Dynamic Pricing Strategies for Short–Term Rentals

Dynamic Revenue Management in Chicago

Introduction

Problem Description. Short–term rental platforms like Airbnb face a fundamental revenue–management challenge: how to set nightly rates that both attract bookings and maximize profit. In urban markets such as Chicago—with highly heterogeneous listings and fluctuating temporal demand—static one–size–fits–all pricing leaves revenue on the table. We therefore seek to implement two layers of price discrimination:

- *Second–degree discrimination*, by segmenting listings into clusters (e.g., *value* vs. *premium*) based on observable features; and
- *Third–degree discrimination*, by varying prices over time (weekends vs. weekdays and seasonal peaks vs. troughs).

Our objective function is the expected nightly profit for listing segment i:

$$\pi_i(x) \;=\; D_i(x)\,\big(x - C_v\big),$$

where $D_i(x)$ is the booking probability at price x and C_v is a constant variable cost per booking (\$50). We optimize this function analytically to derive static optimal prices, then embed those optima in a dynamic policy.

Plan of Action. Our approach integrates *empirical estimation* (forecasting demand) and *analytical optimization* (maximizing profit). Concretely:

1. **Data Preparation:** Clean and group by neighbourhood 5 207 Airbnb listings in Chicago, ensuring completeness in key fields (price, bedrooms, bathrooms, amenities, cleaning fee, entire–home flag, kitchen indicator, booking flag).
2. **Segmentation:** Within each neighbourhood (with sufficient observations), apply k–means clustering on listing attributes to form two clusters—value vs. premium—capturing second–degree discrimination.
3. **Demand Estimation:** For each cluster, fit a logistic demand curve
$$D_i(x) = \frac{1}{1 + e^{\gamma\,(x - x_{\text{mid},i})}},$$
where γ (steepness) is calibrated to historical booking decay, and $x_{\text{mid},i}$ is adjusted by cluster occupancy deviation from the overall average.
4. **Elasticity Estimation:** Compute the price elasticity of demand
$$\epsilon_i(x) = \frac{dD_i(x)}{dx}\,\frac{x}{D_i(x)} = \frac{-\gamma\, e^{\gamma(x - x_{\text{mid},i})}}{\big(1 + e^{\gamma(x - x_{\text{mid},i})}\big)^2}\,\frac{x}{D_i(x)},$$
to assess sensitivity for each cluster.
5. **Analytical Optimization:** Derive the first–order condition $\partial\pi_i/\partial x = 0$ to compute static optima x_i^* for each cluster.
6. **Dynamic Pricing:** Introduce time–varying modifiers—seasonal $s(t)$ and weekend $\omega(t)$—to obtain hybrid prices
$$x_i(t) = x_i^*\big[1 + s(t) + \omega(t)\big].$$

Empirical Section

Data Preparation and Key Features

Our dataset comprises 5 207 nightly listings in the City of Chicago, extracted on May 10, 2017. The raw data included 95 columns (`listings.csv`); after deduplication and cleaning and features analysis, we retained variables:

- **Price:** nightly rate in USD,
- **Bedrooms, Bathrooms:** count per listing,
- **Amenities_count:** number of amenities (parsed from comma–separated list),
- **Entire_home:** binary flag for entire home/apt,
- **Cleaning_fee:** numeric in USD,
- **Has_kitchen:** binary indicator,
- **Booked:** simulated (60% mean) if missing, else actual.

After imputation, there were zero missing values in these columns. Summary: median price \$100, mean bathrooms 1.32, mean cleaning fee \$30.10, overall occupancy 60.0% (Table 1). Conceptual challenges included: (1) unobserved listing quality beyond amenities; (2) potential endogeneity of price and occupancy; and (3) heteroskedasticity across neighbourhoods. We address these by clustering (discrete segmentation) rather than continuous regression.

