Bouncing Back: How Mothballing Curbs Inflation*

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Abstract

We investigate the macroeconomic impact of *mothballed* businesses—that is, temporary closures—on inflation after a negative demand shock. First, we introduce a new establishment-level dataset derived from Google Places and use the COVID-19 pandemic experience in Canada as a case study. We confirm the importance of temporary closures during a recovery. Data on establishment reviews also suggests that preventing productive businesses from permanently exiting could support employment. Second, we embed these findings into a model of heterogeneous firms' dynamics. By maintaining productive capacity during downturns, temporary closures can ease the recovery process by initially supporting employment and subsequently reducing inflationary pressures. Our results suggest that post-pandemic inflation would have been higher without the pandemic-era fiscal support targeting temporary closures.

Keywords: Business entry and exit rate, Temporary business closure, Google Places, Inflation

JEL Codes: D22, E32, C55, C81

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1 Introduction

Large aggregate demand shocks often lead affected businesses to shut down their production. Whether they decide to shut down production today but plan to reopen tomorrow is challenging to measure but decisive for policymakers trying to assess the current supply capacity of the economy. The COVID-19 pandemic was an example of a severe aggregate demand shock especially in the consumer-facing sectors. In these sectors, it led to the temporary closure of many businesses that *mothballed* their way out of the most stringent restrictions, partly supported by extraordinary government measures. As the economy progressively re-opened, fiscal support and supply bottlenecks contributed to large inflationary pressures not experienced for decades. In this paper, we explore the link between temporary business closures and inflation after an aggregate shock.

We highlight a new channel whereby mothballing businesses during an aggregate shock can curb inflationary pressures during the subsequent recovery. First, we estimate the prevalence of temporary business closures with a novel method that leverages the data behind the Google Maps service. We then introduce a mechanism for temporary closures into an otherwise standard model of business dynamics. Following an aggregate exogenous demand shock, the model presents a new channel through which temporary closures initially support employment and then reduce inflation during the re-opening phase, i.e., when the demand shock subsides.

Our contribution is two-fold. While the mothballing of businesses has been studied by economists at least since Dixit et al. (1994), we build a new method for the identification of temporary business closures using Google Places data, the database behind the Google Maps service. By comparing the appearance and disappearance of business establishments on a map between two time points and using the associated metadata, we can distinguish businesses temporarily closing and subsequently re-entering from those exiting permanently, as well as the entry of a new business. We apply this method to the food and retail sectors of major Canadian cities during the COVID-19 pandemic and derive two stylized facts. [1] First, temporary closures substantially contributed to the increase in business entry rates during the re-opening phase of the pandemic. Second, we document a relationship between the number of reviews received by a business and both (i) the likelihood of a business remaining operational, and (ii) increased job vacancies, implying that review activity may be a proxy for business activity. This suggests that preventing businesses with good reviews from permanently exiting during the pandemic could have supported productivity and employment.

We capture these observations by extending a standard firm dynamics model (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993) to allow for temporary business closures. At the beginning of each period, firms observe their realised productivity and decide whether to temporarily close their operations—saving a share of the fixed cost—or to continue operating. The model is calibrated to match the drop in business demand and the share of temporary closures in the food and retail sectors during the pandemic in Canada. Through the lens of our model, we identify a new channel whereby temporary closures dampen inflation after an aggregate demand shock. Under our calibration, had temporary closures not been possible during the pandemic, inflation in the food and retail sector would have been 30 basis points larger in 2022 and 2023 after the lifting of COVID-19 restrictions. Our model is crucial to identify this channel given that we do not observe establishment-level inflation in the Google Places dataset. The rationale for the mechanism is as follows. Temporary closures supported survival rates during the pandemic for borderline productive firms, leading to both (i) higher supply capacity during the re-opening phase and (ii) mothballed firms experiencing lower re-opening costs relative to new firm entries. In contrast, higher fixed costs for new entrants, costly new entry taking up resources (Bilbiie et al., 2012), and limited supply would have put more pressure on employment and prices, leading to higher fixed and wage costs and

[1] In Canada, the food service sector accounts for around 6%, in final consumption spending and 7% of employment. The brick-and-mortar retail sector accounts for around 5% in final consumption spending and 12 % of employment.

ultimately higher inflation.

This research underscores the pivotal role of temporary closures in bolstering economic resilience and limiting inflationary pressures, particularly in the face of business dynamics disrupted by aggregate but temporary demand shocks. The results point to a channel whereby government spending targeted at supporting temporarily closed businesses can generate a *downward* pressure on inflation during the recovery, to be contrasted with the broader view that untargeted government support associated with more corporate debt may create an *upward* pressure on inflation. That said, this paper's parsimonious model of business dynamics does not aim to explain post-pandemic inflation as it does not include many other quantitatively relevant channels.

This work contributes to three strands of the literature. First, we contribute to the literature on the timely measurement of business dynamics and temporary closures. Official statistics are released with a time lag, but the speed of the pandemic highlighted the need for non-traditional real-time statistics on business health. Crane et al. (2022) provides an overview of some non-traditional datasets that can be used to measure business entry and exit dynamics, such as Google searches, paycheck issuance, and phone-tracking data from providers like SafeGraph Places. They find that at least some of these measures can capture the main trends well. For instance, Yelp (2020) used its platform's business reviews by customers to compute the relative importance of temporary and permanent closures during the early phase of the COVID-19 crisis. Statistics Canada (2021) further merge business openings and closures from Google Places with foot-traffic data from Google to create an index of business activity. Experimental estimates of business openings and closures built during the pandemic are now available monthly a three months lag in Canada (Statistics Canada, 2020) or quarterly with a on month lag in the United Kingdom (Office for National Statistics, 2022), compared to previous official statistics that lagged by one year. For the United States, monthly statistics on business applications are now available within a few weeks

(Haltiwanger, 2021). Following our companion proof-of-concept (Duprey et al., 2022) that focused only on the food sector in Ottawa over four months, we provide new insights using Google Places as a timely measure of temporary closures over two years across a range of cities and sectors.

Second, we also contribute to the literature on the macroeconomic relevance of business dynamics during the pandemic. Business entry and exit dynamics are key determinants of long-run productivity (Hamano and Zanetti, 2017; Aghion et al., 2019) and employment (Sedláček, 2020). Using a US sample, Kurmann et al. (2021) find that small businesses that reopened after the pandemic were key drivers of employment dynamics. Gourinchas et al. (2021) highlight that the risk of generous pandemic support policies turning non-productive firms into zombies is not as high as the risk of delayed failure rates for small and medium-sized enterprises due to a contraction of corporate credit. Still, absent government support, financial frictions during a liquidity shock like the pandemic lead to inefficient business exits (Gourinchas et al., 2023). We find that government support aimed at reducing the cost of temporary closures may have helped to support employment and limit inflation. The heterogeneous agent literature that models a distribution of firms explored the link between firm indebtedness and firm dynamics, but without focusing on temporary closures. For instance, in a model calibrated to the 2008 financial crisis, Bustamante (2020) shows that larger firm leverage increases the likelihood of experiencing a debt overhang problem that slows down the recovery and leads to low inflation. Similarly, Khan and Lee (2023) find that a recession that coincides with a rise in leverage leads to fewer producers operating at efficient levels. By contrast, our model abstracts from the role of corporate indebtedness and we instead add the option to temporary close in a standard Hopenhayn (1992) model of firms heterogeneity.

Third, we contribute to the thin literature that directly models mothballing businesses. A firm's optimal option decision to remain idle at certain productivity levels when faced with adverse shocks has been studied theoretically in Dixit (1989); Dixit et al. (1994). Since then a temporary shutdown of production has been studied in quantitative models but has been rarely applied directly to the data. Guerra et al. (2018) theoretically study the conditions under which firms decide to mothball given a price path and find these to be increased when the expectation of the price path is improving and more uncertain (both also apply to the period we study). Hamano and Zanetti (2017, 2022) study firms in a tractable real business cycle and monetary model that have the option to remain idle or produce, but their focus is on productivity effects rather than capacity and inflation. Buera et al. (2015) and Buera et al. (2021) study the quantitative effects of heterogeneous firms that draw a mandated temporary exit shock from production. We endogenise this firm decision to temporarily decision to temporarily shut down.

The remainder of the paper is structured as follows. Section 2 introduces the new method to quantify temporary closures using the data behind the Google Maps platform. Section 3 presents two new stylized facts around temporary closures for our sample of Canadian food and retail businesses. Section 4 embeds those observations into a standard model of business dynamics extended with temporary closures. Section 5 discusses the model simulation results on post-pandemic inflation, and Section 6 concludes.

2 New data on business dynamics

2.1 Data

We use Google Places, the database behind Google Maps, to identify unique businesses in a desired geographic area. Although Google Places is likely to have comprehensive and timely data, the quality of our estimates depends on the underlying quality of the Google Places data, which is beyond our control. The information in business listings is compiled by Google from different sources:[2] business owners who have a business account, customers who provide

[2]Refer to Google's local listings help for more details.

reviews, users who report inaccurate listings, or other publicly available information (e.g., an official website).

For several reasons, we focus on the retail, accommodation, and food service sectors for the downtown core of the following cities: Ottawa/Gatineau, Montreal, Toronto, and Vancouver.[3] First, it is most likely that businesses in sectors with face-to-face consumer interactions would have both timely and accurate reporting because those businesses have the strongest incentive to maintain their online presence on Google Maps. Second, areas with the most foot traffic are likely to have better data quality due to reviews and reporting by Google users. Third, these sectors were the most affected by the COVID-19 crisis and thus most relevant to track in a timely manner.

We use the functionality of "Nearby Search" in our queries to Google Places API,[4] which, instead of searching for a specific business, returns all businesses of a given type within a bounding circle, defined by a point (in latitude and longitude) and a radius (in meters). Out of 96 possible business types returned by the query,[5] we use "`store`", "`gas_station`", "`lodging`", "`restaurant`", "`bar`", "`cafe`", and "`night_club`". Those keywords allow us to match the North American Industry Classification System (NAICS) codes 44/45, 721, and 722 for retail, accommodation, and food sectors, respectively.

2.2 Cross-section of businesses

Each query returns at most 20 places, with a flag indicating whether or not more than 20 places fit the types queried. We use this flag to design a simple bisection algorithm that

[3]Specifically, we focus on the following Forward Sortation Areas (FSA) identified by the first three characters of the postal code: K1A, K1N, K1P, K1R, K1S, K2P, J8X for downtown Ottawa/Gatineau; H2J, H2L, H2T, H2V, H2X, H2Y, H2Z, H3A, H3B, H3C, H3G, H3H, H3J, H3S, H3T, H3V, H3W for downtown Montreal; M4K, M4M, M4W, M4X, M4Y, M5A, M5B, M5C, M5E, M5G, M5H, M5J, M5R, M5S, M5T, M5V, M6G, M6J, M6K for downtown Toronto; V6A, V6B, V6C, V6E, V6G, V6Z, V5T, V7X, V7Y for downtown Vancouver. Starting in April-May 2021, this corresponds to about 24000 businesses a month (initially only 15000 focused on a smaller area) in the retail, food and accommodation sectors.

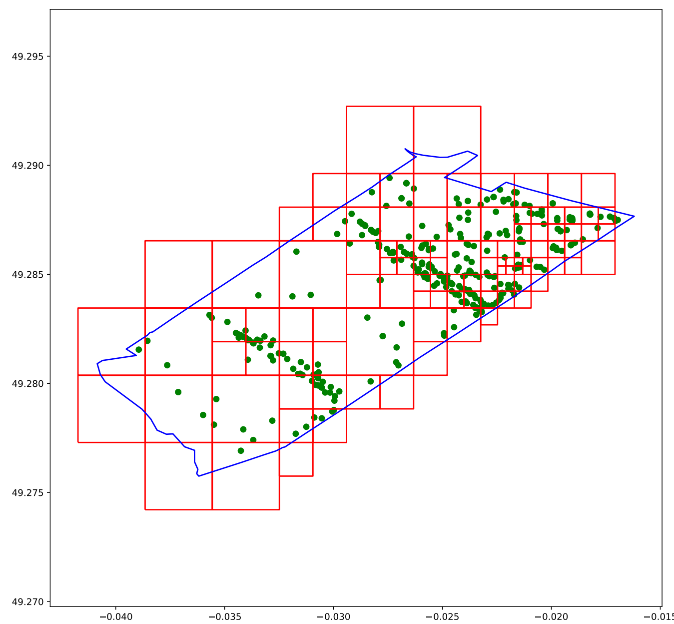
[4]Documentation on Google Places API query options can be found here.

