

# The Impact of COVID-19 on Small Business Dynamics and Employment: Real-Time Estimates With Homebase Data\*

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## Abstract

We use data from Homebase to construct weekly estimates of the impact of the COVID-19 pandemic on small business dynamics and employment. Different from concurrent research, we match the Homebase establishment records to information on business activity from Google, Facebook, and Safegraph to distinguish business closings and new openings from sample churn. This distinction turns out to be critical to properly quantify the important role played by business closings and new openings. We find four key results: (1) employment of small businesses in four of the hardest hit service sectors contracted much more severely in the beginning of the pandemic than employment of larger businesses, but small business employment also rebounded more strongly and has recovered as much as employment of larger businesses; (2) closings account for more than half of the initial decline in small business employment, but many closed businesses have reopened and cumulative closings are not higher than prior to the pandemic; (3) new openings of small businesses have been almost as high as before the pandemic, constituting the main driver of the recovery since mid-June; (4) employment growth, closing rates and new opening rates of small businesses were affected more negatively in localities with large Covid case and death rates, large declines in visits to elementary and secondary schools, high household incomes, delayed access to loans from the Paycheck Protection Program, and low unemployment insurance replacement rates. Our results dispel the popular notion that small businesses have on average been hurt harder by the pandemic than larger businesses. At the same time, our analysis suggests that the local health situation, school closings, and the differential impact of federal economic policies aimed at mitigating the negative effects of the pandemic significantly affected small business activity.

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# 1 Introduction

The COVID-19 pandemic unfolded with tremendous speed and continues to affect the U.S. economy in unprecedented ways. Contrary to other recessions, the disruptions caused by the pandemic are concentrated in service sectors that require in-person interaction. In most of these sectors, establishments with fewer than 50 employees account for more than half of all jobs. It is therefore important to understand the effect that the pandemic has on small businesses, especially because there is widespread concern that independently owned businesses have suffered more than larger multi-establishment companies, and that a disproportionate number of small businesses have closed. To what extent this is the case remains an open question, however, since small businesses closing and opening rates are high even under the best of circumstances and it takes more than a year for official data on small business dynamics and employment to be published.<sup>1</sup> Furthermore, the official data once published is either at quarterly or annual frequency. This lack of timely high-frequency data makes it difficult to measure the current state of the economy and assess the effects on small businesses of different economic policies aimed at mitigating the adverse impacts of the pandemic.

In this paper, we address this challenge by constructing real-time estimates of small business dynamics and employment using data from Homebase, a scheduling and time clock software provider used by more than 100,000 mostly small service-sector businesses in the U.S. Different from the many other studies reviewed below that use Homebase or other high-frequency establishment-level data, we match the Homebase records with information on business activity from Google, Facebook and SafeGraph to distinguish business closings and openings from sample churn; i.e. already operating businesses entering the sample or businesses that continue to operate after exiting the sample. This distinction is critical not only for Homebase data but also for other private-sector databases with large client turnover, and even for the official monthly establishment survey estimates from the Current Employment Statistics (CES).<sup>2</sup>

Based on our estimates of business openings and closings, we construct sector-specific estimates of small business employment, establishment counts, as well as number of hours worked. We benchmark the pre-pandemic estimates against administrative data from the Quarterly Census of Employment and

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<sup>1</sup>The BLS publishes monthly employment estimates but these estimates are not available by establishment size class. Statistics by establishment size and industry are only released late each year for mid-February of that year. It will therefore take until late 2021 for the data incorporating the pandemic to be released. In addition, each quarter the BLS publishes data on establishment openings and closings. Data for the second quarter of 2020 was published in late January 2021 but is not available for different size classes. Alternatively, the U.S. Census Bureau publishes establishment counts, employment, and entry and exit by detailed industry and size class but only with a lag of two to three years and at an annual frequency.

<sup>2</sup>As discussed in more detail below, the employment estimates from the CES historically did not directly take into account establishment entry and exit and instead adjusted employment changes from business birth/death based on historical data. Faced with extraordinary numbers of business closings in the beginning of the pandemic, the BLS modified this procedure in April 2020 but without directly distinguishing business openings and closings from sample churn.

Wages (QCEW) and the Business Employment Dynamics (BED) from the Bureau of Labor Statistics (BLS) as well as the Business Dynamics Statistics (BDS) from the U.S. Census Bureau. We find that for the service sectors hit hardest by the pandemic, our Homebase estimates are surprisingly representative – not just in the cross-section but also with respect to employment growth and business openings and closings. Abstracting from sample churn is critical for this good fit.

Next, we analyze the impact of the pandemic on small businesses and compare our weekly estimates against the official monthly estimates of employment and hours from the CES as well as other estimates in the literature. The main novelty of our analysis is that we directly quantify the importance of business closing and openings for the sharp contraction of employment in March and April 2020 and the subsequent recovery. In addition, we exploit our establishment-level identification of closings and new openings to investigate the extent to which small business activity is associated with highly localized (county and zip-code) variations in pandemic-related health measures, non-pharmaceutical interventions (NPIs), and different economic policies enacted as part of the CARES Act.

Given the coverage of Homebase, we focus our analysis on small businesses with less than 50 employees in four of the sectors that were among the most affected by the pandemic: Retail Trade, Educational & Health, Leisure & Hospitality, and Other Services. Small business employment in these four sectors accounted for 23% of total private sector employment prior to the pandemic.

We find four key results. First, small business employment in the four sectors contracted by an estimated 14 million between mid-February and mid-April – a staggering 46% decline – and then regained about 10 million by mid-June. Between mid-June and the end of 2020, employment gradually recovered most of the losses except in Leisure & Hospitality where employment remains about 15% below the pre-pandemic level.<sup>3</sup> Both the large decline in the beginning of the pandemic and the subsequent rebound are considerably larger than the CES estimates for average employment in the four sectors as well as other prominent estimates by [Cajner et al. \(2020\)](#) and [Chetty et al. \(2020\)](#) based on other private-sector data. Our estimates therefore imply that employment by small businesses contracted more severely in the beginning of the pandemic than employment of larger businesses but then also rebounded more strongly, primarily through rehiring of previously furloughed workers. Moreover, while average weekly hours worked of job stayers declined sharply in the beginning of the pandemic, they recovered quickly and even moved slightly above pre-pandemic levels. Currently, small business employment in the four sectors is somewhat higher relative to pre-pandemic levels than employment of larger businesses, thus

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<sup>3</sup>These estimates, which are available weekly with a lag of only a few days, predicted not only the sharp drop in service-sector employment from mid-March to mid-April and the strong yet partial recovery from mid-April to mid-June that the BLS reported in its [Employment Situation](#) with a lag of several weeks, but also the slowdown in recovery since mid-June.

dispelling the popular notion that small businesses have on average been hurt harder by the pandemic than larger businesses.

Second, we decompose changes in small business employment into different contributions and find that more than half of the large decline in the beginning of the pandemic is due to business closings, which reached 40% in mid-April. Since mid-April, however, about two thirds of closed businesses have reopened while the rest appears to have closed permanently. Relative to before the pandemic, the cumulative annual closing rate of small businesses in the four sectors therefore amounts to about 13%, which is almost exactly the same closing rate as estimated for the years prior. This implies, perhaps surprisingly, that the pandemic has not led to a higher rate of permanent closings.

Third, new businesses openings have added almost 2 million new jobs since the pandemic started and have constituted the strongest driver of the recovery from mid-June onward. The surprisingly high rate of new business openings is consistent with recent findings by Haltiwanger et al. (2020) on new business formations, although we find that compared to 2019, the rate of new business openings is slightly lower. This highlights the crucial role played by new openings for the future of the recovery of small business employment and, by extension, for total employment in these service sectors.

Fourth, establishment-level regressions reveal that employment growth of still active small businesses are lower and business closing rates are higher in counties with large Covid infection and death rates. NPIs intended to contain the spread of the virus, by contrast, exert on average only a relatively modest additional effect on small business activity. This confirms and extends results by Bartik et al. (2020), Chetty et al. (2020) and Goolsbee and Syverson (2020) among others who find that health concerns as opposed to lockdown and reopening measures were the primary driver of the collapse and rebound of local business activity in the beginning of the pandemic. Interestingly, the only NPI that has a sizable adverse effect not only on employment growth but also on closings and new openings is the change in county-level visits to schools, suggesting that availability of in-person education for school children has a significant effect on the labor supply of their parents.<sup>4</sup>

Our estimates also reveal that zip codes with high pre-pandemic household incomes experienced persistently higher closing rates and lower new opening rates over the past year. This is consistent with Chetty et al. (2020) who document that the dramatic reduction in spending on in-person services in the beginning of the pandemic occurred primarily in affluent zip codes. Our results show that this effect not only affected the intensive margin (employment of continuing businesses) but also the extensive margin

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<sup>4</sup>As Bravata et al. (2021), we measure school visits using Safegraph data for elementary and secondary schools. To our knowledge, we are the first to relate this measure to labor market outcomes.

(business closings and new openings), implying that local differences in the recovery of small business activity may be long-lasting. Interestingly, we also find that the gap in closing rates widens temporarily starting in mid-April 2020. This widening, although modest in size, coincides with the disbursement of stimulus checks that were part of the CARES Act and led to an increase in spending by lower-income households, thus providing indirect evidence that the stimulus checks led to a limited demand boost for small business activity in less affluent areas.

Next, we evaluate the impact of government loans made to small businesses through the Paycheck Protection Program (PPP) using a novel research design by Doniger and Kay (2021) that exploits plausibly exogenous local differences in the timing of PPP loans due to the temporary exhaustion of PPP funds in early April. We show that their measure of the share of delayed PPP loans, constructed at the zip-code level from the data made public by the Small Business Administration (SBA), predicts significantly higher closing rates but, quite sensibly, no impact on new business openings. While quantitatively small relative to the wide overall swings in closing rates in the beginning of the pandemic, we find that about half of the impact effect persists through today – presumably because some businesses that did not receive loans in time closed permanently and were not replaced by new businesses. This provides an explanation for the finding by Doniger and Kay (2021) that the share of delayed PPP loans had a negative effect on individuals’ unemployment and non-employment rates even months after additional funding for PPP loans became available.

Finally, we consider the effect of differences in unemployment insurance (UI) replacement rates across counties. As Ganong et al. (2020) show, the weekly \$600 in additional Federal Unemployment Pandemic Compensation (FPUC) as part of the CARES Act nearly tripled typical benefits levels, raising the median replacement rate to 145% with three quarters of eligible workers receiving more in UI benefits than their previous labor earnings. This unprecedented increase in UI benefits could have had both negative incentive effects on labor supply and positive labor demand effects from spending by otherwise borrowing constrained low-income households. Our estimates suggest that this demand effect completely dwarfed any disincentive effect that may have affected labor supply. Small business employment and new opening rates are estimated to be significantly higher and closing rates significantly lower in counties with high replacement rates, consistent with the finding above that relatively affluent (i.e. low replacement rate) localities experienced a larger decline in small business activity. These effects roughly double when UI benefits start to get fully disbursed and only abate after the expiration of FPUC and the \$300 per week of supplemental assistance that was paid out primarily in September and October. Our estimates are consistent with a number of studies finding only limited or no adverse effects of FPUC on local labor

supply (e.g. Dube 2021, Finamor and Scott 2021 and Marinescu et al, 2021) and, simultaneously, the recent findings by Ganong et al. (2021) that FPUC led to large spending responses by lower income groups.

The paper contributes to a now extensive literature measuring the impact of the COVID-19 pandemic on U.S. labor markets and businesses. The Homebase data has been among the most widely used in this respect (e.g. Homebase, Bartik et al. 2020, Bartlett and Morse 2020, Granja et al. 2020, Finamor and Scott, 2021 among others). Other prominent studies that use different private-sector datasets to estimate the impact of the pandemic on employment are Bick and Blandin (2020), Cajner et al. (2020), Chetty et al. (2020), Coibon et al. (2020) and Kahn et al. (2020).<sup>5</sup> To our knowledge, we are the first to match establishment records with other information on business activity to identify business closings and openings and distinguish it from sample churn. As we show, doing so is critical both for estimating the impact of the pandemic on small business employment and to properly benchmark against administrative data from pre-pandemic years. Indeed, one of the perhaps most surprising results of our analysis is that business closings and new openings are, a year after the pandemic started, very similar to previous years. In addition, our approach allows us to directly analyze how business closings and new openings are associated with local differences in pandemic outcomes, NPIs and economic policy responses.

Aside from the already discussed paper by Chetty et al. (2020), the paper closest related to ours is Cajner et al. (2020) who use micro-data from ADP, the biggest payroll processing company in the U.S., and estimate that U.S. private-sector employment declined by about 21% or 26.5 million between mid-February and late April and then rebounded modestly thereafter. Consistent with our estimates, they also find a disproportionate contraction in customer-oriented service sectors and a large effect from small businesses closures. Another closely related paper is Dalton et al. (2020) who use CES microdata to show that employment of small businesses initially contracted more but then also rebounded more strongly than employment of larger businesses. Neither of these papers distinguish business closings and new openings from sample churn.

## 2 Estimating small business dynamics and employment

Our goal is to construct an estimate of small business employment that directly incorporates the effects of establishment openings and closings. For each sector (e.g. Leisure & Hospitality), we start with the CES employment estimate  $\hat{E}_0$  from February 2020 (the reference week) and estimate employment in week

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<sup>5</sup>There are many other papers analyzing the employment impact of the pandemic. We will cite them as the draft progresses.

$t$  as

$$\hat{E}_t = \hat{E}_{t-1} \times \frac{\sum_i \omega_i (\hat{e}_{it}^{\mathcal{A}_{i,t}} + \hat{e}_{it}^{\mathcal{O}_{i,t}})}{\sum_i \omega_i (\hat{e}_{it-1}^{\mathcal{A}_{i,t}} + \hat{e}_{it-1}^{\mathcal{C}_{i,t}})}, \quad (1)$$

where  $\omega_i$  denotes the sampling weight for industry-size cell  $i$ , constructed as the ratio of QCEW establishment counts in 2020:Q1 to HB establishment counts in that industry-size cell;  $\hat{e}_{it}^{\mathcal{A}_{i,t}}$  denotes employment of the set of establishments  $\mathcal{A}_{i,t}$  that are active in HB in both week  $t$  and  $t - 1$ ;  $\hat{e}_{it}^{\mathcal{O}_{i,t}}$  denotes employment of the set of establishments  $\mathcal{O}_{i,t}$  that are newly opening or reopening in week  $t$ ; and  $\hat{e}_{it-1}^{\mathcal{C}_{i,t}}$  denotes employment of the set of establishments  $\mathcal{C}_{i,t}$  that are closing temporarily or permanently in week  $t$ .

