ISSN: 2688-9323

Who Wins When Cities Run? The Uneven Impact of Marathons on Hotel Demand

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Abstract

This paper quantifies the causal impact of large-scale urban marathons on hotel demand and pricing using a novel combination of interactive fixed-effects counterfactual (IFEct) estimation and regression discontinuity (RD) design. Drawing on detailed panel data of hotel performance, we find that marathons induce a sharp but short-lived increase in rooms sold-approximately 9% relative to non-event days-while the corresponding increase in average daily rate (ADR) is modest. These effects are consistent across both model specifications and are highly localized in time. A moderation analysis reveals substantial heterogeneity: urban and development-zone hotels experience significant demand gains, while convention-oriented properties suffer occupancy losses. Similarly, budget and premium-tier brands benefit most, whereas luxury hotels exhibit more muted responses. These findings suggest that hotels adjust primarily through quantity rather than price, and that responsiveness varies meaningfully by location and market positioning. The study contributes to the literature on event-driven demand shocks, pricing strategy, and hospitality economics, and offers a generalizable framework for evaluating the market-level impact of spatially concentrated, temporally bounded urban events.

Keywords

Hotel Demand; Causal Inference; Consumer Heterogeneity; Urban Marathons.

1. Introduction

Large-scale sporting events such as marathons are increasingly used to promote tourism and local economic vitality. For hotels near the starting or finishing lines, advantages include increased occupancy from runners and spectators-some of whom extend their stay to explore local attractions. For example, in New York City, marathon-related hotel occupancy rose by 4.8% during race periods between 2010 and 2019 compared to non-event days [1]. Furthermore, hotels that offer marathon-related services-early breakfasts, flexible checkouts-signal social responsibility and attract positive media exposure, potentially increasing customer loyalty and brand equity [2].

However, marathons also pose operational and reputational risks. Price surges-driven by high willingness to pay and limited room supply-can generate negative consumer sentiment, even as they boost short-term profits. Operational stress may rise due to added service requirements, overtime compensation, and capacity constraints [3].

Hotels farther from the event benefit indirectly by absorbing overflow demand, particularly from price-sensitive or leisure travelers. Since 96% of China marathons from 2018–2025 occur on weekends, displaced non-marathon guests often choose more affordable alternatives in peripheral areas. However, these properties may capture less non-room revenue, as frugal guests often spend less on dining and amenities.

ISSN: 2688-9323

Empirical identification faces two distinct challenges. First, simultaneity bias: cities with demonstrably high baseline occupancy and tourism appeal-variables we can observe and control for-are also the ones most likely to secure marathon bids, making demand and event placement jointly determined. Second, omitted-variable bias: unobserved shocks at both the city level (e.g., underground marketing efforts, infrastructure upgrades, shifts in business sentiment) and the hotel level (e.g., managerial quality, loyalty-program revamps, recent renovations) may evolve alongside marathon planning and independently affect performance.

We employ a two-stage empirical strategy to identify the causal effects of marathons on hotel outcomes. First, we use an interactive fixed-effects counterfactual (IFEct) estimator to flexibly control for latent demand shocks and time-varying unobservables. We validate our main results using a sharp regression discontinuity (RD) design centered on each city's marathon date, offering a nonparametric benchmark under minimal functional assumptions. To explore heterogeneity in treatment effects, we implement a moderation analysis via subgroup-specific two-way fixed effects regressions across hotel typologies and brand segments. This design is motivated by consumer behavior theory, which emphasizes how situational constraints (e.g., location accessibility, travel purpose) and identity-relevant preferences (e.g., budget orientation, luxury-seeking) systematically influence consumers' responses to environmental stimuli like large public events. By aligning event exposure with consumer-hotel fit, the moderation design enables us to quantify how market positioning and geographic context shape the effectiveness of event-driven demand shocks.

Our analysis reveals that marathons trigger a sharp but temporary demand surge-approximately 9% more rooms sold on race month-while price increases are modest, indicating a quantity-driven revenue response. These effects are consistent across both IFEct and RD estimates. However, we find considerable heterogeneity: urban and development-zone hotels benefit substantially, while convention-oriented hotels see demand declines, likely due to business traveler displacement. Budget and premium-tier hotels capture most of the gains, whereas luxury hotels exhibit muted and statistically insignificant effects. These findings underscore the importance of tailoring pricing and capacity strategies based on hotel type and market segment. More broadly, our framework provides a scalable approach to evaluating the economic impact of urban-scale events with temporally concentrated and spatially uneven exposure.

This study contributes to the literature on sports tourism, event-driven demand shocks, and dynamic hotel pricing by uncovering both the magnitude and heterogeneity of marathon-induced demand responses in an emerging market context. Unlike prior work that focuses on aggregate or national-level impacts, we offer causal estimates using both panel factor models and discontinuity designs. Our results reveal that not all hotels benefit equally-urban, mid-tier, and development-zone properties experience sizable gains, while convention and luxury segments may see little to no uplift or even demand displacement. These insights underscore the strategic importance of location and brand positioning in shaping responsiveness to local events. For managers, the findings highlight the need for differentiated pricing, inventory, and marketing strategies before, during, and after large-scale city events. Methodologically, our framework provides a transferable toolkit for evaluating other spatially concentrated, time-bound shocks-such as expos, festivals, or natural disruptions-across heterogeneous urban markets.