[5]The link here contains a full list of supported business types, which are not mutually exclusive.

finds a set of queries for which (1) each query returns no greater than 20 results and (2) a desired geographic area is fully covered.

We begin with a single large square and query the circle that circumscribes it. Whenever the results of a query indicate that there are more than 20 results, we subdivide this square into four smaller squares and re-query on each. This terminates when there are no more than 20 results per query. The details are in Algorithm 1 in Appendix B. An example of the geographic units and the query results of our algorithm arrives at is shown in Figure 1: the higher the density of businesses (the green dots), the finer the search grid needs to be (the squares).[6]

Figure 1: Illustration of Algorithm 1 for keyword "`store`" in downtown Vancouver



Note: The blue shape is the bounding box of the Forward Sortation Area with postal code V6E. The vertical and horizontal axes represent latitude-longitude coordinates. The red squares are those inscribed in the coverage disks of each query, and the green points indicate the places found. Smaller squares are required where the density of the places is higher. Data as of August 23 of 2021. Our codes are provided in the replication package of Duprey et al. (2023).

[6]We required about 1000 queries for downtown Ottawa/Gatineau, 4800 for downtown Toronto, 2100 for downtown Vancouver, 3500 for downtown Montreal, given our chosen coverage of FSAs by city.

2.3 Time series of openings and closures

Since Google Places API returns only the most recent information and not any historical data, we repeatedly scrape the same area at a certain interval (in our case monthly)[7] to build a time series requires. In order to save time and cost per query, instead of beginning each month's data collection with an uninformative grid of a single large square, we initialize Algorithm 1 by using the grid of squares resulting from the previous month's data collection.

Table 1 illustrates our classification based on the possible changes between months $t-1$ and t. We identify an exit if the business unique identifier `place_id` is removed from the dataset. The variable `business_status` indicates whether a business is currently operational or temporarily closed.[8] The closure rate is computed as the fraction of exiting or temporarily closing businesses compared to operational businesses the previous month.[9]

Likewise, we identify an entry when a new unique identifier appears in the dataset. A reopening corresponds to a business previously temporarily closed that is operational again. The opening rate is computed as the fraction of entrant or reopening businesses compared to the number of operational businesses the previous month.

[7] The dataset is updated continuously, so one can consider weekly estimates, especially during a fast-paced crisis. But the use of the Google Places API requires a fixed cost per query, thus we collected monthly data.

[8] Appendix A compares our estimates of temporary closures with the experimental estimates from Statistics Canada. The difference in coverage granularity, definition (enterprise versus establishment-level) as well as the reliance on payroll data is such that those estimates capture no significant increase in temporary closures during the second lockdown of April 2021. Conversely, our estimates derived from Google Places capture a large heterogeneity across space, sectors and time with a spike of temporary closures around the second lockdown.

[9] We can also identify relocations, in which two businesses have the same unique identifier but a change in address. If the relocation is outside the city for which we downloaded the data, it will be treated as an exit. If the relocation occurs within the same city, which is most likely, it is treated as a single continuously operational business, unless it temporarily closes during the move.

	open in t with:		temporarily closed in t	non-existent in t
	≤ 10 reviews	> 10 reviews		
open in t-1	Continuing		Temporary closure	Exit
temporarily closed in t-1	Reopening			
non-existent in t-1	Entry			

Table 1: Business openings (entry and reopening) and closures (exit and temporary closure)

If a business is not immediately captured by Google Places upon opening, it could enter the dataset at a later stage when reporting is improved. Such a business that was opened earlier but only recently entered the dataset is likely to have accumulated customer reviews already. Conversely, if a business is truly opening in a given month, it is unlikely to have a large number of customer reviews at that time. We require new openings in a month to have at most 10 reviews, where the cutoff is informed by a survey of businesses conducted in Ottawa (Duprey et al., 2022).

3 Stylized facts on business dynamics

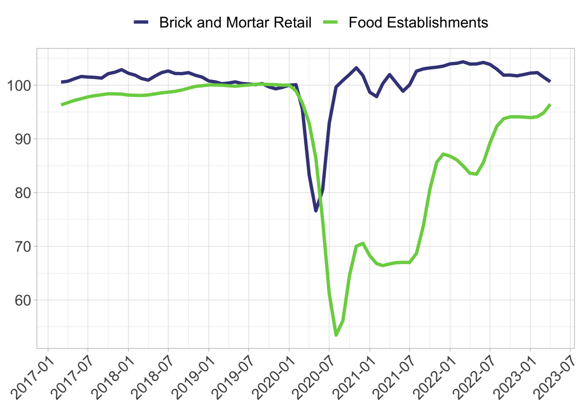
3.1 Temporary closures contribute to a faster recovery

We tracked businesses in downtown Toronto, Vancouver, Montreal and Ottawa from April-May 2021 onwards. Thus the beginning of our data corresponds to lockdowns and stay-at-home orders due to the third wave of COVID with the Delta variant. More than half of the total business openings in June 2021 are driven by re-openings rather than entries of new businesses (Duprey et al., 2023). For Ottawa, the majority of re-openings and entries in the summer of 2021 were confirmed by a survey of businesses (Duprey et al., 2022). The importance of reopenings for the speed of the post-pandemic economic recovery is also in line with Crane et al. (2022) and Kurmann et al. (2021).

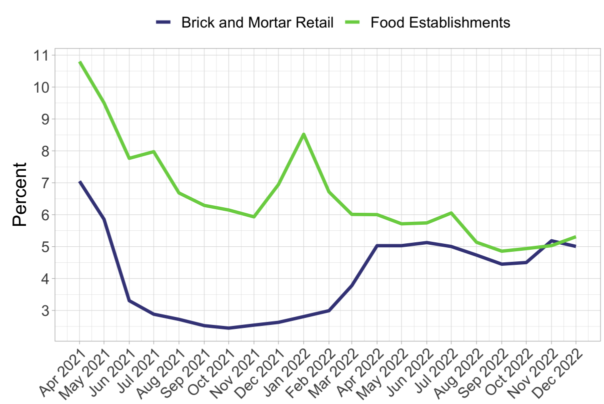
The pandemic in Canada had a heterogeneous impact across sectors. The food and beverage service sector experienced a 47% decline in households expenditure by mid-2020 and not recovering to pre-pandemic levels before 2022. This was partly a substitution to home consumption with a 5% increase in the expenditures for food and beverages consumed at home by mid-2020 (Statistics Canada Table: 36-10-0124-01). Conversely the impact on the retail sector was smaller and shorter, with a 30% decline recovering by mid-2020 (Statistics Canada Table: 36-10-0434-02). Figure 2 displays detrended consumer spending against temporary business closures for each sector. The food sector experienced a sharper drop in consumer spending, a slower recovery and a higher share of temporarily closed businesses at 11% during the third wave of COVID-19. Conversely, the retail sector experienced a smaller and short-lived drop in consumer spending, with only 7% of temporarily closed businesses during the third wave.[10]

Figure 2: Consumer spending and temporary closures around the COVID-19 pandemic

(a) Reduction in real consumer spending



(b) Temporary business closures

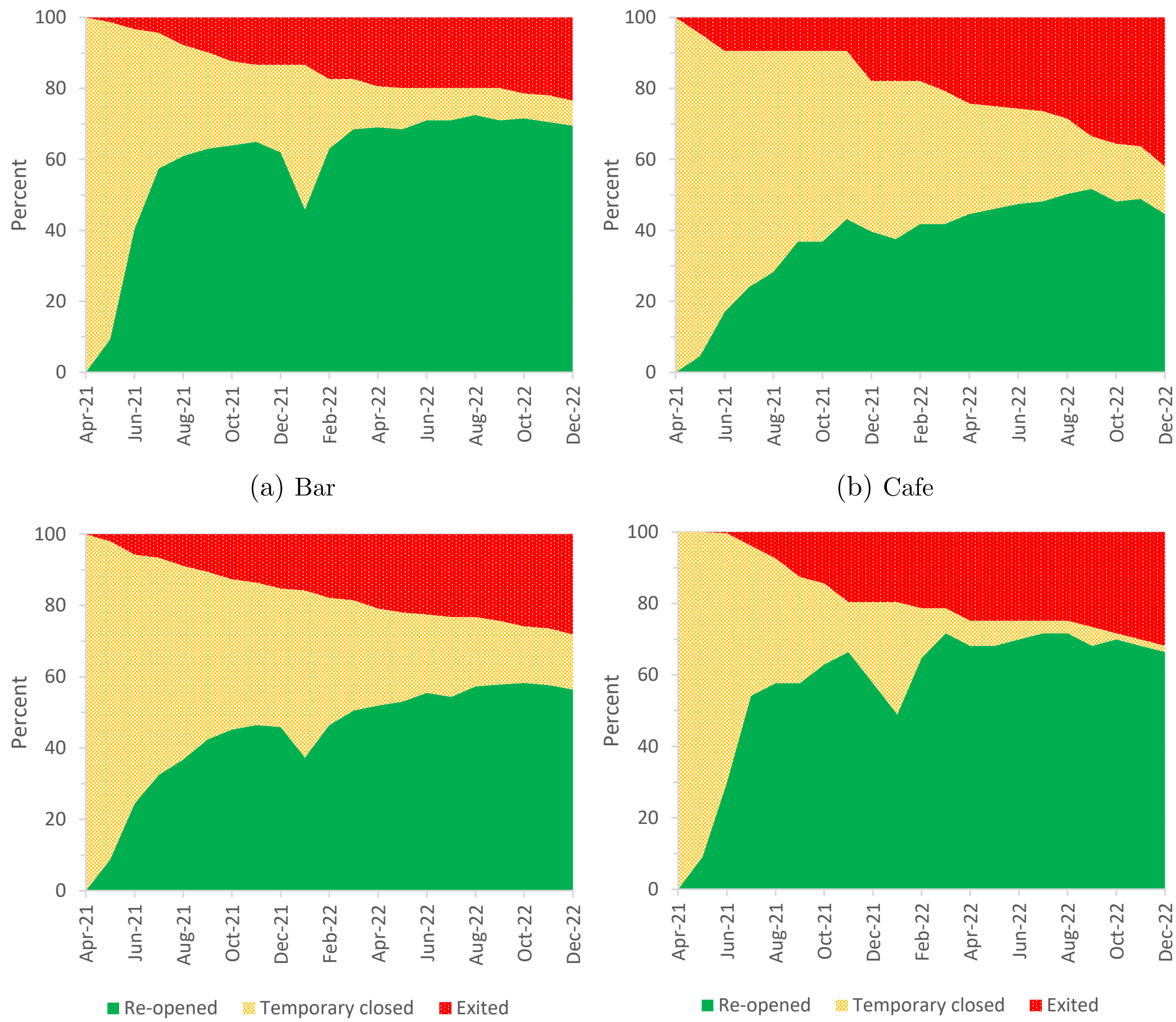


Note: The left chart shows consumer spending on non-online retail (blue) and spending at all food establishments excluding accommodation providers (green) from Statistics Canada (Tables 20-10-0056-01 and 36-10-0124-01). The series are deflated using the consumer price index (Table 18-10-0006-01), detrended with a linear trend between 2017 and 2023, and normalised with January 2020 = 100. The right chart shows the temporary closure rates in the two sectors derived from Google Places using the method in Section 2.

[10] If temporary closures were permanent exits, those businesses should not appear in the UK registry after they exit, given yearly registration fees and penalty fees for late status updates in the UK registry. Duprey et al. (2023) show that the share of temporarily closed businesses in a sample of Google Places data merged with the UK business registry is the same as a broader sample not merged with the registry. This implies that temporary closures most likely capture businesses expecting to reopen later and not permanent exits.

Figure 3 further breaks down the evolution of the status of businesses in the food sector that were initially temporarily closed in April-May 2021 during the lockdown associated with the Delta variant. Overall, about 40% reopened as soon as COVID-19 restrictions were lifted, with another 20 percentage points taking more time to reopen. Bars were the fastest to reopen, with about half reopened already by July 2021. Similarly, the emergence of the Omicron variant in December and January 2022 was associated with new restrictions, leading to more temporary closures in December 2021 and re-openings in January 2022. Some of the businesses that temporarily closed in April-May 2021 had to temporarily close again in January 2022 during the Omicron wave. Government support for temporarily closed businesses during the COVID restrictions may have contributed to a faster recovery. Of those businesses that temporarily closed during the 2021 lockdown, only about one-third permanently exited by the end of 2022. Only one-fourth of bars and restaurants that were initially temporarily closed eventually exited, but it was about half for cafes, the category in our sample that was most severely hit.

