THE CONTROVERSY BETWEEN AIRBNB SHORT-TERM RENTALS AND NOISE COMPLAINTS

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May 11, 2025

Final Project Components

1. Introduction

1.1. Problem

In recent years, New York City has faced growing concerns about neighborhood noise, housing insecurity, and the social impact of short-term rentals. With nearly 5 million adults reporting hearing loss and ringing in their ears, while 1 in 5 residents frequently disturbed by noise at home, the city's soundscape has become a significant public health and quality of life issue. Additionally, New York City welcomed 62.2 million visitors in 2023, further contributing to urban noise levels.

The rapid growth of the short-term rental market has changed the acoustic environment of urban neighborhoods, especially the cities like New York where tourism, housing, and density intersect. New York City residents have made numerous complaints that Airbnb short-term renters negatively impact the environment of their communities, particularly with regard to neighborhood noise. Platforms like Airbnb provide new economic opportunities for property owners and tourists but also raise issues about community environmental quality.

1.2. Policy Background

As cities with these complex problems, regulated policy become more important. New York City passed Local Law 18, aiming to regulate Airbnb and restore peace to residential neighborhoods.

The law requires all short-term rental hosts to register with the city's Office of Special Enforcement (OSE), and prohibits booking platforms such as Airbnb from processing transactions for unregistered rentals. Since September 2023, platforms must verify each listing through the city's official system, ensuring that only authorized short-term rentals remain active. The law also maintains a list of prohibited buildings and exempts only legally classified Class B dwellings used for stays of 30 days or more.

Since the enactment of Local Law 18, the impact on New York City's short-term rental landscape has been swift and significant. Reports indicate that the number of legal short-term listings has sharply declined, with enforcement measures removing thousands of unregistered Airbnb units from the market. Many people believe that implementation of stricter regulations could significantly reduce the scenario of noise compliance issues as long as the amount of short rentals decrease in New York City.

1.3. Motivation

However, whether short-term rentals are related to noise complaints remains an open question. Our research aims to explore whether the decrease in short-term rental activity, prompted by the enforcement of Local Law 18, is accompanied by any observable changes in the residential sound environment. We use 311 noise complaints as a proxy to assess shifts in neighborhood living conditions. The goal is not to evaluate the effectiveness of a specific policy but to contribute to a growing conversation about how cities can meaningfully balance economic, tourism and residential well-being.

Research Question: Is there a correlation between the reduction in Airbnb short term rentals and changes in 311 noise complaints under the LL18 impact?

1.4. Definition of key terms :

a. **Short-Term Rental (STR):** Airbnb short-term rentals: Properties listed on Airbnb for rental periods of fewer than 30 days. (minimum_nights_x<30).
b. **Room Type:** this one explanation based on the airbnb codebook.According to the Inside Airbnb data dictionary, all listings are categorized into three main room types: **Entire place**, **Private room**, and **Shared room**.
    i. **Entire places** are best if you're seeking a home away from home. With an entire place, you'll have the whole space to yourself. This usually includes a bedroom, a bathroom, a kitchen, and a separate, dedicated entrance. Hosts should note in the description if they'll be on the property or not (ex: "Host occupies first floor of the home"), and provide further details on the listing.
    ii. **Private rooms:**Private rooms are great for when you prefer a little privacy, and still value a local connection. When you book a private room, you'll have your own private room for sleeping and may share some spaces with others. You might need to walk through indoor spaces that another host or guest may occupy to get to your room.
    iii. **Shared rooms:** Shared rooms are for when you don't mind sharing a space with others. When you book a shared room, you'll be sleeping in a space that is shared with others and sharing the entire space with other people. Shared rooms are popular among flexible travelers looking for new friends and budget-friendly stays.
c. **311 noise complaints:** Reports submitted to NYC's 311 system regarding noise disturbances, including residential, commercial, and traffic-related noise.
d. **Local Law 18 (LL18):** A regulation enacted by NYC in September 2023 that imposes strict limitations on short-term rentals, effectively reducing Airbnb listings.
e. **Neighborhood Living Environment:**
   The overall quality of life and residential experience within a neighborhood, often influenced by factors such as noise levels, population density, and housing stability.

1.5. Intended Audience

Our research is intended for a diverse audience of urban policy stakeholders and scholars. First, it targets urban policy makers particularly those focused on housing regulation, quality-of-life legislation, and neighborhood stabilization. Additionally, researchers in fields such as urban planning, public health, and data science may show interest. Finally, local residents (especially those living in neighborhoods with high STR density), Airbnb hosts and platform operators (who must navigate the evolving legal environment and adapt their rental strategies) are an important group of stakeholders.

2. Literature Review

2.1. Topic Literature review

Urban noise has become a serious concern in dense cities like New York, especially with the rise of short-term rental platforms such as Airbnb. These platforms can bring economic benefits but may also disrupt daily life in residential neighborhoods.

Tripathi (2023) finds that areas with more Airbnb listings, especially commercial ones (like those with instant booking), tend to have more noise complaints. Interestingly, higher-priced listings were linked to fewer complaints, possibly due to better quality or location. In contrast, Ozer et al. (2020) use a difference-in-differences method and discover that Airbnb's entry into neighborhoods is actually associated with fewer residential noise complaints. They suggest that tourists may spend more time outside, shifting noise to public spaces rather than homes.

Chen et al. (2025) look beyond Airbnb and focus on urban design. Their study shows that building density, greenery, and land use affect noise perception, and that these effects vary depending on time of day and season.

Together, these studies show that both short-term rentals and neighborhood design shape the urban noise experience. However, few have studied how recent policies like Local Law 18 impact this. This research adds to the conversation by examining whether limiting Airbnb listings leads to reduced noise in NYC.

2.2. Methodological Review of Prior Research

The four studies provide diverse methodology approaches to explore the relationship between urban noise complaints and Airbnb activity. From Tripathi (2023), we adopt the use of correlation analysis to explore how Airbnb change relates to neighborhood-level noise complaints. In the article of *Noisebnb: An Empirical Analysis of Home Sharing Platforms and Noise Complaints*, Ozer et al.(2020) applied a difference-in-difference(DID) model. We refer to this method as a key example of empirical policy analysis. Chen at al. (2025) used a multi-scale, spatiotemporal analytical framework by incorporating Spearman correlation, Moran's I, and Geographically Weighted Regression (GWR). Tong and Kang (2021) used GIS to implement spatial analysis and correlation testing to examine noise complaint distribution in different boroughs. Together, these methods widen and develop our mixed approach to analyzing the relationship between short-term Airbnb rentals and noise complaints.

3. Design Rationale

To evaluate the impact of short-term rental regulation on neighborhood noise complaints, this study focuses on a limited number of regions. As highlighted in the literature, there are numerous confounding factors that can obscure policy effects across the broader city. Therefore, narrowing the study area allows for more controlled and focused analysis.

We aim to select neighborhoods with high Airbnb density, as these areas are more likely to be directly affected by the policy. In addition, we include adjacent neighborhoods to observe potential spillover effects and spatial heterogeneity in policy impact.

Based on these criteria, we select two regions for analysis:

- **Williamsburg**, representing one of the highest Airbnb densities in the city;
- **Lower East Side**, a nearby neighborhood that allows us to compare effects across boroughs and understand potential differences between Brooklyn and Manhattan.