The main challenge in constructing this estimator is to distinguish business openings and closings from sample churn. In other words,  $\mathcal{O}_{i,t}$  should not include establishments that appear in HB for the first time in week  $t$  but operated already previously; and  $\mathcal{C}_{i,t}$  should not include establishments that disappear from HB in week  $t$  but continue to operate. Sample churn is important for many establishment-level datasets by private-sector providers that acquire and drop clients on a continuous basis and especially for HB, which has been growing strongly over the past years including during the pandemic. The next two sections explain how we match the HB data with other information to identify sample churn and the extent to which abstracting from sample churn matters.

Our estimator is conceptually similar to the “weighted link-relative technique” behind the CES employment estimate that the BLS reports in the monthly [Employment Situation](#).<sup>6</sup> But there are also important differences. First, (1) is a real-time estimator that can be updated weekly whereas the CES estimate is monthly and becomes available with a lag of 3 to 8 weeks and only for all establishments by sector. Second, our estimator directly includes not only employment changes from businesses that are active in  $t$  and  $t - 1$  but also employment changes from business closings and (re)openings. The CES estimator, in contrast, includes only a portion of the establishments that report zero employment in month  $t$  and establishments that return to positive employment in month  $t$ , respectively, and then adjusts separately for new openings and other closings with an econometric “net birth/death” model based on current and historical data.<sup>7</sup> Third, we measure establishment employment as the number of workers

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<sup>6</sup>See <https://www.bls.gov/web/empsit/cestn.htm> for details on the CES and estimation.

<sup>7</sup>Historically, the CES estimation only included establishments that reported positive employment in both  $t$  and  $t - 1$  and the net/birth death adjustment was based on an econometric model of net birth/death residuals from QCEW data over the preceding five years. By not including establishments that failed to report employment in both months, the CES estimate effectively treated them as deaths and imputed employment growth of the sample of active establishments so as to offset missing employment gains from establishment birth, which are on average closely related to employment losses from establishment death. In light of the large labor market disruptions caused by the COVID-19 pandemic, the BLS changed its birth/death adjustment from the April report on forward by including a portion of reported zeros in the sample employment growth calculation and by adding current period employment growth to the net birth/death adjustment model. See <https://www.bls.gov/web/empsit/cesbd.htm> for details.

with positive hours in a given week, whereas the CES defines employment as the number of workers on payrolls who received pay for any part of the pay period that includes the 12th day of the month, independent of whether they actually worked or not in that week. As we show below, these differences are especially important in a situation such as the beginning of the pandemic when the number of active establishments and the number of employees actually working changed dramatically within just a few days.

To quantify the sources behind employment fluctuations, we decompose (1) into contributions from continuing establishments, establishment closings, establishment reopenings, and new establishment openings, as well as into contributions from gross hirings and separations. The online [Appendix](#) provides details on these decompositions. Furthermore, we quantify small business dynamics by reporting rates of establishment closings, reopenings, and new openings as

$$rate(\mathcal{I}_t) = \frac{\sum_i \omega_i \hat{n}_{it}^{\mathcal{I}_{i,t}}}{\sum_i \omega_i (\hat{n}_{i0}^{A_{i,1}} + \hat{n}_{i0}^{C_{i,1}})}, \quad (2)$$

where  $\hat{n}_{it}^{\mathcal{I}_{i,t}}$  denotes the count of establishments in industry-size cell  $i$  that closed in week  $t$  ( $\mathcal{I}_{i,t} = \mathcal{C}_{i,t}$ ), reopened in week  $t$  ( $\mathcal{I}_{i,t} = \mathcal{R}_{i,t}$ ), or newly opened in week  $t$  ( $\mathcal{I}_{i,t} = \mathcal{N}_{i,t}$ ), with  $\mathcal{O}_{i,t} = \mathcal{R}_{i,t} \cup \mathcal{N}_{i,t}$  by definition; and  $\hat{n}_{i0}^{A_{i,1}} + \hat{n}_{i0}^{C_{i,1}}$  denotes the count of active establishments in the reference week.<sup>8</sup>

Aside from employment and establishment counts, we also estimate average weekly hours (AWH). To do so, we start with the CES estimate  $\widehat{AWH}_0$  from February 2020, and then use our HB data to estimate

$$\widehat{AWH}_t = \widehat{AWH}_{t-1} \times \frac{(\sum_i \omega_i \widehat{wh}_{it}) / (\sum_i \omega_i \hat{e}_{it})}{(\sum_i \omega_i \widehat{wh}_{it-1}) / (\sum_i \omega_i \hat{e}_{it-1})}, \quad (3)$$

where  $\widehat{wh}_{it}$  is estimated total weekly hours worked and  $\hat{e}_{it}$  estimated employment at establishments in industry-size cell  $i$  in week  $t$ . We compute this estimate for three different groups of workers: all workers employed in active establishments in week  $t$ ; all workers employed in establishments that have remained open continuously throughout the entire sample; and all job stayers who remained employed continuously in establishments that have remained open continuously. We consider all three groups to highlight the effects of compositional change, which turns out to play an important role during the pandemic as many workers are getting temporarily furloughed or laid off. This estimation of AWH is different from the “link

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<sup>8</sup>We define these rates relative to the count of active establishments in the reference week as opposed to the count of active establishments around week  $t$  because the count of active establishments varies dramatically in the beginning of the pandemic. In the Appendix, we provide additional evidence on opening and closing rates relative to average counts over the current and previous quarter and compare it to available data from the BED.



and taper technique” used to construct AWH in the CES, which adjusts the current estimate towards the previous estimate so as to keep it close to the overall sample average over time. The CES estimate may therefore not capture large changes in actual AWH that occur in times of economic disruptions, whereas our estimate does because it is based on current information only.<sup>9</sup>

### 3 Data

The Homebase data consists of anonymized daily records of individual hours worked and wages of employees, linked longitudinally to the establishment where they work and the firm that owns the establishment. The data is recorded in real-time through HB’s proprietary software and is used by many of the businesses for payroll processing. HB provides free data access to researchers and updates the data regularly with the latest observations.

In addition to the publicly available data, HB shares with us counts of owners and managers that use the HB software, hours scheduled by employee for establishments that do not track hours, and name and address information for each establishment. As described below, the information on owners and managers allows us to include salaried workers with untracked hours in our measure of employment while the information on establishments with scheduled hours expands our sample. The information on name and address, in turn, allows us to match HB establishments to data by Google, Facebook, and Safegraph so as to determine industry classification and to distinguish business openings and closings from sample churn. For privacy reasons, all of the results reported below are sufficiently aggregated to avoid disclosing information about individual businesses.

#### 3.1 Employment and business activity

For each establishment, we construct weekly employment as the sum of individuals with tracked hours (actual or scheduled) during that week plus owners and managers that show activity in the HB software but do not have tracked hours.<sup>10</sup> As we show in the [Appendix](#), this attenuates the decline in estimated employment during the pandemic because owners and managers with untracked hours have a higher propensity to remain active than employees with tracked hours.

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<sup>9</sup>The link-and-taper estimate used in the CES can be expressed as  $\widehat{AWH}_t = 0.9(\widehat{AWH}_{t-1} - \widehat{awh}_{t-1}) + \widehat{awh}_t$ , where  $\widehat{AWH}_t$  is the official estimate and  $\widehat{awh}_t = (\sum_i \omega_i wh_{it}) / (\sum_i \omega_i e_{it})$ . If  $\widehat{AWH}_{t-1} > \widehat{awh}_{t-1}$  in the previous month, then the current month official estimate will be raised relative to actual data, and vice versa if  $\widehat{AWH}_{t-1} < \widehat{awh}_{t-1}$ . The CES makes a slight adjustment to this estimator to account for atypical reports although it is unclear what makes a report atypical.

<sup>10</sup>For establishments that report both scheduled and actual hours, we compare the two measures and find them to be very close to each other. We are therefore confident that scheduled hours are an accurate measure of actual hours worked.

For an establishment to be included in our sample it must show up at least once for a spell of three consecutive weeks with at least 40 weekly hours of tracked work across all employees. We therefore abstract from establishments that show up in HB for less than 3 weeks since this most likely reflects trials as opposed to true entry and exit. For an establishment in the sample to be active in a given week, it must have employees with tracked hours in that week. Establishment activity is therefore independent of owners and managers logging in to the HB software (e.g. for reporting purposes).

## 3.2 Industry classification

The historical HB data comes with an industry category for each establishment, but the available categories do not directly line up with standard industry classification and for about one third of the records, industry category is missing altogether. This is an important limitation for the purpose of constructing estimates that can be compared to official statistics. One of the contributions of our paper is to match the HB establishment records by name and address to Safegraph’s Core Places data, which contains consistent NAICS-6 industry coding for each establishment.<sup>11</sup> The procedure involves extensive data cleaning and standardization before matching the records sequentially by exact merges and then fuzzy name match and substring match algorithms. The [Appendix](#) provides details on these procedures as well as match statistics. We only retain HB establishment records that match either exactly or with a high match rate.

As shown in the [Appendix](#), establishments of a different HB industry category do not necessarily match to the expected NAICS industry classification. For example, while over 80% of the establishments in the category “food and drink” match to “Food Services and Drinking Places” (NAICS 722), about 5% match to “Food Manufacturing” (NAICS 311), and about 7% match to various industries in “Retail Trade” (NAICS 44-45). We are exploring these correspondences in more detail in ongoing work.

## 3.3 Business openings and closings

One of the main challenges when working with establishment-level datasets is to distinguish business closings and openings from sample churn; i.e. businesses that already operate before entering the sample or businesses that continue to operate after exiting the sample. This is especially important for private-sector data such as HB that are subject to large turnover and expand their client base over time.

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<sup>11</sup>In November 2020, HB independently started publishing NAICS industry classifications for each establishment. This classification is available only for establishments active from that month onward. Since many establishments that were active in 2019 and 2020 are no longer in the HB sample, this NAICS classification is not directly useful for our estimation and benchmarking, which starts in 2019. However, we compare our industry classifications to the one provided by HB and generally find a high level of overlap.

Our strategy to identify business closings and openings consists of using information about business activity from other data that we match with HB at the establishment level. None of this information is perfect or exhaustive but it allows us to provide an estimate of business closings and openings that can, in addition, be benchmarked against administrative data prior to the pandemic to assess its quality.

For closings, we proceed in four steps. First we consider all establishments that become inactive in week  $t$  (called exits from hereon) and check whether they return to activity by the end of the sample. If so, we attribute them to the set of establishments  $\mathcal{C}_{i,t}$  that close in week  $t$ . Second, we match exiting establishments in HB to Google Places using their API service and add the ones with a “temporary closed” or “permanently closed” indicator to  $\mathcal{C}_{i,t}$ . These indicators are reported by business owners and customers and are typically accurate but cover only a subset of all closed establishments. Third, we match the remaining exiting establishments to Facebook using CrowdTangle, Facebook’s research tool, to check whether the establishments with regular posting histories while being active in HB stop posting regularly after exiting HB. If so, we add the establishments to  $\mathcal{C}_{i,t}$ .<sup>12</sup> Fourth, for the exiting establishments that we cannot match to either Google or Facebook or that do not post regularly on Facebook while being active in HB, we add them to  $\mathcal{C}_{i,t}$  with probability equal to the proportion of closings obtained in step three.

For openings, we adopt a similar procedure, except that Google Places does not contain a corresponding indicator for “openings”. First, we consider all establishments that become inactive at some point and add them to the set  $\mathcal{R}_{i,t}$  that reopen in week  $t$  if they return to activity in that week. Second, we match establishments that become newly active in week  $t$  (called new entrants from hereon) to Facebook and check whether they start having a consistent posting history only after entering HB.<sup>13</sup> In each case, we attribute the establishments that satisfy the condition to the set  $\mathcal{N}_{i,t}$  of new openings. Third, for the new entrants that we cannot match to either Facebook or Safegraph or that do not have reliable data on Facebook postings, we add the establishment to  $\mathcal{N}_{i,t}$  with probability equal to the proportion of new openings obtained in step two.

Both the closings and openings procedure entail substantial data preparation and undergo a variety of consistency checks. These steps as well as details about the procedures are described in the [Appendix](#).

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<sup>12</sup>Alternatively, we check whether exiting HB establishments matched to Safegraph show a large drop off in customer visits in Safegraph’s Weekly Patterns data relative to establishments that remain active in HB. If so, we add the establishments to  $\mathcal{C}_{i,t}$ . After extensive analysis, however, we found that Safegraph visits are very noisy at the individual business level. We therefore prefer the approach using Google and Facebook described here. The [Appendix](#) provides more information and results on both the Google-Facebook approach and the Safegraph approach.

<sup>13</sup>Alternatively, we check whether new entrants that we can match to Safegraph show up in Safegraph Core Places data only after entering HB. Safegraph regularly backfills historical visits data, even for newly opened establishments. As a result, we cannot use changes in visits to determine the start of business activity of newly entering businesses.

### 3.4 Sample characteristics and benchmarking

The data used for the results below extends from January 1, 2018 to January 1, 2021. The raw data contains over 100,000 distinct establishments and we retain about 48,000 establishments that are active during the mid-February reference week and can be matched reliably to Safegraph for industry classification.

As shown in the [Appendix](#), most establishments are small, employing fewer than 50 workers. The sample has the largest coverage in Leisure & Hospitality (NAICS 71 and 72), followed by Retail Trade (NAICS 44-45), Education and Health Services (NAICS 61-62), and Other Services (NAICS 81).<sup>14</sup> Aside from coverage, we focus on these customer-oriented sectors because they appear to be particularly vulnerable to the disruptions and stay-at-home orders caused by the COVID-19 crisis. Together, small businesses in the four sectors account for 30 million jobs in February 2020, which is about 50% of total jobs in the four sectors.

To benchmark the HB data, we use administrative data from the QCEW, which also serves as the sample frame for the CES, as well as data on business dynamics from the BED (based on the QCEW) and the BDS. The QCEW is derived from state unemployment insurance records and the publicly available data contains population counts of establishments and employment as well as wages by establishment size category, industry, and geography. This information becomes available about 6 months after the end of the quarter.<sup>15</sup> As shown in the online [Appendix](#), the HB data provides reasonable coverage for establishments with fewer than 50 employees in the selected service-providing sectors but contains only very few establishments with 50 employees or more. We therefore focus most of our analysis on small establishments, i.e. establishments with less than 50 employees. For these small businesses, average employee by size category are close to the ones in the QCEW. Further details on the benchmarking will be included in future drafts.

