Positioning in Time: The Impact of Opening Days on Pricing and Market Competition

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Abstract

This paper examines the timing of product offerings as an additional dimension of competition, expanding the understanding of firms' positioning decisions. The analysis exploits a novel setting in the U.S. coffee shop industry during the COVID-19 pandemic, when labor shortages sharply increased operating costs and induced firms to compete on which days to open. Using mobile tracking and sales data, I estimate a structural model of demand, pricing, and operating-day choices under sticky (uniform) pricing. The results show that higher labor frictions reduce the number of operating days, and that price stickiness amplifies this effect by linking daily operations to weekly pricing incentives. Counterfactual simulations reveal that ignoring this interaction understates the welfare losses from higher operating costs, underscoring the importance of accounting for interdependent competitive dimensions—time and price—in assessing market outcomes.

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§From SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the SafeGraph Community. To enhance privacy, SafeGraph excludes census block group information if fewer than two devices visited an establishment in a month from a given census block group.

1 Introduction

Firms compete for consumer demand along multiple dimensions. The most familiar are prices and product characteristics, but in industries where timing matters—such as the scheduling of radio advertisements Sweeting [2009]—the timing of product provision can also serve as a key competitive margin. However, once firms establish the dimensions on which they compete, those dimensions are typically fixed. It is therefore rare to observe a setting in which firms suddenly expand the scope of competition by introducing an additional strategic variable, such as when to offer their products.

The COVID-19 pandemic provides a unique opportunity to study how firms expand the scope of competition beyond prices and product characteristics to include the timing of operation as an additional competitive dimension. Prior to the pandemic, coffee shops typically operated seven days a week with standardized hours. The pandemic, however, sharply increased the cost of remaining open—most notably through labor shortages (Colorado Restaurant Association [2022])—prompting many coffee shops to reduce the number of days they operated (Axios Denver [2022]). This unexpected shift created a quasi-experimental setting in which local businesses began to compete not only on prices and products but also on when to operate, allowing the timing dimension of competition to be isolated from long-run entry and location choices.

Given this novel setting, this study examines firms' decisions about when to offer products as a form of strategic repositioning. It further investigates whether adjustments in operating decisions—representing a new competitive margin—are influenced by constraints in another dimension, price. Because the pandemic was unforeseeable, firms could not have selected their characteristics in anticipation of such shocks, allowing me to abstract from forward-looking dynamic considerations. Instead, the analysis treats shop attributes as fixed and models a static weekly decision problem: which days to open or remain closed. The interaction between opening days and prices arises from price stickiness, a pervasive feature of industries that maintain uniform pricing across periods (DellaVigna and Gentzkow [2019], Orbach and Einav

[2007], Shiller and Waldfogel [2011], McMillan [2007]).

Building on this framework, the paper examines the relationship between operating days and pricing by analyzing the Nash conditions that characterize firms' optimal responses in both dimensions. Using mobile tracking data to capture consumers' visitation choices and anonymized credit and debit card data to measure sales, I estimate coffee shop demand with a nested logit model. To reflect price stickiness due to menu costs, I assume that firms charge a weekly uniform price—a reasonable assumption since coffee shops rarely vary prices by day. This pricing constraint introduces an additional incentive for temporal differentiation: opening on a highly competitive day reduces prices for the entire week, thereby lowering profits on other days. Accounting for this interaction, firms determine the optimal set of opening days each week, given competitors' choices and the resulting equilibrium price. The model, therefore, includes two Nash conditions—one for opening decisions and one for pricing—that jointly capture firms' differentiation motives, while the estimated market size for each day reveals which days are most popular among consumers.

Using a supply-side model, the paper identifies the cost of opening by exploiting variation in operating days and prices across firms and over time. Because the coffee shops in my sample were already established prior to the pandemic—and new entry was rare during this period—the fixed cost of opening differs from the conventional notion of fixed entry costs. Rather than reflecting capital or facility expenses, which are predetermined, it primarily captures the difficulty of securing workers, which varied over time during the pandemic. The sample period from 2020 to 2022 encompasses two major policy interventions—the Coronavirus Aid, Relief, and Economic Security (CARES) Act and the American Rescue Plan (ARP) Act—that generated exogenous variation in these operational costs. Both programs expanded unemployment assistance, thereby increasing labor market frictions for service-sector businesses. In particular, the Pandemic Unemployment Assistance (PUA) program extended benefits to workers previously ineligible for unemployment insurance, making it more difficult for coffee shops to hire or retain staff.

Consistent with this narrative, the results indicate that the fixed costs of operating were highest in 2020 and 2021. The American Rescue Plan (ARP) Act emphasized the continuation of financial assistance to small businesses, building on the CARES Act, which had initially alleviated some of their burdens. In particular, the ARP introduced the Restaurant Revitalization Fund, providing targeted support to restaurants, bars, and coffee shops. As a result, while 2020 and early 2021 were characterized by elevated operational costs due to labor market frictions, the ARP's targeted financial support in 2021 offered partial relief to these businesses.

Given the estimated demand and supply parameters, the counterfactual analysis explores three hypothetical settings. First, it examines the impact of labor market frictions by lowering the fixed cost of operation and simulating competition over operating days. Second, it isolates the role of price stickiness by simulating operating-day outcomes when the uniform pricing constraint is relaxed. Finally, it combines the two to evaluate the joint effect of labor frictions under price stickiness. Intuitively, if operating on competitive days does not reduce profits on other days, firms would respond less sharply to increases in daily operating costs.

The simulation results show that higher labor frictions not only reduce the number of operating days but also amplify this effect through price stickiness. In equilibrium, when firms maintain lower competition across the week, they can sustain higher margins under uniform pricing. These findings underscore that different dimensions of competition can generate externalities when one dimension is constrained. Ignoring such interactions may bias welfare analysis. For example, omitting price stickiness from counterfactual simulations overlooks the additional incentive to reduce operating days, leading to an underestimation of the benefits of small-business support policies.

This paper contributes to the empirical industrial organization literature on static entry models. Early studies by Mankiw and Whinston [1986] and Bresnahan and Reiss [1991] established the relationship between profitability and entry, while Ciliberto and Tamer [2009] incorporated firm heterogeneity without imposing an equilibrium selection rule. Building on this foundation, the paper introduces time as an additional dimension of competition and examines how price competition interacts with time competition, conditional on firm characteristics. In doing so, it bridges insights from the literature on multi-product firms and endogenous product-type choice, highlighting how the motivations in both frameworks jointly shape firms' operational decisions.

In the multi-product entry literature, firms weigh the incremental gains from offering additional products against fixed costs and cannibalization effects (Eizenberg [2014], Wollmann [2018]). My framework parallels these models by treating each operating day as an additional "product line," but differs in that firms face opportunity costs across weekly configurations rather than independent entry decisions for each product. Because consumers identify with the firm (e.g., Starbucks) rather than a specific day's offering, the weekly schedule jointly determines pricing and competitive differentiation over time.

The paper also extends the endogenous product-type entry literature, which studies differentiation in quality, location, or product attributes (Mazzeo [2002], Seim [2006]). Here, the timing of product provision serves as an additional type dimension through which firms differentiate strategically. While Sweeting [2009] analyzes the timing of commercial breaks in radio markets, I focus on the extensive margin of operation—whether to open at all—and its interaction with a constrained dimension, price stickiness. This dual-margin framework shows how a constraint in one competitive dimension can create externalities in another, shaping both firms' positioning incentives and welfare outcomes.

Taken together, the paper integrates insights from the static entry, multi-product, and endogenous-type literatures to study operational differentiation under pricing constraints. It demonstrates that when firms face labor-supply frictions and price rigidity, the timing of operation becomes an economically meaningful competitive choice. Recognizing these interdependencies is crucial for understanding short-run market structure and for evaluating the effectiveness of small-business support policies during periods of heightened frictions.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents descriptive evidence. Sections 4 and 5 describe the structural model, estimation methodology, and results. Section 6 presents counterfactual simulations. Section 7 concludes.

2 Data

My data mainly consists of three parts from SafeGraph.[1] The sample covers January 2020 through February 2022 for all U.S. states. I focus on 44 states for which I can merge SafeGraph data with state-level minimum wage and housing price information.

The first component is the *Monthly Sales* data, which aggregates anonymized debit and credit card transactions at the shop–month level. It reports total sales, total transactions, quartiles and the median of sales per transaction, average sales per consumer by income bucket, and information on daily opening times throughout the week. I use the quartiles and median of sales per transaction to construct a price index that represents the product prices in coffee shops.