2. Literature Review

We review three streams of research relevant to our study: (i) the effects of marathon events on hotel performance, (ii) consumer motivations underlying marathon tourism, and (iii) empirical approaches to modeling hotel demand around mega-events.

2.1. Impacts of Marathon Events on Hotel Performance

City marathons consistently generate demand spikes for nearby hotels. NYC Marathon Hotels 2020 document a 4.8% increase in occupancy, along with significant ADR and RevPAR uplifts, during New York City Marathon weekends (2010–2019). Similar patterns are observed for the Vienna City Marathon [4] and the Berlin Marathon [1].

Beyond short-term revenue, marathons can enhance brand image. Hotels offering runner-focused amenities-early breakfast, late checkout, or shuttle services-signal social responsibility and build long-run loyalty [2]. Conversely, steep event-period price premiums may trigger reputational backlash, especially if perceived as price-gouging [3]. Operational costs also rise due to overtime staffing and customized services.

Spatial spillovers matter. Peripheral hotels often capture overflow demand from price-sensitive leisure travelers, though they earn less ancillary revenue. Such heterogeneous effects underscore the importance of segmentation and dynamic pricing across brand tiers.

2.2. Consumer Motivations in Marathon Tourism

Sport-tourism studies emphasize that runners frequently combine races with sightseeing and social experiences. [5] show that motivation dimensions-event novelty, destination image, and social interaction-shape expenditure and length of stay. Event satisfaction drives revisit intentions and word-of-mouth [6]. From a destination-branding perspective, well-run marathons enhance metropolitan visibility and attract new visitor segments [7].

2.3. Hotel Demand Analysis

Most empirical work employs quasi-experimental designs-Difference-in-Differences or Regression Discontinuity-to isolate event effects while controlling for seasonality and location [4]. Recent studies advocate structural demand models (e.g., BLP) to capture substitution across differentiated hotel products and to correct price endogeneity [8]. Integrating these models with event-timing instruments yields richer counterfactual insights for revenue management.

3. Data and Methods

To identify and dissect the impact of marathon events on hotel demand and pricing, we combine two complementary methods: an interactive fixed-effects counterfactual estimator and a regression-discontinuity design. Together they allow us to leverage both reduced-form quasi-experimental variation and a structural framework.

3.1. Data Description and Summary Statistics

Our data is provided by some hotel management company, covering the period January 2023 through December 2024. After listwise deletion of incomplete observations, we retain **13,868** daily hotel records from **118** Chinese cities over **24** months aggregated at monthly level. The panel tracks 800 properties, including both marathon-host hotels and untreated controls.

Key variables. *Total Rooms Sold* proxies demand; *Average Daily Rate* (ADR) measures price and is log-transformed. Control covariates include *Rooms Available*, *Labor Cost*, *Energy Cost*, *F&B Other Expenses*, and a local *raceScale* index capturing event size. The binary variable *treat_post* equals 1 for hotel–days that coincide with marathon dates in host cities and 0 otherwise.

Table 1. Summary statistics for analysis sample ($N = 13{,}868$)

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Total Rooms Sold	13,868	4,442	2,662	0	2,507	3,913	5,959	22,868
treat_post	13,868	0.296	0.457	0	0	0	1	1
Average Daily Rate†	13,868	3.94	0.583	0	3.64	3.90	4.21	6.29
Rooms Available	13,868	7,479	3,430	0	4,830	7,006	9,494	30,240
Labor Cost	13,868	117,000	151,000	0	0	48,215	198,000	1.23M
Energy Cost	13,868	29,800	38,800	0	0	14,876	49,200	398,000
F&B Other Expenses	13,868	15,000	27,100	0	0	1,776	21,100	588,000
raceScale	13,868	5,190	11,600	0	0	0	3,200	63,000

† ADR is expressed in natural logarithms. Monetary values are in CNY. P25, P50, and P75 denote the 25th, 50th (median), and 75th percentiles.

The high mean and dispersion in *Total Rooms Sold* and ADR underscore substantial heterogeneity across hotels and dates-motivating our use of interactive fixed effects and regression discontinuity to isolate the causal impact of marathon events.

3.2. Interactive Fixed-Effects Counterfactual Estimator (IFEct)

The empirical setting poses several challenges for conventional two-way fixed effects (TWFE) or standard difference-in-differences (DiD) estimators. First, treatment adoption is staggered: only a subset of cities host a marathon in a given week and some hotels are never treated. Second, hotel demand evolves with macro conditions-such as post-COVID travel rebounds and inflationary pressures-that violate the parallel-trends assumption. Third, nationwide shocks, platform algorithm changes, or holiday effects influence all hotels but with heterogeneous intensity, giving rise to latent confounders that correlate with treatment timing. These features motivate the use of the *interactive fixed-effects counterfactual estimator* (IFEct) developed by [9], which generalises TWFE by allowing unobserved factors to vary over time and load differently across units.