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<sup>14</sup>Other Services includes “Repair and Maintenance” (NAICS 811) and Personal and Laundry Services (NAICS 812), which contains many of the HB establishments categorized under “home and repair, “beauty and personal care”, and “health care and fitness”. Interestingly, the HB data also contains several hundred establishments each in Utilities (NAICS 22), Construction (NAICS 23), Food, Textile and Apparel Manufacturing (NAICS 31) and Real Estate, Rental and Leasing (NAICS 53). We are analyzing these sectors in ongoing work.

<sup>15</sup>Currently, the last available QCEW data is for the third quarter of 2019. Tabulations by establishment size category are available only for the first quarter of the year; i.e currently the first quarter of 2019.

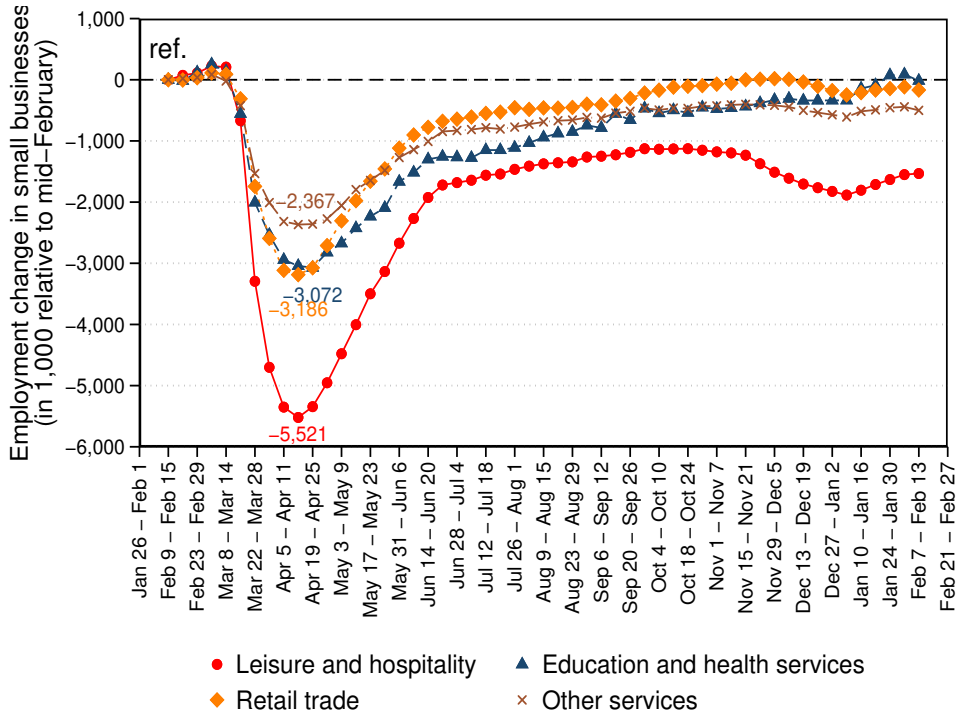
## 4 Small business dynamics and employment in the pandemic

### 4.1 Employment

Figure 1 reports our estimates of the cumulative employment loss since mid-February by small businesses for the selected service-providing sectors. In Leisure & Hospitality, small business employment declined by an estimated 5.5 million between mid-February and mid-April, most of it occurring during the second half of March as States imposed business closures and stay-at-home orders. This represents a 55% decline relative to the 10 million jobs by small businesses in this sector just two months earlier. Between mid-April and mid-June, employment by small businesses recovered 3.8 million or more than half of that loss. Since mid-June, this recovery has slowed down considerably, with employment peaking in mid-November at roughly 1 million below the pre-pandemic level before declining again by almost a million by the end of the year due to renewed restrictions and the effects of colder weather for outdoor dining in many parts of the country. Since the beginning of the year, small business employment in Leisure & Hospitality has regained part of this loss and currently remains about 1.5 million or 15% below the employment level prior to the pandemic.

Small business employment also dropped substantially at the beginning of the pandemic in the other three sectors, although the decline is not as dramatic as in Leisure & Hospitality. Relative to mid-February employment levels, the decline by mid-April amounts to 42% for Retail Trade, 35% for Education and Health Services, and 53% for Other Services. Similar to Leisure & Hospitality, small business employment in the three sectors then regained more than half of the loss by mid-June, and since then the pace of recovery has slowed down considerably. Contrary to Leisure & Hospitality, however, small business employment in the three sectors did not experience a large decline in December, and in Retail Trade and Education & Health small business employment has fully recovered.

Figure 1: Cumulative Employment Loss by Small Businesses

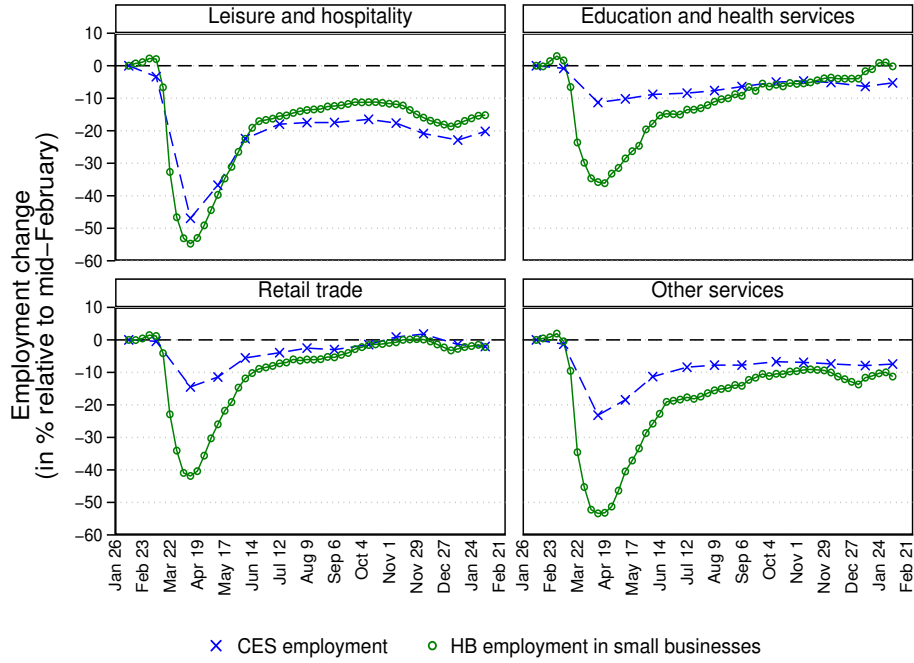


Notes: Estimated employment change (in thousands) of small businesses with less than 50 employees in Retail Trade (NAICS 44-45), Education and Health Services (NAICS 61-62), Leisure and Hospitality (NAICS 71-72), and Other Services (NAICS 81). The estimates are constructed based on February 2020 CES employment estimates (week of Feb 9 – Feb 15) and QCEW shares of small business employment for the first quarter of 2020. The estimates for the weeks of Thanksgiving, Christmas, and New Year are smoothed by using the estimates of adjacent weeks.

Our estimates imply that employment of small businesses in the four service sectors combined declined by 14 million between mid-February and mid-April – a staggering 46% decline – regained about 10 million by mid-June, and since then has recovered another 2.3 million. To put these estimates into perspective, Figure 2 compares the percent change in small business employment relative to the mid-February 2020 reference week implied by our HB estimates with the CES employment estimate, which is for all businesses. None of the estimates are seasonally adjusted.<sup>16</sup> For Leisure & Hospitality, the two estimates track each other relatively closely. The HB small business estimate declines somewhat more between mid-March and mid-April but then also recovers faster and is consistently above the CES all business estimate from June onward. In December, both estimates decline again and then regain part of this decline in January and February, with small business employment ending up about 5% closer to its pre-pandemic level than all business employment.

<sup>16</sup>We do not show seasonally adjusted estimates because the usual adjustment factors may not be appropriate for the type of large changes in employment that we experienced especially during the onset of the pandemic. See Rinz (2020) for a discussion of this point.

Figure 2: Relative employment change compared to CES estimates



*Notes:* Employment change by small businesses with less than 50 employees and all businesses in percent of respective employment level during the week of Feb 9 - Feb 15, 2020 for Retail Trade (NAICS 44-45), Education and Health Services (NAICS 61-62), Leisure and Hospitality (NAICS 71-72), and Other Services (NAICS 81). None of the estimates are seasonally adjusted. The estimates for the weeks of Thanksgiving, Christmas, and New Year are smoothed by using the estimates of adjacent weeks.

For the other three sectors, the percent decline in the HB small business estimate from mid-March to mid-April and the rebound from mid-April to mid-June are both much larger than for the CES all business estimate.<sup>17</sup> From mid-June onward, the HB estimate then continues to recover at a somewhat higher rate and is currently about equal in relative terms to the CES estimate in Retail Trade, slightly higher than the CES estimate in Education & Health Services, and slightly lower than the CES estimate in Other Services.

Taken at face value, the comparison implies that small business employment in the four service sectors fared considerably worse in the beginning of the pandemic than employment by larger businesses, perhaps because small businesses entered the crisis in worse financial health, had more difficulty in accessing emergency loans from the Paycheck Protection Program (PPP), or operated a business model that was more vulnerable to the initial disruptions caused by the pandemic. Remarkably though, small business

<sup>17</sup>Digging deeper, we find that even in retail subsectors considered essential such as Building Material Dealers (NAICS 444), Food and Beverage Stores (NAICS 445), Gasoline Stations (NAICS 447), or General Merchandise Stores (NAICS 452) where the CES estimates show almost no job loss across all businesses, our HB estimates show large declines in small business employment between mid-February and mid-April. See the online [Appendix](#) for details.

employment also rebounded much faster and has at present recovered about equally or even somewhat better from the pandemic than employment by larger businesses, thus dispelling the popular notion that the pandemic continues to affect small business employment more negatively.

The results are broadly consistent with estimates on the initial part of the pandemic and the first part of the recovery reported in [Dalton et al. \(2020\)](#) based on CES microdata and [Cajner et al. \(2020\)](#) based on ADP data. According to their estimates, across all private sectors of the U.S. economy employment in establishments with less than 50 employees declined by almost twice as much between March and April 2020 as employment for larger establishments – essentially what we find on average for the four service sectors considered here – but by the end of June small business employment had recovered a larger fraction of the loss relative to the pre-pandemic level.

At the same time, both the 14 million loss in small business employment between mid-March and mid-April and the rebound of about 10 million between mid-April and mid-June that we estimate are *larger* than the corresponding CES estimates for employment by *all* businesses in the four sectors (13.5 million and about 6 million, respectively).<sup>18</sup> Unless employment in businesses with 50 employees or more in the four sectors increased during the onset of the pandemic and subsequently declined – an implausible scenario by all accounts – this means that either our HB estimates or the CES estimates do not adequately capture the swings in small business employment in the beginning of the pandemic. There are a number of potential explanations for this. One often mentioned in work with HB data is that the publicly available files only cover hourly paid workers who may have been more vulnerable to temporary job loss in the beginning of pandemic than owners, managers and other non-hourly paid workers. By not counting this latter group, HB estimates would therefore overestimate both the initial drop and the subsequent rebound in small business employment. As explained above, however, HB shares with us additional information on owners, managers and any other person within a business that uses the HB software in a given week, and we exploit this information to include these workers in our employment estimate.<sup>19</sup> A second potential explanation is that the businesses using HB may be disproportionately located in affluent zip codes that were hit harder by the pandemic, as shown by [Chetty et al. \(2020\)](#). Again this would lead us to overestimate the initial swing in small business employment with the HB data. Yet, from Figure 2, we know that in Leisure & Hospitality where the difference in employment

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<sup>18</sup>For comparison, the headline CES employment estimate for all private sectors declined by 19 million from mid-February to mid-April on a seasonally unadjusted basis.

<sup>19</sup>As shown in the Appendix, including these non-hourly tracked workers attenuates the swing in estimated employment but has overall a relatively modest effect. Furthermore, we check in the CPS household data whether employment of salaried workers declined by more than employment of hourly-paid workers and find only small differences. So, even if we do not capture all non-hourly tracked workers with our information from HB, it is unlikely that this would explain the difference to the CES estimates.



losses between affluent zip codes versus less affluent zip codes was largest, HB small business employment estimate tracks the CES all business estimates quite closely, implying that over-representation of the HB data in affluent zip codes is unlikely to be quantitatively important.

A third potential explanation concerns differences in how employment is measured in the HB data relative to the CES, and how we take account of openings and closings in our estimator. As described in the previous section, employment in the CES is measured by the number of workers receiving pay for any part of the pay period that includes the 12th of the month independent of whether they actually worked, while employment in HB is measured by the number of workers who logged positive tracked hours plus all workers who used the HB software otherwise in a given week. So, if some workers who were temporarily furloughed in mid-April still received pay even though they were no longer working, then they were counted in the CES but not in the HB data, which would imply that the CES overestimated employment in mid-April. Perhaps more importantly, while our HB estimator directly includes the employment effects of all closings and openings, the CES estimator only includes a portion of the employment changes from establishments reporting zero employment and does not directly incorporate non-reporting establishments. Since, as shown below, almost 40% of all small businesses in our sample closed by mid-April with about two thirds returning by June, it is conceivable that the CES estimator missed some of the employment effects from this large increase in temporary closings.

