The Real Effects of Liquidity Relief:

Commercial Rent Forbearance in the Covid-19 Recession

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Abstract

This paper assesses a key trade-off when providing widespread liquidity relief to businesses during an economic recession: the benefit of saving solvent businesses versus the cost of prolonging survival of insolvent businesses. Using data on business establishments and commercial rent forbearance policies during the Covid-19 recession, I employ a difference-in-differences strategy that compares businesses along the border of adjacent cities that differ in liquidity relief. Overall, I find that liquidity relief reduces closure only for liquidity-constrained but solvent businesses. In the short run, however, the business closure effects are less aligned with business solvency. Importantly, the opportunity cost of this also appears to be low since new businesses do not open to replace closed ones during this period. Along a pecking order of business financing, liquidity relief leads businesses to reduce usage of more costly loans but does not affect usage of grants.

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1 Introduction

With the onset of the Covid-19 pandemic, many businesses experienced a sudden decline in revenue due to transmission of the disease and due to government policies aimed at reducing transmission (Fairlie and Fossen, 2022b). This liquidity shock was thought to be largely divorced from business fundamentals and therefore posed the threat of shuttering businesses that were solvent but temporarily illiquid (Hanson et al., 2020). In response, policymakers enacted a series of unprecedented programs to administer direct aid to businesses. In the U.S., at the national level, the Federal Reserve authorized the Main Street Lending Program and Primary and Secondary Market Corporate Credit Facilities, while the Small Business Administration administered the Paycheck Protection Program and Economic Injury Disaster Loan program. At the regional level, local governments funded business grants and loans and enacted additional liquidity relief such as commercial rent forbearance.

Theoretically, the effectiveness of widespread liquidity relief in a crisis is ambiguous. On one hand, liquidity relief may have permanent real effects by preventing solvent but liquidity-constrained businesses from closing. Excessive liquidation of businesses is of particular concern during an economic crisis when credit markets may not function normally and therefore may not extend sufficient liquidity to solvent businesses. This credit crunch creates a role for policymakers to tide businesses over in the short term. On the other hand, widespread liquidity relief can also prolong business survival irrespective of underlying solvency. This phenomenon is socially costly if it prevents reallocation of resources to more productive businesses. Specifically, by propping up existing businesses, liquidity relief may discourage new entrants and harm overall economic growth. Ultimately, empirical study is necessary to understand the strength of these effects and to characterize this key trade-off when providing widespread liquidity relief to businesses during an economic crisis.

In this paper, I ask the following research questions about liquidity relief to businesses during an economic crisis. How does widespread liquidity relief affect business survival through a recession? And which types of businesses does liquidity relief aid in the shorter run v.s. longer run? To answer these questions, I focus on a setting where liquidity relief is rapidly and widely administered to businesses. At the onset of the Covid-19 pandemic,

some governments enact commercial rent forbearance policies, which temporarily pause but do not forgive the obligation of rent payments for businesses under existing lease contracts. In particular, in the U.S. state of California, commercial rent forbearance is implemented in a unique way that generates granular geographic variation in the policy. The state governor legalizes commercial rent forbearance and then leaves it up to more local governments to choose whether to enact forbearance. Accordingly, some city and county governments enact the policy, while others do not, generating geographic variation in liquidity relief to businesses.

To investigate the effect of this liquidity relief on businesses, I assemble data on commercial rent forbearance policies, business establishments, and business financing in California. For all 483 cities and 58 counties in California, I hand-collect enactments of commercial rent forbearance policies over the period 2020 through 2025 by parsing the local government meeting agendas and minutes. To observe business existence and closure, I construct a dataset that covers the effective universe of customer-facing, brick & mortar business establishments by using SafeGraph Points of Interest (POI) data and cross-checking business status with Google Places. To observe sources of business financing, I access the Economic Injury Disaster Loan, Paycheck Protection Program, and EIDL Advance data from Data.gov and link them at the business establishment level to the business closure existence and closure data.

The challenge of estimating the causal impact of commercial rent forbearance liquidity relief on business closure stems from the fact that liquidity relief is not randomly assigned. In particular, there is reverse causality from business closure likelihood to the liquidity relief policy because the very purpose of enacting liquidity relief is to stave off business closure. Local policymakers regularly gather information about business closure likelihood by monitoring local economic conditions and by hearing directly from their business owner constituents at weekly meetings. This reverse causality results in selection bias where a local government facing more severe business closure selects into enacting stronger liquidity relief policies. Indeed, the data shows that longer commercial rent forbearance policies is correlated with *higher* rates of business closure during the pandemic.

To overcome this selection bias, I set up a geographic border difference-in-differences strategy that compares businesses along the border of neighboring cities that differ in

commercial rent forbearance policy. The motivation for the geographic border approach is that businesses on either side of the border face similar economic conditions but different liquidity relief policies. For these neighboring businesses on the outskirts of their respective cities, liquidity relief policy is arguably as-if randomly assigned and not endogenous to business closure likelihood. The identifying assumption for the difference-in-differences strategy is then that these treated and control businesses would have followed parallel trends in business closure in the absence of the liquidity relief. In the data, I observe evidence of parallel trends in business closure prior to the liquidity relief period, which makes it more likely that the identifying assumption holds.

Using the geographic-border-based difference-in-differences strategy, I turn to estimating the impact of liquidity relief on business closure. Rent forbearance liquidity relief significantly reduces business closure in liquidity-constrained sectors by 9 basis points per quarter, or 1.6 percentage points over the total period of 2020-2024. By contrast, liquidity relief has no impact on closure for less liquidity-constrained sectors. These findings are consistent with binding liquidity constraints being the prerequisite condition for liquidity relief to make a difference for business survival. Businesses without binding liquidity constraints are able to survive even without rent forbearance, which is why we find no impact of liquidity relief on closure for these businesses.

To investigate the "efficiency" of these business closure effects, I next examine how the effectiveness of liquidity relief varies with business solvency. Using pre-pandemic ten-year employment growth as an industry-level proxy for business solvency, I find that liquidity relief is more effective in reducing business closure in industries that are more solvent coming into the pandemic. For instance, a natural juxtaposition arises between retail v.s. accommodation & food services, two industries that are both liquidity-constrained during the Covid-19 recession but that differ substantially in terms of their fundamentals coming into the pandemic. In the decade leading up to the pandemic, food services is among the fastest-growing industries, while retail trade is in the thick of the "retail apocalypse" and among the slowest-growing industries. Forbearance reduces business closure in accommodation & food services by 21 basis points per quarter, or 3.8 percentage points over the period 2020-2024, but makes no significant impact on business closure in retail.

To understand the dynamics of these effects, I distinguish between the "short-run" period when the rent forbearance policy is in place and the "later-run" period when rent

forbearance comes to an end and deferred rent comes due. In the short-run period, the business closure effects of liquidity relief are less aligned with underlying business solvency. This is consistent with liquidity relief preventing business death-by-illiquidity in the short run, which is a mechanism unrelated to business solvency. Importantly, there appears to be a low opportunity cost for less efficient short-run business closure since I find that new businesses do not open to replace closed businesses during this time. Turning to the later-run period, the business closure effects of liquidity relief are more aligned with underlying business solvency. This is consistent with more solvent businesses generating stronger cash flows and now being better able to repay back rent to continue operating. This is also consistent with more solvent businesses having better investment opportunities and therefore making better use of the liquidity relief to emerge in stronger financial condition in the later-run period.

Altogether, these results shed light on the effectiveness of liquidity relief to businesses during a recession. The key trade-off that policymakers face is the benefit of saving liquidity-constrained but solvent businesses versus the cost of prolonging survival of insolvent businesses. I find strong evidence that the former benefit is realized: among liquidity-constrained businesses, liquidity relief is more effective in reducing closure for more solvent businesses. I also find evidence that the policy enables less efficient business survival in the short run. Specifically, the short-run business closure effects of liquidity relief are less aligned with solvency. Importantly, the opportunity cost of less efficient short-run business closure appears to be low during this period because businesses do not tend to open to replace closed ones. Additionally, I do not find evidence that less solvent businesses inefficiently use rent forbearance to extend survival only to strategically default when rent comes due.

Finally, taking stock of the broader universe of business financing opportunities, I use the introduction of rent forbearance to map out a pecking order of business financing. I begin by gathering business-level data on three of the four largest programs of business financing during Covid-19. Broadly speaking, there are two types of financing available to businesses: loans that must be repaid and grants that do not need to be repaid. Functioning as zero-interest liquidity relief, rent forbearance partly crowds out business take-up of more costly loans, such as Economic Injury Disaster Loans, but does not affect business take-up of grants, such as EIDL Advance grants and Paycheck Protection Program

forgivable loans.

Related Literature.

This research connects to the literature on real effects of financial frictions. Prior work has focused on how intermediary and firm financial health impact real outcomes, importantly investment and employment. Studies have traced out a bank lending channel, wherein bank health affects credit supply to firms, which in turn affects real economic outcomes (Alcaraz et al., 2025; Amiti and Weinstein, 2018; Balduzzi et al., 2024; Bentolila et al., 2017; Berton et al., 2018; Chodorow-Reich, 2014; Cingano et al., 2016; Greenstone et al., 2020; Gutierrez et al., 2023; Rosengren and Peek, 2000). Other work has examined the role of firm-level financial conditions, including leverage and debt maturity (e.g. Almeida et al., 2012; Campello et al., 2010; Giroud and Mueller, 2017). This paper examines a policy that reduces credit market frictions for business establishments during the Covid-19 recession and finds significant, sustained reductions in business closure in liquidity-constrained sectors. Therefore this paper shows that credit market frictions matter not just for firm's investment and employment while operating, but also for the extensive-margin outcome of firm survival.[1]

Second, this paper connects to the literature on how firms weather the Covid-19 recession. One strand of this literature aims to understand the role of firms' pre-pandemic financial health. For example, Ding et al. (2021) and Fahlenbrach et al. (2021) show that public firms experience less severe stock price drops if they enter the pandemic with stronger financial positions (in terms of liquidity and profitability) or greater financial flexibility. Relatedly, Barry et al. (2022) examine multiple dimensions of corporate flexibility, which they show to be important determinants of employment and investment plans. Turning to business establishments, Bartik et al. (2020a) and Bartik et al. (2020b) find that pre-existing fundamentals help explain closing and reopening behavior early on. This paper contributes a new finding that underlying business fundamentals also help explain heterogeneity in the effectiveness of liquidity relief. Liquidity relief is more effective in reducing closure for more solvent businesses because liquidity relief gives

[1]Contemporaneous work Alcaraz et al. (2025) also considers firm survival during the Covid-19 recession but focuses on bank credit supply shocks and the universe of firms with bank loans in Mexico. My paper instead exploits commercial rent forbearance as a credit supply shock to brick & mortar business establishments. This approach allows us to additionally consider businesses without bank loans, albeit at the cost of leaving out online businesses.

businesses flexibility in allocating funds, and more solvent businesses have more productive investment opportunities.

Another strand of this Covid-19-related literature examines government interventions in business credit markets (Decker et al., 2021; Wheat et al., 2025). Prior work has evaluated the Paycheck Protection Program (Agarwal et al., 2024; Autor et al., 2022; Bartik et al., 2023; Chetty et al., 2024; Faulkender et al., 2024; Granja et al., 2022; Hubbard and Strain, 2020), the Main Street Lending Program (Hanson et al., 2020; English et al., 2020; Arseneau et al., 2022), and the COVID-19 Economic Injury Disaster Loan Program (Fairlie and Fossen, 2022a; Li, 2021). Relative to this work, my paper contributes an assessment of the trade-off that arises when providing widespread liquidity relief: the benefit of saving solvent businesses v.s. the cost of prolonging the survival of other businesses. I find that the former benefit is substantial, while the latter cost is modest because businesses are unlikely to enter and replace closed ones during this time. Additionally, my paper empirically establishes a pecking order of business financing take-up during this period, wherein businesses take up grants, then lower-cost loans, and then higher-cost loans.