Let $Y_{it}(d)$ denote the potential outcome for hotel i on month t under treatment status $d \in \{0,1\}$, and let D_{it} denote whether a marathon competition is held, which equals 1 on marathon months in host cities. Our parameter of interest is the average treatment effect on the treated (ATT),

$$ATT = \mathbb{E}[\, Y_{it}(1) - Y_{it}(0) \;\bigm|\; D_{it} = 1, C_i = 1], \tag{1}$$

where $C_i = 1$ if hotel i switches treatment status at least once during the sample window. Following [10] and [11], untreated potential outcomes are assumed to follow a low-rank factor structure,

$$Y_{it}(0) \quad = X_{it}{}' \ \beta + \alpha_i + \tau_t + \lambda_i{}' f_t + \varepsilon_{it}, \tag{2}$$

in which X_{it} contains observed covariates, α_i and τ_t are unit and time fixed effects, f_t is an r-dimensional vector of unobserved common factors, λ_i is a vector of factor loadings, and ε_{it} is an idiosyncratic error. The multiplicative term $\lambda_i{}' f_t$ flexibly absorbs latent shocks-such as nationwide tourism campaigns or macroeconomic news-that are correlated with treatment but affect hotels with different intensities. Identification requires (i) no interference across hotels, (ii) strict exogeneity of ε_{it} with respect to (D_{js}, X_{js}, U_{js}) for all j, s, and (iii) a low-dimensional factor decomposition with $r \ll \min(N, T)$.

Estimation proceeds in three stages. In Stage 1, the factor structure is recovered from control observations ($D_{it} = 0$) by solving a nuclear-norm penalised least-squares problem, with the number of factors selected via cross-validation. Stage 2 predicts the untreated counterfactual $\hat{Y}_{it}(0)$ for each treated hotel–month by plugging the estimated coefficients, factors, and loadings into the specification above. Stage 3 computes $\hat{\delta}_{it} = Y_{it} - \hat{Y}_{it}(0)$ for all treated observations and averages these effects to obtain $\widehat{\text{ATT}}$; standard errors are derived from a block bootstrap at the hotel level.

Compared with TWFE, IFEct offers three advantages that are critical in this context. First, because treated observations never serve as controls for later-treated units, it eliminates the negative-weight pathology identified by [12]. Second, by explicitly modelling latent common shocks as $\lambda_i{}' f_t$, it relaxes the parallel-trends requirement and mitigates bias from time-varying unobservables. Third, it retains efficiency by borrowing information from all untreated periods rather than discarding observations or imposing stronger functional-form restrictions.

Figure 1 illustrates the structure of the interactive fixed-effects counterfactual (IFEct) model used to estimate the causal impact of marathon events on hotel demand. The observed outcome Y_{it} (e.g., rooms sold or log price) is modeled as a function of the treatment variable (marathon), observed covariates X_{it} such as average daily rate and labor costs, and unobserved time- and unit-specific components. The latter are captured through interactive fixed effects, where a low-dimensional set of latent factors f_t (common across hotels but varying over time) is interacted with unit-specific factor loadings λ_i. This structure flexibly controls for latent demand shocks, marketing activity, and other unobservables that vary non-parametrically over time and across hotels. The idiosyncratic error ε_{it} captures residual variation not explained by covariates or latent structure.