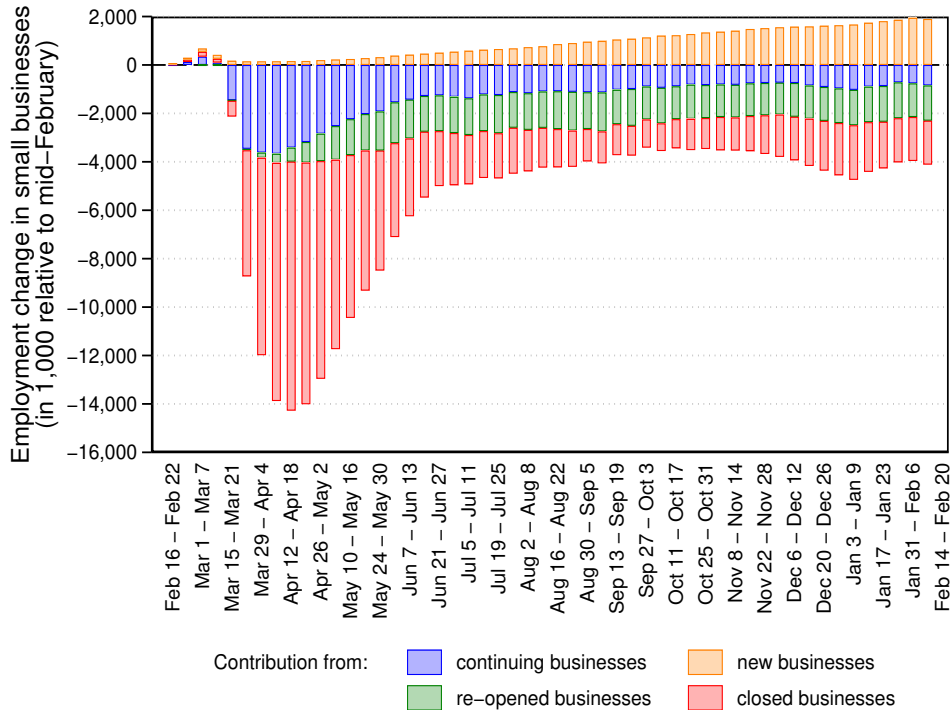
Absent access to the CES microdata, it is not possible to directly assess the quantitative importance of this difference. However, we can compare our estimates to the ones by [Cajner et al. \(2020\)](#) who use data from ADP to quantify the employment effects of the crisis. Their employment concept is pay-based as in the CES and their estimator tracks the CES closely prior to the pandemic. Their estimates, which take into account the effects of all exits and re-entry of businesses in the ADP imply that employment of *all* businesses in the four sectors that we consider declined by 20.2 million between mid-February and late April. Given that businesses with fewer than 50 employees accounted for almost half of employment in the four sectors prior to the pandemic and small business employment declined by almost twice as much as employment of larger businesses, this estimate is closely aligned with our estimated decline in small business employment of 14 million during the same time frame.

## 4.2 The importance of small business closings and openings

To illustrate the importance of small business closings and openings we decompose the combined employment change across the four service sectors into the contributions from businesses that continue to operate from mid-February until at least week  $t$  (and possibly longer), businesses that closed at some

point after the mid-February reference week but reopened by week  $t$ , businesses that operated in mid-February but are closed in week  $t$  (temporarily or permanently), and businesses that newly opened between mid-February and week  $t$ .<sup>20</sup>

Figure 3: Contribution of Small Business Closings, Reopenings and New Openings to Cumulative Employment Loss



Notes: Contribution to total employment change in Leisure and Hospitality, Retail Trade, Education and Health Services, and Other Services by businesses that continued operating from mid-February until at least week  $t$  (blue bars), businesses that closed at some point after mid-February and but reopened by week  $t$  (green bars), employment changes from businesses that operated in mid-February but are closed in week  $t$  (red bars), and employment changes from new businesses that opened between mid-February and week  $t$  (orange bars). The estimates for the weeks of Thanksgiving, Christmas, and New Year are smoothed by using the estimates of adjacent weeks.

As Figure 3 shows, business closings account for about 70% of the 14 million employment decline across the four sectors from mid-March to mid-April while job losses by continuing businesses only account for 30% of the decline. Reopenings of closed businesses also drives most of the rebound in employment between mid-April and mid-June, even though the reopened businesses operate at lower employment than in mid-February. By the end of the year, continuing businesses recovered almost completely while job losses from businesses that were closed and reopened or remain closed continue to impact employment

<sup>20</sup>See the Appendix for details on the decomposition. The employment losses from closed business nets out gains from establishments that were active in HB prior to the mid-February reference week, temporarily closed in the reference week, and then reopened at some point thereafter (e.g. seasonal businesses). By netting out these gains, the contribution from closings represents the employment losses over and above the usual employment losses from business that temporarily close. See below for further discussion.

negatively by about 3.5 million. At the same time, job gains from new businesses openings gradually increase from May onward, adding almost 2 million new jobs by mid-February and thus constitute the main source of recovery since mid-June. As shown in the Appendix, this decomposition is qualitatively similar for each of the four sectors, although there are sensible quantitative differences. In particular, in Leisure & Hospitality, job loss from continuing, reopened and still closed businesses remain relatively large and job gains from new openings are modest, whereas in Retail Trade continuing businesses currently employ more workers than in February 2020 and job gains from new openings are larger than losses from closings and reopened businesses.

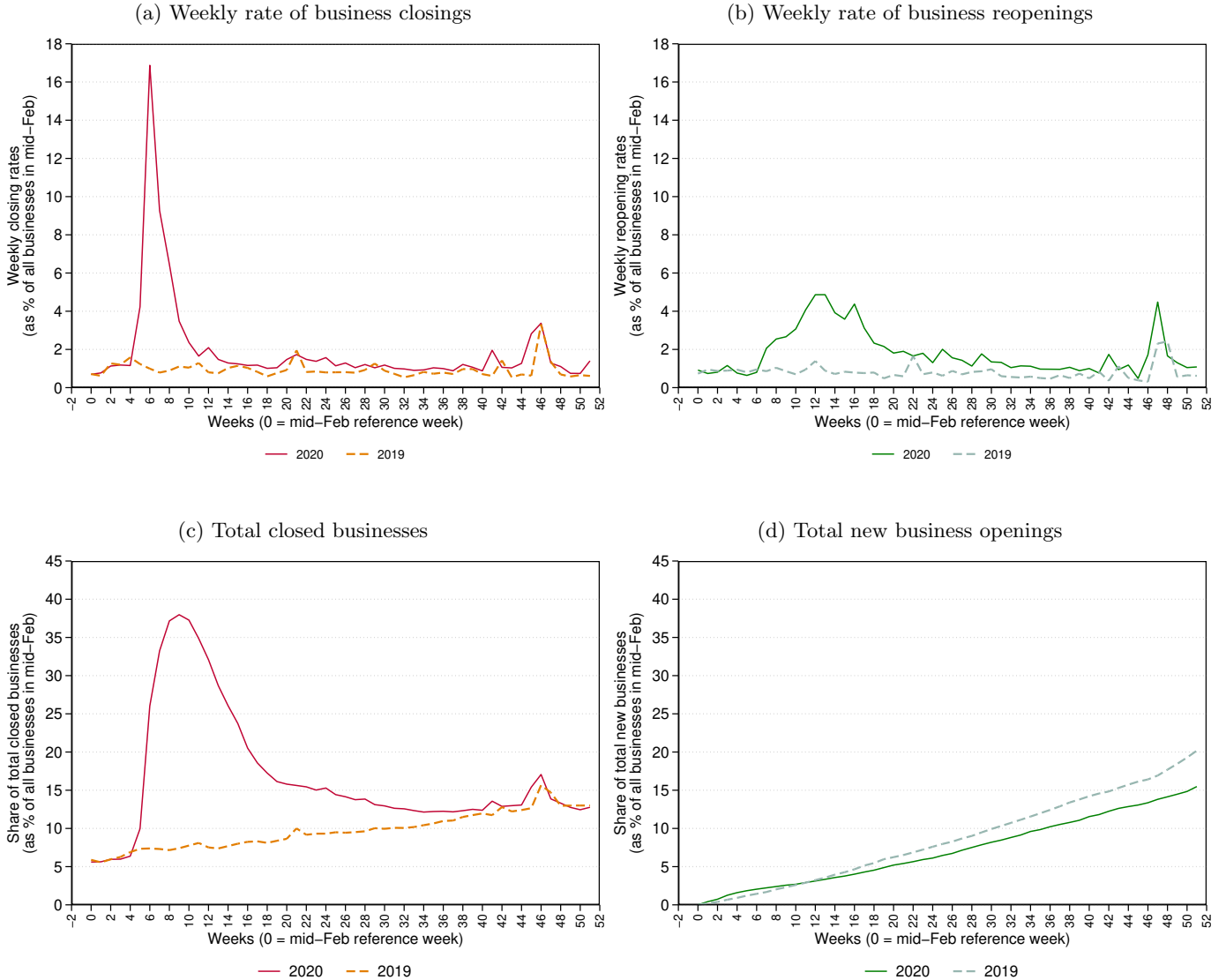
Figure 4 provides further evidence on the rates of business closings, reopenings, and new openings since the pandemic started and contrasts these results to data for the same time period a year earlier. As shown in Panels (a) and (b), the weekly rate of business closings spiked to more than 16% in the week of March 22 - March 28 and then sharply declined to about 2% by mid-April before further declining to near the pre-pandemic average of about 1% per week. Concurrent with the decline in business closings in April, reopenings start to increase, reaching a rate of almost 5% per week in early May before gradually declining back to the 1.5-2% range between July and September and then the 1-1.5% range thereafter, just slightly above the pre-pandemic rate.

Panel (c) displays the cumulative effect of these closings and reopenings on the total stock of closed businesses relative to all active businesses in the mid-February reference week. Note first that for both 2019-2020 and for 2020-21, total closed businesses average about 5% of active businesses in the mid-February reference week, indicating that a substantial fraction of businesses are temporarily closed at any point in time. From mid-March onward, total closings rise steeply and peak at 37% in mid-April. From mid-April onward, the cumulative closure rate declines, steeply initially as reopenings rise and then more gradually to a low of about 13% by November. This suggests that only about one third of all closings of all closings in mid-March are permanent.<sup>21</sup> Perhaps surprisingly, the cumulative rate of closings after one year of the start of the pandemic is almost exactly the same as the cumulative closing rate during the same period in 2019-20, indicating that the pandemic did not lead more small business closings in the four sector than what we usually observe.

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<sup>21</sup>According to analysis shown in the Appendix, the majority of establishments that closed for more than 10 weeks remain closed.

Figure 4: Small business closings, reopenings, and new openings



Notes: Cumulative establishment closures and new establishments relative to count of active establishments in HB data in Leisure and Hospitality, Retail Trade, Education and Health Services, and Other Services (top panel), and rate of new business closures and business reopenings in the same sectors (bottom panel).

Panel (d), finally, shows total new business openings relative to total active businesses in mid-February. This rate rises gradually, even during the worst of the pandemic in March and April, picking up pace from August onward and finishing at about 15% by the end of the year. This is consistent with the surprisingly large rate of new business formations reported by the U.S. Census Bureau (see [Haltiwanger \(2020\)](#)), although compared to 2019-20, we estimate that new business openings are about 5% lower after one year whereas new business formations (not necessarily employer businesses) are in fact higher since the pandemic than previously.

The take-away from Figures 3 and 4 is that temporary closings and reopenings are the primary driver of the large initial contraction and subsequent rebound in small business employment in the four service sectors considered. Likewise, the primary reason for the slowdown in recovery since mid-June is that employment losses from business closings and reopenings have essentially stopped shrinking. Indeed, absent the job gains from new openings, employment would be substantially lower. This implies that the pandemic led to substantial churn in small businesses, with a substantial excess closings relative to pre-pandemic circumstances, and that the future of the recovery depends crucially on the extent to which new businesses openings will continue.

### 4.3 The importance of taking into account new openings and closings

As described above, one of the key challenges in estimating employment with private-sector establishment-level data such as HB is to distinguish business closings and openings from sample churn. We illustrate the importance of this issue here by computing different counterfactual employment estimates from our data and discuss how they relate to results presented in the literature.

Figure 5 shows the results, both for mid-February 2019 to mid-February 2020 and mid-February 2020 to mid-February 2021. The green line with dots shows our headline estimate and the blue line with crosses shows the CES all business estimate for the four sectors combined (the black dot in mid-February 2020 shows the QCEW estimate for small businesses). For both years, the two lines end up almost exactly on top of each other at the end of the sample, indicating the quality of our estimate.

The other lines are computing as follows:

- the teal line with crosses shows the estimate if we use only locations present in beginning of sample

that continue all the way through  $t$ ; i.e.  $\hat{E}_t = \hat{E}_0 \times \frac{\sum_i \omega_i \hat{e}_{it}^{A^{(t)}}}{\sum_i \omega_i \hat{e}_{i0}^{A^{(t)}}}$ .

- red line with triangles includes all exits (i.e. treating all exits all closings) and reopenings; i.e.

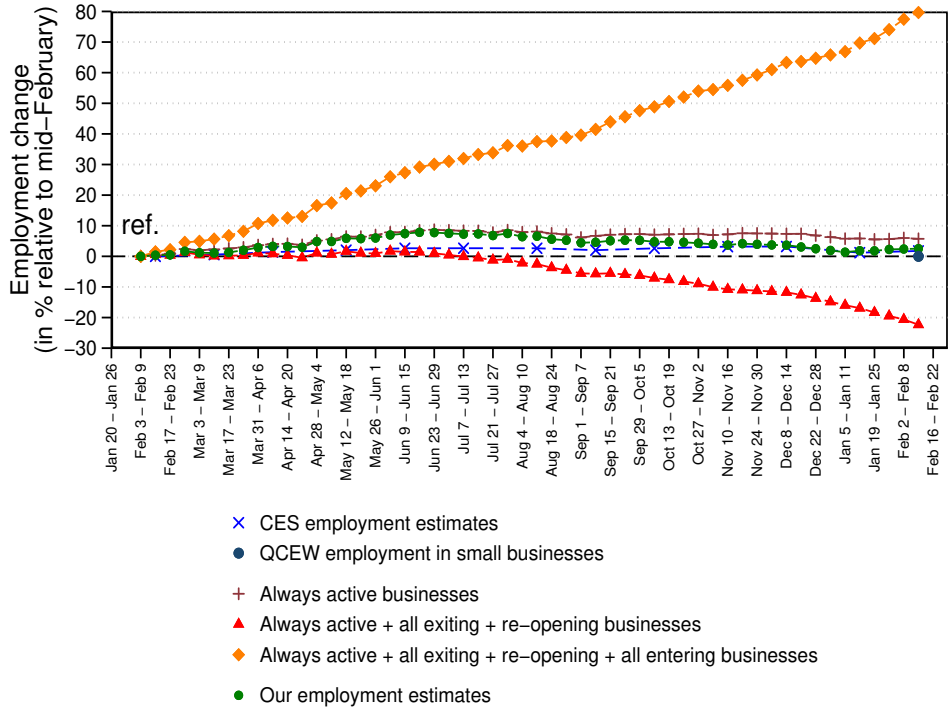
$$\hat{E}_t = \hat{E}_{t-1} \times \frac{\sum_i \omega_i (\hat{e}_{it}^{A^{(t)}} + \hat{e}_{it}^{\mathcal{R}_{i,t}})}{\sum_i \omega_i (\hat{e}_{it-1}^{A^{(t)}} + \hat{e}_{it-1}^{\mathcal{X}_{i,t}})}$$

- the orange line with diamonds adds all entries (i.e. treating all entries as new openings); i.e.