Finally, this paper connects to the literature on the efficiency of economic recessions. Building on the notion of "creative destruction" in Schumpeter (1939, 1942), the "cleansing effects" hypothesis proposes that less productive firms close during recessions (e.g., Caballero and Hammour, 1994, 1996). Meanwhile, competing hypotheses point to other frictions, such as credit market frictions, as drivers of firm closure during recessions (e.g., Barlevy, 2002, 2003; Osotimehin and Pappadà, 2017; Ouyang, 2009). Empirically, the evidence has been mixed, with the Great Recession exhibiting less efficient reallocation and prior recessions exhibiting more efficient reallocation (e.g., Davis et al., 2012; Davis and Haltiwanger, 1992; Davis et al., 1996; Foster et al., 2016, 2001). Recent work on the Covid-19 recession asks whether Covid-19 is a reallocation shock (Barrero et al., 2020; Bloom et al., 2025) and finds some evidence of cleansing effects which may be muted by health and business support policies (Archanskaia et al., 2022; Ascari et al., 2023; Kozeniauskas et al., 2022; Merikül and Paulus, 2024). By exploiting a policy that dispenses liquidity relief irregardless of business solvency, this paper empirically tests both the "credit constraints" and "cleansing effects" hypotheses for the Covid-19 recession. I find evidence of illiquidity-induced business closure, which points to credit constraints being a selector of firms in this recession. However, I also find relatively "efficient" business survival condi-

tional on liquidity relief, which points to "cleansing effects." In short, this paper makes the new point that liquidity relief enables cleansing effects in the Covid-19 recession.

This paper proceeds as follows. Section 2 develops a conceptual framework of commercial rent forbearance in liquidity provision. Section 3 describes the data sources and provides summary statistics. Section 4 develops the geographic border-based difference-differences strategy and estimates the impact of liquidity relief on business closure. Section 6 investigates the impact of liquidity relief on business financing. Finally, Section 7 concludes.

2 Conceptual framework

In this section, I develop a conceptual framework for the impact of commercial rent forbearance liquidity relief on business closure. Section 2.1 gives background on the commercial rent forbearance policy. Section 2.2 provides illustrative examples of different commercial rent forbearance policies. Section 2.3 develops hypotheses for the impact of commercial rent forbearance liquidity relief on business closure.

2.1 Background on commercial rent forbearance

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

The stated goal of the policy is to prevent business closure by pausing the obligation

of rent payments and pausing eviction proceedings. The direct consequence of the policy is liquidity relief. By pausing rent payments, the policy effectively requires a landlord to offer its business tenant zero-interest, non-forgivable credit with face value equal to the amount of rent accrued during the policy period. Therefore, the policy is essentially a credit policy where businesses can borrow from their landlord by delaying rent payment. The framing of rent forbearance as liquidity relief is backed by anecdotal evidence. For example, in response to eviction moratorium in San Jose, one landlord commented, "I'm the pop half of a mom and pop landlord team... Let's call this what it is: a mandatory unsecured zero-interest loan demanded of the San Jose housing providers." The household debt relief literature has also thought consumer rent forbearance as liquidity relief to households. For example, Cherry et al. (2021) finds that the large majority (4/5) of households take up rent forbearance and interprets this as forbearance effectively serving as a credit line for households.

Commercial rent forbearance policies are enacted by local governments, rather than the federal government. While the start date of the policy is almost uniformly March 2020, there is variation in the end date across states. For example, in Massachusetts, the legislature and Governor approved a bill pausing non-essential small business evictions through October 2020. In Texas, multiple county courts paused non-essential commercial eviction hearings for varying amounts of time. In California, the Judicial Council enacted a pause on eviction proceedings through September 2020, while the Governor gave city and county governments the option to enact commercial rent forbearance through September 2021.

2.2 Illustrative examples of commercial rent forbearance policies

Figure 1 provides illustrative examples of the timeline of a commercial rent forbearance policy. Panel A shows that in Oakland, California, the policy is enacted in March 2020, at which point the obligation of rent payment is paused. The policy lasts for 19 months and ends in September 2021, at which point the obligation of rent payment resumes. Additionally, all back rent comes due. To concretely understand how the policy provides liquidity relief, Panel B presents an illustrative example of the effective loan balance that businesses can borrow under the policy in Oakland, California. Businesses can steadily

borrow each month by deferring monthly rent until the policy ends, at which point they must repay the loan balance. Specifically, given a restaurant with monthly rent of $5,000, the policy would enable the business to borrow $95,000 (19 * $5,000) over 19 months at zero interest.

2.3 Hypothesis development

The research question that I aim to answer is: How does liquidity relief affect business closure during a recession? Specifically, which types of businesses does it save? What is the tradeoff between saving productive businesses and zombie-ing along less productive businesses?

I consider first the role of business liquidity, which I reason is the precondition for liquidity relief to have any effect on business closure. Let us consider first the case of a business that is not liquidity constrained. Such a business generates strong cash flows and/or has sufficient access to credit. Therefore it has sufficient cash to meet immediate financial obligations and to make productive investments. In other words, its financial position is strong enough and does not constrain its operations. This business would survive with or without additional liquidity relief. Therefore, liquidity relief has no impact on its survival.

Now let us consider a business that is liquidity constrained. During economic recessions, however, private markets may not function normally since financial intermediaries themselves also face binding liquidity constraints (e.g., Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014). Under these conditions, there is a role for liquidity relief to prevent closure for a liquidity-constrained business. Such a business may be at risk of closing in short run because it can't meet immediate obligations like payroll, rent, supplier payment or at risk of closing in the later run because it cannot invest. There is now scope for liquidity relief to make a difference in this business's survival. Concretely, commercial rent forbearance in my setting allows this business to defer rent payment for 1.5 years, freeing up substantial cash for other survival-critical expenses. Liquidity relief in short can prevent closure for this business. Altogether, this leads us to our first hypothesis.

Hypothesis 1: Commercial rent forbearance liquidity relief reduces closure of liquidity-

constrained businesses and has no impact on closure of liquidity-unconstrained businesses.

Liquidity relief improves business liquidity but not solvency. Concretely, commercial rent forbearance is a relatively pure case of liquidity relief. The policy specifically states that it defers but does not forgive rent. Also, I find no impact of rent forbearance policy on new lease prices as shown in Table A.III. If commercial rent forbearance forces landlords to provide solvency relief (downward renegotiated rents), then we would expect this behavior to show up in the pricing of new leases.

Moreover, commercial rent forbearance is a form of liquidity relief with serious consequences for defaulting, which further point to little solvency relief. After the liquidity relief draws to a close, the business owes back rent, and failing to repay it places them in violation of their lease. Businesses are on the hook for deferred rent with serious consequences for defaulting. Because this liquidity relief is administered through existing commercial leases, the consequences for defaulting on this liquidity relief are simply the consequences for defaulting on your lease. It has become common practice for landlord to require a personal guarantee from the business owner for the commercial lease.[2] This means that the business owner is held personally liable for the balance of the commercial lease. If the business is defaults on the rent payment or breaks the lease, the landlord can pursue the business owner's personal assets in order to recoup unpaid rent. This can also affect the business owner's personal credit record if for example the landlord reports the default to the credit bureau, sends the defaulted amount to collections, or places a lien on personal property.

These features of liquidity relief imply that more solvent businesses benefit more from liquidity relief in terms of staving off closure. Specifically, when forbearance comes to an end, more solvent businesses are more able to pay back rent because they generate stronger cash flows now that economic conditions have recovered to a degree. Additionally, more solvent businesses are better able to use the financial flexibility afforded to them by the commercial rent forbearance to make productive investments (e.g. capital expenditure, supplies, retain employees) that can aid in their survival. This brings us to

[2]See for example https://www.thamesmarkey.law/blog/2025/02/do-you-need-a-personal-guarantee-for-a-commercial-lease/ and https://frannet.com/resources/business-opportunity-2/guarantees-in-commercial-leases-and-what-franchisees-should-know/.

our second hypothesis.

Hypothesis 2: Among liquidity-constrained businesses, commercial rent forbearance is more effective in reducing closure for more solvent businesses.

I turn next to understand the dynamics of the effect. Liquidity relief reduces business closure in the short run by preventing death-by-illiquidity, such as being unable to make payroll or rent because revenue is temporarily low. This effect is less connected to business solvency because solvent and insolvent businesses alike may be at risk of death-by-illiquidity. Relatedly, rent forbearance is untargeted policy that applies to all businesses. Businesses can take up rent forbearance to stave off closure irrespective of solvency, although businesses should think twice given serious consequences of defaulting.

In the later run, economic conditions recover to some degree and liquidity relief comes to an end. These two events coinciding is not a coincidence. Rather it is the doing of policymakers and stems from their objective function. As onset of pandemic, there is severe liquidity shock which makes economic conditions dire, policymakers are concerned about losing solvent businesses to illiquidity, so they provide liquidity relief to tide businesses over. Week to week, policymakers (e.g. city council) monitor conditions. As economic conditions recover, policymakers become less concerned about illiquidity business deaths and more concerned about zombieing along businesses / placing undue burden on landlords, so at some point they bring the liquidity relief to an end: back rent comes due. Similar logic applies to other emergency business relief programs, such as PPP.

Liquidity relief may continue to take effect after policy comes to an end. For example, Howell (2017) and Aydin and Kim (2025) find that alleviating liquidity constraints for small firms has long-lived effects on investment and performance. Liquidity relief reduces business closure in the later run by enabling businesses to emerge at that point in better financial condition. This later-run effect has more to do with solvency. First, more solvent businesses are now generating stronger cash flows and are better able to repay back rent, which enables them to continue operating in that space. Second, more solvent businesses also had better investment opportunities that they were able to use the liquidity relief to invest in, e.g. capex, payroll. Therefore more solvent businesses benefit more from liquidity relief, and this closure effect shows up in the later run. This delivers our

third hypothesis.

Hypothesis 3: The short-run business closure effects of liquidity relief align less strongly with business solvency, while the later-run effects align more strongly with business solvency.

To test these hypotheses, I next turn to assembling the data, designing the identification strategy, and conducting the empirical analysis.

3 Data and summary statistics

My sample of study focuses on California, where commercial rent forbearance is enacted by local governments for varying amounts of time during the Covid-19 pandemic. California serves as an ideal laboratory for commercial rent forbearance because of its decentralized implementation which creates variation in commercial rent forbearance across space and time that I exploit in the empirical analysis. Another advantage of studying California is that it contains a significant share of U.S. businesses. According to the Small Business Administration, in 2019, there were 4.0 million small businesses employing 7.1 million individuals in California, which accounts for 13% of the number of small businesses and 12% of the small business employment in the United States.

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

3.1 Commercial rent forbearance data

One challenge of assessing the impact of commercial rent forbearance on business closure is data availability. Commercial rent forbearance is a policy enacted by local governing bodies, rather than the federal government. Accordingly, commercial rent forbearance varies across geographies, and information about the policy is scattered across local gov-

ernment documents. Furthermore, commercial rent forbearance is a real-time response to business stress, which makes it necessary to continuously monitor the policy over time for any extension or premature termination.

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

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

28 of the 58 counties in California exercised the option and enacted commercial rent forbearance. 18 counties enacted commercial rent forbearance over unincorporated areas only, while 10 counties enacted commercial rent forbearance county-wide. County-enacted commercial rent forbearance averaged 0.39 years (4.6 months) in length with an additional 0.08 years (1.0 month) of repayment time. The vast majority of county-enacted commercial rent forbearance policies allow for back rent to be paid in a single installment on the due date. 156 of the 482 cities in California exercised the option and enacted commercial rent forbearance. City-enacted commercial rent forbearance averaged 0.35 years (4.2 months) in length with an additional 0.13 years (1.6 months) of repayment time. The vast majority of city-enacted commercial rent forbearance also allow for back rent to be paid in a single installment on the due date.

