with CEM. If firm f survives until $t = \infty$ in state S_∞, its value to private investors will be:

$$\begin{aligned} V_\infty^c(f, S_\infty) &= \frac{1}{1-\delta} \cdot \min\{X_\infty^c(f, R_{S_\infty}), 0\} \\ &= \frac{1}{1-\delta} \cdot [\mu + \gamma - R_{S_\infty} - \Delta \times f] \cdot 1_{\{f \leq \bar{F}_{S_\infty}\}} \end{aligned} \tag{A.21}$$

where $1_{\{f \leq \bar{F}_{S_\infty}\}}$ is a binary indicator that switches on when $f \leq \bar{F}_{S_\infty}$.

Interim date: $t = 2$

We next backwards induct to state S_2 at $t = 2$. Suppose all firms $f \in [0, F_1]$ survived at $t = 1$. If the mass of firms that continue operating in state S_2 at $t = 2$ is equal to F_{S_2}, the private value of firm f will be:

$$\begin{aligned} V_2^c(f, R_{S_2}, F_{S_2}) &= \min\{X_2^c(f, R_{S_2}, F_{S_2}) + \delta \cdot V_\infty^c(f, R_{S_\infty}), 0\} \\ &= \min\{[\mu + \gamma \times F_{S_2} - R_{S_2} - \Delta \times f - \rho] \\ &+ \delta \cdot \frac{1}{1-\delta} \cdot [\mu + \gamma - R_{S_\infty} - \Delta \times f] \cdot 1_{\{f \leq \bar{F}_{S_\infty}\}}, 0\} \end{aligned} \tag{A.22}$$

There are two cases.

Case 1: $V_2^c(F_1, R_{S_2}, F_1) \geq 0$
In other words, all firms that survive at $t = 1$ are privately valuable in state S_2 at $t = 2$. Then no additional firms will be shut down in S_2. In sum, we have $F_{S_2}^{c*} = F_1$.

Case 2: $V_2^c(F_1, R_{S_2}, F_1) < 0$
In other words, the marginal firm that survives in $t = 1$ has negative private value in state S_2 at $t = 2$. The marginal firm will be shut down in S_2. Then $F_{S_2}^{c*} = \hat{F}_{S_2}^{c*} < F_1$ where $\hat{F}_{S_2}^{c*}$ is the solution to $V_2^c(\hat{F}_{S_2}^{c*}, R_{S_2}, \hat{F}_{S_2}^{c*}) = 0$. Solving for $\hat{F}_{S_2}^{c*}$, we have:

$$\hat{F}_{S_2}^{c*} = \frac{(1-\delta) \cdot (\mu - R_{S_2} - \rho) + \delta [\mu + \gamma - R_{S_\infty}]}{(1-\delta) \cdot (\Delta - \gamma) + \delta \cdot \Delta} \tag{A.23}$$

Initial date: t = 1

Finally, we consider what happens at t = 1. If the mass of firms that continue operating at $t = 1$ is equal to F_1, then the private value of firm f is given by:

$$\begin{aligned} V_1^c(f, F_1) &= \min\{X_1^c(f, R_1) \\ &+ (1-\phi) \cdot \delta \cdot ((1-p) \cdot V_2^c(f, R_{G_2}, F_{G_2}^{c*}(F_1)) \\ &+ p \cdot V_2^c(f, R_{B_2}, F_{B_2}^{c*}(F_1))), 0\} \end{aligned} \tag{A.24}$$

where $\phi \in (0, 1)$ reflects the credit market frictions that exist at $t = 1$ and $F_{S_2}^{c*} = \min\{F_1, \hat{F}_{S_2}^{c*}\}$ is agents' rational expectation of the mass of firms that will continue operating in state S_2

at $t = 2$ if all firms $f \in [0, F_1]$ continue operating at $t = 1$. Thus, the marginal firm who continues operating at $t = 1$ satisfies $0 = V_1^c(F_1^{c*}, F_1^{c*})$, or:

$$\begin{aligned}
0 = &[\mu + \gamma - R_1 - \Delta \times F_1^{c*} + \rho] \\
&+ (1-\phi) \cdot (1-p) \cdot \delta \cdot ([\mu + \gamma \times F_1^{c*} - R_{G_2} - \Delta \times F_1^{c*} - \rho] \\
&+ \frac{\delta}{1-\delta} \cdot [\mu + \gamma - R_{G_\infty} - \Delta \times F_1^{c*}]) \cdot 1_{\{F_1^{c*} \leq \hat{F}_{G_2}^{c*}\}} \\
&+ (1-\phi) \cdot p \cdot \delta \cdot ([\mu + \gamma \times F_1^{c*} - R_{B_2} - \Delta \times F_1^{c*} - \rho] \\
&+ \frac{\delta}{1-\delta} \cdot [\mu + \gamma - R_{B_\infty} - \Delta \times F_1^{c*}]) \cdot 1_{\{F_1^{c*} \leq \hat{F}_{B_2}^{c*}\}}
\end{aligned} \tag{A.25}$$

Comparing equation (A.25) with (A.6) sheds light on the relationship between F_1^{c*} and F_1^*. For all firms, forbearance adds cash flow ρ at $t = 1$. For those firms that choose to continue operating at $t = 2$, they will have to repay ρ. In sum, the positive cash flow of forbearance is unconditionally provided to all firms at $t = 1$ while the negative cash flow of forbearance is conditionally repaid by firms that continue operating at $t = 2$. It becomes clear that the right-hand side of (A.32) is higher relative to the right-hand-side of (A.6) holding fixed F_1. Therefore, it must be the case that $F_1^{c*} > F_1^*$.

Let $\bar{F}_1^c = \dfrac{\mu + \gamma - R_1 + \rho}{\Delta} < 1$ denote the index of the firm that generates zero free cash flows at $t = 1$. We assume $\bar{F}_1^c < \hat{F}_{G_2}^{c*}$. This means that, when CEM provides cash flow ρ to firms at $t = 1$, there are still firms who require outside investment to survive at $t = 1$, i.e. firms with negative free cash flow that have positive value in state G_2 at $t = 2$. This assumption then implies that the marginal firm who continues operating at $t = 1$ must satisfy $\bar{F}_1^c < F_1^{c*} < \hat{F}_{G_2}^{c*}$.

There are then 2 relevant cases.

Case 1: $\hat{F}_{B_2}^{c*} < F_1^{c*} < \hat{F}_{G_2}^{c*}$
In other words, the marginal firm who continues operating at $t = 1$ survives in the good state at $t = 2$ but is shut down in the bad state. In this case, the marginal firm that survives at $t = 1$ is given by:

$$\begin{aligned}
F_1^{c*} = &\frac{(1-\delta) \cdot [\mu + \gamma - R_1 + \rho]}{(1-\delta) \cdot \Delta + (1-\phi) \cdot (1-p) \cdot \delta \left[(1-\delta) \cdot (\Delta - \gamma) + \delta \cdot \Delta\right]} \\
&+ \frac{(1-\phi) \cdot (1-p) \cdot \delta \cdot [(1-\delta) \cdot (\mu - R_{G_2} - \rho) + \delta \cdot (\mu + \gamma - R_{G_\infty})]}{(1-\delta) \cdot \Delta + (1-\phi) \cdot (1-p) \cdot \delta \left[(1-\delta) \cdot (\Delta - \gamma) + \delta \cdot \Delta\right]}
\end{aligned} \tag{A.26}$$

Case 2: $F_1^{c*} \leq \hat{F}_{B_2}^{c*} < \hat{F}_{G_2}^{c*}$
In other words, the marginal firm that continues operating at $t = 1$ survives in both states at $t = 2$. In this case, the marginal firm that survives at $t = 1$ is given by:

$$F_1^{c*} = \frac{(1-\delta) \cdot [\mu + \gamma - R_1 + \rho] + (1-\phi) \cdot \delta \cdot [(1-\delta) \cdot (\mu - \bar{R}_{S_2} - \rho) + \delta \cdot (\mu + \gamma - \bar{R}_{S_\infty})]}{(1-\delta) \cdot \Delta + (1-\phi) \cdot \delta \left[(1-\delta) \cdot (\Delta - \gamma) + \delta \cdot \Delta\right]} \tag{A.27}$$

where $\bar{R}_2 = pR_{B_2} + (1-p)R_{G_2}$ is the average recession severity at $t = 2$ and $\bar{R}_\infty = pR_{B_\infty} + (1-p)R_{G_\infty}$ are the average recession severity at $t = \infty$.

What are the conditions for being in case 1 or case 2? Given that we must have $\bar{F}_1^c < F_1^{c*}$, we will be in case 1 (where the marginal firm operating at $t = 1$ fails in state B_2) if $\hat{F}_{B_2}^{c*} < \bar{F}_1^c$. Otherwise, we will be in case 2 (where the marginal firm operating at $t = 1$ survives in both states at $t = 2$) if $\hat{F}_{B_2}^{c*} > \bar{F}_1^c$ and $0 < V_1(\hat{F}_{B_2}^*, \hat{F}_{B_2}^*)$.

