A Model for Monthly, Local-Level Airbnb Changes Using Public Dataset

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Abstract: This study presents a novel methodological framework for estimating monthly variations in Airbnb listings across Seoul's administrative districts from 2017 to 2019, leveraging publicly available datasets. The proposed model integrates key factors such as housing supply, lodging unit density, proximity to tourist attractions, and retail sector activity, using negative binomial regression to quantify their impact on Airbnb dynamics. Our analysis demonstrates significant variations in these effects across different districts, with the model achieving superior statistical accuracy (average Pseudo R^2 of 0.7922) compared to baseline approaches. These findings underscore the utility of using accessible, timely data for capturing short-term rental market trends and highlight the model's potential applicability in diverse urban tourism settings. The research contributes valuable insights for tourism management, helping to develop policies that align with sustainable tourism growth and local economic development. The results indicate that proximity to major tourist destinations and the number of foreign visitors are among the most influential factors in determining Airbnb activity, highlighting the strong connection between short-term rentals and tourism demand. Lodging unit density and retail composition also play significant roles in shaping the distribution of Airbnb listings, suggesting that tourism infrastructure and commercial activity are key determinants of short-term rental market expansion. The study finds that certain districts experience high Airbnb concentrations due to their tourism appeal, whereas others exhibit minimal short-term rental activity, reflecting the heterogeneous nature of urban tourism accommodation demand. Our monthly regression analysis captures dynamic fluctuations in Airbnb listings, addressing the limitations of traditional models that rely on annual data. This research has critical implications for tourism stakeholders, including policymakers, destination managers, and hospitality businesses. By incorporating real-time, publicly available datasets, our approach facilitates responsive and data-driven decision-making to manage the short-term rental market effectively while fostering sustainable tourism growth. Future studies can extend this model to other urban contexts to explore how different socio-economic and regulatory environments influence short-term rental patterns. The adaptability of this methodology makes it a valuable tool for ongoing research in tourism analytics and policies.

Keywords: Urban tourism, Short-term rentals, Airbnb, Tourism accommodation, Spatial analysis, Public data

1. Introduction

Over the past decade, Airbnb has emerged as a pivotal model enabling new local tourism cultures (Adamiak et al., 2019, Guttentag, 2015). New dynamics of Airbnb cause the trend how the supply and demand of tourism accommodation have been changed in the area (Kadi et al., 2022, Stors, 2022, Petruzzi et al., 2020). Due to the easy online platform registration and management process, Airbnb hosts are sensitive to their surroundings (Gibbs et al., 2018). Day-to-day changes of pricing, revenue, and number of listings are more fluctuating than legacy accommodation (Wang et al., 2024). Rapid changing trends of Airbnb in the local area impact not only tourism but also housing markets (Jordan and Moore, 2018, Palos-Sanchez and Correia, 2018, Avdimiotis and Poulaki, 2019). There are significant concerns among urban planners and policymakers noticing such impacts: the transformation of properties traditionally reserved for long-term residency into accommodation units; a subsequent reduction in the housing supply without a corresponding decline in housing demand; and an increasing propensity for housing rent prices to escalate, driven by competition with established accommodation facilities (Wachsmuth and Wisler, 2018, Hassanli et al., 2022, Crommelin et al., 2020). With increasing worries on these rapid changes of Airbnb that might cause distruption of long-term and sustainable market policy, monitoring and predicting the Airbnb changes have been required by policymakers and urban planners (Wegmann and Jiao, 2017, Tang and Sangani, 2015, Luo et al., 2019, Quattrone et al., 2018).

Thus, there are pressing needs to develop a predictive model for understanding Airbnb changes. Given the rapid pace of change in the short-term rental market, however, collecting relevant data in spatially and temporally fine-grained level is challenging (Wang et al., 2023). Existing models face several limitations (Ki and Lee, 2019, Morris, 2019).

- Data Availability: Traditionally, accessing Airbnb-related data (e.g., transaction data) has been difficult due to its proprietary nature. Platforms like AirDNA offer some insights, but reliance on publicly available data remains crucial for broader accessibility and research (Gy´odi, 2023).
- Short-Term Predictability: Most existing models are designed to reflect changes on an annual basis, which is insufficient for capturing the dynamic nature of Airbnb. There is a need for models capable of estimating more short-term, monthly variations (Jain et al., 2021, Wang et al., 2023, Chen et al., 2021).
- Local-Level Predictability: these models often operate at a city-wide level, failing to capture the concentrated nature of Airbnb activity in specific districts, particularly in high-demand urban centers (Morris, 2019, Garcıa-Lamarca, 2021, Sykora and Spackova, 2022). Collecting and utilizing data at smaller geographic scales, such as census tracts, remains a significant challenge.

