Commercial Eviction Moratoria, Liquidity Relief and Business Closure

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November 2023
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Abstract

In this paper, I estimate the effects of the commercial eviction moratorium (CEM) policy on business closure and employment during the Covid-19 pandemic. CEM temporarily prohibits commercial evictions and gives business tenants more time to pay rent, thereby providing liquidity relief. I construct an instrument for CEM using pre-pandemic partisanship and controlling for alternative channels through which partisanship may affect businesses. I find that CEM significantly reduces business closure in the short run in both retail and food services but has long-run effects only in food services. Consistent with the mechanism that CEM provides liquidity relief, CEM is more effective in reducing long-run closure for businesses that are more solvent coming into the pandemic, and CEM reduces business take-up of costly loans but does not affect take-up of grants. Turning to employment, the impact of CEM operates along an extensive margin through a reduction in business closure, rather than along an intensive margin through a change in employment while a business is in operation. The total impact of CEM on employment is a preservation of 0.98 percentage points of pre-pandemic employment, which equals 39% of the estimated effects of the Paycheck Protection Program.

Keywords: Commercial eviction moratoria, government intervention, Covid-19, liquidity, solvency, business closure, employment
JEL Codes: G18, G23, G32

[1]Email: angelama@g.harvard.edu. Harvard University. I am deeply grateful to my advisors Jeremy Stein (chair), Robin Greenwood, Adi Sunderam, Emily Williams, and Ed Glaeser for invaluable guidance and support throughout this project. I am also grateful to Hyuntae Choi for excellent research assistance and to Trepp (Erin Timko and Lonnie Hendry), SafeGraph, Dewey (Evan Barry) and Homebase (Joey Nedland) for generously making their data available and providing support. For helpful comments, I thank Andrei Shleifer, Varanya Chaubey (Econscribe), Jessica Bai, Leonardo D'Amico, Sebastian Hillenbrand, Dominic Russel, Claire Shi, Jennifer Walsh, Sasha Watkins, especially Miles Zheng, and participants in the Harvard doctoral finance seminar, doctoral contracts seminar, and doctoral economic history seminar. I gratefully acknowledge support from the Paul & Daisy Soros Fellowship and the NSF Graduate Research Fellowship. All errors are my own.

1 Introduction

To combat the severe shock of the Covid-19 pandemic for a broad swath of businesses, policymakers reacted by enacting a series of unprecedented programs. First, the federal government intervened in extraordinary ways to aid businesses. For example, 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. Second, local governments also responded in unprecedented ways. Commercial eviction moratoria (CEM) were widely enacted and provided liquidity to businesses through rent deferral. 30 states in the U.S. enacted state-wide CEM, applying to 67% of U.S. small businesses. While the policy was widespread, its impact is not well understood. This paper fills the gap by providing the first evaluation of CEM.

In this paper, I address three research questions. First, what is the impact of CEM on business closure? Second, which types of businesses are aided by CEM in the short run and long run? Third, what is the impact of CEM on business employment? To answer these questions, I hand-collect all enactments and updates of CEM policy for the 482 incorporated cities and 58 counties in California over the period March 2020 through May 2023.[1] To identify the causal effect of CEM, I construct an instrument based on pre-pandemic partisanship, measured as the difference between the share of Democratic and Republican voter registration. I first show that more Democratic places enact longer CEM relative to more Republican places, confirming the relevance of the instrument. To address the exclusion restriction, my empirical strategy also controls for several alternative channels, including pre-pandemic characteristics, consumer stay-at-home behavior, business financial support, and exposure to the Covid-19 shock.

My main findings are as follows. CEM reduces business closure in the short run in both retail and food services but has long-run effects only in food services. Consistent with the mechanism that CEM provides liquidity relief, I show first that CEM is more effective in reducing long-run closure for businesses that are more solvent coming into

[1] California serves as an ideal laboratory for CEM because of its decentralized implementation. Governor Gavin Newsom gave cities and counties the legal option to enact CEM if they so choose. This feature creates variation in CEM 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.

the pandemic. Additionally, CEM reduces business take-up of costly loans but does not affect take-up of grants. Turning to employment, the impact of CEM operates along an extensive margin through a reduction in business closure, rather than along an intensive margin through a change in employment while a business is in operation. The total impact of CEM on employment is a preservation of 0.98 percentage points of pre-pandemic employment, which equals 39% of the estimated effects of PPP.

The direct consequence of CEM is liquidity relief. By pausing rent payments, CEM effectively requires landlords to offer business tenants zero-interest, non-forgivable credit with face value equal to the amount of rent accrued during the policy period. In the face of substantial frictions in credit markets, CEM provides a source of liquidity that can help liquidity-constrained but solvent businesses survive in both the short run and long run. For these businesses, CEM is bridge financing that enables them to survive in the short run and that they repay to continue operating in the long run. However, since CEM does not improve business solvency, the policy only puts off the inevitable for liquidity-constrained, insolvent businesses. While these businesses can use the liquidity relief of CEM to survive in the short run, they are unable to repay their borrowing and ultimately close in the long run. In contrast, CEM would have no effect on liquidity-unconstrained businesses that already have sufficient access to credit.

The challenge of identifying the causal impact of CEM stems from reverse causality from business closure to CEM. Because the purpose of enacting CEM 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 CEM. Indeed, the data shows that longer CEM is correlated with higher rates of business closure during the policy period. However, the causal effect of CEM remains unclear because, even if the true effect of CEM is to reduce business closure, the selection bias may result in the observed, positive relationship between CEM and business closure.

To overcome this selection bias, I instrument for CEM policy using pre-pandemic partisanship. Specifically, I compute the net political leaning of an area prior to the pandemic using the Democratic-Republican spread, which is the difference between the share of Democratic and Republican voter registration as of February 2019. Democratic governments are associated with a greater propensity for government intervention relative to Republican governments, which are by contrast associated with a more laissez-faire approach. I find that pre-pandemic partisanship significantly predicts CEM policy; specifically, a 10 percentage point increase in the Democratic-Republican spread predicts a longer CEM (including repayment time) by 3.3 months. Therefore, pre-pandemic partisanship strongly predicts the enactment of CEM.

The exclusion restriction of my instrumental variable strategy is that pre-pandemic partisanship does not affect business closure except through CEM. There are three main alternative channels through which partisanship may affect business closure: consumer stay-at-home behavior, business financial support, and exposure to the Covid-19 economic shock. First, in more Democratic cities, consumers may be more likely to stay at home, thereby reducing demand for businesses and increasing the likelihood of business closure. Second, more Democratic governments may be more likely to intervene during the pandemic by allocating funds to business grants and thereby reducing the likelihood of business closure. Third, differently partisan areas may be differently exposed to the economic shock of the Covid-19 pandemic, leading to differences in likelihood of business closure. Therefore, I construct measures of these three channels and control for them, as well as for pre-pandemic economic characteristics, in both the first and second stages of the instrumental variable approach.

After confirming that the instrumental variable satisfies the first stage and controlling for alternative channels to make it more likely that the exclusion restriction holds, I estimate the causal effect of CEM on business closure. I find that CEM reduces business closure in the short run in both retail and food services but has long-run effects only in food services. In retail, the likelihood of business closure falls by 0.28 percentage points in 2020 and 0.54 percentage points in 2021, which is partly reversed by 0.44 percentage points in 2022. In food services, the likelihood of business closure falls by 0.60 percentage points in 2020, 0.94 percentage points in 2021, and 0.71 percentage points in 2022, which totals 2.24 percentage points over the period 2020-2022. The estimate suggests that the average CEM policy preserves 1,913 food services businesses in California.

I next examine how the effectiveness of CEM varies with business solvency. Using the 5-year pre-pandemic employment growth rate as a sub-industry-level proxy for business solvency, I find that CEM is more effective in reducing business closure in sub-industries that are more solvent coming into the pandemic, which is consistent with substantial frictions in credit markets. Specifically, greater business solvency strengthens the effectiveness of CEM in reducing closure primarily in the later period after CEM is lifted. The results suggest that CEM provides a source of liquidity that prevents the closure of liquidity-constrained but solvent businesses in the long run.

I then turn to the effect of CEM on business financing. By providing liquidity relief, CEM may affect business take-up of other sources of financing. Overall, there are two other 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 CEM and away from loan financing because the loan is more costly than the zero-interest liquidity relief of CEM. Second, there is grant financing that does not need to be repaid, such as the EIDL advance program and PPP. There is unlikely to be substitution between CEM and grants because grants improve business solvency. Turning first to the EIDL loan program, I find that the average CEM policy leads to a reduction in borrowing by approximately $14,300 per business, consistent with substitution towards CEM and away from loan financing. Turning next to the EIDL advance program and PPP, I find that CEM does not affect business take-up of these grants, consistent with businesses seeking out grants irrespective of CEM policy.

I next assess the employment effects of CEM. The finding that CEM reduces business closure implies that CEM preserves employment along an extensive margin. Specifically, through its effect on business closure, the average CEM policy preserves employment over the period 2020-2022 by a combined 0.98 percentage points of pre-pandemic employment. I then estimate the impact of CEM on employment along an intensive margin, i.e. conditional on the business being alive. Implementing the same empirical strategy of instrumenting for CEM with pre-pandemic partisanship, I find no effect of CEM on intensive-margin employment over the period 2020-2022 in both retail and food services. The effect of CEM on employment therefore operates primarily along the extensive margin. The total impact of the average CEM policy on employment is a preservation of 0.98 percentage points of pre-pandemic employment, which equals 39% of the effects of PPP estimated by Chetty et al. (Forthcoming). This is striking when we consider that CEM is a government intervention that does not inject government funds into businesses.

Finally, I discuss the policy implications of the results. I find that CEM temporarily reduces business closure in retail and permanently reduces business closure in food services. Moreover, CEM is more effective in reducing long-run closure for businesses that are more solvent prior to the pandemic. The efficiency implications of the results are nuanced and require additional consideration. CEM may prolong the survival of some insolvent businesses, which could prevent reallocation towards more solvent businesses and deteriorate the financial health of commercial landlords who perform the valuable economic role of maintaining and filling spaces for businesses. I discuss the policy implications in more detail in Section 7.

Related Literature.

This paper relates to several strands of literature in financial economics. First, this paper connects to the literature on government intervention 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.

Second, it connects to the literature on business closure. Prior to the 2020 crisis, this literature primarily used "traditional" business data sources from the Bureau of Labor Statistics and U.S. Census Bureau. During the Covid-19 pandemic, in order to monitor business closure and employment in a more real-time way, this literature employed "alternative" data sources such as Google Maps (Rigobon et al., 2022), SafeGraph/Advan (de Vaan et al., 2021), Yelp (Bartik et al., 2020a), ADP (Cajner et al., 2020), Homebase (Bartik et al., 2020b), Womply (Chetty et al., Forthcoming), and Alignable (Bartik et al., 2020a, 2023). One striking pattern documented by Iverson et al. (2022) is that there has been significantly less business closure & bankruptcy than would be expected based on historical precedent. This paper shows that CEM is one policy that reduces business closure in retail and food services during the Covid-19 crisis.