Based on insights from the literature review, we utilize the paired-sample t-test at a weekly temporal granularity to evaluate whether 311 noise complaints decreased after the policy intervention.

To guide our analysis, we propose the following research hypotheses:

- H1. *The number of Airbnb listings decreased after the implementation of the short-term rental policy.*
  This hypothesis will be tested using the paired t-test to examine whether the policy intervention led to the 311 noise changes.
- H2. *In areas where Airbnb listings decreased following the policy, noise complaints also declined.*
  This hypothesis explores whether there is a relationship between the reduction in short-term rentals and changes in noise complaints, reflecting a potential social effect of the policy.

Further, in order to investigate how the policy impact varies across space, we adopt a **grid-based spatial analysis** using a uniform **500ft × 500ft fishnet grid**. This method addresses potential biases caused by inconsistent geographic units such as zip codes or administrative boundaries, ensuring a more standardized comparison.

4. Data Preparation & Cleaning:

4.1. Data Preparation:

a. **311 Noise Complaints data**: Noise complaint record data between Sep 1 2022 to Aug 31 2024 in the Manhattan study area and the Brooklyn study area from NYC Open Data. (Noise_Complaints_chinatown_22-24.csv, Noise_Complaints_williamsburg_22-24.csv)
b. **Modified Zip Code Tabulation Areas** (MODZCTA) from NYC Open Data
c. **Airbnb Data:** Airbnb listing data in New York City for the years 2023 and 2024 from Inside Airbnb. (NYC-Airbnb-2023.csv, NYC-Airbnb-2024.csv)
d. **Geospatial boundary data:** Study area boundaries (zipcodeboundary_chinatown.geojson; zipcodeboundary_williamsburg.geojson)and treet segment geometries (streetsegment_chinatown.geojson;streetsegment_williamsburg.geojson) from NYC Open Data. Clipped in ArcGIS Pro.

4.2. Data Cleaning:

a. **Noise Complaints Data**

i) Check the missing values and incident zip. Filter the zip code 11211 (Brooklyn study area) and 10002 (Manhattan study area)data. Filter the data with “Noise - Residential”.

ii) Keep the data only with relevant columns: 'Created Date','Closed Date', 'Complaint Type','Descriptor','Borough','Location Type','Latitude', 'Longitude'. Delete the data without geographic information and the duplicate rows. Create a GeoDataFrame based on the cleaned data.

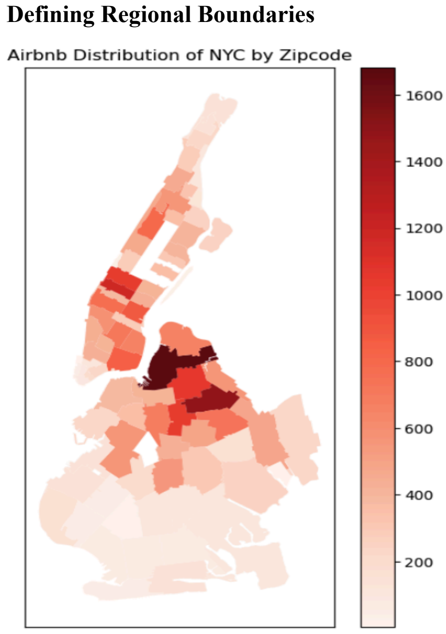
iii) Convert the “Date” column to “Datetime” format, saving it as a new column called `datetime_fmt`. Extract the “date” and ”time”, “month” and “hour” into four new columns: “date_fmt”, “time_fmt”, “month_fmt”, “hour”. Check the coordinate system. Print the minimum and maximum timestamps to confirm the time range.

b. **Airbnb Data**

i) Column Selection: From both raw datasets, we selected the following columns:'id', 'name', 'neighbourhood_group', 'latitude','longitude', 'room_type', 'price', 'minimum_nights','neighbourhood'. The filtered columns were stored in the df_2023 and df_2024 DataFrames.
ii) Merging for Year-over-Year Comparison:To compare listing patterns over time, we merged the 2023 and 2024 datasets by listing ID, keeping price and minimum_nights changes.
iii) Spatial Filtering by ZIP Code: After initial exploratory mapping of Brooklyn, Williamsburg (ZIP code 11211) and the Lower East Side Chinatown (ZIP code 10002) were selected as the study areas for further analysis. After aligning all datasets to EPSG:4326, Airbnb data is cropped by using the boundary geographical data, only the spatial elements in these two areas are retained.
iv) Exporting Cleaned Dataframe: The ‘Manhattan_merged_df’ refers to the full dataset for Manhattan, while ‘Manhattan_final_merged_df’ refers specifically to the cleaned subset for ZIP code 10002. Similarly, ‘merged_df’ represents the complete Brooklyn dataset, and ‘final_merged_df’ is the filtered and cleaned version focusing on the Williamsburg area (ZIP code 11211).
v) Outlier Removal: To better capture the central tendency of the dataset, we applied the IQR method to filter out extreme values. Since our focus is on general patterns rather than outlier behavior, we excluded data below the 25th percentile and above the 75th percentile.

5. Analysis:

5.1. Defining Regional Boundaries



To identify suitable study areas for focused analysis, we began with a borough-wide spatial analysis of Airbnb listings across New York City.
We geocoded Airbnb listings using latitude and longitude, spatially joined them with NYC ZIP code boundaries, and aggregated counts to visualize the distribution of short-term rentals across Brooklyn and Manhattan using a choropleth map.

The map revealed that ZIP code 11211 (Williamsburg) had the highest concentration of Airbnb listings (1,613), marking it as Brooklyn’s most active short-term rental zone. Based on this insight, Williamsburg was selected as the primary study area. To enhance representativeness and explore potential patterns across boroughs, we also included ZIP code 10002 (Lower East Side, Manhattan), which is geographically close to Williamsburg. This dual-region approach addresses the limitations of analyzing a single district and supports more generalizable findings.

5.2. Basic Statistics of Dataset

Table 1 Basic Statistics of Dataset

Variable	Sample Size	Mean	Median	Max	Min	Sum	Standard Deviation
Days Change(Brooklyn)	4312	23.5	27.00	32.0	-3.00	NA	9.4
Days Change(Williamsburg)	444	24.8	27.00	30.00	-2.00	NA	7.3
Days Change(Manhattan)	3431	17.1	26	30	-3	NA	13.2
Days Change(Lower East Side)	194	19.2	26	29.0	-1.0	NA	12.2
2022.9-2023.8 Daily Residential Loud Music/Party Noise Complaint Counts (Williamsburg)	365	7.3	4	64	0	2634	8.6
2023.9-2024.8 Daily Residential Loud Music/Party Noise Complaint Counts (Williamsburg)	365	6.3	3	74	0	2263	8.4
2022.9-2023.8 Daily Residential Loud Music/Party Noise Complaint Counts (Lower East Side)	365	4.6	4	24	0	1693	4.4
2023.9-2024.8 Daily Residential Loud Music/Party Noise Complaint Counts (Lower East Side)	365	4.4	3	35	0	1607	4.5

For Airbnb Dataset: Since we are comparing the change in minimum stay days between 2023 and 2024, our goal is to understand the range of changes—specifically, the minimum and maximum number of days—under the short-term rental housing policy. Therefore, we conduct a statistical analysis based on this comparison. After selecting Williamsburg (ZIP Code 11211) and Lower East Side (ZIP Code 10002) as the study area, we analyzed the year-over-year changes in short-term rental distribution between 2023 and 2024. The key steps included:

- Extracting short-term rentals from the merged dataset, isolating listings where minimum_nights_x (2023) was less than 30 days.
- Computing changes in minimum_nights_y (2024) to determine how rental policies evolved over time.