Figure 3: Evolution of the status of businesses temporarily closed in April-May 2021



(a) Bar

(b) Cafe

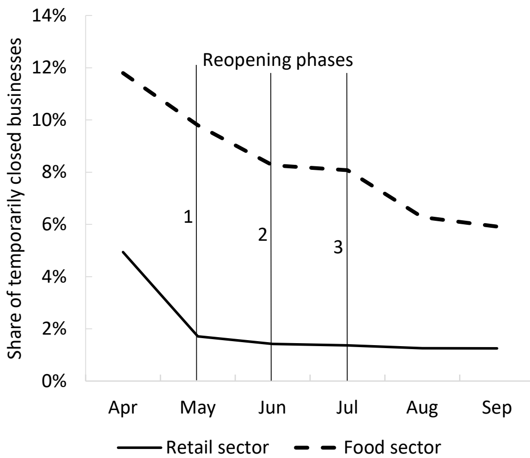
(c) Restaurant

(d) Night club

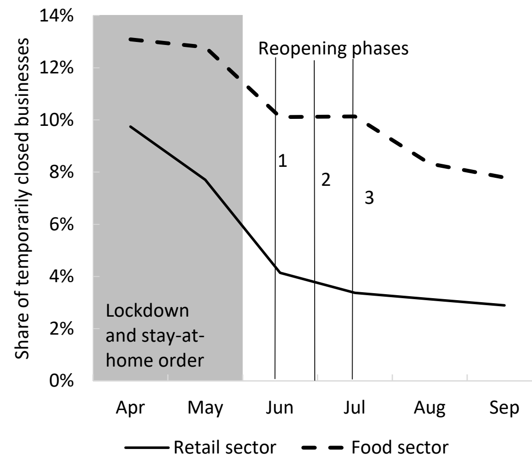
Note: The figure displays the evolution of the status of 1008 businesses identified as temporarily closed in Google Places in the food sector at the beginning of our data collection period in April 2021, during the third wave of COVID-19 (Delta variant) associated with lockdowns and stay-at-home orders. The drop in businesses re-opening around December 2021 corresponds to the fifth wave of COVID-19 (Omicron variant) that led to new restrictions in parts of Canada. Businesses temporarily closed in April 2021 can either remain temporarily closed, re-open, or exit in the subsequent months. The few cases where businesses are identified in a given month as permanently exited but re-appear in the dataset in subsequent months are re-labelled as temporary closures prior to re-opening.

The timing of the pandemic restrictions and the cross-section of business types across cities confirm the relevance of our dataset on business dynamics during the pandemic. Figure 4 displays the share of businesses identified as temporarily closed by business types and city around the restriction dates. Figure C.1 in Appendix C displays entry and exit rates split

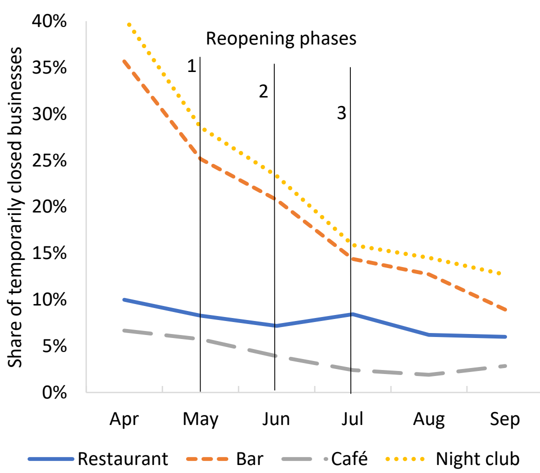
Figure 4: Evolution of the rate of businesses temporarily closed by sector in 2021



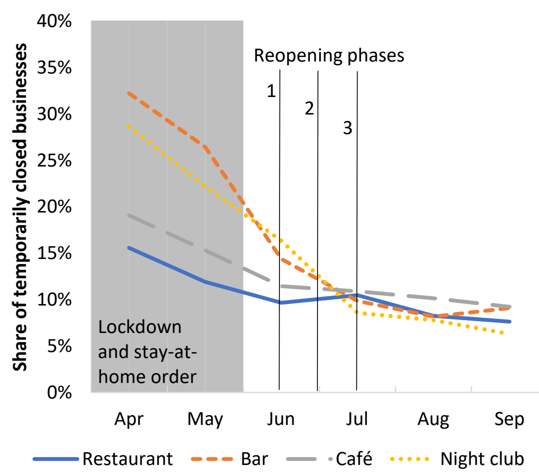
(a) Retail and food: Vancouver



(b) Retail and food: Toronto and Ottawa



(c) Food breakdown: Vancouver



(d) Food breakdown: Toronto and Ottawa

Note: The figure displays the monthly rate of temporarily closed businesses derived from Google Places for Vancouver (in the province of British Columbia) and Toronto and Ottawa (both in the province of Ontario). Vertical shading and lines correspond to the timing of the provincial lockdown and phased re-opening, as detailed in Table D.1. The retail sector corresponds to NAICS 44-45. The food sector corresponds to NAICS 722 and is the aggregation of the results by the keywords `bar`, `cafe`, `restaurant`, and `night_club`. In April, we did not collect data for any of the food sub-sectors for Toronto. The month of April for the retail sector is only an estimate based on a smaller sample.

by business types and city during the third wave of COVID with the Delta variant.[11]

British Columbia (the province where Vancouver is located) did not have a lockdown in April 2021, with stores largely remaining open. In fact, the share of retail businesses temporarily closed was only about 5% in April in Vancouver (Figure 4a). Thus, we observe fewer entries, exits and almost no re-openings in Vancouver for the retail sector compared to cities in other provinces (Figure C.1a). Most restrictions in Vancouver targeted social gathering, with 40% of night clubs, 35% of bars and 10% of restaurants temporarily closed in April 2021 (Figure 4c). Major restrictions in were lifted in May (for restaurants) and July (for nightclubs). As expected, we observe larger re-opening rates in May and July in Vancouver (Figure C.1e and C.1f), with some nightclubs re-opening earlier, likely if they are also serving food as a restaurant.[12]

Conversely, Ontario (the province where both Toronto and Ottawa are located) experienced a lockdown and a stay-at-home order starting in April 2021. At least 10% of businesses in the retail sector and about 15% of businesses in the food sector were temporarily closed in Toronto and Ottawa (Figure 4b). The major restrictions were lifted in June (for retail and restaurants) and July (for restaurants and nightclubs). Re-openings in the retail sector peaked in June (Figure C.1a) with the share of temporarily closed retail stores falling most that month (Figure 4b). For the food sector, more restaurants (+5 percentage points) and cafes (+15 percentage points) were temporarily closed in April in Ontario during the lockdown than in British Columbia without the lockdown (Figure 4c and 4d). Re-openings peaked in June, one month later than in Vancouver that started to re-open the food sector

[11]Table D.1 in Appendix D provides a timeline of the changes in restrictions affecting the retail and food sectors in the provinces of British Columbia (for Vancouver) and Ontario (for Ottawa and Toronto). We started collecting information at the end of the post-lockdown restrictions for Montreal, such that we do not include it in Figure 4 for instance. Our narrow geographical and sectoral focus prevents us from direct comparisons with publicly available official statistics on entry and exit rates as the data coverage do not match. For a sample of UK data, Duprey et al. (2023) fuzzy-merged data from Google Places with the UK registry using the name of the establishment with a success rate of 40%.

[12]Note that businesses identified as night clubs were not all temporarily closed because many of them are also simultaneously self-identified as restaurants, for instance, if a restaurant has a dance floor or if a night club serves food. For the same reason, some re-openings for nightclubs started before the official re-opening if they did take-out or had seated-only guests.

in May (Figure C.1b). For the subset of sectors and areas where we have data for May in Ontario, there is a sharp increase in re-openings, from close to zero in May, to a peak in June, especially for bars, cafes and night club (Figure C.1c, C.1d and C.1f).

3.2 Reviews and changes in business status

In the dataset of retail, food and accommodation sectors for the four main cities in Canada, about 80% of businesses have at least one review. We provide preliminary evidence that reviews left by customers can reveal valuable information associated with business dynamics.

First, we observe in Figure 5a that businesses that exit (or enter) exhibit statistically different distributions in their number of new reviews when compared to businesses that remain operational. Namely, when compared to businesses that remain, entries tend to accrue more reviews, while exits gain fewer.[13] As a result, changes in reviews may be a useful—and unique—proxy for a business' level of activity.

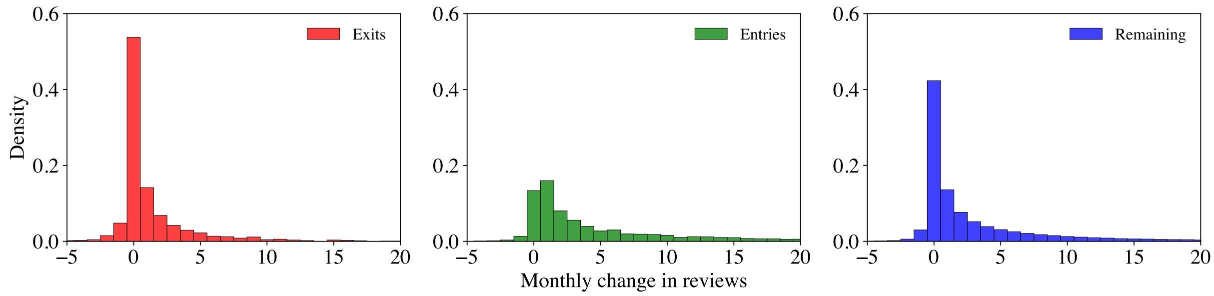
In addition, among businesses that remain operational, those that exit *in the next period* tend to have fewer reviews in *the current* period. Thus, the change in reviews can also be a potential early indicator of a business exit. Figure 6a shows the distribution of the number of new reviews in a given month if a business remains operational or exits in the subsequent month. We find a statistically significant difference in the distribution, suggesting that businesses that are generating fewer reviews during a month are more likely to exit over the next month.

So far, Figures 5a and 6a use the raw number of change in reviews. However, these observed differences could be driven by time, sector, and location fixed effects. Alternatively, we can

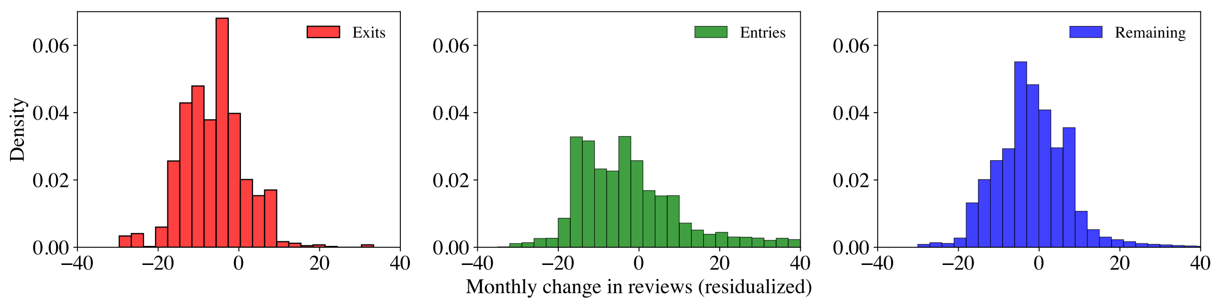
[13] Note that the number of new reviews is computed over the month in which we observed an entry or an exit. Therefore, the smaller number of reviews for exiting businesses may result both from fewer reviews per day and fewer days of operation before exiting during that month. In addition, we observe instances where the number of reviews decreases over a month, for instance if users or businesses delete reviews.