Third, this paper connects to the growing literature on commercial real estate. Studies have examined the different nodes of the commercial real estate ecosystem, including commercial leasing (Moszkowski and Stackman, 2023), commercial mortgage lending (Glancy et al., 2021, 2022), commercial property investing (Allan et al., 2021), the office-use submarket (Gupta et al., 2023; Sadikin et al., 2021), and the retail-use submarket (Liebersohn et al., 2022; Moszkowski and Stackman, 2023). This paper contributes to the literature by evaluating the effects of a commercial rent forbearance policy.

Finally, this paper connects to the literature on non-bank financial intermediaries. In many financial markets, non-bank intermediaries have been shown to fill a gap left by banks. In the consumer loan market, payday lenders provide short-term financing to underbanked individuals who cannot access traditional credit (e.g. Morse, 2011; Di Maggio et al., 2022). In the corporate loan market, CLOs provide financing to leveraged borrowers with low or no credit ratings (Benmelech et al., 2012). In the corporate going-public market, SPACs take smaller, riskier, higher-growth companies public (Klausner et al., 2022; Gahng et al., 2023; Bai et al., 2023). This paper contributes to the literature by evaluating the real effects of a policy that requires landlords to effectively act as non-bank intermediaries by extending credit to businesses during a crisis.

This paper proceeds as follows. Section 2 develops a conceptual framework of CEM in liquidity provision. Section 3 describes the data sources and provides summary statistics. Section 4 develops the instrumental variable empirical strategy and estimates the impact of CEM on business closure. Section 5 investigates the impact of CEM on business financing. Section 6 evaluates the impact of CEM on business employment. Section 7 discusses policy implications. Finally, Section 8 concludes.

2 A conceptual framework of CEM in liquidity provision

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

2.1 Background on commercial eviction moratoria

Enacted during the Covid-19 pandemic to combat business stress, CEM prohibits commercial evictions under certain conditions. While CEM 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.[2] Evictions may still proceed if the tenant violates its lease in other ways, e.g. by damaging property or committing illegal acts. Enforcement of CEM happens through the judicial courts. If a landlord initiates commercial eviction proceedings, CEM can be cited by the business tenant as a legal defense. The vast majority of CEM apply to all businesses and are not targeted.

The stated goal of CEM is to prevent business closure by pausing eviction proceedings. The direct consequence of CEM is liquidity relief. By pausing rent payments, CEM 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, CEM is essentially a credit policy where businesses can borrow from their landlord by delaying rent payment.[3]

CEM is enacted by local governments, rather than the federal government. While the start date of CEM is almost uniformly March 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 CEM through September 2020, while the Governor gave city and county governments the option to enact CEM through September 2021.

2.2 Illustrative examples of commercial eviction moratoria

Figure 1 provides illustrative examples of the timeline of CEM policy. Panel A shows that in Oakland, California, CEM 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

[2]CEM also prohibits commercial evictions in the case of property foreclosure. That is, if a commercial property enters foreclosure, the new property owner may not evict existing tenants while the CEM is in effect. However, the focus of this paper will be on the primary function of CEM, which is barring commercial evictions on the basis of non-payment of rent.

[3]The potential second consequence of CEM 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 CEM.

due. Panel B shows that in San Diego, California, CEM is similarly enacted in March 2020 and ends in September 2021. In the case of San Diego, however, the local government gave businesses additional repayment time of 6 months, such that back rent comes due in March 2022. Therefore, the length of CEM plus repayment time (CEM+R) is 19 months in Oakland and 25 months in San Diego.

To concretely understand how CEM is a liquidity relief policy, Figure 2 presents illustrative examples of the effective loan balance that businesses can borrow under the CEM policy in these two cities. Panel A shows that in Oakland, California, businesses can steadily borrow each month by deferring monthly rent until CEM ends, at which point they must repay the loan balance. Specifically, given a restaurant with monthly rent of $5,000, CEM would enable the business to borrow $95,000 (19 * $5,000) over 19 months at zero interest. Panel B shows that in San Diego, CA, businesses can steadily borrow each month by deferring monthly rent. Then, they can maintain the loan balance until the additional 6 months of repayment time pass, at which point they must repay the loan balance. Under this policy, for the same restaurant with monthly rent of $5,000, CEM would enable the business to borrow $95,000 (19 * $5,000) over 25 (19 + 6) months at zero interest.

2.3 Model setting

To develop a conceptual framework for the impact of CEM 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 CEM policy into the model and analyze the impact of CEM 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 CEM 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 CEM on business closure, I augment the model by introducing CEM as mandated zero-interest lending to businesses in amount ρ between $t = 1$ and $t = 2$. Specifically, if CEM is enacted, then businesses are injected with ρ at $t = 1$ and must repay ρ at $t = 2$.

2.4 The impact of CEM 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 $f \in [0, F_{S_{t-1}}]$ 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:

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

Let $F^*_{S_t}$ denote the cutoff in the private market outcome without CEM, and let $F^{c*}_{S_t}$ denote the cutoff in the private market outcome with CEM. 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 CEM than without CEM.
Specifically, we have: $F_1^{c*} - F_1^* > 0$.

By providing financial support to all businesses, CEM 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 CEM 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 CEM mandates that commercial landlords provide liquidity relief to their business tenants, these businesses are preserved by CEM at $t = 1$ when they would not have survived without CEM.

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

Proposition 2

Under the assumptions outlined above, CEM 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 CEM borrowing and continue operating. By contrast, less solvent businesses will be more likely to shut down at $t = 2$. By accepting the liquidity relief of CEM at $t = 1$, they have used up the credit of CEM. 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 financial frictions, CEM reduces closure for businesses in the short run.

Prediction 2

Under substantial financial frictions, CEM 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 CEM is enacted by local governments for varying amounts of time during the Covid-19 pandemic. California serves as an ideal laboratory for CEM because of its decentralized implementation which creates variation in CEM 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 CEM on business closure and employment, it is necessary to collect the enactments and updates of CEM and to observe the closure and employment behavior of businesses. To do so, I hand-collect CEM 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 eviction moratoria data

One challenge of assessing the impact of CEM on business closure is data availability. CEM is a policy enacted by local governing bodies, rather than the federal government. Accordingly, CEM varies across geographies, and information about the policy is scattered across local government documents. Furthermore, CEM 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 CEM enacted throughout California during the Covid-19 pandemic. Specifically, I record the following details about CEM: 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 CEM at the state, county, and city level. At the state level, the California Judicial Council enacted a CEM 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 CEM until September 30, 2021.

28 of the 58 counties in California exercised the option and enacted CEM. 18 counties enacted CEM over unincorporated areas only, while 10 counties enacted CEM county-wide. County-enacted CEMs 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 CEMs 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 CEM. City-enacted CEMs 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 CEMs 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 CEM is the one that is most generous to business tenants. At the city level, binding CEMs 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 CEM policies allow for back rent to be paid in a single installment on the due date.

Figure 3 illustrates the length of CEM enacted throughout California. The three categories of CEM length correspond intuitively to three categories of local government behavior. The lightest blue category (with CEM of 6 months) consists of cities and counties that deferred to the state-wide CEM enacted by the California Judicial Council. These areas did not enact CEM for any longer than the state policy, although they did have the legal option to do so. The medium blue category (with CEM of 7 to 19 months) consists of cities and counties that exercised their option to enact CEM. The dark blue category (with CEM greater than 19 months) consists of cities and counties that extended their CEM past the maximum date set by Governor Newsom.

3.2 Business closure data

The business closure data comes from SafeGraph (now Advan) and covers the effective universe of all business establishments. SafeGraph collects and reconciles business information 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 business closure date variable (*closed_on*) is expected to be accurate within 60 days.

There are a few exceptions to the accuracy of the business closure date. Specifically, there are mechanical spikes in business closure attributed to October 2021, March 2022, April 2022, and June 2022. Non-chain businesses marked as closed on October 2021 actually closed before October 2021, but SafeGraph is not able to pinpoint when. Because some of these business closures could have happened even before the pandemic period, I remove these cases of inaccurate business closure date. After investigation and discussion with the SafeGraph & Dewey teams,[4] I learned that the closure date in March 2022, April 2022, and June 2022 is primarily accurate for businesses that also register customer foot traffic. Therefore, I keep the business closures on these three dates using this criteria and remove cases of inaccurate business closure date. My final sample consists of businesses where the closure date is accurate within 60 days with relatively high confidence.

Using the cleaned sample of business closures, Figure 4 illustrates the cumulative percentage decline in number of businesses in California from January 2020 through December 2022 for all industries and for retail and food services. Across all industries, approximately 5% of businesses operating in January 2020 close by the end of 2022. In retail and food services, two industries that are severely affected by the pandemic and that will be the focus of my study, approximately 10% of businesses operating in January 2020 close by the end of 2022.

Panel A of Table 2 provides summary statistics for the SafeGraph business closure data in the industries of retail and food services. Of the retail businesses identified as open in

[4] Please see the discussion post here for more detail: https://community.deweydata.io/t/spike-in-safegraph-closed-on-values-that-is-not-already-discussed-in-documentation/26331/4.

January 2020, 1.86% close in 2020, 1.53% close in 2021, and 4.32% close in 2022. Of the food services businesses identified as open in January 2020, 3.23% close in 2020, 2.80% in 2021, and 7.58% in 2022.

3.3 Business employment data

Business employment data comes from Homebase, a company that provides hourly clock in & out software to small businesses. This data captures business employment at the employee shift level. As documented in the literature, it is not possible to discern whether a business stops appearing in the dataset because it has closed or because it has stopped using the Homebase software, and it can be economically meaningful to distinguish between the two causes (Kurmann et al., 2022; Chetty et al., Forthcoming). Consistent with the literature, I will rely on this dataset to analyze business employment *conditional* on the business being alive.

An important step of data cleaning is to focus on periods when businesses are actively and continuously using Homebase for their employment. First, I define a business as being alive when it first uses the software for 3 consecutive months and as being no longer alive when it stops using the software for 3 consecutive months. This step removes ramp-up periods when a business is only trying out Homebase software and ramp-down periods when a business is phasing out its usage of Homebase software. Next, I distinguish between cases where the business has paused operations during the pandemic (such that employment is truly zero) and cases where the business has stopped using Homebase software (such that employment is non-zero but unobservable in Homebase data). Specifically, if a business stops using Homebase for more than 12 months, it is more likely that the business has stopped using Homebase software than that it has paused operations. Therefore, I drop observations from the 12-month absence on.

Figure 5 illustrates the monthly employment of retail and food services businesses in Homebase from 2020 through 2022. Panel A plots the number of businesses identified as alive on the platform, which declines over time. Panel B plots the average monthly hours worked as a share of hours worked in January 2020. This value declines to approximately 75% in March 2020 and 50% in April 2020 and then recovers in 2021 and 2022 for businesses that remain alive. Panel C plots the average monthly number of shifts worked as a share of number of shifts worked in January 2020. Similarly, this value declines to approximately 75% in March 2020 and 50% in April 2020 and then recovers in 2021 and 2022 for businesses that remain alive.

Panel B of Table 2 provides summary statistics for businesses in retail and food services in the Homebase data. Retail businesses employed workers for an average of 652.1 hours in January 2020, while food services businesses employed workers for an average of 1,067.0 hours in January 2020. As a share of January 2020 hours worked, the hours worked for retail businesses is on average 83% in 2020, 103% in 2021, and 111% in 2022 conditional on the business remaining alive. Meanwhile, as a share of January 2020 hours worked, the hours worked for food services businesses is on average 78% in 2020, 94% in 2021, and 101% in 2022 conditional on the business remaining alive.