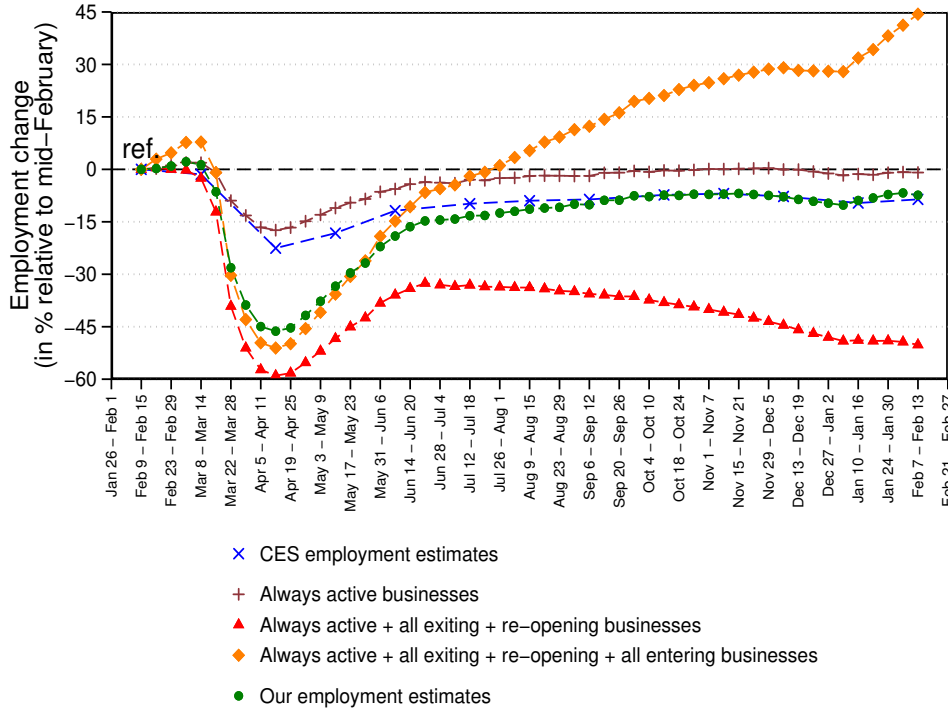
$$\hat{E}_t = \hat{E}_{t-1} \times \frac{\sum_i \omega_i (\hat{e}_{it}^{A^{(t)}} + \hat{e}_{it}^{\mathcal{E}_{i,t}})}{\sum_i \omega_i (\hat{e}_{it-1}^{A^{(t)}} + \hat{e}_{it-1}^{\mathcal{X}_{i,t}})}$$

Figure 5: Comparison of different employment estimators

(a) 2019 estimates



(b) 2020 estimates



Notes: Estimated employment change (in thousands) of small businesses with less than 50 employees in Retail Trade (NAICS 44-45), Education and Health Services (NAICS 61-62), Leisure and Hospitality (NAICS 71-72), and Other Services (NAICS 81). The estimates are constructed based on February 2020 CES employment estimates (week of Feb 9 – Feb 15) and QCEW shares of small business employment for the first quarter of 2020. The estimates for the weeks of Thanksgiving, Christmas, and New Year are smoothed by using the estimates of adjacent weeks.

The differences are remarkable, illustrating the importance of accounting for sample churn and in particular entry of previously operating businesses.

## 5 A closer look

### 5.1 Average weekly hours

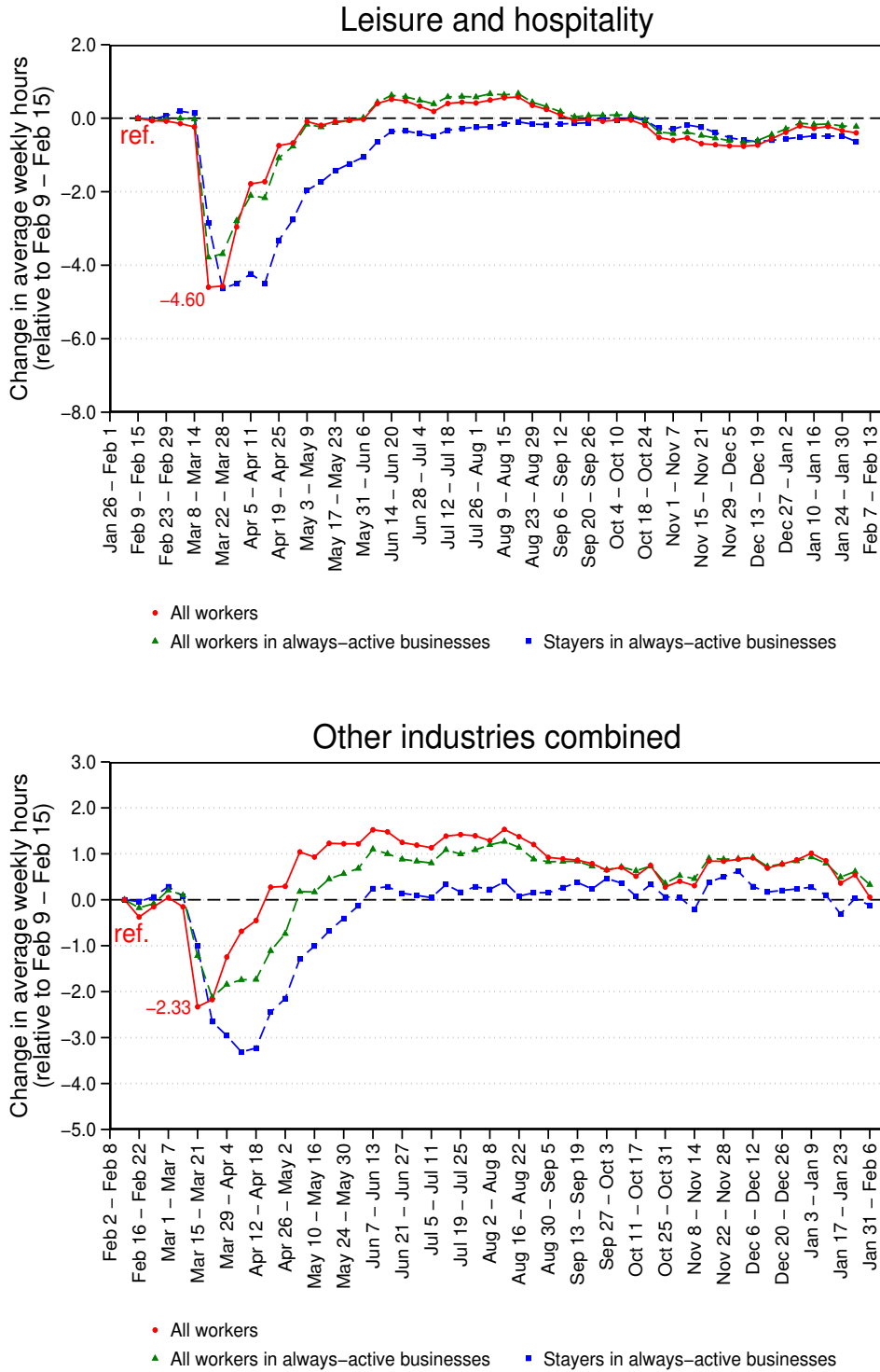
The other important dimension of employment to consider is hours worked per employee. Figure 6 shows different estimates of average weekly hours (AWH), one for all workers employed in week  $t$ , one for all workers employed in week  $t$  in businesses that operated continuously throughout the entire sample, and one for all job stayers.

As shown in the top panel for Leisure & Hospitality, AWH for all workers (red solid line) and AWH for all workers in businesses that remained active throughout the sample (green dashed line) both declined sharply in the third week of March but have since fully recovered and currently exceed pre-pandemic levels somewhat. The sharp decline precedes the week of March 22-28, the week of the largest employment decline and is driven both by the reduction in AWH of job stayers (blue line) and the fact that some of the laid off and furloughed workers stopped working mid-week. Interestingly, AWH of job stayers remains about 5 hours lower all through mid-April and does not fully recover. As we analyze below, this difference is driven by compositional change: job stayers work on average more hours per week than the workers that were laid off or temporarily furloughed. As layoffs and furloughs increased, this changed the composition of workers towards job stayers, thus increasing AWH of all workers and AWH of all workers in continuously active businesses.

For the other three sectors considered, shown in the bottom panel, the overall picture is similar although the magnitudes are different. AWH also declined in the second half of March but to a lesser extent than in Leisure & Hospitality. Thereafter, AWH for all workers and AWH for workers in continuously active businesses recovered relatively quickly and has been above the mid-February level for the last three months. In comparison, AWH of job stayers continued to decline until mid-April and then recovered gradually to its pre-pandemic level. As discussed above for the case of Leisure & Hospitality, this difference is driven by compositional change towards job stayers who work on average more hours per week.

Overall, the two graphs show that hours of workers in small service-sector businesses who stayed in their job have recovered, which stands in large contrast to all the millions of workers who have lost their jobs.

Figure 6: Average Weekly Hours of Small Business Employees



*Notes:* Average weekly hours of employees in small businesses in Leisure and Hospitality (top panel) and Retail Trade, Education and Health Services, and Other Services (bottom panel), constructed based on February 2020 CES estimate (week of Feb 9 – Feb 15). The solid red line shows the change in average weekly hours of all workers employed in all small businesses. The dashed green line shows the change in average weekly hours of all workers employed in small businesses that remain active throughout the entire sample. The blue dashed line shows the change in average weekly hours of job stayers; i.e. workers who remained employed in the same small businesses throughout the entire sample.



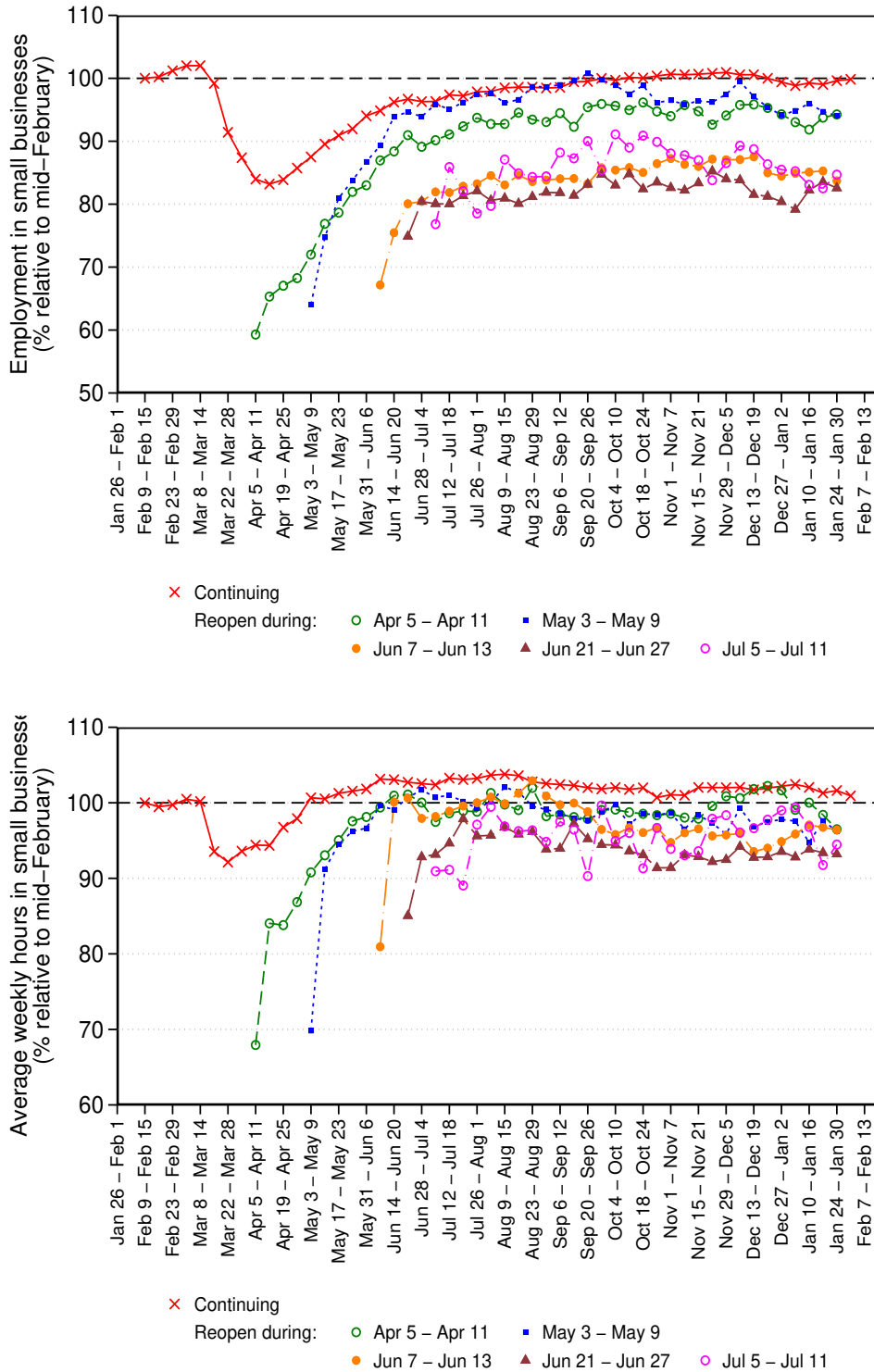
## 5.2 Continuously open versus reopened small businesses

Our estimates imply that small service-sector businesses have regained about half of the lost jobs since mid-April but that the recovery has stalled since the end of June. We now analyze this recovery further by comparing businesses that remained open throughout the pandemic with businesses that closed and have since reopened.

As shown in the top panel of Figure 7, continuing businesses that never closed decreased employment on average by about 40% by mid-April and then regained about half of that loss by the end of June. Consistent with above results, this recovery then stalled and employment remains about 20% below the pre-pandemic level. Businesses that closed temporarily first reopen with very little employment but then ramp up jobs rapidly. For businesses that reopened by mid-May, this ramping up was so large that they are now at the same employment relative to pre-pandemic levels as continuing businesses that never closed. For businesses that reopened after mid-May, in contrast, relative employment seems to level out at a lower rate of 60-70%. This suggests that there may be noticeable scarring among small businesses that closed for a longer period and reopened later.

