Restaurant Closures during the COVID-19 Pandemic: A Descriptive Analysis

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Abstract

This paper analyzes restaurant closure patterns during the first year of the COVID-19 pandemic. Using establishment-level data from Yelp and SafeGraph, I describe restaurant and location characteristics related to the closure decisions. Lower-rated restaurants and restaurants located closer to the city center were more likely to close in 2020.

Keywords: Restaurant closures; COVID-19 pandemic; Turnover.

JEL codes: L83, I12, L20, L10.

1 Introduction

During 2020, the first year of the COVID-19 pandemic, restaurants suffered from reduced consumer traffic due to multiple factors: lockdowns, operations restrictions and social distancing. Which restaurants were more likely to exit the industry in this challenging time? I provide descriptive evidence on this question in the context of major US urban areas using data from the review platform Yelp and the location data company SafeGraph. Specifically, I explore location- and restaurant-specific characteristics that explain variation in restaurant closure decisions.

First, I document the across-cities differences in restaurant exit rates, which range from 9.6% in El Paso to 21.5% in Honolulu. Next, I estimate binary response econometric models and summarize the association between restaurant characteristics and exit. I find that higher rating scores and review counts are robustly associated with lower restaurant exit probabilities. A 1-star increase in the restaurant's rating is associated with a roughly 1.2% lower chance of restaurant closure. Additional 100 reviews at the beginning of the observation period are associated with a 0.9-1.8% lower probability of restaurant exit. Also, restaurants relying on the foot traffic generated due to their within-city location were relatively less likely to survive the pandemic year.

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This paper contributes to several strands of literature. First, it adds to the growing research on business disruptions during the pandemic (e.g. Bartik et al. (2020), Fairlie (2020), Koren and Peto (2020)) and provides a unique focus on the restaurant industry. Second, this paper expands the research describing factors specifically related to restaurant exit decisions (e.g. Parsa et al. (2011), Luo and Stark (2014), Parsa et al. (2021)) by employing Yelp and SafeGraph data from multiple major US cities and by concentrating on restaurant closures during the COVID-19 pandemic. Finally, this paper is related to the IO literature dealing with turnover and firm entry/exit decisions (see early surveys by Geroski (1995) and Caves (1998) and subsequent updates by e.g., Audretsch et al. (2000), Agarwal and Audretsch (2001), Fackler et al. (2013)).

The rest of the paper is structured as follows. Section 2 presents key facts about the data. Section 3 describes the econometric analysis of factors related to restaurant exit decisions. Section 4 concludes.

2 Data

Two data sources are used for the analysis discussed in this paper. The data from the Yelp restaurant review platform provides information on restaurant characteristics and exit decisions. I also use data from the location data company SafeGraph, which collects information on US points-of-interest (defined as places outside of home where people spend time and/or money), to construct additional covariates related to restaurant location characteristics. The combined dataset covers 128,285 restaurants in 42 major US cities.

The timing of Yelp data collection allows me to concentrate on the first year of the COVID-19 pandemic. The data on restaurants' names, locations and characteristics was first collected in late 2019 using a scraping routine that systematically parsed Yelp Fusion API[2]. The second round of data collection was done in early 2021, using the previously gathered set of unique Yelp restaurant identifiers. The target element of interest during the second round was the *restaurant-closed* indicator, which I view as the ground truth on restaurant exit for the purposes of this paper[3].

Next, thanks to the July 2019 extract of SafeGraph data, I can observe the locations of roughly 4.4 mln US establishments across multiple industries and quantify the proximity of restaurants to other businesses (see Abbiasov and Sedov (2021) or Sedov (2021) for a more detailed description of the SafeGraph dataset). Specifically, I use the counts of establishments in the 500-meter radius of each sample restaurant to quantify the likely restaurant reliance on the traffic generated by nearby establishments. Table 1 provides the summary statistics on the resulting dataset.

Several facts about the data are worth stating. 15.2% of restaurants in the sample closed in 2020. To illustrate the geographic variation in restaurant closures, Figure 1 depicts the exit rates across sample cities. Honolulu featured the highest exit rate of 21.5% among the sample cities, while El Paso's exit rate was the lowest at 9.6%. Figure 2 displays the relationship between market size (measured as restaurant count on the city level) and restaurant closure rates. Larger markets have experienced higher restaurant exit rates: a 1000-increase in restaurant count is associated with a 0.46% increase in the restaurant closure rate.

[2]The initial set of restaurants was obtained from the SafeGraph database of points-of-interest and complemented with a search for "food" around a dense grid of points corresponding to Census Block Group centroids.

[3]Yelp describes this field as indicating "whether business has been (permanently) closed", but is not explicit whether the field is self-reported or crowd-sourced from the platform users.