Neighbourhood Clustering

To capture listing heterogeneity, we performed k–means clustering ($k = 2$) within each neighbourhood with at least 20 listings. Features used:

$$\{\text{bedrooms},\ \text{entire\_home},\ \text{cleaning\_fee},\ \text{has\_kitchen}\}.$$

This yielded two clusters per neighbourhood—*value* (lower price, higher occupancy) and *premium* (higher price, lower occupancy). We focus on three representative neighbourhoods:

Lincoln Square 29 premium (median \$142, occ. 48.3%) vs. 40 value (median \$80, occ. 67.5%).

Uptown 32 premium (median \$156, occ. 46.9%) vs. 122 value (median \$75, occ. 68.0%).

Hyde Park 13 premium (median \$120, occ. 76.9%) vs. 67 value (median \$70, occ. 58.2%).

Table 2, 3, 4 reports cluster counts, median prices, occupancies, bathrooms, and fees. Premium clusters command a 75–80% price premium but suffer 10–20 pp lower occupancy versus value clusters.

Logistic Demand Estimation

We model each cluster's booking probability by a logistic function,

$$D_i(x) = \frac{1}{1 + e^{\gamma\,(x - x_{\mathrm{mid},i})}},$$

where:

- x is the nightly price,
- $\gamma = 0.05$ is the steepness, calibrated to observed booking decay (cf. Phillips 2005; Talluri and van Ryzin 2004),
- $x_{\text{mid},i} = \text{MedianPrice}_i \big[1 + (\text{Occ}_i - \overline{\text{Occ}}) \big]$ adjusts the 50% booking midpoint by cluster's occupancy deviation.

Figure 1 shows these static demand curves.

Elasticity Estimation

We derive the point-wise price elasticity for each cluster:

$$\epsilon_i(x) = \frac{dD_i(x)}{dx} \, \frac{x}{D_i(x)} = \frac{-\gamma \, e^{\gamma(x - x_{\text{mid},i})}}{\big(1 + e^{\gamma(x - x_{\text{mid},i})}\big)^2} \, \frac{x}{D_i(x)}.$$

At the static optimum x_i^*, these elasticities quantify demand sensitivity and inform potential welfare impacts.

Analytical Section

Profit Function and Optimization

Given $D_i(x)$, per-night profit for cluster i is

$$\pi_i(x) = D_i(x) \, (x - C_v), \quad C_v = \$50.$$

Maximizing $\pi_i(x)$ yields

$$\frac{d\pi_i}{dx} = D_i'(x) \, (x - C_v) + D_i(x) = 0.$$

We solve numerically for the static optimum x_i^*. Table 5,6,7 lists x_i^* and $\pi_i(x_i^*)$ for each cluster.

Second-degree Discrimination. Charging x_0^* to value and x_1^* to premium extracts surplus from higher-valuation guests while maintaining volume in the budget segment.

Dynamic Pricing Extensions

To capture temporal fluctuations we add:

1. **Seasonal factor $s(t)$:** sine-wave with amplitude $\alpha = 0.10$ ($\pm 10\%$), phase-shifted to peak mid-July:
$$s(t) = \alpha \sin\!\big(\tfrac{2\pi(t - \delta)}{365}\big).$$
2. **Weekend uplift $\omega(t)$:** fixed 5% increase on Fri–Sun.

Then

$$x_i(t) = x_i^* \big[1 + s(t) + \omega(t) \big].$$

We compare static, seasonal-only, weekend-only, and hybrid. Figure 2 depicts the hybrid path over one year.

Analytical Results Summary. We computed both static and dynamic optimal prices for each cluster i. For example, in Lincoln Square the value cluster's static optimum $x_0^* \approx \$110.87$ yields $\pi_0(x_0^*) \approx \$40.98$ per booking; its average annual prices under the seasonal dynamic, weekend dynamic, and hybrid dynamic strategies are \$111.12, \$112.20, and \$112.34, respectively. Likewise, the cluster's static option $x_1^* \approx \$88.13$ yields $\pi_1(x_1^*) \approx \$18.04$ per booking; its corresponding average annual dynamic prices are \$88.14, \$88.70, and \$88.75. Uptown and Hyde Park clusters exhibit similar patterns (see Tables 5–7 for prices and Table 8 for cumulative profits) as well as Figure 2.