As shown in the bottom panel of Figure 7, continuing businesses decreased AWH of their workers by just over 10% within one week in mid-March. AWH then recovered by early April and has since increased slightly to about 4% above the pre-pandemic level. In comparison, businesses that temporarily closed reopen initially with substantially lower AWH. Some of this difference may be due to the rapid rehiring of workers when businesses reopen, with some of these rehires starting mid-week which would artificially reduce AWH. After a few weeks, AWH then returns to essentially the pre-pandemic level and then increases slightly above, independent of the date of reopening. Given the large and persistent employment decline across all of these businesses, the relatively small decline in AWH during the worst of the crisis and the subsequent recovery are surprising and suggest the presence of strong labor market indivisibilities (e.g. fixed costs, worker-specific economies of scale) that make it optimal for small businesses to employ fewer full-time workers as opposed to more part-time workers.

Figure 7: Employment and AWH of Continuing vs Reopened Small Businesses

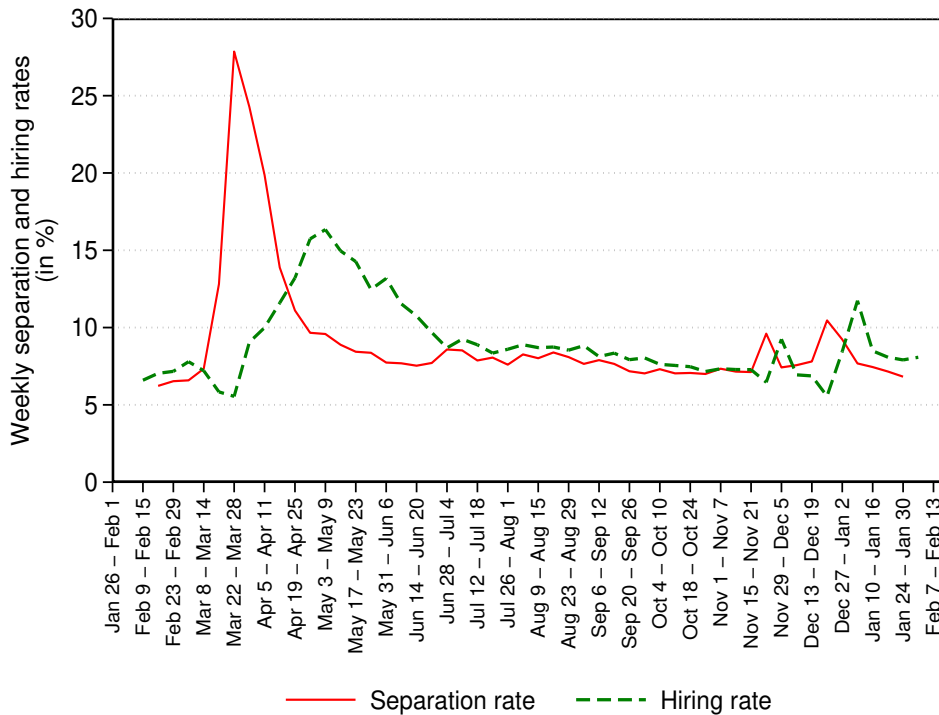


Notes: Employment and average weekly hours relative to week of February 9-16 of small businesses in Leisure and Hospitality, Retail Trade, Education and Health Services, and Other Services. The red solid line shows the results for small businesses that continued operating throughout the entire sample while the other lines show the results for small businesses that temporarily closed and reopened but the indicated date.

### 5.3 Separations, recall, and new hires

The matched worker-establishment structure of the HB data also allows us to provide a detailed account of gross flows. We decompose employment losses by small businesses in the selected sectors into gross hiring and separation flows.

Figure 8: Gross Hiring and Separation Rates of Small Businesses

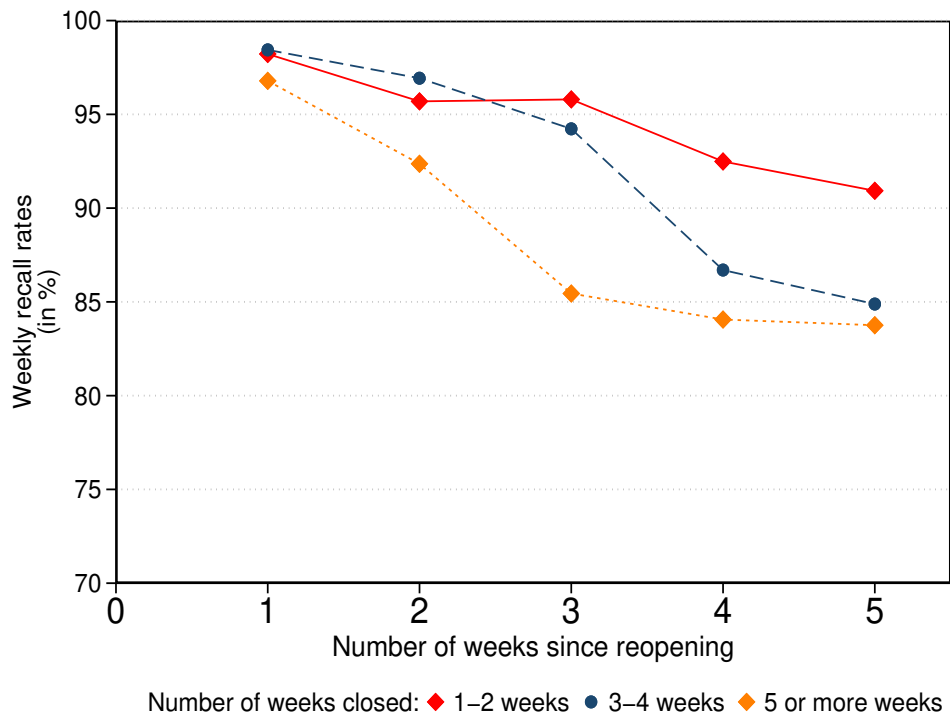
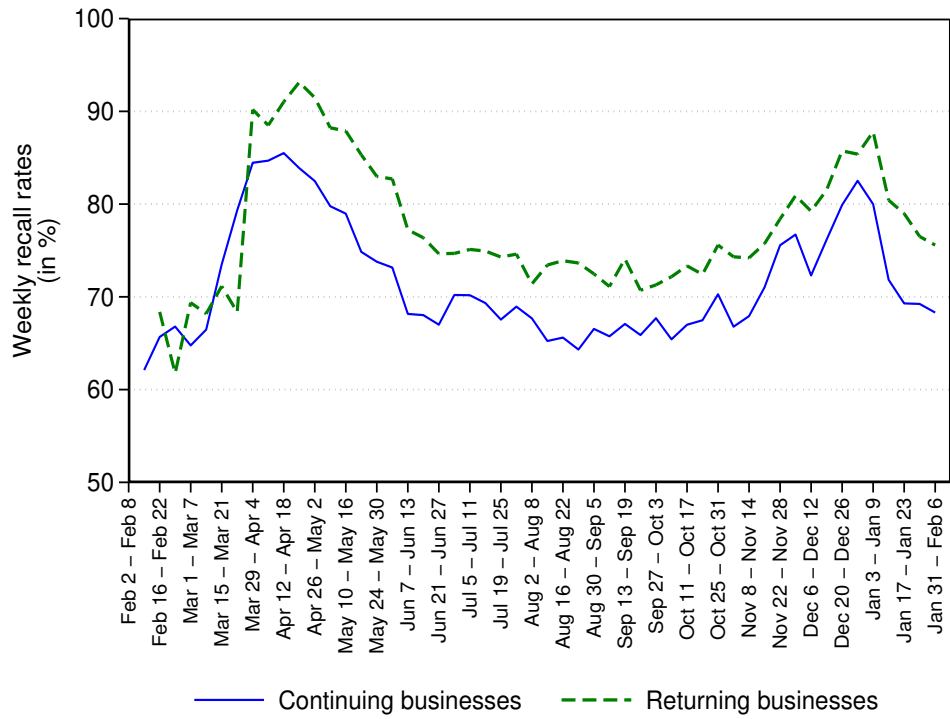


*Notes:* Gross hiring and separation rates of small businesses in Leisure and Hospitality, Retail Trade, Education and Health Services, and Other Services. See the Appendix for definitions.

As Figure 8 shows, the separation rate spiked in the week of March 22-28, the same week as business closures spiked, while the hiring rate dropped only slightly. Separations therefore account for the bulk of the large employment losses in the second half of March. From early April to early May, the hiring rate increased gradually and peaked at 15%, about double the pre-crisis rate. As we will see below, this increase in the hiring rate is in large part driven by recalls. Since early May, the hiring rate has declined gradually and stands just below 10% since mid-June. This is about the same rate as the separation rate since mid-June, thus providing another way of understanding the stalled recovery of small business employment.

Next we look at the rate of recalled workers relative to total hiring.

Figure 9: Recall of Small Business Employees



Notes: Rate of employees returning to the same business relative to all new hires in small businesses in Leisure and Hospitality, Retail Trade, Education and Health Services, and Other Services.

We define a recalled worker as any hire who has previously worked for the same business.<sup>22</sup> As shown in the top panel of Figure 9, both continuing small businesses and businesses that temporarily closed have primarily regained employment since early April by recalling furloughed employees. Interestingly, until mid-June, this recall rate has been on average about 10% higher for small businesses that temporarily closed than for small businesses that remained open throughout the pandemic. For both continued and temporarily closed small businesses, this recall rate has declined gradually between mid-April and mid-June and then leveled out around 70%.

The bottom panel of Figure 9 explores recall further by reporting average recall rates by number of weeks of business closure. Recalls account for 90% to 95% of total hiring in the first week of reopening, independent of whether businesses were closed for 1-2 weeks, 3-4 weeks or 5 or more weeks. This recall rate then declines steadily with the number of weeks since reopening and after five weeks, the recall rate is about 70%. This suggests that at least so far, the worker-firm match of furloughed workers have remained relatively strong independent of the number of weeks that small businesses closed temporarily.

## 6 Relation to local differences in health and policy responses

Our analysis reveals that after the initial wave of small business closings, many of the closed businesses reopened and that one year after the pandemic started, the rate of total closings is approximately the same as the year before. Similarly, the rate of small businesses new openings throughout the pandemic is somewhat below the rate one year earlier. We now exploit our data to investigate the extent to which small business activity is associated with local variations in pandemic-relevant indicators and economic policy responses. We focus on four key aspects: (i) local differences in Covid-19 health outcomes and non-pharmaceutical interventions (NPIs); (ii) local differences in average household income; (iii) local differences in initial access to loans from the Paycheck Protection Program (PPP); and (iv) local differences in average UI replacement rates. We consider these particular differences because they have been the intense focus of the recent literature but, to our knowledge, their relation to small business dynamics and employment – in particular with respect to closings and new openings – has so far not been investigated in a unified econometric framework.

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<sup>22</sup>Our recall rates may therefore include employees who work regularly for a given business but not in every week. This would somewhat artificially inflate our recall rates. We will investigate this possibility in future drafts.

We estimate the following regression

$$\begin{aligned}
y_{l,t} = & \sum_{t=0}^{52} \alpha_t 1(\text{week} = t) + \mathbf{X}'_{c,t} \boldsymbol{\beta}_1 \\
& + \sum_{t=0}^{52} \beta_{2t} 1(\text{week} = t) \times HHincome_c \\
& + \sum_{t=0}^{52} \beta_{3t} 1(\text{week} = t) \times PPPdelayedshare_c \\
& + \sum_{t=0}^{52} \beta_{4t} 1(\text{week} = t) \times UIrate_c \\
& + \Gamma'_{c,t} \boldsymbol{\gamma} + \mu_l + \varepsilon_{l,t}
\end{aligned} \tag{4}$$

where  $y_{l,t}$  is either the percent deviation of employment in week  $t$  of a continuing establishment  $l$  relative to its employment in the reference week; the probability of establishment  $l$  being closed in week  $t$ ; or the probability of establishment  $l$  being newly opened in week  $t$  (with  $t = 0$  denoting the mid-February 2020 reference week). The  $\alpha_t$  are weekly fixed effects;  $\mathbf{X}_{c,t}$  is a vector measuring the Covid health situation and NPIs in effect in week  $t$  in zip-code, county or state  $c$  in which establishment  $l$  is located;  $HHincome_c$  is a measure of average pre-pandemic household income in zip code  $c$ ;  $PPPdelayedshare_c$  is the share of delayed PPP loans in zip code  $c$  as explained in detail below; and  $UIrate_c$  is the UI replacement rate including FPUC in county  $c$  inferred from pre-pandemic average earnings in the four sectors considered. Finally,  $\Gamma_{c,t}$  is a vector of potentially time-varying controls,  $\mu_l$  is an establishment-specific fixed effect, and  $\varepsilon_{l,t}$  is the error term.

In the different regressions, we always include the full set of week fixed effects to capture average variations across  $y_{l,t}$  as well as the vector measuring the Covid health situation and NPIs, and the time fixed effects interacted with the measure of household income that control for key differences across localities. We then add either the weekly interactions with  $PPPdelayedshare_c$  or the weekly interactions with  $UIrate_c$  to investigate their effects. This means that all of our estimates report effects relative to the trend. We intentionally leave out state or regional time fixed effects because we want to explore the association of our outcome variables with local differences in the regressors, which vary importantly across states and broader regions of the U.S. The drawback of this approach is that the estimates may pick up the effects of omitted variables that simultaneously impact the outcome variables. We therefore stop short of interpreting our estimates as causal and discuss possible identification issues for each of the cases. Nevertheless, given the strength of some of our results combined with evidence from other studies

suggest at least some degree of causality and warrant further investigation.

The regressions for employment growth are estimated using all in-scope establishments that are active both in the beginning and in the end of the sample; the regressions for closing rates are estimated using all in-scope establishments that are active or temporarily closed in the reference week; and the regression for new opening rates are estimated using all in-scope establishment that are either active or temporarily closed in the reference period or newly open at some point thereafter. By definition of running these regressions at the establishment level, we weigh by establishment counts within zip code or county (depending on the aggregation level fo the regressor).<sup>23</sup> Standard errors are clustered at the location level.

## 6.1 Covid-19 health situation and NPIs

To measure the Covid health situation, we use the county-level rate of new Covid cases and new Covid-related deaths per 100,000 of population, obtained from Johns Hopkins University. For NPIs, we consider seven state-level indicators ranging from workplace closings to stay-at-home orders from the Oxford COVID-19 Government Response Tracker (Hale et al. 2020). For ease of presentation, our baseline regression summarizes these indicators by a “containment index” that is constructed as an equally weighted average of the different indicators, ranging from 0 (no containment policies) to 100 (maximum containment policies).