Inspiring approach tries to examine the spatial distribution of Airbnb in local level, by using public data (Ki and Lee, 2019, Voltes-Dorta and Sanchez-Medina, 2020, Perez-Sanchez et al., 2018). By incorporating neighborhood-level variables and publicly available statistics, they highlighted the importance of local environmental factors in explaining Airbnb distribution.

This study aims to develop a model utilizing publicly available datasets to estimate the number of Airbnb listings at the local district level on a monthly basis. Our approach focuses on several key areas to achieve this goal. First, we will analyze how local variables such as housing supply changes, shifts in the accommodation industry, commercial area developments, and fluctuations in tourist arrivals influence local Airbnb trends (Eugenio-Martin et al., 2019, Adamiak et al., 2019). By considering these factors, we aim to account for the inherent characteristics of housing-based Airbnb and their impact on the local environment.

Second, we seek to refine our model to estimate monthly changes in Airbnb listings. This will allow us to capture the rapid and dynamic nature of the Airbnb market, providing more timely and relevant insights for stakeholders (Wegmann and Jiao, 2017). Accurate monthly forecasting is essential for understanding the short-term fluctuations and immediate impacts of Airbnb on local tourism dynamics.

Finally, the model aims to inform policymakers and tourism managers, offering a robust tool to balance tourism demand with stable supply and community sustainability (Nieuwland and Van Melik, 2020, Pareja-Eastaway and Sanchez-Martinez, 2022). By providing actionable insights, we hope to support the development of effective policies that address the challenges posed by the rapid growth of Airbnb, ensuring sustainable tourism development and harmonious coexistence with local communities.

2. Methodology

2.1 Research Area and Data Source

This study develops a methodological approach to analyze monthly changes in Airbnb listings at a local district level, utilizing publicly available and frequently assessed datasets.

We select Seoul, Korea, as our research site due to its diverse range of urban districts and tourism patterns. With 9 million inhabitants, the city features varying levels of tourism demand across districts, making it suitable for studying short-term rental market dynamics. The absence of Airbnb-targeted regulations in Seoul allows for an examination of natural market dynamics, potentially mirroring other cities with similar policy environments. This aspect enhances the generalizability of our findings.

We collect Airbnb data from AirDNA[1], which provides monthly hosting information related to Airbnb listings (Wang et al., 2023). The public data policy of Seoul facilitates detailed analysis through access to spatio-temporal data, including smartphone-assessed population distribution[2], public transportation records[3], and annual censuses for housing, economy, and population changes[4].

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[1] Available at https://www.airdna.co/ (accessed 27 Nov 2024)

[2] Available at https://data.seoul.go.kr/dataVisual/seoul/seoulLivingPopulation.do (accessed 27 Nov 2024)

[3] Available at https://data.seoul.go.kr/dataList/OA-12914/A/1/datasetView.do (accessed 27 Nov 2024)

[4] Available at https://www.census.go.kr/ (accessed 27 Nov 2024)

Our analysis spans three years (2017-2019), allowing us to study time-series changes in the Airbnb market. This timeframe, which excludes the pandemic period, captures a phase of rapid growth and transformation in Seoul's tourism sector, providing insights into the interplay between Airbnb and urban tourism dynamics. The analysis covers 421 administrative districts of Seoul, as illustrated in Figure 1.