Figure 5: Entries (exit) accrue more (less) reviews than remaining businesses

(a) Raw number



(b) Residualized number



Note: Data collected from downtown Toronto, Vancouver, Montreal and Ottawa, covering about 400000 observations from Google Places in the retail, food and accommodation sectors from April 2021 to December 2022. Entries and exits were assessed according to the classification in Table 1. Panel (a) displays the change in the number of new reviews for businesses exiting, entering, and remaining operational. Panel (b) displays the equivalent residuals from Equation (1) net of temporal, sectoral and location-fixed effects.

regress a business' change in reviews on time, sector and location dummy variables, as

$$\begin{aligned}\text{ChangeInReviews}_{it} = &\ \text{IsFood}_i + \text{IsAccommodation}_i + \ldots \\ &\ \text{IsInToronto}_i + \text{IsInMontreal}_i + \ldots \\ &\ \mathbb{1}\{t=1\} + \ldots + \mathbb{1}\{t=20\} + \varepsilon_{it}\end{aligned} \tag{1}$$

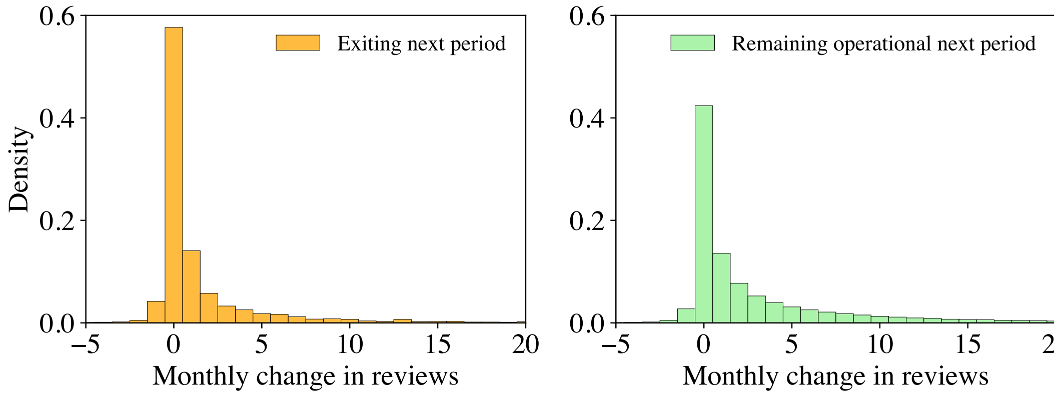
where i indicates a unique business, and t indicates an index of a month in which we collected data.

Figures 5b and 6b now display the residuals ε_{it} instead of the change in the number of reviews.[14] We find the same qualitative differences and the resulting distributions are sta-

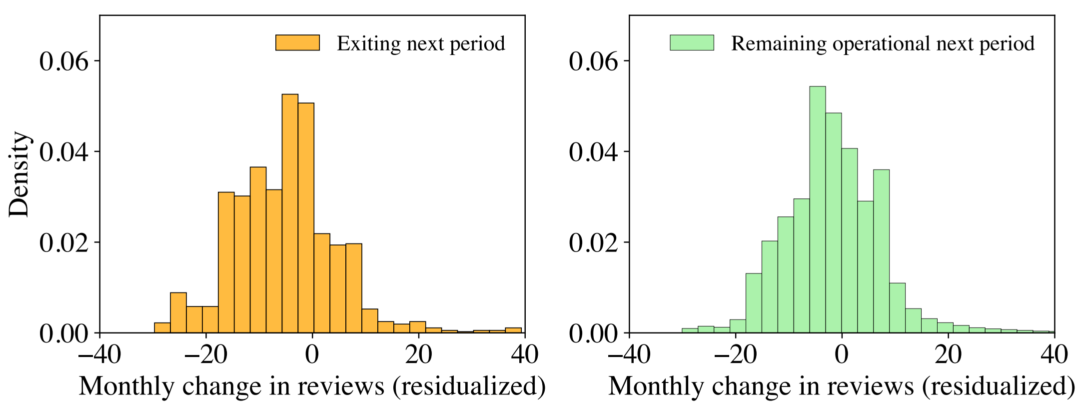
[14] The coefficient estimates are left for Appendix E.

Figure 6: More rated businesses are more likely to remain in business

(a) Raw number



(b) Residualized number



Note: Downtown Toronto, Vancouver, Montreal and Ottawa, covering about 400000 observations from Google Places in the retail, food and accommodation sectors from April 2021 to December 2022. Remaining and exiting businesses were assessed according to the classification in Table 1. Panel (a) displays the change in the number of reviews for businesses exiting or entering next month. Panel (b) displays the equivalent residuals from Equation (1) net of temporal, sectoral and location fixed effects.

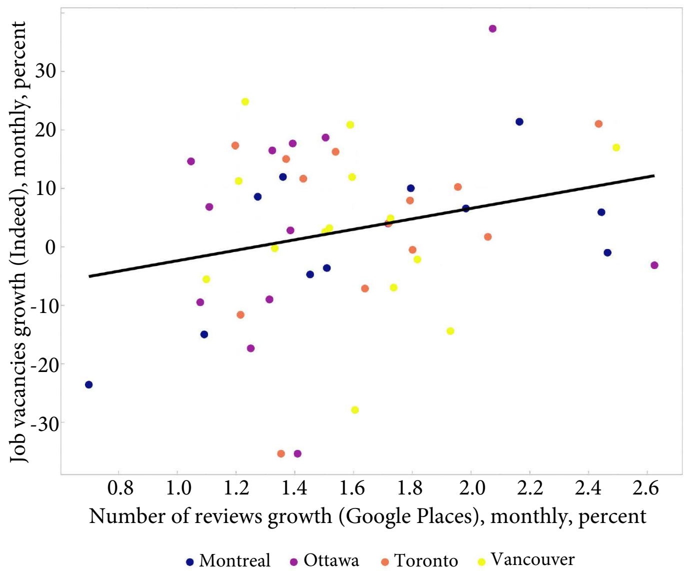
tistically different from each other.

These observations can also be validated through another data source on job vacancies. Figure 7 shows how the monthly growth in the number of reviews from Google Places for establishments in each city in our sample correlates with the monthly growth of all job vacancies per city from the job listing website 'Indeed'. Despite the coverage difference in the two dataset, we find a strong positive relationship at the city/month level, suggesting that businesses that are generating more reviews are also the ones most dynamic in terms of employment growth. This may be an economically significant aggregate effect if one considers that the sectors we cover account for up to 20% of the total employment in Canada (respectively 12%, 6% and 1.5% of total employment in the retail, accommodation, and food service sectors; see Statistics Canada Table 14-10-0202-01). A similar positive correlation is obtained when restricting both dataset to cover the food and accommodation sector only, at the cost of losing the cross-city comparison as the breakdown by both sector and city is not available from our 'Indeed' dataset. Better rated businesses on average are also correlated with more job listings. This is consistent with Bahaj et al. (2022), who find that job vacancies from the website 'Indeed' correlates with post-pandemic firms creation in the UK, and with Kurmann et al. (2021), who find that small businesses re-opening after COVID were key drivers of employment dynamics.

4 Modelling temporary closures

Our new establishments-level data highlights that some firms permanently shut down in response to an aggregate shock, while other firms only temporarily close their operations. Data on establishment reviews presented in the previous section also indicates that preventing productive businesses, which experience continued demand for their services as proxied for by their review number, from permanently exiting could support employment. This behaviour supports the idea that, following a temporary decline in demand as observed during

Figure 7: A higher number of new reviews correlates with an increase in vacancies



Note: Data from April 2021 to December 2022. For Google Places, data averaged across downtown of the four cities for the retail, food and accommodation sectors. For Indeed, data averaged across the four metropolitan areas for all business types. Source: Figure 5 of Duprey et al. (2023).

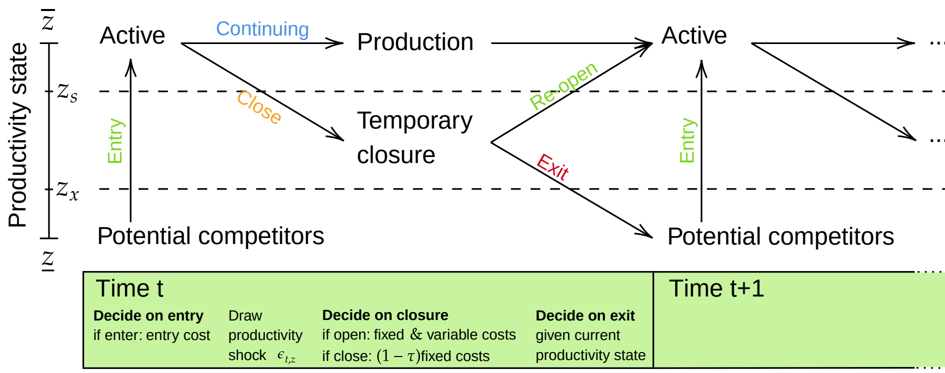
the pandemic, mothballing operations is also a rational response for firms. To prevent permanent exits and avoid a sluggish recovery it may be desirable for governments to subsidize temporary closures.

We capture these observations in a firm dynamics model as first outlined in Hopenhayn (1992) and Hopenhayn and Rogerson (1993). We depart from the baseline model in one crucial way: at the beginning of each period, firms observe their realised productivity and decide whether to temporarily close their operations in, saving a share of the fixed cost, or to continue operating. The timing of the model is represented in Figure 8. Our model provides evidence for the fast recoveries when firms have, in the spirit of Dixit et al. (1994), the option to temporarily shut down production.

4.1 Individual firm production

Firms produce in a competitive market taking the market price p and wages w as given. Each firm uses only labour to produce and has an idiosyncratic productivity state z. The

Figure 8: Timing of the model of firm dynamics extended to temporary closures



productivity state of the firms is described by a persistent stochastic auto-regressive process,

$$z' = \rho_z z + \epsilon_z, \tag{2}$$

where $\rho_z \in (0, 1)$ is the persistence parameter and $\epsilon_z \sim N(0, \sigma_z^2)$ are idiosyncratic and identically distributed shocks. The firm's period profit function when the firm is producing is

$$\pi(p, z) = \max_n \left[p \exp(z) n^\alpha - wn - wf\right]. \tag{3}$$

The labor cost wn varies with the size of the firm with fixed cost wf scaled by the size of the firm. The optimal labour choice in this case is $n^* = (\frac{\alpha p \exp(z)}{w})^{\frac{1}{1-\alpha}}$ and the optimal output for a firm is $y^* = z(\frac{\alpha p \exp(z)}{w})^{\frac{\alpha}{1-\alpha}}$.

At the beginning of each period, after observing the firm's current period productivity realisation z, the firm's management decides whether to produce or to temporarily close for the current period. When the firm exits temporarily, it can save on fixed costs τwf, such that the fraction $(1-\tau)$ is the cost of maintaining the business while it is closed temporarily, for instance through partial wage payments, tax payments or upkeep. The firm solves the following optimization problem whether to produce or temporarily close their production,

$$\max\{\pi(p, z);\ -(1-\tau)wf\}. \tag{4}$$

At the end of every period, the firm's management decides on whether to permanently exit or to continue to the next period. When the firm permanently exits, the future value of the firm is 0. Equation 5 describes the firm's value function,

$$V(p,z) = \max\{\pi(p,z);\ -(1-\tau)wf\} + \beta \max\{\mathbb{E}(V(p',z'));\ 0\}. \tag{5}$$

Proposition 1. *Firms below a productivity state z_s will exit production temporarily, while firms below a productivity state z_x will exit permanently. Given $\tau \in (0,1]$, there exists an equilibria where $z_x < z_s$ in a given period.*

Proof. Assume z_x is at an arbitrary level $\mathbb{E}(V(p',z'|z_x)) = 0$ and $p = p'$. This means that for a slightly higher productivity $z^+ = z_x + \delta$, $\mathbb{E}(V(p,z'|z^+)) > 0$. At this productivity level, however, $\pi(p,z^+) < 0$ is possible as the firm may have a positive expectation about the next period's productivity outweighing any losses from the current period. This will be the case when $z_x < 0$ as then $\mathbb{E}(z') > z_x$ and $\mathbb{E}(\pi(p,z')) > \pi(p,z_x)$. It is then clear that there exists a value of τ where the firm will prefer to stay closed at the productivity level $z_s \geq z^+ > z_x$. □

4.2 Aggregate dynamics

We discretize the idiosyncratic productivity space for firms over n_z. The law of motion of all firms in the economy is driven by the transition matrix by firms between states $\Pi_{z'|z}$ and the choice of firms to exit $\mathbb{1}_{z>z_x}$. We assume that new firms enter by paying entry cost C_e given by

$$C_e = \left(\frac{E}{E^*}\right)^{\xi} c_e w\ . \tag{6}$$

We choose a convex parameter for the entry cost ξ to capture that a lot of demand for entry will contest the input factors required for entry and increase the cost of firms entry.[15]

Here E^* is the steady state level of entry, meaning that in steady state $c_e w$ is the entry

[15] Our main qualitative results also hold for linear cost of entry.

cost paid by a firm. c_e is an exogenous cost controlling the amount of labour needed to set up the firm. Firms enter the market in the next period and draw their initial productivity state from the long-run distribution of productivity z, Π_0. Firms optimally enter until the expected value of entering equals the cost,

$$\left(\frac{E}{E^*}\right)^{\xi} c_e w = \beta \mathbb{E}\left(\Pi_0 V(p', z')\right) \ . \tag{7}$$

In steady state, Equation (7) simplifies to $c_e w = \beta \Pi_0 V(p, z)$.