This price index is interpreted as a predicted latte price. For firms, it serves as a proxy for the average revenue per coffee-purchasing customer when pricing decisions do not explicitly model menu-level optimization. For consumers, it approximates the price signal they actually use when choosing among coffee shops: most customers recall or compare prices of a few popular items—such as a latte—rather than the full menu. Although this proxy abstracts from detailed menu heterogeneity, it captures the relevant relative price differences across shops that drive consumer choice. I estimate the relationship between sales distribution measures and observed state-level average latte prices, and then use the estimated coefficients to generate the shop-level price index.

In detail, to estimate the coefficients for the price index, I use cross-sectional data on latte prices by brand, state, and product, collected from fastfoodmenuprices.com. Historical prices are retrieved through the Internet Archive's Wayback Machine using the September 2020 snapshot, which falls within the sample period. The dataset reports the average latte price for each brand–state combination. I then estimate the following regression:

[1]This data was sourced from SafeGraph, and Advan Research through the Dewey Data platform. This paper uses a 2022 version of the data produced by SafeGraph, which may differ in coverage and methodology from the current data available from SafeGraph and Advan via the Dewey Data platform.

$$\begin{aligned} \overline{Latte\,price}_{jst} &= \beta_0 + \beta_1 \overline{25th\,percentile}_{jst} + \beta_2 \overline{Mean}_{jst} \\ &+ \beta_3 \overline{Median}_{jst} + \beta_4 \overline{75th\,percentile}_{jst} + \beta_5 D_{jst} + \varepsilon_{jst} \end{aligned} \tag{1}$$

where the regressors are the averaged distributional statistics of sales per transaction at the brand('j')-state('s')-month('t') level, weighted by the number of observations used in each average. D_{jst} is a dummy variable indicating whether the brand sells donuts or bagels, included to control for systematic differences in pricing behavior across shop types.

I then obtain the shop-level predicted price index as

$$\begin{aligned} \widehat{Latte\,price}_{j(k)s(l)t} &= \hat{\beta}_0 + \hat{\beta}_1\, 25th\,percentile_{j(k)s(l)t} + \hat{\beta}_2\, Mean_{j(k)s(l)t} \\ &+ \hat{\beta}_3\, Median_{j(k)s(l)t} + \hat{\beta}_4\, 75th\,percentile_{j(k)s(l)t} + \hat{\beta}_5\, D_{j(k)s(l)t}, \end{aligned} \tag{2}$$

where $j(k)$ denotes shop k belonging to brand j, and $s(l)$ denotes the location l of the shop in state s, allowing predicted prices to vary across shops within the same brand and state. By construction, $D_{j(k)s(l)t} = D_{jst}$, since the donut/bagel indicator is defined at the brand–state level. This predicted price index serves as the price variable in the subsequent demand estimation.

The second component is the *Weekly Visiting* data, which records mobile device visits to each shop. A visit is defined as a device entering a marked location and remaining there for more than four minutes. Most variables, such as the number of visitors in each time bucket and the number of visitors from each census block, are aggregated at the week–shop level. Crucially, the data also disaggregate visits by day, allowing me to compute the daily share of visits for each shop. Because my demand model treats visits as discrete choices of shops, each visit is interpreted as a quantity measure of consumer demand.

The visiting data are potentially noisy because they do not distinguish between consumers and employees. Following the SafeGraph documentation, I approximate the number of workers using visits recorded in the time bucket "longer than 240 minutes." Using this information, I can also infer shop openings and temporary closures: days with zero visits indicate that no individuals, including workers, entered the shop. In the estimation, I conservatively combine this information with the *Monthly Sales* data, which explicitly reports closure status. If a shop records no visits during an entire day or is labeled as "closed," I classify it as closed for that day. This is distinct from a permanent market exit, as locations that exit the market are no longer tracked in the Visiting data.

The third component is the *Place* data, which contains time-invariant characteristics of each shop. These include the shop's location, brand, size, parking availability, inclusion within larger venues, six-digit NAICS codes, and text-based category descriptions. Using this information, I restrict the sample to establishments classified under NAICS code 722515 ("Snack and Nonalcoholic Beverage Bars") and described as "Coffee Shop."

		Shares			Space Size			Price Index			
Year	Quarter	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	N
2020	1	0.27	0.32	0.13	419.35	2085.72	221.00	4.31	0.30	4.29	500992
2020	2	0.30	0.33	0.17	358.39	1394.18	221.00	4.34	0.34	4.32	481421
2020	3	0.28	0.32	0.15	442.26	2340.72	220.00	4.27	0.33	4.25	522974
2020	4	0.29	0.32	0.15	455.88	2488.12	221.00	4.28	0.35	4.26	515452
2021	1	0.29	0.32	0.15	449.46	2408.11	221.00	4.19	0.34	4.18	532293
2021	2	0.29	0.32	0.15	446.20	2302.13	221.00	4.11	0.34	4.07	539987
2021	3	0.28	0.32	0.15	438.97	2106.24	221.00	4.02	0.33	3.99	541038
2021	4	0.28	0.32	0.14	437.17	1991.05	223.00	4.01	0.36	3.97	534756
2022	1	0.28	0.32	0.14	442.84	2156.86	223.00	3.92	0.34	3.89	329071

Table 1: Quarterly Summary Statistics

Notes: This table summarizes SafeGraph coffee shop data across 44 U.S. states, aggregated by year and quarter. "Shares" denote the daily visit share of each shop within its local market. "Space Size" is measured in square meters. "Price Index" is the predicted latte price based on the distribution of sales per transaction.

	Shares			Space Size			Price Index			
Brands	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	N
Big Apple Bagels	0.25	0.33	0.10	261.99	132.93	208.00	3.89	0.41	3.85	6379
Biggby Coffee	0.27	0.30	0.14	625.90	1883.61	239.00	4.07	0.36	4.02	113144
Black Rock Coffee Bar	0.16	0.12	0.14	781.30	547.02	1233.00	4.09	0.41	4.04	975
Caffè Nero	0.10	0.09	0.07	391.80	264.75	432.00	4.54	0.42	4.55	3271
Caribou Coffee	0.44	0.37	0.36	624.07	1293.74	206.00	4.35	0.39	4.36	44627
Coffee Culture	0.07	0.02	0.07	640.00	0.00	640.00	4.75	0.05	4.75	56
Cruisin Coffee	0.27	0.36	0.12	71.80	26.83	66.00	4.04	0.27	4.05	1749
Donut Connection	0.48	0.47	0.16	214.19	71.25	223.00	3.89	0.44	3.86	1698
Dunkin’	0.31	0.34	0.16	416.11	1615.71	227.00	4.06	0.30	4.06	2729421
Dutch Bros Coffee	0.23	0.24	0.14	101.67	125.42	69.00	4.20	0.38	4.23	84801
Joe & The Juice	0.00	0.00	0.00	642.00	0.00	642.00	3.84	0.23	3.93	47
Juan Valdez Café	0.00	0.00	0.00	112.00	0.00	112.00	4.32	0.59	4.73	70
Krispy Kreme Doughnuts	0.13	0.17	0.06	548.16	1716.20	330.00	3.74	0.41	3.65	94677
Manhattan Bagel	0.16	0.19	0.10	465.37	1255.57	182.00	4.30	0.42	4.30	23354
Peet’s Coffee and Tea	0.08	0.09	0.06	294.37	1085.09	176.00	4.49	0.36	4.49	8698
Port City Java	0.42	0.41	0.28	219.42	22.26	220.00	4.35	0.28	4.32	2246
Starbucks	0.25	0.28	0.13	490.05	3422.08	194.00	4.49	0.30	4.49	1122807
Tim Hortons	0.28	0.32	0.14	320.15	526.13	280.00	4.09	0.31	4.08	257146
Winchell’s Donut House	0.01	0.01	0.01	157.10	45.14	154.00	3.81	0.45	3.73	367
Zero Degrees	0.02	0.03	0.02	148.47	59.70	139.00	4.35	0.57	4.44	2451

Table 2: Brand-level Summary Statistics
Notes: This table reports summary statistics for major coffee shop brands in the SafeGraph data across 44 U.S. states from January 2020 to February 2022. “Shares” denote each shop’s daily visit share within its local market. “Space Size” is measured in square meters. “Price Index” is the predicted latte price constructed from monthly sales data as described in Section 2.

All SafeGraph components share a unique identifier for each shop, which enables consistent merging across datasets. Tables 1 and 2 present summary statistics for 44 states after excluding extreme outliers and days when shops were closed. The average predicted price is approximately $4. At the brand level, larger chains such as Starbucks exhibit higher average prices compared to other brands of similar size, suggesting that brand-specific factors play an important role in pricing within this industry.