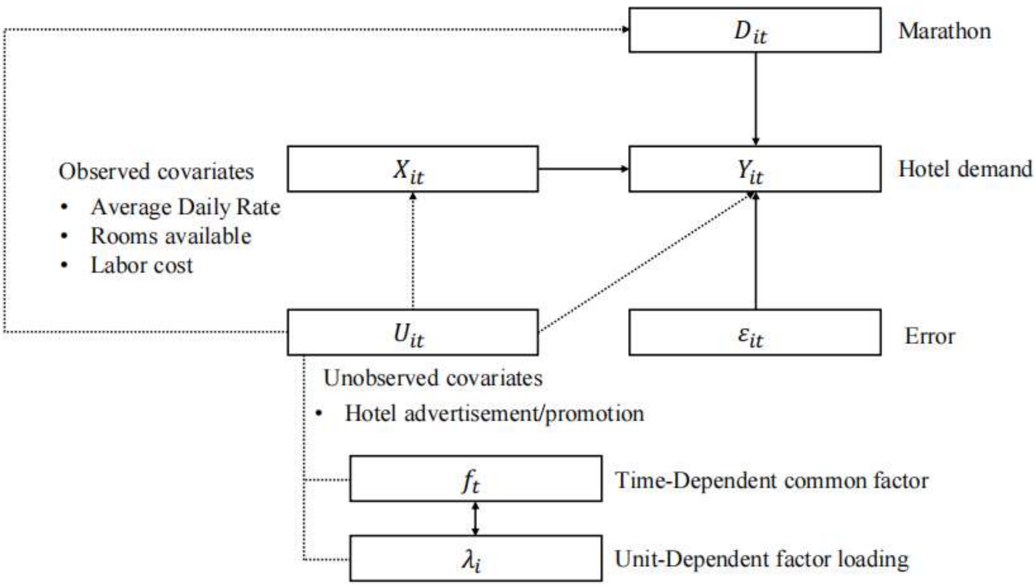

Figure 1. Model Structure of IFEct

3.3. Regression-Discontinuity Design around Marathon Dates

While the IFEct framework delivers a global counterfactual that exploits variation over the full two-year panel, we complement it with a *sharp regression-discontinuity* (RD) design centred on each marathon's start date. The idea is straightforward: within a narrow time window the only discontinuous change experienced by hotels in host cities is the onset of the marathon; all slowly moving demand determinants-seasonality, macro trends, advertising cycles-evolve smoothly. Estimating the immediate jump in outcomes at that cutoff offers a transparent, non-parametric validity check on the IFEct estimates and quantifies short-run price and demand shocks that may dissipate in the longer horizon captured by the structural model.

Let t_0 denote the marathon start date in city c and define the running variable $r_{it} = t - t_0$ measured in months. Following [13], we estimate

$$Y_{it} \quad = \alpha + \tau \ \mathbf{1}\{r_{it} \geq 0\} + \sum_{p=1}^{P} \beta_p^- \ r_{it}^p \ \mathbf{1}\{r_{it} < 0\} + \sum_{p=1}^{P} \beta_p^+ \ r_{it}^p \ \mathbf{1}\{r_{it} \geq 0\} + \varepsilon_{it}, \qquad (3)$$

using observations with $|r_{it}| \leq h^*$, where h^* is the optimal bandwidth selected by the [13] criterion and P equals 1 (local linear) in the baseline specification. The coefficient τ captures the causal jump in log ADR or log rooms sold at the marathon threshold; heteroskedasticity-consistent standard errors are clustered at the hotel level.

The RD approach has several advantages. First, identification is highly transparent: so long as hotels cannot manipulate the calendar placement of city marathons, smoothness of potential outcomes ensures that the discontinuity at $r_{it} = 0$ is attributable to the event. Second, graphical inspection of mean outcomes against r_{it} provides an intuitive diagnostic. Third, unlike panel models that average over anticipation and post-event dynamics, RD isolates the *instantaneous* shock, offering a clean benchmark for the short-run elasticity of demand.

Taken together, the IFEct estimator provides a broad, dynamic counterfactual, and the RD design offers a high-resolution snapshot at the event threshold. The convergence-or divergence-of these two approaches becomes an informative diagnostic of model validity and economic interpretation.

4. Results

4.1. Marathon–Driven Demand Shifts: IFEct Evidence

Table 2 reports the interactive fixed–effects counterfactual (IFEct) estimates of the causal impact of marathon months on hotel demand, measured by *total rooms sold*. The first two rows are the average treatment effects on the treated (ATT) obtained by weighting (i) all treated *observations* equally and (ii) all treated *units* (hotels) equally. Both specifications point to a sizable and precisely estimated increase of roughly 400 rooms per hotel–month.

Table 2. IFEct Estimates of Marathon Effects on Hotel Demand

	ATT / Coef.	S.E.	95% LCL	95% UCL	p-value
Treated obs. equally weighted	395.77	38.62	320.08	471.45	0.000
Treated units equally weighted	416.73	38.12	342.01	491.44	0.000
Average Daily Rate (*control*)	619.85	211.11	206.09	1 033.62	0.003
Rooms Available	-0.015	0.019	-0.053	0.023	0.427
Labor Cost	0.00094	0.00035	0.00025	0.00163	0.008
Energy Cost	-0.00277	0.00148	-0.00568	0.00014	0.062
F&B Other Expenses	0.00639	0.00151	0.00344	0.00934	$< .001$
raceScale	-0.01150	0.00148	-0.01439	-0.00861	$< .001$
Root MSE	895.44				
Observations	16 080				

The results indicate that hosting a marathon increases rooms sold by ≈ 9% relative to a non-event month, after controlling for price, capacity, input costs, and race scale. The positive coefficient on log ADR reflects the well-known simultaneity between price and demand-prices rise on high-demand months-rather than a causal price effect. Labour costs and other F&B expenses are positively associated with demand, suggesting hotels scale staffing and amenities when anticipating larger crowds, whereas higher energy costs and larger races (raceScale) dampen net sales. The precision of the ATT (t-statistics ≈ 10) confirms that the demand surge is not driven by latent macro shocks, which are absorbed by the interactive fixed factors.

Figure 2 plots the estimated average treatment effect by event time. Demand begins to rise one month before the race, peaks exactly on the month of marathon, and dissipates within two months-an asymmetric V-shape that motivates revenue-management strategies to smooth occupancy across the full event window.