Degree of Discrimination & Surplus Extraction.

- *Second-degree* via a *menu* of static prices x_0^* vs. x_1^* for value and premium segments.
- *Third-degree* by time (weekend vs. weekday, seasonal peaks vs. troughs) through $s(t)$ and $\omega(t)$.

This approach functions like a block-pricing scheme—different "bundles" of price–quality for each segment—extracting more consumer surplus than a single uniform rate. We did not implement two-part tariffs or explicit bundling, but our cluster menu could be extended in that direction in future work.

From Airbnb's standpoint, this hybrid dynamic pricing strategy delivers multiple operational and financial benefits. By aligning nightly rates with predictable seasonal peaks and weekend surges, hosts can capture higher willingness to pay during high-demand windows while avoiding underpricing in off-peak periods. This improves overall occupancy stability, reduces vacancy risk, and enhances revenue per available night (RevPAN). Moreover, dynamic adjustments require minimal incremental infrastructure—leveraging existing calendar APIs and pricing engines—allowing rapid deployment across thousands of listings. The two-tier segmentation (value vs. premium) ensures that entry-level properties remain competitive, protecting brand reputation among budget travelers, while premium units fully realize their pricing power. Collectively, this approach deepens market responsiveness, maximizes host earnings, and strengthens Airbnb's position as a data-driven platform in the sharing-economy lodging sector.

Strategy Evaluation

Candidate Strategies

Based on our static-and-dynamic framework, we compare four candidate pricing policies:

- **Static Pricing:** Constant nightly rate x_i^* for each cluster.
- **Seasonal Dynamic:** $x_i(t) = x_i^*\bigl[1 + s(t)\bigr]$, adjusting for ±10% seasonal swings.
- **Weekend Dynamic:** $x_i(t) = x_i^*\bigl[1 + \omega(t)\bigr]$, applying a 5% uplift on Fri–Sun.
- **Hybrid Dynamic:** $x_i(t) = x_i^*\bigl[1 + s(t) + \omega(t)\bigr]$, combining both effects.

Policy Comparison

We simulate each policy over a 365-day horizon. On day t, cluster i earns

$$\pi_i(t) \;=\; D_i\bigl(x_i(t)\bigr)\;\bigl[x_i(t) - C_v\bigr],$$

and cumulative annual profit is $\sum_{t=1}^{365} \sum_i \pi_i(t)$.

Counterfactual Profits

Table 8 in the Appendix reports annual profits under each strategy. Key takeaways:

- **Lincoln Square:** Static \$14 958/\$6 586 → Hybrid \$15 454/\$6 848 (+3.3%/+4.0%).
- **Uptown:** Static \$5 755/\$17 517 → Hybrid \$5 988/\$18 072 (+4.0%/+3.2%).
- **Hyde Park:** Static \$18 764/\$3 975 → Hybrid \$19 345/\$4 137 (+3.1%/+4.1%).

Seasonal-only and weekend-only strategies capture part of the gain, but the hybrid policy consistently delivers the highest revenue across all clusters.

Conclusion and Recommendation

We recommend adopting the *hybrid dynamic* policy—combining ±10% seasonality and +5% weekend uplifts—layered on top of second-degree segmentation by cluster. From the renter's perspective, this approach brings more transparent, fair pricing: off-peak nights become more affordable, while high-demand periods remain competitive, improving access to value options and reducing vacancy for premium listings. Hosts benefit from smoother occupancy rates and higher overall RevPAN, and Airbnb strengthens its reputation as a customer-centric platform by aligning prices with real-time demand signals. A phased rollout on existing rate-calendar tools, with rolling recalibration of γ, α, and ω, will lock in 3–5% incremental profit while enhancing guest satisfaction and market responsiveness. Compared to the static average nightly rate (e.g. \$110–\$120 across our clusters), the hybrid approach delivers an annual profit uplift of roughly 3–5% per segment—equating to an extra \$500–\$600 in revenue per cluster—without raising baseline prices. Renters in turn enjoy deeper off-peak discounts (up to 10% below static levels), more predictable and transparent pricing, and clearer demand signals, enabling more affordable booking decisions and greater consumer surplus.