Using the same logic, we also compare the broader Brooklyn and Manhattan regions to explore regional differences in Airbnb listing behavior. Table 1 presents the summary statistics of daily listing duration changes across four key areas. In **Brooklyn**, the average change in minimum stay is **23.5 days**, with a median of **27.0**, and values ranging from **–3.0 to 32.0 days**. The standard deviation of **9.4** indicates moderate variability. In **Williamsburg**, a subregion of Brooklyn, the average change is slightly higher at **24.8 days**, but the variation is smaller (**standard deviation: 7.3**), suggesting more stable and uniform rental policy adjustments within that neighborhood. In contrast, **Manhattan** shows a lower average change of **17.1 days** and a median of **26.0**, with a wider spread (**standard deviation: 13.2**), indicating more inconsistency in rental durations. The **Lower East Side**, as a specific case within Manhattan, has a slightly higher mean of **19.2 days**, but still with substantial variability (**standard deviation: 12.2**), comparable to the rest of Manhattan.

These results suggest that **Brooklyn—especially Williamsburg—has more consistent and slightly longer minimum stay adjustments**, while **Manhattan displays greater volatility and shorter average changes**, possibly reflecting differences in regulatory pressures or market dynamics.

For 311 noise dataset:

To evaluate potential shifts in residential livability following the enforcement of Local Law 18, we analyzed daily Residential type noise complaints across Williamsburg and the Lower East Side within the pre-policy one-year period (2022.9–2023.8) and post-policy one-year period (2023.9–2024.8). The key steps included:

- Converting the ‘data_fmt’ column in the cleaned dataset to datetime format, and extracting ‘month’, ‘day’, and ‘hour’ for further analysis.
- Dividing the dataset into pre- and post-policy periods.
- Calculating daily and yearly complaints counts for each residential noise type by ‘Descriptor’ column.

We focused on the ‘Loud Music/Party’ noise type. As shown in Table 1, Williamsburg had accumulated 2634 yearly complaints and an average of 7.3 daily complaints in the pre-policy period (2022.9–2023.8) , with counts ranging from 0 to 64 and a standard deviation of 8.6, indicating substantial variability and occasional spikes in complaint volume. In the post-policy period (2023.9–2024.8), the total declined to 2263 and the average declined slightly to 6.3, though the maximum increased to 74, and the standard deviation remained relatively stable at 8.4. This suggests that while average complaints decreased modestly, certain areas saw intensified disturbances.

In the Lower East Side, the total number of complaints declined slightly from 1,693 to 1,607 over the course of a year (using 365 days as the sample size), indicating a net decrease of 86 complaints. Average daily complaints dropped marginally from 4.6 to 4.4, with minimal change in both maximum values (24 vs. 35) and standard deviations (4.4 vs. 4.5), reflecting relatively stable noise patterns over time. Across both neighborhoods, the minimum remained at 0, showing that some locations had no complaints on certain days.

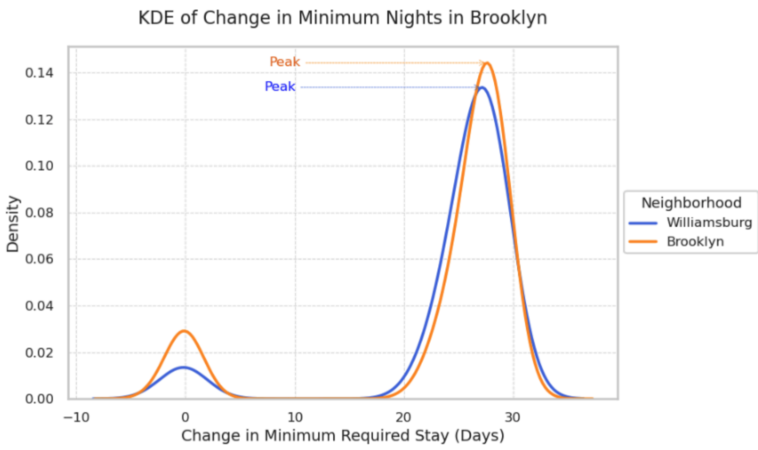
Although average complaint counts declined in both areas, the persistence of high maximum values and wide standard deviations indicates uneven improvements at the neighborhood level. These findings suggest that Local Law 18 may have contributed to marginal reductions in noise, particularly in Williamsburg, but spatial disparities remain—highlighting the need for finer-grained, map-based analyses to identify where conditions improved and where disturbances persisted.

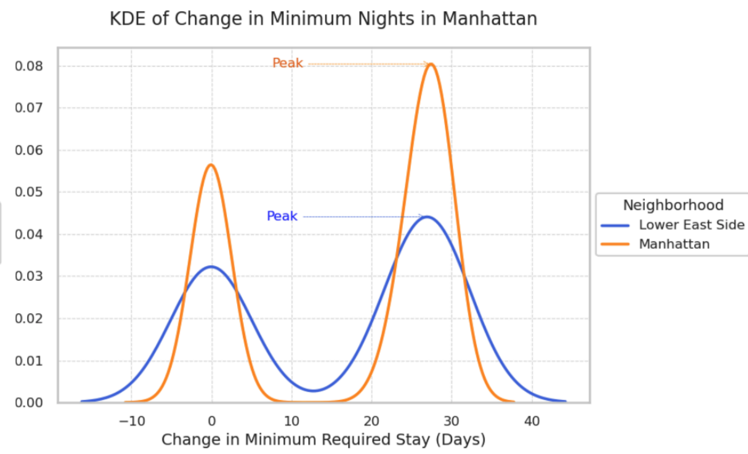
5.3. Airbnb Exploratory Data Analysis

5.3.1. Distribution of Days Change Following the Same Trend in Both Brooklyn and Manhattan

To understand how short-term rental policies may have influenced host behavior, we analyzed the change in minimum stay requirements (change_in_minimum_nights) between 2023 and 2024. We used Kernel Density Estimation (KDE) to visualize the distribution of changes for listings in both Brooklyn (including Williamsburg) and Manhattan (including the Lower East Side).

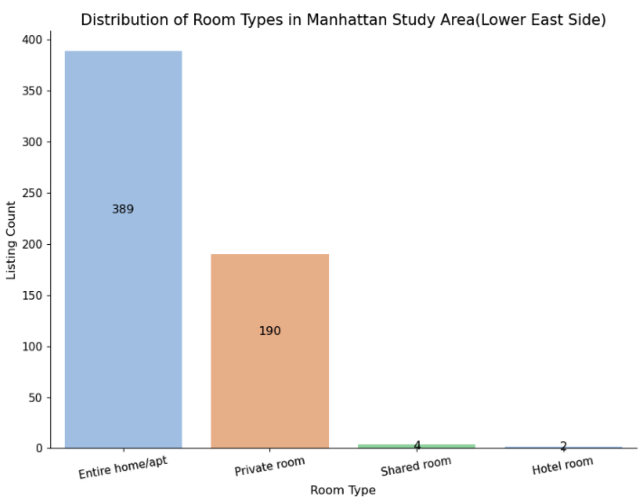
In Brooklyn, both Williamsburg and the borough as a whole show a strong peak around 30 days, indicating a widespread shift toward longer minimum stay requirements. A smaller peak near 0 suggests that a portion of hosts maintained short-term rental durations. Williamsburg’s curve is slightly narrower, suggesting more consistency in host behavior compared to the wider Brooklyn distribution. In Manhattan, we observe a similar trend. The KDE for the Lower East Side displays two prominent peaks—one near 0 and another near 30—highlighting variation in host responses. These patterns suggest that across both boroughs, many hosts adjusted their listings in response to regulatory pressures, with 30-day minimum stays emerging as a common standard.