After analyzing the nationwide patterns, I restrict the sample to Colorado for the structural estimation in order to reduce computational burden. Colorado provides a suitable case study because it has a sufficiently large and diverse population and land area to support meaningful variation in market structure. Summary statistics for Colorado are reported in Appendix A.1. Over time, average predicted prices in Colorado are higher than the national mean. The state's coffee shop market features a relatively small number of brands, making it reasonable to assume that shops are aware of other local coffee shops' opening and closing decisions.

In addition to the SafeGraph data, I use state–year minimum wage data from Federal Reserve Bank of St. Louis [1968-2022] and state–quarter house price indices from Federal Housing Finance Agency [1991-2022]. Monthly CPI from World Bank [1970-2022] (Ha et al. [2023]) is used to deflate prices and minimum wages.

3 Descriptive Evidence

In this section, I present descriptive evidence that coffee shops vary in their opening days throughout the week and that these operational choices respond to competitive conditions both on the same day and across other days within the week. The results suggest that the sticky-pricing channel may influence which days shops choose to open.

I define each *market* at the daily–city level, capturing the idea that Monday's coffee cannot substitute for Tuesday's coffee. This definition allows me to analyze competition among shops operating in the same city on the same day.

3.1 Patterns of Operation

I begin by documenting that shops do not consistently close on the same specific day each week.

Table 3 shows that the share of shops closed is similar across weekdays. The small variation in closing ratios indicates that the pattern is not driven solely by shops that remain closed on all weekdays or all weekends. Instead, some shops selectively close on particular days, such

Weekday	Opening Ratio	Closing Ratio
Mon	0.860	0.140
Tue	0.862	0.138
Wed	0.864	0.136
Thu	0.862	0.138
Fri	0.860	0.140
Sat	0.852	0.148
Sun	0.848	0.152

Table 3: Opening and Closing Information by Weekday
Notes: This table reports the ratio of open and closed coffee shops by weekday across 44 U.S. states. Ratios are computed as the share of shops open (or closed) on each day relative to the total number of shops observed in the sample. The similar ratios across weekdays indicate that closures are not concentrated on a single day of the week, suggesting that shops choose different non-operating days. Comparable results for the Colorado sample are provided in Appendix A.2.

as Monday or Wednesday. This pattern remains consistent in the Colorado sample: as shown in Appendix A.2, the ratios of open and closed shops across weekdays are evenly distributed, mirroring the national pattern in Table 3.

One possible concern is that variation in opening hours, rather than in opening days, might be the primary source of operational differences across shops.

Variable	Mean	SD	N
Within-shop variance in opening hours	0.69	–	7,394
Within-shop range of opening hours	0.96	1.85	7,394

Table 4: Variation in Opening Hours (Unit: hours)
Notes: This table reports the variation in opening hours within individual coffee shops. The *within-shop variance in opening hours* measures the variance of daily opening hours across days when the shop operates. The *within-shop range of opening hours* is the difference between the maximum and minimum daily opening hours within the same shop. Results are based on 7,394 independent coffee shops in the national sample that report information on opening hours.

The evidence in Table 4 indicates that variation in opening and closing hours is not the primary source of operational differences among coffee shops. Table 4 summarizes the within-shop variation in opening hours (measured in hours). The variable *within-shop variance in opening hours* measures the variance of daily opening hours across days when the shop operates, while the *within-shop range of opening hours* captures the difference between the maximum and minimum opening hours within each shop. For 7,394 independent shops, the small values of both measures suggest that opening hours are relatively stable, implying that most operational variation arises from differences in opening-day choices rather than hour-to-hour adjustments.

Another potential concern is that opening decisions reflect brand-level operating policies rather than shop-level strategic choice. To assess this, I focus on brand–market cells with multiple outlets of the same brand in the same market.

Brand	Within-Market Opening-Day Variance		
	Mean	Max	N
Biggby Coffee	0.03	0.50	45,199
Caribou Coffee	0.06	0.50	980
Dunkin'	0.03	0.50	1,762,201
Dutch Bros Coffee	0.10	0.50	64,092
Krispy Kreme Doughnuts	0.01	0.50	26,768
Peet's Coffee and Tea	0.12	0.50	56
Starbucks	0.19	0.50	1,028,832
Tim Hortons	0.11	0.50	200,767
Winchell's Donut House	0.00	0.00	42

Table 5: Variance in Opening Days within Market–Brand
Notes: This table reports the within-market variation in opening-day decisions across shops of the same brand. For each brand–market pair, the variance of the opening dummy across shops is calculated, and both the mean and maximum of these market-level variances are presented. The sample includes only shops that have at least one same-brand competitor in the same city. A larger variance indicates greater heterogeneity in opening-day choices within the brand's local markets.

Table 5 shows that, except for Krispy Kreme Doughnuts and two other brands (Peet's Coffee and Tea and Winchell's Donut House), which have too few observations, all other brands exhibit variation in opening-day decisions within markets. It is important to note that achieving a large variance in opening days is mechanically difficult because most shops open on the majority of weekdays, leading to overlapping schedules. For example, even if two shops strategically choose different opening days, their schedules may look like Monday, Tuesday, Thursday, Friday, Saturday and Monday, Tuesday, Wednesday, Thursday, Friday, which would still yield a relatively small numerical variance in opening days.

3.2 Competition and Opening Decisions

Next, I show that when prices are sticky due to menu costs, operating on highly competitive days can lower the profitability of opening on other days, as competition on one day transmits to adjacent days—most plausibly within the same week—through the sticky-pricing channel. To examine this mechanism, I construct measures of competitive pressure for shop j in market m:

1. **Same-day competitor ratio** ($r_{-j,m}$): the share of competitors that are open in the same city on the same day, excluding the shop itself from the count.

2. **Average competitor ratio on other days** ($\bar{r}_{j,-d}$): the average of *same-day competitor ratio*s for the shop's *other* days within the same week.

Because shops already internalize the total number of competitors established in the market, these measures capture short-term fluctuations in competitive intensity across days rather than long-run entry decisions. This approach mitigates concerns about entry-level endogeneity.

Prices. I begin by estimating linear regressions of prices on the competition measures:

$$\text{Price}_{jm} = \alpha + \pi_1\, r_{-j,m} + \pi_2\, \bar{r}_{j,-d} + \gamma' X_{jm} + \delta_{\text{year}(m)} + \phi_{\text{weekday}(m)} + \varepsilon_{jm}, \tag{3}$$

where X_{jm} includes space size, an indicator for being located in an enclosed area, the number of online transactions, the availability of a parking lot, the (approximated) number of workers, and the local house price index. The terms $\delta_{\text{year}(m)}$ and $\phi_{\text{weekday}(m)}$ denote year and weekday fixed effects, respectively. Coefficient π_1 captures contemporaneous (same-day) competitive pressure, and π_2 measures cross-day spillovers consistent with sticky pricing.

Opening. I then estimate logit models for the opening decision:

$$\Pr(\text{Open}_{jm} = 1) = \Lambda\Big(\alpha + \beta_1\, r_{-j,m} + \beta_2\, \bar{r}_{j,-d} + \gamma' X_{jm} + \delta_{\text{year}(m)} + \phi_{\text{weekday}(m)}\Big), \tag{4}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. Coefficient β_1 captures contemporaneous (same-day) competitive pressure, and β_2 captures cross-day spillovers consistent with sticky pricing.

All regressions use the national sample covering 44 states. A corresponding falsification exercise using the average competitor ratio on closed days is reported in Appendix A.3.

	Dependent Variable: Price	
	Model 1	Model 2
Same-Day Competitor Ratio ($r_{-j,m}$)	-0.00	-0.00
	(0.00)	(0.00)
Average Competitor Ratio on Other Days ($\bar{r}_{j,-d}$)	-0.02^{***}	-0.02^{***}
	(0.00)	(0.00)
Year Fixed Effects	Yes	Yes
Weekday Fixed Effects	No	Yes
Shop Characteristics	Yes	Yes
Observations	5,211,934	5,211,934
R^2	0.99	0.99

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 6: Effects of Competitor Ratios on Pricing Decisions (Main Specification)
Notes: Each column reports results from linear regressions of daily shop-level prices on measures of competitive intensity. Both specifications include the same-day competitor ratio ($r_{-j,m}$) and the average competitor ratio on other days ($\bar{r}_{j,-d}$). Model 2 additionally includes weekday fixed effects. All specifications control for shop characteristics, including space size, enclosed location, number of online transactions, availability of a parking lot, approximated number of workers, and local house price index.

Table 6 presents the results of regressions of prices on the measures of competitive intensity. The significant negative coefficients in columns (1) and (2) for the other-day competitor ratios indicate that operating on more competitive days exerts downward pressure on prices, consistent with sticky-pricing behavior. The lack of significance for same-day competition may arise because, under near-uniform pricing within a week, most of the price variation is already explained by competition on other days.