Appendix

Tables and Figures

Table 1: Summary Statistics

Table 1: Key summary statistics for all cleaned listings (n=5 207)

Variable	Mean	Median
Price ($)	112.3	100.0
Bedrooms	1.45	1.0
Bathrooms	1.32	1.0
Amenities_count	17.8	15.0
Cleaning fee ($)	30.1	20.0
Occupancy rate	0.60	0.60

Table 2: Cluster Summary for Lincoln Square

Table 2: Lincoln Square – Cluster Summaries

Cluster	Count	Median Price ($)	Occupancy Rate	Mean Baths	Mean Cleaning Fee ($)
0	29	142	0.483	1.62	74.00
1	40	80	0.675	1.05	13.95

Table 3: Cluster Summary for Uptown

Table 3: Uptown – Cluster Summaries

Cluster	Count	Median Price ($)	Occupancy Rate	Mean Baths	Mean Cleaning Fee ($)
0	122	75	0.680	1.15	12.61
1	32	156	0.469	1.39	76.94

Table 4: Cluster Summary for Hyde Park

Table 4: Hyde Park – Cluster Summaries

Cluster	Count	Median Price ($)	Occupancy Rate	Mean Baths	Mean Cleaning Fee ($)
0	13	120	0.769	1.38	123.62
1	67	70	0.582	1.21	16.13

Table 5: Average Annual Prices by Strategy – Lincoln Square

Table 5: Lincoln Square: Average annual price ($) per cluster and strategy

Cluster	Static	Seasonal Dynamic	Weekend Dynamic	Hybrid Dynamic
0	110.87	111.12	112.20	112.34
1	88.13	88.14	88.70	88.75

Table 6: Average Annual Prices by Strategy – Uptown

Table 6: Uptown: Average annual price ($) per cluster and strategy

Cluster	Static	Seasonal Dynamic	Weekend Dynamic	Hybrid Dynamic
0	85.45	85.89	86.02	86.42
1	118.23	118.12	119.56	119.52

Table 7: Average Annual Prices by Strategy – Hyde Park

Table 7: Hyde Park: Average annual price ($) per cluster and strategy

Cluster	Static	Seasonal Dynamic	Weekend Dynamic	Hybrid Dynamic
0	121.57	121.54	122.91	123.00
1	80.77	80.99	81.15	81.34

Table 8: Annual Cumulative Profits

Table 8: Annual cumulative profits ($) under four strategies

Nbrhd	Strategy	Cl. 0	Cl. 1
Lincoln Square	Static	14,958	6,586
	Seasonal dynamic	15,010	6,630
	Weekend dynamic	15,403	6 805
	Hybrid dynamic	15 454	6 848
Uptown	Static	5 755	17 517
	Seasonal dynamic	5 796	17 569
	Weekend dynamic	5 947	18 022
	Hybrid dynamic	5 988	18 072
Hyde Park	Static	18 764	3 975
	Seasonal dynamic	18 815	4 006
	Weekend dynamic	19 296	4 106
	Hybrid dynamic	19 345	4 137