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

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

3.2 Business data

The business data set covers the effective universe of customer-facing, brick & mortar business establishments. The data is constructed using SafeGraph Points of Interest (POI) data and cross-checking business status against Google Places or Yelp. SafeGraph collects points of interest (i.e. physical locations of interest) on a monthly basis from many sources, including first-party data providers and open-source data sources. Similarly, Google Places and Yelp each collect points of interest from many sources, including first-party data providers, open-source data sources, data collaborations, and importantly their users, which include consumers and businesses. The starting point is SafeGraph's closed_on variable, which estimates the closure date for a business. SafeGraph estimates this date by flagging the first month in which a business disappears from its data pipeline and stays absent.

SafeGraph launched its data pipeline approach of business closure tracking in July 2019. The strength of SafeGraph's data pipeline approach is that it identifies business closure in a high-frequency way, which are estimated to be accurate within 60 days for the most part. The caveat of SafeGraph's data pipeline approach however is that there are cases of data staleness, which motivates using Google Places and Yelp to cross-check business status. Certain businesses may forever remain in the data pipeline not because they exist to this day but rather because they closed and were not updated in the data sources. I cross-check these cases against Google Places to confirm whether such a business is

truly operating to this day. Relatedly, certain business closures may be stale because the business closes but does not yet disappear from the data pipeline for some time. I also cross-check these cases against Google Places or Yelp to confirm whether the business closed at a time in line with SafeGraph's estimate. In sum, the final dataset covers business establishments as of July 2019 (when SafeGraph's data pipeline begins) and tracks their survival and closure over time. Table 2 presents summary statistics for this business data.

4 Impact of liquidity relief on business closure

This section examines the impact of liquidity relief on business closure and investigates the determinants of this effect across businesses and across time. Section 4.1 tests Hypothesis 1 by first developing a geographic border-based difference-in-differences strategy and then identifying the causal impact of liquidity relief on business closure. Section 4.2 tests Hypothesis 2 by examining the relationship between business solvency and the effectiveness of liquidity relief. Section 4.3 tests Hypothesis 3 by distinguishing between short-run versus later-run effects and examining their determinants.

4.1 Identifying the impact of liquidity relief on business closure

In this section, I aim to identify the causal effect of liquidity relief on business closure. The primary challenge I face is the reverse causality from business closure to the liquidity relief policy, which arises from local policymakers enacting the policy precisely to address the threat of business closure. For example, in April 2020, the city of San Jose prepared a memo assessing the extent of business financial stress and stating that the aim of the policy is to prevent unnecessary business closure.[3]

To overcome this selection bias, I set up a geographic border difference-in-differences strategy that compares businesses along the border of neighboring cities that differ in

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

commercial rent forbearance policy. The criteria for identifying these borders is that one city has no forbearance in place, while the neighboring city has substantial rent forbearance in place. I define substantial rent forbearance as lasting through September 30, 2021, which is the date through which Governor Newsom legalizes commercial rent forbearance. For each border, I identify zip codes that lie along the border. I require that one zip code does not comprise the majority of the city, otherwise the zip code is effectively equivalent to the city and the rent forbearance policy is endogenous to business closure for the zip code. Figure 3 presents an illustrative example two neighboring cities that differ in their liquidity relief and the zip codes along the border that I hone in on to gather treated and control businesses. Altogether, I identify 49 city-city borders where the neighboring cities experience a difference in commercial rent forbearance policy. The motivation for the geographic border approach is that businesses on either side of the border likely face similar economic conditions but then different liquidity relief policies. The liquidity relief policy is arguably as-if randomly assigned and less endogenous to business closure likelihood because these businesses lie on the outskirts of the city.

The identifying assumption for the difference-in-differences strategy is that these treated and control businesses would have followed parallel trends in business closure in the absence of the liquidity relief. Figure 4 plots quarterly coefficients of the difference-in-differences regression of business closure for treated businesses relative to control businesses along a border before versus after the enactment of liquidity relief. SafeGraph business closure tracking launched in 2019 Q3, which gives us three pre-treatment quarters. I observe parallel trends in business closure for treated and control businesses prior to the liquidity relief treatment, which provides evidence in favor of the parallel trends identification assumption.

To assess the impact of liquidity relief on business closure, we estimate the following business $\times$ quarter-level specification:

$$\begin{aligned}\text{Business Closure}_{i,t} = \alpha_0 + \alpha_1 \cdot \text{Treated}_{j(i)} \cdot \text{Post}_t + \alpha_2 \cdot \text{Treated}_{j(i)} + \alpha_3 \cdot \text{Post}_t \\ + \rho_{k(i)} + \lambda_{\ell(i)} + \varepsilon_{i,t}\end{aligned}$$

$\text{Business Closure}_{i,t}$ is an indicator equal to one if business i closes in quarter t, and zero otherwise. $\text{Treated}_{j(i)}$ is an indicator equal to one if the city j where business i operates

enacts substantial commercial rent forbearance, and zero otherwise. Post_t is an indicator equal to one if quarter t is after the liquidity relief policy, and zero otherwise. $\rho_{k(i)}$ is a fixed effect for the city-city-border k where business i lies. $\lambda_{\ell(i)}$ is a fixed effect for the sector ℓ that business i operates in. Standard errors are clustered by city-city-border k.

Table 3 presents the quarterly impact of liquidity relief on business closure for more versus less liquidity-constrained sectors. More (less) liquidity-constrained sectors are defined as those NAICS sectors with with an above-median (below-median) share of temporary business closure at the onset of the pandemic, as captured in the April 2020 installment of the Small Business Pulse Survey conducted by the Census Bureau.[4] Among more liquidity-constrained sectors, liquidity relief reduces business closure by 8.8 basis points per quarter, or 1.6 percentage points over the period of 2020-2024. By contrast, the liquidity relief has no effect on business closure in less liquidity-constrained sectors. These results are consistent with liquidity constraints being the prerequisite condition for commercial rent forbearance liquidity relief to make a difference on business survival.

4.2 Business solvency & the effectiveness of liquidity relief

In this section, I analyze the relationship between business solvency and the effectiveness of liquidity relief. I begin by constructing a measure of business solvency. It is not possible to estimate solvency at the business establishment level because the SafeGraph does not include business balance sheet data. Instead, we estimate business solvency at the industry level by using the ten-year pre-pandemic employment growth rate. Figure A.2 presents the business closure effects of liquidity relief by industry. Specifically, the y-axis is the quarterly impact of liquidity relief on business closure in basis points, and the x-axis is the ten-year pre-pandemic employment growth rate for the industry. Table 4 extends the baseline difference-in-differences specification to examine the the relationship between business solvency and the impact of liquidity relief on business closure across in-

[4]Using this classification, I identify the more liquidity-constrained NAICS sectors to be NAICS 72: Accommodation and food services, NAICS 71: Arts, entertainment, and recreation, NAICS 61: Educational services, NAICS 62: Health care and social assistance, NAICS 81: Other services (except public administration), NAICS 44–45: Retail trade, and NAICS 48–49: Transportation and warehousing. I identify the less liquidity-constrained industries to be NAICS 11: Agriculture, forestry, fishing and hunting, NAICS 23: Construction, NAICS 31–33: Manufacturing, NAICS 42: Wholesale trade, NAICS 51: Information, NAICS 53: Real estate and rental and leasing, NAICS 54: Professional, scientific, and technical services, NAICS 55: Management of companies and enterprises, and NAICS 56: Admin. and support and waste management services.

dustries. A clear pattern emerges, which is that the more solvent industries are the places where liquidity relief had the strongest effect in terms of reducing business closure.

Table 5 highlights this point by juxtaposing retail v.s. food services. Both industries were liquidity-constrained during the pandemic. However, they had very different fundamentals coming into the pandemic. As well documented in the news & literature, there was a retail apocalypse phenomenon already underway prior to the pandemic.[5] By contrast, food services was among the fastest growing industries in the decade before the pandemic. Focusing on the early period of the Covid-19 crisis, Bartik et al. (2020b) find that pre-pandemic firm health predicts a lower likelihood of firm closure and a higher likelihood of firm reopening. I find a similar pattern of pre-pandemic firm health mattering for firm survival that occurs at the industry level and over a longer horizon (2020-2022).

4.3 Short-run v.s. later-run effects

To investigate how liquidity relief affected business closure in the short run, I re-estimate the business closure effects using the post treatment period through 2021q3, which is the end date that the California state governor specified and therefore the end date of most commercial rent forbearance policies enacted by city and county governments in California.

Figure 7 and Table 6 present the shorter-run and later-run business closure effects along the axis of business solvency. In the short run, the relationship between liquidity relief effectiveness v.s. business solvency is muted compared to in the later run. In other words, the business closure effects of liquidity relief are less "efficient" in the short run, which points to liquidity relief reducing business closure irrespective of business solvency in the short run. In the longer run, the business closure effects of liquidity relief become more aligned with business solvency as businesses are required to repay their delayed rent payments. In sum, I find evidence of the liquidity relief prolonging business survival in the shorter run in a way that is less aligned with business solvency.

[5]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.

5 Assessing trade-offs in liquidity relief

This section takes stock of the overall trade-off that policymakers face when extending widespread liquidity relief to businesses during an economic recession. Section 5.1 assesses the possible benefit of liquidity relief in terms of preserving solvent businesses. Section 5.2 assesses the possible ocst of liquidity relief in terms of prolonging insolvent businesses. Section 5.3 considers reallocation during this period, specifically examining the repsonse of business openings.

5.1 Evidence on preserving solvent businesses

The tests of Hypotheses 1 and 2 show that liquidity relief is effective in reducing business closure. Commercial rent forbearance reduces business closure for liquidity-constrained sectors by 8.8 basis points per quarter, or 1.6 percentage points over the period 2020-2024, with no corresponding effect for liquidity-unconstrained sectors. Moreover, among liquidity-constrained businesses, commercial rent forbearance is most effective in reducing closure for more solvent businesses. For example, let us consider the three fastest-growing and arguably more solvent sectors: Forbearance reduces business closure by 3.8 percentage points in accommodation & food services, 3.2 percentage points, and 2.2 percentage points over the 2020-2024 period.

The test of Hypothesis 3 helps explain why liquidity relief has stronger effects for more solvent businesses. We decompose the business effects into the short run when rent forbearance is in place and the later run when rent forbearance comes to an end and deferred rent comes due. We find that it is the later-run business closure effects that are aligned with solvency, not the short-run business closure effects. The mechanism for liquidity relief to reduce business closure in the later run is that the business benefited from the financial flexibility during the depths of the liquidity crisis and now emerges from forbearance in stronger financial condition or operating condition. Relatedly, a business must pay back deferred rent to "lock in" its survival during this time, otherwise it can now be evicted. More solvent businesses are likely to have better investment opportunities to apply this financial flexibility to and are likely to generate stronger cash flows to enable paying back the rent. Accordingly, it's the later-run business closure effects of liquidity relief that align with business solvency and that help realize the policymaker

goal of preserving solvent businesses.

5.2 Evidence on prolonging insolvent businesses

I turn now to assessing the potential cost of liquidity relief, which is prolonging the survival of insolvent businesses. The test of Hypothesis 3 shows that the short-run business closure effects of liquidity relief do not align with solvency and are arguably less efficient. This makes sense when we consider how liquidity relief reduces business closure in the short run: by preventing death-by-illiquidity. This is a mechanism that is unrelated to business solvency because solvent and insolvent businesses can both be illiquid and take up forbearance to stave off closure in the short run.

To take this one step further, I can then ask: do less solvent businesses use liquidity relief to over-extend their survival and strategically default on deferred rent? If this strategic "zombie" survival of less solvent businesses takes place, it should manifest as liquidity relief causing *increases* in business closure in the later run period after forbearance comes to an end. Furthermore, if businesses are very strategic and knowingly take out liquidity relief that they can not repay, then we should observe a specific spike in business closure at the forbearance end date, which is September 30, 2021 for most of the treated businesses in my sample. Panel B of Figure 7 rules out this possibility by showing that less solvent businesses, such as those in the retail and other services sectors, do not experience increases in business closure in the later-run period. More precisely, there is no rebound in business closure around September 30, 2021 when forbearance comes to an end.