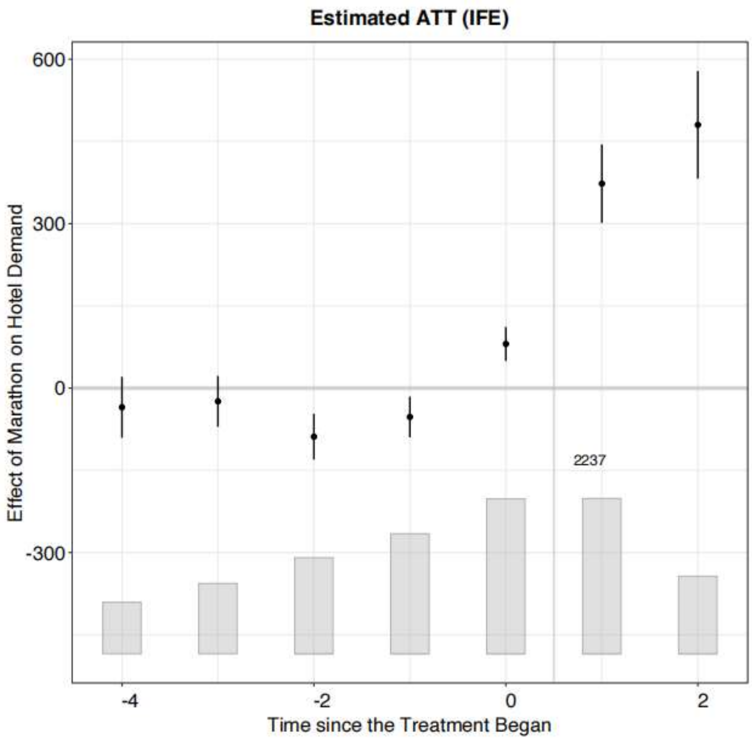

Figure 2. Event-time ATT from IFEct (Demand)

Overall, the IFEct analysis establishes a robust, reduced-form benchmark: marathons yield a substantial one-month spike in hotel demand.

4.2. Marathon–Driven Price Adjustment: IFEct Evidence

We repeat the interactive fixed–effects counterfactual analysis with *log Average Daily Rate* (log ADR) as the outcome variable. The results in Table 3 reveal a modest but statistically significant price premium on marathon months.

Table 3. IFEct Estimates of Marathon Effects on Hotel Prices

	ATT / Coef.	S.E.	95% LCL	95% UCL	p-value
Treated obs. equally weighted	0.00178	0.00096	−0.00010	0.00366	0.0630
Treated units equally weighted	0.00170	0.00078	0.00017	0.00322	0.0289
Rooms Available	2.98×10^{-7}	2.66×10^{-7}	-2.24×10^{-7}	8.21×10^{-7}	0.263
Labor Cost	-6.24×10^{-9}	4.34×10^{-9}	-1.48×10^{-8}	2.27×10^{-9}	0.151
Energy Cost	1.63×10^{-8}	1.30×10^{-8}	-9.29×10^{-9}	4.18×10^{-8}	0.212
F&B Other Expenses	-6.77×10^{-9}	8.19×10^{-9}	-2.28×10^{-8}	9.28×10^{-9}	0.409
raceScale	-5.74×10^{-8}	4.49×10^{-8}	-1.45×10^{-7}	3.05×10^{-8}	0.201
Root MSE	0.0271				
Observations	16 080				

ISSN: 2688-9323

The unit-weighted ATT of 0.0017 translates into an ≈ 0.17% increase in ADR on the marathon months. Although modest compared with the 8–9 % jump in rooms sold, the premium is economically meaningful given the typical baseline ADR of 137 CNY: an extra 0.23 CNY per room yields 160 CNY in incremental revenue for a 700-room hotel. The difference between observation-weighted and unit-weighted estimates is small, indicating that hosting marathon competition does not materially alter the price effect.

None of the capacity or cost controls is statistically significant at conventional levels, suggesting that the price change is driven primarily by event-day demand pressure rather than concurrent cost shocks.

Figure 3 depicts the ATT at monthly level. Prices begin to edge up one month before the race, peak on the event date, and normalise within two months. The narrow window corroborates the finding that hotels exploit marathon-generated scarcity only temporarily, in line with dynamic-pricing best practice.