	% NA	Q10	Q25	Med	Q75	Q90	Mean	SD
Closed	0.00	0.00	0.00	0.00	0.00	1.00	0.15	0.36
Price	16.61	1.00	1.00	2.00	2.00	2.00	1.57	0.61
Rating	0.00	2.50	3.00	4.00	4.00	4.50	3.59	0.88
Reviews	0.00	4.00	14.00	54.00	177.00	425.00	168.50	365.25
# categories	0.00	1.00	1.00	2.00	3.00	3.00	1.99	0.84
City center dist. (km)	0.00	1.27	3.23	7.30	12.89	18.66	8.89	7.44
Est. nearby	0.00	17.00	33.00	63.00	137.00	332.00	136.84	210.48

Table 1: Restaurants dataset summary statistics. Number of observations: 128,285.

3 Exit-related factors

To understand the role of different factors shaping restaurant exit decisions, I estimate binary response models (LPM, logit and probit) linking closures and restaurant characteristics.

In my empirical specification, restaurant characteristics include variables related to both the features of a restaurant itself and to the features of its location. Restaurant-specific characteristics include dummies for price categories, Yelp rating score and review count, primary cuisine category dummy and the total number of restaurants' cuisine categories. Restaurant location features consist of city dummies, latitude and longitude, the count of nearby establishments as well as the distance from the city center.

Table 2 presents the coefficient estimates for the alternative binary response variables. Column (1) represents the LPM with city and cuisine category fixed effects, while column (2) represents the LPM with the interacted city-cuisine fixed effects. Column pairs (3)-(4) and (5)-(6) show the analogous estimates for logit and probit models respectively. The estimated coefficient signs are the same across specifications for all variables of interest. Moreover, the coefficient estimates appear to be robust to the alternative sets of fixed effects.

I first discuss the restaurant characteristics coefficient estimates. The coefficient on the $-dummy is negative, indicating that, relative to the missing price label, $-priced restaurants were less likely to close in 2020. The coefficients on $$, $$$ and $$$$ are positive: higher-priced restaurants were more likely to close relative to the baseline. The coefficient on the $$$$-dummy, however, is not significant at the 5% level across all specifications. The rating and review count coefficients are negative and significant, implying that higher-quality and more frequently reviewed restaurants were less likely to close during the observation period. The total number of cuisine categories was estimated to have negative coefficients: restaurants with more diverse food were more likely to survive during 2020.

Several coefficients on the location-specific restaurant features provide additional insight. The coefficient on the count of nearby establishments is positive, indicating that restaurants that are located close to many other businesses were more likely to close. These restaurants likely relied on the foot traffic generated by the nearby establishments, and probably suffered relatively more from the pandemic, which is one of the channels that could result in higher exit rates among such restaurants. The negative coefficient on the variable measuring the distance from the city center indicates that centrally located restaurants were more likely to exit the business. Again, this may be related to a relatively higher fall of foot traffic to central city areas during the 2020 pandemic.

To compare the alternative models, I also report the Average Partial Differences (APDs) corre-