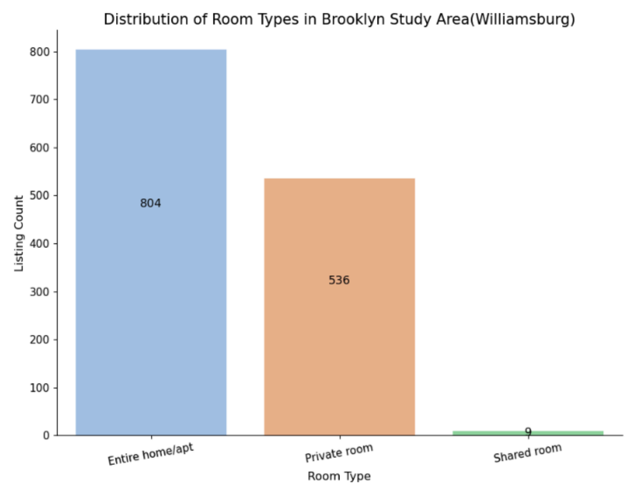




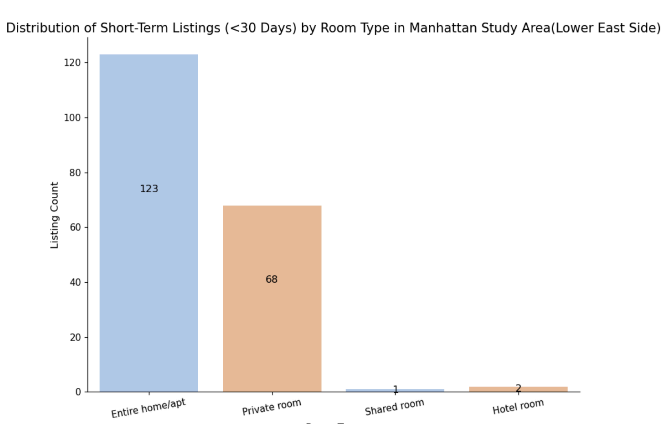
Furthermore, Williamsburg proves to be a suitable sample for representing Brooklyn—not only because it has the highest density of Airbnb listings, but also because the distribution of day changes in both areas shows a similar pattern. Meanwhile, the Lower East Side also proves to be a suitable representative sample for Manhattan.

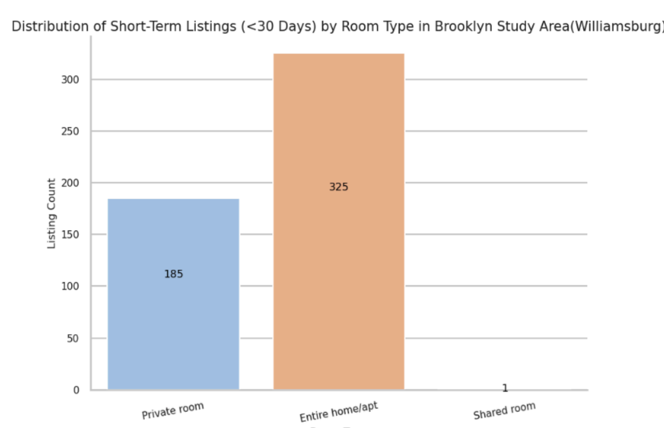
5.3.2. Distribution of Room Types in Williamsburg and Lower East Side





To compare the distribution of different room types across neighborhoods in New York City, we created two bar charts illustrating the number of listings by room type in Williamsburg and Manhattan. These visualizations use bar height to represent the number of listings, with distinct colors for each room type. To enhance clarity, the exact listing counts are labeled on top of each bar. From the charts, we observe that Entire home/apartment listings dominate in both areas, with 804 listings in Williamsburg and 389 in Manhattan. Williamsburg has a significantly higher total count, suggesting that this area may have a higher concentration of Airbnb activity overall. According to Airbnb's definition, a Private room refers to a space where guests have their own private sleeping area but may share common spaces. The notable number of private rooms, especially in Manhattan (190 listings), suggests that many users may be renting these spaces for temporary stays, possibly as a more affordable or flexible living arrangement. Interestingly, the chart also reveals a small number of hotel listings in Manhattan, particularly on the Lower East Side. This could reflect differences in zoning or traveler preferences, as well as the unique characteristics of each neighborhood.



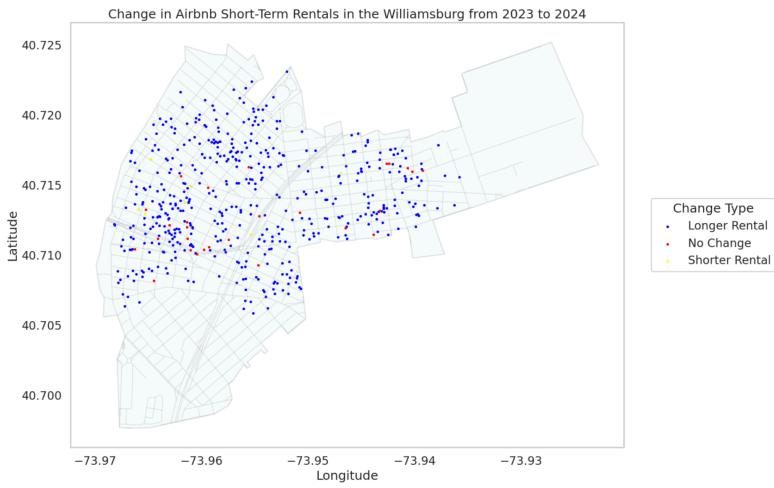


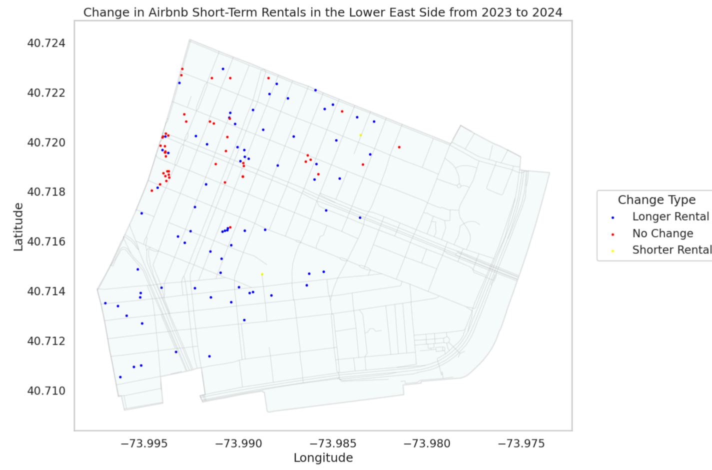
Regional Preference Heterogeneity and Airbnb Listing Diversity is different in these Two regions. Williamsburg shows a higher density of Airbnb listings overall, with a heavy skew toward full-unit rentals. This may be contributing to housing availability pressures in the area. In contrast, Manhattan presents fewer listings and a more balanced distribution between entire homes and private rooms, which could be a result of stricter local regulations or market saturation.