I next examine how μ affects $F_{S_2}^{c*} - F_{S_2}^*$. The relevant case to focus on is when $F_{S_2}^* = F_1^*$. Intuitively, this means that in the world without forbearance, all firms that survive at $t = 1$ also survive at $t = 2$ because the initial shock at $t = 1$ is sufficiently severe. There are then two cases to consider.

First, I consider the case where $F_{S_2}^{c*} = F_1^{c*}$. In this case, the effect of CEM is $F_{S_2}^{c*} - F_{S_2}^* = F_1^{c*} - F_1^*$. From equation (A.25) and (A.6), we know that $F_1^{c*} - F_1^* > 0$ and that an increase in ϕ (i.e. an increase in the severity of credit market frictions) increases $F_1^{c*} - F_1^* > 0$ (strengthens the effect of CEM) because F_1^{c*} decreases less than F_1^* decreases, leading $F_1^{c*} - F_1^*$ to increase. From equation (A.22), we observe that an increase in μ increases V_2 and decreases $F_{S_2}^*$, making it more likely that we are in the case where $F_{S_2}^* = F_1^*$. In sum, for firms with sufficiently high μ, CEM will be effective and specifically more effective as credit market frictions are more severe.

Second, I consider the case where $F_{S_2}^{c*} = \hat{F}_{S_2}^{c*}$. In this case, the effect of CEM will be smaller than in the case of $F_{S_2}^{c*} = F_1^{c*}$. Because $\hat{F}_{S_2}^{c*} \leq F_1^{c*}$ in this case (such that F_1^{c*} is not he limiting factor on business survival at $t = 2$) and F_1^* is continuous in μ, then $\hat{F}_{S_2}^{c*} - F_1^*$ is upper bounded by $F_1^{c*} - F_1^*$. Specifically, forbearance may reduce, have no effect on, or even increase business closure. From equation (A.22), we observe that a decrease in μ decreases V_2 and decreases $F_{S_2}^*$, making it more likely that we are in the case where $F_{S_2}^* = \hat{F}_{S_2}^{c*}$. In sum, for firms with sufficiently low μ, CEM will be less effective.

I next examine how the effectiveness of forbearance changes with μ within each of these cases. First, I consider the case where $F_{S_2}^{c*} = F_1^{c*}$. There are two scenarios for the value of F_1^{c*} as shown in (A.26) and (A.27). Under the first scenario in (A.26), the partial derivative of F_1^{c*} with respect to μ is:

$$\frac{\partial F_1^{c*}}{\partial \mu} = \frac{1 - \delta + (1-\phi)(1-p)\delta}{(1-\delta)\Delta + (1-\phi)(1-p)\delta\left[(1-\delta)\cdot(\Delta-\gamma) + \delta\cdot\Delta\right]}$$

$$= \frac{1 - \delta + (1-\phi)(1-p)\delta}{(1-\delta)\Delta + (1-\phi)(1-p)\delta A} \tag{A.28}$$

where A denotes the quantity $[(1-\delta)\cdot(\Delta-\gamma) + \delta\cdot\Delta] > 0$.

Under the second scenario in (A.27), the partial derivative of F_1^{c*} with respect to μ is:

$$\frac{\partial F_1^{c*}}{\partial \mu} = \frac{(1-\delta) + (1-\phi)\delta}{(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A} \tag{A.29}$$

As a reminder, the relevant case we focus on is when $F_{S_2}^* = F_1^*$. There are two scenarios for the value of F_1^* as shown in (A.7) and (A.8). Under the first scenario in (A.7), the partial derivative of F_1^* with respect to μ is:

$$\begin{aligned}\frac{\partial F_1^*}{\partial \mu} &= \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta + (1-\phi)(1-p)\delta\left[(1-\delta)\cdot(\Delta-\gamma)+\delta\cdot\Delta\right]} \\ &= \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta + (1-\phi)(1-p)\delta A}\end{aligned} \tag{A.30}$$

where A denotes the quantity $[(1-\delta)\cdot(\Delta-\gamma)+\delta\cdot\Delta] > 0$.

Under the second scenario in (A.8), the partial derivative of F_1^* with respect to μ is:

$$\frac{\partial F_1^*}{\partial \mu} = \frac{(1-\delta) + (1-\phi)\delta}{(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A} \tag{A.31}$$

We will never be in the scenario of (A.27) and (A.7) because $F_1^{c*} > F_1^*$ and it will never be the case that F_1^{c*} takes on the lower scenario value while F_1^* takes on the higher scenario value. If we are in the scenarios of (A.26) and (A.7), then the partial derivative of $F_{S_2}^{c*} - F_{S_2}^*$ with respect to μ is 0. If we are in the scenarios of (A.27) and (A.8), then the partial derivative of $F_{S_2}^{c*} - F_{S_2}^*$ with respect to μ is 0. If we are in the scenarios of (A.26)

and (A.8), then the partial derivative of $F_{S_2}^{c*} - F_{S_2}^{*}$ with respect to μ is:

$$\begin{aligned}
\frac{\partial}{\partial \mu}(F_{S_2}^{c*} - F_{S_2}^{*}) &= \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta+(1-\phi)(1-p)\delta A} - \frac{1-\delta+(1-\phi)\delta}{(1-\delta)\Delta+(1-\phi)\delta A} \\
&= \frac{[1-\delta+(1-\phi)(1-p)\delta]*[(1-\delta)\Delta+(1-\phi)\delta A]}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&- \frac{[1-\delta+(1-\phi)\delta]*[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&= \frac{(1-\delta)(1-\phi)\delta A+(1-\phi)(1-p)\delta(1-\delta)\Delta}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&- \frac{(1-\delta)(1-\phi)(1-p)\delta A+(1-\phi)\delta(1-\delta)\Delta}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&= \frac{p(1-\delta)(1-\phi)\delta A-p(1-\phi)\delta(1-\delta)\Delta}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&= \frac{p(1-\delta)(1-\phi)\delta(A-\Delta)}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]} \\
&= \frac{p(1-\delta)(1-\phi)\delta\gamma(\delta-1)}{[(1-\delta)\Delta+(1-\phi)(1-p)\delta A]*[(1-\delta)\Delta+(1-\phi)\delta A]}
\end{aligned} \tag{A.32}$$

In all of the scenarios within this case, $F_{S_2}^{c*} - F_{S_2}^{*}$ does not change with μ when $\gamma = 0$.

Second, I consider the case where $F_{S_2}^{c*} = \hat{F}_{S_2}^{c*}$. The partial derivative of $F_{S_2}^{c*}$ with respect to μ is:

$$\begin{aligned}
\frac{\partial \hat{F}_{S_2}^{c*}}{\partial \mu} &= \frac{1}{(1-\delta)\cdot(\Delta-\gamma)+\delta\cdot\Delta} \\
&= \frac{1}{A}
\end{aligned} \tag{A.33}$$

Again, we consider the two scenarios for the value of F_1^* as shown in (A.7) and (A.8).

Under the first scenario in (A.7), the partial derivative of F_1^* with respect to μ is:

$$\frac{\partial F_1^{c*}}{\partial \mu} = \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta+(1-\phi)(1-p)\delta\left[(1-\delta)\cdot(\Delta-\gamma)+\delta\cdot\Delta\right]}$$

$$= \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta+(1-\phi)(1-p)\delta A} \tag{A.34}$$

Therefore, the partial derivative of $F_{S_2}^{c*} - F_{S_2}^*$ with respect to μ is:

$$\frac{\partial}{\partial \mu}(F_{S_2}^{c*} - F_{S_2}^*) = \frac{1}{A} - \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta+(1-\phi)(1-p)\delta A}$$

$$= \frac{(1-\delta)\Delta+(1-\phi)(1-p)\delta A - A(1-\delta+(1-\phi)(1-p)\delta)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)}$$

$$= \frac{(1-\delta)(\Delta-A)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)}$$

$$= \frac{(1-\delta)(\Delta-(1-\delta)\cdot(\Delta-\gamma)-\delta\cdot\Delta)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)}$$

$$= \frac{\gamma(1-\delta)^2}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)}$$

$$> 0 \tag{A.35}$$

Under the second scenario in (A.8), the partial derivative of F_1^* with respect to μ is:

$$\frac{\partial F_1^*}{\partial \mu} = \frac{(1-\delta)+(1-\phi)\delta}{(1-\delta)\cdot\Delta+(1-\phi)\cdot\delta A} \tag{A.36}$$

Therefore, the partial derivative of $F_{S_2}^{c*} - F_{S_2}^{*}$ with respect to μ is:

$$\begin{aligned}
\frac{\partial}{\partial \mu}(F_{S_2}^{c*} - F_{S_2}^{*}) &= \frac{1}{A} - \frac{(1-\delta) + (1-\phi)\delta}{(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A} \\
&= \frac{(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A - A[(1-\delta) + (1-\phi)\delta]}{A[(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A]} \\
&= \frac{(1-\delta)(\Delta - A)}{A[(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A]} \\
&= \frac{\gamma(1-\delta)^2}{A[(1-\delta)\cdot\Delta + (1-\phi)\cdot\delta A]} \\
&> 0
\end{aligned} \tag{A.37}$$

In sum, in this case, $F_{S_2}^{c*} - F_{S_2}^{*}$ increases with μ.