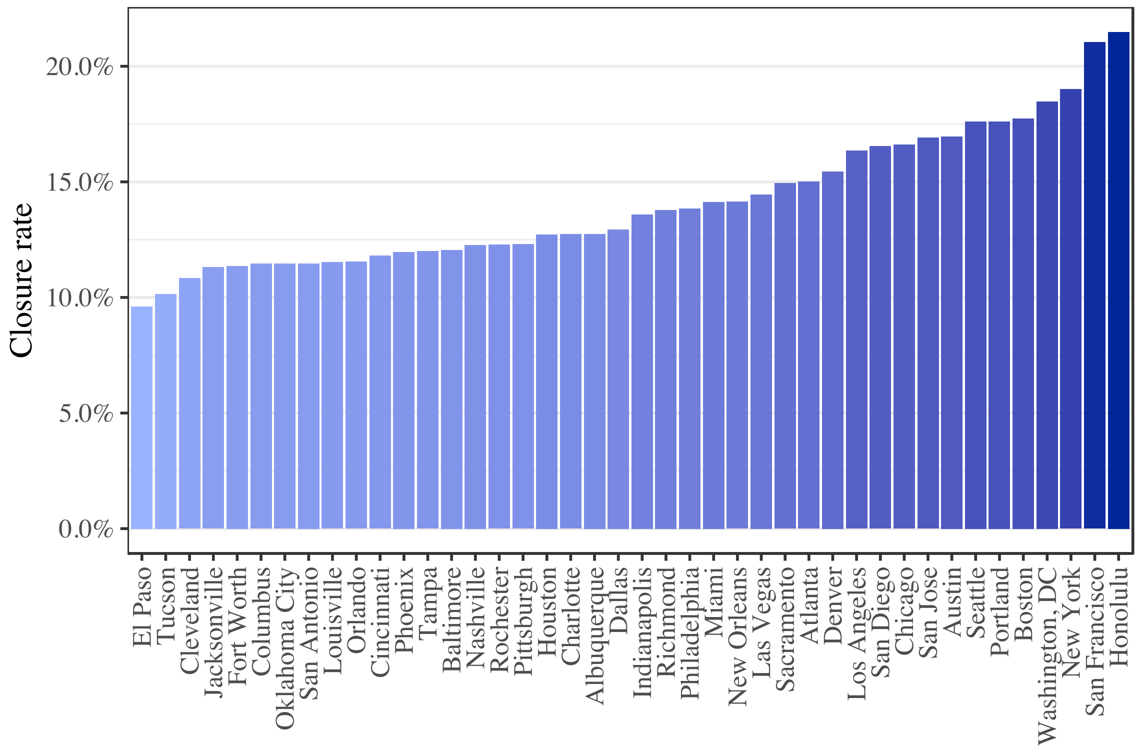

Figure 1: Restaurant closure rates across major US cities between late 2019 and early 2021.

sponding to the variables of interest in Table 3. APDs describe the average change in the probability of restaurant closure conditional on a marginal increase in the respective variable (or a change from the baseline to the target value in case of a dummy variable). Formally, an Average Partial Difference is defined exactly as an Average Partial Effect (see Wooldridge (2010)), but substituting *effect* with *difference* since the estimates of this paper are meant to be purely descriptive.

The estimated APDs appear to be of similar magnitude in the LPM, logit and probit models. The change from the reference price category (missing) to the $-category is associated with a 1.4-2% drop in the closure probability. In turn, the change from the baseline to $$ category is associated with a 1.2-2.7% increase in the probability of restaurant exit. A restaurant with an extra star of the rating score can be expected to have a 1.2-1.4% higher probability of survival. A restaurant with an additional cuisine category is observed to be 0.4-0.7% less likely to close. The APD associated with the review count (in 100s) is between −0.9% and −1.8% depending on the specification. A 100-increase in the number of nearby establishments is associated with a roughly 1% higher exit probability. Finally, a restaurant located 1 km further from the city center is expected to have a 0.2-0.3% lower closure probability.

4 Conclusion

This paper describes the restaurant exit patterns during 2020, the first year of the COVID-19 pandemic. Using data from Yelp and SafeGraph, I determine the restaurant- and location- specific factors related to closure decisions.

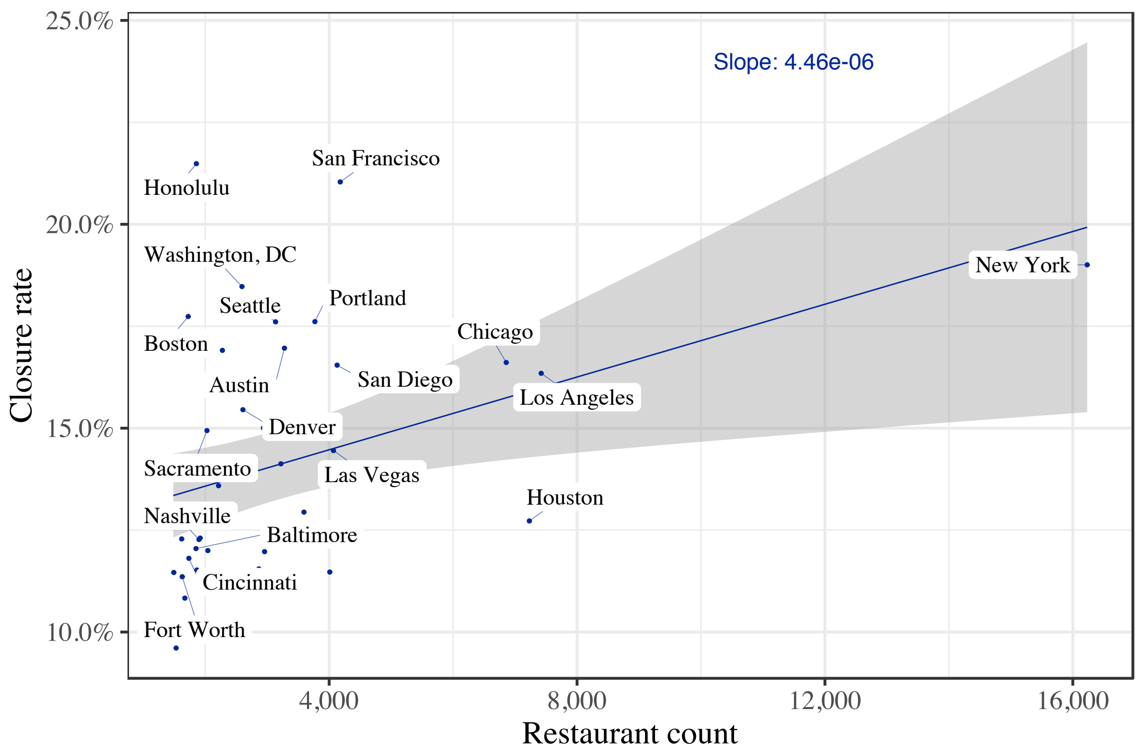

Figure 2: Restaurant closure rates by market size (restaurant count).