In addition, to measure school closings, we follow the recent paper by Bravata et al. (2021) and use our Safegraph data to construct log changes in school visits relative to one year earlier. Specifically, we identify Safegraph places that are associated with NAICS code 611110 (“elementary and secondary schools”) and aggregate the number of visits by week to the county level,  $v_{ct}$ . Then, similar to Goolsbee and Syverson (2020), we construct the log change in visits in week  $t$  as

$$\Delta \ln(\text{school}_{ct}) = \ln(v_{ct}) - \ln(v_{ct-52}) \tag{5}$$

Compared to alternative measures of school closings (e.g. Burbio or the Covid School Dashboard) the advantage of using (5) is that it is available across all counties and weeks, and includes not only public schools but also private, charter and parochial schools, which have in many cases reopened earlier and to a larger extent than public schools.

In the Appendix, we report distributional statistics of  $\Delta \ln(\text{school}_{ct})$  across all counties and weeks.

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<sup>23</sup>See Solon et al. (201x).

The distribution is strongly skewed to the left with a median of  $-0.49$  across all counties and weeks and an interquartile range of  $[-1.14, -0.11]$ . As shown in Bravata et al. (2021), there is substantial variation in this distribution both across time and regions of the U.S.

The first three rows of Table 1 show the relation between our outcome variables and the different Covid health and NPI measures. New cases and new deaths have a significant adverse effect on both employment growth of surviving businesses and the closing rate. The new death rate also has a significant and in fact positive effect on the new opening rate, although this effect is very small in comparison to the closing rate. This is in part because the variation in business closings is so important during the early part of the pandemic whereas new openings increase gradually. Consistent with results for larger businesses by Barrero, Bloom and Davis (2020), this opposite effect of closings and openings suggests that changes in consumer demand away from in-person services towards alternative service delivery (e.g. take-out, online retail) triggered a reallocation of small business activity.

In terms of quantitative importance, the average weekly new case rate across all counties and weeks is about 65 times larger than the average weekly new death rate (21.7 per 100,000 versus 0.34 per 100,000) and varies importantly across time within counties. So, both new cases and deaths have a sizable effect not only for employment at continuing small businesses but also for closings. This is consistent with a case study by Goolsbee and Syverson (2020) using Safegraph data on visits to businesses, and likely reflects health concerns that reduce both demand for in-person services and make employees reluctant to return to work.<sup>24</sup>

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<sup>24</sup>The labor force participation rate remains more than 2 percent below its pre-covid level, and a recent survey by the U.S. Census Bureau finds that over 4 million adults are not working because of fear of Covid.



Table 1: Relation of small business dynamics with Covid health and NPI indicators

|                                    | A. Percent change in employment of surviving businesses | B. Percent of closed businesses (including temp closed) | C. Percent of newly opened businesses |
|------------------------------------|---|---|---------------------------------------|
| Covid new cases per 100k (county)  | -0.02***<br>(0.01)                                      | 0.01***<br>(0.00)                                       | 0.00<br>(0.00)                        |
| Covid new deaths per 100k (county) | -2.15***<br>(0.18)                                      | 1.53***<br>(0.10)                                       | 0.05***<br>(0.02)                     |
| Containment index (state)          | -0.07***<br>(0.02)                                      | 0.03***<br>(0.01)                                       | -0.00<br>(0.00)                       |
| Log school visit change (county)   | 1.98***<br>(0.20)                                       | -0.38***<br>(0.09)                                      | 0.22***<br>(0.03)                     |
| R2                                 | 0.08  | 0.11  | 0.09                                  |
| N                                  | 1,887,825   | 2,603,663   | 3,721,707                             |
| Controls                           |   |   |                                       |
| Relative ZIP income x Week         | Y   | Y   | Y                                     |
| Establishment FE                   | Y   | Y   | Y                                     |
| Week FE                            | Y   | Y   | Y                                     |

*Notes:* Standard errors are clustered at the establishment level; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . All regressions are estimated over all weeks between February 9-15, 2020 and January 31 - February 6, 2021. Table only shows coefficient estimates for Covid health and NPI regressors. Percent change in employment of surviving businesses in Panel A is computed as percentage change of employment relative to reference week (Feb 9-15, 2020) for locations active in reference week and in last week of sample. Percent of closed businesses in Panel B is computed as the count of businesses closed (either temporarily or permanently) in week  $t$  relative to the count of businesses in the reference week. Percent of newly opened businesses in Panel C is computed as the cumulative count of new businesses as of week  $t$  relative to the count of businesses in the reference week and businesses that newly open after the reference week.

Turning to NPIs, the state containment index has a statistically effect on both employment growth and the closing rate but not on the opening rate. The containment index ranges from 0 to 100 with an average of 50 for all states and weeks. So a 10 point increase implies an average decline in employment of continuing businesses of 0.7% and an increase in closings of 0.3%. This is relatively modest and echoes earlier findings by Bartik et al. (2020), Chetty et al. (2020) or Goolsbee and Sverson (2020) that NPIs were in and of themselves not a major factor for the decline in employment in the beginning of the pandemic. In terms of components of the containment index, we show in the Appendix that all but “no gatherings above 100 people” have a significant effect on employment growth and the closing rate, while only “workplace closings” and “stay at home orders” have a significant effect on the new opening rate. But as for the containment index, the quantitative importance of these effects is modest.

In comparison, the county change in school visits has a significant and sizable adverse effect on all three outcome variables. Consider for example the last week of September 2020, where the log school visit change for the bottom quarter is  $-0.72$ . Compared to a county with no change in school visits, the point estimate in the fourth row of Table 1 imply that everything else the same, this county is associated with 1.43% lower employment for continuing small businesses, a 0.27% higher closing rate, and a 0.16% lower new opening rate.

## 6.2 Household income and stimulus payments

To measure differences in affluence, we take zip-code level average household income from the U.S. Census Bureau prior to the pandemic and normalize it relative to household income of the median zip code, so that a value of 1 is associated with a zip-code that has a 100% higher average household income than the median zip code.<sup>25</sup> The inclusion of this variable in our regression is motivated by three reasons. First, as shown in Chetty et al. (2020), affluent zip-codes have seen a more important decline in spending on in-person services and small business employment. We want to investigate to what extent this effect is driven by the extensive margin (closings and new openings) as opposed to the intensive margin (changes in employment at continuing businesses). Second, in our unified framework, it is important to control for differences in local demand effects, which we can do in a roundabout way through the interaction of time fixed effects with our zip-code income measure. Third, as discussed in detail in Chetty et al. (2020), the federal government as part of the CARES Act sent stimulus payments to households with income below a certain threshold.<sup>26</sup> More than 75% of these payments were deposited on April 14 and 15 and had a sizable effect on consumer spending on non-durables in low income zip codes. See also Coibon et al. (2020) for independent survey evidence. While Chetty et al. (2020) report that there are no sizable differences in small business employment for high-income versus low-income zip codes around that date, we want to see to what extent this result holds up in our data.

Table 1 shows the interaction of the week fixed effects with our measure of household income for select weeks (the interaction is estimated for all weeks but the table is only showing a few key weeks to save on space). The estimates reveal that small businesses in zip codes with high pre-pandemic household incomes experienced persistently larger employment losses and higher closing rates over the past year. Similarly, new opening rates are persistently lower in these zip codes.

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<sup>25</sup>Alternatively, we could use average zip-code household income as in Chetty et al. (2020) and would obtain very similar results. However, we find our estimates easier to interpret with this transformation.

<sup>26</sup>Individuals with 2019 earnings below \$75,000 received \$1,200 and married couples with 2019 earnings below \$150,000 received \$2,400. In addition, households received an additional \$500 for each dependent they claimed. The payments gradually phased out for households with incomes above these thresholds, reaching zero above \$99,000 for single filers without dependents and \$198,000 for married couples without dependents.

Table 2: Relation of small business dynamics with relative household income

|                                      | A. Percent change in<br>employment of surviving<br>businesses | B. Percent of closed businesses<br>(including temp closed) | C. Percent of newly opened<br>businesses |
|--------------------------------------|---|--|--|
| Relative ZIP household income × Week |   |  |  |
| February 16 - February 22            | 0.10<br>(0.74)  | 0.02<br>(0.09)   | -0.02<br>(0.02)                          |
| March 22 - March 28                  | -5.63***<br>(0.60)  | 3.60***<br>(0.45)  | -0.05<br>(0.04)                          |
| April 5 - April 11                   | -6.17***<br>(0.75)  | 3.76***<br>(0.52)  | -0.09**<br>(0.04)                        |
| April 19 - April 25                  | -7.16***<br>(0.76)  | 4.65***<br>(0.52)  | -0.13***<br>(0.04)                       |
| May 3 - May 9                        | -8.38***<br>(0.77)  | 5.37***<br>(0.50)  | -0.16***<br>(0.04)                       |
| May 17 - May 23                      | -8.60***<br>(0.82)  | 5.86***<br>(0.48)  | -0.14***<br>(0.05)                       |
| August 16 - August 22                | -6.13***<br>(0.96)  | 2.99***<br>(0.39)  | -0.25***<br>(0.08)                       |
| November 15 - November 21            | -4.45***<br>(0.90)  | 2.39***<br>(0.35)  | -0.60***<br>(0.11)                       |
| January 31 - February 6              | -5.56***<br>(0.91)  | 2.75***<br>(0.35)  | -0.86***<br>(0.12)                       |
| R2                                   | 0.08  | 0.11   | 0.09                                     |
| N                                    | 1,887,825   | 2,603,663  | 3,721,707                                |
| Controls                             |   |  |  |
| Health, Containment, School visits   | Y   | Y  | Y  |
| Establishment FE                     | Y   | Y  | Y  |
| Week FE                              | Y   | Y  | Y  |

Notes: Standard errors are clustered at the establishment level; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. All regressions are estimated over all weeks between February 9-15, 2020 and January 31 - February 6, 2021. Table only shows coefficient estimates for Covid health and NPI regressors. Percent change in employment of surviving businesses in Panel A is computed as percentage change of employment relative to reference week for locations active in reference week (Feb 9-15, 2020) and in last week of sample (Jan 31 - Feb 6, 2021). Percent of closed businesses in Panel B is computed as the count of businesses closed (either temporarily or permanently) in week t relative to the count of businesses in the reference week. Percent of newly opened businesses in Panel C is computed as the cumulative count of new businesses as of week t relative to the count of businesses in the reference week and businesses that newly open after the reference week. Relative household income denotes zip code average household income relative to average household

Quantitatively, the zip code at the 95th percentile has an average household income that is 90% higher than the zip code with median household income; and the 5th percentile has an average household income that is 33% lower than the median. So, the coefficient estimates for the week of April 5-11 (around the time of maximum employment losses across the four sectors) imply that the decline in employment of surviving businesses in the top 5th percentile zip code was on 7.6% lower and business closings 4.6% higher than in the bottom 5th percentile zip code. For new opening rates, the estimates are substantially smaller but accumulate over time so that one year after the pandemic, the new opening rate in the top 5th percentile zip code is more than 1% lower in the bottom 5th percentile zip code.

The difference in small business activity by zip-code affluence is broadly consistent with Chetty et al. (2020) who document that the dramatic reduction in spending on in-person services in the beginning of the pandemic occurred primarily in high income zip codes and led to sizable differences in small business employment. Our results show that this effect not only affected the intensive margin (employment of continuing businesses) but also the extensive margin (business closings and new openings), implying that

local differences in recovery of small business activity may be long-lasting.

Much of the gap in small business employment and closing rates across zip codes with different incomes that opens up in the first month of the pandemic persists to the end of the sample. At the same time, this gap widens temporarily from mid-April to about mid-June 2020i.e. the rebound in small business employment that occurred in that period as documented in the previous sections was stronger in low income zip codes than in high income zip codes. This widening in the gap, although modest in size, coincides with the disbursement and spending of stimulus payments that went primarily to lower-income households, thus providing suggestive evidence that the stimulus checks led to a limited demand boost for small business activity at least in less affluent areas.

### 6.3 Delays in PPP loans

To evaluate the effects of PPP loans to small businesses, we adopt a novel research design by Doniger and Kay (2021) that exploits local differences in the timing of PPP loans due to the temporary exhaustion of PPP funds in early April. As explained in detail in their paper, the CARES Act appropriated \$349 billion in PPP loans to support firms with fewer than 500 employees prior to the pandemic.<sup>27</sup> Loan application was administered through local lenders and the first loans were approved on April 3, with most initial loans going to larger businesses with well-established banking connections. The demand for loans was so overwhelming that by April 16, the appropriated funds were depleted. In response and after considerable uncertainty, Congress voted on an additional \$321 billion in PPP funding that the President signed into law on April 24. Banks started issuing new loans on April 27 and demand spiked immediately and remained strong for the next two weeks before abating.

Doniger and Kay show that the exhaustion of the initial PPP appropriation was distributed very unevenly across regions of the U.S., due in large part to the relative expediency with which local banks processed and approved loan applications (also see Grania et al., 2020). Using data from the CPS, they then estimate that the share of delayed PPP loans at the CBSA level has a negative effect on individuals' unemployment and non-employment rates even months after the original PPP program ended, in particular for individuals previously employed in small businesses. This provides indirect evidence that timely access to PPP loans allowed businesses to weather the worst of the initial crisis. At the same time, the long-lasting effects raise questions for why employment in regions with a delayed access PPP loans

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<sup>27</sup>For multi-establishment firms in food services, this threshold was even higher. Qualifying businesses could apply for up to 2.5 times the average total monthly payroll for each employee. The loans had a duration of two years at a 1% annual interest rate but were forgivable if the business disbursed the loan amount within 8 weeks after disbursement, with at least 75% being spent on qualified payroll expenses.

did not catch back up after the end of April when the additional funding became available. Here, we assess the robustness of Doniger and Kay’s results and try to answer this question with establishment data as opposed to individual worker data.

We follow the approach of Doniger and Kay and measure delayed access to PPP loans by the share of PPP loans issued during the week of April 26 (the week when additional PPP funding became available) relative to the total amount of PPP loans issued during the weeks of April 12 (the week when initial PPP funding ran out), April 19, and April 26. The loans made during these three weeks account for about one third of all loans. Different from Doniger and Kay who aggregate loans to the county and CBSA level, the HB data allows us to construct this measure at the zip-code level using the data on all loans made public by the Small Business Administration (SBA). Short of matching individual SBA loan records to particular HB establishments, this results in a highly localized and timely measure of PPP loan supply.<sup>28</sup>

As shown in the Appendix, the distribution of share of delayed PPP loans at the zip-code level is wide, with a median of 0.45 and an interquartile range of [0.29,0.64]. Furthermore and consistent with Doniger and Kay (2021), the share of delayed loans is concentrated importantly among small loan amounts, presumably loans going to smaller establishments, and in urban zip codes with relatively large populations.

