NYC Airbnb, What Drives Price

Introduction

This report provides an executive view of pricing in New York City's Airbnb market, written for Airbnb leaders in strategy, product, and host operations. Our business question is simple: **What drives listing price in NYC, and which customer segments can boost revenue under current rules?**

We analyse listings from 2019 and interpret findings as well as explore the implications of Local Law 18, which reduced short term entire home supply and shifted demand patterns, with reported distributional effects across boroughs and lower visitor spending in outer areas (Airbnb Newsroom, 2024, ShortTermRentalz, 2023).

Data & Methodology

We use Airbnb NYC 2019 with about 48,000 listings covering borough, neighbourhood, room type, price, availability, and reviews. We merged each listing's latitude and longitude with official New York data, computing distance to the nearest subway, the nearest airport, and Central Park using (NY.gov) sources, reflecting how transport and attractions shape urban stays (State of New York, 2025, Gutiérrez et al., 2017). Before modelling we cleaned the data, removed duplicates, checked plausible ranges for price and nights, and addressed price skew. We then fit a linear regression to quantify how features relate to price, and apply KMeans to group similar listings into practical segments for decision making (Aggarwal and Reddy, 2013).

Exploratory Analysis

Skewed Prices: Airbnb prices are heavily skewed, the mean is **$146**, while the median is only **$106** so averages can mislead. **Figure 1** shows the raw distribution is far from normal, which supports using a log scale to reduce the pull of luxury listings. The log transformed view in **Figure 2** is more regular and suitable for modelling (Osborne, 2010).

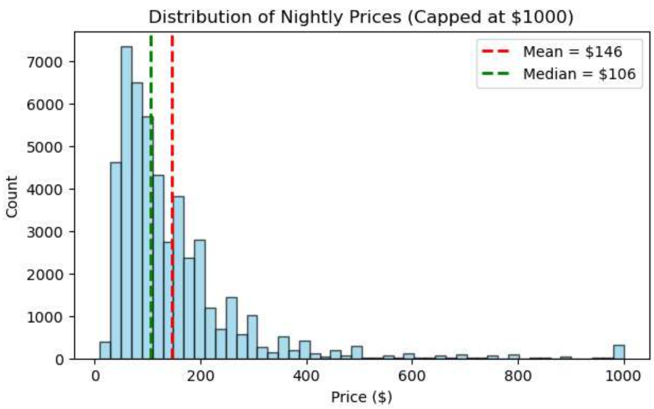

Figure 1: Not normal distribution of price

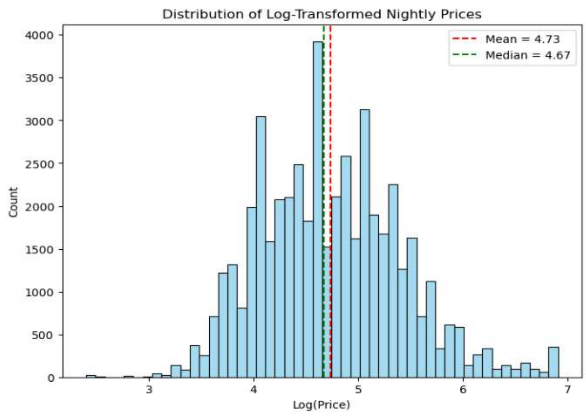

Figure 2: Normal transformed log of price

Geography matters. A clear Manhattan premium emerges having the highest average prices, and the expected room type order appears, entire homes costing the most, above private rooms which are above shared rooms. This is consistent across all 5 boroughs. Emerging patterns match evidence that neighbourhood attributes and property type are first order price drivers in peer-to-peer markets and that spatial structure tracks urban amenities and transport (Benítez Aurioles, 2018, Gutiérrez et al., 2017).