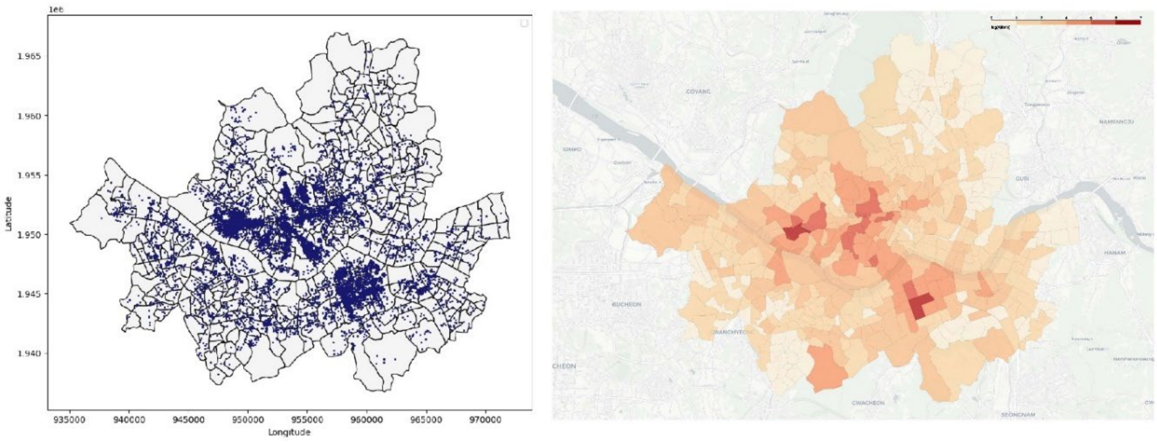

Figure 1: Spatial distribution of Airbnb in 421 administrative districts, Seoul, Korea. (Left) Location of Airbnb listings in Jan. 2017; (Right) Airbnb counts in districts from 2017 to 2019 (log scale)

2.2 Metric for Housing-Related Airbnb

In examining the changes in Airbnb listings within a local district, our analysis focuses on specific Airbnb transformed from residential properties. This approach acknowledges the significant difference between the impacts of various types of short-term rental properties on the housing market.

The original dataset obtained for this study comprises monthly records of Airbnb listings. Within this dataset, a key methodological step involved distinguishing between listings directly related to the housing market and those not. To achieve this, we categorized the listings based on their property type in Table 1. Listings that were classified as traditional accommodation facilities, such as hotels, were excluded from the analysis. This exclusion is based on the rationale that such property types, while part of the broader short-term rental market, do not directly reflect the dynamics of the housing market and thus may not accurately represent the impact of Airbnb on residential housing.

The focus of this study is on Airbnb listings operated in properties that are primarily residential – what we refer to as ’housing-related’ Airbnb properties. This categorization allowed us to hone in on the segment of the Airbnb market that most closely intersects with, and potentially influences, the residential housing sector. For each administrative district in Seoul, we calculated the monthly counts of these housing-related Airbnb listings. These counts were then treated as the dependent variable in our analysis, labelled ‘the number of Airbnb listings (Airbnb counts)’.

Table 1: Property types in Airbnb dataset

Property type	Record in dataset	Counts	Ratio(%)
Housing-related	Entire apartment, Private room in house, House, Private room in apartment, etc.	1,544,270	75.8
Hotel-related	Room in hotel, Hostel, Guesthouse, Room in boutique hotel, Resort, Condominium (condo), Condo, etc.	476,751	23.4
Other type	Cabin, Place, Camper/RV, Bungalow, Tower, Barn, Bus, etc.	16,298	0.8

2.3 Variable Selection

Our regression analysis incorporates variables that influence Airbnb listing patterns within specific regions. The selection, detailed in Table 2, emphasizes variables with shorter assessment periods to capture temporal dynamics accurately. For housing characteristics, we include the number of residential units in each district from annual censuses. Local economic factors, including retail stores and lodging units, are processed as ratio values relative to the total number of industries in each district.

Table 2: Descriptive Statistics of Variables

Variable	Mean	Median	Std Dev.	Min	Max
No. of Airbnb listings	20.81	6.00	73.46	0.00	2,386.00
No. of housing units	7,078.64	6,747.00	3,157.47	6.00	19,814.00
Ratio of lodging units	0.01	0.01	0.01	0.00	0.13
Ratio of retail stores	0.20	0.19	0.07	0.02	0.59
Avg. proximity to tourism places	0.01	0.01	0.02	0.01	0.36
No. of foreign visitors	612.01	157.12	1,792.72	11.32	34,582.21

A significant factor in analyzing Airbnb patterns is the accessibility to major tourist attractions. Areas with better access to these sites typically show higher Airbnb activity. We quantify this by measuring the distance from each district to ten major tourist destinations designated by the Korea Tourism Organization. To account for seasonal trends and changing preferences, we incorporate a weighting factor based on monthly public transportation usage at these locations.

Additionally, we include the number of foreign visitors in each district, measured through smartphone-sensing location data, as an indicator of international tourism activity. This variable provides insights into tourism patterns that may influence short-term rental market dynamics.