Table 7 reports the average marginal effects of the competitor ratios on each shop's opening decision. The significant negative coefficients on the other-day competitor ratio in columns (1) and (2) indicate that operating on more competitive days reduces the likelihood of opening, consistent with the idea that competition on one day can lower profitability on adjacent days through sticky pricing.

Notably, the price regressions in Table 6 yield patterns consistent with the sticky-pricing hypothesis, reinforcing the interpretation that competitive pressures interact across days within a week through menu-cost-induced price rigidity.

	Dependent Variable: Opening	
	Model 1	Model 2
Same-Day Competitor Ratio ($r_{-j,m}$)	0.13^{***}	0.13^{***}
	(0.00)	(0.00)
Average Competitor Ratio on Other Days ($\bar{r}_{j,-d}$)	-0.12^{***}	-0.11^{***}
	(0.00)	(0.00)
Year Fixed Effects	Yes	Yes
Weekday Fixed Effects	No	Yes
Shop Characteristics	Yes	Yes
Observations	5,211,934	5,211,934

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 7: Average Marginal Effects of Competitor Ratios on Opening Decisions (Main Specification)
Notes: Each column reports average marginal effects from logit regressions of shop opening decisions on measures of competitive intensity. Both specifications include the same-day competitor ratio ($r_{-j,m}$) and the average competitor ratio on other days ($\bar{r}_{j,-d}$). Model 2 additionally includes weekday fixed effects. All specifications control for shop characteristics, including space size, enclosed location, number of online transactions, availability of a parking lot, approximated number of workers, and local house price index.

4 Model and Empirical Methodology

The model predicts (i) demand for coffee shops, (ii) weekly prices, and (iii) day–of–week operating decisions for each shop. The timing follows four stages. In Stage 1, a potential supplier decides whether to establish a shop (incurring facility fixed costs). In Stage 2, an active shop chooses which days (Monday–Sunday) to operate. In Stage 3, given operating days, the shop sets a *weekly uniform price* (sticky price within the week). In Stage 4, idiosyncratic demand shocks are realized, and consumers choose where to buy. I solve by backward induction and estimate demand and supply in sequence.

4.1 [Stage 4] Consumer Demand

Let j index shops, t index weeks, τ index the day of the week (Monday–Sunday), and c index the city. Markets are defined by the triplet (t, τ, c). This daily definition is natural, as consumers typically make coffee purchases on a day-by-day basis, i.e., Monday's coffee is not a perfect substitute for Tuesday's coffee.

Since coffee consumption is highly habitual, some individuals consistently abstain from consuming coffee, while others are regular coffee drinkers. Hence, using information on the total number of devices in my data would exaggerate the potential number of consumers and substantially overstate the market size.[2] Due to this data limitation, the model assumes that consumers first make an exogenous decision about whether to purchase coffee outside the home and, conditional on that decision, choose among open coffee shops within the city.

Empirical evidence suggests that franchise coffee chains and local independent shops often operate in partially distinct competitive spaces. For instance, Adams et al. [2018] find that the entry of chain stores in Melbourne has little effect on the exit or entry of independent cafes, implying weak strategic interaction across these segments. Evidence from UK independent cafés further shows that owners primarily evaluate success through customer satisfaction and loyalty, while none report using market share as a performance measure (Douglas et al. [2018]). Together, these findings suggest that independent shops maintain relatively stable customer bases and do not actively engage in direct market-share competition with large franchises. To focus on supply-side strategic interactions among franchises, I therefore model consumers as choosing among branded coffee shops while treating visits to any local independent cafes as the outside option. This approach abstracts from explicit modeling of small independent operators. This setup defines the relevant market and leads to the following individual-level utility specification.

Utility of consumer n in market (t, τ, c) for shop j in the nested logit model is

$$u_{nt\tau cj} = z'_{t\tau cj}\beta + \alpha p_{tcj} + \xi_{t\tau cj} + \zeta_{nt\tau cg} + (1-\sigma)\varepsilon_{nt\tau cj}, \tag{5}$$

where $\varepsilon_{nt\tau cj}$ is i.i.d. and follows a Type I Extreme Value distribution, $\zeta_{nt\tau cg}$ is common to all products in nest g, and $\zeta_{nt\tau cg} + (1-\sigma)\varepsilon_{nt\tau cj}$ is also distributed Type I Extreme Value.[3]

Let $j \in \mathcal{J}$ denote branded coffee shops, such as Starbucks. In the nested logit framework,

[2]Including all devices as potential consumers decreases the estimated market shares of coffee shops by more than a hundredfold.

[3]To focus on the supply side, the demand specification is simplified. While an extended model could incorporate consumer habit formation or intertemporal substitution, modeling time-dependent decisions on both the demand and supply sides would add substantial complexity without altering the main supply-side argument.

one nest comprises all branded coffee shops, while the other represents the outside option. The utility of the outside option is normalized to zero, and closed shops are excluded from the consideration set.

$\xi_{t\tau cj}$, $\zeta_{nt\tau cg}$, and $\varepsilon_{nt\tau cj}$ are unobserved components. The variable p_{tcj} denotes the weekly uniform price index, and $z_{t\tau cj}$ includes a time trend and observable shop characteristics. The time trend captures changes in the valuation of outside options as well as demand shocks related to the timing of COVID-19 outbreaks in each state. Shop characteristics include brand dummies, floor area, the degree of online engagement, and an indicator for whether the shop is located within a larger complex (e.g., a mall or food court).

To address potential endogeneity of price and within-nest shares in the nested logit model, I use cost shifters as instruments. These include the deflated rental price weighted by the size of the shop and the deflated minimum wage weighted by the number of workers. Because the analysis focuses on short-run operational variations—where the entry of new establishments is predetermined—I do not use the number of shops as an instrument to maintain a conservative identification strategy.

The demand model could be extended to a random-coefficients specification, but it remains deliberately simple as a nested logit. This choice reflects the paper's primary focus on the supply side and on predicting shops' opening decisions under varying market conditions. Moreover, the nested logit structure provides closed-form expressions for market shares, profits, and consumer surplus without requiring numerical integration. Given the computational intensity of the supply-side estimation and counterfactual simulations, the tractability advantages of the nested logit model are substantial.

4.2 [Stage 3] Supply: Optimal Pricing

In Stage 3, given operational decisions, coffee shops choose weekly prices to maximize profits while anticipating the effect of prices on market shares. This setup imposes a simplified but realistic form of sticky price: shops adjust prices at most a weekly frequency, reflecting the presence of menu costs and coordination with weekly operational planning. While this assumption could be relaxed in other industry applications, it aligns well with the short-run focus of this study.

Franchises belonging to the same brand are treated as independent owners. This assumption is consistent with market conditions in the United States, where franchisees are typically permitted to set prices independently.[4] For notational simplicity, I omit the city subscript c in the supply-side exposition that follows.

As previously discussed, coffee shops set prices uniformly within each week. The optimal weekly price for shop j in week t therefore maximizes weekly profit:

$$\pi_{jt}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t; \theta) = (p_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t)\, w_{j\tau t} - \sum_{\tau} FC_{jt}\, w_{j\tau t}, \tag{6}$$

where $\vec{w}_{jt} = (w_{jt\tau})_{\forall\tau}$, and $w_{jt\tau} = 1$ if shop j is open on day τ of week t and 0 otherwise. The term $s_{j\tau t}$ denotes the market share (multiplied by the market size) for day τ, since market size may vary across days of the week and across regions.

Hence, the optimal pricing condition is

$$(p_{jt} - mc_{jt}) \sum_{\tau} \frac{\partial s_{j\tau t}}{\partial p_{jt}}\, w_{j\tau t} + \sum_{\tau} s_{j\tau t}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t)\, w_{j\tau t} = 0, \tag{7}$$

and the corresponding moment condition is

$$\frac{1}{JT} \sum_{j,t} g_{1jt}\, Z_{1jt} = 0, \tag{8}$$

where

$$g_{1jt} = mc_{jt} - p_{jt} - \frac{\sum_{\tau} s_{j\tau t}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t)\, w_{j\tau t}}{\sum_{\tau} \left(\frac{\partial s_{j\tau t}}{\partial p_{jt}}\right) w_{j\tau t}}. \tag{9}$$

The instrument vector Z_{1jt} includes the time trend, predetermined shop characteristics, and regressors from the marginal cost specification.