To understand the impact of the policy change on Airbnb usage, we analysed the short-term listing ratio (i.e., the proportion of listings available for stays under 30 days) for each room type in both Williamsburg and Manhattan. In Manhattan, the room type with the highest short-term conversion rate—excluding hotel rooms—was Private room, with a ratio of 35.8%, followed by Entire home/apartment at 31.6%, and Shared room at 25.0%. In Williamsburg, the trend is slightly different. Entire home/apartment had the highest short-term ratio at 34.8%, followed by Private room at 30.6%. Shared rooms and hotel rooms were negligible in both total count and short-term conversions and are therefore not considered in this comparison.

This comparison suggests that regional differences strongly influence how Airbnb is used, especially among short-term visitors. Williamsburg appears to cater more to travelers seeking full-unit accommodations, while Manhattan may attract guests who are more comfortable renting private rooms within shared homes. These distinctions reflect not only traveler preferences, but also local policy enforcement, housing stock, and socioeconomic dynamics in each area.

5.3.3. Distribution of Room Types in Williamsburg and Lower East Side from 2023 to 2024





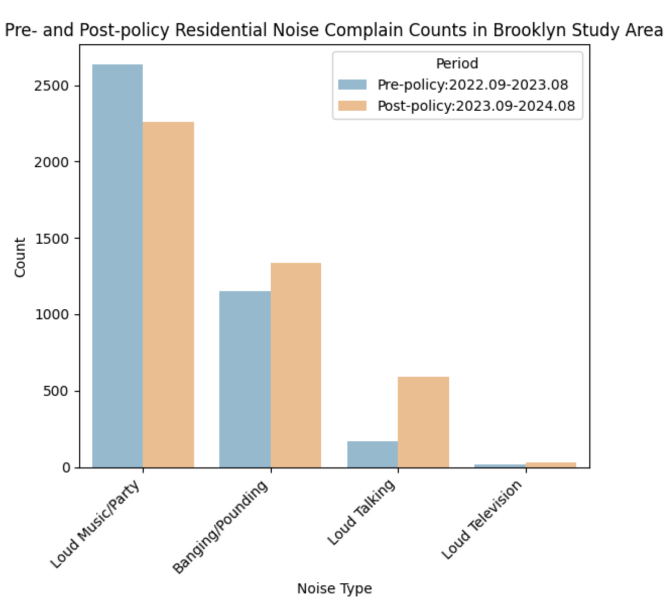
This research classified the rental shifts into three categories: Longer Rental: short-term rentals converted to long-term rentals; No Change: rentals that remained short-term; Shorter Rental: short-term rentals converted to even shorter stays. We then visualized the changes in short-term rental availability from 2023 to 2024 (before and after LL18). Additionally, we used the street map from the GeoDataFrame street_gdf, displayed in light gray lines, to provide geographic context. Airbnb listings were categorized by rental change type and visualized as follows: blue represents rentals that became longer-term, red indicates rentals with no change, and yellow shows rentals that became shorter-term. With the same logic, we created the map of the Lower East Side as well.

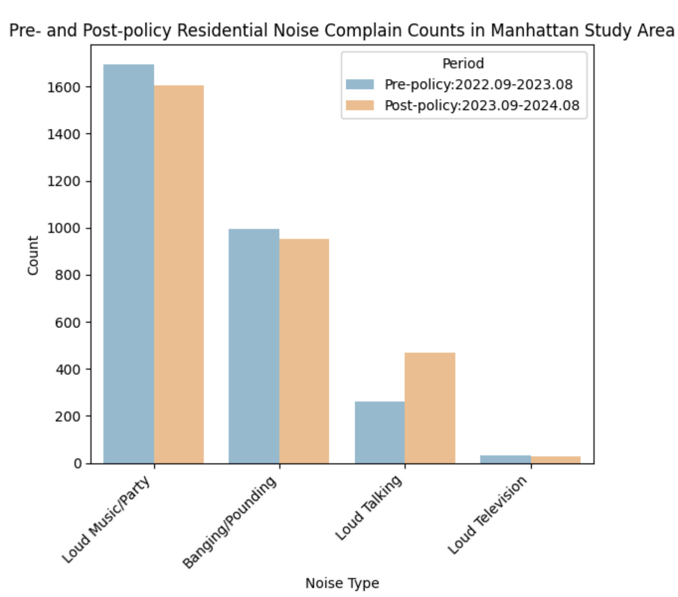
Thus, we created the Categorical Point Distribution Map. This map allows us to visually detect the spatial pattern of rental behavior changes after the implementation of Local Law 18. It helps identify which parts of the Lower East Side saw the most conversions from short-term to long-term rentals, as well as areas where Airbnb usage remained stable or even shortened. By overlaying these rental transitions on a base map of streets and boundaries, we can understand the geographic clustering of policy impact and host adaptation behavior.

Based on the graph, the majority of listings turned into longer rentals (blue) and are widely distributed across the area. No-change listings (red) are clustered in specific pockets—possibly neighborhoods where compliance is harder to enforce or demand remains high. A few shorter rentals (yellow) are scattered, suggesting very few listings decreased their stay length. Based on this, we have confidence that the future steps of airbnb short term rentals may influence the noise compliance issues. This research also observed noticeable gaps in data coverage, particularly along the pier-side and peripheral areas of both Williamsburg and the Lower East Side. These gaps are not the result of visualization errors, but instead reflect the actual absence of Airbnb listings in those regions. Many of these areas, particularly those near the waterfront, are zoned for industrial, commercial, or public use(e.g., warehouses, parks, transit infrastructure) rather than residential living. As such, they are not eligible or suitable for Airbnb-type listings. This spatial analysis helps us understand not only the impact of regulatory change, but also the heterogeneity of host behavior and enforcement patterns across different parts of the city. It may also have future implications for issues like housing availability, noise complaints, and neighborhood change.

