

The Impact of Short-Term Rentals on Long-Term Housing Market in New York City

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Abstract

Short-Term rental(STR) density—measured as Airbnb listings per square kilometer—is positively associated with elevated housing prices across New York City boroughs. Using multiple regression models with structural and geographic controls, we find that an increase in STR density corresponds with a measurable rise in housing prices. Machine learning models further highlight STR density as the most important predictor of price, identifying nonlinear thresholds and interaction effects. While some models detect a statistically significant relationship between STR activity and price volatility, the magnitude is economically limited. These results suggest that STR platforms play a key role in shaping urban housing costs and warrant targeted regulation to preserve affordability.

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Introduction

Airbnb is a peer-to-peer platform allowing individuals to rent out properties or rooms for short-term stays. Consumers favor short-term rental (STR) platforms like Airbnb for their flexibility and cost-effectiveness compared to hotels. While STRs reduce market friction and improve housing resource utilization, they also cause local market fluctuations and negative externalities [4].

Economic theories suggest STRs affect residential housing markets. Data from FRED shows the median U.S. house price increased from 165,300 dollars in Q1 2000 to 419,200 dollars in Q4 2024 [3]. Barron, Kung, and Proserpio [2] found a 10% rise in Airbnb listings leads to a 0.76% increase in house prices. In Virginia, STRs like Airbnb removed 7,000 to 13,500 units from New York City’s long-term housing market, impacting high-priced housing [13]. Filippas and Horton [4] note that high Airbnb density causes noise pollution, reducing housing prices [12]. In London, a 10% increase in Airbnb listings is linked to a 3% rise in burglaries and five additional robberies per 100 properties [7]. These externalities harm local housing markets [4].

This study initially introduces the Airbnb-Housing Ratio (AHR) as a preliminary metric to explore potential relationships between short-term rental activity and housing market trends. However, AHR is not used in the core statistical models due to its sensitivity to local sample sizes and aggregation levels. It primarily serves an exploratory role to identify borough-level patterns. For more rigorous analysis, the study relies on short-term rental(STR) density—defined as the number of Airbnb listings per square kilometer—which emerges as the most significant and consistent metric throughout both regression and machine learning sections.

New York City serves as a case study due to its strong tourism industry and high short-term rental demand [13]. The analysis integrates the USA Real Estate Dataset [10] and the New York City Airbnb Open Data [5], containing housing prices and 2019 Airbnb listings, respectively. The datasets were cleaned and merged using Python and Jupyter Notebook.

Key variables are summarized through tables and visualizations. Violin plots compare pre- and post-2019 New York housing counts, while the Airbnb-Housing Ratio examines housing price trends. Although AHR-based plots provide preliminary observations, they do not reveal a stable or statistically supported link between Airbnb concentration and price growth. In summary, plots do not reveal a clear relationship between the Airbnb-Housing Ratio and housing price growth. Additionally, some graphs suggest that higher Airbnb-Housing Ratios are associated with greater long-term housing price variability in certain boroughs. Geographical maps show that Manhattan generally has higher STR density, median prices over the years, and price volatility, followed by Queens and Brooklyn. To explore these relationships more rigorously, the paper introduced multiple OLS regression models incorporating STR density, price volatility, and structural housing features like bed and bath counts. The results confirmed a statistically significant and positive association between Airbnb density and both housing price and price variability, particularly after including fixed effects by borough. Additionally, geographical visualizations reinforced this result by highlighting spatial clustering of STR intensity and housing volatility.

To supplement the OLS analysis, machine learning models such as regression trees and random forests were applied to uncover non-linear relationships and variable interactions. These models highlighted pattern thresholds and ranked STR density as the most influential factor in predicting price, providing a more flexible view of housing dynamics. Compared to OLS, which offers interpretable coefficients and statistical inference, machine learning emphasizes predictive accuracy and structural complexity, thus reveals hidden effects that may not be shown by OLS.

This combined strategy allows the paper to balance statistical rigor with pattern discovery, strengthening the case for STR density as a meaningful factor in the housing market.

Summary Statistics and Visualizations

A comparison of key variables across boroughs (Table 1) reveals striking differences in housing availability and price structure. Generally, Brooklyn has the highest number of housing units (2,038) with a median price of \$799,750, followed by Queens at \$799,000. However, Queens has significantly fewer units (139). Manhattan has the highest median price at \$1,195,000, and also the highest price variation (\$4,305,856). Staten Island has the largest median house size (1,524 sqft) and the highest average number of bathrooms (2.6). Bronx has the most bedrooms on average of 3.5, but its median price is the lowest at \$582,500. Notably, the distribution of unit sizes and prices reflects distinct market dynamics in each borough, which may shape how STR activity influences affordability.