I specify marginal costs as

$$mc_{jt} \;=\; \gamma_1' x_{jt} \;+\; \varepsilon_{jt}, \tag{10}$$

[4] Technically, Starbucks operates under a licensing structure rather than a traditional franchise model, but licensed stores retain similar flexibility in local pricing decisions. For example, prices at Dunkin' Donuts outlets in Princeton differ from those in Orlando.

where x_{jt} includes observable cost shifters (state minimum wage and shop size), and ε_{jt} is an expectational error term capturing unobserved cost variation from the econometrician's perspective. Firms set prices based on the systematic component of costs, while ε_{jt} represents the researcher's approximation error relative to firms' true expectations. It is not observed by firms at the time of their pricing and opening decisions.

Both the state minimum wage and shop size are treated as exogenous cost shifters. Although one could use the number of workers as an endogenous regressor and instrument it with shop size, worker counts are measured approximately in my data. I therefore include shop size directly in x_{jt} instead.

During the COVID-19 period, cost shocks were driven primarily by state-level forces (policy changes, wage floors, and federal programs). I rely on this state–time variation for identification and treat finer geographic shocks (e.g., census-block or city-specific) as second-order relative to state-level movements.

4.3 [Stage 2] Supply: Operating-Day Decisions

In Stage 2, shops choose which days to operate during the week. Because changes in operating days may alter the optimal weekly price, the Nash equilibrium condition on operation decisions must consider total weekly profits. Specifically, given the operation choices of other shops, any unilateral deviation in operating days—along with the corresponding re-optimized price—should not increase profits. Formally,

$$\begin{aligned}
&(p_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t)\, w_{j\tau t} - \sum_{\tau} FC_{jt}\, w_{j\tau t} \\
&\geq (\tilde{p}_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{\tilde{w}}_{jt}, \vec{w}_{-jt}, \tilde{p}_{jt}, p_{-jt})\, \tilde{w}_{j\tau t} - \sum_{\tau} FC_{jt}\, \tilde{w}_{j\tau t},
\end{aligned} \tag{11}$$

for all deviations in operating decisions $\tilde{w}_{j\tau t}$ and the corresponding re-optimized prices $\tilde{p}_{jt}$. The term $s_{j\tau t}$ again denotes the market share (multiplied by the market size, which varies across the week and regions).

I use this condition to construct a penalty function following Crawford and Yurukoglu [2012]. For any deviation, it is possible to form inequality moments that penalize cases where deviation profits exceed equilibrium profits:

$$\min\left(0,\ \frac{1}{JT}\sum_{j,t} g_{2jt} Z_{2jt}\right), \tag{12}$$

where the profit difference is defined as

$$\begin{aligned} g_{2jt} = &\Big[(p_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{w}_{jt}, \vec{w}_{-jt}, \vec{p}_t)\, w_{j\tau t} - \sum_{\tau} FC_{jt}\, w_{j\tau t}\Big] \\ &- \Big[(\tilde{p}_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{\tilde{w}}_{jt}, \vec{w}_{-jt}, \tilde{p}_{jt}, p_{-jt})\, \tilde{w}_{j\tau t} - \sum_{\tau} FC_{jt}\, \tilde{w}_{j\tau t}\Big]. \end{aligned} \tag{13}$$

Here g_{2jt} measures the profit gain from deviating to an alternative operating pattern $\vec{\tilde{w}}_{jt}$ with the corresponding re-optimized price $\tilde{p}_{jt}$. The moment condition penalizes instances where this deviation profit is positive, enforcing the necessary condition for Nash equilibrium in operating-day choices.

For the moment condition, I use instruments Z_{2jt} that capture exogenous factors affecting shops' opening decisions. Specifically, Z_{2jt} includes a time trend and shop size—the same variables that enter the fixed-cost specification—which are assumed exogenous with respect to the unobserved fixed-cost component. These variables therefore serve to enforce the orthogonality condition $E[g_{2jt} Z_{2jt}] \geq 0$.

To obtain the tightest bound implied by the Nash equilibrium condition, the deviation profit

$$(\tilde{p}_{jt} - mc_{jt}) \sum_{\tau} s_{j\tau t}(\vec{\tilde{w}}_{jt}, \vec{w}_{-jt}, \tilde{p}_{jt}, p_{-jt})\, \tilde{w}_{j\tau t} - \sum_{\tau} FC_{jt}\, \tilde{w}_{j\tau t}$$

should be evaluated at the most profitable deviation $\vec{\tilde{w}}_{jt}$ and the corresponding best-response price $\tilde{p}_{jt}$. Computing this global maximum requires considering all $2^7 - 1$ non-empty day-set deviations with price re-optimization, which is computationally intensive. To reduce the burden in estimation, I instead consider a one-day add/drop deviation and hold price fixed at p_{jt} (i.e., without re-optimizing $\tilde{p}_{jt}$). This delivers a conservative (lower-bound) inequality: any violation under this restricted deviation set would also violate the full condition. However, in counterfactual simulations, I reoptimize prices and evaluate all $2^7 - 1$ possible deviation conditions to recover the complete equilibrium response.[5]

[5] A tighter yet still tractable alternative is to take the maximum over the seven one-day deviations while still holding price fixed.

I specify fixed costs as

$$FC_{jt} = \gamma_2' x_{jt} + \nu_{jt}, \tag{14}$$

where x_{jt} includes year fixed effects and shop size, and ν_{jt} is an approximational error term capturing residual variation in operating costs not explained by observables.

In this specification, FC_{jt} in Stage 2 represents daily operating frictions, assuming that facilities have already been established in Stage 1. Year fixed effects capture changes over time in the ease of finding workers to operate each day. To ensure that these effects are not confounded by inflation, all prices and wages are deflated in both the demand and supply estimations. Shop size also enters the specification because larger stores generally face different staffing and operational challenges than smaller ones. While both the marginal- and fixed-cost specifications include shop size, the former captures its effect on per-unit costs (e.g., labor intensity), whereas the latter captures its effect on the overall scale of daily operations. Year fixed effects in the latter isolate temporal variation in labor frictions rather than production costs.

4.4 [Stage 1] Supply: Entry Decision

In Stage 1, potential suppliers decide whether to establish a shop, incurring longer-term fixed costs such as facility investments and equipment purchases. This entry decision represents the extensive-margin choice in the full dynamic model.

In the present analysis, I abstract from Stage 1 because the data capture short-run adjustments in openings and closures during the COVID-19 period rather than long-run entry dynamics. Since the pandemic was largely unanticipated at the time of shop establishment, the Stage 1 entry decision can be treated as predetermined and thus is omitted from the empirical estimation.

4.5 Supply: Summary of Moments

Because preference shocks are realized in the final stage of the model, the supply-side moments can be estimated separately from the demand side. For computational tractability, I estimate the model sequentially from Stage 4 onward rather than jointly across all stages. This approach may sacrifice some statistical efficiency but greatly reduces the computational burden.

Following Crawford and Yurukoglu [2012], I estimate the coefficients on fixed costs by minimizing the empirical moment conditions described above, assigning equal weights to each condition. Standard errors are computed under the assumption that the inequality moments are not binding.[6]

5 Estimates

I focus the estimation on the Colorado sample. The first confirmed COVID-19 cases in Colorado were reported in March 2020, followed by a substantial surge later that year (Colorado Dept. of Public Health and Environment 2020). Focusing on a single state reduces computational burden while retaining sufficient variation across local markets, as Colorado includes both large metropolitan areas and smaller regional towns.

5.1 Demand Estimation Results

	Nested Logit
Year 2020	1.83^{**} (0.70)
Year 2021	1.64^{*} (0.66)
Year 2022	1.30^{*} (0.63)
Price	-0.76^{***} (0.17)
Dunkin (brand)	-0.77^{***} (0.05)
Starbucks (brand)	-0.19^{***} (0.04)
Space size (per 100 m^2)	-0.02^{***} (0.00)
Located in enclosed area	-1.59^{***} (0.13)
Online transactions	-0.00^{***} (0.00)
Number of observations	66,374

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 8: Demand Estimation Results in Colorado
Notes: Standard errors are in parentheses. The model includes year fixed effects, brand dummies for major franchise chains, and a single nest encompassing all branded coffee shops. Because some brands operate only a few stores within each city, nesting at the individual brand level is not feasible.

[6] The bootstrap method was not implemented because of its computational burden.