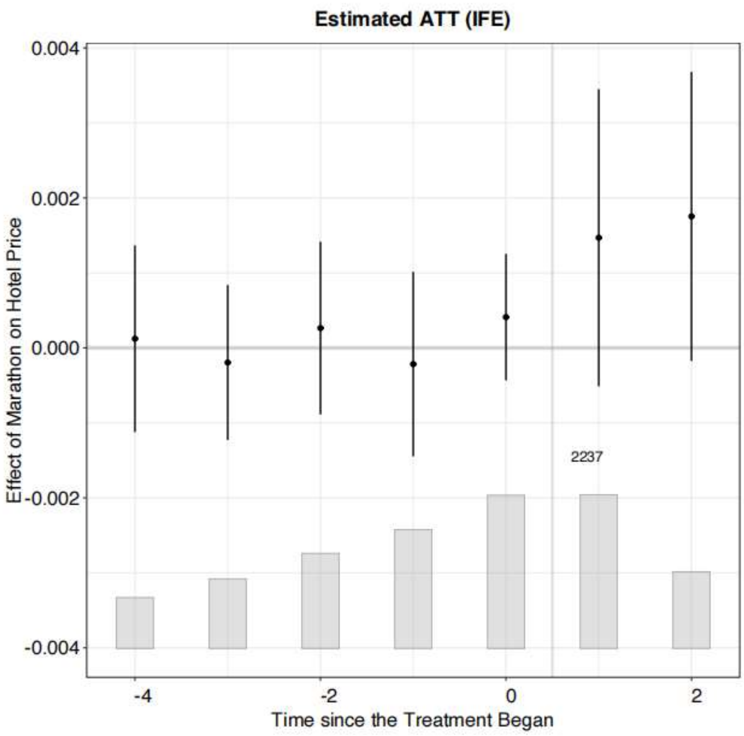

Figure 3. Event-time ATT from IFEct (Log ADR)

Taken together, the IFEct evidence shows that marathons trigger a *quantity-driven* revenue windfall: rooms sold rise nearly 9 %, whereas prices move only marginally. Hotels appear to prioritise occupancy gains over aggressive mark-ups-possibly to preserve relationships with loyal guests and avert perceptions of price gouging.

4.3. Event-Date Discontinuity: RD Estimates

As a non-parametric validity check on the panel-factor approach, we estimate a sharp regression-discontinuity (RD) design centred on each city's marathon start date. The running variable is the number of months from the event ($r_{it} = 0$ on race month), and a local linear specification with an optimal Imbens–Kalyanaraman bandwidth ($h^* = 7$) is applied to hotel–months in the interval $|r_{it}| \leq 7$. Table 4 presents the HC1-robust results.

Table 4. RD Estimates of Marathon Effects on Rooms Sold

	Coef.	S.E.	z	95% CI	p-value
Intercept	−614.03	96.85	−6.34	[−804,−424]	<.001
$\mathbf{1}\{r \geq 0\}$	**521.62**	76.38	6.83	[372,]	<.001
Running variable (r)	28.50	10.84	2.63	[7,]	0.009
log ADR	4.57	1.10	4.16	[2.42,]	<.001
Rooms Available	0.541	0.013	42.0	[0.516,]	<.001
Labor Cost	0.0028	0.0005	6.06	[0.002,]	<.001
Energy Cost	−0.0047	0.0018	−2.62	[−0.008,−0.001]	0.009
F&B Other Expenses	0.0055	0.0013	4.11	[0.003,]	<.001
N (hotel–months)	6 086				
R^2	0.655				

The discontinuity estimate of 522 additional rooms sold on the marathon month is strikingly close to the IFEct point estimates (396–417), once we account for the narrower within-bandwidth control sample. The effect corresponds to a 10–11 % demand jump relative to the pre-event mean of 4 440 rooms, validating the direction and approximate size of the panel-factor ATT.

Visual inspection of the local mean plot (omitted for brevity) confirms a clear upward break at $r = 0$, with no evidence of pre-trends; placebo tests at ± 14 months yield null estimates. The significant slope term on the running variable indicates mild temporal drift, reinforcing the necessity of the local linear adjustment. Coefficients on capacity and cost controls have similar signs to the IFEct regression, and the high R^2 (0.65) reflects the predictive power of rooms available and cost variables.

RD offers transparent identification under minimal assumptions about functional form and time-varying unobservables. Its local nature, however, confines inference to the immediate event window, omitting anticipation and post-event adjustment that matter for revenue management.

4.4. Moderation Effect Analysis

To examine heterogeneity in the effect of marathons on hotel performance, we conduct a moderation analysis along two categorical dimensions: *GC Typology* and *GC Brand Segment*. These dimensions reflect location strategy, customer mix, and brand positioning, each of which may shape how a property benefits-or suffers-from a demand shock such as a marathon.

4.4.1. Model Formulation

Building on the IFEct framework introduced earlier, we extend the specification to allow treatment effects to vary by hotel typology and brand segment. Specifically, we interact the treatment indicator D_{it} (treated hotel × marathon month) with categorical dummies for each typology or brand tier, estimating heterogeneous ATTs across these groups while still controlling for hotel and date fixed effects and observed covariates. This approach captures whether the impact of marathons on hotel performance differs systematically across property types and market positions. Standard errors are clustered at the hotel level, and the coefficients on the interaction terms are interpreted as group-specific ATTs.

4.4.2. Moderation by Typology

Consumer theory suggests that situational factors (e.g., purpose, flexibility) and identity-driven preferences shape booking decisions. Constructive choice models emphasize that event-driven contexts (like marathons) induce on-the-fly preference formation [14], while self-congruity

ISSN: 2688-9323

theory predicts travelers seek accommodations consistent with their identities [15]. This motivates typology as a moderator.