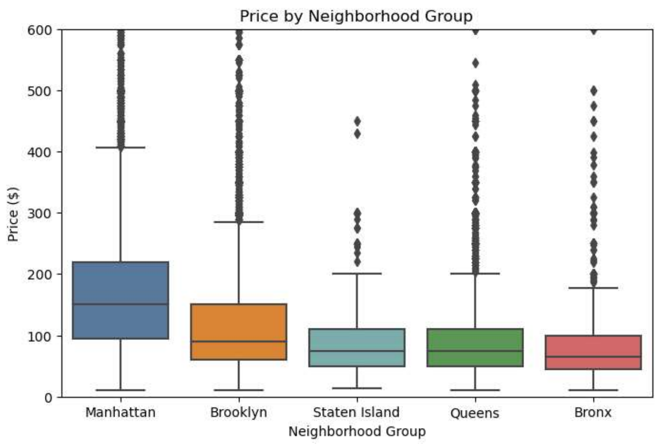

Figure 3: Box & Whisker plot showing price spread by borough

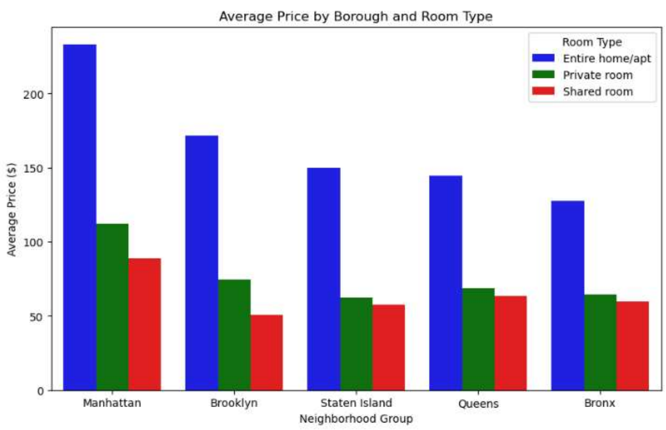

Figure 4: Average listing price for each room-type across boroughs

Figure 5 shows deep competition in Manhattan, about 23 percent of listings have no reviews versus roughly 16 to 20 percent in outer boroughs, suggesting a crowded premium market and the need for targeted launch support to secure early reviews.

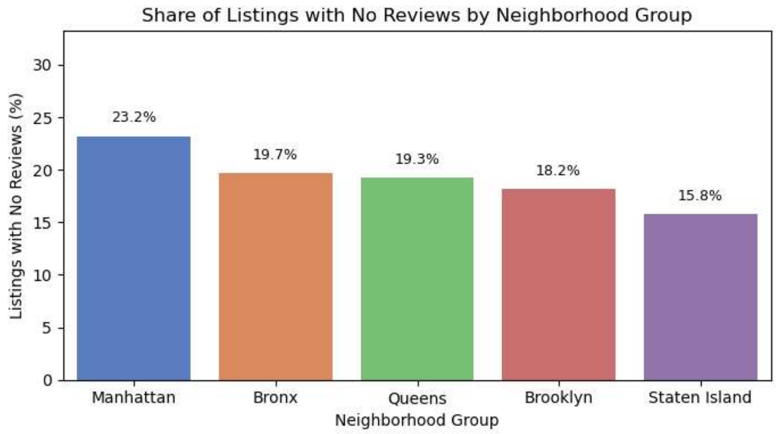

Figure 5: Percent of listings in each borough with no reviews

Proximity to certain points of interest play a small role. Prices are slightly higher nearer Central Park and subways, little link appears with airport distance **Figure 6**. The listing prices aren't grouped up, so proximity to these points fine tunes price rather than setting it, which aligns with the literature that places neighbourhood and property signals ahead of simple distance measures in dense cities (Benítez Aurioles, 2018).