2.4 Statistical Analysis of Monthly Airbnb Patterns

Our analysis examines monthly changes in Airbnb listings using concurrent independent variables. We conduct monthly regression analyses from January 2017 to December 2019, allowing us to understand the dynamic nature of the short-term rental market.

We employ negative binomial regression due to the overdispersion characteristic of our dependent variable (Airbnb counts). This approach is particularly suitable for count data where variance exceeds the mean. The independence of Airbnb counts across districts ensures our analysis captures distinct local characteristics without cross-contamination.

The regression equation is formulated as:

$$\log(\mu_{i,t+1}) = \beta_0 + \beta_1 H_{it} + \beta_2 \left(\frac{L_{it}}{I_{it}}\right) + \beta_3 \left(\frac{R_{it}}{I_{it}}\right) + \beta_4 A_{it} + \beta_5 F_{it} \tag{1}$$

where,

- $\mu_{i,t+1}$ is the number of Airbnb listings in local district i in next month $t+1$,
- H_{it} denotes the number of residential houses in district i in month t,
- L_{it}/I_{it} represents the ratio of lodging units to all industries in district i in month t,
- R_{it}/I_{it} signifies the ratio of retail stores to all industries in district i in month t
- A_{it} indicates the proximity to tourism places in district i in month t,
- F_{it} is the number of foreign visitors in district i in month t,
- I_{it} is the total number of industries in district i in month t,
- β_0 is the intercept, and
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the coefficients for the respective independent variables.

To ensure robust results, we conducted a Variance Inflation Factor (VIF) test to address multicollinearity, setting a threshold of 5 for all variables. We compare our results with a baseline model from Ki and Lee (2009), which considers various housing, neighborhood, and tourism factors at the local level.

3. Results

3.1 Monthly Changes of Airbnb in Local Districts

The temporal dynamics of Airbnb listings across the administrative districts of Seoul are illustrated in Appendix Figure 1. These visual representations provide a clear picture of the changing landscape of Airbnb presence from 2017 to 2019.

An overall increasing trend in Airbnb listings is observed during this period, indicating a growing influence of the platform within the city's accommodation sector. However, this upward trend is not uniform across all districts. The variation in the number of Airbnb listings in different areas reflects a considerable diversity in how Airbnb has been embraced or developed in these regions. Some districts show a rapid increase in listings, while others exhibit more moderate growth.

Table 3 presents measures of Airbnb distribution across various local districts, encompassing average, standard deviation, minimum, and maximum values of Airbnb listings from 2017 to 2019. The average number of Airbnb indicates a higher concentration of Airbnb listings in districts renowned for their tourist attractions (Appendix Tabel 1). During the research period, the tourist-centric districts exhibited significant fluctuations in Airbnb numbers, with variations ranging from approximately 50% below to 150% above the average at different times, reflecting the dynamic and highly variable nature of the short-term rental market. It is noteworthy that there were a number of districts where the Airbnb count remained at zero throughout the research period, while popular districts near the urban core have a large number of Airbnb. This disparity highlights a pronounced concentration of Airbnb listings in urban core areas, as opposed to peripheral or less tourist-centric districts, underlining the uneven spatial distribution of short-term rental accommodations within the city.

Table 3: Airbnb distribution across local administrative districts in Seoul

District	avg. Airbnb	std.	min	max	avg. houses	intensity
Seogyo	1701.94	344.58	1005	2284	8899	0.27
Yeoksam	534.69	69.35	375	690	13188	0.07
Yeonnam	476.61	146.54	229	739	5256	0.12
Myeongdong	352.53	38.28	253	450	763	0.92
Shinchon	334.42	113.50	147	549	7735	0.10
Cheongpa	333.92	79.29	147	502	6110	0.08
Itaewon-1	265.97	37.94	180	329	1960	0.15
Namyeong	250.81	22.42	183	279	2646	0.16
Jongno	231.72	30.68	144	317	2857	0.20
Hoehyeon	225.33	14.00	202	251	1710	0.18
...	...	...	...	...	...	...
Geoyeo-1	0.00	0.00	0	0	3404	0.00
Sanggye-8	0.00	0.00	0	0	8768	0.00
Siheung-4	0.00	0.00	0	0	5744	0.00
Sangmun-2	0.00	0.00	0	0	6319	0.00

3.2 Analysis of factors influencing local Airbnb

We examined the stability of our regression analysis and the explanatory power of each variable. The analysis results (Pseudo R^2 = 0.8093) presented in Table 4 offer detailed insights into the factors associated with Airbnb listings in Seoul, analyzing data from December 2019 to understand patterns in January 2020. Each independent variable shows a statistically significant correlation with the number of Airbnb listings. Variance Inflation Factor (VIF) values below 5 for all independent variables suggest that multicollinearity is not a concern in this analysis (Table 4). This statistical significance confirms the robustness of our approach and the reliability of the variables in explaining variations in Airbnb patterns.