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	Dependent variable: restaurant closed					
	LPM		*Logit*		*Probit*	
	(1)	(2)	(3)	(4)	(5)	(6)
\$	−0.020	−0.020***	−0.118***	−0.115***	−0.077***	−0.076***
	(0.017)	(0.005)	(0.025)	(0.025)	(0.013)	(0.014)
\$\$	0.012	0.012*	0.207***	0.206***	0.096***	0.095***
	(0.011)	(0.006)	(0.024)	(0.025)	(0.014)	(0.014)
\$\$\$	0.016	0.016	0.269***	0.273***	0.127***	0.128***
	(0.012)	(0.009)	(0.047)	(0.048)	(0.027)	(0.027)
\$\$\$\$	0.002	0.003	0.145	0.161	0.061	0.067
	(0.014)	(0.014)	(0.096)	(0.097)	(0.054)	(0.055)
Rating	−0.014**	−0.014***	−0.099***	−0.103***	−0.054***	−0.056***
	(0.005)	(0.002)	(0.010)	(0.010)	(0.006)	(0.006)
Reviews (100s)	−0.009***	−0.009***	−0.140***	−0.143***	−0.067***	−0.068***
	(0.001)	(0.000)	(0.005)	(0.005)	(0.002)	(0.002)
Est. nearby (100s)	0.012***	0.012***	0.069***	0.069***	0.042***	0.042***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)
City center dist. (km)	−0.002***	−0.002***	−0.024***	−0.024***	−0.012***	−0.012***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
# categories	−0.007	−0.007***	−0.034***	−0.035***	−0.020***	−0.021***
	(0.005)	(0.001)	(0.010)	(0.010)	(0.005)	(0.006)
City FE	✓		✓		✓	
Category FE	✓		✓		✓	
City-Category FE		✓		✓		✓
Observations	128,281	128,281	128,281	128,281	128,281	128,281
R^2	0.026	0.033				
Adjusted R^2	0.025	0.026				
Log Likelihood			−52765.3	−52217.4	−52811.5	−52267.0
Note:						*p<0.05; **p<0.01; ***p<0.001

Table 2: Coefficient estimates for the binary response models. Standard errors clustered at the FE levels for the LPM models. Latitude and longitude were included as covariates in all of the specifications but were omitted from the table; the corresponding coefficient estimates were insignificant. 4 observations were omitted from the analysis due to missing latitude / longitude.

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	Response: probability of restaurant closing					
	LPM		*Logit*		*Probit*	
	(1)	(2)	(3)	(4)	(5)	(6)
$	-0.020^{*}	-0.020^{***}	-0.014^{***}	-0.014^{***}	-0.017^{***}	-0.017^{***}
	(0.017)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
$$	0.012^{*}	0.012^{*}	0.027^{***}	0.026^{***}	0.023^{***}	0.022^{***}
	(0.011)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
$$$	0.016^{*}	0.016^{*}	0.036^{***}	0.037^{***}	0.030^{***}	0.031^{***}
	(0.012)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
$$$$	0.002	0.003	0.018^{*}	0.021^{*}	0.014^{*}	0.016^{*}
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Rating	-0.014^{**}	-0.014^{***}	-0.012^{***}	-0.013^{***}	-0.012^{***}	-0.013^{***}
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Reviews (100s)	-0.009^{***}	-0.009^{***}	-0.018^{***}	-0.018^{***}	-0.015^{***}	-0.015^{***}
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Est. nearby (100s)	0.012^{***}	0.012^{***}	0.009^{***}	0.009^{***}	0.010^{***}	0.010^{***}
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
City center dist. (km)	-0.002^{***}	-0.002^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# categories	-0.007^{*}	-0.007^{***}	-0.004^{***}	-0.004^{***}	-0.005^{***}	-0.005^{***}
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
City FE	✓		✓		✓	
Category FE	✓		✓		✓	
City-Category FE		✓		✓		✓

Table 3: Average Partial Differences for the binary response models. Standard errors clustered at the FE level in LPM specifications.

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