4 The impact of CEM on business closure

In this section, I estimate the causal impact of CEM on business closure. In Section 4.1, I identify the causal impact of CEM on business closure by developing an instrument for CEM based on pre-pandemic partisanship after controlling for alternative channels. I also estimate the impact by year and by industry. In Section 4.2, I test the relationship between pre-pandemic business solvency and the effectiveness of CEM in reducing business closure.

4.1 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.[5] Panel A of Figure 6 shows

[5]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.

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 6 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.[6]

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 7 and column 1 of Table 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. Sec-

[6] Figure B.1 shows a binned scatter plot of business closure rate in 2020-2022 vs. length of CEM (including repayment time) for unincorporated cities, which are cities that have no municipal government and therefore cannot enact their own CEM. For unincorporated cities, the CEM policy will be determined at the county and state level. The relationship between CEM and business closure is mitigated for these unincorporated cities that do not set their own CEM. In my main analysis, I exclude unincorporated cities because of lack of voting registration data needed for my instrumental variable strategy.

ond, 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 B.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 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.[7] 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 mea-

[7]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.

sure 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.[8] Column 1 of Table B.2 shows that there is a negative, statistically significant relationship between partisanship and change in foot traffic. After controlling for this change in foot traffic, column 3 of Table 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.[9] Column 2 of Table B.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 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.[10] 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 B.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 3 shows that the relationship between partisanship and length of CEM remains statistically significant and economically meaningful.

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

[9] 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.

[10] 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.

Finally, after controlling for all three alternative channels, column 6 of Table 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.[11] Table B.3 shows that this relationship holds true when we instead measure the strength of CEM policy using the length of CEM only (not including repayment time R). Table B.6 shows that this relationship holds true when we instead control non-parametrically for alternative channels by using quintile fixed effects. Table B.9 shows that this relationship holds true when we instead control non-parametrically for both alternative channels and pre-pandemic characteristics using quintile fixed effects. In sum, the pre-pandemic partisanship instrument maintains a strong first stage in predicting CEM policy after addressing pre-pandemic economic characteristics and alternative channels during the pandemic.

Table 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 ob-

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

serve 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. Table B.4 shows that this finding holds true when we instead measure the strength of CEM policy using the length of CEM only (not including repayment time R). Table B.7 shows that this finding holds true when we instead control non-parametrically for alternative channels by using quintile fixed effects. Table B.10 shows that this finding holds true when we instead control non-parametrically for both alternative channels and pre-pandemic economic characteristics by using quintile fixed effects. In sum, the results suggest that CEM reduces business closure in 2020 and 2021 while the policy is in effect.

Next, I consider the differential effect of CEM in retail vs. food services. Table 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 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. Table B.5 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). Table B.8 shows that the finding holds true when we instead control non-parametrically for alternative channels by using quintile fixed effects. Table B.11 shows that the finding holds true when we instead control non-parametrically for both alternative channels and pre-pandemic characteristics uisng quintile fixed effects.

4.2 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 8 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. Meanwhile, 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).[12] Panel B of Figure 8 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).

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

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 9 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. Figure B.2 shows that this relationship holds true when we instead measure CEM business closure effects as a percentage of the closure rate over the period 2020-2022. Figure B.3, Figure B.4, and Figure B.5 show that this relationship holds true when we instead proxy for industry solvency using the 5-year pre-pandemic growth in sales, number of firms, or number of establishments, respectively.

Table 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 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 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 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 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.[13] 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).

5 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. Therefore, in Section 5.1, I estimate the effect of CEM on business borrowing and grant take-up from federal government programs. Additionally, by requiring commercial landlords to provide liquidity relief, CEM may have effects on their financial health. The reason that CEM may have ripple effects on commercial landlords and affect their financial health is because they can have commercial mortgages and CEM does not pause their payment obligations. Therefore, in Section 5.2, I estimate the effect on of CEM on the performance of commercial mortgages contained in commercial mortgage-backed securities.

5.1 The financing effects on businesses

In this section, I estimate the effect of CEM on business take-up of other sources of financing. There are two other types of financing available to businesses during the Covid-19 pandemic. 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

[13]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.

examine business take-up of loans from the Economic Injury Disaster Loan program in Section 5.1.1. 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 Section 5.1.2.

5.1.1 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.[14] Throughout the U.S., the COVID EIDL program disbursed $\sim$3.9 million loans totaling $\sim$\$380 billion. In my sample of California, the program disbursed $\sim$600,000 loans totaling $\sim$\$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

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

behavior of the average business in the zip code.

Table 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.

5.1.2 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 operating expenses during the Covid-19 pandemic. EIDL advances do not need to be repaid.[15] Meanwhile, the Paycheck Protection Program provides forgivable loans to small businesses to be used primarily for payroll, rent, utilities, and interest on mortgages.[16] The

[15]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.

[16]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.

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

Table 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 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.

5.2 The financing effects on commercial landlords

In this section, I estimate the effect of CEM on commercial landlord financial health. Specifically, I examine the performance of commercial mortgages contained in commercial mortgage-backed securities (CMBS). CMBS are formed by pooling and tranching commercial mortgages in order to offer investors different exposures to credit risk. The CMBS market is therefore one source of financing for commercial property purchases. Relative to bank loans, CMBS loans tend to fund larger property purchases and have lower down payment requirements, lower interest rates, and longer terms. Additionally, because there are multiple CMBS investors in contrast to one bank lender, CMBS loans are managed by a third-party CMBS servicer. It can be relatively more difficult therefore to negotiate forbearance in the case that a CMBS loan becomes distressed. Because CMBS have regular reporting requirements, I focus on the CMBS market and use the performance of CMBS loans as a proxy for commercial landlord financial health.

CEM requires commercial landlords to provide tenants with liquidity relief in the form of rent deferral. However, commercial landlords may face their own financial constraints in the form of impending interest and principal payments on mortgages. If the requirement to provide liquidity relief is sufficiently burdensome for commercial landlords, then CEM may erode commercial landlord financial health.

I obtain data from Trepp on retail-use commercial mortgages contained in CMBS, including their payment behavior and performance on a monthly basis. In my sample of California, I observe nearly 1,000 retail-use CMBS loans with outstanding balance of $\sim$\$17 billion as of January 2020. My analysis proceeds at the loan level. My measure of loan distress is an indicator of 60+ day delinquency.[17]

Table 10 presents the results on the effect of CEM on CMBS loan delinquency. 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 a higher likelihood of loan delinquency. In column 2, after controlling for zip code characteristics, I observe that the coefficient on length of CEM changes from positive to negative. In column 3, instrumenting for CEM reveals that a longer CEM leads to an increase in loan delinquency. The coefficient is insignificant but still economically meaningful. An additional year of CEM+R leads to an increase in the likelihood of delinquency by 2.04 percentage points (which is 28.5% of its mean). In the last 3 columns, I find that CEM increases the likelihood of loan delinquency in 2020, 2021, and 2022, with increased magnitude over time, although the coefficients are statistically insignificant. In sum, the results show some evidence of the effects of CEM on commercial landlord financial health, although statistical significance is weak because this test is under-powered given the sample of less than 1,000 retail-use CMBS loans in California.

6 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 Section 6.1, I estimate the impact of CEM on employment conditional on the business being alive, i.e. along an intensive margin. In Section 6.2, I take stock of the extensive and intensive mar-

[17]The findings are robust to measuring loan distress using 30+ day delinquency, rather than 60+ day delinquency.

gin employment effects and benchmark the overall employment effect of CEM against the Paycheck Protection Program.

6.1 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 11 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 magnitude 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 12 presents the analysis split by retail vs. food services, where we again find statistically insignificant effects for each sector and in each year.[18] In sum, the results suggest that there is no significant effect of

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

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.[19] 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.

6.2 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 percentage points relative to employment in January 2020.[20]

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.[21] 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

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

[20] 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.

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

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.

7 Policy discussion

In this section, I discuss the policy implications of the results. The first implication is on the effectiveness of CEM in reducing business closure. The reduced-form relationship between CEM and business closure during the pandemic reveals that places with longer CEM tended to experience higher rates of business closure. This should not lead us to conclude that CEM has no effect or even counter-productively increases business closure. Estimating the causal effect of the policy requires overcoming reverse causality from business closure to CEM, stemming from the fact that local policymakers choose CEM to respond to business closure. Using plausibly exogenous variation in CEM from pre-pandemic partisanship orthogonalized with respect to pre-pandemic economic characteristics and alternative channels during the pandemic, I find that CEM significantly reduces business closure in retail and food services while the policy is in effect. These business closure reductions are sustained in food services even after the policy is lifted. Therefore, identifying the causal effect of CEM reveals that the policy is effective in temporarily reducing business closure and in some cases even effective in permanently reducing business closure.

The second implication of the results is on the effectiveness of CEM for different types of businesses. As discussed in Section 2, in the face of substantial frictions in credit markets, CEM can reduce closure for liquidity-constrained, solvent businesses in the long run. Meanwhile, it can only temporarily reduce closure for liquidity-constrained, insolvent businesses. Using pre-pandemic employment growth as a proxy for business solvency, I find that sub-industries with faster pre-pandemic employment growth experience greater CEM-induced reductions in business closure than sub-industries with slower pre-pandemic employment growth. Therefore, investigating heterogeneity in CEM effectiveness along the axis of business solvency reveals that CEM is more effective in reducing long-run closure for businesses that are fundamentally healthier prior to the pandemic.

The above results suggest that CEM is effective overall in reducing business closure and thereby preserving employment. However, drawing conclusions about the efficiency of CEM as a policy requires additional consideration. One consideration is the efficiency of the impact of CEM on business closure. It is socially valuable for CEM to help some solvent businesses survive the crisis. However, because CEM is a broad stroke policy, it also applies to insolvent businesses and can temporarily keep them alive, which has both benefits and costs. A major benefit of doing so is preserving the employment of these businesses during the crisis period. A major cost is preventing reallocation of their labor and capital towards more solvent businesses.

Another consideration is that CEM is rapid and low cost for the government to implement relative to other programs such as the Paycheck Protection Program, Economic Injury Disaster Loan Program, and Main Street Lending Program. Enacting CEM requires only the approval of local government officials and is a zero-expenditure, budget-neutral policy for the government. Indeed, in my sample of California, CEM is enacted within weeks or even days of the state's declaration of emergency. Additionally, by relying on pre-existing relationships between business tenants and commercial landlords, CEM requires no additional intermediation from banks or government agencies and dispenses rent-based liquidity relief that is naturally tied to business operating expenses.

Relatedly, a third consideration is that CEM shifts the burden of credit risk onto commercial landlords. In particular, the continuation of insolvent businesses is costly for their commercial landlords. CEM stipulates that landlords provide zero-interest, non-forgivable credit to all businesses, regardless of solvency. Therefore, insolvent businesses reap benefits from this policy by borrowing from their landlords at no cost despite being unable to repay, and landlords must absorb losses from the inefficient continuation of insolvent businesses. If CEM substantially deteriorates commercial landlord financial health, the policy can force landlords out of business and stop them from performing the valuable economic role of maintaining space and searching for tenants. In sum, my paper evaluates the causal effect of CEM on business closure and employment. Understanding the efficiency of these effects will require holistically taking into account these considerations, which requires further research.