Visuals Representation

Figure 1: Static Demand & Profit Curves

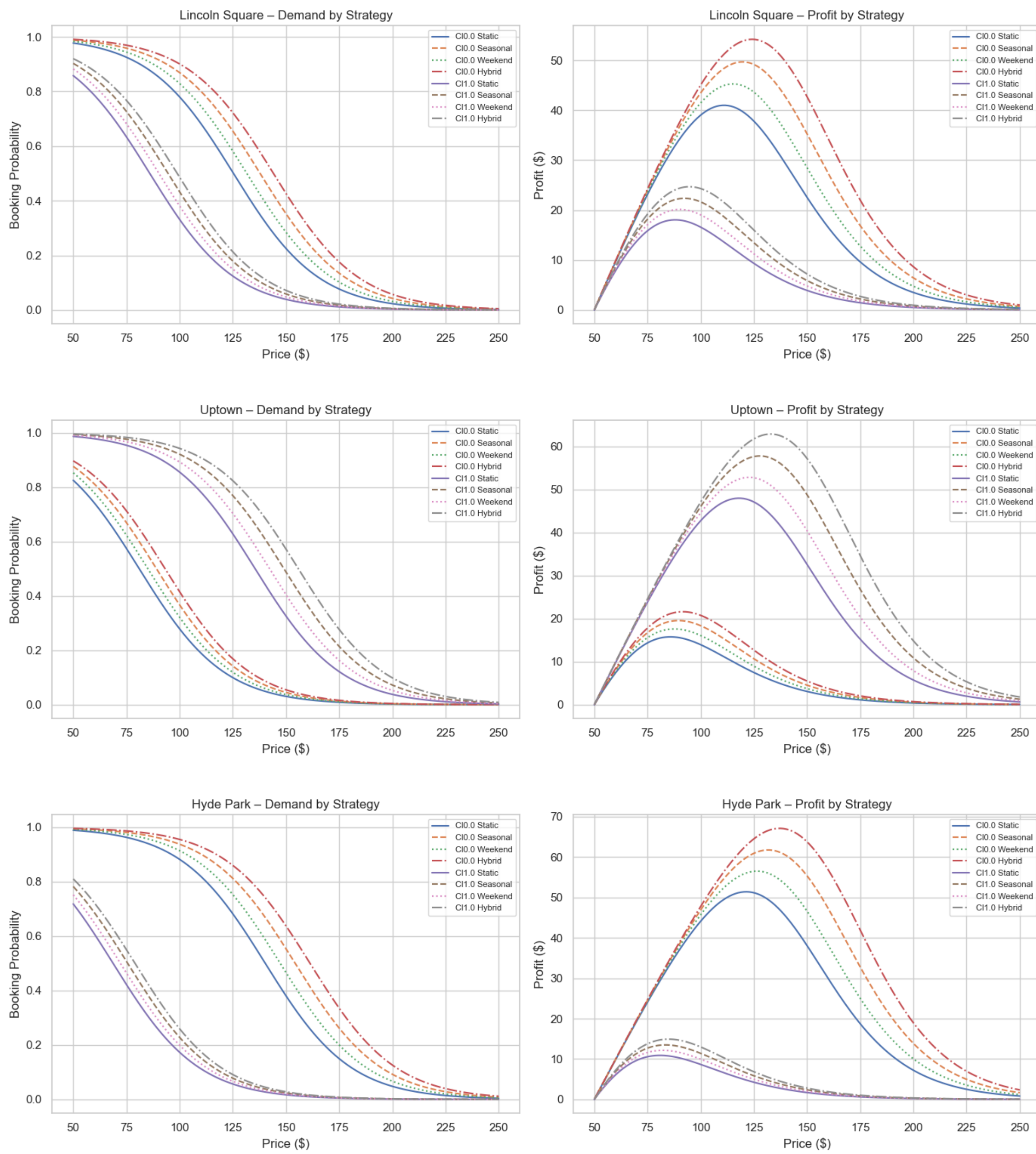

Figure 1: Static booking-probability and profit curves for each cluster in three neighbourhoods. Top: Lincoln Square, middle: Uptown, bottom: Hyde Park. Each panel overlays the four pricing strategies' demand and profit functions.