Table 8 presents the estimated demand parameters obtained using the `pyblp` package developed by Conlon and Gortmaker [2020]. The nested logit specification includes a single nest encompassing all branded coffee shops. Year fixed effects are incorporated by including all year dummies and excluding the constant term, which facilitates comparison across years. These fixed effects capture changes over time in the valuation of the outside option. Because the consideration set in each market excludes shops that are temporarily closed, the positive year effects for 2022 suggest that consumers particularly preferred local small shops when they were open. One plausible explanation is that local shops are located closer to residential areas, and consumers were less willing to travel long distances as the COVID-19 situation worsened.[7] It is important to note that the 2022 sample covers only January and February. Since the CDC revised its indoor mask guidelines in late February and March, the relaxation of COVID-19 restrictions is not yet reflected in this sample period.[8]

The estimated price coefficient is -0.76 in the nested logit model. On average, the implied price elasticity of demand in Colorado is 12.82 in absolute value. This relatively high elasticity partly reflects the large estimated nesting parameter (0.76), which amplifies within-nest substitution among branded coffee shops.[9]

The estimated coefficients on the *Starbucks* and *Dunkin* dummies indicate that consumers are relatively less likely to choose these stores compared with other branded coffee shops. I do not include fixed effects for all individual brands because, in the Colorado sample, most other brands operate only one store per market. Including a full set of brand dummies would therefore lead to near-multicollinearity and provide insufficient variation to identify brand-specific effects.

Space size is measured in square meters. When expressed in units of 100 m^2, the estimated coefficient of -0.02 indicates a preference for smaller spaces. This result is consistent with the interpretation that consumers preferred to avoid large or crowded environments during the COVID-19 period. As discussed in the Introduction, given the short sample period and the

[7]If data on local COVID-19 outbreaks were available, this hypothesis could be tested directly using peak-period or infection-rate indicators instead of year fixed effects.

[8]See `https://www.cdc.gov/museum/timeline/covid19.html`.

[9]The detailed estimates are -0.75518 for the price coefficient and 0.76330 for the nesting parameter.

unanticipated onset of the pandemic, it is reasonable to assume that shop characteristics—such as brand affiliation and floor space—were determined prior to the pandemic and are not endogenous responses to competitors' temporary closures.

The variable *Located in enclosed area* indicates whether a coffee shop is situated within a larger venue such as an airport or shopping mall. The negative coefficient on this variable aligns with the interpretation proposed by Relihan [2022], who document that the COVID-19 pandemic increased U.S. households' online retail purchases, thereby altering their bundled-trip behavior. If consumers previously visited coffee shops as part of multi-purpose trips to such venues, the expansion of online retail options during the pandemic likely reduced these bundled trips, making enclosed coffee shops relatively less attractive.

The coefficient on *Online transactions* further shows that shops with higher online popularity tend to be less preferred for offline visits, consistent with a substitution pattern between online and in-person consumption.

5.2 Cost Estimation Results

	Supply side
Constants	0.879^{**} (0.286)
Minimum wage	0.295^{***} (0.025)
Space size (normalized)	1.692^{**} (0.128)
Number of observations	54,194

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 9: Marginal Cost Estimation Results in Colorado
Notes: Standard errors are in parentheses. The model estimates marginal cost parameters from the Stage 3 pricing decision, as described in Section 4. Minimum wage and space size are included as cost shifters, and coefficients are identified through variation in observed prices and quantities.

Tables 9 and 10 report the estimated coefficients for the supply side. Table 9 presents the marginal cost estimates based on all city samples in Colorado. For the fixed cost estimation, I focus on individual cities to capture localized shocks associated with COVID-19 and to reduce computational complexity. Table 10 reports the fixed cost estimates for Denver, while results for other cities are provided in the Appendix.

	Supply side
Year 2020	40.605*** (6.359)
Year 2021	34.252*** (9.671)
Year 2022	−16.699 (24.992)
Space size (normalized)	−127.733*** (8.173)
Number of observations	17,248

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 10: Fixed Cost Estimation Results for Denver, Colorado
Notes: Standard errors are in parentheses. The model estimates fixed cost parameters from the Stage 2 daily operation decision, as described in Section 4. Year fixed effects capture temporal variation in operating frictions, while shop size accounts for differences in the scale of daily operations.

There are two important notes regarding the estimation results. First, the minimum wage variable is deflated to remove the influence of inflation and ensure that the estimated coefficients capture real, rather than nominal, cost effects. Second, the space size variable is normalized by subtracting its mean and dividing by its standard deviation, which results in some negative values for space size.

The fixed cost estimation for daily operations includes year fixed effects, which capture year-specific variation in operational frictions—hypothetically arising from the difficulty of securing workers—and shop size, which accounts for potential differences in this difficulty across establishments. It is important to note that the estimated fixed cost does not represent direct financial expenses such as wages, which are already incorporated in the marginal cost, nor facility costs associated with shop entry. As explained in the model section, shop entry is taken as given in this stage. Instead, the estimated daily fixed cost reflects the friction or effort required to open and operate the shop each day, expressed in monetary terms.

The estimated fixed costs for daily operations of a shop of average size in 2020, 2021, and 2022 are approximately \$40.61, \$34.25, and −\$16.70, respectively. These values are expressed in dollars per day and should be interpreted as the monetary equivalent of daily operational frictions rather than literal financial outlays. An increase of one standard deviation in space size reduces the fixed cost by about \$127.73 per day. The pattern of year fixed effects—interpreted as the daily operational frictions given that facilities are already established—partly reflects the timeline of federal relief programs such as the CARES (Coronavirus Aid, Relief, and Economic

Security) Act and the ARP (American Rescue Plan) Act. As shown in Table 10, 2020 exhibits the highest daily operational costs, while 2022 shows the lowest.

In 2020 and 2021, the CARES Act and the ARP Act expanded unemployment assistance,[10] which likely reduced labor supply and increased the difficulty of finding workers. This labor shortage elevated daily operating frictions, reflected in higher estimated fixed costs for those years. In contrast, the ARP Act in 2021 emphasized continued financial support for small businesses, including through the Restaurant Revitalization Fund, which helped mitigate some of these operational burdens for restaurants, bars, and coffee shops.

The other estimates also display signs consistent with economic intuition. An increase in the minimum wage raises marginal costs, while larger spaces are also associated with higher marginal costs. The positive relationship between marginal costs and space size likely reflects that larger establishments require more workers to operate effectively. In contrast, the negative coefficient on space size in the fixed cost estimation suggests that, during the COVID-19 period, larger coffee shops may have faced lower daily operational frictions. One possible explanation is that larger shops could implement safety measures more easily and offer more stable employment, which helped attract or retain workers despite heightened labor shortages.

[10]The Pandemic Unemployment Assistance (PUA) program extended eligibility to workers who were not covered by traditional unemployment insurance.

6 Counterfactuals

	Price Stickiness (Weekly Uniform Pricing)	**No Stickiness (Daily Pricing)**
Current coefficients	$CS_{Sticky,Friction}$	$CS_{No,Friction}$
2020 year fixed effect in fixed costs = 0	$CS_{Sticky,No}$	$CS_{No,No}$
Difference	$\mathit{Friction\ Effect}_{Sticky}$	$\mathit{Friction\ Effect}_{No}$

Table 11: Counterfactual Scenarios
Notes: The table summarizes the four counterfactual settings considered in the analysis. Along one dimension, I either maintain weekly uniform pricing, which introduces price stickiness, or allow daily price adjustments ("No stickiness"). Along the other dimension, I vary supply-side frictions by either retaining all estimated coefficients or setting the 2020 year fixed effect in fixed costs to zero. $\mathit{Friction\ Effect}_{Sticky}$ measures the change in consumer surplus between these two fixed-cost settings under weekly pricing, while $\mathit{Friction\ Effect}_{No}$ measures the same change under daily pricing.

The goal of the counterfactual analysis is to quantify how supply-side frictions influence shops' daily operating decisions and consumer surplus under varying degrees of price stickiness. The analysis focuses on a single market (Denver) and one representative period in 2020. Table 11 summarizes the counterfactual settings.

The first dimension of variation concerns the degree of price stickiness. I either maintain the baseline assumption of weekly uniform pricing, which imposes a mild form of price stickiness, or relax this constraint to allow daily price adjustments ("No stickiness"). The second dimension varies the extent of supply-side frictions. As described in the model section, the fixed cost in the second stage represents a friction associated with securing sufficient labor to open a store on a given day, conditional on existing facilities. Accordingly, policy interventions such as direct operational subsidies or reductions in labor frictions would effectively lower these fixed costs. To capture this mechanism, I either retain all estimated coefficients or set the 2020 year fixed effect in fixed costs to zero, representing a scenario with reduced supply-side frictions.

In Table 11, $\mathit{Friction\ Effect}_{Sticky}$ measures the change in consumer surplus between the two fixed-cost settings under weekly uniform pricing, while $\mathit{Friction\ Effect}_{No}$ measures the same change under daily pricing.