Table 1: NYC Housing Market Summary

City	Count	Med Price	STD Price	Med Size	Avg Bed	Avg Bath
Manhattan	120	\$1,195,000	\$4,305,856	1,062 sqft	2.0	2.0
Brooklyn	2,038	\$799,750	\$816,291	1,230 sqft	3.0	2.0
Queens	139	\$799,000	\$846,474	920 sqft	3.0	2.0
Bronx	185	\$582,500	\$538,558	1,428 sqft	3.5	2.0
Staten Island	214	\$650,000	\$594,275	1,524 sqft	3.0	2.6

Table 2 introduces the Airbnb-Housing Ratio (AHR), offering a preliminary look at the concentration of STRs across boroughs.

Table 2: Housing and Airbnb Summary

City	Housing Count	Airbnb Count	AHR
Manhattan	3,482	7,918	2.27
Brooklyn	4,200	8,900	2.12
Queens	1,100	1,200	1.09
Bronx	850	400	0.47
Staten Island	800	200	0.25

According to Figure 1, Brooklyn, Queens, and Bronx exhibit moderate fluctuations, with price growth generally remaining within $\pm 50\%$. In contrast, Manhattan demonstrates

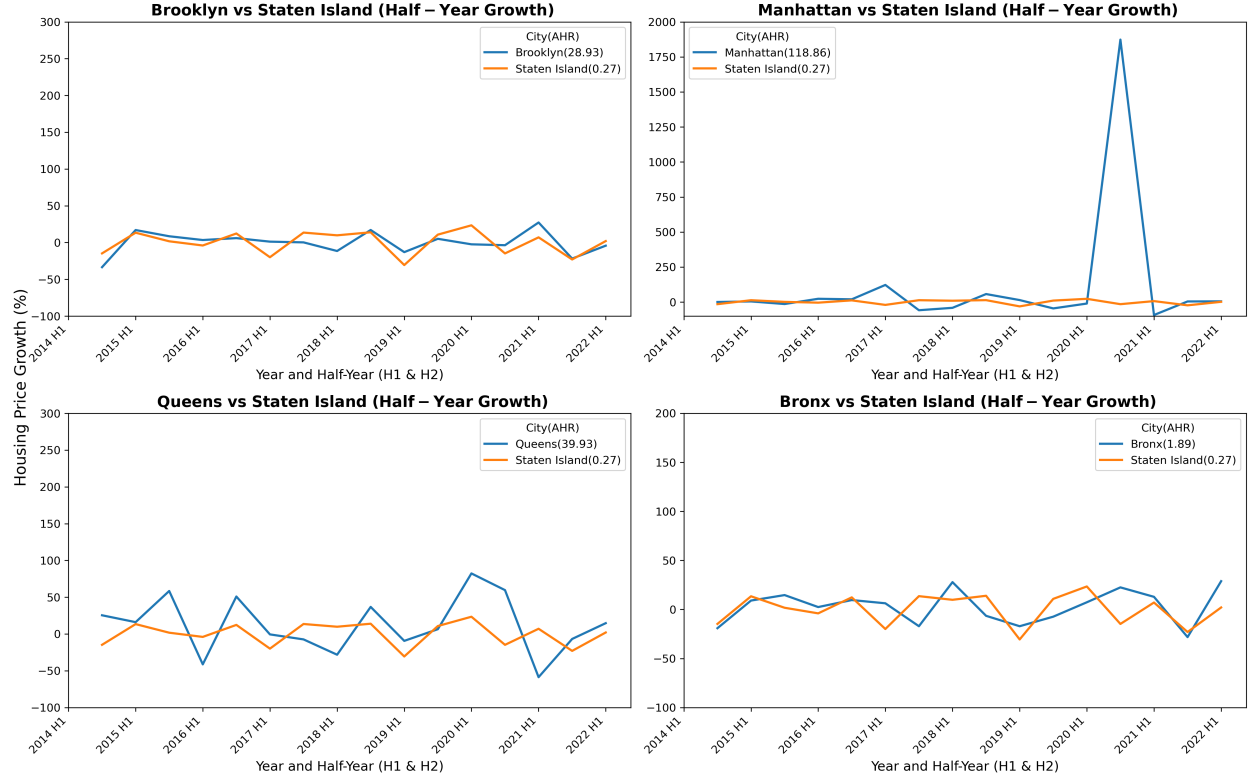


Figure 1: Comparative Half-Year Housing Price Growth across NYC Boroughs with AHRs

extreme volatility, with a peak exceeding 5000% in early 2020, followed by sharp declines. Queens and Brooklyn have moderate peaks around 100% and 80%, respectively, while the Bronx fluctuates within a narrower range. Staten Island remains relatively stable, with price changes mostly between -10% and 20%.

While AHR provides a useful initial insights, its sensitivity to sample size makes it less reliable for statistical inference. Instead, STR density is used in all formal models to ensure comparability across neighborhoods.