Table 1: Impact of liquidity relief on business closure:
Liquidity-constrained industries and similar business tax rate

Appendix B: Instrumental Variable Strategy

In this section, I estimate the impact of liquidity relief on business closure using an instrumental variable empirical strategy. To begin, I identify the causal impact of liquidity relief on business closure by developing an instrument for commercial rent forbearance based on pre-pandemic partisanship after controlling for alternative channels. I also estimate the impact by year and by industry. Finally, I test the relationship between pre-pandemic business solvency and the effectiveness of CEM in reducing business closure.

1 Estimating the causal impact of CEM on business closure

In this section, I identify the causal effect of CEM on business closure. The main challenge is the reverse causality from business closure to CEM, which arises from local policymakers enacting CEM precisely to address business closure. For example, in April 2020, the city of San Jose prepared a memo assessing the extent of business financial stress and stating that the aim of CEM is to prevent business closure.[11] Panel A of Figure 3 shows a binned scatter plot of the business closure rate in 2020-2022 vs. the length of CEM (including repayment time) for cities in California. There is a positive relationship between business closure rate and length of CEM. Panel B of Figure 3 shows a binned scatter plot of the length of CEM (including repayment time) vs. change in unemployment rate from 2019 to 2020 for cities in California. There is also a positive relationship between length of CEM and the change in unemployment rate, suggesting that cities that are more economically affected by the pandemic also enact longer CEM.

[11] Specifically, the memo states, "During this rapidly changing environment caused by the COVID-19 pandemic small businesses across the city are experiencing widespread financial injury. The introduction of a temporary moratorium banning the eviction of small business tenants for the nonpayment of rent directly impacted by the COVID-19 pandemic aims to mitigate preventable business failure and support the city's economy." The document can be found at https://sanjose.legistar.com/LegislationDetail.aspx?ID=4400682&GUID=D54AC5C9-09E6-46DD-8338-1FF8E6A05A05.

1.1 Developing an instrument for commercial eviction moratoria

To address this endogeneity between CEM and business closure, I instrument for CEM using pre-pandemic partisanship, measured as the Democratic-Republican spread of the population as of 2019. The key intuition is as follows. Democratic governments have been associated with a greater propensity for government intervention, while Republican governments have been associated with a more laissez-faire approach (Lewis, 2018). To capture the net political leaning of a city, I compute the Democratic-Republican spread as the share of voters registered as Democratic minus the share of voters registered as Republican. This measure of pre-pandemic partisanship is likely to predict the extent of a city government's intervention via CEM. The higher the Democratic-Republican spread prior to the pandemic, the more likely a city government is to enact a longer CEM.

There are two requirements for the validity of the instrument: the first stage instrument relevance condition and the exclusion restriction. Figure C.1 and column 1 of Table C.3 present the first stage of the instrument. Observations are businesses in the retail and food services industries as of January 2020 in California. There is a positive, statistically significant relationship between partisanship and CEM, wherein a 10 percentage point increase in the Democratic-Republican spread predicts a longer CEM plus repayment time (CEM+R) by 0.28 years (0.10 * 2.77), or 3.3 months. The results confirm the strong first stage of the instrument relevance condition. Next, I consider ways in which the exclusion restriction may be violated by partisanship affecting business closure through non-CEM channels. First, I investigate and control for pre-pandemic economic characteristics to capture the ways that differently partisan places may differ *prior to* the pandemic. Second, I investigate and control for 3 alternative channels that may operate *during* the pandemic, which address consumer stay-at-home behavior, government financial support for businesses, and economic exposure to the Covid-19 shock.

Turning first to pre-pandemic economic characteristics, Table C.1 illustrates the balance of pre-pandemic covariates along the axis of pre-pandemic partisanship. Specifically, the table summarizes the way that more Democratic places observably compare to more Republican areas within California using zip code-level data as of 2019 from the

5-year American Community Survey. For each variable, the first 3 columns provide summary statistics for places with above-median Democratic-Republican spreads, while the next 3 columns provide summary statistics for places with below-median Democratic-Republican spreads. The last column computes the difference in mean and tests whether it is statistically significantly different from zero.

I find no significant difference between the two groups in terms of population, income, unemployment rate, or share of businesses in retail or food services. The observable differences are as follows. Relative to more Republican places, more Democratic places have a higher non-white population share, a lower homeownership rate, a higher population density, and a greater likelihood of being an urban area. After controlling for these pre-pandemic economic characteristics, column 2 of Table C.3 shows that the relationship between partisanship and length of CEM remains statistically significant and economically meaningful.

Next, I consider 3 alternative channels that may operate during the pandemic, where partisanship may affect business closure through non-CEM channels. First, in more Democratic cities, individuals may be more likely to stay home. This can occur because more Democratic governments enact more pandemic restrictions, more Democratic individuals are more likely to adhere to those restrictions, and more Democratic individuals are more likely to stay at home even in the absence of restrictions.[12] Greater consumer stay-at-home behavior would reduce consumer demand and increase the likelihood of business closure. If not addressed, this channel could lead to under-estimating the impact of CEM on business closure. I address this threat to the exclusion restriction by controlling for a measure of consumer stay-at-home behavior using SafeGraph foot traffic data. Specifically, I compute the decline in number of visits to all businesses in a city from January 2020 to the latter half of 2020.[13] Column 1 of Table C.2 shows that there is a negative, statistically significant relationship between partisanship and change in foot traffic. Af-

[12] Gollwitzer et al. (2020) document "partisanship differences in physical distancing." The Washington Post has documented less citizen adherence to coronavirus restrictions in Republican counties. Wang et al. (2021) documents that Democratic governors are more likely to issue stay-at-home orders. Canes-Wrone et al. (2022) document that more Democratic populations are more likely to wear masks and practice social isolation.

[13] For the latter half of 2020, I use the number of visits to businesses averaged over the months of July through December 2020.

ter controlling for this change in foot traffic, column 3 of Table C.3 shows that the relationship between partisanship and length of CEM remains statistically significant and economically meaningful.

Second, more Democratic governments may be more likely to engage in intervention that financially supports businesses, which would in turn reduce business closure. If not addressed, his channel could lead to over-estimating the impact of CEM on business closure. To address this threat to the exclusion restriction, I collect data on pandemic business grant programs administered by cities and control for an indicator of having a pandemic business grant program.[14] Column 2 of Table C.2 shows that there is a positive relationship between partisanship and an indicator for the city administering a pandemic business grant program. After controlling for this city business grant support, column 4 of Table C.3 shows that the relationship between partisanship and length of CEM remains statistically significant and economically meaningful.

Third, more Democratic places may be differently exposed to the Covid-19 shock relative to more Republican places, which in turn leads to differences in business closure.[15] If more Democratic places are more (less) exposed to the Covid-19 shock, then this channel could lead to under-estimating (over-estimating) the impact of CEM on business closure. To address this threat to the exclusion restriction, I use the change in unemployment rate from 2019 to 2020 as a proxy for the economic severity of the pandemic for a city. Column 3 of Table C.2 shows that there is a positive, statistically significant relationship between partisanship and change in unemployment rate. After controlling for the change in unemployment rate, column 5 of Table C.3 shows that the relationship between partisanship and length of CEM remains statistically significant and economically meaningful.

Finally, after controlling for all three alternative channels, column 6 of Table C.3 shows that a 10 percentage point increase in the Democratic-Republican spread significantly predicts a longer CEM by 0.15 years (0.10 * 1.54), or 1.8 months.[16]

[14]The main findings are similar if I instead control more continuously for city business support by using the share of city business grant funding over the city's federal funding received from the American Recovery Plan Act.

[15]For example, the New York Times has documented that more Democratic areas are harder hit by the disease due to more densely populated areas, greater share of ethnic minorities and lower-income individuals.

[16]The coefficient on the Democratic-Republican spread is 1.54 in column 6 relative to 2.77 in column

Table C.4 presents the second-stage estimate of the impact of CEM on business closure. In the second stage, I control for the 3 alternative pandemic channels as well as pre-pandemic zip code-level characteristics, which makes it more likely that the instrument exclusion restriction holds. The identifying assumption is that conditional on consumer stay-at-home behavior, business grant funding, exposure to the Covid-19 economic shock, and pre-pandemic characteristics, partisanship does not affect business closure except through CEM. In the first 3 columns, I progress from the OLS to the IV regression specification. In column 1, I regress an indicator for business closure in 2020-2022 on the length of CEM+R in years. The result shows that an additional year of CEM+R is associated with a higher probability of business closure, which stems from the endogenous relationship between CEM and business closure. In column 2, I control for pre-pandemic zip code-level characteristics, which leads to a reduction in the economic magnitude and statistical significance of the coefficient on length of CEM. In column 3, I estimate the instrumented specification, which changes the sign of the coefficient from positive to negative and reveals a significant, negative effect of CEM on business closure. The results suggest that after addressing the reverse causality issue and mitigating threats to the exclusion restriction, CEM has an overall negative causal effect on business closure.

In the last 3 columns, I estimate the impact of CEM on business closure by year. I observe reductions in business closure in 2020 and 2021, where the results are especially economically meaningful and statistically significant for 2021. An additional year of CEM+R leads to a reduction in business closure by 0.30 percentage points in 2020 and 0.55 percentage points in 2021 (12.8% and 27.8% of the mean, respectively). Then in 2022, after CEM is lifted, there is no further effect.