8 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, local governments rapidly enacted CEM for the first time, aiming to prevent immediate business closure by pausing eviction proceedings and to prevent permanent business closure by spurring renegotiation between businesses and landlords.

In this paper, I conduct the first evaluation of the effects of CEM on business closure and employment. Using pre-pandemic partisanship as an instrument, I find that CEM reduces the likelihood of business closure in food services by 0.49 percentage points in 2020 and 0.77 percentage points in 2021. These reductions in business closure are sustained. Meanwhile, in retail, CEM reduces the likelihood of business closure by 0.23 percentage points in 2020 and 0.44 percentage points in 2021, which are partly offset by a rebound of 0.36 percentage points in 2022. I find that CEM is more effective in sustainably reducing closure for more solvent businesses, which is consistent with substantial frictions in credit markets and CEM providing liquidity relief to businesses.

Turning to employment, I find no effect of CEM on intensive-margin employment conditional on the business being alive. Instead, the employment effect of CEM operates along the extensive margin through reduction in business closure. The estimated total impact of CEM on business employment is an increase of 0.98 percentage points, which is 39% of the employment effects of PPP estimated by Chetty et al. (Forthcoming). These effects are notable when we consider that CEM is an intervention that does not inject government funds into businesses but rather provides businesses with liquidity relief from their landlords.

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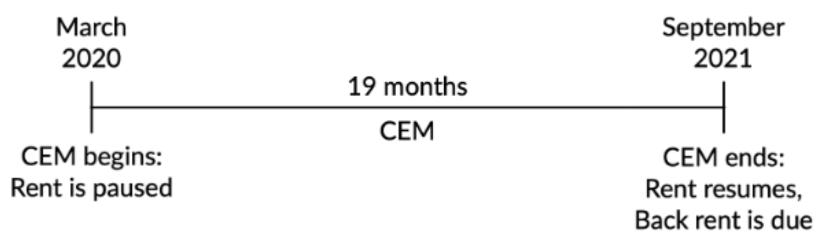
Figure 1: Illustrative examples of timeline of commercial eviction moratoria

This figure presents illustrative examples of the commercial eviction moratoria (CEM) policy. Panel A presents a timeline of CEM policy in Oakland, CA. Panel B presents a timeline of CEM policy in San Diego, CA.

Panel A: Commercial eviction moratoria policy in Oakland, CA



Panel B: Commercial eviction moratoria policy in San Diego, CA

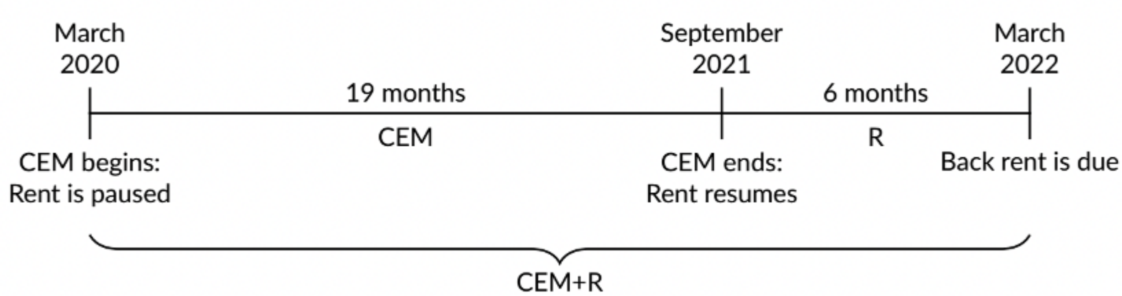
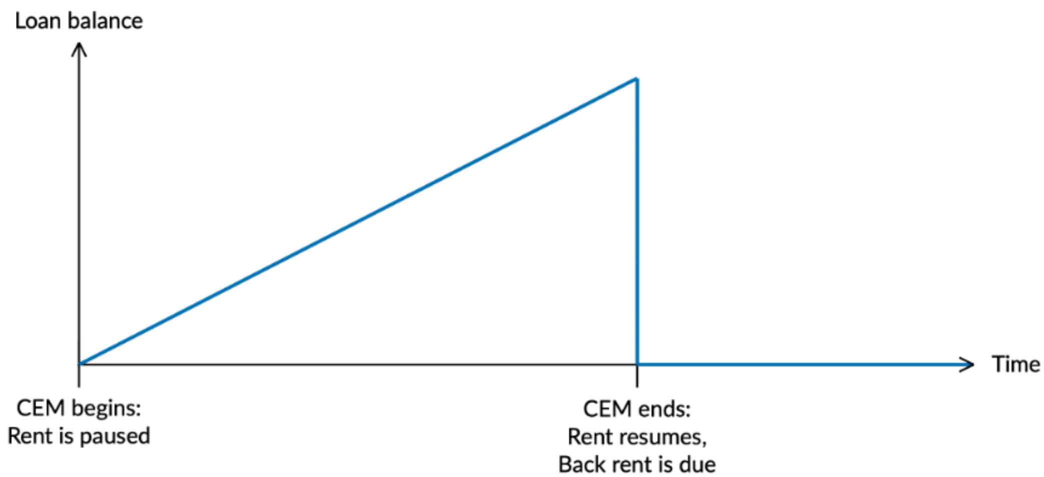


Figure 2: Illustrative examples of effective borrowing enabled by commercial eviction moratoria

This figure presents illustrative examples of liquidity relief from commercial eviction moratoria (CEM) policy. Panel A presents the effective loan balance that businesses can incur under the CEM policy of Oakland, CA. Panel B presents the effective loan balance that businesses can incur under the CEM policy of San Diego, CA.

Panel A: Commercial eviction moratoria policy in Oakland, CA



Panel B: Commercial eviction moratoria policy in San Diego, CA

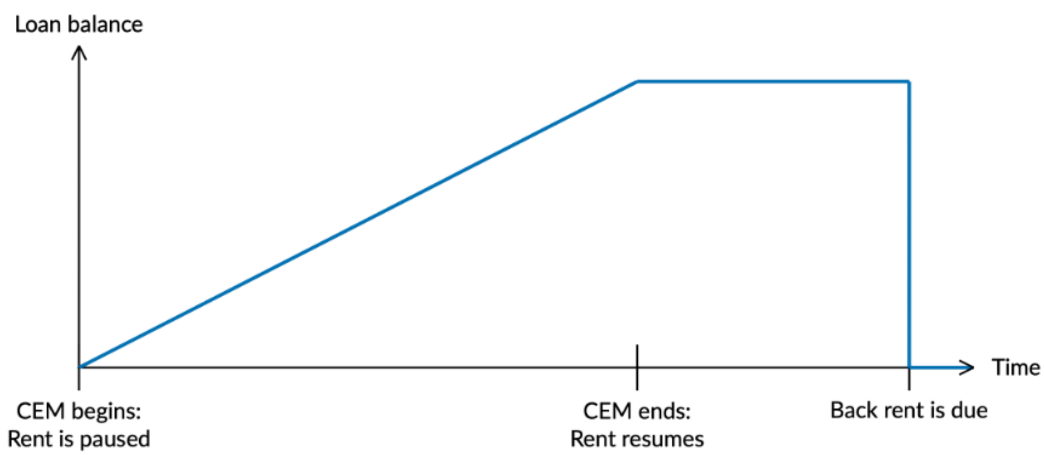


Figure 3: Commercial eviction moratoria in California

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

Panel A: City-level CEM

Panel B: County-level CEM

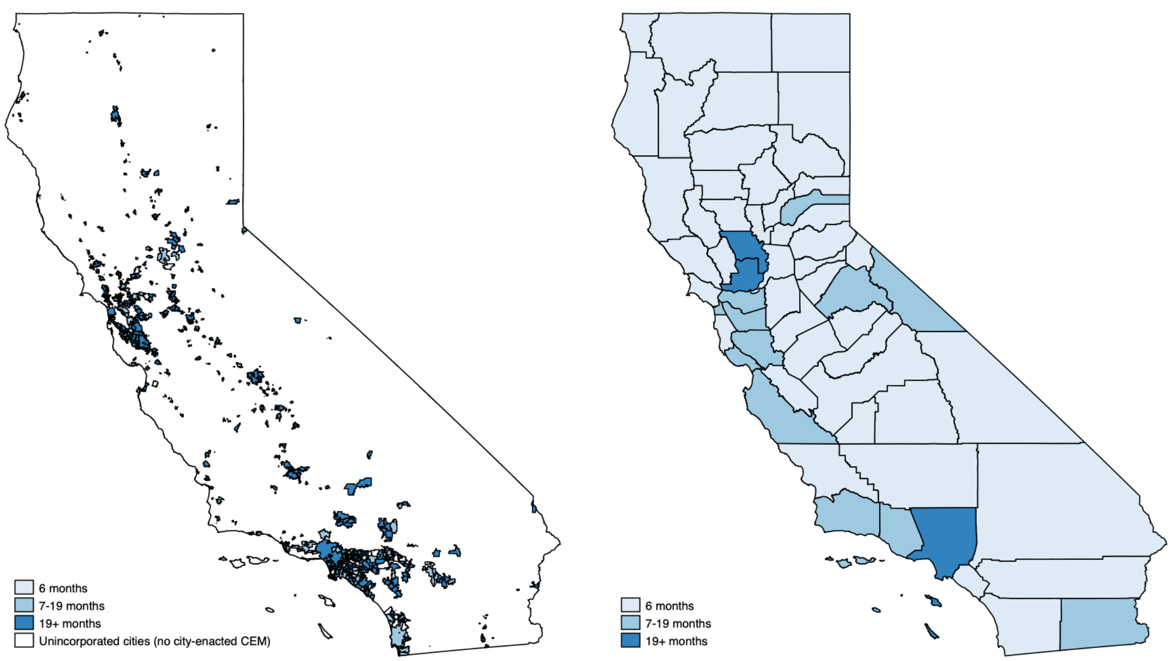


Figure 4: Closure of retail and food services businesses in California

This figure illustrates the cumulative percentage decline in number of businesses in California from January 2020 through December 2022 using SafeGraph data. Panel A examines all industries, while Panel B focuses on retail & food services.