Figure 2: Daily Hybrid Dynamic Paths

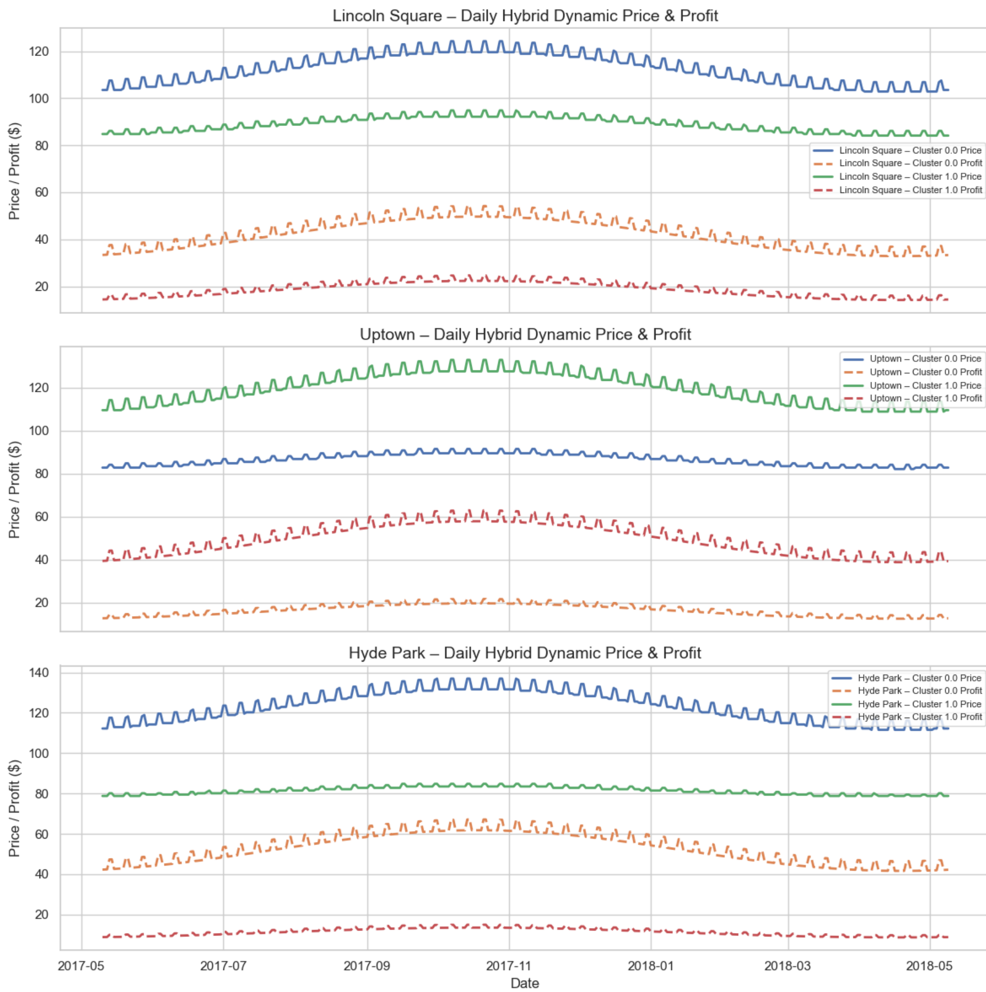

Figure 2: Hybrid-dynamic daily prices (solid lines) and profits (dashed lines) over one year for each cluster in Lincoln Square, Uptown, and Hyde Park.

Project Limitations

While our analysis demonstrates meaningful profit improvements through dynamic pricing, several practical and academic constraints limit its direct applicability:

Data Completeness and Representativeness We rely on a one-year snapshot of Airbnb listings scraped in 2017 for Chicago. This dataset omits many real-world factors—such as last-minute cancellations, multi-night booking patterns, and host responsiveness—that significantly influence actual occupancy and yield. Furthermore, our simulated "booked" indicator (generated via a simple binomial draw) cannot capture heterogeneous guest behavior or platform-level heuristics, which may lead to biased estimates of true demand sensitivity.