Next, I consider the differential effect of CEM in retail vs. food services. Table C.5 presents the results for retail in the first 4 columns and food services in the last 4 columns. Turning first to retail, column 1 shows that an additional year of CEM+R reduces business closure by 0.31 percentage points over the period 2020-2022. By year, columns 2 through 4 show that an additional year of CEM+R reduces business closure by 0.23 percentage

1, which suggests, that pre-pandemic partisanship maintains 56% of its strength in predicting CEM policy after controlling for pre-pandemic characteristics and addressing the 3 alternative channels during the pandemic.

points in 2020 and 0.44 percentage points in 2021, which are partly reversed by an increase in business closure of 0.36 percentage points in 2022. Turning next to food services, column 5 shows that an additional year of CEM+R significantly reduces business closure by 1.84 percentage points over the period 2020-2022, which is a significantly larger effect than in retail. By year, columns 6 through 8 show that, an additional year of CEM+R reduces business closure by 0.49 percentage points in 2020, 0.77 percentage points in 2021, and 0.58 percentage points in 2022. Given that the total number of food services establishments in California in 2019 is 85,223 from the Statistics of U.S. Businesses (SUSB) data, these estimates implies that an additional year of CEM+R preserves 1,568 food services businesses in California over the period 2020-2022. When we consider that the average length of CEM+R is 1.22 years, these estimates suggest that the average CEM policy preserves 1,913 food services businesses in California over the period 2020-2022.

The finding that CEM is substantially more effective in reducing business closure in food services than in retail holds true when we conduct the following robustness exercises. **??** shows that the finding holds true when we instead measure the strength of CEM policy using the length of CEM only (not including repayment time R).

1.2 Business solvency & the impact of CEM on business closure

In this section, I analyze the relationship between business solvency and the impact of CEM on business closure.

Motivated by the differing effectiveness of CEM in retail v.s. food services, I consider differences in business solvency as one explanation. Prior to the pandemic, the retail industry was experiencing loss of market share to e-commerce while the food services industry was experiencing steady growth. Panel A of Figure C.2 presents the evolution of employment for non-farm industries overall and for retail and food services specifically. Employment is indexed to 2010. The growth of employment in retail has slowed and even turned negative over the last 10 years, such that employment in retail has grown substantially more slowly than in non-farm employment overall. This fact is reflective of the "retail apocalypse" phenomenon established in the news and academic literature. Mean-

while, employment in food services has grown substantially more rapidly than non-farm industries overall and retail. In sum, this pre-pandemic context of the retail apocalypse and the steady growth of food services suggests that, coming into the pandemic, businesses in food services were relatively more solvent compared to businesses in retail.

To discipline this hypothesis, I take advantage of variation within the retail industry and test the prediction that CEM is more effective in reducing business closure in retail sub-industries that are more solvent coming into the pandemic. Specifically, I split the broad retail industry (NAICS 2-digit) into ten sub-industries (NAICS 3-digit).[17] Panel B of Figure C.2 presents the evolution of employment in sub-industries within retail. Over the period 2010-2019, the sub-industry with the fastest growth in employment is motor vehicle & parts dealers (NAICS 441), while the sub-industry with the slowest growth in employment is electronics & appliance stores (NAICS 443).

Using pre-pandemic employment growth rate as a proxy for business solvency, I examine the relationship between business solvency and the impact of CEM on business closure across sub-industries. Figure C.3 plots the impact of CEM on business closure vs. the 5-year pre-pandemic employment growth across sub-industries. Retail sub-industries with faster pre-pandemic growth (e.g. motor vehicle & parts dealers, gas stations) tend to experience greater CEM-induced reductions in business closure relative to retail sub-industries with slower pre-pandemic growth (e.g. clothing & accessories stories, electronics & appliances stores). Also included in the figure is food services, which is already classified as a sub-industry (NAICS 3-digit). Food services experienced higher pre-pandemic employment growth than every retail sub-industry and accordingly a significant reduction in business closure from CEM.

Table C.6 examines the role that pre-pandemic growth plays in determining the effect of CEM on business closure. Specifically, I conduct the same analysis as in Table C.5 but add an interaction term between length of CEM+R and the growth in sub-industry employment prior to the pandemic (from 2014 to 2019). The coefficient on this interaction term captures the way that an additional percentage point of pre-pandemic employment growth changes the effectiveness of CEM in reducing business closure. In column 1, I find

[17] Note that food services is already classified as a sub-industry (NAICS 3-digit).

that an additional percentage point of pre-pandemic employment growth leads an additional year of CEM+R to further reduce business closure by 0.035 percentage points over the period 2020-2022. In columns 2 through 4, I decompose this effect by year, finding that an additional percentage point of pre-pandemic employment growth leads an additional year of CEM+R to further reduce business closure by 0.021 percentage points in 2021 and 0.032 percentage points in 2022. Previously Table C.5 established that, in the retail industry, CEM leads to reductions in business closure in 2020 and 2021, which are partly reversed in 2022 as CEM policies are lifted. The finding in Table C.6 additionally reveals that pre-pandemic growth has the largest effect on the effectiveness of CEM in 2022 and therefore makes CEM more effective by preventing increases in business closure in 2022 when CEM is lifted.

As well documented in the news & literature, there was already a retail apocalypse phenomenon underway prior to the pandemic.[18] While both retail and food services are very exposed to the pandemic, they had been experiencing different trends leading up to the pandemic, which can explain why food services experienced permanent reductions in business closure due to CEM while retail experienced temporary reductions. Focusing on the early period of the Covid-19 crisis, Bartik et al. (2020b) find that pre-pandemic firm health predicts a lower likelihood of firm closure and a higher likelihood of firm reopening. I find a similar pattern of pre-pandemic firm health mattering for firm survival that occurs at the industry level and over a longer horizon (2020-2022).

2 The impact of CEM on business financing

In this section, I investigate the impact of CEM on business financing. By providing liquidity relief, CEM may have effects on business take-up of other sources of financing. The reason that CEM may have ripple effects on businesses and shift their usage of other financing is because CEM is the lowest-cost form of financing with an interest rate of zero. There are two other types of financing available to businesses during the Covid-19 pan-

[18] For example, Trepp has reported that the Covid-19 crisis amplified the retail apocalypse phenomenon. The article can be found at https://www.trepp.com/trepptalk/covid-accelerated-the-retail-apocalypse.

demic. One type of financing is loans, which must be repaid. In this case, there is likely to be substitution away from loan financing and toward CEM liquidity relief because the loan is more costly than the zero-interest liquidity relief of CEM. Specifically, I examine business take-up of loans from the Economic Injury Disaster Loan program in Section 5.2. Another type of financing is grants, which do not need to be repaid. In this case, there is unlikely to be substitution because grants improve business profitability. Specifically, I examine business take-up of grants from the EIDL Advance program and the Paycheck Protection Program in **??**.

2.1 Impact of CEM on business borrowing from EIDL

In this section, I estimate the effect of CEM on business borrowing from the Economic Injury Disaster Loan (EIDL) program. Through this federal business loan program, the Small Business Administration provides low-interest, fixed-rate, long-term loans directly to small businesses that can be used for working capital, operating expenses and debt repayment during the Covid-19 pandemic. To be eligible, a business must have fewer than 500 employees and must not have access to other credit. Under the latest program guidelines, EIDL loans have a maximum amount of $2 million, a term of 30 years, and a fixed interest rate of 3.75%. No payment is required for the first 2 years, and there is no penalty for prepayment. The program opened for applications in March 2020 and closed by January 2022.

CEM is a lower-cost source of liquidity relief for businesses than EIDL. While EIDL allows businesses to borrow at 3.75%, CEM effectively allows businesses to borrow at 0% interest. Therefore, if businesses are not so constrained that they demand full liquidity relief of both EIDL and CEM, then they will substitute away from the higher-cost EIDL borrowing and towards the lowest-cost CEM. In this case, CEM will have a negative effect on EIDL borrowing.

I obtain details on loans administered through this program from the public database on federal spending.[19] Throughout the U.S., the COVID EIDL program disbursed ∼3.9

[19]Specifically, the data is available at USASpending.gov.

million loans totaling ∼$380 billion. In my sample of California, the program disbursed ∼600,000 loans totaling ∼$68 billion. My analysis proceeds at the zip code level. After connecting SafeGraph business establishment data and EIDL loan data at the zip code level, I compute the average dollars of borrowing per business by dividing the total dollars of EIDL loans disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore represents the EIDL borrowing behavior of the average business in the zip code.

Table C.7 presents the results on the effect of CEM on EIDL borrowing. In the first 3 columns, I progress from the OLS to the IV specification. In column 1, I find that an additional year of CEM+R is associated with higher EIDL borrowing. This remains true in column 2, after controlling for zip code characteristics. In column 3, instrumenting for CEM using pre-pandemic partisanship reveals that an additional year of CEM+R leads to a statistically significant reduction in EIDL borrowing by $11,717 (25.0% of its mean). Given that CEM+R is 1.22 years on average, the average CEM policy reduces EIDL borrowing by $14,295 per business. Therefore, I find overall evidence of businesses substituting away from EIDL borrowing in response to CEM liquidity relief.