Table 3: Housing Market Summary by Borough (Pre-2019 vs. Post-2019)

City	Avg Med Price Pre-2019	Avg Med Price Post-2019	Price Volatility	Airbnb Density
Manhattan	\$1,142,800	\$1,201,125	0.3802	361.73
Brooklyn	\$840,000	\$888,000	0.2775	110.78
Queens	\$750,000	\$890,000	0.4832	19.64
Bronx	\$570,000	\$590,000	0.0757	9.81
Staten Island	\$620,000	\$675,000	0.1104	2.44

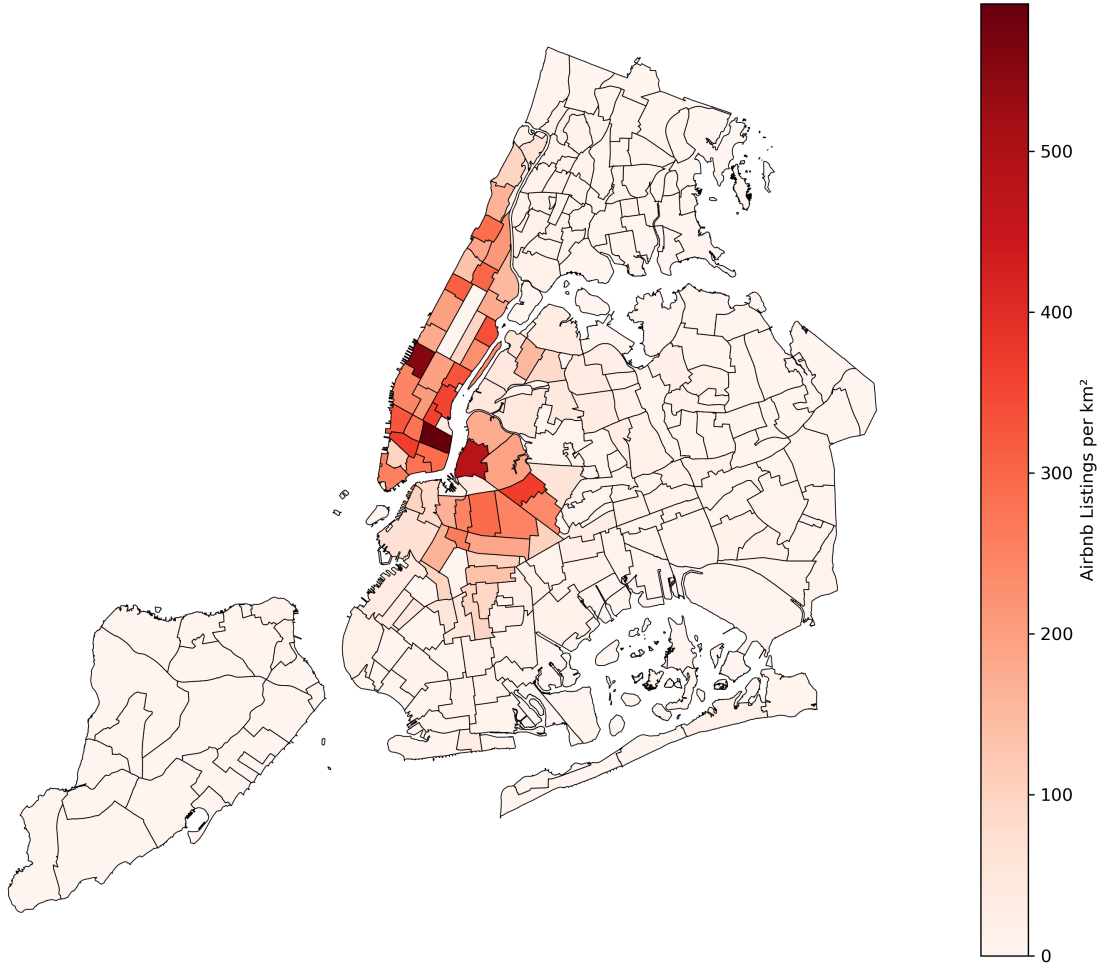


Figure 2: Airbnb Density by NYC Neighborhood

To complement the borough-level summary, Table 3 compares pre and post-2019 housing prices, volatility, and Short-term rental(STR) density. It is calculated as:

$$\text{STR Density} = \frac{\text{Number of Airbnb Listings}}{\text{Neighborhood Area (km}^2\text{)}}$$

Manhattan shows extreme volatility, peaking sharply in early 2020, while Queens and Brooklyn show more moderate fluctuations. The Bronx and Staten Island remain relatively stable. This preliminary observation supports the hypothesis that STR activity may amplify market volatility. This pattern suggests a potential link between STR intensity and long-term affordability concerns.

Figure 2 shows that STR units are highly concentrated in central Manhattan neighborhoods such as Midtown, Chelsea, and the Lower East Side, where density exceeds 500 listings per square kilometer. Elevated densities are also visible in parts of Brooklyn, including Williamsburg and Downtown Brooklyn. This localized clustering may contribute to the borough-level trends observed in earlier tables.