Finally, the law of motion all firms in all states M is

$$M' = \Pi_{z'|z} \, \mathbb{I}_{z>z_x} \, M + \Pi_0 E \ . \tag{8}$$

M is the vector of all firms ordered along discretized states. Here $\mathbb{I}_{z>z_x}$ refers to a $n_z \times n_z$ matrix where rows and columns representing z above z_x form an identity submatrix and all other values are 0. In steady-state, we can solve for the equilibrium firm distribution as a function of entries, $M = (\Pi_0 E)(I - \Pi_{z'|z}\mathbb{I}_{z>z_x})^{-1}$, with I an identity matrix.

These allow us to compute the equilibrium aggregate supply. Aggregate supply Y is the total production of all firms in the market. It is the sum of all firms that choose to produce $\mathbb{I}_{z>z_s}$ weighted by the vector of existing firms in all states M, and expressed as

$$Y = \int_{\underline{z}}^{\bar{z}} (\mathbb{I}_{z>z_s} M y^*) dz = \int_{z_s}^{\bar{z}} M z \left(\frac{\alpha p \exp(z)}{w}\right)^{\frac{\alpha}{1-\alpha}} dz \ . \tag{9}$$

Here, $\mathbb{I}_{z>z_s}$ refers to a $n_z \times n_z$ matrix where rows and columns representing z above z_s form an identity submatrix and all other values are 0.

As in Hopenhayn (1992) and Hopenhayn and Rogerson (1993), the equilibrium price p in the market is then given by the exogenous demand $\bar{D}$ over supply,

$$p = \frac{\bar{D}}{Y}. \tag{10}$$

We can also calculate aggregate firm employment. This is the sum of the employment of firms operating, the payments on fixed cost for temporary closed firms, and the payments to enter the market by entering firms, given by

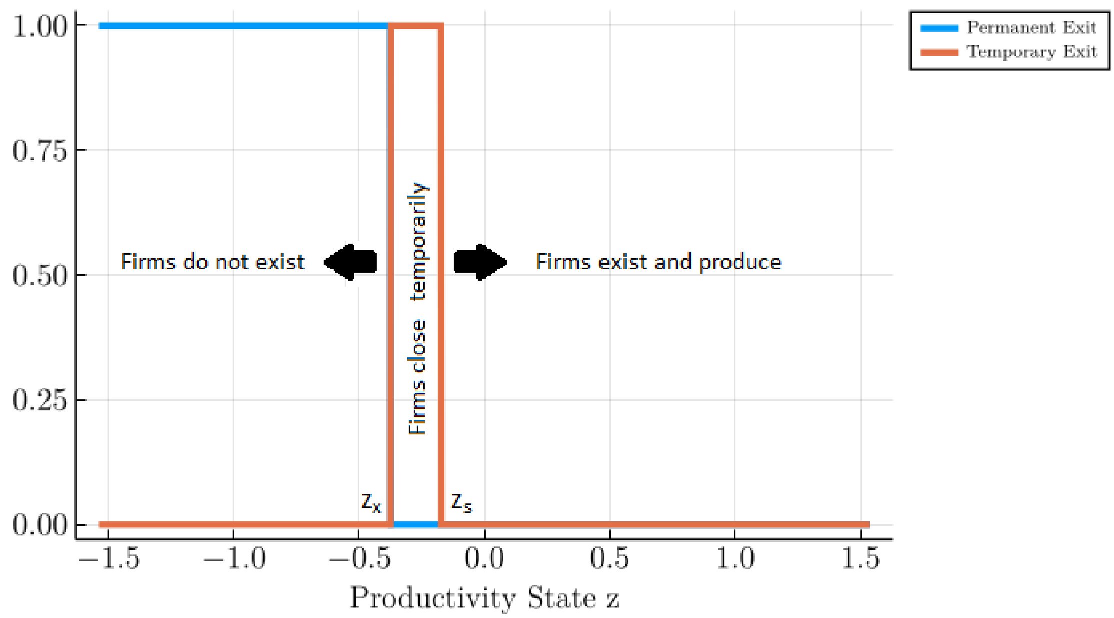
$$L = \int_{z_s}^{\bar{z}} \mathbb{I}_{z>z_x} M n^*(z) dz + \int_{z_x}^{z_s} (\mathbb{I}_{z>z_x} - \mathbb{I}_{z>z_s}) M(1-\tau) f dz + \frac{EC_e}{w} \ . \tag{11}$$

4.3 Simulation approach

We perform simulations for the retail and food production sectors that experienced a severe decline in demand—proxied by consumer spending—and increase in temporary closures (Figure 2). As in the data, we simulate a stronger and more persistent effect for food establishments. This phenomenon is also observed in the yearly employment data (Statistics Canada Table 14-10-0202-01), with a 7% decrease in the number of retail jobs in 2021 compared to 2020 that fully recovered in 2021, versus a 23% drop for the food services and drinking places in 2020 that has not fully recovered as of 2022.

We calibrate the model to match the long-run entry rate and the measured temporary closure rate in equilibrium. The calibration parameters are in Table 2. The calibrated steady-state entry and permanent exit rate is 1% to match the the monthly entry rates in the food and accommodation, and the retail sector reported by Statistics Canada (2020). The steady-state temporary closure rate is calibrated to 5%, as inferred from our data in Figure 2b. Figure 9 shows that, in our model calibration, the model steady-state exhibits idiosyncratic productivity states for firms where these choose to exit temporarily. Of these temporarily exited firms the more productive choose to remain in the market at the end of the period

Figure 9: Firms status as a function of their productivity in steady state



Note: Steady-state of the model showing firms status as a function of their productivity state. Status is 1 for firms that exit (permanently in blue or temporarily in red) and status is 0 for firms that continue operating given their productivity realisation z.

to receive a new realisation of their idiosyncratic productivity in the next period while the firms with lower idiosyncratic productivity realisations choose to exit permanently at the end of the period.

We simulate the decline in demand proxied by consumer spending (Figure 2a) as an MIT shock following Boppart et al. (2018). Thus we assume that the decline in demand is known from 2020 onwards and firms expect demand to go back to equilibrium in July 2023. Concretely, we solve the optimal entry and exit path for firms of all states iteratively from the deviations in equilibrium demand $\bar{D} = 100$ and the equilibrium price. We assume that after the observed demand changes, demand stays at the equilibrium level $\bar{D} = 100$ for the rest of time. Our iteration converges to a dynamic equilibrium consistent of the state vector of firms, the path of entrants, the decisions for permanent and temporary exits, and the price $\{M, \mathbb{1}_{z>z_x}, \mathbb{1}_{z>z_s}, p\}_{t=0}^{\infty}$.[16]

[16] Further computational details are in Appendix F.1.

Parameter	Value	Description
β	0.9966	Monthly discount factor for an annual discount factor of 0.96
ψ_m	0	Idiosyncratic mean log productivity
ψ_ρ	0.95	Persistence of idiosyncratic firm productivity process
ψ_σ	0.2	Volatility of idiosyncratic firm productivity shocks
α	0.67	Exponent on labour
c_e	2.65	Equilibrium entry cost
c	0.2	Equilibrium fixed cost
ξ	2	Convex increase of entry cost
w	2	Wage
$\bar{D}$	100	Normalised equilibrium demand
τ – Share of the fixed cost that can be saved when temporarily shutting down		
	0.275	Baseline
	0	First counterfactual - No temporary closures
	0.3025	Second counterfactual - Subsidised temporary closures

Table 2: Model calibration

5 Simulation results and policy implications

We show the impact of temporary closures in our model by comparing the dynamics of entry, prices, exits and firm numbers during the COVID-19 pandemic to two counterfactuals. The scenarios differ only in the calibration of the share τ of fixed cost that can be saved when temporarily shutting down, as shown in Table 2. In the first counterfactual, we do not allow firms to temporarily close from 2020 until January 2022. This is equivalent to calibrating the share of fixed cost that can be saved when temporarily shutting down to zero, i.e. a temporary closure yields no savings. In the second counterfactual, firms that choose to temporarily close from 2020 until January 2022 enjoy a 10% larger savings on fixed cost. This approximates additional government subsidies that would have incentivized more firms to shut down production only temporarily. Both counterfactuals assume that, from February 2022 onwards, firms can temporarily close and save the baseline share of fixed cost. This ensures that both counterfactuals converge to the same steady state as the baseline scenario in the long run.

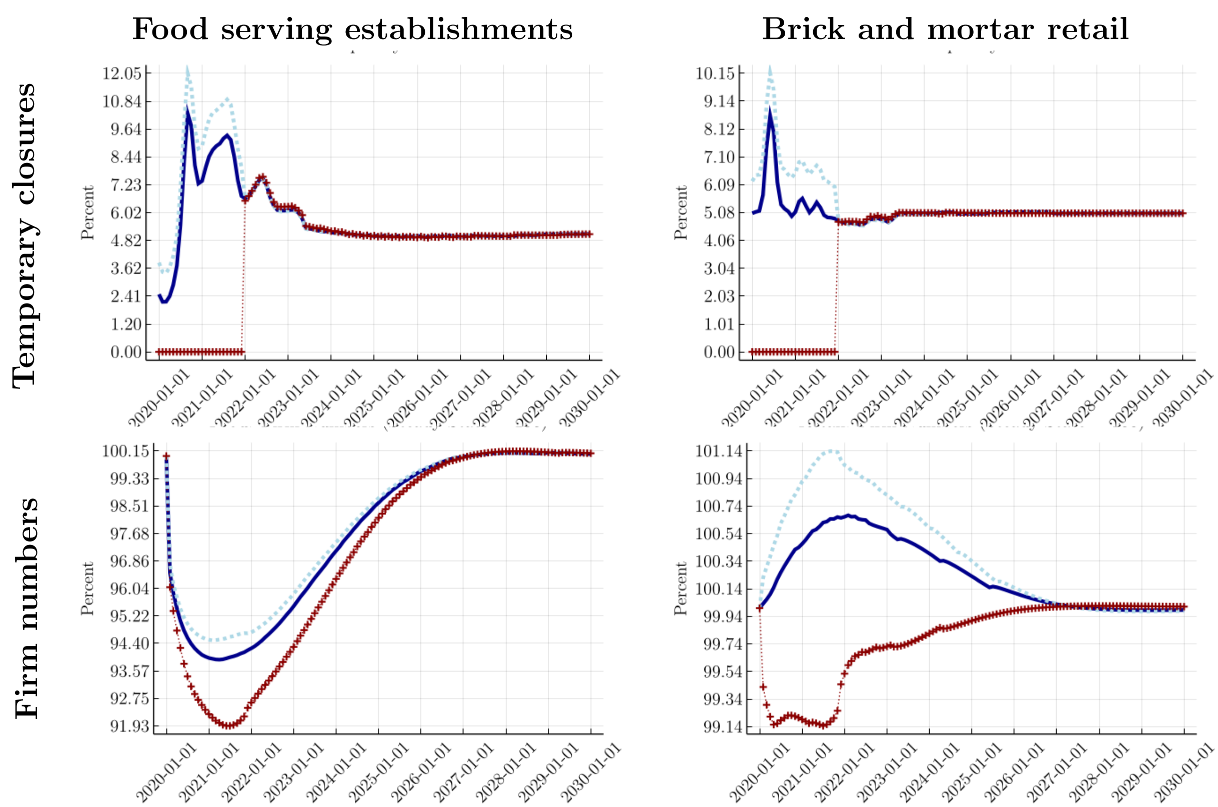
The top row in Figure 10 shows our main variable of interest, the share of temporary closures for the food sector (left) and the retail sector (right).[17] As expected, our simulated decline in demand shown in Figure 2a leads to an increase in the share of firms temporarily closing in the baseline scenario (plain blue line). The dynamics across sectors differ due to the size of the demand shock. For brick-and-mortar retailers, the smaller size of the initial negative demand shock leads more low productivity firms to decide to close temporarily instead of exiting permanently, such that they are ready to re-open once the aggregate shock passes. In contrast, the large size of the initial negative demand shock for food serving establishments leads to relatively more permanent exits for low productivity firms rather than temporary closures in the hope for a better productivity draw next period. As the aggregate shock passes, higher productivity firms receiving negative shocks enter the productivity parameter space where it is optimal for them to close temporarily, driving the temporary closure rate up. We observe similar dynamics but a higher rate of temporary closures for the counterfactual case when the incentives to close temporarily are increased (dashed blue line). The temporary closure rate is zero by assumption in the case where temporary closure is not possible for two years (crossed red line).