In the counterfactual simulations, a potential issue arises from the presence of multiple equilibria. The algorithm selects the equilibrium in firms' operating decisions that is closest to the observed outcome. The rationale is that, when multiple equilibria exist, the realized outcome may correspond to the one that arises with the highest probability due to unobserved market-specific factors. Therefore, choosing the equilibrium most similar to the observed pattern provides a natural and comparable benchmark for the counterfactual analysis.

	Price Stickiness (Weekly Uniform Pricing)	**No Stickiness (Daily Pricing)**
Current coefficients	\$2.59	\$3.06
2020 year fixed effect in fixed costs = 0	\$2.64	\$3.06
Difference	\$0.05	\$0.00

Table 12: Counterfactual Summary: Weekly Expected Utility per Individual
Notes: The table reports simulated consumer surplus (CS) under each counterfactual setting, focusing on one representative period in Denver in 2020. Consumer surplus represents an individual's weekly expected utility, expressed in dollar terms. Along one dimension, I either maintain weekly uniform pricing, which introduces price stickiness, or allow daily price adjustments ("No stickiness"). Along the other dimension, I vary supply-side frictions by either retaining all estimated coefficients or setting the 2020 year fixed effect in fixed costs to zero.

Table 12 summarizes the results of the counterfactual simulations. The (ex-ante) consumer surplus corresponds to an individual's weekly expected utility, measured in dollar units.

The results indicate that under price stickiness, the impact of supply-side frictions is amplified. Given that the weekly uniform pricing assumption represents only a mild form of stickiness, this finding suggests that neglecting interdependencies across competitive dimensions can lead to a substantial underestimation of the effects of supply-side support. The model with interdependent markets captures that a reduction of approximately \$40.61 in the fixed cost per shop increases each consumer's expected weekly utility by about \$0.05, whereas the model with daily pricing predicts a smaller effect (around \$0). Although this magnitude appears modest, it should be interpreted in the context of the relatively low prices and consumption values for coffee, combined with the large number of potential consumers in each market.

The interaction between frictions in the timing dimension of competition and constraints in the pricing dimension is generalizable to many other industries in which firms decide not only what price to charge but also when to sell. In many markets, pricing decisions are subject to menu costs, managerial inertia, or high adjustment costs arising from consumer expectations, creating interdependencies across these competitive dimensions. The coffee shop industry during the COVID-19 pandemic provides a unique and novel setting to isolate these mechanisms: long-term choices such as entry and store characteristics were largely predetermined and exogenous, while timing had not previously been a meaningful competitive dimension. In contrast, in most other settings, both entry and store characteristics are endogenous to timing decisions, and firms can differentiate either through product attributes or through operating schedules, making it difficult to disentangle strategic behavior along the time dimension using observational data.

In the following subsections, I describe each counterfactual simulation in detail.

6.1 Summary of Counterfactual Cases

	Case 1	**Case 2**	**Case 3**	**Case 4**
	Sticky &	**Sticky &**	**No Stickiness &**	**No Stickiness &**
	Friction	**No Friction**	**Friction**	**No Friction**
Shops open each day	16	16 (Mon–Wed), 17 (Thu–Sun)	16	16
Average price ($)	4.74	4.72	4.99	4.99
Weekly consumer surplus ($)	2.59	2.64	3.06	3.06

Table 13: Summary of Four Counterfactual Cases
Notes: Each case represents a combination of pricing flexibility (price stickiness vs. no stickiness) and supply-side frictions (friction vs. no friction). Cases 1 and 3 use estimated fixed costs, while Cases 2 and 4 set the 2020 year fixed effect in fixed costs to zero to represent the no-friction scenario. Consumer surplus represents an individual's weekly expected utility, expressed in dollar units.

Table 13 summarizes operating decisions, consumer surplus, and average prices across the four counterfactual settings. Cases 1 and 3 correspond to the baseline level of supply-side frictions, while Cases 2 and 4 set the 2020 year fixed effect in fixed costs to zero, representing reduced frictions—hereafter referred to as the "no-friction" case. The first two cases impose weekly uniform pricing (price stickiness), whereas the latter two allow daily price adjustments (no stickiness).

Across all cases, nineteen shops operate in the market. Under both the baseline and daily-pricing scenarios (Cases 1, 3, and 4), sixteen shops remain open every day of the week. When frictions are reduced under weekly pricing (Case 2), one additional shop opens on some days, resulting in seventeen shops operating from Thursday through Sunday. Consumer surplus and prices respond accordingly: with lower fixed costs, the weekly expected consumer surplus increases from approximately \$2.59 to \$2.64 under sticky prices, while the average price decreases slightly from \$4.74 to \$4.72. In contrast, when daily pricing is allowed (Cases 3 and 4), the equilibrium number of open shops and average prices (\$4.99) remain unchanged, yielding a higher overall consumer surplus of about \$3.06. These results indicate that supply-side relief has stronger welfare effects when prices are sticky, since reduced frictions translate more directly into expanded operation and higher consumer surplus when firms cannot flexibly adjust prices across days.

6.2 Case 1: Current Friction, Weekly Pricing

Under the baseline with estimated frictions and weekly uniform pricing, sixteen of the nineteen shops operate each day on average. The weekly ex-ante consumer surplus per individual who purchases coffee daily equals \$2.59, while the average price is about \$4.74 (range \$4.14–6.73). This scenario serves as the reference point for evaluating the effects of friction reduction and pricing flexibility.

6.3 Case 2: No Friction, Weekly Pricing

Reducing daily fixed costs by removing the 2020 year effect—effectively eliminating the additional friction estimated for 2020—raises the number of open shops to seventeen on some days of the week. Consumer surplus increases slightly to \$2.64 (a 2 percent gain) and the average price falls marginally to \$4.72 (range \$4.09–6.73). When prices remain sticky across the week, lowering daily operating frictions primarily induces additional openings but does not substantially affect pricing behavior.

6.4 Case 3: Current Friction, Daily Pricing

Allowing prices to adjust by day makes competition more responsive to day-specific demand conditions. The number of active shops remains roughly unchanged, yet consumer surplus rises substantially to \$3.06 (about 18 percent higher than in Case 1). The average price increases to \$4.99, largely because one outlier charges nearly \$14, while most others price between \$3.95 and \$6.71. Overall, relaxing price rigidity reallocates competition across days and improves welfare even when operating frictions persist.

6.5 Case 4: No Friction, Daily Pricing

When both frictions are lowered and daily pricing is allowed, equilibrium outcomes remain almost identical to Case 3. The same number of shops operate, and weekly ex-ante consumer surplus and prices change little (\$3.06 and \$4.99, respectively). Once prices can vary freely across days, small reductions in operating frictions no longer influence opening decisions or welfare.

7 Conclusion

This paper shows that the timing of product offerings can serve as an economically meaningful dimension of competition when firms face labor-supply frictions and price rigidity. By extending the classical static entry framework to include firms' short-run operational decisions, I highlight how constraints in one dimension of competition—pricing—can generate interdependencies across markets and influence entry behavior along another dimension—time.

Using the U.S. coffee shop industry during the COVID-19 pandemic as a natural experiment, I estimate a structural model that links demand, pricing, and operating-day choices under uniform pricing. The results indicate that higher labor frictions reduce the number of operating days, and that price stickiness amplifies this effect by coupling daily operations with weekly pricing incentives.

Counterfactual simulations show that neglecting this interaction leads to an underestimation of policy effectiveness: subsidies that offset operating costs or ease labor frictions have larger welfare impacts when inter-market dependencies are considered. These findings underscore the importance of incorporating interdependent competitive dimensions—time and price—into analyses of firm strategy and policy design, particularly during periods of heightened supply frictions.

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A Appendix

A.1 Additional Summary Statistics

Tables 14 and 15 report additional summary statistics for the Colorado estimation sample after excluding extreme outliers and days when shops were closed.

		Shares			Space Size			Price Index			
Year	Quarter	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	N
2020	1	0.04	0.05	0.02	331.04	770.27	205.00	4.50	0.24	4.50	6021
2020	2	0.05	0.07	0.02	292.51	594.26	204.00	4.51	0.36	4.56	5805
2020	3	0.05	0.06	0.02	342.02	798.30	200.00	4.48	0.30	4.54	6408
2020	4	0.05	0.07	0.02	336.83	760.18	204.00	4.45	0.33	4.47	6070
2021	1	0.05	0.06	0.02	285.38	547.24	200.00	4.41	0.32	4.43	6163
2021	2	0.05	0.06	0.02	286.36	549.55	200.00	4.32	0.30	4.36	6176
2021	3	0.05	0.06	0.02	286.21	553.98	197.00	4.26	0.29	4.30	6077
2021	4	0.05	0.07	0.02	287.53	560.62	197.00	4.22	0.31	4.23	5929
2022	1	0.05	0.07	0.02	297.27	581.37	200.00	4.13	0.29	4.21	3377

Table 14: Colorado Quarterly Summary Statistics
Notes: This table summarizes SafeGraph coffee shop data in Colorado aggregated by year and quarter. “Shares” denote the daily visit share of each shop within its local market. “Space Size” is measured in square meters. “Price Index” is the predicted latte price based on the distribution of sales per transaction. For comparison, nationwide quarterly statistics are presented in Table 1.