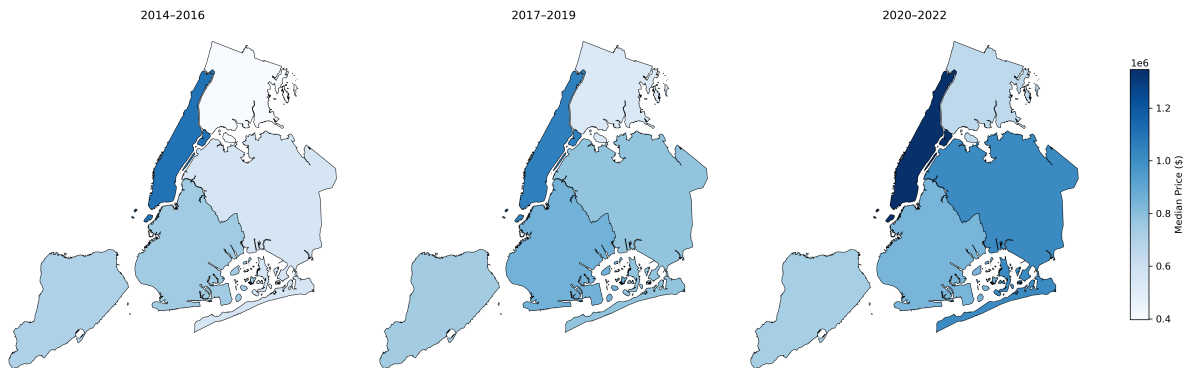


Figure 3: NYC Median Housing Prices by Period

The median prices for housing over time are presented in Figure 3. Housing prices generally rise over time, reaching a peak during the period 2020-2022. This trend is likely influenced by the dynamics of the post-COVID housing market. As Mondragon and Wieland (2022) note, the shift to remote work during the pandemic significantly increased housing demand, accounting for at least half of the recent national house price growth[8].

Manhattan remains the borough with the highest median housing prices across all three periods. Brooklyn and Queens show consistent upward trends, while other boroughs exhibit more modest changes. The spatial distribution and upward trajectory of housing prices correspond to areas with high short-term rental (STR) density observed in Figure 2. This suggests a potential association between STR activity and housing market pressures.

Figure 4 shows the housing price distribution for different boroughs using violin plots. Manhattan again has the highest price and price range among all boroughs, with prices extending to nearly 50 million dollars. Queens exhibits an increased price range, but overall housing availability appears to decrease, as the post-2019 violin for Queens is thinner than

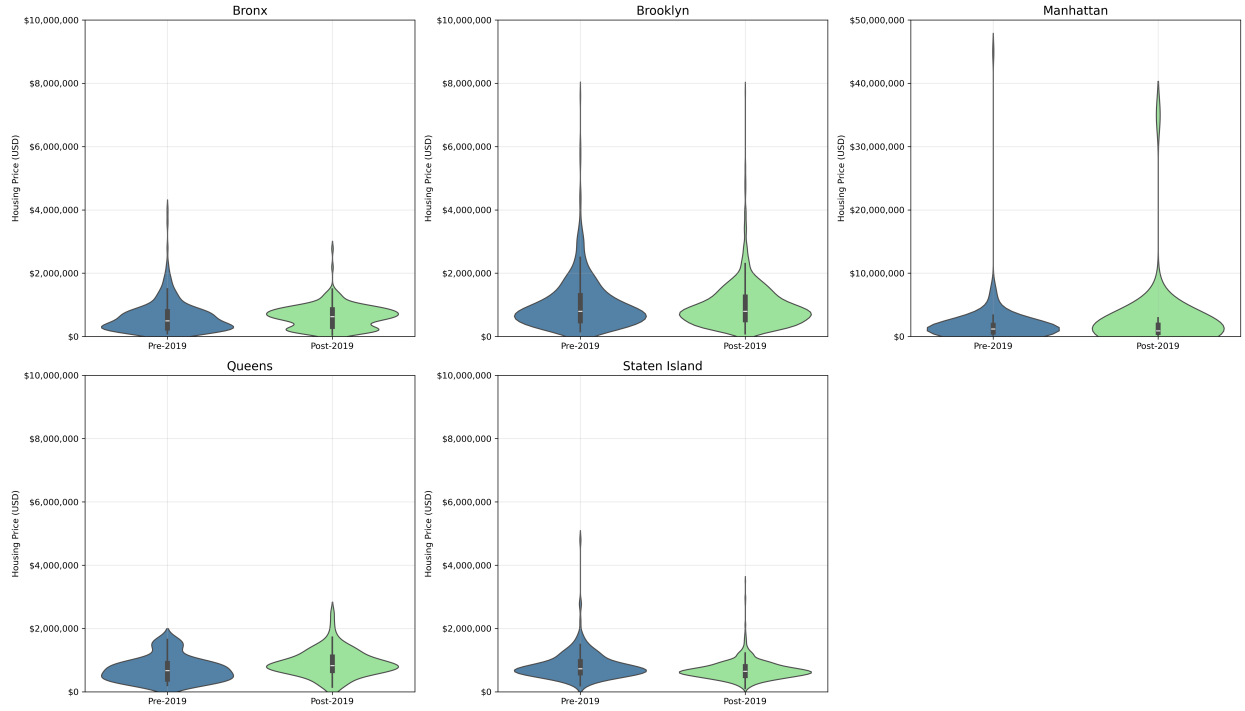


Figure 4: Housing Price Distribution (Pre-2019 vs. Post-2019)