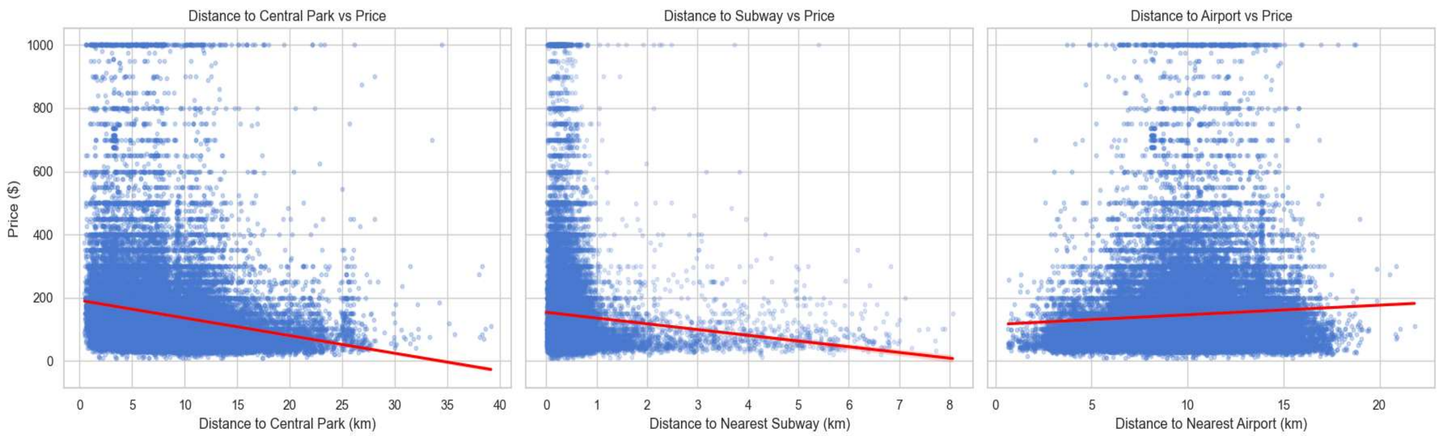

Figure 6: Influence of the distances from Central Park, the nearest subway and nearest airport on price

Modelling Approach and Validation

We use linear regression for transparency. It estimates how each feature relates to price while holding others constant, and with log(price) the coefficients read as approximate percent changes. We trained on eighty percent of listings and tested on twenty percent. Test results, R^2 about 0.49 and MAE about 56 dollars, mean the model explains roughly half of price variation and is typically within 56 dollars per night, suitable for decision making though not exact at the listing level. We also apply KMeans to group similar listings without using price as a target, creating usable customer segments for marketing and product decisions (Aggarwal and Reddy, 2013).

Regression Findings

Figure 7 shows room type and borough dominate pricing. Private rooms are about 53 percent cheaper than entire homes, shared rooms about 68 percent cheaper. Borough premiums are large, Manhattan about 36 percent above the Bronx, Staten Island about 33 percent, Queens about 28 percent, Brooklyn about 13 percent. Proximity to Central Park adds a small premium of about 4 percent, subway and airport effects are weaker. More reviews are modestly linked to lower price, likely reflecting higher turnover at lower rates. Overall, neighbourhood and property attributes drive price, with distance metrics as refinements (Benítez Aurioles, 2018, Gutiérrez et al., 2017). For action, anchor pricing guidance on borough and room type, then apply small proximity adjustments near Central Park and subways.

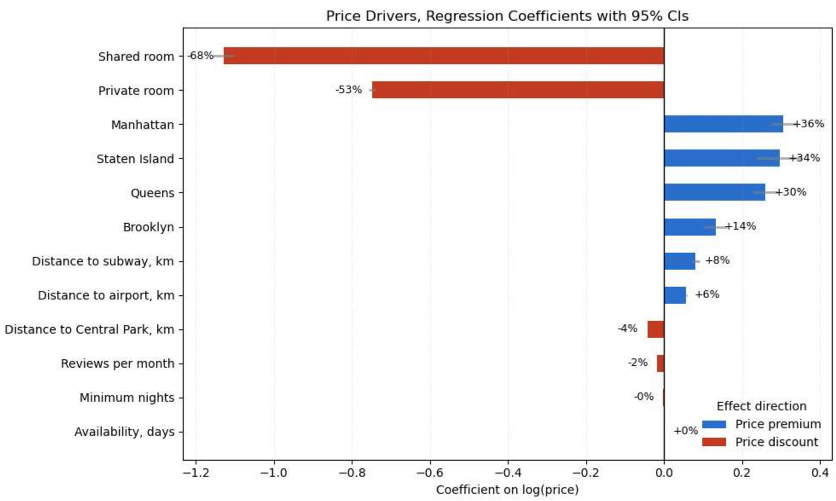

Figure 7: Strongest influencers on listing price

Clustering Findings: Customer Segments

KMeans produces four clear segments that match how guests shop and how hosts position listings, which aligns with practical guidance in business analytics on building usable segment playbooks without needless complexity (Aggarwal and Reddy, 2013).