I then decompose EIDL loan-takeup into the extensive margin (the likelihood of taking out an EIDL loan) and intensive margin (the size of EIDL loans taken out). In column 4, I find that an additional year of CEM+R leads to a statistically significant reduction in likelihood of borrowing by 7.42 percentage points, while in column 5, I find that an additional year of CEM+R leads to a statistically significant reduction in the amount of EIDL loans by $8,723 (8.1% of its mean). In sum, the liquidity relief of CEM leads businesses to substitute away from EIDL borrowing. This happens primarily through the intensive margin as businesses take out loans of smaller amounts.

2.2 Impact of CEM on government grant take-up

In this section, I examine the effect of CEM on business grant take-up from the EIDL advance program and Paycheck Protection Program. The EIDL advance program provides grants of up to $15,000 to businesses that can be used for working capital and operat-

ing expenses during the Covid-19 pandemic. EIDL advances do not need to be repaid.[20] Meanwhile, the Paycheck Protection Program provides forgivable loans to small businesses to be used primarily for payroll, rent, utilities, and interest on mortgages.[21] The loan amount is determined as a multiple of a business's monthly payroll cost. Loans are fully forgiven if the business retains employees and uses at least 60% of funds for payroll. In this way, PPP is effectively a business grant, albeit one with conditions attached.

While CEM gives businesses more time to pay rent without forgiving rent, grants give businesses funds that do not need to be repaid. Therefore, businesses will seek out grants irrespective of CEM policy because grants improve business profitability. As a result, there is unlikely to be substitution away from grants toward CEM liquidity relief, and it is likely that CEM has no effect on business grant take-up.

I obtain details on grants administered through the EIDL advance program from the public database on federal spending and details on forgivable loans administered through PPP from the Small Business Administration website. Throughout the U.S., the EIDL advance program disbursed $\sim$1 million grants totaling $\sim$\$7.5 billion. In my sample of California, the program disbursed $\sim$150,000 grants totaling $\sim$\$1 billion. Throughout the U.S., PPP disbursed $\sim$11.8 million forgivable loans totaling face value of $\sim$\$800 billion. In my sample of California, the program disbursed $\sim$1.3 million forgivable loans totaling face value of $\sim$\$100 billion. My analysis proceeds at the zip code level. I compute the average dollars of EIDL advance grants per business by dividing the total dollars of EIDL advances disbursed to a zip code by the total number of business establishments in the zip code. Similarly, I compute the average dollars of PPP forgivable loans per business by dividing the total dollars of PPP disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore captures the

[20] This program consists of two parts. First, the targeted EIDL advance provides grants of up to \$10,000 to hard-hit businesses. To be eligible, a business must be located in a low-income community, experience a 30% or greater economic loss over an 8-week period during the pandemic, and have no more than 300 employees. Second, the supplemental EIDL advance provides additional grants of up to \$5,000 for especially hard-hit businesses. To be eligible, a business must experience a 50% or greater economic loss and have no more than 10 employees.

[21] PPP loans are disbursed in three rounds. The first round allocated \$349 billion to businesses over the course of two weeks in April 2020. The second round allocated \$176 billion to businesses between April and August 2020. The third round allocated \$284 billion to businesses between January and June 2021.

EIDL advance take-up and PPP take-up of the average business in the zip code.

Table C.8 presents the results on the effect of CEM on EIDL advance take-up. In the first 3 columns, I progress from the OLS to the IV specification. In column 1, I find that an additional year of CEM+R is associated with higher EIDL advance take-up, which is consistent with cities enacting longer CEM in response to greater business closure likelihood and distress. This relationship persists after controlling for zip code characteristics in column 2. In column 3, instrumenting for CEM using pre-pandemic partisanship reveals that an additional year of CEM+R has no statistically significant effect on EIDL advance take-up. In column 4, I find that CEM has no significant effect on the extensive margin of EIDL advance take-up, which is the likelihood of receiving an EIDL advance. In column 5, I find that CEM has no significant effect on the intensive margin of EIDL advance take-up, which is the average size of EIDL advances.

Table C.9 presents the results on the effect of CEM on PPP take-up. In the first 3 columns, I progress from the OLS to the IV specification. In column 1, I find that an additional year of CEM+R is associated with higher PPP take-up. In column 2, controlling for zip code characteristics reduces the economic magnitude and statistical significance of the coefficient on length of CEM. In column 3, instrumenting for CEM change the sign of the coefficient from positive to negative. In column 4, I find that CEM has no significant effect on the extensive margin of PPP take-up, which is the likelihood of receiving PPP. In column 5, I find that CEM has no significant effect on the intensive margin of PPP take-up, which is the average size of PPP forgivable loans. In sum, CEM does not significantly affect grant-takeup from the EIDL advance and PPP programs. Along with the findings on the EIDL loan program, these results are consistent with the hypothesis that by providing low-cost liquidity relief, CEM crowds out take-up of other sources of liquidity but not take-up of solvency relief.

3 The impact of CEM on business employment

The impact of CEM on business closure established in the last section implies that CEM affects business employment along an extensive margin. In this section, I estimate the

impact of CEM on business employment along an intensive margin by re-employing the instrumental variable approach and applying it to business payroll data. In **??**, I estimate the impact of CEM on employment conditional on the business being alive, i.e. along an intensive margin. In **??**, I take stock of the extensive and intensive margin employment effects and benchmark the overall employment effect of CEM against the Paycheck Protection Program.

3.1 The intensive-margin impact of CEM on business employment

To measure business employment, I use hours worked, which is the total number of hours worked by all employees of a business in the Homebase data. Because hours worked captures employment conditional on the business being alive, it is an intensive-margin measure of employment. To make this measure comparable across businesses, I next scale hours worked by the pre-pandemic benchmark of hours worked in January 2020. To understand the construction of the scaled variable, consider this simple example. Suppose a business had 100 hours worked in January 2020. In March 2020, when the pandemic begins, the business reduces hours worked to 50 hours. The scaled hours worked in March 2020 is therefore 50 / 100, or 0.5, which indicates that the business is operating at half of its pre-pandemic benchmark employment. While the SafeGraph business closure data captures the effective universe of business establishments, the Homebase data tends towards small businesses and contains the subset of small businesses that use the Homebase software. Therefore, in this section, I interpret the findings as the impact of CEM on intensive-margin employment for smaller businesses and acknowledge that this analysis works with a smaller sample by nature of the data source.

Table C.10 presents the results on the impact of CEM on intensive-margin employment. In the first 3 columns, I progress from the OLS to the IV regression specification. In column 1, I find that an additional year of CEM+R is associated with lower employment. In column 2, controlling for zip code characteristics changes the sign of the coefficient on length of CEM from negative to positive, though it is statistically insignificant. In column 3, instrumenting for CEM using pre-pandemic partisanship further increases the magni-

tude of the coefficient, though it remains statistically insignificant. In the next 3 columns, I examine the impact of CEM on employment by year. I find statistically insignificant effects of CEM on employment in 2020, 2021, and 2022. Table C.11 presents the analysis split by retail vs. food services, where we again find statistically insignificant effects for each sector and in each year.[22] In sum, the results suggest that there is no significant effect of CEM on intensive-margin employment in this sample of smaller businesses.

To provide a sense of how precisely estimated these non-effects are, I consider their 95% confidence intervals. 95% confidence interval for the estimated effect of CEM on intensive-margin employment ranges from -4.2% to +4.4% of pre-pandemic employment for the overall period 2020-2022. By year, the 95% confidence interval ranges from -3.6% to +4.6% of pre-pandemic employment for 2020, -1.9% to +8.3% of pre-pandemic employment for 2021, and -3.6% to +8.2% of pre-pandemic employment for 2022.[23] One possible explanation for CEM having no intensive-margin effect on employment is that businesses bucket their expenses by category. As a result, they may not change their prioritization of payroll relative to rent in response to CEM.

3.2 The total impact of CEM on business employment

The total effect of CEM on business employment consists of both the extensive-margin and intensive-margin effects. The results in the last section show no intensive-margin effect. I now turn to the extensive-margin effect, which is captured by the results on business closure. This is because 100% of its employment is lost when a business closes. The results in Section 4.1 show an overall 0.80 percentage point decline in business closure likelihood over the period 2020-2022. This implies that the total impact of an additional year of CEM+R on business employment is approximately 0.80 percentage points of January 2020 employment. When we consider that the average length of CEM+R is 1.22 years, the total impact of average CEM+R on business employment is an increase of 0.98

[22] Table C.12 and Table C.13 show that these findings hold true when we measure employment using the number of shifts worked instead of hours worked.

[23] The precision of the estimate decreases in the later period because of the reduction in number of observations.

percentage points relative to employment in January 2020.[24]

To benchmark the economic significance of the employment effects of CEM, we take stock of the employment effects of PPP estimated in the literature. Chetty et al. (Forthcoming) find that PPP increased the number of jobs by 2.48 percentage points of January 2020 employment.[25] The overall employment effects of CEM that I estimate are approximately 39% (0.98 / 2.48) of the employment effects of PPP. This is striking when we consider that CEM is an intervention that does not inject government funds into businesses and that instead provides liquidity relief through delayed rent payment. Another notable difference is that CEM and PPP have different units of policy. CEM is measured in number of years, such that policymakers must choose how long to pause evictions and delay rent payment. In comparison, PPP is measured in dollars of loans, such that policymakers must choose how much funding to inject into businesses.