Model Simplifications Our logistic demand model assumes price is the sole driver of booking probability, abstracting away seasonally changing guest preferences beyond a fixed sine-wave, competitor reactions, minimum-stay requirements, and platform-imposed rules (e.g., cleaning fees, security deposits). In practice, hosts adjust several menu attributes simultaneously (amenities, cancellation policy, two-part tariffs), and platforms employ machine-learning–powered yield management—dimensions that we are unable to replicate with our limited, static feature set.

Feasibility of Implementation Although ±10% seasonal and +5% weekend adjustments can be programmed on many rate-calendar platforms, real-time dynamic repricing typically requires sophisticated infrastructure, seamless data pipelines (e.g., channel managers), and continuous performance monitoring. Small hosts or property managers may lack the technical resources or risk appetite to deploy such systems without clear evidence of return on investment.

Academic Context and External Validity As an academic exercise, we prioritize analytical transparency and tractability over black-box predictive accuracy. Consequently, our parameter calibration (steepness, base-x_{mid}) is driven by median cluster statistics rather than individualized learning algorithms. While this facilitates comparative statics, the results may understate the full potential of personalized, real-time optimization in commercial environments.

In sum, our project provides a proof-of-concept for dynamic pricing in short-term rentals but should be interpreted with caution when extrapolating to live marketplaces. Future work integrating richer booking logs, competitor pricing feeds, and host-level operational constraints would help bridge the gap between theoretical gains and operational deployment.

Assumptions and Sources

Table 9: Key modeling assumptions and their sources

Assumption	**Source / Justification**
Weekend price uplift of 5% on Fridays–Sundays	Kimes (2010); Doğru et al. (2019)
Seasonal price amplitude of ±10% (peak mid-July)	Guillet & Kucukusta (2016); Wang & Nicolau (2017)
Variable cost per booking set at $50	Project assumption based on average cleaning/service fees
Logistic demand form with steepness parameter = 0.05	Phillips (2005); Talluri & van Ryzin (2004)
Two clusters per neighbourhood ($k = 2$)	Standard revenue-management segmentation practice
Base 60% occupancy rate for missing bookings (binomial simulation)	Chicago Airbnb occupancy 69% in 2021–22 (Airbtics); 60% is conservative and allows imputation
Base $\$\mathrm{x}_{\mathrm{mid}}\$adjustedbyclusteroccupancydeviation$	Model design to capture willingness-to-pay heterogeneity across segments
Price grid $50–$250 (300 points) covering observed listing range	Project design based on empirical price distribution in the data

Potential Profit Gain

Table 10: Annual Profit Gain: Hybrid vs Static Pricing

Neighborhood	Cluster	Static ($)	Hybrid ($)	Gain ($)	Gain (%)
Lincoln Square	0	14,958	15,454	496	3.32%
	1	6,586	6,848	262	3.98%
Uptown	0	5,755	5,988	233	4.05%
	1	17,517	18,072	555	3.17%
Hyde Park	0	18,764	19,345	581	3.10%
	1	3,975	4,137	162	4.08%

Bibliography

References

Doğru, T., Mody, M., and Suess, C. (2019). The impact of dynamic pricing on Airbnb revenue-management. *Tourism Management*, 70:34–46.

Guillet, B. D. and Kucukusta, D. (2016). The investigation of dynamic pricing in the UK Budget airlines. *Journal of Revenue and Pricing Management*, 15(3):165–176.

Kimes, S. E. (2010). Organizing pricing and revenue management. *PHR Summit Proceedings*, pages 23–34.

Phillips, R. (2005). *Pricing and Revenue Optimization*. Stanford University Press.

Talluri, K. T. and van Ryzin, G. J. (2004). *The Theory and Practice of Revenue Management*. Springer.

Wang, D. and Nicolau, J. L. (2017). Price determinants of sharing economy based accommodation rental: A study of listings from Airbnb. *International Journal of Hospitality Management*, 62:120–131.

Airbtics (2022). Chicago Airbnb occupancy report: 2021–22 market insights. https://www.airbtics.com/chicago-market-insights.