The bottom row in Figure 10 shows the number of firms where the steady state has been normalised to hundred, so that changes can be interpreted as percentages of the steady state. The large shock in the food sector leads to the number of firms falling by 6% in the baseline scenario (plain blue line). The option to temporarily close reduces this fall compared to the counterfactual without temporary closures (crossed red line) by around 2 percentage points. As expected, more firms would have survived in the counterfactual where temporary closures is further subsidised (dashed blue line). The response of the retail sector in our model is particularly interesting. Figure 2a shows that, in this sector, the negative demand shock was smaller and shorter-lived, followed by an increase in demand as consumers started to spend more in retail shops to substitute for experiences and outside food consumption. The shock

[17]The dynamics of entry, permanent exit, equilibrium prices and employment are plotted in Figure F.2 for the baseline and the two counterfactuals in Appendix F.2.

therefore leads to an increase in temporary closures, but this increase creates incentives for new entrants to come into the market in the hope of receiving a better productivity draw at an increased price level. The increased entry and decreased permanent exits shown in Figure F.2 in Appendix F confirm this interpretation. As a result, the total number of firms varies less but increases in the cases where we allow for temporary closure. An increase in business creation in the retail sector during the pandemic has been well documented in the data (Decker and Haltiwanger, 2023; Duguid et al., 2023) and opportunities created for entrants by businesses temporarily closing as predicted by the model may contribute to explaining it.

Figure 10: Firm dynamics in the baseline and counterfactuals



Note: The solid blue line is the baseline scenario with a share of fixed cost that can be saved when temporarily shutting down $\tau = 0.275$. The crossed red line shows the counterfactual where firms cannot exit temporarily $\tau = 0$. The dashed blue line shows the counterfactual where firms save an additional 10 % of the fixed cost when exiting production for the period ($\tau = 0.3025$). From February 2022 onwards, all firms can temporarily close and save the baseline share of fixed cost across all scenarios to ensure convergence back to the steady state. Temporary closures are calculated as a percentage of operational firms. Firm numbers are normalised to equal 100 in the steady state.

Figure 11 shows the consequences of temporary closures on prices and employment, expressed as the percentage difference of the two counterfactuals to the baseline scenario.[18] The plain cyan line in the top panels shows that, absent temporary closures, the price level would have been larger during the re-opening and post-pandemic phase in 2023. Prices would have been 0.57 percent higher than in the baseline in July 2024 for the food sector and 0.37 percent higher in the retail sector. Note, that our estimated price changes are strictly speaking Laspeyres price changes, as we do not allow for substitution effects on spending when prices change.[19] Given the large demand changes and the small additional price changes in our model we don't expect spending shifts to have a large effect on our estimates.

The dotted purple line in the top panels shows that subsidising temporary closures 10% more until January 2022 would have reduced the post-pandemic price level compared to the baseline. Intuitively, the reason is that temporary closures prevent frictional costs from firms exiting and re-entering the market. Thus when lower productivity firms have incentives to temporarily close their production, they are ready to provide supply when demand in the economy recovers, limiting the supply bottlenecks that were observed during the re-opening phase of the pandemic. Thus, the price level rises by less and fewer new entrants (that need to pay a fixed cost of entry) are needed to bring it back to the steady state.

Thus, our results suggest the existence of a new channel, whereby temporary closures and government subsidies designed to temporarily help struggling businesses, prevent additional price pressures after a large demand shock like the pandemic. In our simulations, temporary closures prevented an additional 0.3% of inflation in the years 2022 and 2023. Of course, our simple model of business dynamics does not include other channels that may be quantitatively relevant. We do not assess the overall impact of government spending during the pandemic that may have been an upward pressure on post-pandemic inflation. We merely state that targeted government spending supporting temporarily closed businesses

[18] For completeness, Figure F.3 in Appendix F display the percentage difference of the two counterfactuals to the baseline scenario for the other firm dynamics variables.

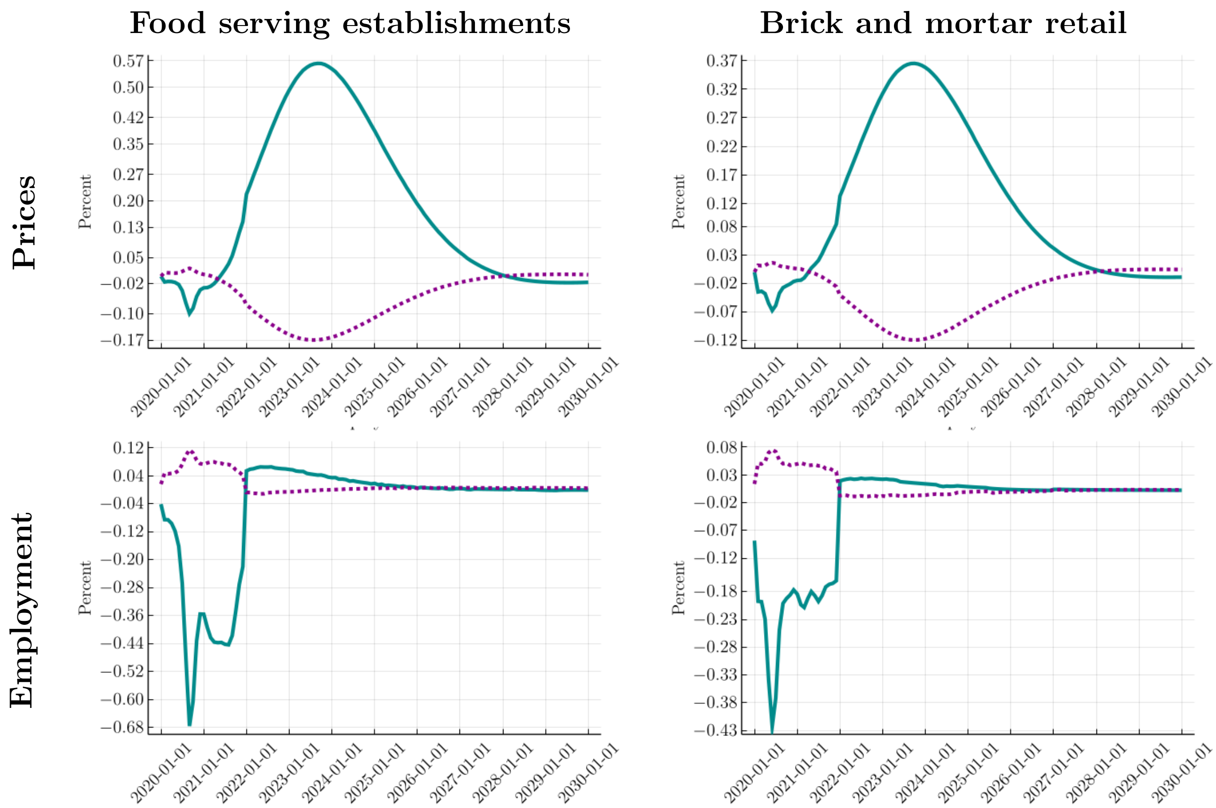
[19] For instance, an increase in the prices of restaurants would not lead to substitution and households shifting spending, for example, to home cooking.

(e.g., subsidized furlough programs) may have been a *downward* pressure on post-pandemic inflation.

The bottom panel of Figure 11 shows the total employment, defined as total salary payments, by firms for the counterfactual scenarios relative to the baseline. The plain cyan line shows that, in both sectors, employment would have fallen by more relative to the baseline scenario if temporary closure had not been an option for firms. The employment loss would have been stronger in the food than in the retail sector. Both sectors enjoy a brief period of increased employment during the recovery, driven by the labour effort necessary to establish new entrants. This is consistent with the labour shortage experienced during the recovery phase of the pandemic. The dotted purple line shows that, with further government subsidy increasing the share of temporarily closing firms, employment would have fallen less than in the baseline. This is non-obvious as a subsidised temporary closure would decrease salary payments by a firm. However, this within-firm wage bill reduction is outweighed by more firms surviving and thereby overall providing more employment opportunities.

Our simulations, calibrated to the temporary closure rates computed from Google Places, show that temporary closure meant more firms survived the observed consumption shock triggered by the COVID-19 pandemic in the food and retail sectors. This provided the economy with a higher supply capacity during the re-opening phase of the pandemic. For the two sectors we consider, our counterfactual simulations show that temporary closures resulted in lower unemployment during the pandemic, lower labor shortages in 2022 and 2023, and lower inflation in 2022 and 2023. Further subsidizing temporary closures by governments during the pandemic would have been associated with additional downward pressure on the price level.

Figure 11: Prices and employment in the counterfactuals relative to the baseline



Note: The solid cyan line shows the percent change from the baseline scenario when firms cannot exit temporarily until January 2022. The dotted purple line shows the percent change from the baseline scenario when temporary closure is subsidised 10% more than in the baseline until January 2022. From February 2022 onwards, all firms can temporarily close and save the baseline share of fixed cost across all baseline and counterfactual scenarios to ensure convergence back to the steady state. Employment is defined as the total salary payments.

6 Conclusion

In this paper, we highlight a possible channel whereby mothballed businesses can curb inflation after a severe demand shock. As a case study, we use the post COVID-19 reopening of two industries: brick-and-mortar retail and food-serving establishments in urban areas in Canada. We first present a new way to measure temporary closures with Google Places that highlights the relevance of establishments-level metadata for small businesses. On the one hand, the temporary closure flag reflects the active operation of an establishment, something that is not captured well by the usual annual updates in administrative data. On the other hand, business reviews correlate with business dynamics and job vacancies, such that preventing well rated businesses from permanently exiting could support employment.

We then proceed to develop a heterogeneous model of firm dynamics where firms differ in their productivity and activity states. We add the option for firms to temporarily close (that is, save on their cost of operating) or of permanently exit depending on their individual productivity state and expected demand. After a negative demand shock, some firms will only temporarily close, such that the economy saves on the cost of reentry (Bilbiie et al., 2012) and retains more productive capacity, implying a reduction in price pressures. When applying our framework to the COVID-19 episode, we find that the "mothballing" of establishments helped preserve employment. Absent temporary closures, the food-serving sector and the brick-and-mortar retail sector would have faced more inflationary pressures, respectively an additional 30 and 20 basis points of inflation per year in both 2022 and 2023. Eventually, our counterfactual shows that government subsidies for temporarily closed businesses likely contributed to this deflationary pressure. Still, our work focuses on one specific channel and thus abstracts from other mechanisms, such that future research should consider introducing business reviews and temporary closures into larger-scale general equilibrium models of firm dynamics.