5.4. 311 Noise Compliance Exploratory Data Analysis

5.4.1. Distribution of Residential Noise Complaint Types Before and After Short-Term Rental Regulation (LL18)

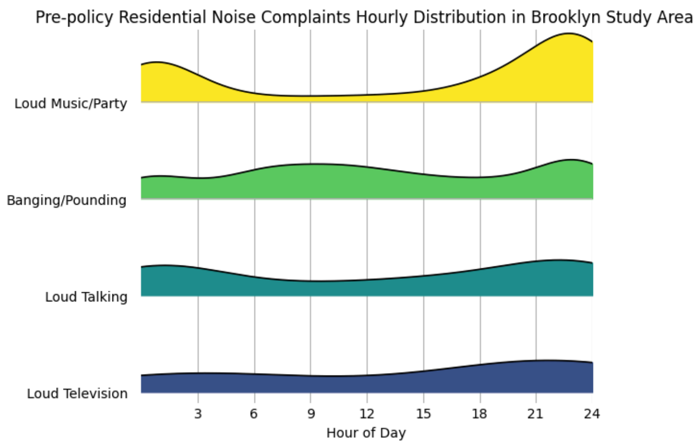


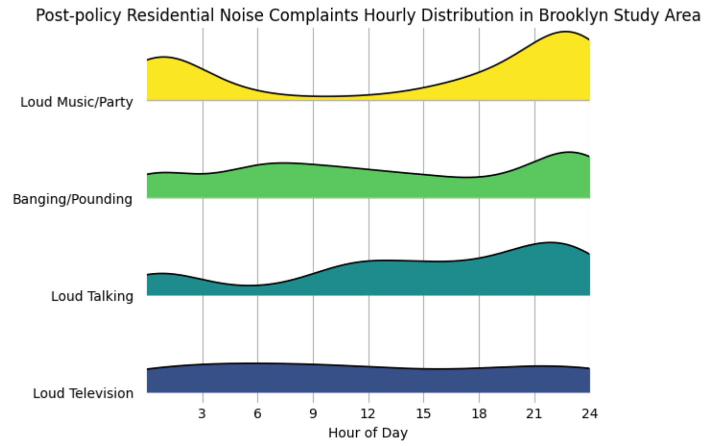


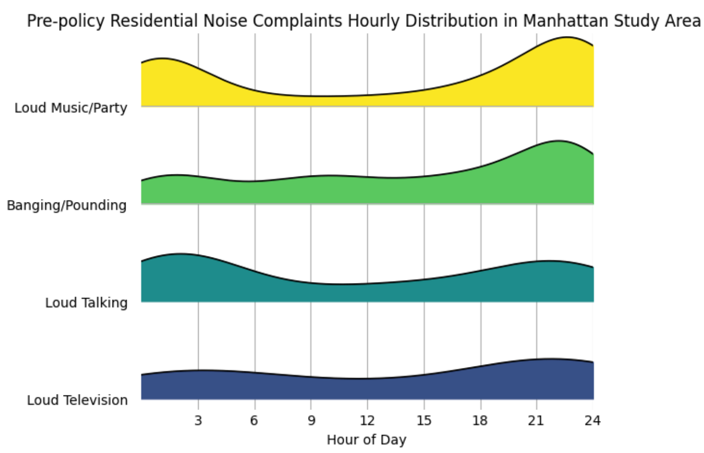
These two bar charts aim to respectively show how four descriptors of residential noise complaints changed before and after the LL18 policy in Brooklyn and Manhattan. The bar charts were selected because they visually compare the amount of different categories of noise complaints-before and after the policy implementation-in two key boroughs with high Airbnb density in both study areas.

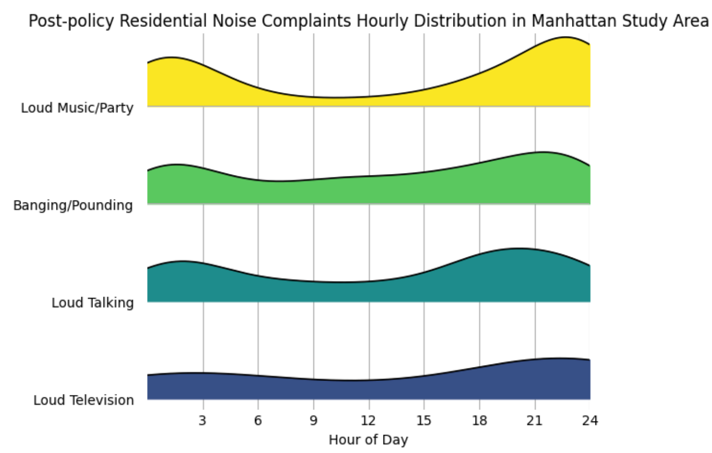
From both charts, there is a noticeable decline in complaints of "loud music/parties" after the policy. However, from the Brooklyn chart, other types like "Banging/Pounding" and "Loud Talking" increased slightly while, in Manhattan, "Loud Talking" showed a sharp increase. The result indicates a partial reduction in certain disruptive actions potentially related to short-term guests. More importantly, both boroughs of Brooklyn and Manhattan saw a drop in "Loud music/Party" noise complaints. It suggests that implementation of LL18 had effect in the party-related disturbances. But the increase in talking and pounding sounds in both Brooklyn and Manhattan shows there are potentially other factors like different communities, housing type, density etc. might lead to the result.

5.4.2. Pre- and Post-Policy Noise Compliance Hourly Distribution for the Brooklyn and Manhattan Study Areas









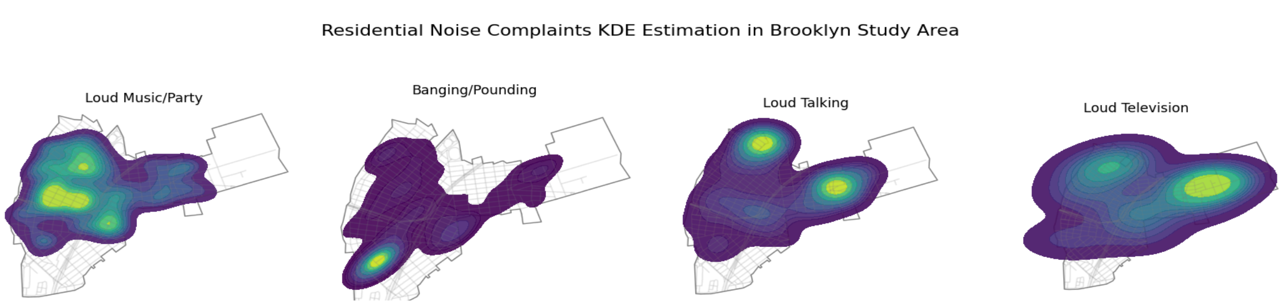
Ridgeline plots (also known as joyplots) were used to visualize the hourly distribution of different types of residential noise complaints before and after the implementation of LL18. These plots help illustrate how complaint patterns change over the course of a day across two study areas — Brooklyn and Manhattan.

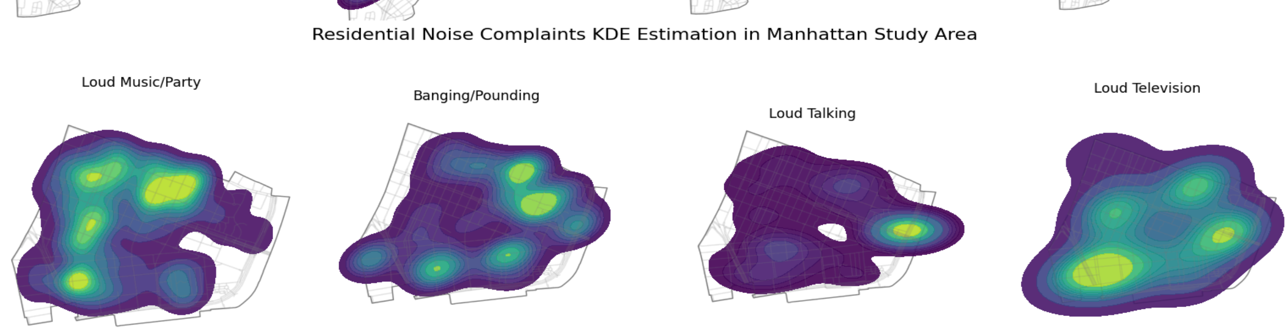
The analysis mainly used the "hour", "Descriptor" columns respectively in pre-policy and post policy data frame. Complaints were then aggregated and normalized to display hourly distribution trends. The charts show that:

- "Loud Music/Party" complaints peaked between 10 PM and midnight in both boroughs and showed a slight decline after the policy.
- "Loud Talking" complaints increased during afternoon and evening hours, especially post-policy in Brooklyn.
- While both boroughs exhibit similar temporal trends, Brooklyn shows a flatter distribution, suggesting a more even spread of complaints across the day.