	Shares			Space Size			Price Index			
Brands	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	N
Caribou Coffee	0.02	0.01	0.01	131.54	19.81	148.00	4.49	0.30	4.55	1468
Dunkin'	0.02	0.02	0.02	246.86	95.91	228.00	4.06	0.27	4.04	10145
Dutch Bros Coffee	0.09	0.07	0.08	107.95	68.75	75.00	4.14	0.24	4.15	3402
Krispy Kreme Doughnuts	0.02	0.04	0.00	4734.38	2279.07	5935.00	4.15	0.42	4.28	257
Starbucks	0.05	0.07	0.02	317.11	643.30	200.00	4.49	0.28	4.49	36529
Winchell's Donut House	0.01	0.01	0.01	166.92	54.79	142.00	3.96	0.42	3.90	225

Table 15: Colorado Brand-level Summary Statistics

Notes: This table reports summary statistics for major coffee shop brands located in Colorado, which serves as the estimation sample in the structural analysis. "Shares" denote each shop's average daily visit share within its local market. "Space Size" is measured in square meters. "Price Index" is the predicted latte price constructed from monthly sales data as described in Section 2. For comparison, nationwide brand-level statistics are presented in Table 2.

A.2 Opening and Closing Patterns in Colorado

Table 16 summarizes the distribution of opening and closing decisions across weekdays in Colorado, showing that openings and closures are approximately evenly distributed throughout the week.

Weekday	Opening Ratio	Closing Ratio
Mon	0.720	0.280
Tue	0.720	0.280
Wed	0.725	0.275
Thu	0.725	0.275
Fri	0.719	0.281
Sat	0.730	0.270
Sun	0.703	0.297

Table 16: Opening and Closing Information by Weekday in Colorado
Notes: This table reports the ratio of open and closed coffee shops by weekday for the Colorado sample. Ratios are computed as the share of shops open (or closed) on each day relative to the total number of shops observed in the state. The similar ratios across weekdays suggest that shop closures are not concentrated on a particular day, mirroring the national pattern reported in Table 3.

A.3 Falsification Exercises

As a falsification test of the sticky-pricing mechanism, I replace the cross-day competition variable with a measure based on days when the shop itself is closed:

1. **Average competitor ratio on closed days** ($\bar{r}^{\text{closed}}_{j,-d}$): the average of *same-day competitor ratio*s for the shop's *other closed* days within the same week, excluding the current day. This measure serves as a falsification test, since competition on days when the shop is closed should not affect prices through the sticky-pricing channel.

I then estimate the following specification for prices:

$$\text{Price}_{jm} = \alpha + \pi_1 \, r_{-j,m} + \kappa \, \bar{r}^{\text{closed}}_{j,-d} + \gamma' X_{jm} + \delta_{\text{year}(m)} + \phi_{\text{weekday}(m)} + \varepsilon_{jm}, \tag{15}$$

where X_{jm} includes space size, an indicator for being located in an enclosed area, the number of online transactions, the availability of a parking lot, the (approximated) number of workers, and the local house price index. Coefficient π_1 captures contemporaneous (same-day) competitive pressure, while κ tests whether competition on closed days influences prices—an effect.

I also estimate a corresponding logit model for the opening decision:

$$\Pr(\text{Open}_{jm} = 1) = \Lambda\Big(\alpha + \beta_1 \, r_{-j,m} + \theta \, \bar{r}^{\text{closed}}_{j,-d} + \gamma' X_{im} + \delta_{\text{year}(m)} + \phi_{\text{weekday}(m)}\Big), \tag{16}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. Coefficient β_1 captures contemporaneous (same-day) competitive pressure, while θ tests the falsification implication that competition on closed days should not transmit through pricing.

Table 17 reports the results of regressions using the average competitor ratio on closed days as a falsification test. In contrast to the main text results, the coefficients on the closed-day competition measure in columns (1) and (2) are not negative, indicating that competition on days when a shop is closed does not affect prices through the sticky-pricing channel. This finding supports the validity of the mechanism identified in the main analysis.

Table 18 presents the falsification results using the average competitor ratio on closed days. The coefficients in columns (1) and (2) are also negative and significant. This pattern suggests that the sticky-pricing mechanism may not be the sole driver of observed opening behavior,

	Dependent Variable: Price	
	Model 1	Model 2
Same-Day Competitor Ratio ($r_{-j,m}$)	-0.27^{***}	-0.27^{***}
	(0.01)	(0.01)
Average Competitor Ratio on Closed Days ($\bar{r}^{\text{closed}}_{j,-d}$)	0.19^{***}	0.19^{***}
	(0.01)	(0.01)
Year Fixed Effects	Yes	Yes
Weekday Fixed Effects	No	Yes
Shop Characteristics	Yes	Yes
Observations	962,071	962,071
R^2	0.99	0.99

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 17: Effects of Competitor Ratios on Pricing Decisions (Falsification Specifications)
Notes: Each column reports results from linear regressions of daily shop-level prices on measures of competitive intensity. Both specifications include the same-day competitor ratio ($r_{-j,m}$) and the average competitor ratio on closed days ($\bar{r}^{\text{closed}}_{j,-d}$). Model 2 additionally includes weekday fixed effects. All specifications control for shop characteristics, including space size, enclosed location, number of online transactions, availability of a parking lot, approximated number of workers, and local house price index.

	Dependent Variable: Opening	
	Model 1	Model 2
Same-Day Competitor Ratio ($r_{-j,m}$)	1.03^{***}	1.00^{***}
	(0.01)	(0.01)
Average Competitor Ratio on Closed Days ($\bar{r}^{\text{closed}}_{j,-d}$)	-0.88^{***}	-0.85^{***}
	(0.01)	(0.01)
Year Fixed Effects	Yes	Yes
Weekday Fixed Effects	No	Yes
Shop Characteristics	Yes	Yes
Observations	962,071	962,071

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 18: Average Marginal Effects of Competitor Ratios on Opening Decisions (Falsification Specifications)
Notes: Each column reports average marginal effects from logit regressions of shop opening decisions on measures of competitive intensity. Both specifications include the same-day competitor ratio ($r_{-j,m}$) and the average competitor ratio on closed days ($\bar{r}^{\text{closed}}_{j,-d}$). Model 2 additionally includes weekday fixed effects. All specifications control for shop characteristics, including space size, enclosed location, number of online transactions, availability of a parking lot, approximated number of workers, and local house price index.

since competition on days when a shop is closed should not directly affect profitability through the sticky-pricing channel.

However, these correlations likely arise because certain holidays or typical closure days—such as Easter, Christmas, or Thanksgiving—are common across shops, creating mechanical co-movement in closed-day measures. They may also reflect residual within-week shocks, such as fluctuations in demand or operating conditions (e.g., weather or local events), that simultaneously increase competitors' propensity to open and influence a shop's decision to open on nearby days.

Although the opening-day falsification test may be noisy and cannot fully account for all local-level patterns, the counterfactual analyses comparing sticky-pricing and daily-pricing regimes remain informative if the sticky-pricing channel indeed operates. To mitigate potential biases from unobserved correlations in operating conditions, I deliberately focus on weeks with relatively balanced opening patterns across days when constructing these counterfactuals.

A.4 Fixed Cost Estimation Results

Table 19 presents fixed cost estimation results for other Colorado cities with a sufficient number of branded coffee shops. The results are qualitatively similar to those for Denver in the main text, showing elevated operational frictions in 2020 and a gradual decline by 2022.

	Aurora	Colorado Springs	Lakewood
Year 2020	66.894*** (9.775)	101.599*** (19.088)	375.296*** (43.501)
Year 2021	35.005*** (10.071)	118.088*** (18.216)	−374.997*** (45.985)
Year 2022	−38.596 (28.755)	21.971 (22.762)	−26.778 (39.382)
Space size (normalized)	−51.309 (78.605)	−213.358 (129.538)	−347.066 (296.365)
Number of observations	9,492	12,208	5,327

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 19: Fixed Cost Estimation Results by City in Colorado
Notes: Standard errors are in parentheses. The table reports fixed cost estimates from the Stage 2 daily operation decision for Aurora, Colorado Springs, and Lakewood. Year fixed effects capture temporal variation in operational frictions, while shop size accounts for differences in scale.