Cluster	Dominant Borough(s)	Avg. Price ($)	Min. Nights	Reviews/Month	Availability (days)	Dist. from nearest Subway (km)	Dist. from nearest Airport (km)	Dist. from Central Park (km)
1	Manhattan	183.98	8.47	0.98	112.92	0.3	9.49	4.61
2	Brooklyn	118.85	5.89	1.06	102.09	0.39	11.81	11.19
3	Queens	96.27	4.97	1.55	145.09	1	5.41	10.08
4	Staten Island	103.42	4.83	1.58	199.68	1.69	11.18	22.65

- **Cluster 1, Manhattan premium**, highest prices, close to attractions, strong fit for business and luxury stays
- **Cluster 2, Brooklyn mid range**, balanced prices and availability, family and value focused
- **Cluster 3, Queens budget, airport oriented**, lowest prices, high turnover, convenient short stays
- **Cluster 4, Staten Island extended**, lower prices, long availability, suited to longer stays and students

These segments let Airbnb tailor playbooks, premium upsells for Cluster 1, value and short stay bundles for Cluster 3, long stay offers for Cluster 4, family focused positioning for Cluster 2.

Implications of 'Local Law 18'

Local Law 18, effective September 2023, requires registration for short stays and in practice restricts entire home rentals. Industry reports show a sharp drop in short term supply and uneven impacts across boroughs, which reshapes short stay strategy and visitor spending patterns (Airbnb Newsroom, 2024, ShortTermRentalz, 2023). In this context, our results serve as a pre law baseline, borough and room type remain the dominant price signals, proximity provides only small refinements, and the composition of demand shifts toward private rooms and longer stays, especially outside Manhattan.

Conclusion

The analysis shows how price is formed in New York City, borough and room type are the strongest levers, proximity adds small adjustments. Private rooms price about fifty three percent below entire homes, shared rooms about sixty eight percent below, Manhattan carries about a thirty six percent premium, and proximity to Central Park adds roughly four percent. Segmentation reveals four usable markets, premium Manhattan, mid range Brooklyn, budget airport oriented Queens, and extended stay Staten Island. In line with the business question, anchor host guidance and pricing tools on borough and room type first, apply modest proximity premiums near Central Park and subways, activate segment specific playbooks for premium, mid range, budget, and extended stay needs, and, under current rules, emphasise private rooms and thirty plus day stays where demand has shifted. These steps remain consistent with broader evidence on urban accommodation markets (Zervas et al., 2017, Dogru et al., 2020, Wachsmuth and Weisler, 2018).

Bibliography

Airbnb Newsroom (2024) *New report finds NYC's short-term rental law takes toll on outer boroughs*. Available at: https://news.airbnb.com/new-report-finds-nycs-short-term-rental-law-takes-toll-on-outer-boroughs/

Aggarwal, C.C. and Reddy, C.K. (eds.) (2013) *Data clustering: Algorithms and applications*. Boca Raton: Chapman & Hall/CRC.

Benítez-Aurioles, B. (2018) 'Neighbourhood determinants of Airbnb prices: Evidence from Madrid', *Tourism Economics*, 24(6), pp. 600–617.

Bishop, C. and Bishop, H. (2023) *Deep learning: Foundations and concepts*. Cham: Springer.

Dogru, T., Mody, M. and Suess, C. (2020) 'Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets', *Tourism Management*, 77, 104004.

Freedman, D. and Diaconis, P. (1981) 'On the histogram as a density estimator: L2 theory', *Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete*, 57, pp. 453–476. Available at: https://link.springer.com/article/10.1007/BF01025868

Gutiérrez, J., García-Palomares, J.C., Romanillos, G. and Salas-Olmedo, M.H. (2017) 'The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona', *Tourism Management*, 62, pp. 278–291.

Osborne, J.W. (2010) 'Improving your data transformations: Applying the Box–Cox transformation', *Practical Assessment, Research & Evaluation*, Available at: https://www.researchgate.net/publication/284261483_Improving_your_data_transformations_Applying_Box-Cox_transformations_as_a_best_practice

Rousseeuw, P.J. 1987. 'Silhouettes, a graphical aid to the interpretation and validation of cluster analysis'. *Journal of Computational and Applied Mathematics*,

ShortTermRentalz (2023) *Airbnb and hosts urge reversal of New York City's Local Law 18*. Available at: https://shorttermrentalz.com/news/airbnb-new-york-city-urge-reversal-local-law-18/

State of New York (2025) *MTA Subway Stations [Dataset]*. Available at: https://data.ny.gov/Transportation/MTA-Subway-Stations/39hk-dx4f/about_data

Wachsmuth, D. and Weisler, A. (2018) 'Airbnb and the rent gap: Gentrification through the sharing economy', *Environment and Planning A: Economy and Space*, 50(6), pp. 1147–1170.

Zervas, G., Proserpio, D. and Byers, J. (2017) 'The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry', *Journal of Marketing Research*, 54(5), pp. 687–705.