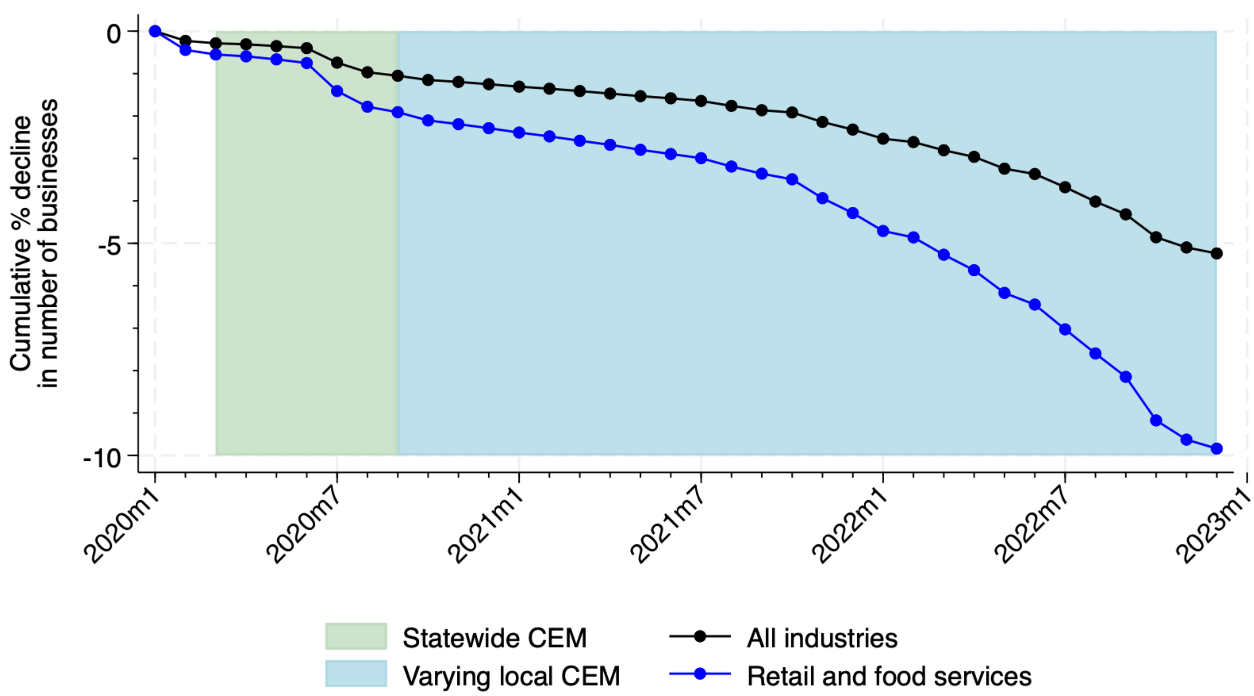


Figure 5: Employment of businesses in California

This figure illustrates the monthly employment of retail & food services businesses in Homebase from 2020 through 2022. Specifically, Panel A plots the number of businesses identified as alive on the platform, which declines over time. Panel B plots the monthly hours worked scaled by hours worked in January 2020. Panel C plots the monthly number of shifts worked scaled by number of shifts worked in January 2020.

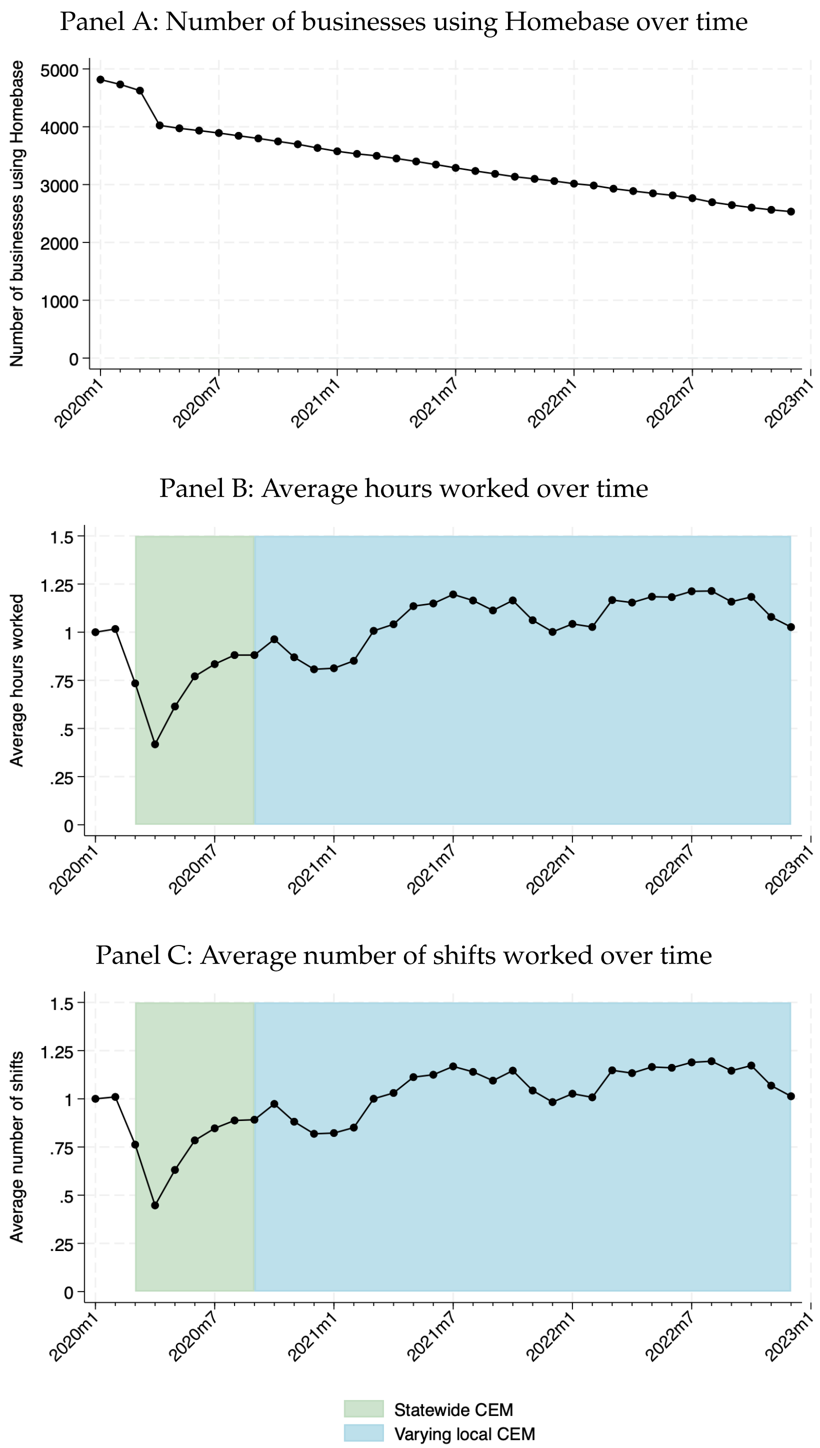
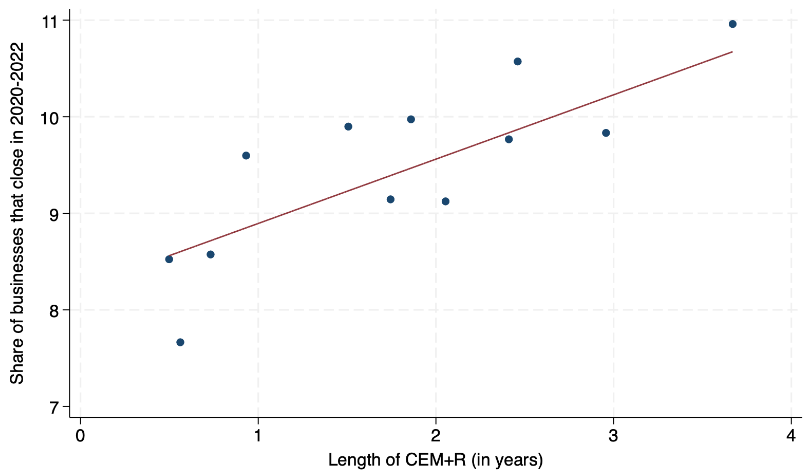


Figure 6: Relationship between CEM, business closure, and unemployment

This figure illustrates the binscatter relationship between commercial eviction moratoria 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 CEM (plus repayment time). Panel B presents a binscatter of length of CEM (plus repayment time) v.s. change in unemployment rate from 2019 to 2020.

Panel A: Relationship between business closure and CEM



Panel B: Relationship between CEM and unemployment

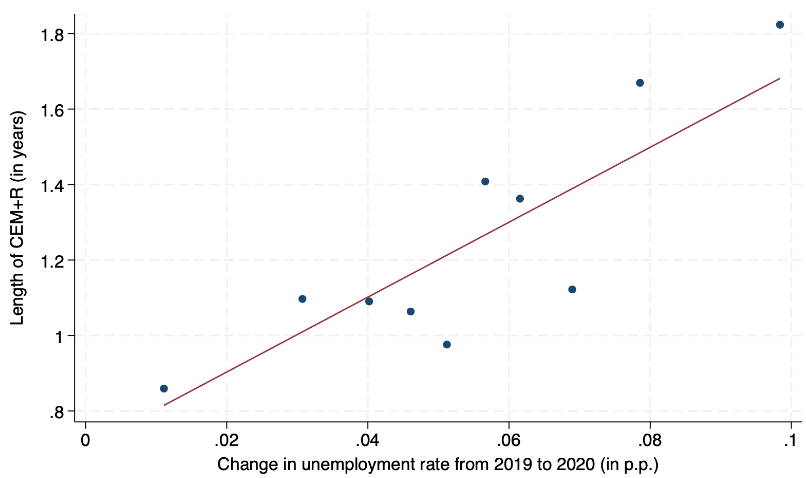


Figure 7: Relationship between CEM and partisanship

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.

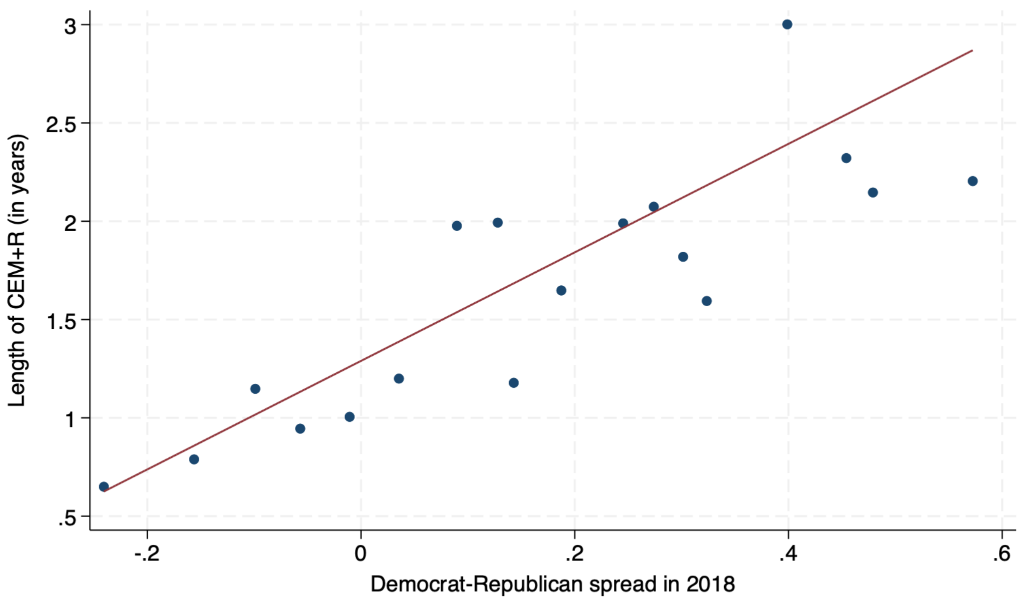
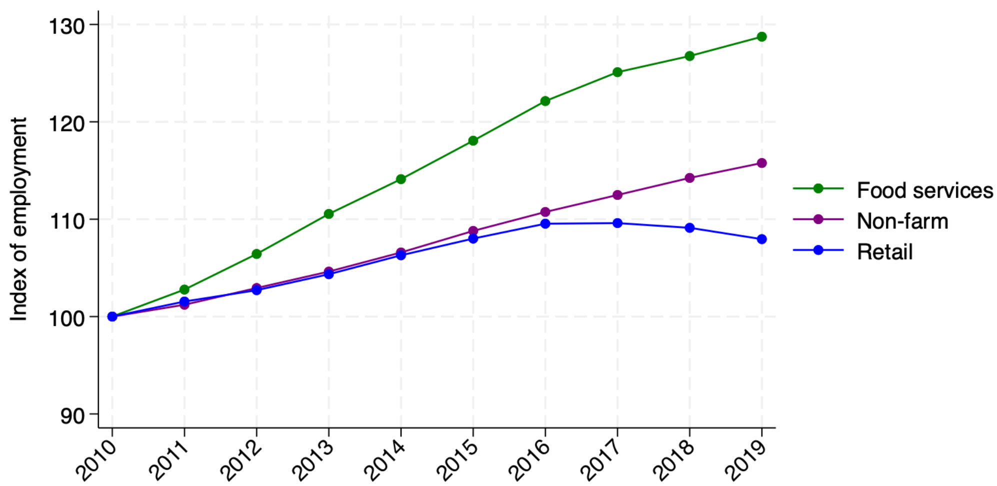