Table 3 shows the interaction of week fixed effects with the share of delayed PPP loans (as mentioned before, the regression controls for week fixed effects, the different Covid health and NPI measures as well as the relative zip-level average household income interacted with the weekly fixed effects). The estimates imply that zip codes with a higher share of delayed loans saw lower employment growth for surviving businesses, although this effect is not significant, and significantly higher closing rates. Quite sensibly, there is no impact for new business openings. The effect on both employment and closing rates is delayed, starting only in the week of May 3 (the week after the additional PPP loans started to be issued) and there is no significant difference prior to the initial PPP loans issuance, implying that access to PPP loans is not driven by pretrends. Furthermore, while the negative effect on employment by surviving businesses completely disappears by the end of the sample, about half of the impact effect on closing rates persists through today – presumably because some of the businesses that did not receive a loan in time closed permanently. Our estimates therefore provide an explanation for why the worker employment effects found by Doniger and Kay (2021) are long-lasting.

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<sup>28</sup>Given that HB provides us with business names and addresses, matching individual SBA records to HB establishments is possible. An initial analysis revealed that match rates are relatively low, however, presumably because the quality of name and address information in the SBA data is of varying quality. We plan to continue exploring this avenue in future work.

Table 3: Relation of small business dynamics with share of delayed PPP loans

|                                      | A. Percent change in<br>employment of surviving<br>businesses | B. Percent of closed businesses<br>(including temp closed) | C. Percent of newly opened<br>businesses |
|--------------------------------------|---|--|--|
| Share of delayed PPP loans × Week    |   |  |  |
| February 16 - February 22            | 0.67<br>(0.59)  | 0.04<br>(0.18)   | 0.03<br>(0.02)                           |
| March 22 - March 28                  | -0.56<br>(1.18)   | 0.31<br>(0.77)   | 0.10<br>(0.06)                           |
| April 5 - April 11                   | 1.56<br>(1.33)  | -1.37<br>(0.91)  | 0.07<br>(0.06)                           |
| April 19 - April 25                  | 0.62<br>(1.34)  | -0.40<br>(0.92)  | 0.07<br>(0.06)                           |
| May 3 - May 9                        | -1.37<br>(1.39)   | 1.69*<br>(0.88)  | 0.11<br>(0.08)                           |
| May 17 - May 23                      | -2.02<br>(1.45)   | 2.24***<br>(0.82)  | 0.14<br>(0.09)                           |
| August 16 - August 22                | -0.52<br>(1.71)   | 1.35**<br>(0.68)   | 0.04<br>(0.14)                           |
| November 15 - November 21            | -1.03<br>(1.58)   | 1.43**<br>(0.62)   | 0.06<br>(0.19)                           |
| January 31 - February 6              | -0.02<br>(1.50)   | 1.15*<br>(0.62)  | 0.02<br>(0.21)                           |
| R2                                   | 0.086   | 0.11   | 0.09                                     |
| N                                    | 1,859,096   | 2,561,239  | 3,649,025                                |
| Controls                             |   |  |  |
| Health, Containment, School visits   | Y   | Y  | Y  |
| Relative ZIP household income x Week | Y   | Y  | Y  |
| Establishment FE                     | Y   | Y  | Y  |
| Week FE                              | Y   | Y  | Y  |

Notes: Standard errors are clustered at the establishment level; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . All regressions are estimated over all weeks between February 9-15, 2020 and January 31 - February 6, 2021. Table only shows coefficient estimates for Covid health and NPI regressors. Percent change in employment of surviving businesses in Panel A is computed as percentage change of employment relative to reference week for locations active in reference week (Feb 9-15, 2020) and in last week of sample (Jan 31 - Feb 6, 2021). Percent of closed businesses in Panel B is computed as the count of businesses closed (either temporarily or permanently) in week  $t$  relative to the count of businesses in the reference week. Percent of newly opened businesses in Panel C is computed as the cumulative count of new businesses as of week  $t$  relative to the count of businesses in the reference week and businesses that newly open after the reference week. Share of delayed PPP loans denotes the total zip-code amount of PPP loans issued during the week of April 26 relative to the total zip-code amount of PPP loans issued during the weeks of April 12, April 19, and April 26.

Quantitatively, the estimates imply that if the initial PPP allocation had been large enough to avoid any funding delays, permanent exits could have been reduced by more than 1 percent. Given the average cumulative closing rate of about 13% by the end of the sample (panel (c) of Figure 4) this substantial and at the same time suggests that the PPP loans did have an important effect reducing small business closings, which may explain in part the result of the previous section that cumulative closings one year after the pandemic started are no higher than the year prior. More generally, our estimates are consistent with a growing literature documenting that limited cash-on-hand and working capital adversely affects labor demand and makes businesses more sensitive to negative shocks (e.g. Chodorow-Reich 2014, Bacchetta et al. 2019, Barrot and Nanda 2020, Mehrotra and Sergeyev, 2020 among others).

## 6.4 UI replacement rates

The last exercise is with respect to UI replacement rates. As discussed in detail in Ganong et al. (2021) among others, the CARES Act stipulated an additional \$600 per week of Federal Pandemic Unemployment Compensation (FPUC) that was added uniformly to state UI compensation from the beginning of April to the end of July for everyone who qualified for UI.<sup>29</sup> Importantly for our estimates below, the unprecedented increase in jobless claims in the beginning of the pandemic led to substantial backlogs across many states in processing UI payments, which meant that a large part of eligible workers received their first UI check only with several weeks of delays. However, claimants typically received backpay for delayed payments.

After FPUC expired, the President issued an executive order on August 8 for continued UI supplements that was set to \$300 per week and ran from August 1 to September 5. Since these additional supplements were not administered through the state UI systems but through the Federal Emergency Management Agency, payment in many states was delayed by several weeks and in most states occurred after the September 5 expiration.

FPUC led to a massive increase in UI replacement rates for workers most likely to be subject to employment loss during the pandemic. Ganong et al. (2020) estimate based on CPS data that the \$600 supplement nearly tripled typical benefit levels, raising the median replacement rate to 145% with three quarters of eligible workers receiving more in UI benefits than their previous labor earnings. The total amount in UI claims disbursed was equally impressive, totaling \$263 billion for the \$600 supplements from April through July with one quarter of all working-age individuals receiving benefits during that period.

The size and persistence of the increase in replacement rates raised concerns that unemployed workers would be disincentivized to return to work, although several studies including by Dube (2021), Finamor and Scott (2021) and Marinescu et al. (2021) do not find evidence for such effects. At the same time, Ganong et al. (2021) document that the rise in UI replacement rates had important distributional consequences and resulted in large spending increases by individuals immediately after receipt of UI benefits with a concurrent decline after the \$600 expired. Spending then increased again temporarily with the availability of the \$300 per week in supplements.

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<sup>29</sup>The CARES Act also expanded eligibility for UI to self-employed and gig workers through the Pandemic Unemployment Assistance (PUA). Unemployed workers who qualified for UI under PUA also received the \$600 in FPUC. Furthermore, the CARES Act extended benefit eligibility through the Pandemic Emergency Unemployment Compensation (PEUC) by an additional thirteen weeks for individuals who exhausted state benefits. Since most states themselves extended eligibility, this means that most eligible workers did not exhaust benefits during the sample under consideration. See Ganong et al. (2021) for further discussion.

Here we investigate to what extent this large changes in UI replacement rates and spending by mostly lower income individuals affect small business dynamics in our data. To do so, we compute UI replacement rates by county using average quarterly earnings from the QWI prior to the pandemic by county and NAICS2 belonging to the four sectors under study. For each of these county-industry cells, we compute UI benefits using Ganong et al.’s (2020) UI calculator and aggregate the resulting replacement rate including the \$600 in weekly FPUC to the county level using county-industry employment weights from the QWI. Despite the fact that we are using average earnings by county-industry as opposed to individual earnings for workers likely to receive UI benefits, the county-distribution of UI replacement rates is remarkably similar to the one reported by Ganong et al. (2020). As shown in the Appendix, the distribution is skewed, with a median replacement rate of 1.25 (i.e. 125%) and an interquartile range of [1.15, 1.38].<sup>30</sup>

As described in equation (4), we interact these county UI replacement rates with weekly time fixed effect to estimate how small businesses in counties with high replacement rates fare relative to counties with low replacement rates. As before, we control for weekly fixed effects, local health and NPI measures as well as relative zip level household income interacted with the weekly fixed effects.

Table 4 reports the results. The replacement rate is a highly significant and persistent predictor of employment growth for surviving businesses, the closing rate, as well as the new opening rate. Since labor earnings and thus household income are inversely related to UI replacement rates, the estimates now have the opposite sign of the ones reported in Table 2 but the story remains the same: small business activity suffers more in affluent counties.<sup>31</sup>

Quantitatively, the effects are substantial despite the fact that the regressions control for relative zip-level household income. For the mid-April week when the initial drop in business activity is largest, small businesses in the county at the bottom quartile of the replacement rate distribution are predicted to have 3.5% lower employment growth, a 3% higher closing rate, and a 0.12% lower opening rate relative to small businesses in the county at the top quartile. The estimates approximately double by mid-May – right around when most state UI systems have resolved their backlog and benefits are disbursed with backpay – even though by that time, the recovery in small businesses activity is well on its way. These large estimates persist through August when FPUC expires and only start to diminish after the supplemental \$300 weekly benefits end in early September (except for new openings which are cumulative).

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<sup>30</sup>The main reason why we are somewhat off from the distributional statistics by Ganong et al is because of aggregation but because our HB data does not include data for all the counties.

<sup>31</sup>Indeed, household income and UI replacement rates are strongly negatively related: a regression of relative zip-level household income on the county replacement rate yields a slope coefficient of -0.89 with a standard error of 0.008. The R2 remains low at 0.13, however, implying that each of the variables has substantial explanatory power. As a result, relative zip-level household income remains a highly significant although quantitatively smaller predictor during the first months of the pandemic.



Overall the results show that similar to household income, UI replacement rates pick up the differential response in spending and small business employment across localities of varying affluence. In addition, our estimates suggest that the large increase in spending by lower income groups in response to the disbursement of much higher than usual UI benefits documented by Ganong et al. (2021) spurred demand in local services that stimulated small business activity and employment. The delayed timing of these effects can be explained both by initial backlog in UI disbursement and the fact that employment, respectively openings and closings of businesses, lags behind demand.

Table 4: Relation of small business dynamics with UI replacement ratio

|                                       | A. Percent change in<br>employment of surviving<br>businesses | B. Percent of closed businesses<br>(including temp closed) | C. Percent of newly opened<br>businesses |
|---------------------------------------|---|--|--|
| UI+600 county replacement rate × Week |   |  |  |
| February 16 - February 22             | 1.36<br>(1.36)  | -0.13<br>(0.29)  | -0.01<br>(0.04)                          |
| March 22 - March 28                   | 17.00***<br>(1.71)  | -14.67***<br>(1.14)  | 0.27**<br>(0.11)                         |
| April 5 - April 11                    | 15.60***<br>(1.99)  | -13.41***<br>(1.36)  | 0.52***<br>(0.12)                        |
| April 19 - April 25                   | 19.09***<br>(2.06)  | -15.53***<br>(1.36)  | 0.44***<br>(0.12)                        |
| May 3 - May 9                         | 27.99***<br>(2.11)  | -21.06***<br>(1.29)  | 0.54***<br>(0.14)                        |
| May 17 - May 23                       | 36.49***<br>(2.24)  | -22.86***<br>(1.20)  | 0.67***<br>(0.15)                        |
| August 16 - August 22                 | 42.20***<br>(2.66)  | -19.26***<br>(1.03)  | 1.28***<br>(0.23)                        |
| November 15 - November 21             | 29.77***<br>(2.47)  | -14.43***<br>(0.95)  | 1.95***<br>(0.30)                        |
| January 31 - February 6               | 23.38***<br>(2.34)  | -12.52***<br>(0.94)  | 2.12***<br>(0.33)                        |
| R2                                    | 0.08  | 0.11   | 0.09                                     |
| N                                     | 1,887,825   | 2,603,663  | 3,721,656                                |
| Controls                              |   |  |  |
| Health, Containment, School visits    | Y   | Y  | Y  |
| Relative ZIP household income x Week  | Y   | Y  | Y  |
| Establishment FE                      | Y   | Y  | Y  |
| Week FE                               | Y   | Y  | Y  |

Notes: Standard errors are clustered at the establishment level; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. All regressions are estimated over all weeks between February 9-15, 2020 and January 31 - February 6, 2021. Table only shows coefficient estimates for Covid health and NPI regressors. Percent change in employment of surviving businesses in Panel A is computed as percentage change of employment relative to reference week for locations active in reference week (Feb 9-15, 2020) and in last week of sample (Jan 31 - Feb 6, 2021). Percent of closed businesses in Panel B is computed as the count of businesses closed (either temporarily or permanently) in week t relative to the count of businesses in the reference week. Percent of newly opened businesses in Panel C is computed as the cumulative count of new businesses as of week t relative to the count of businesses in the reference week and businesses that newly open after the reference week. UI+600 county replacement rate equals the weekly replacement rate including \$600 of FPUC computed using the calculator by Ganong et al. (2020) based on average weekly QWI earnings by county and each of the four considered service sectors, aggregated to the county level.

## 7 Conclusion

In this paper, we combine high-frequency data on small businesses in the service sectors hit hardest by the pandemic with independent data on business activity to distinguish business closings and new openings from sample churn. This distinction turns out to be critical to properly quantify the important role played by business closings and new openings. We find four key results: (1) employment of small businesses in

four of the hardest hit service sectors contracted much more severely in the beginning of the pandemic than employment of larger businesses, but small business employment also rebounded more strongly and has recovered as much as employment of larger businesses; (2) closings account for more than half of the initial decline in small business employment, but many closed businesses have reopened and cumulative closings are not higher than prior to the pandemic; (3) new openings of small businesses have been almost as high as before the pandemic, constituting the main driver of the recovery since mid-June; (4) closing and new opening rates are both higher in counties with high death rates, suggesting reallocation of small business activity; and both closing and new openings rates were affected more adversely in affluent zip codes and zip codes with larger shares of delayed PPP loans. Our results dispel the popular notion that small businesses have on average been hurt harder by the pandemic than larger businesses. At the same time, our analysis suggests that the local health situation and to a lesser extent the differential impact of federal economic policies significantly affected small business activity.

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