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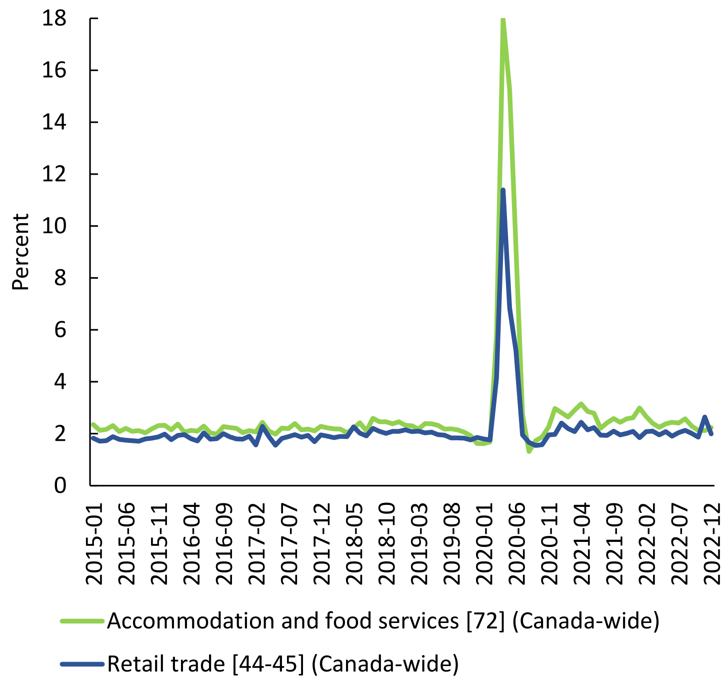
A Comparison with Statistics Canada estimates

The publicly available estimates of temporary closures produced by Statistics Canada in Figure A.1 do not have the granular breakdown we have in our sample and rely on a different definition of temporary closures. Because this Statistics Canada data relies on monthly payroll records, the temporary closure estimates reflect enterprise-level temporary closures and capture only temporary closures for businesses with at least one employee. To be classified as a temporarily closing business, a business must have paid employment in the previous month but no paid employment in the given month. A business classified as a permanent exit would have paid employment before but no paid employment in the given month and any of the subsequent periods. Instead, in our dataset derived from Google Places, we capture establishment-level closures for businesses, irrespective of the number of employees, and temporary closures correspond to the actual establishment not being opened for business to the public, even if some employees remain on the payroll.

Figure A.1: Temporary closures with the experimental estimates from Statistics Canada



Note: Ratio of temporary closures in a given month compared to the number of active businesses from the previous month, Canada-wide estimates. The estimates capture only businesses with employees because the underlying micro-data is from monthly payroll records from the Canada Revenue Agency combined with the Business Register. For example, to be classified as a temporarily closing business in March 2020, a business must have paid employment in February 2020 but no paid employment in March 2020. In contrast, to be classified as a permanent exit in the first quarter of 2020, the business must not have paid employment in any of the subsequent quarters. Source: Statistics Canada experimental estimates for business openings and closures (Table: 33-10-0270-01).

This difference in definitions likely explain the significant difference in the magnitude of our estimates of temporary closures. From the Statistics Canada data in Figure A.1, we observe that the temporary closure rate spiked at 18.0 and 11.4 percent around the first lockdown in March 2020, respectively for the accommodation and food sector and the retail trade sector. This is an increase by 16.3 and 9.6 percentage points, compared to an increase by 0.4 and 0.2 percentage points during the second lockdown in April 2021, respectively for each sector. Alternatively with our estimates in Figure 2b, although we did not collect data on the first lockdown, we observe a large increase in temporary closure rates during the second lockdown in April 2021. Our temporary closure rates peaks at 11 and 7 percent, respectively for each sector, compared to a long term trend of 5 percent for both sector.

B Scraping algorithm

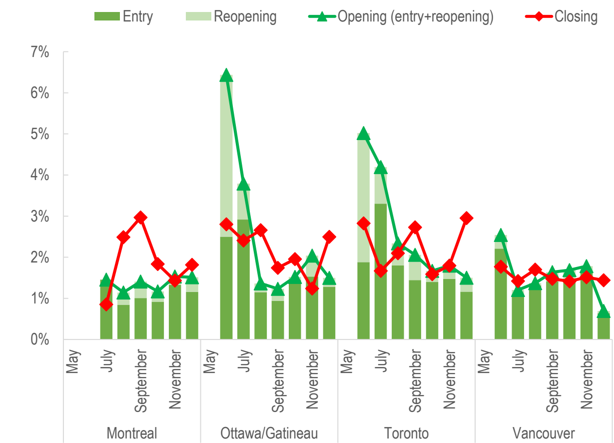
Algorithm 1 Algorithm to collect data from Google Places

Precondition: A is a two-dimensional polygon in latitude-longitude coordinates. *df* is globally initialized to be a (initially empty) DataFrame of query results.

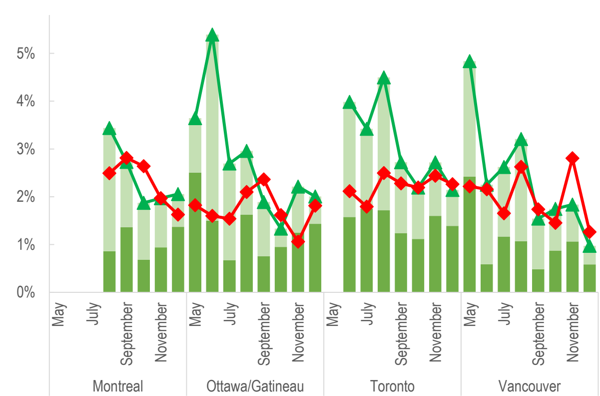
function SCRAPE(A)
    Compute $B((x, y), r)$ to be the smallest circle containing area A centered over the coordinates (x, y) with a radius r
    $results$, $flag \leftarrow$ QUERY($B((x, y), r)$)
    if $flag$ **then**
        Compute $A_1, \ldots, A_4 = B((x \pm \frac{r}{2}, y \pm \frac{r}{2}), \frac{r}{2})$
        for $i = 1, \ldots, 4$ **do**
            Add SCRAPE(A_i) to *df*
        end for
    else
        Add *results* to *df*
    end if
    return *df*
end function

C Graphical appendix

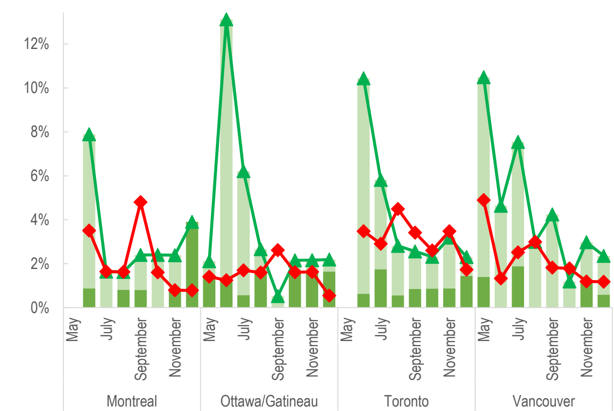
Figure C.1: Phased re-opening after the April 2021 lockdowns, across sectors and cities



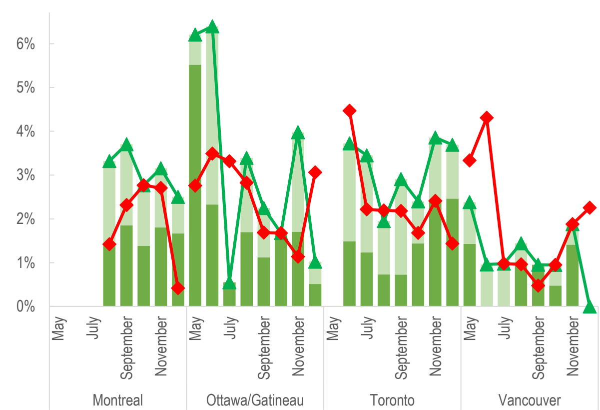
(a) Retail sector, NAICS 44-45



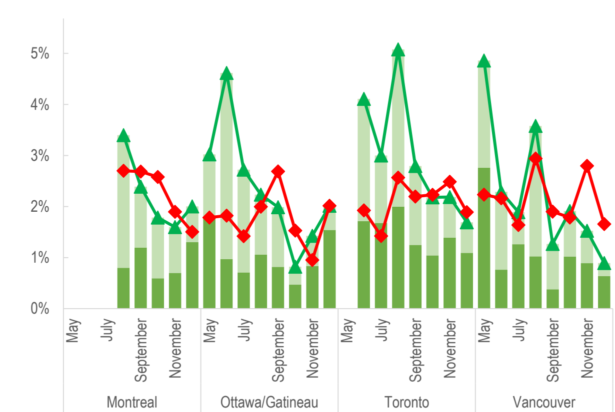
(b) Food sector, NAICS 722



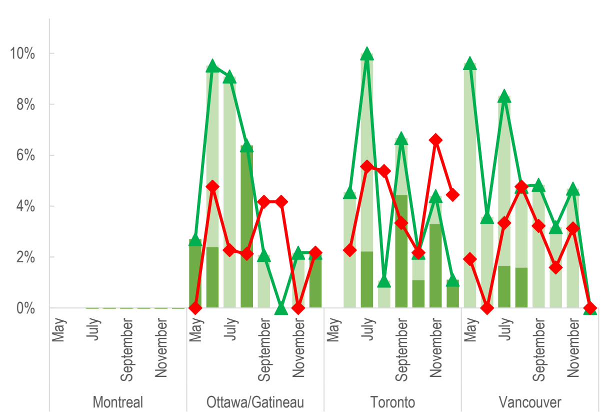
(c) Bar



(d) Cafe



(e) Restaurant



(f) Night club

Note: The figure displays the monthly opening and closure rates for Downtown Toronto, Vancouver and Ottawa/Gatineau derived from Google Places data, split by sectors and keywords. The food sector is the aggregation of the results by the keywords `bar`, `cafe`, `restaurant`, and `night_club`. In April, we did not collect data for the retail sector across cities nor for the food sector for Toronto, so the opening and closure rates are not computed for May. For Montreal (province of Quebec), systematic data collection started only after the re-opening phase of the pandemic and too few observations are available for night clubs.

D Timeline of changes in COVID-19 restrictions

Month	British Columbia	Ontario
April		3-Apr. Four-week lockdown for the entire province 8-Apr. Stay-at-home order for the entire province
May	25-May. Phase 1 reopening: indoor and outdoor dining with capacity limits	
June	15-Jun. Phase 2 reopening: maximum of 50 people for outdoor social gatherings and 50 people for seated indoor organized gatherings	2-Jun. Ontario's stay-at-home order expired 11-Jun. Step 1 of reopening: outdoor dining with up to four people per table, non-essential retail at 15% capacity, essential retail at 25% capacity; retail stores in malls remain closed unless they have a street-facing entrance 30-Jun. Step 2 of reopening: outdoor dining with up to six people per table, non-essential retail at 25% capacity, essential retail at 50% capacity
July	1-Jul. Phase 3 reopening; night clubs reopen with capacity limits; return to normal hours for liquor service at restaurants and bars	16-Jul. Step 3 of reopening: indoor dining with no limits per table, essential and non-essential retail with capacity limited to the number of people that can maintain physical distancing, night clubs at up to 25% capacity or up to 250 people
August		
September		24-Sep. Capacity limits eased for settings where proof of vaccination is required

Note: The metropolitan area of Ottawa/Gatineau is divided by a river with the city of Ottawa on one side (province of Ontario) and the city of Gatineau on the other side (province of Quebec), such that the two sides had different sets of restrictions. However, Gatineau accounts for fewer observations of the Ottawa/Gatineau area, and the area around Gatineau followed a similar timing to Ontario, with a lockdown in April and the start of the reopening from May 31 onward and then throughout June.

Table D.1: Phased reopening across provinces for retail and food sectors in 2021

E Residualizing change in reviews

Variable	Coefficient	Standard Error
Sector=Food	3.31***	(0.61)
Sector=Retail	-8.09***	(0.58)
Sector=Accommodation	5.76***	(0.82)
City=Vancouver	-0.25	(0.73)
City=Montreal	10.92***	(0.72)
City=Toronto	7.00***	(0.63)
Date=May. 2021	197.78***	(1.37)
Date=Jun. 2021	14.40***	(1.32)
Date=Jul. 2021	1.17	(1.26)
Date=Aug. 2021	2.96**	(1.27)
Date=Sep. 2021	1.94	(1.27)
Date=Oct. 2021	1.59	(1.27)
Date=Nov. 2021	1.68	(1.27)
Date=Dec. 2021	0.35	(1.27)
Date=Jan. 2022	-0.42	(1.27)
Date=Feb. 2022	3.71***	(1.27)
Date=Mar. 2022	1.66	(1.26)
Date=Apr. 2022	0.86	(1.26)
Date=May, 2022	1.13	(1.26)
Date=Jun. 2022	2.72**	(1.26)
Date=Jul. 2022	2.60**	(1.26)
Date=Aug. 2022	5.53***	(1.26)
Date=Sep. 2022	2.90**	(1.26)
Date=Oct. 2022	0.97	(1.26)
Date=Nov. 2022	1.88	(1.26)
Date=Dec. 2022	1.14	(1.26)
R-squared	0.1163	
R-squared Adj.	0.1162	

Note: Coefficients from the estimation of Equation (1) used to residualize individual establishments' change in reviews. The constant term, and the dummy variable "City=Ottowa/Gatineau" are not included to avoid collinearity with temporal fixed effects. Standard errors in parentheses. Significance denoted by: $*p < .1$, $**p < .05$, $***p < .01$.