[24] The benchmark is based on the employment in January 2020 because the sample of my business closure results requires a business to operate as of January 2020.

[25] Autor et al. (2022), Granja et al. (2022), and Hubbard and Strain (2020) also find similarly small effects of PPP on employment.

Figure C.1: Relationship between CEM and partisanship

This figure illustrates the binscatter relationship between the length of CEM (plus repayment time) and the Democrat-Republican spread in 2019 for retail and food services businesses in California.

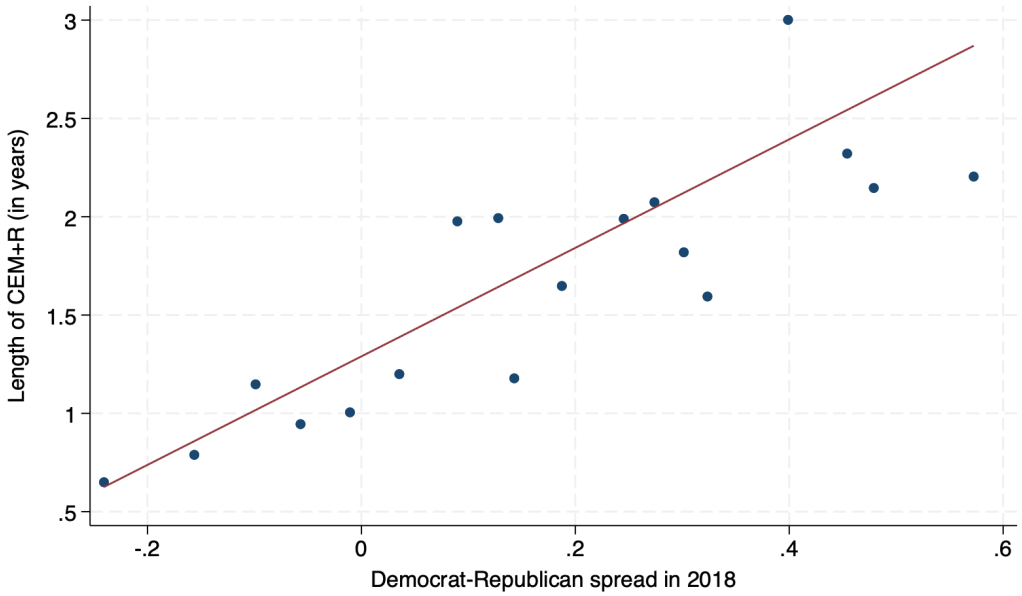
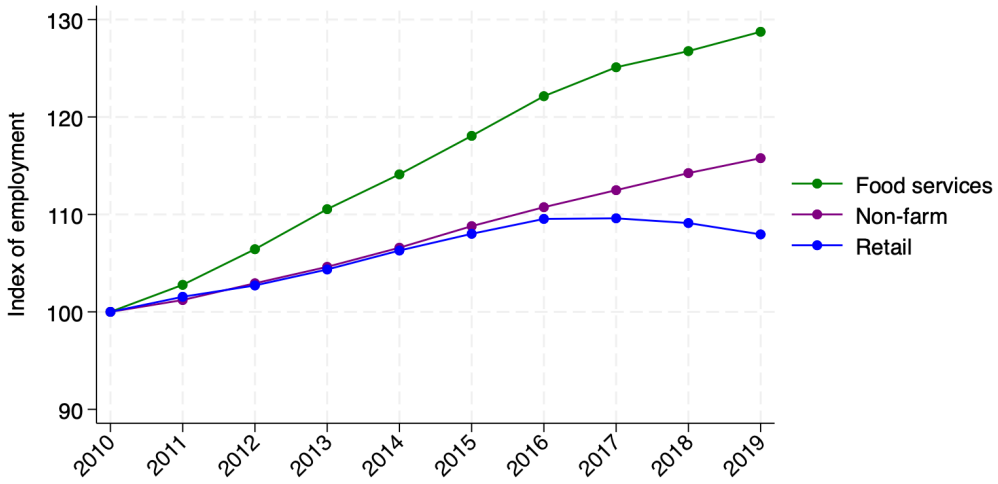


Figure C.2: Index of employment for non-farm, retail, and food services

This figure shows employment in different industries. Panel A presents non-farm, retail, and food services employment. Panel B presents employment for sub-industries within retail.

Panel A: Employment by industry



Panel B: Employment of sub-industries in retail

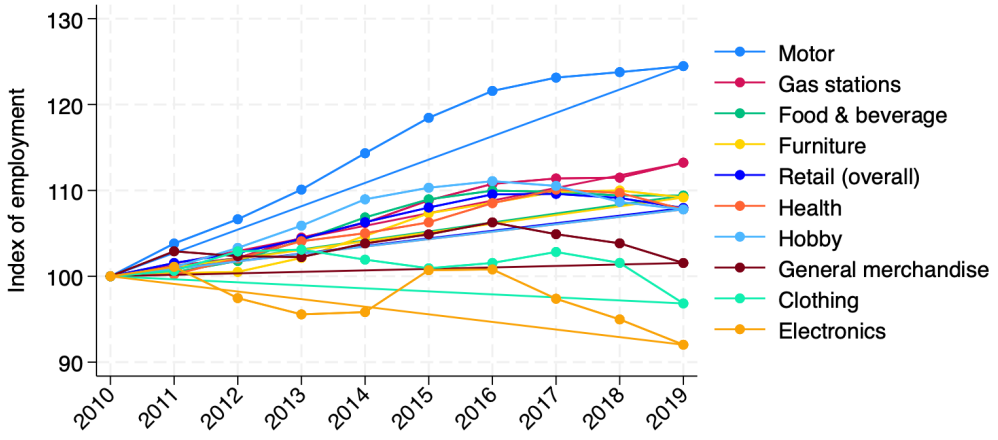


Figure C.3: Relationship between pre-pandemic employment growth and CEM business closure effects

This figure shows the relationship between the 5-year pre-pandemic employment growth and the effect of CEM on business closure for subindustries in retail and food services.

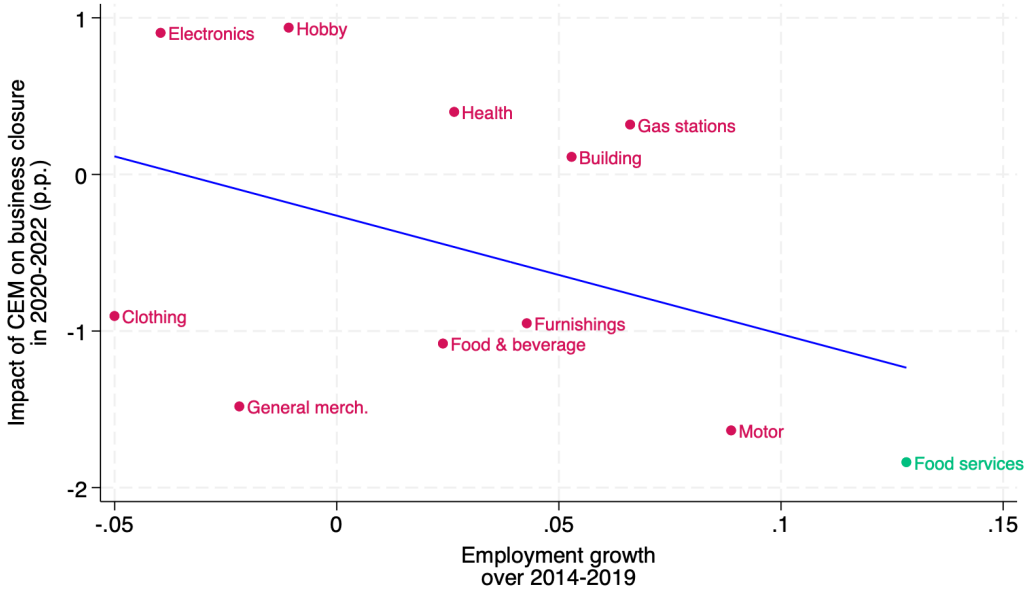


Table C.1: Covariate balance along the axis of pre-pandemic partisanship

This table presents the balance of covariates along the axis of pre-pandemic partisanship. Observations are at the zip code level. For each variable, the first 3 columns provide summary statistics for places with above-median Democratic-Republican spreads, while the next 3 columns provide summary statistics for places with below-median Democratic-Republican spreads. The last column computes the difference in mean and tests whether it is statistically significantly different from zero.

