CHEER-UP's FSDS Group Project

Declaration of Authorship

We, CHEER UP Group, confirm that the work presented in this assessment is our own. Where information has been derived from other sources, we confirm that this has been indicated in the work. Where a Large Language Model such as ChatGPT has been used, we ensure that we have made its contribution to the final submission clear.

Date: 18 Dec 2023

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Project Github: https://github.com/hanukikanker/fsds-group-cheers

Brief Group Reflection

What Went Well	What Was Challenging
Insight from data analysis: Identifying that entire homes positively impact property crime provides valuable insight to inform targeted solutions.	Data Limitations: The difficulty in detailing whether crimes occurred within specific Airbnb listings due to data limitations poses a challenge in formulating precise recommendations.
Policy recommendations: We provided comprehensive recommendations for the government, Airbnb and users, covering various aspects, including background checks, regulations, security measures, and public awareness, demonstrating a holistic approach to addressing the challenges.	Potential Causation: Why certain areas exhibited higher crime levels, e.g. a higher density of Airbnb rentals, specifically entire homes/apartments, may attract more tourists. This, in turn, could render these areas more susceptible to criminal activities, as tourists are often perceived as attractive targets for theft or scams.
Group dynamics: We distributed the tasks among the group but regrouped regularly to discuss our findings and the next steps.	Difficult in collaboration and prioritisation leading up to exam week.

Priorities for Feedback

- Correctness of our quantitative methods
- Cleanness of codes

Response to Questions

1. Who collected the data?

Inside Airbnb was founded by Murray Cox, who conceived the project and keeps updating and analysing Airbnb data (*About Inside Airbnb*).

2. Why did they collect it?

Murray Cox and Co. aim to make Airbnb's data more transparent and accessible to the public. In addition to creating visual dashboards of different cities, they wrote many reports based on these data. For example, they criticised Airbnb's New York data as misleading (Cox and Slee, 2016). This is meant to benefit others in different ways:

- Consumers can understand market trends more efficiently, which help them make more informed decisions and choose accommodation that fits their needs and budget;
- Landlords can have transparency of information, and that can promote fair competition and maintain the stability of short-term rental market prices;
- Academics can use these data to explore how Airbnb relates to many factors in urban development.
- Governments can understand the current situation of the short-term rental market and try to control the phenomenon that could be more conducive to the stable development of the city by establishing more supervision regulations.

3. How was the data collected?

Inside Airbnb uses web scraping scripts to extract publicly available information from Airbnb's website every quarter. These scripts navigate the Airbnb site, accessing various pages to retrieve data such as listing titles, descriptions, hosts, pricing, and more. The collected data is verified, cleaned, and made available on the Inside Airbnb website for users to explore online or download for analysis. In addition to providing a snapshot, Inside Airbnb conducts in-depth investigations using this raw data to derive more insightful information for users. For instance, the platform employs a proprietary "San Francisco Model" to estimate the frequency with which an Airbnb listing is rented out and to approximate a listing's income.

4. How does the method of collection impact the accuracy of its representation of the process it seeks to study, and what broader issues does this raise?

Several potential issues with this method of data collection may challenge the validity of any research work done based on it:

1. Pricing and availability, among others, are highly dynamic attributes set by hosts that cannot be captured accurately with web-scraping, which only reflects a snapshot of the website at one specific moment. Data capture can only capture real-time Airbnb data, and long-term comparative analysis requires data collection in advance and at higher frequencies
2. Data quality is susceptible to changes in the website's structure. Web scraping also only accesses publicly available listings.
3. Data quality depends on user input and does not guarantee accuracy (e.g. bogus listings)
4. Has ethical and legal implications, which will be discussed in the next section

5. What ethical considerations does the use of this data raise?

- First, landlords and renters have the right to request that their personal information not be made public elsewhere. Therefore, using this data may be needed to handle sensitive personal information and consider hosts' privacy and home security.
- Second, it may cause data misuse to affect public opinion (D'Ignazio and Klein, 2020). For example, the rental activities of a particular group may be negatively analysed, reinforcing the stereotype of this group and then triggering discrimination and antagonism toward society.
- Third, power always influences data settings (D'Ignazio and Klein, 2020). Airbnb often leaves out reviews that aren't friendly to properties and focuses on those that are profitable, such as setting its recommendation algorithm to favour partners.