Our regression analysis over the 36-month period reveals nuanced dynamics between Airbnb listings and various urban factors in Seoul. The number of residential houses in a district shows a consistent positive correlation with Airbnb listings, though with a modest impact (average coefficient value = 0.000127). This suggests that while housing availability supports Airbnb activity, it is one of several factors influencing Airbnb's presence.

Table 4: Variables of our model that correlates with Airbnb in January 2020

Coefficient	Estimate	Std. Error	z value	Pr(> |z|)	VIF
Constant	0.7038	0.2314	3.0416	0.0024	-
residential houses	0.0001	0.0000	6.7036	<0.0001	3.7212
lodgings	32.9637	4.0727	8.0938	<0.0001	1.3971
retail stores	-1.7752	0.7986	-2.2230	0.0262	4.4912
proximity to tourism places	71.3362	4.2428	16.8136	<0.0001	3.5886
foreign visitors	0.0004	0.0000	10.1854	<0.0001	2.6005

Notably, the effect of lodging units strengthened over time, with coefficient values increasing from 19.93 to 32.96 during the study period (Figure 2). This trend underscores a growing synergy between Airbnb listings and the broader tourism and hotel industry in Seoul, suggesting Airbnb's increasing integration into the city's accommodation sector.

Proximity to tourist places remains a decisive factor, with a strong positive average coefficient of 76.35, indicating that districts near tourist sites are prime areas for Airbnb listings. This persistent trend underscores the direct connection between tourist activities and the demand for short-term accommodations, a finding consistent with expectations.

The number of foreign visitors also proves to be significant, as indicated by consistently low p-values, well below the 0.001 threshold, across the study period. The coefficient for foreign visitors, while showing slight variations, averages at 0.000428, suggesting a positive but modest influence on Airbnb listings in a district. This reveals a tangible, albeit nuanced, impact of international tourism on the demand for Airbnb, highlighting the platform's role in accommodating global visitors.

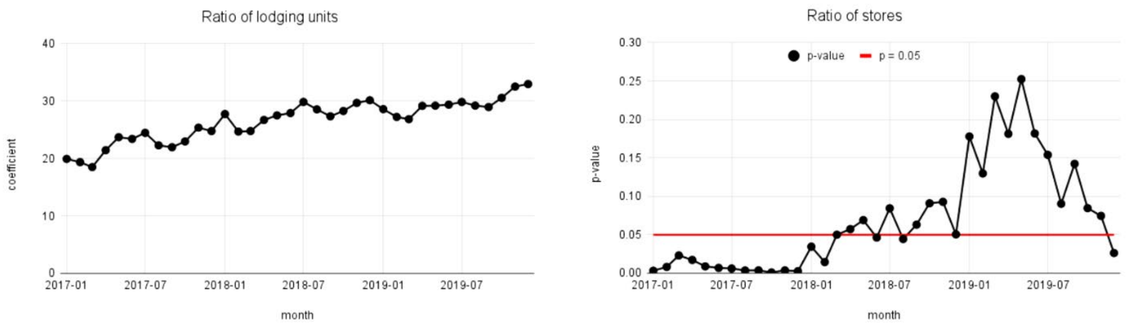

Figure 2: (Left) Coefficient of variable 'ratio of lodging' for 36 months, (Right) p-value of variable 'ratio of stores' for 36 months

3.3 Comparative Analysis of Model Performance

The performance of our model, as depicted in Figure 3, consistently outperforms the baseline across the study period from February 2017 to January 2020 (representing predicting months). A comparative analysis of the monthly performance reveals that our model demonstrates a higher average Pseudo R^2 of 0.7922 compared to the baseline's average of 0.7125. This improved performance is indicative of our model's enhanced predictive accuracy and its capability to more effectively capture the dynamics of Airbnb count fluctuations.