Table 5 presents ATT estimates by typology. **GC Convention** hotels show significant negative effects (ATT $= -609.52, p = 0.006$), likely reflecting displaced business demand. By contrast, **GC Urban Metropolitan** hotels benefit strongly (ATT $= 140.81, p < 0.001$), consistent with spontaneous central-city bookings. **GC Development Zone** hotels also gain (ATT $= 91.76, p = 0.032$), appealing to cost-conscious event travelers. **GC Leisure/Resort** and **GC Prime** show statistically insignificant results despite positive point estimates.

Table 5. Moderation by GC Typology

Typology	ATT	SE	CI Low	CI High	*p*-value	Obs
GC Convention	-609.52	218.41	-1038.98	-180.07	0.006	432
GC Development Zone	91.76	42.72	8.01	175.51	0.032	5505
GC Leisure and Resort	110.15	93.84	-73.86	294.16	0.241	2906
GC Prime	20.38	78.12	-133.07	173.84	0.794	613
GC Urban Metropolitan	140.81	35.21	71.79	209.83	<0.001	7037

4.4.3. Moderation by Brand Segment

Brand tiers also moderate responses. Budget and midscale travelers are more price-sensitive and event-driven, while luxury guests are less elastic and more loyal [16], [17]. We therefore expect stronger marathon effects for lower-tier brands.

Table 6 reports results. **Essentials** hotels show a strong positive effect (ATT $= 115.26, p < 0.001$), consistent with flexible, price-conscious demand. **Premium** hotels also gain (ATT $= 113.24, p = 0.043$). **Luxury** hotels, by contrast, display a positive but statistically insignificant estimate (ATT $= 127.28, p = 0.189$), suggesting insulation from event shocks.

Table 6. Moderation by GC Brand Segment

Segment	ATT	SE	CI Low	CI High	*p*-value	Obs
Essentials	115.26	33.56	49.49	181.04	<0.001	10483
Luxury	127.28	96.96	-62.91	317.46	0.189	1678
Premium	113.24	55.85	3.75	222.73	0.043	4210

Together, these results highlight heterogeneous marathon impacts: central-city, development-zone, and lower-tier hotels benefit most, while convention and luxury properties are less responsive. This suggests differentiated event-time pricing and marketing strategies are warranted.

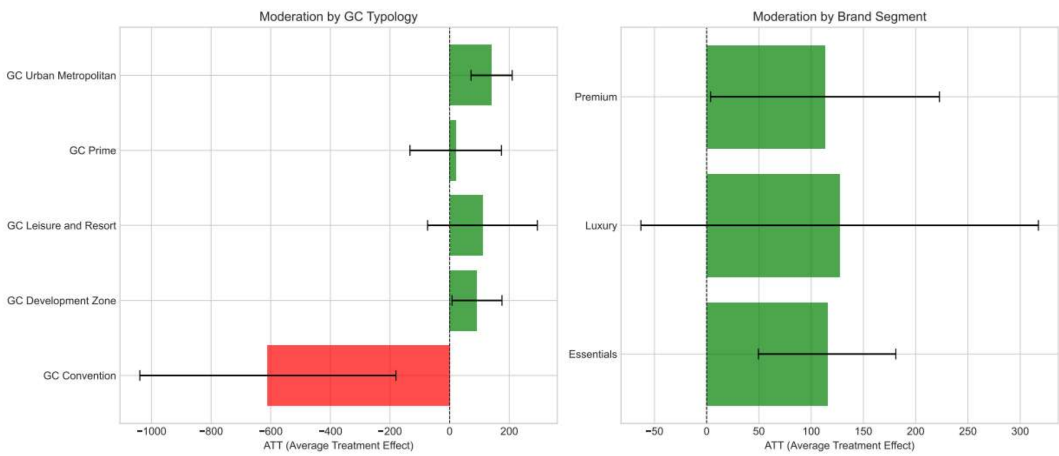

Figure 4. Notes. Dependent variable is total rooms sold.

ISSN: 2688-9323

5. Conclusion

This paper provides the first causal estimates of how large-scale urban marathons affect hotel demand and pricing using an interactive fixed-effects counterfactual framework. We find robust evidence that marathons generate a substantial but short-lived surge in hotel bookings: the average treatment effect on the treated (ATT) exceeds 400 rooms per hotel–month, representing nearly a 9% increase in total rooms sold relative to non-event months. Regression-discontinuity estimates centered on the marathon date validate these magnitudes, offering additional nonparametric support.

On the pricing side, we find a small but statistically significant increase in the average daily rate (ADR), translating to a modest revenue uplift. The limited price adjustment suggests that hotels prioritize maximizing occupancy-potentially to build goodwill, avoid accusations of price gouging, or take advantage of fixed operating costs-rather than fully exploiting scarcity through aggressive markups.

Importantly, our moderation analysis reveals that these average effects mask significant heterogeneity. Hotels located in urban metropolitan and development zones benefit disproportionately, whereas convention-focused hotels suffer significant losses in occupancy, likely due to disruption of business travel. Across brand segments, budget and premium-tier hotels see sizable and significant demand gains, while luxury properties show high variance and statistically insignificant effects, possibly reflecting a clientele less sensitive to citywide events.