its pre-2019 counterpart. The Bronx shows a contraction in the price range of around 4 million to 3 million dollars, along with a decrease in total housing supply. Staten Island also shows a reduced price range to approximately 3.75 million dollars, though this contraction is concentrated in high-priced units, which likely have minimal impact on the broader market [11].

Together, the descriptive statistics and visualizations, especially Figure 5, highlight consistent patterns: boroughs with higher STR activity tend to show elevated prices and, in some cases, greater volatility. These observations motivate a more rigorous empirical analysis, which follows in the regression section.

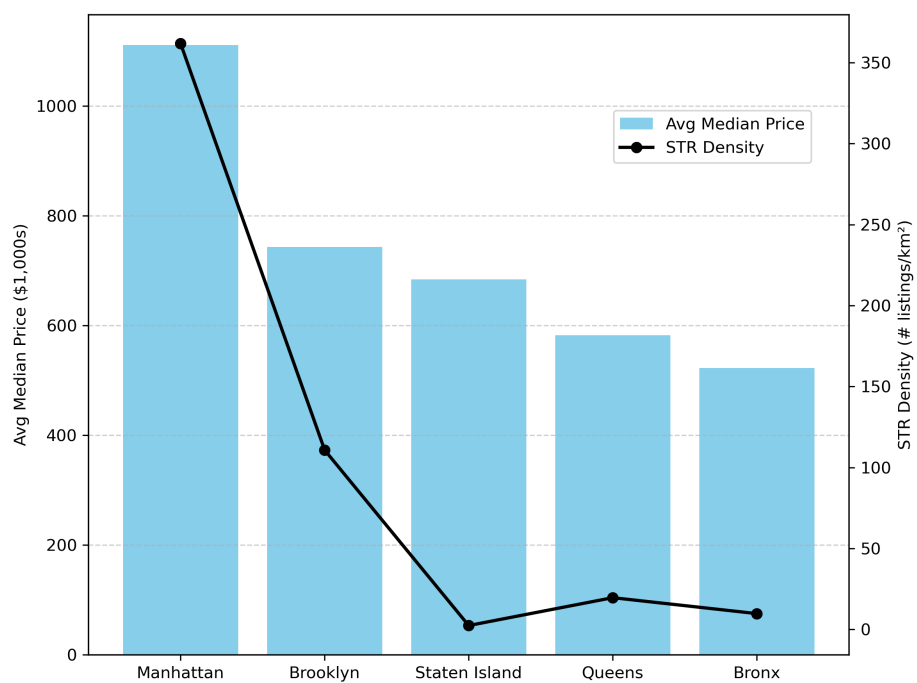


Figure 5: Average Median Housing Price and STR Density in NYC Boroughs

Regression Results

Modeling Housing Price

$$\text{Price}_i = \beta_0 + \beta_1 \cdot \text{STRDensity}_i + \beta_2 \cdot \text{Volatility}_i + \beta_3 \cdot \text{Bedrooms}_i + \beta_4 \cdot \text{Bathrooms}_i + \delta_{\text{City}_i} + \epsilon_i$$

Table 4: Regression Table on Short-Term Rental Density and Housing Price

<i>Dependent variable: price</i>				
	Baseline (1)	Property Controls (2)	Market Trends (3)	Full Model (4)
C(city)[T.Brooklyn]				-125098.917*** (41760.436)
C(city)[T.Manhattan]				33477.036*** (11656.327)
C(city)[T.Queens]				332458.177*** (87203.759)
C(city)[T.Staten Island]				21053.140 (51918.974)
Intercept	656018.704*** (21352.974)	-210860.905*** (39195.175)	-328677.339*** (43548.699)	-230214.232*** (55542.338)
airbnb_density	3298.870*** (200.406)	4345.057*** (201.249)	3927.142*** (211.750)	4784.460*** (248.261)
bath		313267.146*** (18159.617)	309075.626*** (18088.632)	308123.587*** (18420.752)
bed		18451.681 (12189.524)	26173.636** (12199.183)	26604.750** (12356.301)
price_volatility			1161807.549*** (190813.449)	128652.644*** (32988.401)
Observations	4288	3872	3872	3872
R^2	0.059	0.206	0.213	0.213
Adjusted R^2	0.059	0.205	0.212	0.212
Residual Std. Error	1047768.692	984427.825	979869.372	979930.101
F Statistic	270.963***	333.530***	261.749***	174.731***

Note: *p<0.1; **p<0.05; ***p<0.01

To assess whether short-term rental (STR) activity influences long-term housing prices in New York City, four regression models are estimated. The dependent variable is housing price, and the main independent variable is STR density. We assume a linear relationship between STR density and housing prices, controlling for housing characteristics and borough-

level effects.