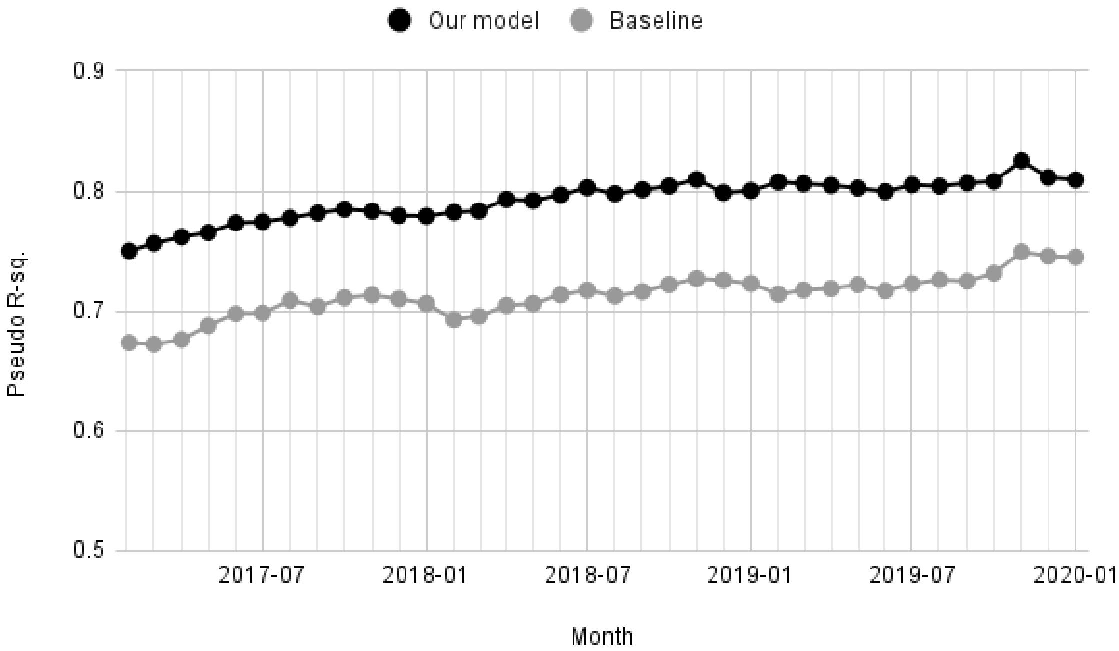

Figure 3: Comparing Pseudo R^2 of baseline and our model for 36 months

Additionally, goodness-of-fit measures including deviance and Pearson χ2 show improvement over the baseline approach. These statistical measures reflect our model's closer fit to the observed data. Lower deviance and Pearson χ2 values suggest more accurate representation of the underlying patterns.

This monthly regression analysis underscores our approach's effectiveness in capturing the dynamic nature of the short-term rental market. The consistent statistical performance over an extended period highlights its value as an analytical tool for tourism managers and policymakers, offering reliable insights for understanding urban tourism and short-term rental market patterns.

4. Conclusion

Our examination of Airbnb's impact on local tourism from 2017 to 2019 reveals complex patterns in how this platform integrates into urban tourism landscapes. By analyzing monthly data across Seoul's administrative districts, we shed light on the spatial and temporal dynamics of short-term rentals, using readily available public datasets to understand these evolving patterns.

The analysis reveals intricate relationships between Airbnb presence and various urban characteristics. Housing stock, lodging infrastructure, retail density, tourist site proximity, and tourism visitor flows all shape Airbnb distribution, though their influence varies markedly across districts. Our statistical approach proved particularly effective at capturing these local variations, achieving stronger explanatory power (Pseudo $R^2 = 0.7922$) than previous methods (0.7125). This improvement reflects our success in capturing the better ways Airbnb integrates into different urban contexts.

These findings carry significant implications for tourism research and practice. They demonstrate how data-driven approaches can illuminate the complex ways sharing economy platforms reshape urban tourism. Our methodology offers tourism managers and policymakers a clearer view of how short-term rentals interact with local tourism dynamics, enabling more targeted and responsive policy interventions.

Yet our study faces certain constraints. Its replication elsewhere depends heavily on access to specific data sources, particularly smartphone-based visitor tracking, which may not be available in all cities. Future research could valuably extend this work to other urban contexts, examining how Airbnb's impact varies under different socio-economic and regulatory conditions. Scholars might also explore the long-term effects of Airbnb on tourism development and neighborhood character. The COVID-19 pandemic's profound disruption of travel patterns opens another important avenue for research, as changing tourist behaviors may reshape the short-term rental market in ways that demand policy adaptation.