Table E.1: Regression to residualize establishments' change in reviews

F Model appendix

F.1 Computational details

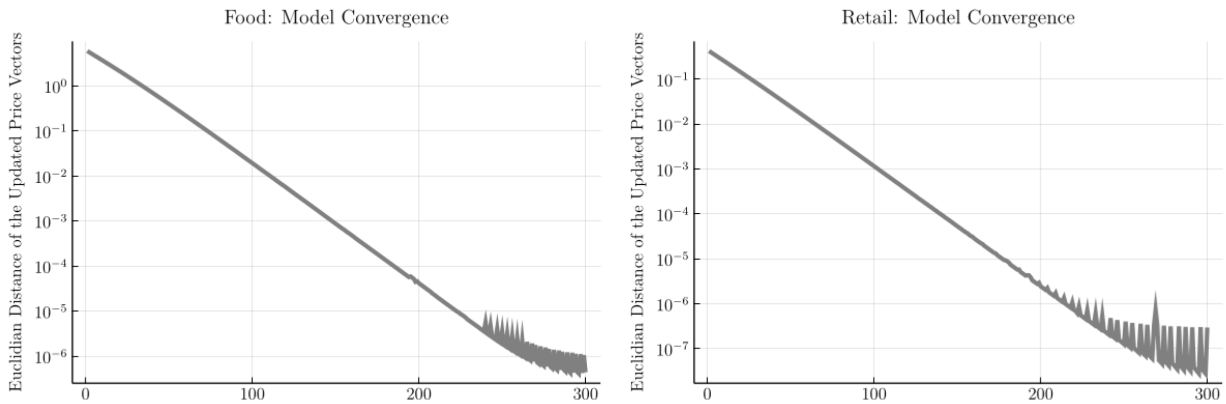
To compute the transitions of idiosyncratic firm productivity, we discretize the firm state space over a grid of 2000 points. The points and transition matrices for these points are provided by the Tauchen (1986) method for discretizing an AR(1) process.

We solve the model for each sector separately, taking demand and the wage level as given. We solve first for the steady state of the model with temporary closures. Then we simulate an MIT shock where the demand path follows observed demand from January 2020 until May 2023. From that point on, we assume that the demand path is constant at 100 (the pre-pandemic normalized level after detrending) until January 2042, where we assume the model has converged back to the steady state. Thus approximately 20 years after the pandemic.

We solve the model in the following way. Supply Y is determined by the number and distribution of firms in the market over time. We solve for supply by solving for the equilibrium path of optimal entry, permanent exit and temporary closure choices of firms given a guessed price path p^0. Given entry and exit choices, we then compute firm output, firm numbers and aggregate supply Y^0. From aggregate supply, we can calculate an updated price level $p^0_{updated}$ using Equation (10) and the exogenous path for aggregate demand. We then update the next period's guess for the price level in small steps $p^1 = (1-\lambda)p^0 + \lambda p^0_{updated}$, with $\lambda = 0.01$. We iterate until the update steps become small signifying that we have reached a dynamic equilibrium path.

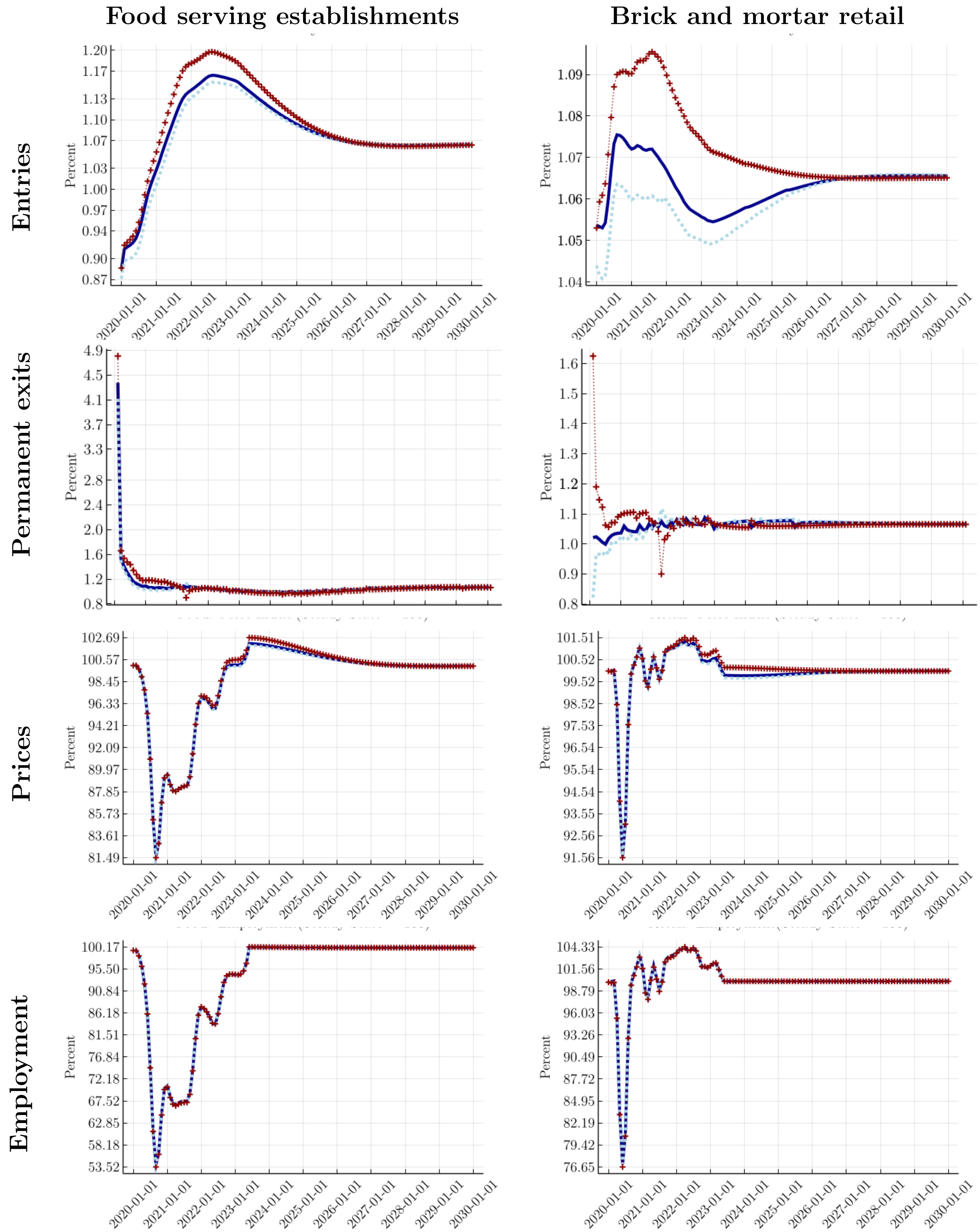
The model converges quickly to the equilibrium price path and after 300 iterations no meaningful difference between price path updates p^{299} and p^{300} can be detected. The summed Euclidian differences in the price vector are in this case below 10^{-6} as shown in Figure F.1.

Figure F.1: Convergence of the price path to equilibrium as the Euclidian distance between price path updates $(p^x - p^{x+1})^2$ shrinks.



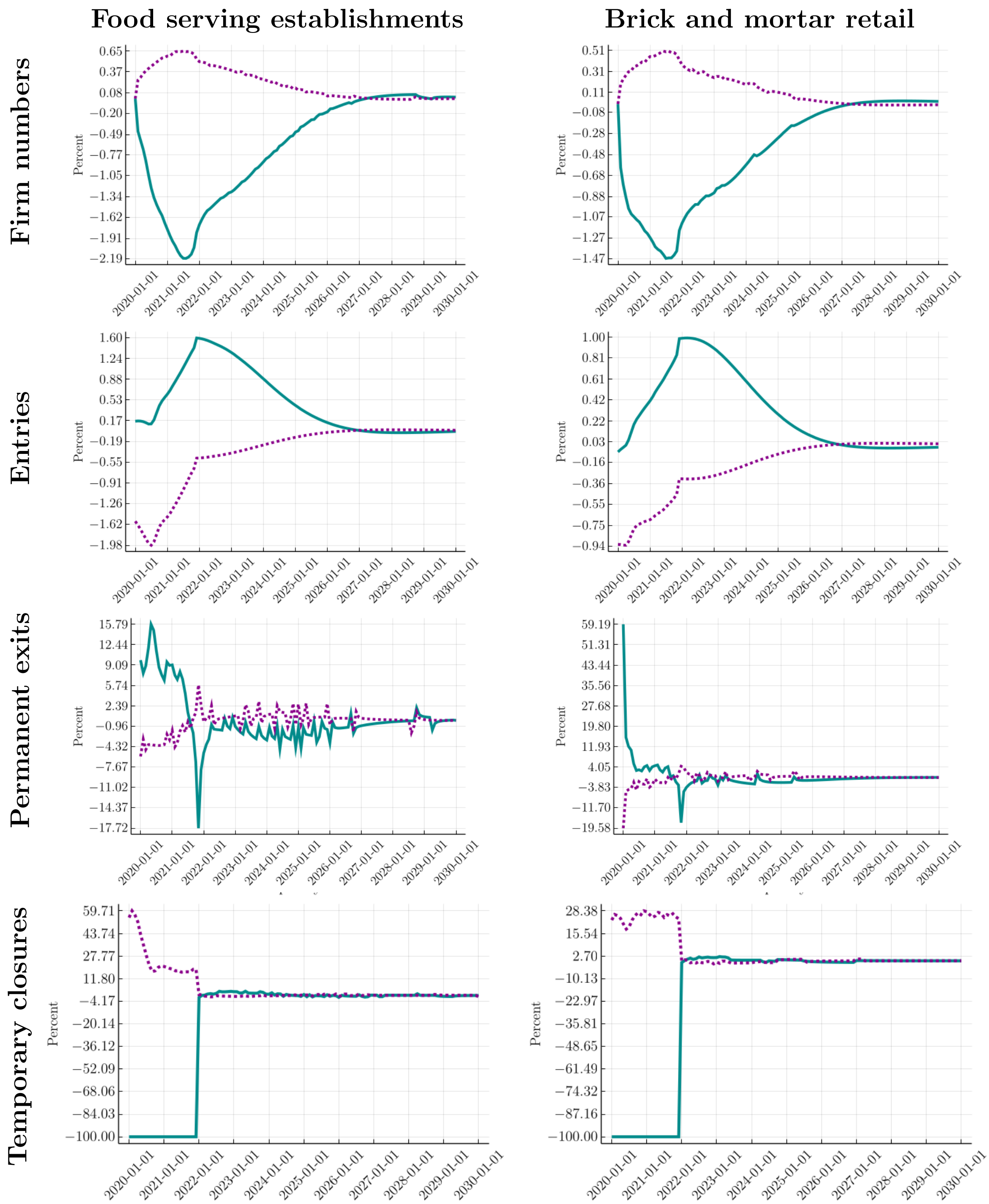
F.2 Additional model output

Figure F.2: Model simulations in the baseline and counterfactuals



Note: The solid blue line is the baseline scenario with a share of fixed cost that can be saved when temporarily shutting down $\tau = 0.275$. The crossed red line shows the counterfactual where firms cannot exit temporarily $\tau = 0$. The dashed blue line shows the counterfactual where firms save an additional 10 % of the fixed cost when exiting production for the period ($\tau = 0.3025$). From February 2022 onwards, all firms can temporarily close and save the baseline share of fixed cost across all scenarios to ensure convergence back to the steady state. Entries and permanent exits are calculated as a percentage of operational firms. Prices and employment are normalised to equal 100 in the steady state. Employment is defined as the total salary payments.

Figure F.3: Firm dynamics in the counterfactuals relative to the baseline



Note: The solid cyan line shows the percent change from the baseline scenario when firms cannot exit temporarily until January 2022. The dotted purple line shows the percent change from the baseline scenario when temporary closure is subsidised 10% more than in the baseline until January 2022. From February 2022 onwards, all firms can temporarily close and save the baseline share of fixed cost across all baseline and counterfactual scenarios to ensure convergence back to the steady state.