In sum, the empirical evidence points to modest costs of liquidity relief in terms of prolonging insolvent businesses. The short-run business closure effects of liquidity relief are not well aligned with business solvency, suggesting some inefficiency in the short run. However, I also do not find evidence of less solvent businesses over-using liquidity relief to survive and strategically defaulting when forbearance comes to an end.

5.3 Reallocation dynamics

To give context to this trade-off of liquidity relief, I turn to examining reallocation during this time, specifically how business opening responds to commercial rent forbearance

liquidity relief.

Business openings data comes from SafeGraph as well. Using a similar data pipeline approach, SafeGraph captures business openings for "branded" businesses, i.e. businesses with multiple locations under the same brand.[6] Similar to the business closure data, the business opening data starts in 2019 Q3 and enables us to observe business entry over time at a relatively high frequency. The caveat however is that business opening data is only available for "branded" businesses.

Using the same empirical machinery, I now ask: how does liquidity relief affect business openings? If there is strong reallocation in the sense that new businesses replace businesses that close, then holding existing businesses in place via liquidity relief also holds back business openings. In fact, if reallocation is perfect, then we should estimate a business opening effect of liquidity relief that is precisely equal to the business closure effect. By contrast, if there is little to no reallocation in the sense that new businesses do not tend to replace businesses that close, then holding existing businesses in place via liquidity relief has no impact on business openings. In short, there are no prospective business on the sidelines ready to assume the storefronts of closed ones.

To assess the impact of liquidity relief on business opening, I now estimate the following business $\times$ quarter-level specification:

$$\begin{aligned}\text{Business Opening}_{i,t} = \beta_0 + \beta_1 \cdot \text{Treated}_{j(i)} \cdot \text{Post}_t + \beta_2 \cdot \text{Treated}_{j(i)} + \beta_3 \cdot \text{Post}_t \\ + \rho_{k(i)} + \lambda_{\ell(i)} + \varepsilon_{i,t}\end{aligned}$$

$\text{Business Opening}_{i,q}$ is an indicator equal to one if business i opens in quarter t, and zero otherwise. $\text{Treated}_{j(i)}$ is an indicator equal to one if the city j where business i operates has a commercial rent forbearance policy, and zero otherwise. Post_t is an indicator equal to one if quarter t is after 2020 Q1 (when commercial rent forbearance policies began), and zero otherwise. $\rho_{k(i)}$ is a fixed effect for the city-city-border k where business i lies. $\lambda_{\ell(i)}$ is a fixed effect for the sector ℓ that business b operates in. Standard errors are clustered by city-city-border k.

[6]The reason that SafeGraph only tracks openings for "branded" businesses has to do with its data pipeline approach. Safegraph uses "store locators" from brand websites as a primary, high-authority source for tracking openings and closures because they automatically update when a new location opens. By contrast, it is challenging to accurately track mom-and-pop business openings using primary sources and the data pipeline approach.

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

The low level of reallocation during this period also helps us contextualize the key benefit and cost of liquidity relief. Low reallocation means that it is especially important for a social planner to preserve existing, solvent businesses, which is the key benefit of liquidity relief. If these businesses close, there are not yet any new businesses ready to replace them, so their closure is allocatively inefficient and a real loss. Low reallocation also means that it is more permissible for a social planner to accept less efficient short-run business closure effects. If liquidity relief extends the survival of less solvent businesses, for example, there is a low opportunity cost to doing so because there are not any new businesses ready to enter and make better use of those resources.

6 Pecking order of business financing

This section establishes a pecking order of business financing during the Covid-19 pandemic. Section 6.1 outlines the sources of financing available to businesses during the Covid-19 pandemic. Section 6.2 estimates the impact of commercial rent forbearance liquidity relief on business take-up of other financing.

6.1 Sources of business financing during Covid-19 pandemic

According to the 2021 Small Business Credit Survey, the main sources of pandemic-related financial assistance that businesses sought out were: the Economic Injury Disaster Loan (63% of respondents), the Paycheck Protection Program forgivable loan (51% of respondents), state and local government grants (48% of respondents), and the EIDL Advance grant (36%). Broadly speaking, there are two types of financing available to businesses. First, there is loan financing that must be repaid, such as the EIDL loan program. There is likely to be substitution towards commercial rent forbearance usage and away from loan

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

The EIDL advance program provides grants of up to $15,000 to businesses that can be used for working capital and operating expenses during the Covid-19 pandemic. EIDL advances do not need to be repaid.[7] I obtain details on grants administered through the EIDL advance program from the public database on federal spending. Throughout the U.S., the EIDL advance program disbursed ∼1 million grants totaling ∼$7.5 billion. In my sample of California, the program disbursed ∼150,000 grants totaling ∼$1 billion.

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

The Economic Injury Disaster Loan (EIDL) Program provides low-interest, fixed-rate, long-term loans from the Small Business Administration directly to small businesses that

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

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

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. I obtain details on loans administered through this program from the public database on federal spending.[9] Throughout the U.S., the COVID EIDL program disbursed ∼3.9 million loans totaling ∼$380 billion. In my sample of California, the program disbursed ∼600,000 loans totaling ∼$68 billion. I connect SafeGraph business data to EIDL advance grant data, PPP forgivable loan data, and EIDL loan data by matching business name and address.

6.2 Impact of liquidity relief on take-up of other financing

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

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

To assess the impact of liquidity relief on business financing, we estimate the following business-level specification:

$$\text{Business Financing}_i = \gamma_0 + \gamma_1 \cdot \text{Treated}_{j(i)} + \rho_{k(i)} + \lambda_{\ell(i)} + \varepsilon_i$$

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

$\text{Financing}_{i,t}$ is a measure of business financing take-up by business i. $\text{Treated}_{\mathcal{J}(i)}$ is an indicator equal to one if the city $\mathcal{J}$ where business i operates has a commercial rent forbearance policy, and zero otherwise. $\rho_{k(i)}$ is a fixed effect for the city-city-border k where business i lies. $\lambda_{\ell(i)}$ is a fixed effect for the sector ℓ that business i operates in. Standard errors are clustered by city-city-border k.

Table 8 presents the impact of liquidity relief on business financing take-up from the EIDL Advance grant program, Paycheck Protection forgivable loan program, and the Economic Injury Disaster Loan program. My empirical specification is now a difference between businesses along the border of neighboring cities with differing liquidity relief policy.[10]

In Panel A, I focus on the more liquidity-constrained industries. In the first 2 columns, I estimate the effect of liquidity relief on take-up from the EIDL advance program. In column 1, I find that forbearance has no significant effect on the extensive margin of EIDL advance take-up, which is the likelihood of receiving an EIDL advance. In column 2, I find that liquidity relief has no significant effect on the intensive margin of EIDL advance take-up as captured by the log EIDL advance grant amount. In the next two columns, I estimate the effect of liquidity relief on usage of the PPP forgivable loan program. I find that the liquidity relief similarly has no significant effect on the extensive margin of PPP take-up or intensive margin of amount of PPP. In the next 2 columns, I estimate the effect of liquidity relief on usage of the EIDL loan program. I find that the liquidity relief reduces the likelihood of having EIDL by 87 basis points and reduces the loan amount by approximately 9%. In sum, I observe liquidity relief crowding out more costly loan financing more than it crowds out grant financing or forgivable loan financing. In Panel B, I turn to the less liquidity-constrained industries and find no effect of the liquidity relief on any of the types of business financing.

7 Conclusion

In this paper, I assess a key tradeoff that arises when enacting widespread liquidity relief for businesses. One key benefit of liquidity relief is the opportunity to save liquidity-

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

constrained but solvent businesses, while one key cost is the possibility of prolonging survival of less solvent businesses. Using the setting of commercial rent forbearance during the Covid-19 recession, I find that liquidity relief significantly reduces closure of liquidity-constrained businesses by 9 basis points per quarter, or 1.6 percentage points over the 2020-2024 period. Moreover, among liquidity-constrained businesses, liquidity relief is more effective in reducing closure for more solvent businesses, which points to the effectiveness of liquidity relief in preserving businesses that would have otherwise perished in the thick of the liquidity crisis of the pandemic.

In the short run, however, business closure effects of liquidity relief are substantially less aligned with solvency, which is consistent with the policy temporarily enabling less efficient business survival. The opportunity cost of less efficient short-run business closure appears to be low, however, because businesses do not tend to open to replace closed ones during this time. Additionally, I do not find evidence that less solvent businesses use the commercial rent forbearance liquidity relief to extend survival and then strategically default when forbearance ends. Finally, along the pecking order of business financing opportunities, I show that the liquidity relief does not affect business take-up of grants and only partly crowds out business take-up of more costly loan financing as credit constraints remain severe during this time.

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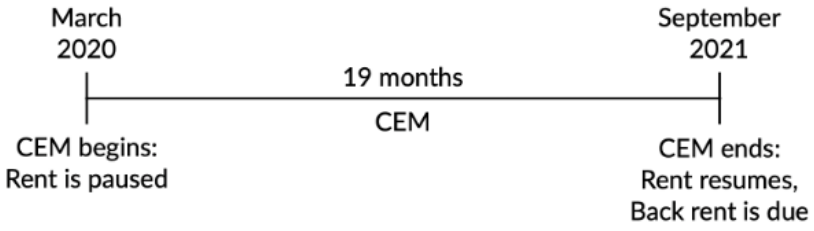
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Figure 1: Illustrative example of commercial rent forbearance

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



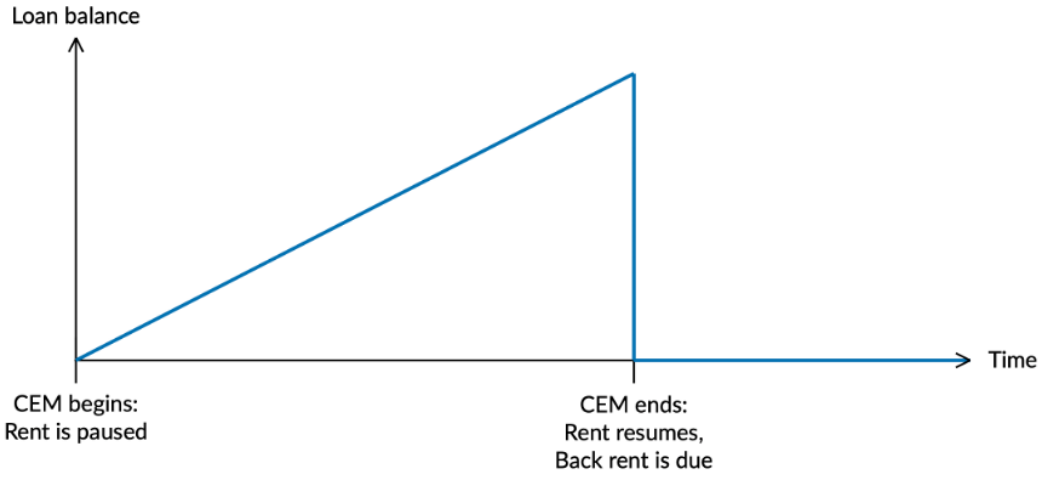
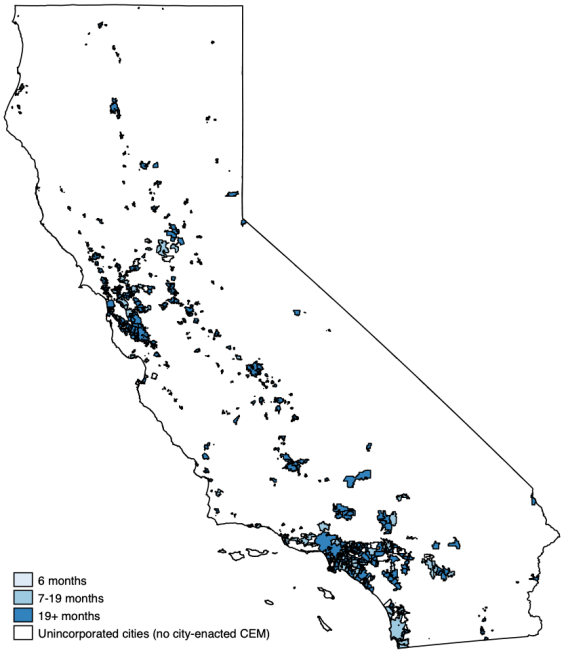