Figure 8: Index of employment for non-farm, retail, and food services

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

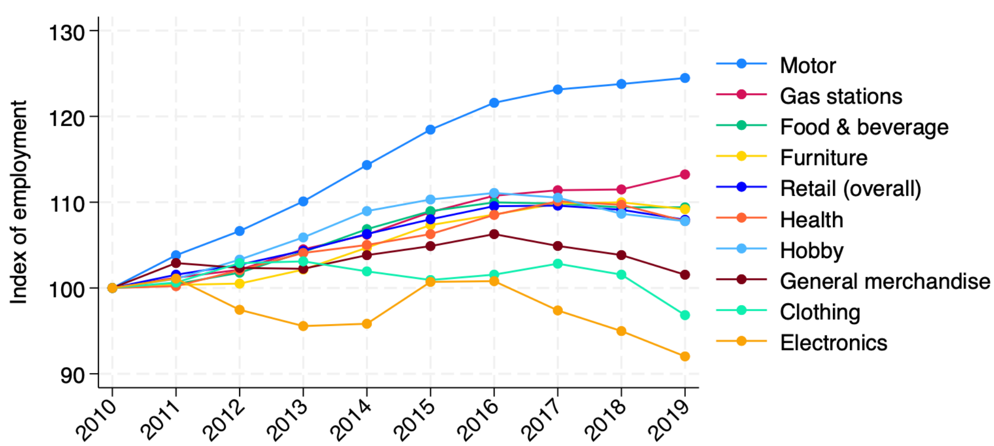


Figure 9: Relationship between pre-pandemic employment growth and CEM business closure effects

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.

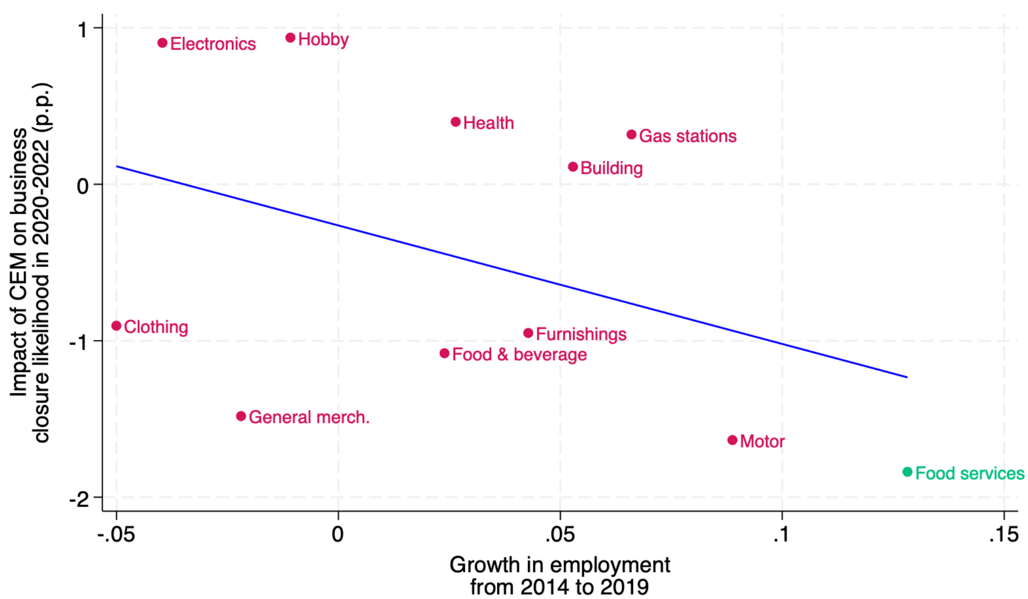


Table 1: Summary statistics for commercial eviction moratoria

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

Panel A: State-level commercial eviction moratoria policy

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

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

Panel B: County-level commercial eviction moratoria policy

	Obs.	Min.	Median	Max.	Mean	Std dev.
Indicator of CEM enacted by county	58	0.00	0.00	1.00	0.48	0.50
Indicator of CEM applying to unincorporated areas only	58	0.00	0.00	1.00	0.31	0.47
Indicator of CEM applying to entire county	58	0.00	0.00	1.00	0.17	0.38
CEM enacted by county:						
Length of CEM (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 CEM+R (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 eviction moratoria policy

	Obs.	Min.	Median	Max.	Mean	Std dev.
Indicator of CEM enacted by city	482	0.00	0.00	1.00	0.32	0.47
CEM enacted by city:						
Length of CEM (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 CEM+R (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
CEM that binds:						
Length of CEM (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 CEM+R (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 and employment

This table provides summary statistics for SafeGraph business closure data in the industries of retail & food services. Observations are at the business level.

Panel A: SafeGraph business closure data				
Retail and food services				
	Obs.	Median	Mean	Std dev.
Likelihood of business closure:				
2020	340,343	0.00	2.35	15.16
2021	340,343	0.00	1.98	13.93
2022	340,343	0.00	5.49	22.78
2020-2022	340,343	0.00	9.83	29.77
Retail				
Likelihood of business closure:				
2020	218,335	0.00	1.86	13.52
2021	218,335	0.00	1.53	12.26
2022	218,335	0.00	4.32	20.33
2020-2022	218,335	0.00	7.71	26.67
Food services				
Likelihood of business closure:				
2020	122,008	0.00	3.23	17.68
2021	122,008	0.00	2.80	16.49
2022	122,008	0.00	7.58	26.47
2020-2022	122,008	0.00	13.61	34.29
Panel B: Homebase business payroll data				
Retail and food services				
	Obs.	Median	Mean	Std dev.
Average hours worked in January 2020	4,242	701.0	990.1	943.0
Scaled hours worked for:				
2020	4,242	0.78	0.79	0.33
2021	3,180	0.89	0.96	0.54
2022	2,688	0.93	1.02	0.57
2020-2022	2,688	0.89	0.95	0.44
Retail				
	Obs.	Median	Mean	Std dev.
Average hours worked in January 2020	787	418.7	652.1	727.0
Scaled hours worked for:				
2020	787	0.81	0.83	0.35
2021	580	0.94	1.03	0.60
2022	487	0.98	1.11	0.64
2020-2022	487	0.94	1.02	0.49
Food services				
	Obs.	Median	Mean	Std dev.
Average hours worked in January 2020	3,455	783.1	1,067.0	969.3
Scaled hours worked for:				
2020	3,455	0.77	0.78	0.33
2021	2,600	0.88	0.94	0.53
2022	2,201	0.92	1.01	0.55
2020-2022	2,201	0.88	0.93	0.43

Table 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	2.77***	1.85***	1.59***	1.89***	1.73***	1.54***
of population in 2019	(0.29)	(0.43)	(0.46)	(0.41)	(0.42)	(0.46)
City-level characteristics						
Change in foot traffic from January			-2.68**			-2.43**
to July-December 2020			(1.12)			(1.07)
Indicator of having a pandemic				0.27***		0.18*
business grant program				(0.087)		(0.10)
Change in unemployment rate					9.07*	7.24
from 2019 to 2020					(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 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 to July-December 2020			-3.09	-0.97	-2.15**	0.032
			(1.91)	(0.78)	(1.02)	(0.80)
Indicator of having a pandemic business grant program			0.11	0.018	0.065	0.028
			(0.31)	(0.072)	(0.12)	(0.20)
Change in unemployment rate from 2019 to 2020			12.1	2.41	3.80	5.95
			(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 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 to July-December 2020	-0.88	-0.67	-1.52*	1.31	-8.40**	-1.93	-3.45**	-3.03*
	(1.37)	(0.63)	(0.91)	(1.28)	(3.96)	(1.45)	(1.40)	(1.79)
Indicator of having a pandemic business grant program	0.073	0.14	0.080	-0.15	0.070	-0.24*	0.0099	0.30
	(0.28)	(0.10)	(0.12)	(0.18)	(0.50)	(0.14)	(0.14)	(0.32)
Change in unemployment rate from 2019 to 2020	11.3*	1.10	3.71	6.46**	16.1	5.87	4.02	6.26
	(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 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 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 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 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 to July-December 2020			-86,248***	-17.2	-95,203**
			(32,312)	(26.4)	(43,246)
Indicator of having a pandemic business grant program			4,992	8.47**	-1,211
			(5,090)	(3.63)	(4,822)
Change in unemployment rate from 2019 to 2020			197,666**	778***	-349,584**
			(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 10: Impact of commercial eviction moratoria on CMBS loan delinquency

This table presents the second-stage estimate of the impact of CEM on CMBS loan delinquency. Observations are CMBS loans. The outcome variable is the percentage point likelihood of the CMBS loan becoming delinquent by 60+ days. 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)	(6)
	Likelihood of loan delinquency in 2020-2022			Likelihood of loan delinquency in		
				2020	2021	2022
Specification:	OLS	OLS	IV	IV	IV	IV
Years of CEM+R	0.024	-1.44	2.04	0.90	3.96	5.57
	(1.21)	(1.69)	(3.46)	(3.67)	(3.51)	(4.32)
City-level characteristics						
Change in foot traffic from January			29.5	27.8	30.6	39.3
to July-December 2020			(26.8)	(24.9)	(21.0)	(28.8)
Indicator of having a pandemic			3.26	1.44	-0.29	0.12
business grant program			(2.71)	(2.94)	(2.26)	(2.09)
Change in unemployment rate			29.2	56.6	36.4	19.1
from 2019 to 2020			(59.7)	(45.9)	(59.9)	(68.3)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	7.12***	14.7	25.7	5.64	7.12	19.3
	(2.21)	(29.1)	(27.9)	(26.2)	(38.4)	(30.4)
Observations	796	796	796	909	861	796
R-squared	0.000	0.015				

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

Table 11: 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 to July-December 2020			0.35***	0.28***	0.42***	0.35**
			(0.12)	(0.089)	(0.14)	(0.15)
Indicator of having a pandemic business grant program			0.0026	-0.0013	-0.00063	0.026
			(0.021)	(0.018)	(0.022)	(0.024)
Change in unemployment rate from 2019 to 2020			0.37	0.34	0.49	-0.43
			(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 12: 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 to July-December 2020	0.46	0.40	0.50	0.45	0.32***	0.26***	0.40***	0.32**
	(0.33)	(0.26)	(0.31)	(0.48)	(0.11)	(0.073)	(0.14)	(0.13)
Indicator of having a pandemic business grant program	-0.037	0.033	-0.073*	-0.045	0.0081	-0.0091	0.014	0.036
	(0.038)	(0.025)	(0.039)	(0.047)	(0.023)	(0.021)	(0.024)	(0.026)
Change in unemployment rate from 2019 to 2020	-0.51	-0.29	-0.56	-0.98	0.59*	0.46	0.80*	-0.27
	(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

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 CEM. Section 1.2 provides the social planner's solution. In the next section, I will solve for the private market outcome with CEM.