Zip code-level characteristics as of 2019							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Above-median Democratic			Below-median Democratic			
As of 2019:	Number of obs.	Mean	Std dev.	Number of obs.	Mean	Std dev.	Difference in mean
Ln(Population)	626	10.19	0.92	616	10.23	0.90	-0.039
Ln(Per-capita income)	628	10.50	0.58	616	10.48	0.46	0.018
Unemployment rate	628	0.06	0.03	616	0.06	0.03	-0.001
Share of population that is non-white	628	0.45	0.20	616	0.30	0.15	0.15***
Homeownership rate	628	0.48	0.19	616	0.60	0.16	-0.12***
Population density	628	6,998	7,030	616	3,142	3,237	3,856***
Indicator of urban area	628	0.60	0.49	616	0.47	0.50	0.13*
Ln(Number of businesses)	626	6.25	2.11	616	6.02	2.14	0.231**
Share of businesses in retail	628	0.18	0.14	616	0.17	0.12	0.009
Share of businesses in food services	628	0.11	0.11	616	0.10	0.12	0.004

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C.2: Alternative channels through which partisanship may affect business closure

This table presents the relationship between pre-pandemic Democratic-Republican spread and the alternative channels through which partisanship may affect business closure during the pandemic. Observations are at the city level.

	City-level characteristics		
	(1) Change in foot traffic from January to July-December 2020	(2) Indicator of having a pandemic business grant program	(3) Change in unemployment rate from 2019 to 2020
Democrat-Republican spread of population in 2019	-0.11***	0.11	0.020**
	(0.029)	(0.14)	-0.0086
Constant	-0.42***	0.59***	0.051***
	(0.018)	(0.036)	-0.003
Observations	465	465	465
R-squared	0.041	0.003	0.031

*** p<0.01, ** p<0.05, * p<0.1

Table C.3: First stage of pre-pandemic partisanship instrument for commercial eviction moratoria policy

This table shows the relationship between Democratic-Republican spread and length of CEM+R, controlling for zip code-level economic characteristics prior to the pandemic and city-level alternative channels through which partisanship may affect business closure during the pandemic. Observations are at the business level. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
			Years of CEM+R			
Democrat-Republican spread of population in 2019	2.77***	1.85***	1.59***	1.89***	1.73***	1.54***
	(0.29)	(0.43)	(0.46)	(0.41)	(0.42)	(0.46)
City-level characteristics						
Change in foot traffic from January to July-December 2020			-2.68**			-2.43**
			(1.12)			(1.07)
Indicator of having a pandemic business grant program				0.27***		0.18*
				(0.087)		(0.10)
Change in unemployment rate from 2019 to 2020					9.07*	7.24
					(5.37)	(4.94)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	1.29***	-2.25	-1.31	-1.92	-3.58*	-2.25
	(0.18)	(2.16)	(2.39)	(2.09)	(1.88)	(2.07)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.345	0.467	0.501	0.477	0.486	0.519
F-statistic	88.4	102.6	178.2	117.0	83.0	150.6

*** p<0.01, ** p<0.05, * p<0.1

Table C.4: Impact of commercial eviction moratoria on business closure

This table presents the second stage estimate of the impact of CEM on business closure after controlling for non-CEM channels through which partisanship may impact business closure. Observations are businesses in the industries of retail and food services. The first three columns progress from the OLS specification to the IV specification, while the last three columns decompose the IV estimate by year. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Likelihood of business closing in: 2020-2022			Likelihood of business closing in: 2020	2021	2022
Specification:	OLS	OLS	IV	IV	IV	IV
Years of CEM+R	0.65***	0.11	-0.80	-0.30	-0.55***	0.049
	(0.079)	(0.12)	(0.50)	(0.19)	(0.19)	(0.22)
City-level characteristics						
Change in foot traffic from January			-3.09	-0.97	-2.15**	0.032
to July-December 2020			(1.91)	(0.78)	(1.02)	(0.80)
Indicator of having a pandemic			0.11	0.018	0.065	0.028
business grant program			(0.31)	(0.072)	(0.12)	(0.20)
Change in unemployment rate			12.1	2.41	3.80	5.95
from 2019 to 2020			(9.41)	(3.00)	(3.63)	(4.14)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	8.66***	-10.9*	-14.1**	-4.28**	-3.42***	-6.41
	(0.20)	(6.08)	(6.03)	(2.03)	(1.28)	(4.08)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.001	0.003				

*** p<0.01, ** p<0.05, * p<0.1

Table C.5: Impact of commercial eviction moratoria on business closure by year: Retail v.s. food services

This table presents the second stage estimate of the impact of CEM on business closure by industry and by year. Observations are businesses in the industries of retail and food services. In the first four columns, I present the result for the retail industry, while in the last four columns, I present the result for the food services industry. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Retail				Food services			
	Likelihood of business closing in:				Likelihood of business closing in:			
	2020-2022	2020	2021	2022	2020-2022	2020	2021	2022
Years of CEM+R (instrumented)	-0.31	-0.23	-0.44**	0.36**	-1.84**	-0.49*	-0.77***	-0.58
	(0.38)	(0.16)	(0.18)	(0.17)	(0.81)	(0.28)	(0.27)	(0.50)
City-level characteristics								
Change in foot traffic from January	-0.88	-0.67	-1.52*	1.31	-8.40**	-1.93	-3.45**	-3.03*
to July-December 2020	(1.37)	(0.63)	(0.91)	(1.28)	(3.96)	(1.45)	(1.40)	(1.79)
Indicator of having a pandemic	0.073	0.14	0.080	-0.15	0.070	-0.24*	0.0099	0.30
business grant program	(0.28)	(0.10)	(0.12)	(0.18)	(0.50)	(0.14)	(0.14)	(0.32)
Change in unemployment rate	11.3*	1.10	3.71	6.46**	16.1	5.87	4.02	6.26
from 2019 to 2020	(5.83)	(3.35)	(3.13)	(2.96)	(19.0)	(4.25)	(5.68)	(11.3)
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.73*	-2.58	-1.98*	-5.16	-23.0**	-8.03***	-5.21**	-9.74
	(5.05)	(1.96)	(1.20)	(3.16)	(9.98)	(2.97)	(2.46)	(7.57)
Observations	218,335	218,335	218,335	218,335	122,008	122,008	122,008	122,008

*** p<0.01, ** p<0.05, * p<0.1

Table C.6: Impact of commercial eviction moratoria on business closure: Variation in pre-pandemic growth within the retail industry

This table presents the second stage estimate of the impact of CEM on business closure by year for the retail industry. Observations are businesses in the retail industry. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)
	Retail			
	Likelihood of business closing in:			
	2020-2022	2020	2021	2022
Years of CEM+R (instrumented)	-0.17	-0.21	-0.43**	0.47**
	(0.33)	(0.19)	(0.18)	(0.22)
Growth in sub-industry employment from 2014 to 2019	-0.18***	-0.13***	0.0040	-0.051**
	(0.028)	(0.026)	(0.020)	(0.024)
Years of CEM+R x Growth in sub-industry employment from 2014 to 2019 (instrumented)	-0.035	0.018	-0.021*	-0.032***
	(0.025)	(0.016)	(0.012)	(0.013)
City-level characteristics				
Change in foot traffic from January to July-December 2020	-0.64	-0.41	-1.64*	1.41
	(1.26)	(0.65)	(0.96)	(1.43)
Indicator of having a pandemic business grant program	0.14	0.12	0.066	-0.040
	(0.28)	(0.10)	(0.12)	(0.19)
Change in unemployment rate from 2019 to 2020	9.61*	-0.26	4.12	5.75
	(5.17)	(3.22)	(3.08)	(3.85)
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes
Constant	-6.05	-1.07	-1.77	-3.20
	(4.92)	(2.09)	(1.32)	(2.81)
Observations	192,247	192,247	192,247	192,247

*** p<0.01, ** p<0.05, * p<0.1

Table C.7: Impact of commercial eviction moratoria on business borrowing from the EIDL loan program

This table presents the second-stage estimate of the impact of CEM on average business borrowing from the Economic Injury Disaster Loan program. Observations are zip codes that contain at least 20 businesses. The three columns progress from the OLS specification to the IV specification. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)
	Dollars of EIDL loan per business			Likelihood of taking out EIDL loan	Average size of EIDL loan
Specification:	OLS	OLS	IV	IV	IV
Years of CEM+R	4,948	6,898	-11,713*	-7.42*	-8,723*
	(3,336)	(5,048)	(6,356)	(4.46)	(4,920)
City-level characteristics					
Change in foot traffic from January to July-December 2020			-59,394**	-21.9	-80,733***
			(25,414)	(18.9)	(17,446)
Indicator of having a pandemic business grant program			10,648***	6.81***	6,350*
			(3,768)	(2.21)	(3,450)
Change in unemployment rate from 2019 to 2020			554,494***	553***	-97,905
			(172,538)	(146)	(69,249)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes
Constant	39,248***	-133,266	-189,112***	-211***	123,131
	(3,756)	(81,209)	(61,096)	(59.8)	(87,463)
Observations	977	977	977	977	977
R-squared	0.020	0.112			

*** p<0.01, ** p<0.05, * p<0.1

Table C.8: Impact of commercial eviction moratoria on business grant takeup from the EIDL advance program