Figure 2: Commercial rent forbearance in California

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

Panel A: City-level commercial rent forbearance



Panel B: County-level commercial rent forbearance



Figure 3: Illustrative example of geographic border-based empirical strategy

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

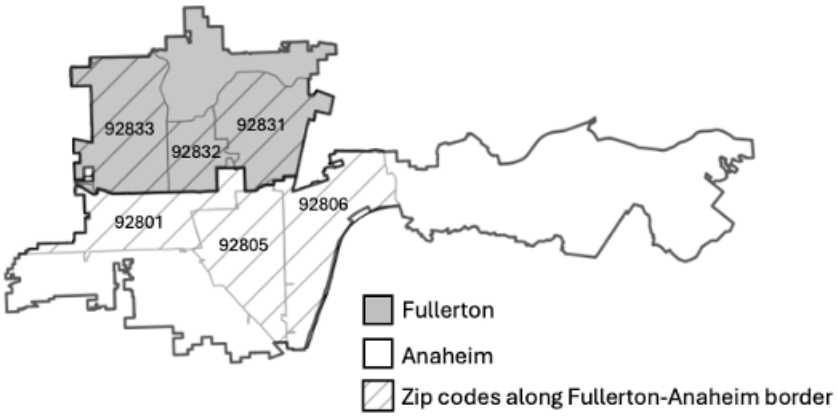


Figure 4: Impact of liquidity relief on business closure:
Liquidity-constrained industries

The figure plots the coefficients of the business × quarter-level difference-in-differences analysis around commercial rent forbearance policies. The outcome variable is business closure measured in basis points. 90% confidence intervals are given based on standard errors clustered at the city-city border level.

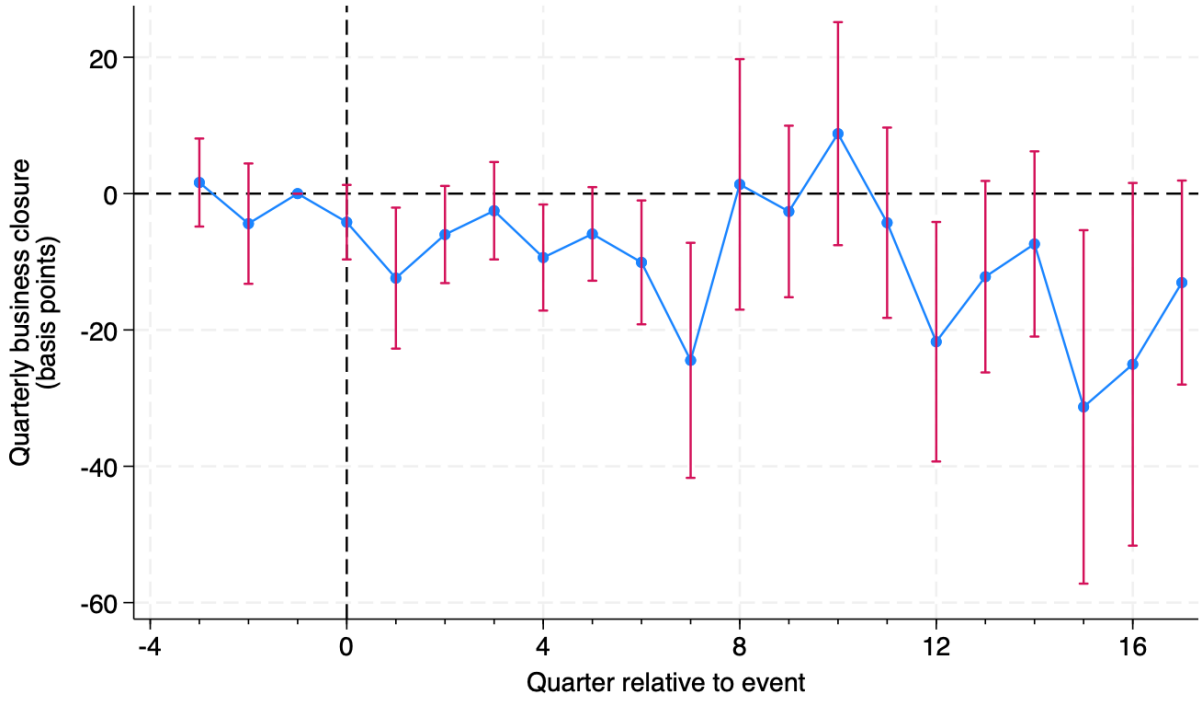


Figure 5: Employment over time: By sector

This figure shows the employment of sectors over time, indexed to employment in 2010.

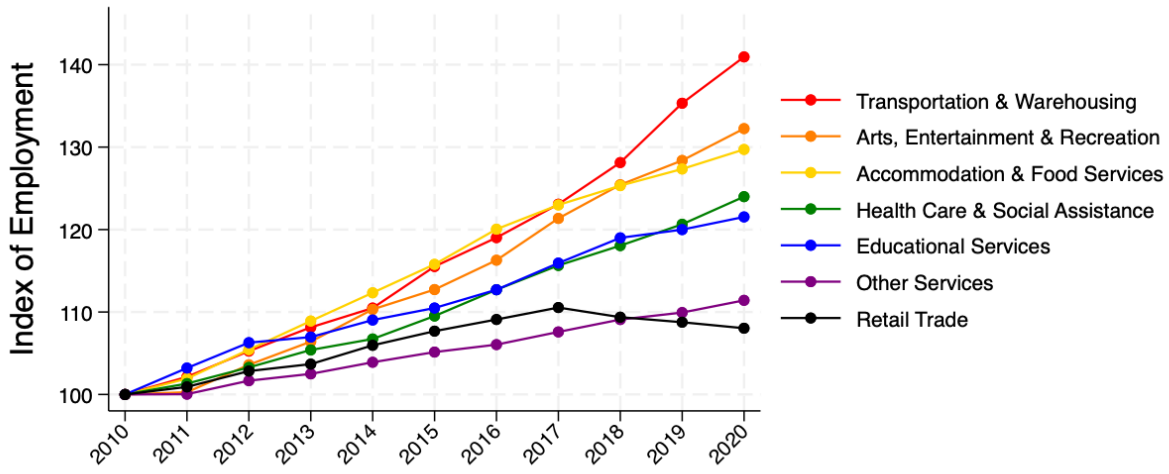


Figure 6: Impact of liquidity relief on business closure: By industry

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

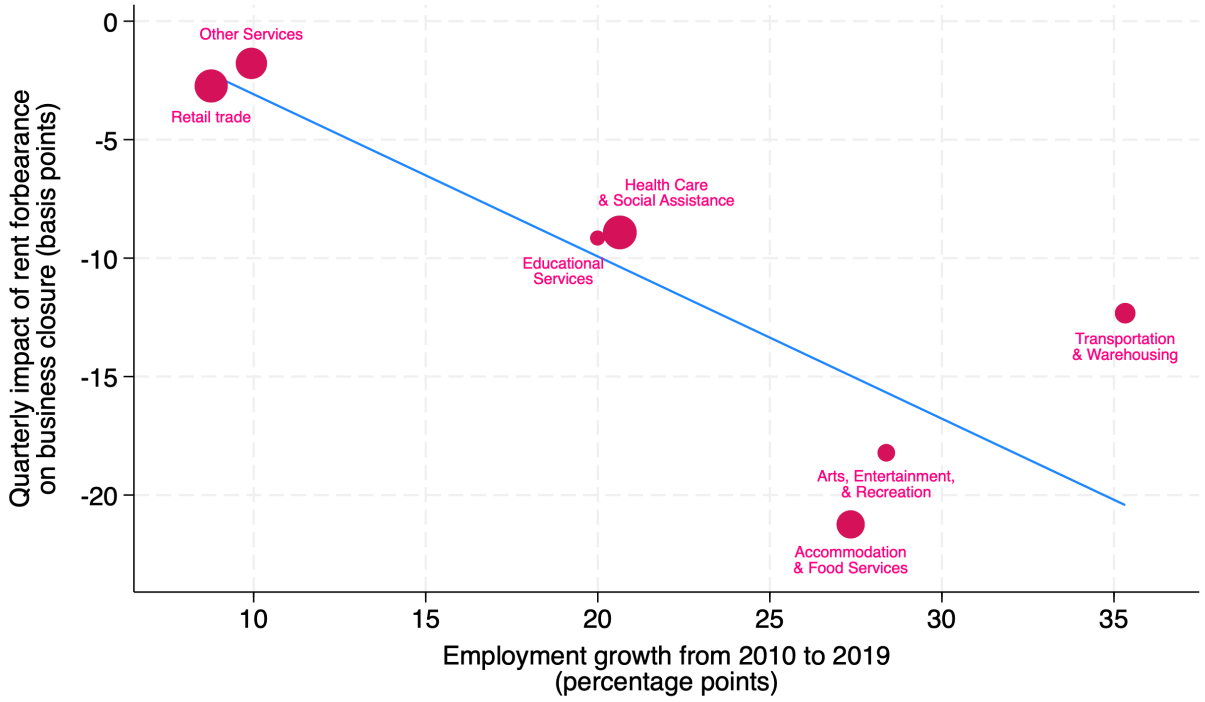


Figure 7: Impact of liquidity relief on business closure: By industry and horizon