Model 1 serves as a baseline, including only STR density as a predictor. Model 2 adds structural controls—number of bedrooms and bathrooms—to account for differences in property features. Model 3 incorporates housing price volatility to capture the influence of local market instability. Model 4 adds fixed effects for boroughs to control for unobserved spatial heterogeneity. This final specification is preferred, as it accounts for both observable housing traits and geographic differences across boroughs.

Across all models, STR density is positively and statistically significantly associated with housing prices. In Model 4, a one-unit increase in STR density is associated with an estimated increase of approximately \$4,784 in housing price. Price volatility is also positively associated with housing price.

Property characteristics behave as expected: homes with more bathrooms and bedrooms command higher prices. In Model 4, each additional bathroom is associated with an increase of approximately \$308,124, while each additional bedroom adds around \$26,605. This implies that bathrooms contribute more to perceived property value than bedrooms. Using the Bronx as the reference group, Queens is associated with a significantly higher average housing price—about \$332,458 more—while Brooklyn shows a negative coefficient of roughly \$125,099, indicating lower prices compared to the Bronx after controlling for all other factors.

The adjusted R^2 rises from 0.059 in the baseline model to 0.212 in the full model, indicating improved explanatory power as controls are added. The consistently strong F-statistics also support the overall fit of the models.

Overall, the regression results confirm that STR density is a robust and meaningful predictor on housing prices in New York City. As more properties are diverted to short-term rental use, the supply of long-term housing contracts, placing upward pressure on prices and reducing affordability.

Modeling Price Volatility

$$\text{Volatility}_i = \gamma_0 + \gamma_1 \cdot \text{STRDensity}_i + \gamma_2 \cdot \text{Price}_i + \gamma_3 \cdot \text{Bedrooms}_i + \gamma_4 \cdot \text{Bathrooms}_i + \delta_{\text{City}_i} + \epsilon_i$$

Table 5: Regression Table on Short-Term Rental Density and Housing Price Volatility

	<i>Dependent variable: price_volatility</i>			
	Baseline (1)	Property Controls (2)	Market Trends (3)	Full Model (4)
C(city)[T.Brooklyn]				-0.082*** (0.000)
C(city)[T.Manhattan]				0.011*** (0.000)
C(city)[T.Queens]				0.399*** (0.000)
C(city)[T.Staten Island]				0.041*** (0.000)
Intercept	0.088*** (0.002)	0.101*** (0.003)	0.103*** (0.003)	0.068*** (0.000)
airbnb_density	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
bath		0.004** (0.002)	0.001 (0.002)	-0.000*** (0.000)
bed		-0.007*** (0.001)	-0.007*** (0.001)	-0.000* (0.000)
price			0.000*** (0.000)	-0.000*** (0.000)
Observations	4288	3872	3872	3872
R^2	0.108	0.126	0.134	1.000
Adjusted R^2	0.108	0.125	0.133	1.000
Residual Std. Error	0.086	0.083	0.082	0.000
F Statistic	518.774***	185.126***	149.408***	6100261701165939425280.000***

Note: *p<0.1; **p<0.05; ***p<0.01

This analysis now turns to housing price volatility as the outcome of interest, using a similar modeling structure as in the previous section. The dependent variable here is the price volatility index, and the focus is on whether STR activity contributes to instability in long-term housing prices.

According to the four models, short-term rental (STR) density has a consistent, positive, and statistically significant relationship with price volatility. In the full model (Model 4). For instance, each additional STR listing per square kilometer is associated with an increase of approximately 0.001 in price volatility. While several variables are statistically significant, some have coefficients close to zero—indicating that their effects, though statistically detectable, are not economically meaningful.

Using the Bronx as a baseline for borough-level comparisons, Queens exhibits the largest increase in volatility, with a coefficient of 0.399, while Brooklyn shows a decrease of 0.082. Manhattan and Staten Island also show statistically significant but smaller increases in volatility.

Overall, the regression models in Tables 4 and 5 show that STR density is positively associated with both housing prices and price volatility. For instance, each additional STR density unit increase is associated with an increase of approximately \$4784.46 in price. While the table 5 identify statistically significant relationships between STR density and price volatility, the economical explanatory power remains limited. In Tables 4 and 5, we observe low R-squared values. This is because housing prices and volatility are influenced by many other unobserved factors, such as noise pollution [4] and natural hazards [9], which we did not introduce into the regression.

Machine Learning vs. OLS Regression

In addition to the OLS regression, a regression tree and random forest model were applied to examine nonlinear patterns in the data.