This table presents the second-stage estimate of the impact of CEM on average business grant takeup from the EIDL advance program. Observations are zip codes that contain at least 20 businesses. The three columns progress from the OLS specification to the IV specification. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)
	Dollars of EIDL advance per business			Likelihood of receiving EIDL advance	Average size of EIDL advance
Specification:	OLS	OLS	IV	IV	IV
Years of CEM+R	119**	-5.42	62.7	0.50	135
	(54.0)	(38.3)	(93.6)	(0.66)	(244)
City-level characteristics					
Change in foot traffic from January to July-December 2020			696**	4.98*	-411
			(352)	(2.54)	(1,304)
Indicator of having a pandemic business grant program			7.62	0.078	18.6
			(52.0)	(0.37)	(215)
Change in unemployment rate from 2019 to 2020			5,986***	43.0***	7,886*
			(1,396)	(10.2)	(4,706)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes
Constant	651***	4,991***	4,233***	31.3***	21,285***
	(92.4)	(1,166)	(1,026)	(7.45)	(2,833)
Observations	977	977	977	977	977
R-squared	0.020	0.377			

*** p<0.01, ** p<0.05, * p<0.1

Table C.9: Impact of commercial eviction moratoria on forgivable loan takeup from the PPP program

This table presents the second-stage estimate of the impact of CEM on forgivable loan takeup from the Paycheck Protection program. Observations are zip codes that contain at least 20 businesses. The three columns progress from the OLS specification to the IV specification. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)
	Dollars of PPP per business			Likelihood of receiving PPP	Average size of PPP
Specification:	OLS	OLS	IV	IV	IV
Years of CEM+R	1,136	3,526	-4,789	-8.58	-148
	(1,600)	(2,347)	(6,909)	(5.31)	(7,226)
City-level characteristics					
Change in foot traffic from January			-86,248***	-17.2	-95,203**
to July-December 2020			(32,312)	(26.4)	(43,246)
Indicator of having a pandemic			4,992	8.47**	-1,211
business grant program			(5,090)	(3.63)	(4,822)
Change in unemployment rate			197,666**	778***	-349,584**
from 2019 to 2020			(83,410)	(186)	(144,363)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes
Constant	66,275***	-60,795	-39,847	-373***	323,109***
	(4,044)	(97,808)	(91,600)	(107)	(122,676)
Observations	977	977	977	977	977
R-squared	0.001	0.159			

*** p<0.01, ** p<0.05, * p<0.1

Table C.10: Impact of commercial eviction moratoria on business employment

This table presents the second stage estimate of the impact of CEM on business employment. Observations are businesses in the industries of retail and food services. The measure of employment is hours worked scaled by hours worked in January 2020. The first three columns progress from the OLS specification to the IV specification, while the last three columns decompose the IV estimate by year. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scaled hours worked in 2020-2022			Scaled hours worked in 2020	2021	2022
Specification:	OLS	OLS	IV	IV	IV	IV
Years of CEM+R	-0.014**	0.0050	0.0013	0.0049	0.032	0.023
	(0.0070)	(0.0063)	(0.022)	(0.021)	(0.026)	(0.030)
City-level characteristics						
Change in foot traffic from January			0.35***	0.28***	0.42***	0.35**
to July-December 2020			(0.12)	(0.089)	(0.14)	(0.15)
Indicator of having a pandemic			0.0026	-0.0013	-0.00063	0.026
business grant program			(0.021)	(0.018)	(0.022)	(0.024)
Change in unemployment rate			0.37	0.34	0.49	-0.43
from 2019 to 2020			(0.41)	(0.34)	(0.45)	(0.52)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	0.97***	2.19***	2.03***	1.64***	2.27***	2.07***
	(0.013)	(0.50)	(0.43)	(0.17)	(0.43)	(0.68)
Observations	2,688	2,688	2,688	4,242	3,180	2,688
R-squared	0.001	0.016				

*** p<0.01, ** p<0.05, * p<0.1

Table C.11: Impact of commercial eviction moratoria on business employment by year: Retail v.s. food services

This table presents the second stage estimate of the impact of CEM on business employment by industry and by year. Observations are businesses in the industries of retail and food services. The measure of employment is hours worked scaled by hours worked in January 2020. In the first four columns, I present the result for the retail industry, while in the last four columns, I present the result for the food services industry. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Retail				Food services			
	Scaled hours worked in:				Scaled hours worked in:			
	2020-2022	2020	2021	2022	2020-2022	2020	2021	2022
Years of CEM+R (instrumented)	-0.0094	0.032	0.040	-0.0053	0.0028	-0.000046	0.029	0.028
	(0.034)	(0.046)	(0.039)	(0.050)	(0.022)	(0.018)	(0.026)	(0.032)
City-level characteristics								
Change in foot traffic from January	0.46	0.40	0.50	0.45	0.32***	0.26***	0.40***	0.32**
to July-December 2020	(0.33)	(0.26)	(0.31)	(0.48)	(0.11)	(0.073)	(0.14)	(0.13)
Indicator of having a pandemic	-0.037	0.033	-0.073*	-0.045	0.0081	-0.0091	0.014	0.036
business grant program	(0.038)	(0.025)	(0.039)	(0.047)	(0.023)	(0.021)	(0.024)	(0.026)
Change in unemployment rate	-0.51	-0.29	-0.56	-0.98	0.59*	0.46	0.80*	-0.27
from 2019 to 2020	(1.20)	(0.90)	(1.30)	(1.12)	(0.34)	(0.33)	(0.44)	(0.51)
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.36	1.20**	0.47	-0.017	2.38***	1.77***	2.64***	2.51***
	(0.96)	(0.52)	(1.29)	(1.39)	(0.45)	(0.22)	(0.42)	(0.68)
Observations	487	787	580	487	2,201	3,455	2,600	2,201

*** p<0.01, ** p<0.05, * p<0.1

Table C.12: Impact of CEM on number of shifts

This table presents the second stage estimate of the impact of CEM on business employment. Observations are businesses in the industries of retail and food services. The measure of employment is number of shifts worked scaled by number of shifts worked in January 2020. The first three columns progress from the OLS specification to the IV specification, while the last three columns decompose the IV estimate by year. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scaled number of shifts in: 2020-2022			Scaled number of shifts in: 2020	2021	2022
Specification:	OLS	OLS	IV	IV	IV	IV
Years of CEM+R	-0.014*	0.0046	0.0034	-0.0013	0.036	0.032
	(0.0079)	(0.0070)	(0.022)	(0.022)	(0.027)	(0.031)
City-level characteristics						
Change in foot traffic from January			0.31**	0.23**	0.41***	0.32**
to July-December 2020			(0.12)	(0.092)	(0.13)	(0.16)
Indicator of having a pandemic			0.0019	0.0033	-0.0034	0.016
business grant program			(0.020)	(0.018)	(0.019)	(0.023)
Change in unemployment rate			0.17	0.41	0.29	-0.71
from 2019 to 2020			(0.40)	(0.36)	(0.42)	(0.49)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	0.98***	1.88***	1.77***	1.50***	1.91***	1.89***
	(0.015)	(0.43)	(0.38)	(0.18)	(0.38)	(0.58)
Observations	2,688	2,688	2,688	4,242	3,180	2,688
R-squared	0.001	0.018				

*** p<0.01, ** p<0.05, * p<0.1

Table C.13: Impact of CEM on number of shifts by year and by industry

This table presents the second stage estimate of the impact of CEM on business employment by industry and by year. Observations are businesses in the industries of retail and food services. The measure of employment is number of shifts worked scaled by number of shifts worked in January 2020. In the first four columns, I present the result for the retail industry, while in the last four columns, I present the result for the food services industry. Zip code-level controls include log population, log per-capita income, unemployment rate, proportion of population that is non-white, homeownership rate, population density, indicator of urban area, log number of businesses, share of businesses in retail, and share of businesses in food services as of 2019. Standard errors are clustered by county, and robust standard errors are given in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Retail				Food services			
	Scaled number of shifts in:				Scaled number of shifts in:			
	2020-2022	2020	2021	2022	2020-2022	2020	2021	2022
Years of CEM+R (instrumented)	-0.015	0.015	0.022	-0.0056	0.0052	-0.0046	0.036	0.038
	(0.040)	(0.046)	(0.041)	(0.053)	(0.023)	(0.019)	(0.028)	(0.036)
City-level characteristics								
Change in foot traffic from January	0.37	0.28	0.43	0.38	0.29***	0.23***	0.39***	0.29**
to July-December 2020	(0.30)	(0.23)	(0.29)	(0.45)	(0.10)	(0.078)	(0.12)	(0.13)
Indicator of having a pandemic	-0.079*	0.027	-0.12***	-0.13*	0.016	-0.0022	0.019	0.040*
business grant program	(0.048)	(0.026)	(0.040)	(0.065)	(0.022)	(0.021)	(0.023)	(0.024)
Change in unemployment rate	-0.51	-0.19	-0.34	-0.77	0.37	0.53	0.54	-0.61
from 2019 to 2020	(1.13)	(0.85)	(1.23)	(1.04)	(0.35)	(0.34)	(0.41)	(0.52)
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.34	0.85*	-0.35	-0.82	2.19***	1.67***	2.37***	2.45***
	(0.83)	(0.51)	(1.23)	(1.14)	(0.42)	(0.21)	(0.39)	(0.62)
Observations	487	787	580	487	2,201	3,455	2,600	2,201

*** p<0.01, ** p<0.05, * p<0.1