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 $f \leq \bar{F}_{S_\infty} = \dfrac{\mu + \gamma - R_{S_\infty}}{\delta}$) 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:

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

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 CEM policy

In this section, I solve for the private market outcome with CEM. CEM requires landlords to provide liquidity to business tenants by prohibiting evictions and pausing the obligation of rent payments. Because CEM is a mandated liquidity policy, commercial landlords do not optimize over a lending decision. CEM 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 CEM.

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 CEM:

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

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 CEM.

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

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

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

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

Steady state: $t = \infty$
We start in state S_∞ at $t = \infty$. Since the CEM 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:

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

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

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:

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

There are two cases.

Case 1: $V_2^c(F_1, R_{S_2}, F_1) \ge 0$
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, CEM 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 CEM is unconditionally provided to all firms at $t = 1$ while the negative cash flow of CEM 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:

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

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:

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

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 CEM, 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, CEM 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 CEM 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 $F^{c*}_{S_2} - F^*_{S_2}$ with respect to μ is:

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

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

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

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

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:

$$\begin{aligned}
\frac{\partial}{\partial \mu}(F_{S_2}^{c*} - F_{S_2}^*) &= \frac{1}{A} - \frac{1-\delta+(1-\phi)(1-p)\delta}{(1-\delta)\Delta+(1-\phi)(1-p)\delta A} \\
&= \frac{(1-\delta)\Delta+(1-\phi)(1-p)\delta A - A(1-\delta+(1-\phi)(1-p)\delta)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)} \\
&= \frac{(1-\delta)(\Delta-A)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)} \\
&= \frac{(1-\delta)(\Delta-(1-\delta)\cdot(\Delta-\gamma)-\delta\cdot\Delta)}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)} \\
&= \frac{\gamma(1-\delta)^2}{A((1-\delta)\Delta+(1-\phi)(1-p)\delta A)} \\
&> 0
\end{aligned} \tag{A.35}$$

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 $F^{c*}_{S_2} - F^{*}_{S_2}$ with respect to μ is:

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

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

Appendix B: Figures & Tables

Figure B.1: Relationship between length of CEM and business closure

This figure presents the binscatter relationship between length of CEM (plus repayment time) and business closure rate in 2020-2022 for unincorporated cities in California.

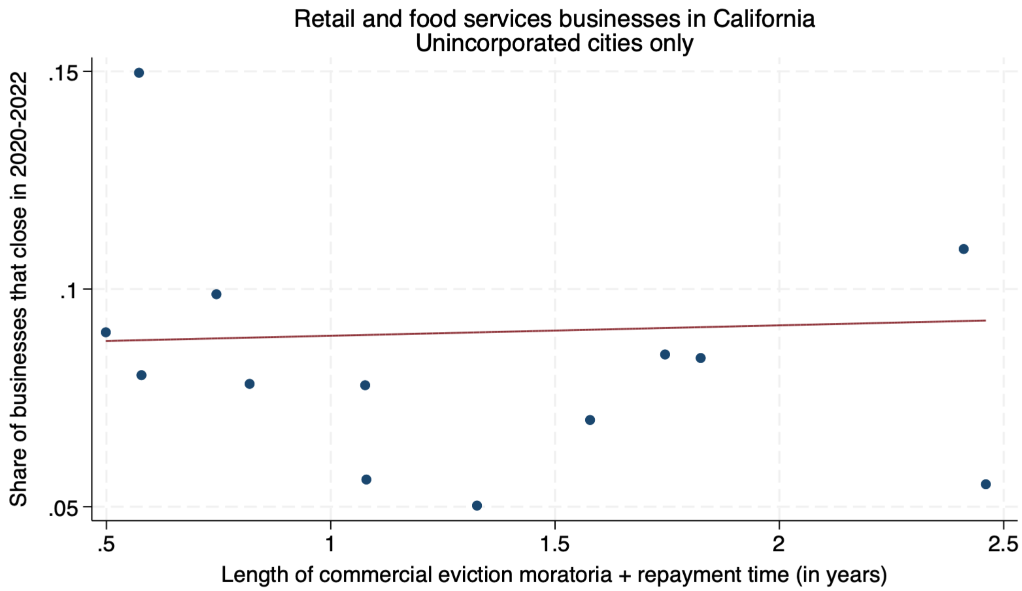


Figure B.2: Robustness check on pre-pandemic growth and business closure effects of CEM: Scaling business closure effects

This figure shows the relationship between the 5-year pre-pandemic employment growth and the effect of CEM on business closure as a percentage of the mean business closure rate in 2020-2022 for subindustries in retail and food services.

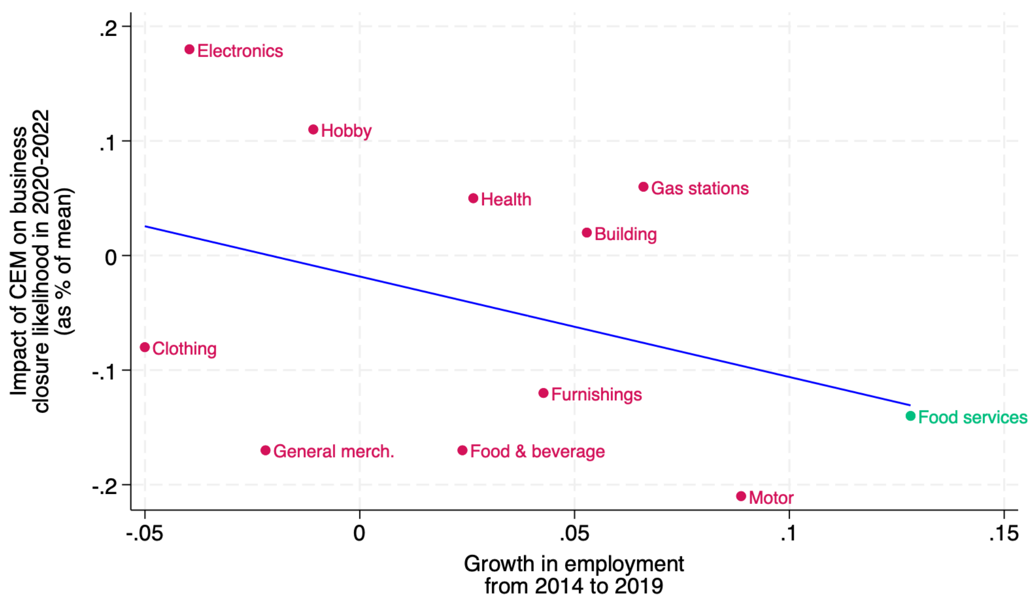


Figure B.3: Robustness check on pre-pandemic growth and business closure effects of CEM: Alternative measure of industry solvency

This figure shows the relationship between pre-pandemic growth in sales and the effect of CEM on business closure for sub-industries in retail and food services.

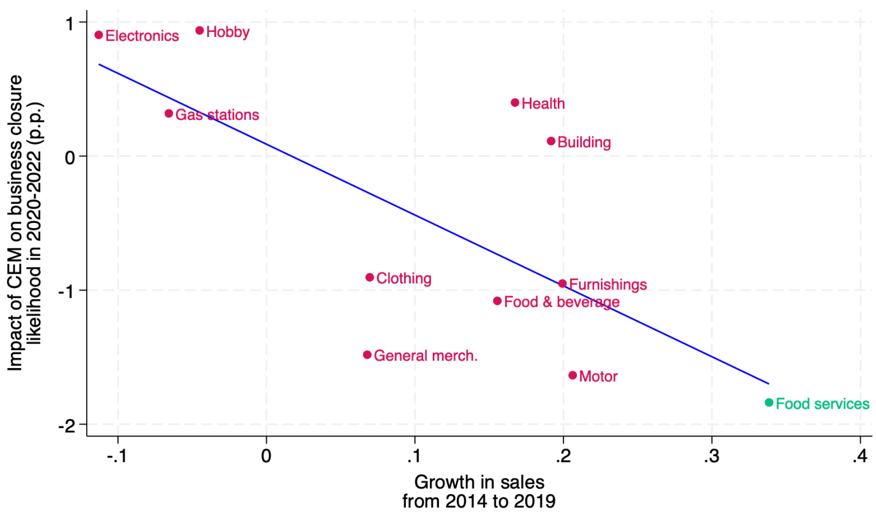


Figure B.4: Robustness check on pre-pandemic growth and business closure effects of CEM: Alternative measure of industry solvency

This figure shows the relationship between pre-pandemic growth in number of firms and the effect of CEM on business closure for sub-industries in retail and food services.

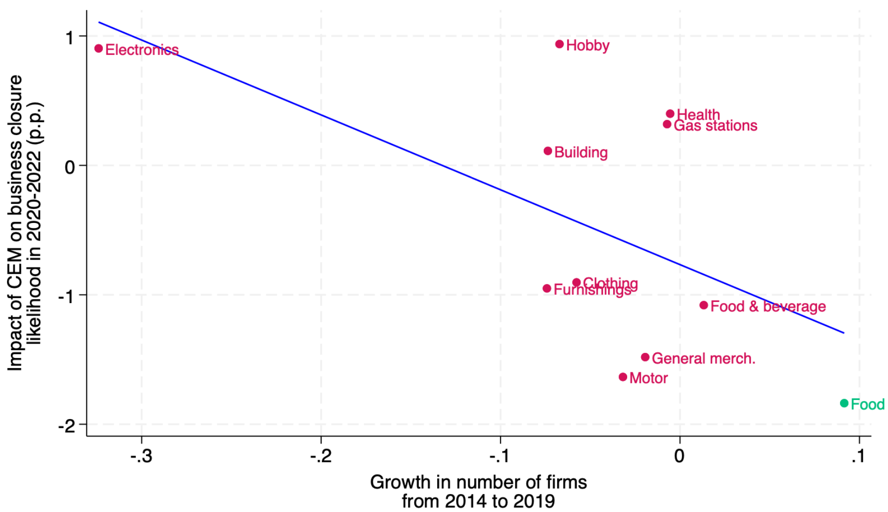


Figure B.5: Robustness check on pre-pandemic growth and business closure effects of CEM: Alternative measure of industry solvency

This figure shows the relationship between pre-pandemic growth in number of establishments and the effect of CEM on business closure for sub-industries in retail and food services.