As shown in Figure 6, the regression tree reveals a clear threshold effect: A sharp price increase when the number of bathrooms exceeds two and Airbnb density rises above 236, which are not captured by linear models. These splits highlight interaction effects between housing characteristics and STR density that influence rental prices in a segmented way. Additionally, it suggest that STR effects may intensify only beyond certain levels of market saturation, particularly in areas where short-term rentals are dense enough to significantly constrain long-term housing supply.

Figure 7 shows that the random forest model supports the OLS findings by identifying STR density as the most important predictor of rental price, followed by the number of bathrooms and bedrooms.

Unlike OLS, the random forest does not rely on p-values, offering a model-agnostic measure of variable importance. Together, the machine learning models confirm the central role of STR activity in shaping price patterns, while providing a more flexible view of how housing features interact.

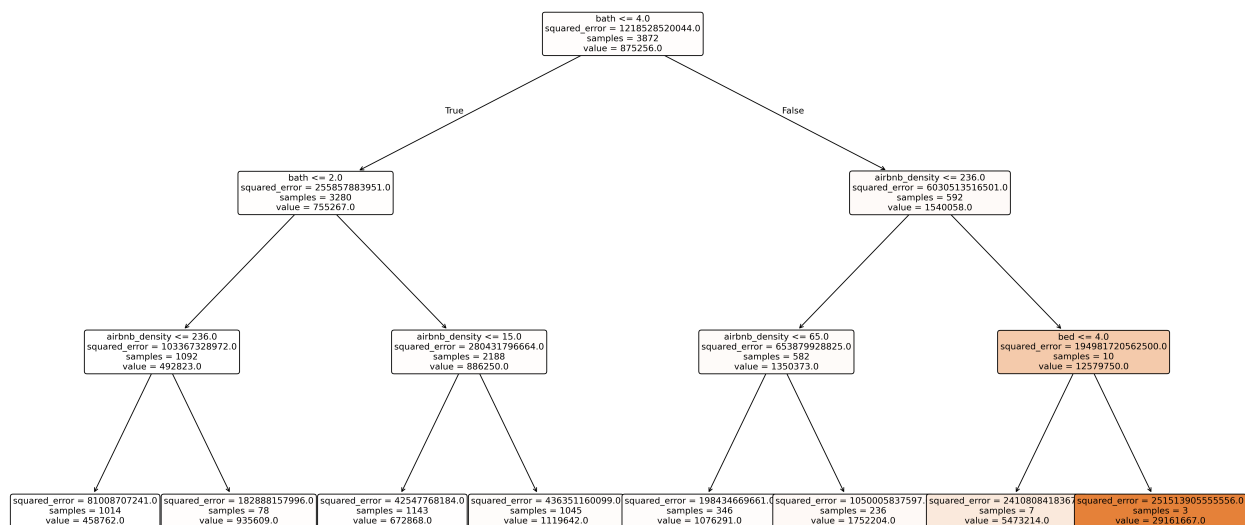


Figure 6: Regression Tree of Predicting Rental Price

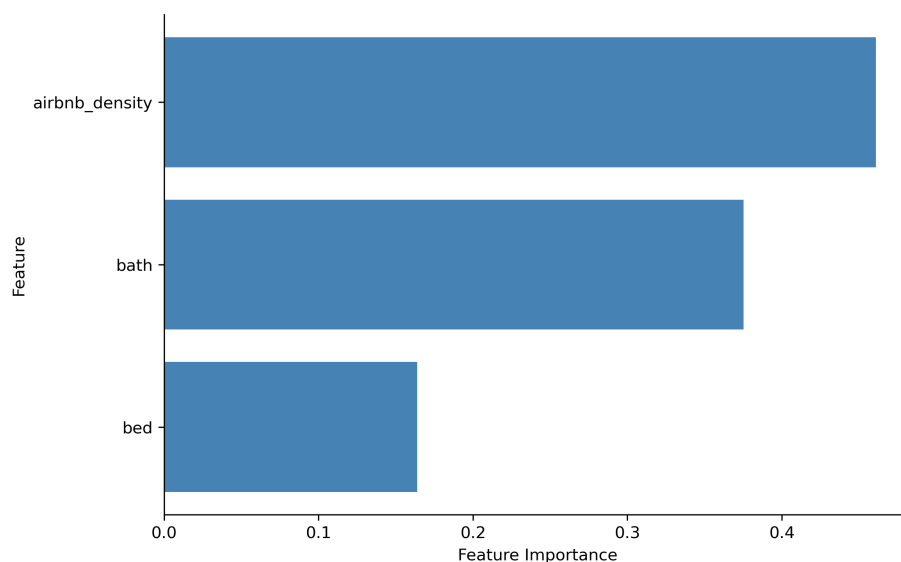


Figure 7: Random Forest Feature Importance (Predicting Rental Price)

Conclusion

In this paper, we show that the concentration of short-term rentals (STRs), particularly through platforms like Airbnb, is positively associated with higher long-term housing prices in New York City. This relationship holds across multiple model specifications, including OLS regressions with borough fixed effects and machine learning models such as regression trees and random forests. These results suggest that increased STR density places measurable upward pressure on housing prices, especially in high-demand boroughs like Manhattan and Brooklyn. For instance, the full OLS model estimates that each additional STR listing per square kilometer is associated with a \$4,784 increase in housing price, holding other factors constant. Property characteristics such as the number of bedrooms and bathrooms also play a significant role; each additional bathroom contributes approximately \$308,124 to the price, while each bedroom adds about \$26,605. Queens stands out as the borough with the largest positive price differential relative to the Bronx, with an estimated coefficient of \$332,458.