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

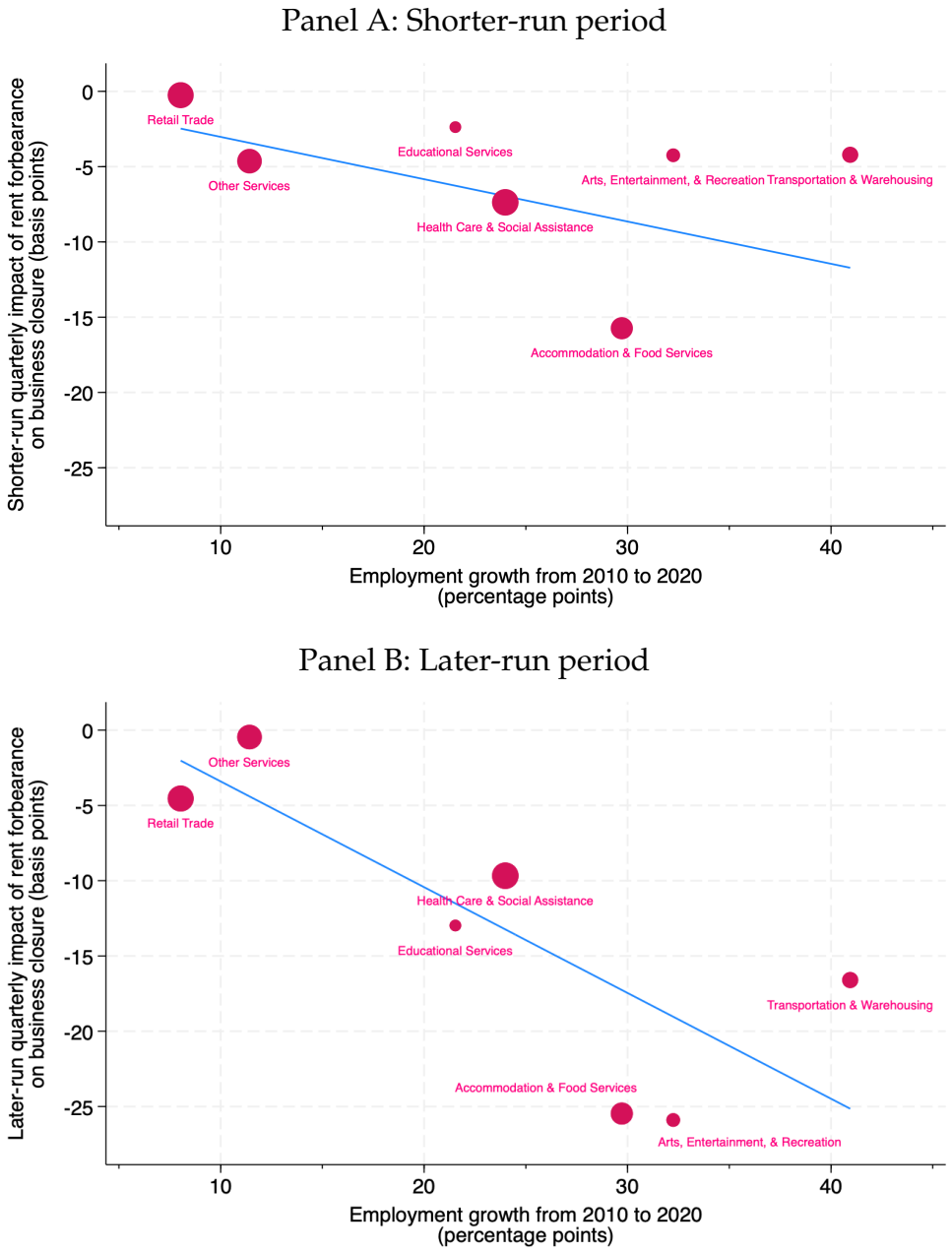


Figure 8: Pecking order of business financing during the Covid-19 recession

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

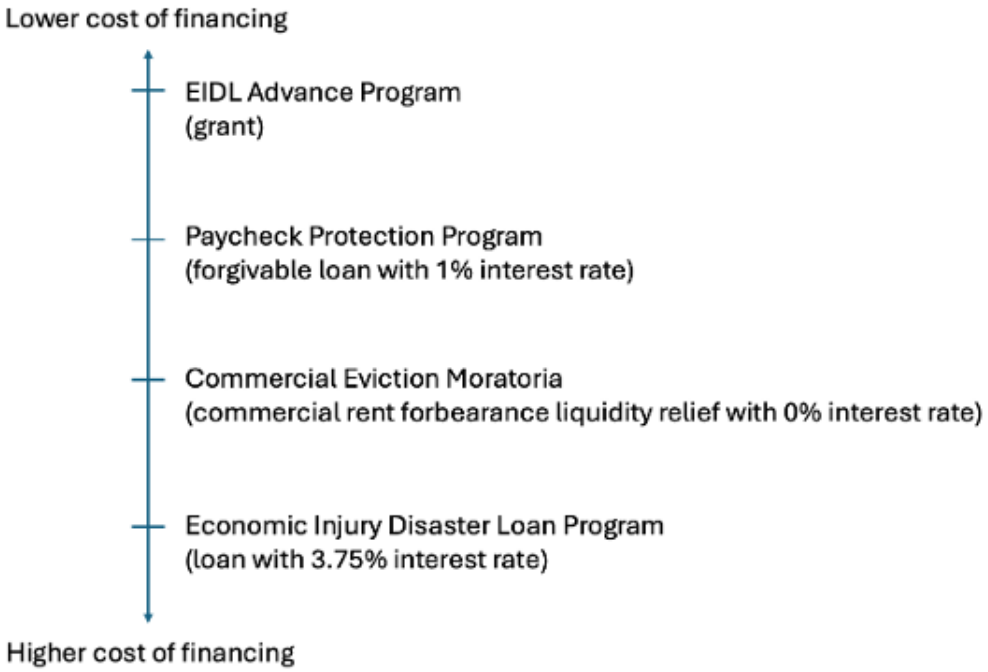


Table 1: Summary statistics for commercial rent forbearance

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

Panel A: State-level commercial rent forbearance policy

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

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

Panel B: County-level commercial rent forbearance policy

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

Panel C: Incorporated city-level commercial rent forbearance policy

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

Table 2: Summary statistics for business closure

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

NAICS sector:	Number of business establishments	Likelihood of closure (pps)						
		2019–2024	2019	2020	2021	2022	2023	2024
Agriculture, forestry, fishing and hunting	1,454	11.28	0.14	0.28	0.41	0.69	5.30	4.47
Construction	36,461	17.33	0.49	0.74	0.66	4.38	4.50	6.55
Manufacturing	19,666	13.82	0.20	0.64	0.52	4.89	3.07	4.51
Wholesale trade	7,637	11.69	0.13	1.47	1.28	3.38	2.32	3.12
Retail trade	184,564	26.55	0.38	1.70	1.56	9.95	5.22	7.75
Transportation and warehousing	48,494	4.99	0.14	0.29	0.28	1.44	1.33	1.50
Information	16,018	25.71	0.19	4.60	1.35	7.17	5.87	6.52
Real estate and rental and leasing	70,920	10.39	0.17	1.02	0.61	3.22	1.84	3.53
Professional, scientific, and technical services	64,521	15.75	0.24	0.50	0.50	3.16	4.02	7.33
Management of companies and enterprises	4,120	0.36	0.00	0.05	0.02	0.02	0.07	0.19
Admin. and support and waste mgmt. services	21,171	14.43	0.54	0.75	0.66	3.16	4.65	4.69
Educational services	27,550	11.32	0.28	0.74	0.64	3.05	2.11	4.50
Health care and social assistance	184,010	11.15	0.15	0.60	0.53	4.55	2.10	3.22
Arts, entertainment, and recreation	51,478	16.75	0.34	1.15	0.89	4.87	3.42	6.08
Accommodation and food services	135,838	28.78	0.51	2.55	2.24	9.24	6.33	7.91
Other services	162,643	16.59	0.63	1.74	1.23	4.74	3.32	4.93

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

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

	More liquidity-constrained sectors			Less liquidity-constrained sectors		
	Quarterly business closure (bps)			Quarterly business closure (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-8.729**	-8.777**	-8.803**	2.110	2.208	2.269
	(3.716)	(3.719)	(3.732)	(5.243)	(5.264)	(5.279)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
City-city border	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	2,586,512	2,586,512	2,586,512	835,148	835,148	835,148
R-squared	0.001	0.003	0.003	0.001	0.002	0.002

Table 4: Impact of liquidity relief on business closure: By sector growth

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. In the first two columns, the sample is restricted to retail trade businesses. In the last two columns, the sample is restricted to accommodation & food services businesses. The outcome variable is business closure measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. Sector growth is the sector's employment growth from 2010 to 2020 in percentage points. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median house price, log median gross rent, log per capita income, poverty rate, high school education rate, and partisanship spread. Standard errors are clustered at the sector level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained sectors		Less liquidity-constrained sectors	
	Quarterly business closure (bps)		Quarterly business closure (bps)	
	(1)	(2)	(3)	(4)
Treated x Post x Sector growth	-0.741**	-0.739**	0.148	0.143
	(0.284)	(0.286)	(0.360)	(0.363)
Treated x Post	Yes	Yes	Yes	Yes
Treated x Sector growth	Yes	Yes	Yes	Yes
Post x Sector growth	Yes	Yes	Yes	Yes
Treated	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes
Fixed effects:				
City-city border	Yes	Yes	Yes	Yes
NAICS sector	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	2,586,512	2,586,512	832,618	832,618
R-squared	0.003	0.003	0.002	0.002

Table 5: Impact of liquidity relief on business closure:
Accommodation & food services v.s. retail trade

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

	Accommodation & food services		Retail trade	
	Quarterly business closure (bps)		Quarterly business closure (bps)	
	(1)	(2)	(3)	(4)
Treated x Post	-21.31**	-21.24**	-2.649	-2.733
	(8.475)	(8.448)	(6.577)	(6.592)
Treated	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes
Fixed effects:				
City-city border	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	402,915	402,915	582,650	582,650
R-squared	0.002	0.003	0.002	0.002

Table 6: Impact of liquidity relief on business closure: Short-run v.s. later-run effects

The table presents results of the business x quarter-level difference-in-differences analysis around commercial rent forbearance policies. In the first two columns, the sample is restricted to the shorter run period when the policy is in place (through 2021q3). In the last two columns, the sample is restricted to the later run period (from 2021q4 on). The outcome variable is business closure measured in basis points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Post is a dummy variable that takes a value of one (zero) in the quarters after (before) the commercial rent forbearance policy. Sector growth is the sector's employment growth from 2010 to 2020 in percentage points. A city-city border encapsulates the area along the border of neighboring cities with differing commercial rent forbearance policies. Control variables include indicator of chain business, log median house price, log median gross rent, log per capita income, poverty rate, high school education rate, and partisanship spread. Standard errors are clustered at the sector level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained sectors			
	Shorter run		Later run	
	Quarterly business closure (bps)		Quarterly business closure (bps)	
	(1)	(2)	(4)	(5)
Treated x Post x Sector growth	-0.334*	-0.334*	-0.965*	-0.960*
	(0.171)	(0.171)	(0.421)	(0.426)
Treated x Post	Yes	Yes	Yes	Yes
Treated x Sector growth	Yes	Yes	Yes	Yes
Post x Sector growth	Yes	Yes	Yes	Yes
Treated	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes
Fixed effects:				
City-city border	Yes	Yes	Yes	Yes
NAICS sector	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	1,162,012	1,162,012	1,815,360	1,815,360
R-squared	0.001	0.001	0.004	0.005

Table 7: Impact of liquidity relief on business opening

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

	More liquidity-constrained sectors			Less liquidity-constrained sectors		
	Quarterly business opening (bps)			Quarterly business opening (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-0.567	-0.567	-0.567	1.846	1.846	1.846
	(0.866)	(0.866)	(0.866)	(1.433)	(1.433)	(1.433)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
City-city border	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	2,741,172	2,741,172	2,741,172	869,694	869,694	869,694
R-squared	0.000	0.001	0.001	0.000	0.003	0.003

Table 8: Impact of liquidity relief on usage of other financing

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

Panel A: More liquidity-constrained sectors						
	EIDL Advance grant		PPP forgivable loan		EIDL loan	
	Indicator	Ln(1 + Amount)	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)
Treated	-0.00660	-0.0550	-0.0167	-0.189	-0.00866**	-0.0968*
	(0.00726)	(0.0619)	(0.0107)	(0.116)	(0.00424)	(0.0488)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,574	129,574	129,574	129,574	129,574	129,574
R-squared	0.028	0.028	0.027	0.026	0.019	0.017
Panel B: Less liquidity-constrained industries						
	EIDL Advance grant		PPP forgivable loan		EIDL loan	
	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)	Indicator	Ln(1+Amount)
Treated	0.00180	0.0322	-0.00916	-0.147	0.00177	-0.0293
	(0.00859)	(0.0737)	(0.0125)	(0.152)	(0.00634)	(0.0740)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,248	41,248	41,248	41,248	41,248	41,248
R-squared	0.022	0.023	0.066	0.071	0.019	0.019

Appendix A: Additional Figures & Tables

Figure A.1: Impact of liquidity relief on business closure: By industry

This figure plots for each sector the pre-pandemic growth in number of establishments v.s. the business closure effects of liquidity relief.