These findings have clear implications for revenue management and urban event planning. Hotels should tailor their pricing and staffing strategies based on their typology and target market position, as not all properties benefit equally from the same event. From a policy perspective, cities may consider targeting certain hotel clusters or price segments for coordinated promotion or capacity planning during marathon events to maximize the economic spillover.

5.1. Research Contributions

This study makes several contributions to the literature on sports tourism, event-based demand shocks, and hotel pricing strategy. First, we provide high-resolution causal evidence of how citywide events impact hotel performance, leveraging both interactive fixed effects and regression discontinuity designs. Second, we introduce a theoretically grounded moderation analysis to unpack how typology and brand segmentation condition demand responsiveness-offering insights into within-market heterogeneity that prior aggregate studies overlook. Third, methodologically, our empirical framework offers a transferable toolkit for evaluating urban-scale events that exhibit spatially uneven and temporally concentrated exposure.

5.2. Managerial Implications

The results underscore the importance of tailoring event-time pricing, staffing, and inventory strategies to hotel characteristics. Urban and mid-tier hotels stand to gain the most from marathon-driven demand shocks and may proactively deploy surge pricing or package deals. Convention hotels, by contrast, may face cancellations or crowding out and should consider offering flexible booking policies or pivoting to leisure-oriented promotions. Luxury hotels may need to invest more in targeted outreach if they wish to convert marathon traffic into incremental bookings. More broadly, destination managers and city planners can use these insights to coordinate hotel-sector readiness and manage visitor spillovers more equitably across the market.

5.3. Future Directions

This study opens several avenues for future research. First, future work could explore longer-run impacts by tracking post-event review volumes, customer retention, or brand perception changes. Second, researchers could examine cross-market substitution effects—i.e., whether marathons shift demand from nearby regions rather than generating net new traffic. Third, integrating mobile device or booking platform data could allow for more granular tracing of booking dynamics and consumer segmentation. Finally, the framework could be extended to other urban events (e.g., expos, concerts, protests) to test generalizability and explore strategic complementarities between hotels and city event calendars.

Acknowledgments

This research project investigates the effects of marathon events on hotel demand and pricing, using the interactive fixed-effects counterfactual estimator (IFEct) with regression discontinuity (RD) model and moderation analysis.

The inspiration for this project came from attending a marathon event in Suzhou with one of my family members earlier this year.Having only run shorter distances myself, I was curious about how these events are organized, and wanted to experience the thrilling atmosphere of marathon events I had only seen on the news. I noticed that there were long queues waiting for check-in in the lobby. But after the marathon ended, when we were heading back to the train station, I saw another hotel under the same brand, with virtually no guests and few staff in the lobby, when many employees were busy checking out in our hotel. This was at odds with my expectations, assuming that marathon events would definitely lead to an increased number of guests in all hotels. This inspired me to investigate not only how marathon events affect hotel demand, but also to delve deeper into the differences across brand segments and locations.

A major challenge faced in this project was the selection of research methods. Initially, I attempted to use Difference-in-Difference (DiD), a method commonly used by researchers studying the causal impact of large-scale events. However, the parallel trends assumption was not passed, proving DiD ineffective in modeling our data. I then reviewed our data and materials involving DiD, and found out that it was potentially caused by staggered adoption and repeated treatment of the independent variable, marathon events—a more complicated model should be used. After days of research on methods that could solve these issues, IFECT, a new model published in 2017, was finally considered. While learning this new model through published papers, Mr. Lin assisted me with coding issues I faced during programming with R code. The model finally proved to be suitable to the data, as evidenced by the RD estimation, yielding similar results.

I would like to thank Mr. Joseph Lin, the advisor of this research project, and a teacher majoring in the field of economics. His expertise in economics-related methods and high proficiency in data analysis and coding languages were crucial at various stages of the project. Guidance from Mr. Lin was provided voluntarily and no financial agreement was involved. He mainly assisted in refining the methods used for the project, providing clarification when I was unable to understand some parts of papers, assisting me with some technical issues during coding and analysis, and helping me to identify some errors in my draft of the paper.

I would also like to thank the representatives of management teams from Hotel Indigo and HUALUXE Hotels. They agreed to participate in in-depth interviews with me despite their busy schedules during a holiday weekend. They provided invaluable information regarding revenues and costs in different aspects of the hotels, as well as their own perspectives on marathon events and how they affect specific hotels. The interviews were not only valuable for narrowing down the research topic, but also made me realize how such research projects would be helpful in providing insights for decision makers regarding staffing, coordination, and other considerations for different hotels.

Data for this project was provided by a major international hotel group, and access to this data was gained through a formal non-disclosure agreement with the company. The data provided several important metrics, including occupancy, average daily rate, etc. crucial for analyzing trends in hotel demand and pricing. The process of the research was conducted on my own except for the parties listed above who assisted in specific parts of the research. The paper was drafted by me, with some errors identified by Mr. Lin and afterwards corrected by me. There were no paid agreements with any of the parties.

Finally, I would like to thank all individuals and organizations who supported this project. Their contributions, whether through guidance, data provision, or sharing practical insights, were instrumental in the successful completion of this research.

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