While our analysis also explored the relationship between STR activity and price volatility, the evidence there was weaker—statistically significant in some models but economically modest, and inconsistent across methods. In the volatility models, each unit increase in STR density is associated with a small rise in price volatility (about 0.001), suggesting that although the direction of the effect is consistent, the practical impact is limited. Additionally, some boroughs showed contrasting effects—for example, Brooklyn was associated with a reduction in volatility compared to the Bronx, while Queens showed a sizable increase.

Our findings imply that housing affordability in urban markets is affected not only by underlying property characteristics but also by the reallocation of housing stock into short-term rental markets. If STR activity continues to grow, housing prices may remain elevated or accelerate further, especially in areas with constrained supply. If STR regulations are tightened or platform activity slows, affordability pressures may ease. Geographical visualizations reinforce these findings: boroughs with high STR density—particularly central Manhattan and parts of Brooklyn—also exhibit elevated median prices and more intense

price variation. These spatial patterns align with the regression results, indicating that STR density and housing market outcomes are geographically clustered.

Given the role of STR platforms in shaping both housing availability and price structure, policy interventions—such as STR registration, caps on density, or localized taxation—may be needed to preserve long-term rental stock. The effectiveness of such interventions, along with the evolving response of the housing market, will be critical areas for future research and policymaking.

Appendix

References

- [1] AirDNA. (2023). *Why Airbnb’s 2023 summer release focuses on private rooms*. AirDNA Blog. Retrieved from <https://www.airdna.co/blog/why-airbnbs-2023-summer-release-focuses-on-private-rooms>
- [2] Barron, K., Kung, E., & Proserpio, D. (2019). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science*, 40(1), 23–47. <https://doi.org/10.1287/mksc.2020.1232>
- [3] Federal Reserve Bank of St. Louis. (n.d.). *Median sales price of houses sold for the United States* [Data set]. FRED. Retrieved February 6, 2025, from <https://fred.stlouisfed.org/series/MSPUS>
- [4] Filippas, A., & Horton, J. J. (2023). *The tragedy of your upstairs neighbors: The negative externalities of home-sharing platforms*. Retrieved from <https://apostolos-filippas.com/papers/airbnb.pdf>
- [5] Gomonov, D. (n.d.). *New York City Airbnb Open Data* [Data set]. Kaggle. Retrieved from <https://www.kaggle.com/datasets/dgomonov/new-york-city-airbnb-open-data>
- [6] Koster, H. R. A., van Ommeren, J., & Volkhausen, N. (2024). The impact of short-term rental activity on house prices. *Annals of Regional Science*. <https://doi.org/10.1007/s00168-024-01122-3>
- [7] Lanfear, C., & Kirk, D. (2024). The promise and perils of the sharing economy: The impact of Airbnb lettings on crime. *Criminology*, 62(1), 123–145. <https://onlinelibrary.wiley.com/doi/10.1111/1745-9125.12383>

- [8] Mondragon, J. A., & Wieland, J. F. (2022). *Housing demand and remote work* (NBER Working Paper No. 30041). National Bureau of Economic Research. <https://doi.org/10.3386/w30041>
- [9] Mueller, J. M., Loomis, J. B., & González-Cabán, A. (2009). Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. *The Journal of Real Estate Finance and Economics*, 38(2), 155–172. <https://doi.org/10.1007/s11146-007-9083-1>
- [10] Sakib, A. S. (n.d.). *USA Real Estate Dataset* [Data set]. Kaggle. Retrieved from <https://www.kaggle.com/datasets/ahmedshahriarsakib/usa-real-estate-dataset>
- [11] Texas 2036. (n.d.). *Are institutions to blame for high housing prices?* Retrieved from <https://texas2036.org/posts/are-institutions-to-blame-for-high-housing-prices/>
- [12] Trojanek, R. (2023). How do different noise pollution sources affect apartment prices? *International Journal of Strategic Property Management*, 27(6), 351–361. <https://doi.org/10.3846/ijspm.2023.20563>
- [13] Wachsmuth, D., Kerrigan, D., Chaney, D., & Shillolo, A. (2018). *The high cost of short-term rentals in New York City*. McGill University, Urban Politics and Governance Research Group. <https://www.mcgill.ca/newsroom/files/newsroom/channels/attach/airbnb-report.pdf>