The observed changes in complaint timing and intensity provide preliminary evidence that the policy may have contributed to modest behavioral adjustments in nighttime noise activities.

5.4.3. Spatial Distribution and KDE of Residential Noise Complaints in Brooklyn and Manhattan

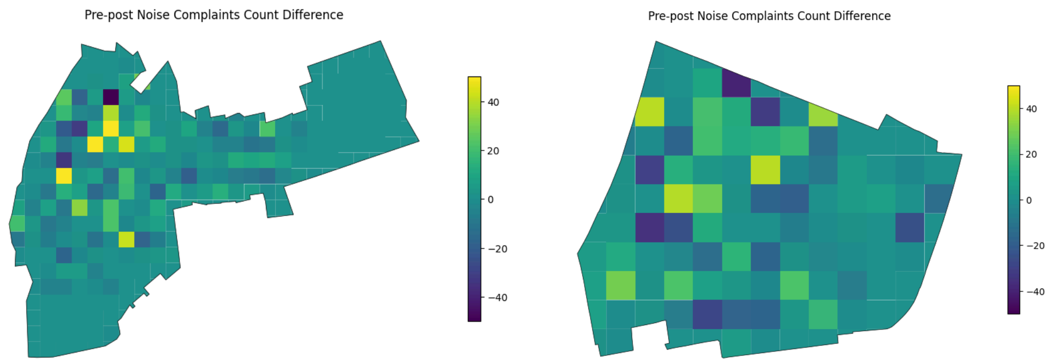




This set of diagrams illustrates the spatial distribution of residential noise complaints in Manhattan using kernel density estimation (KDE) for four major complaint descriptors. KDE is a valuable spatial analysis method that enables us to identify geographic areas with high concentrations of noise complaints, providing insight into how different types of residential noise are distributed across the city.

The visualizations reveal that different types of noise complaints are spatially concentrated in distinct regions. For example, construction-related noise is primarily clustered along redevelopment corridors and busy thoroughfares, while music-related disturbances are concentrated in areas known for nightlife and entertainment. These patterns offer a data-driven foundation for understanding how various forms of residential noise manifest across the urban landscape. The findings directly support our research objective: to examine how the type and location of noise complaints vary by descriptor.

5.4.4. Pre-Post Spatial Patterns of 311 Noise complaint changes under LL18



Brooklyn Study Area (ZIP code 11211) & Manhattan Study Area (ZIP code 10002)

The fishnet grid-based figure is chosen to further explore the spatial distribution of changes in noise complaints before and after the implementation of LL18. Traditional geographic units like ZIP codes or census tracts can obscure localized trends because they're too broad or misaligned with complaint locations. By applying a fishnet grid composed of equal-sized 500ft × 500ft cells across the study area, we reduce the risk of boundary-related errors and improve spatial resolution. This provides a consistent spatial unit that allows us to compare changes in both variables over time and space, independent of street-level inconsistencies. The specific methodology is described below:

Step 1: **Fishnet grid creation**: A 500-feet fishnet grid is generated within the defined study area (ZIP code 11211 in Brooklyn, 10002 in Manhattan).

Step 2: **Data filtering**: Noise complaints are filtered to include only the months of August and September, as LL18 was implemented in August.

Step 3: **Grid assignment**: Each data point is assigned to the nearest grid cell based on geographic coordinates.

Step 4: **Calculate changes**:

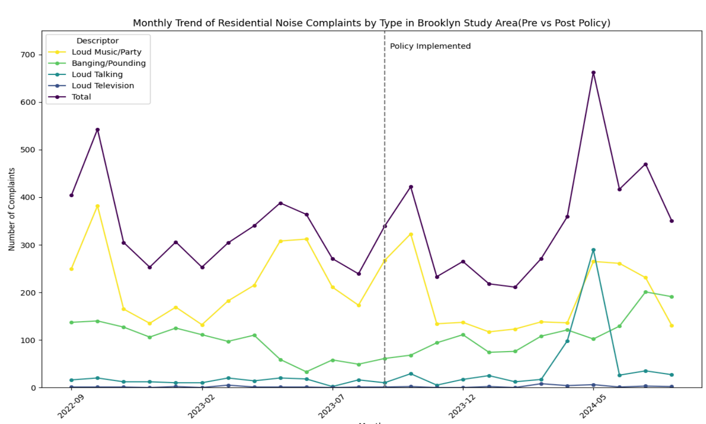
Count the number of noise complaints per cell in August and September.

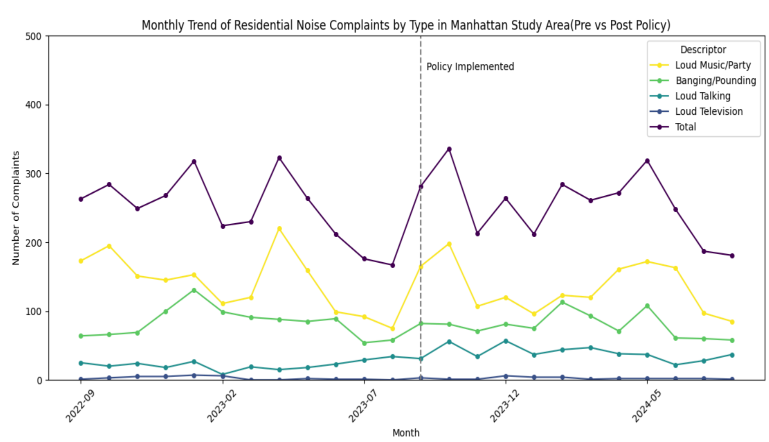
Calculate monthly change for 2022 and 2023 separately.

Compute the policy-adjusted difference:final_diff = (2023 Sept - Aug) - (2022 Sept - Aug)

The resulting differences are mapped to show where counts increased, decreased, or remained stable, using color to indicate direction and intensity of change. In these figures, we can see the distribution of noise complaint changes happen after the implementation of LL18 in both study areas of Brooklyn and Manhattan.