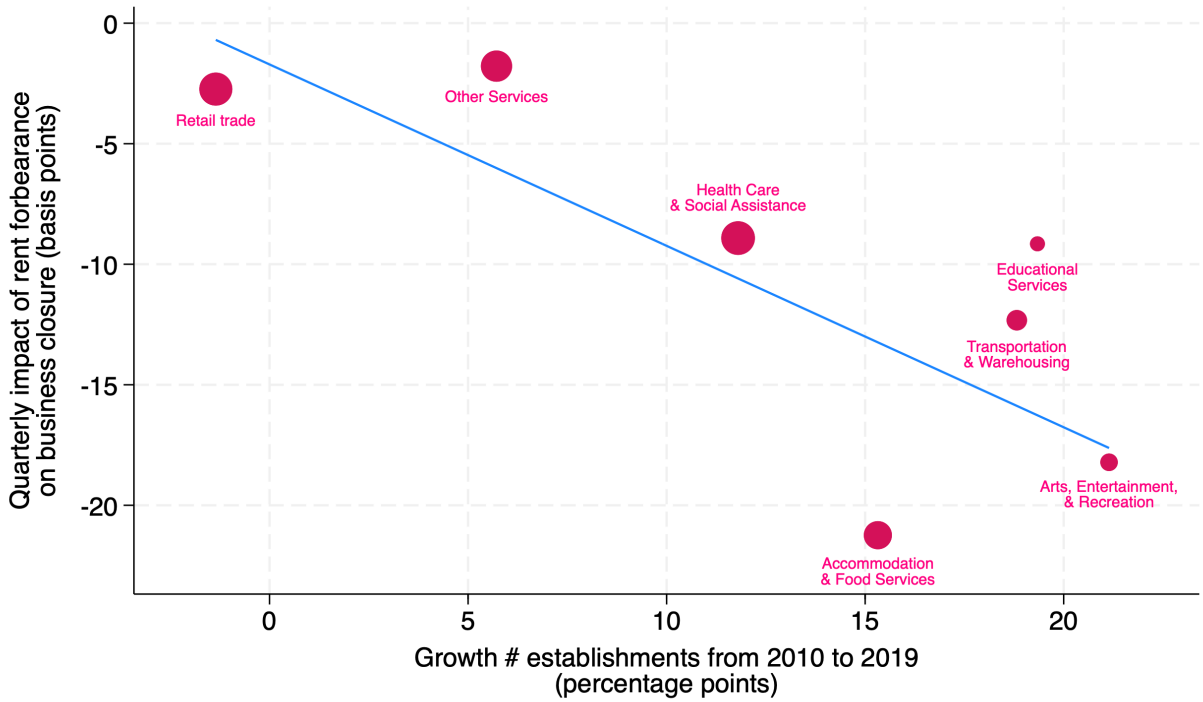


Figure A.2: Impact of liquidity relief on business closure: By industry

This figure plots for each sector the pre-pandemic growth in number of firms v.s. the business closure effects of liquidity relief.

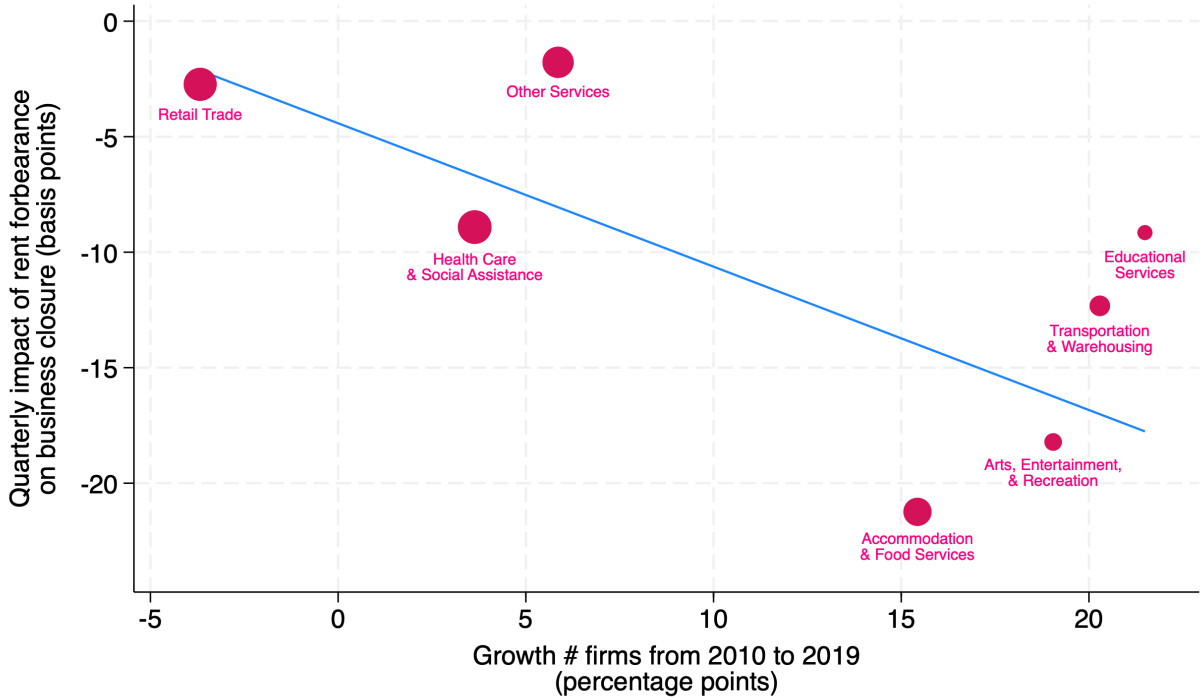


Table A.I: Correlation between business closure and commercial rent forbearance

The table presents original least squares estimates of the relationship between business closure and commercial rent forbearance. Observations are at the business level. In the first three columns, the sample is restricted to above-median liquidity-constrained sectors. In the last three columns, the sample is restricted to below-median liquidity-constrained sectors. The outcome variable is business closure in percentage points. Treated is an indicator variable that takes a value of one if the business is subject to a commercial rent forbearance policy, and zero otherwise. Control variables include indicator of chain business, log median house price, log median gross rent, log per capita income, poverty rate, high school education rate, and partisanship spread. Standard errors are clustered at the city level and reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	More liquidity-constrained sectors			Less liquidity-constrained sectors		
	Business closure (pps)			Business closure (pps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	2.307***	2.456***	1.273***	2.092***	1.833***	0.751*
	(0.802)	(0.619)	(0.317)	(0.431)	(0.381)	(0.403)
Fixed effects:						
NAICS sector	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	712,248	712,248	712,248	219,263	219,263	219,263
R-squared	0.001	0.040	0.048	0.001	0.016	0.022

Table A.II: Impact of liquidity relief on new lease pricing

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

	More liquidity-constrained sectors			Less liquidity-constrained sectors		
	Net effective rent ($)			Net effective rent ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-0.967	-0.0967	0.576	-5.011	-5.633	-4.313
	(2.230)	(2.283)	(2.416)	(4.360)	(4.277)	(3.828)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
City-city border	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	1,052	1,052	1,052	773	773	773
R-squared	0.080	0.173	0.285	0.168	0.207	0.307

Table A.III: Impact of liquidity relief on business closure: Low eviction rate

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

	More liquidity-constrained sectors		Less liquidity-constrained sectors	
	Quarterly business closure (bps)		Quarterly business closure (bps)	
	(1)	(2)	(4)	(5)
Treated x Post x Low eviction rate	-12.02*	-12.05*	-5.916	-6.051
	(6.891)	(6.915)	(10.58)	(10.60)
Treated x Post	Yes	Yes	Yes	Yes
Treated x Low eviction rate	Yes	Yes	Yes	Yes
Post x Low eviction rate	Yes	Yes	Yes	Yes
Treated	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes
Fixed effects:				
City-city border	Yes	Yes	Yes	Yes
NAICS sector	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	2,586,512	2,586,512	835,148	835,148
R-squared	0.003	0.003	0.002	0.002

Table A.IV: Impact of liquidity relief on business closure: Standalone v.s. chain establishments

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

More liquidity-constrained sectors						
	Standalone establishments			Chain establishments		
	Quarterly business closure (bps)			Quarterly business closure (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated x Post	-8.475**	-8.549**	-8.552**	-11.01	-10.79	-10.73
	(4.054)	(4.064)	(4.062)	(8.013)	(7.996)	(8.019)
Treated	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
City-city border	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	2,282,595	2,282,595	2,282,595	303,917	303,917	303,917
R-squared	0.001	0.003	0.004	0.001	0.002	0.002

Appendix B: Theoretical Framework

Section 1 introduces the setup of the model of commercial rent forbearance in liquidity provision during the Covid-19 crisis. Section 2 analyzes the impact of commercial rent forbearance on business closure and discusses empirical predictions.

1 Model setting

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

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

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

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

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

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

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:

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

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:

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

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

2 The impact of commercial rent forbearance on business closure

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

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

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

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

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

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

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

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

Proposition 1
Under the assumptions outlined above, strictly more businesses operate at $t = 1$ with commercial rent forbearance than without commercial rent forbearance.
Specifically, we have: $F_1^{c*} - F_1^* > 0$.

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

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

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

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

The propositions yield the following empirical predictions.

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

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

Appendix C: Theoretical Framework Solutions

1 Baseline model

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

1.1 Private market outcome

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

Steady state: $t = \infty$

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

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

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:

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

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:

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

Combining these two cases, we have:

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

Initial date: t = 1

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

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

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

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

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:

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

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:

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

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.

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

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:

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

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:

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

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

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

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:

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

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

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

Writing this out, we obtain:

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

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:

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

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:

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

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

2 Private market outcome with commercial rent forbearance policy

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

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

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

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

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

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

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

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

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

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

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

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

Interim date: $t = 2$

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

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

There are two cases.

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

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

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

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:

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

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:

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

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

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

There are then 2 relevant cases.

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

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

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

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

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

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

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

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

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

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

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

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

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:

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

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:

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

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:

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

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

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

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

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

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

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

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix D: Instrumental Variable Strategy

In this section, I estimate the impact of liquidity relief on business closure using an instrumental variable empirical strategy and business closure data as of November 2023. To begin, I identify the causal impact of liquidity relief on business closure by developing an instrument for commercial rent forbearance based on pre-pandemic partisanship after controlling for alternative channels. I also estimate the impact by year and by industry. Finally, I test the relationship between pre-pandemic business solvency and the effectiveness of CEM in reducing business closure.

1 Estimating the causal impact of CEM on business closure

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

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

1.1 Developing an instrument for commercial eviction moratoria

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

1.2 Business solvency & the impact of CEM on business closure

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

Motivated by the differing effectiveness of CEM in retail v.s. food services, I consider differences in business solvency as one explanation. Prior to the pandemic, the retail industry was experiencing loss of market share to e-commerce while the food services industry was experiencing steady growth. Panel A of Figure C.2 presents the evolution of employment for non-farm industries overall and for retail and food services specifically. Employment is indexed to 2010. The growth of employment in retail has slowed and even turned negative over the last 10 years, such that employment in retail has grown substantially more slowly than in non-farm employment overall. This fact is reflective of the "retail apocalypse" phenomenon established in the news and academic literature. 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).[17] Panel B of Figure C.2 presents the evolution of employment in sub-industries within retail. Over the period 2010-2019, the sub-industry with the fastest growth in employment is motor vehicle & parts dealers (NAICS 441), while the sub-industry with the slowest growth in employment is electronics & appliance stores (NAICS 443).

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

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

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

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

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

2 The impact of CEM on business financing

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

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

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.

2.1 Impact of CEM on business borrowing from EIDL

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

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

I obtain details on loans administered through this program from the public database on federal spending.[19] Throughout the U.S., the COVID EIDL program disbursed ∼3.9 million loans totaling ∼$380 billion. In my sample of California, the program disbursed ∼600,000 loans totaling ∼$68 billion. My analysis proceeds at the zip code level. After connecting SafeGraph business establishment data and EIDL loan data at the zip code level, I compute the average dollars of borrowing per business by dividing the total dol-

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

lars of EIDL loans disbursed to a zip code by the total number of business establishments in the zip code. Each zip code-level observation therefore represents the EIDL borrowing behavior of the average business in the zip code.