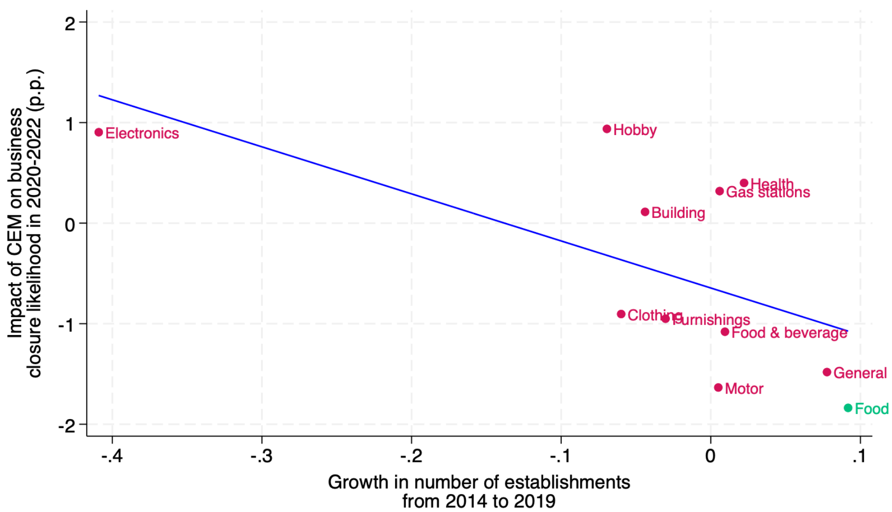


Table B.1: Covariate balance along the axis of pre-pandemic partisanship

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 B.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 B.3: First stage of pre-pandemic partisanship instrument for commercial eviction moratoria policy: Alternative measure of CEM policy

This table shows the relationship between Democratic-Republican spread and length of CEM (which does not include repayment time 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					
Democrat-Republican spread	2.38***	1.54***	1.40***	1.57***	1.41***	1.32***
of population in 2019	(0.37)	(0.36)	(0.36)	(0.34)	(0.32)	(0.35)
City-level characteristics						
Change in foot traffic from January			-1.44			-1.18
to July-December 2020			(1.05)			(0.94)
Indicator of having a pandemic				0.21***		0.13
business grant program				(0.071)		(0.081)
Change in unemployment rate					9.98**	8.92**
from 2019 to 2020					(3.97)	(3.77)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	1.05***	-1.78	-1.27	-1.52	-3.24***	-2.52**
	(0.14)	(1.36)	(1.65)	(1.30)	(1.01)	(1.20)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.345	0.481	0.494	0.489	0.511	0.524
F-statistic	41.1	193.9	220.0	212.8	112.8	155.6

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

Table B.4: Impact of commercial eviction moratoria on business closure: Alternative measure of CEM policy

This table presents the second stage estimate of the impact of CEM on business closure. The strength of CEM policy is measured length of CEM (which does not include repayment time R). 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	0.68***	0.098	-0.94*	-0.35*	-0.64***	0.056
	(0.099)	(0.13)	(0.54)	(0.20)	(0.20)	(0.26)
City-level characteristics						
Change in foot traffic from January to July-December 2020			-2.24	-0.65	-1.56*	-0.020
			(1.44)	(0.61)	(0.83)	(0.72)
Indicator of having a pandemic business grant program			0.088	0.0094	0.049	0.029
			(0.28)	(0.069)	(0.10)	(0.19)
Change in unemployment rate from 2019 to 2020			14.7	3.35	5.52	5.79
			(9.71)	(3.16)	(3.53)	(4.70)
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	8.82***	-11.0*	-14.7**	-4.49**	-3.79***	-6.37
	(0.20)	(5.91)	(6.48)	(2.18)	(1.30)	(4.14)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.000	0.003				

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

Table B.5: Impact of commercial eviction moratoria on business closure by year: Retail v.s. food services: Alternative measure of CEM policy

This table presents the second stage estimate of the impact of CEM on business closure by industry and by year. The strength of CEM policy is measured length of CEM (which does not include repayment time R). 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 (instrumented)	-0.36	-0.27	-0.50***	0.41**	-2.16**	-0.57*	-0.90***	-0.69
	(0.42)	(0.18)	(0.19)	(0.19)	(0.88)	(0.32)	(0.30)	(0.56)
City-level characteristics								
Change in foot traffic from January to July-December 2020	-0.56	-0.43	-1.07	0.94	-6.36**	-1.39	-2.60**	-2.38*
	(1.12)	(0.51)	(0.76)	(1.20)	(3.19)	(1.16)	(1.13)	(1.39)
Indicator of having a pandemic business grant program	0.064	0.13	0.069	-0.14	0.0094	-0.25*	-0.015	0.28
	(0.27)	(0.099)	(0.11)	(0.18)	(0.46)	(0.14)	(0.13)	(0.30)
Change in unemployment rate from 2019 to 2020	12.1**	1.71	4.85	5.53*	23.7	7.87	7.16	8.66
	(6.16)	(3.43)	(3.17)	(3.29)	(20.1)	(4.90)	(5.32)	(12.7)
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.93*	-2.74	-2.26*	-4.93*	-24.3**	-8.37***	-5.74**	-10.1
	(5.22)	(2.07)	(1.33)	(2.98)	(10.9)	(3.21)	(2.35)	(8.07)
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 B.6: First stage of partisanship instrument for commercial eviction moratoria: Control non-parametrically for alternative channels

This table shows the relationship between Democratic-Republican spread and length of CEM+R. The columns control 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. City-level characteristics are controlled for non-parametrically by including quantile fixed effects. 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	2.77***	1.85***	1.40***	1.89***	1.70***	1.41***
of population in 2019	(0.29)	(0.43)	(0.44)	(0.41)	(0.42)	(0.48)
City-level characteristics						
Change in foot traffic from January to July-December 2020: Quantile fixed effects			Yes			Yes
Indicator of having a pandemic business grant program				Yes		Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects					Yes	Yes
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	1.29***	-2.25	1.23	-1.92	-3.19	0.91
	(0.18)	(2.16)	(3.19)	(2.09)	(2.07)	(2.84)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.345	0.467	0.540	0.477	0.483	0.555
F-statistic	88.4	102.6	179.1	117.0	77.7	239.8

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

Table B.7: Impact of commercial eviction moratoria on business closure: Control non-parametrically for alternative channels

This table presents the second stage estimate of the impact of CEM on business closure. The strength of CEM policy is measured length of CEM+R. City-level characteristics are controlled for non-parametrically by including quantile fixed effects. 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	-0.86	-0.30	-0.58***	0.022
	(0.079)	(0.12)	(0.57)	(0.19)	(0.21)	(0.26)
City-level characteristics						
Change in foot traffic from January to July-December 2020: Quantile fixed effects			Yes	Yes	Yes	Yes
Indicator of having a pandemic business grant program			Yes	Yes	Yes	Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects			Yes	Yes	Yes	Yes
Zip code-level characteristics as of 2019		Yes	Yes	Yes	Yes	Yes
Constant	8.66***	-10.9*	-11.8*	-3.09*	-1.47	-7.26
	(0.20)	(6.08)	(6.16)	(1.81)	(1.81)	(4.56)
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 B.8: Impact of commercial eviction moratoria on business closure by year: Retail v.s. food services: Control non-parametrically for alternative channels

This table presents the second stage estimate of the impact of CEM on business closure by industry and by year. The strength of CEM policy is measured length of CEM+R. City-level characteristics are controlled for non-parametrically by including quantile fixed effects. Observations are businesses in the industries of retail and food services. 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)	-0.33	-0.20	-0.47**	0.34*	-2.02**	-0.54*	-0.81***	-0.67
	(0.40)	(0.16)	(0.21)	(0.18)	(1.01)	(0.29)	(0.26)	(0.65)
City-level characteristics								
Change in foot traffic from January to July-December 2020: Quantile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicator of having a pandemic business grant program	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code-level characteristics as of 2019	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.53*	-1.60	-0.67	-7.26*	-16.5*	-6.22*	-2.29	-8.00
	(5.66)	(1.58)	(1.69)	(4.21)	(9.32)	(3.20)	(2.78)	(6.93)
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 B.9: First stage of partisanship instrument for commercial eviction moratoria: Control non-parametrically for alternative channels & pre-pandemic characteristics

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. City-level and zip code-level characteristics are controlled for non-parametrically by including quantile fixed effects. 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***	1.74***	1.33***	1.77***	1.60***	1.34**
	(0.29)	(0.44)	(0.46)	(0.44)	(0.50)	(0.51)
City-level characteristics						
Change in foot traffic from January to July-December 2020: Quantile fixed effects			Yes			Yes
Indicator of having a pandemic business grant program				Yes		Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects					Yes	Yes
Zip code-level characteristics as of 2019: Quantile fixed effects		Yes	Yes	Yes	Yes	Yes
Constant	1.29***	0.52**	1.37***	0.43*	0.47*	1.24**
	(0.18)	(0.25)	(0.49)	(0.25)	(0.27)	(0.47)
Observations	340,343	340,343	340,343	340,343	340,343	340,343
R-squared	0.345	0.488	0.557	0.494	0.499	0.567
F-statistic	88.4	1066.2	62135.4	1862.9	9223.4	63207.5

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

Table B.10: Impact of commercial eviction moratoria on business closure: Control non-parametrically for alternative channels & pre-pandemic characteristics

This table presents the second stage estimate of the impact of CEM on business closure. The strength of CEM policy is measured length of CEM+R. City-level and zip code-level characteristics are controlled for non-parametrically by including quantile fixed effects. 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***	0.14	-0.89	-0.30*	-0.58**	-0.015
	(0.079)	(0.12)	(0.64)	(0.18)	(0.23)	(0.31)
City-level characteristics						
Change in foot traffic from January to July-December 2020: Quantile fixed effects			Yes	Yes	Yes	Yes
Indicator of having a pandemic business grant program			Yes	Yes	Yes	Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects			Yes	Yes	Yes	Yes
Zip code-level characteristics as of 2019: Quantile fixed effects		Yes	Yes	Yes	Yes	Yes
Constant	8.66***	6.94***	8.47***	1.89***	2.19***	4.39***
	(0.20)	(0.78)	(1.38)	(0.43)	(0.47)	(0.72)
Observations	340,343	340,343	340,343	340,343	340,343	340,343

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

Table B.11: Impact of commercial eviction moratoria on business closure by year: Retail v.s. food services: Control non-parametrically for alternative channels & pre-pandemic characteristics

This table presents the second stage estimate of the impact of CEM on business closure by industry and by year. The strength of CEM policy is measured length of CEM+R. City-level and zip code-level characteristics are controlled for non-parametrically by using quantile fixed effects. Observations are businesses in the industries of retail and food services. 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 (instrumented)	-0.41	-0.22	-0.45**	0.27	-2.05*	-0.51*	-0.84**	-0.70
	(0.48)	(0.18)	(0.19)	(0.23)	(1.14)	(0.27)	(0.33)	(0.67)
City-level characteristics								
Change in foot traffic from January to July-December 2020: Quantile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicator of having a pandemic business grant program	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in unemployment rate from 2019 to 2020: Quantile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code-level characteristics as of 2019: Quantile fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.40***	1.31***	1.60***	2.50***	13.8***	2.96***	3.20***	7.66***
	(1.28)	(0.43)	(0.43)	(0.65)	(2.10)	(0.70)	(0.69)	(1.16)
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 B.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 B.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