This investigation advances tourism management while providing practical tools for addressing the challenges posed by short-term rental platforms. Our use of public datasets demonstrates how researchers can overcome data access barriers through innovative methodological approaches. The integration of fine-grained temporal data with statistical analysis creates a framework adaptable to diverse urban settings, deepening our understanding of how short-term rentals reshape tourism landscapes.

In an era of rapid change in urban tourism, evidence-based analysis becomes increasingly vital for effective planning and policy-making. As cities continue evolving, our analytical approaches must keep pace with the changing dynamics of platform-mediated tourism. This study represents a step toward more accessible, empirically grounded tourism research, offering insights that can help cities better manage the growing complexity of their short-term rental markets.

Data availability

The local population and foreign tourists data that support the findings of this study are available in Seoul Open Data Platform at [https://data.seoul.go.kr/], These data were derived from the following resources available in the public domain: [https://data.seoul.go.kr/dataVisual/seoul/seoulLivingPopulation.do]

The public transportation data that support the findings of this study are available in Seoul Open Data Platform at [https://data.seoul.go.kr/], These data were derived from the following resources available in the public domain: [https://data.seoul.go.kr/dataList/OA-12914/A/1/datasetView.do]

The housing and industry data that support the findings of this study are available in Statistics Korea at [https://kostat.go.kr/]. These data were derived from the following resources available in the public domain: [https://sgis.kostat.go.kr/view/pss/openDataIntrcn]

The Airbnb data that support the findings of this study are available from AirDNA at [https://www.airdna.co/]. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at [https://www.airdna.co/] with the permission of AirDNA.

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AI declaration: The authors report there are no use of AI tool in this research.

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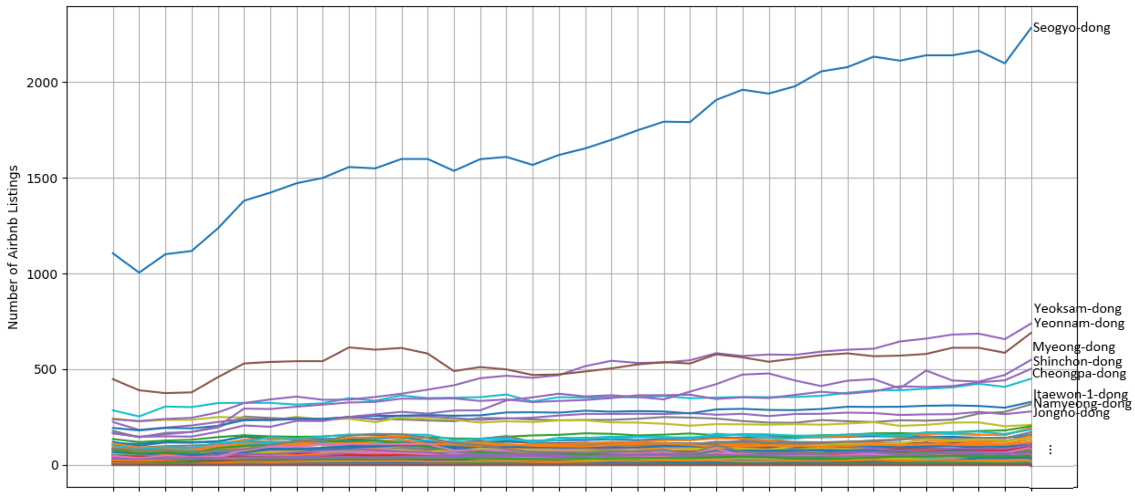
Appendix

Appendix Table 1: Characteristics of Top 10 districts in Seoul

Rank	District code	District	Characteristics
1	11140660	Seogyo	Vibrant arts and culture scene
2	11230640	Yeoksam	Hipster haven with lively cafes
3	11140710	Yeonnam	Dynamic business and tech hub
4	11020550	Myeongdong	Tourism and nightlife Hub
5	11130750	Shinchon	Quiet residential with historic sites
6	11030710	Cheongpa	Train station and tourism spot
7	11030650	Itaewon-1	Diverse and international nightlife
8	11030530	Namyeong	Guest houses with local charm
9	11010610	Jongno	Historic center of Seoul
10	11020540	Hoehyeon	Traditional markets and culture



Appendix Figure 1: Monthly trend of Airbnb listings in every administrative districts in Seoul