5.4.5. Monthly Trend of Residential Noise Complaints by Type in Brooklyn Study and Manhattan Study Area

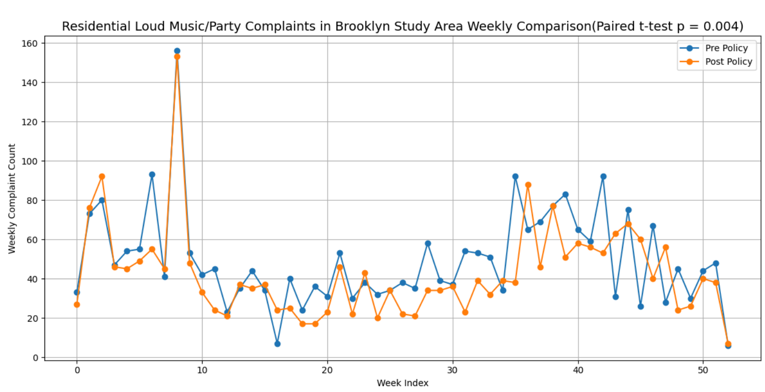


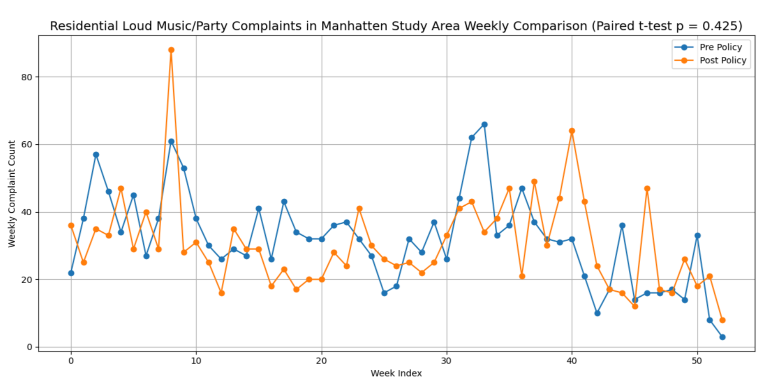


These two charts show how monthly noise complaints of four main descriptors changed before and after LL18 in Brooklyn and Manhattan.

In the Brooklyn study area, there's a noticeable drop in Loud Music/Party complaints right after the policy started, which suggests the new Airbnb rules may have helped reduce party-related noise. However, other types of complaints, like Banging/Pounding and Loud Talking, didn't change much or even increased a bit. The total number of complaints went up again around mid-2024, possibly due to seasonal events. In the Manhattan study area, the changes are less obvious. Party noise went down a little, but Loud Talking slowly increased, and overall noise levels stayed about the same or slightly rose.

5.5. Before-and-After Comparison using Paired t-test





To account for the strong seasonal and cyclical patterns in noise complaints, and to ensure a sufficient number of observations for statistical testing, we aggregated data at the weekly level and conducted paired t-tests to test whether noise complaints had a significant change across two neighborhoods. Line plots were chosen to highlight week-to-week trends and detect potential shifts before and after the policy.

Brooklyn study area: The test shows a statistically significant reduction in weekly residential loud music/party noise complaints after the policy took effect (p=0.004), suggesting a potential link between short-term rental regulations and noise reduction in this high-Airbnb-density area.

Manhattan study area: In contrast, no significant change was detected (p=0.425). While this may reflect differences in short-term rental intensity or community response, we cannot conclusively attribute the effect to policy alone. The results indicate potential spatial heterogeneity, which led us to further investigate neighborhood-level patterns through grid-based correlation analysis.

5.6. Correlation analysis

The t-test analysis focused on the overall policy effect over time (temporal dimension), it did not reveal how changes are distributed across space. To complement this, we conducted a **spatial analysis**. We aimed to explore whether changes in Airbnb short-term rental activity align spatially with changes in 311 noise complaints. In other words, did the two variables tend to increase or decrease in the same places? To answer this, we used **Pearson correlation analysis**, applied to fishnet grid cells across each study area.

Pearson correlation measures the strength and direction of linear association between two variables. In our research, these are changes in Airbnb short-term rental listings and changes in 311 noise complaints within each grid cell. A positive r-value indicates that increases in one variable are associated with increases in the other (and vice versa). A value near zero suggests little or no spatial alignment.

Results of correlation analysis

Brooklyn (ZIP code 11211 / Williamsburg area) **r = 0.223**

This indicates a weak positive spatial correlation. In areas with high pre-policy short-term rental density, increases in Airbnb activity were accompanied by increases in noise complaints. This suggests LL18 may have helped reduce noise in certain high-impact zones.

Manhattan (ZIP code 10002 /Chinatown) **r = 0.170**

This is a very weak or negligible correlation, meaning changes in Airbnb listings and noise complaints were not spatially aligned. In this area, short-term rentals do not appear to be a significant driver of noise complaint patterns.

The results reveal a clear spatial heterogeneity in how short-term rental regulations have impacted noise complaints. In some high-density Airbnb neighborhoods, the policy may have led to a noticeable reduction in noise complaints. However, this outcome is not universal. In other areas, such as Chinatown, noise complaints did not decrease in line with the reduction in short-term rentals. To fully understand this relationship, we need to examine a broader range of neighborhoods and incorporate additional spatial variables into the analysis.

6. Next Steps & Reflections

6.1. Challenges and Limitations

We encountered several challenges during the research, which also highlight areas for improvement. First, we relied solely on 311 noise complaints as our primary dataset. However, this data is influenced by individuals' willingness to report, which can vary across different communities and demographic groups. Second, our analysis focused only on two boroughs—Brooklyn and Manhattan—so the findings may not be fully representative of the entire city. Third, the nature of noise complaints may differ by neighborhood, making it essential to conduct interviews and surveys with local residents to gain a deeper understanding of the issues. While these limitations added complexity to our research, they also revealed the potential and richness of the underlying questions.

6.2. Conclusion

This project set out to explore the relationship between Airbnb short-term rentals and residential noise complaints in New York City, especially in the context of Local Law 18. By focusing on Williamsburg and Chinatown—two neighborhoods with high Airbnb activity—we compared pre- and post-policy patterns by using 311 complaint data and spatial analysis. Our results show that noise complaints related to "Loud Music/Party" slightly decreased in Williamsburg after the implementation of policy, indicating that the regulation may have helped reduce certain types of disturbances regarding noise. However, the correlation between Airbnb activity and noise complaints was not strong enough to conclude on the relevance, and the effects in Manhattan were less clear. These findings show that policies like LL18 may help improve the community conditions on noise level, but it might be influenced by many other factors, such as building types, different districts, etc.

Through this project, we also learned how to work with open data, apply statistical tests, and use mapping tools to understand the real-world issues. Besides, although our analysis has some limitations, such as focusing on only two areas, it provides a good starting point for the research. In the future, we intend to expand our study and include more data, which could help us better understand how short-term rental impacts city life.

6.3. Reflections

While our project provides meaningful insights regarding the relationship between short-term rentals and noise complaints, there are several limitations to consider. First, our analysis only focused on two ZIP code areas—Williamsburg and Chinatown, which means that the results might not be fully representative of the whole city. Second, we used 311 noise complaint data as the proxy for neighborhood livability, but this data depends on individuals' willingness to report, which may vary by community and demographic. Also, our study range is a relatively short time frame(one year before and after LL18), so it may not capture long-term effects or seasonal patterns fully. There are also spaces that could be improved that other potential influences on noise, such as nightlife, construction or population density might affect the result. Finally, our correlation findings do not prove causation, and more detailed modeling would be needed to explore causal relationships.

Therefore, moving forward, our next steps include:

a. Incorporate additional variables: Include socio demographic data such as income, housing type, nightlife density.
b. Expand the geographic scope: Apply our framework to additional neighborhoods beyond Williamsburg and Manhattan to see whether patterns work for the whole city.
c. Qualitative context: Enrich our findings with interviews or surveys of residents and hosts in key areas to validate patterns and gather insight into lived experiences.
d. Interactive visualization: If time permits, we aim to build an interactive visualization dashboard to make our findings more accessible to policymakers and community stakeholders.

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