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

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

2.2 Impact of CEM on government grant take-up

In this section, I examine the effect of CEM on business grant take-up from the EIDL advance program and Paycheck Protection Program. The EIDL advance program provides grants of up to $15,000 to businesses that can be used for working capital and operating expenses during the Covid-19 pandemic. EIDL advances do not need to be repaid.[20]

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

Meanwhile, the Paycheck Protection Program provides forgivable loans to small businesses to be used primarily for payroll, rent, utilities, and interest on mortgages.[21] The loan amount is determined as a multiple of a business's monthly payroll cost. Loans are fully forgiven if the business retains employees and uses at least 60% of funds for payroll. In this way, PPP is effectively a business grant, albeit one with conditions attached.

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

I obtain details on grants administered through the EIDL advance program from the public database on federal spending and details on forgivable loans administered through PPP from the Small Business Administration website. Throughout the U.S., the EIDL advance program disbursed ∼1 million grants totaling ∼$7.5 billion. In my sample of California, the program disbursed ∼150,000 grants totaling ∼$1 billion. Throughout the U.S., PPP disbursed ∼11.8 million forgivable loans totaling face value of ∼$800 billion. In my sample of California, the program disbursed ∼1.3 million forgivable loans totaling face value of ∼$100 billion. 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 C.8 presents the results on the effect of CEM on EIDL advance take-up. In the first 3 columns, I progress from the OLS to the IV specification. In column 1, I find that an additional year of CEM+R is associated with higher EIDL advance take-up, which is consistent with cities enacting longer CEM in response to greater business closure likelihood

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

and distress. This relationship persists after controlling for zip code characteristics in column 2. In column 3, instrumenting for CEM using pre-pandemic partisanship reveals that an additional year of CEM+R has no statistically significant effect on EIDL advance take-up. In column 4, I find that CEM has no significant effect on the extensive margin of EIDL advance take-up, which is the likelihood of receiving an EIDL advance. In column 5, I find that CEM has no significant effect on the intensive margin of EIDL advance take-up, which is the average size of EIDL advances.

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

3 The impact of CEM on business employment

The impact of CEM on business closure established in the last section implies that CEM affects business employment along an extensive margin. In this section, I estimate the impact of CEM on business employment along an intensive margin by re-employing the instrumental variable approach and applying it to business payroll data. Specifically, I estimate the impact of CEM on employment conditional on the business being alive, i.e. along an intensive margin. Then, I take stock of the extensive and intensive margin employment effects and benchmark the overall employment effect of CEM against the

Paycheck Protection Program.

3.1 The intensive-margin impact of CEM on business employment

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

Table C.10 presents the results on the impact of CEM on intensive-margin employment. In the first 3 columns, I progress from the OLS to the IV regression specification. In column 1, I find that an additional year of CEM+R is associated with lower employment. In column 2, controlling for zip code characteristics changes the sign of the coefficient on length of CEM from negative to positive, though it is statistically insignificant. In column 3, instrumenting for CEM using pre-pandemic partisanship further increases the 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 C.11 presents the analysis split by retail vs. food services, where we again find statistically insignificant effects for

each sector and in each year.[22] In sum, the results suggest that there is no significant effect of CEM on intensive-margin employment in this sample of smaller businesses.

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

3.2 The total impact of CEM on business employment

The total effect of CEM on business employment consists of both the extensive-margin and intensive-margin effects. The results in the last section show no intensive-margin effect. I now turn to the extensive-margin effect, which is captured by the results on business closure. This is because 100% of its employment is lost when a business closes. The results in Section 4.1 show an overall 0.80 percentage point decline in business closure likelihood over the period 2020-2022. This implies that the total impact of an additional year of CEM+R on business employment is approximately 0.80 percentage points of January 2020 employment. When we consider that the average length of CEM+R is 1.22 years, the total impact of average CEM+R on business employment is an increase of 0.98 percentage points relative to employment in January 2020.[24]

To benchmark the economic significance of the employment effects of CEM, we take stock of the employment effects of PPP estimated in the literature. Chetty et al. (2024) find that PPP increased the number of jobs by 2.48 percentage points of January 2020 em-

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

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

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

ployment.[25] The overall employment effects of CEM that I estimate are approximately 39% (0.98 / 2.48) of the employment effects of PPP. This is striking when we consider that CEM is an intervention that does not inject government funds into businesses and that instead provides liquidity relief through delayed rent payment. Another notable difference is that CEM and PPP have different units of policy. CEM is measured in number of years, such that policymakers must choose how long to pause evictions and delay rent payment. In comparison, PPP is measured in dollars of loans, such that policymakers must choose how much funding to inject into businesses.

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

Figure C.1: Relationship between CEM and partisanship

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

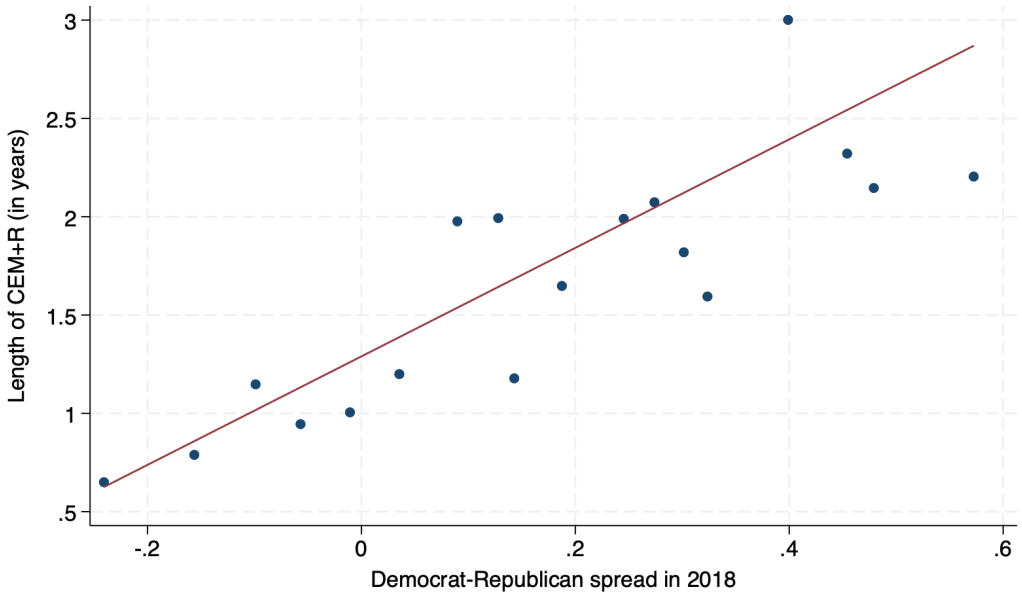
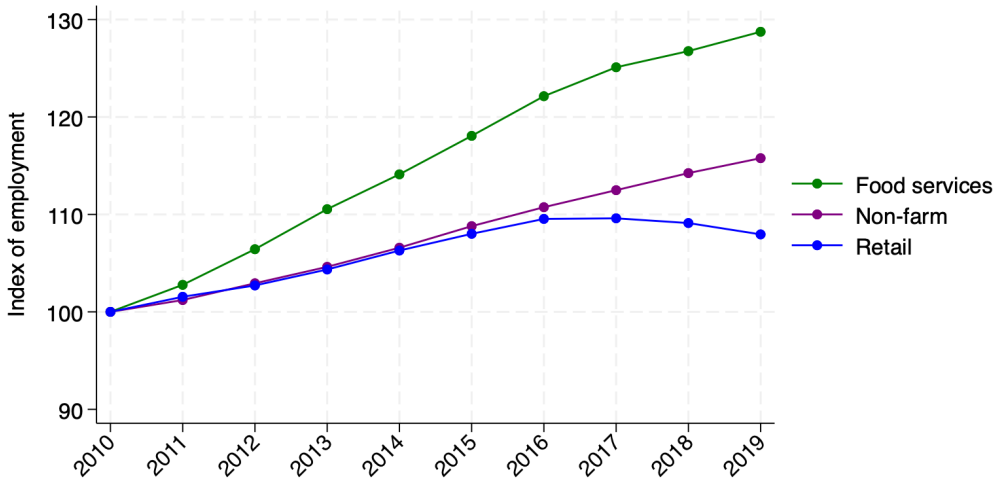


Figure C.2: Index of employment for non-farm, retail, and food services

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

Panel A: Employment by industry



Panel B: Employment of sub-industries in retail

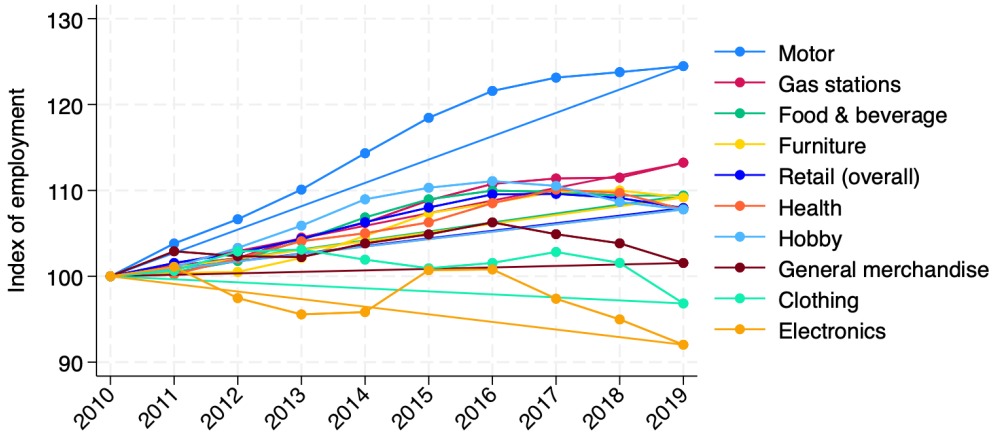


Figure C.3: Relationship between pre-pandemic employment growth and CEM business closure effects

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

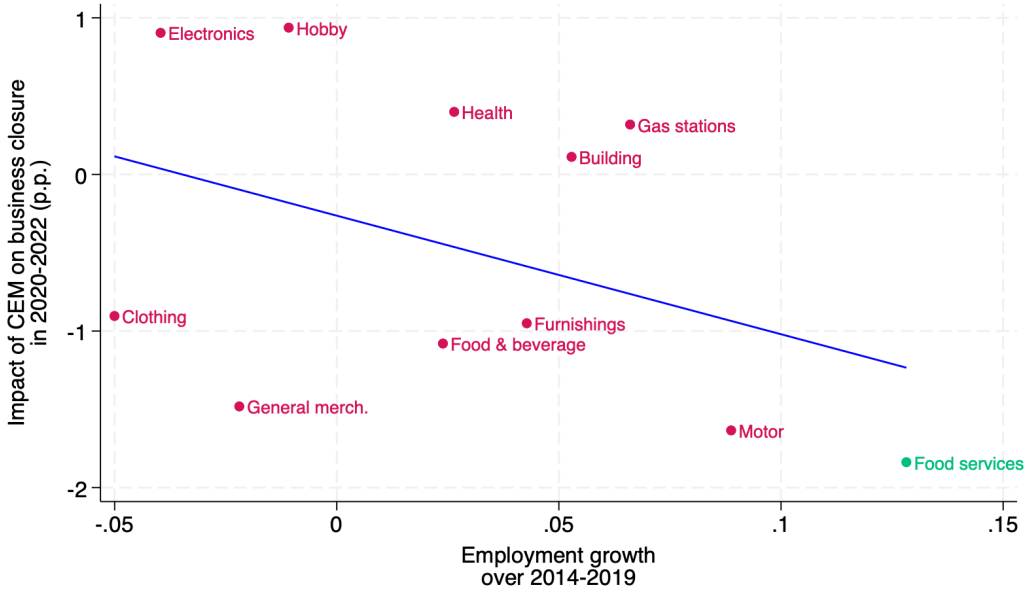


Table C.1: Covariate balance along the axis of pre-pandemic partisanship

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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