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6. With reference to the data, what does an analysis of Listing types suggest about the nature of Airbnb lets in London?

Background and research question

As a short-term rental platform, the mobility of tenants is one of its major characteristics. Mobility is a factor in crime (Mburu and Helbich, 2016), so recently there has been increasing concern about whether Airbnb, which brings high mobility to the local community, could be linked to an increase or decrease in crime. For example, Xu, Pennington-Gray and Kim (2019) studied the relationship between Airbnb density and crime in Florida and found that certain types of listings do have a significant impact on crime. Therefore, we try to explore whether Airbnb in London could also have an impact on crime based on Lower Layer Super Output Areas (LSOAs) level. The reason why we choose LSOA level as this allows for a more detailed examination of localized patterns and variations within a borough. Different neighborhoods within a borough can exhibit distinct characteristics that might be overlooked in a broader borough-level analysis as crime rates and housing patterns can vary significantly from one neighborhood to another.

In short, our research question is: Does the type of Airbnb listing have an impact on crime in the neighbourhood?

Data source

The Airbnb dataset is from the September 2023 updated version provided by Inside Airbnb. The crime dataset is from data.police.uk and has the same time dimension as Airbnb's. The spatial partitioning dimension in this study is LSOA and is from the Office of National Statistics website.

Defining the data

In order to examine the nature of short-lets and crime relationship, we want to first establish the parameters to focus on just a subset. As Xu, Pennington-Gray, and Kim (2019) mentioned different types of short-lets have different impacts, we refer to their classification standards defining them as follows (*Data Dictionary*, nd):
- *Entire home:* Tenants can enjoy an entire whole listing.
- *Private room:* The tenant has a private bedroom but may need to share some space with others such as the kitchen.

We **excluded Hotel rooms** (listings by actual hotels and hostels) since they are not the subject of this research and are also few in numbers. We also **exclude Shared rooms** due to thier limited number in London. Lastly, we trimmed listing price outliers to filter out bogus listings. Figure 1a and 1b shows the listing price distribution of different room types, before and after filtering.

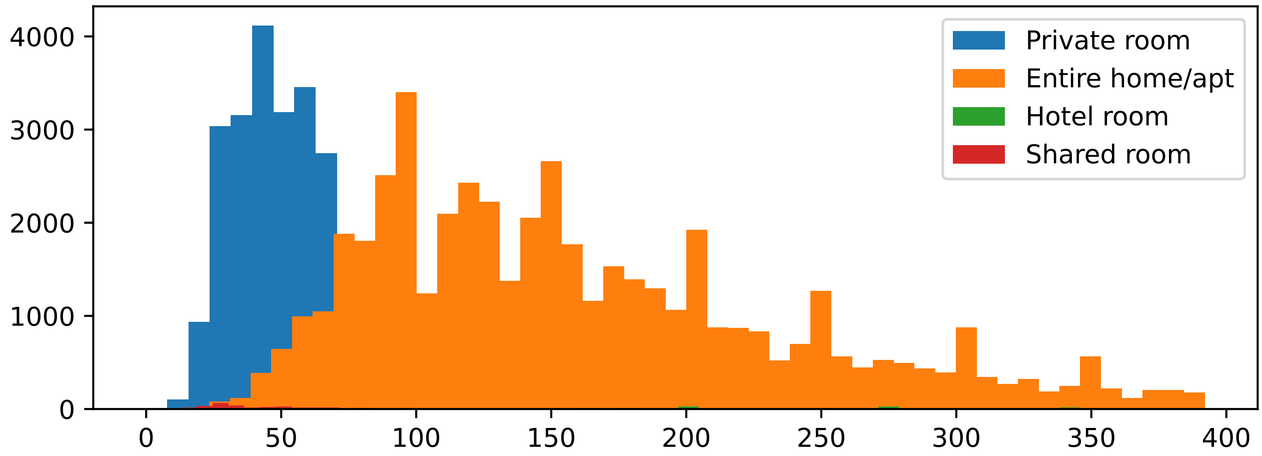

Figure 1a: Histogram of Airbnb listing price by room type - Sept 2023

As for crime data, as we wanted to make recommendations more specific to different categories of crime, we classified crime into the following types (Xu, Pennington-Gray and Kim, 2019; Flatley, 2016): - **Public order:** public order, drugs, possession of weapons, anti-social behaviour. - **Violent** (**involve force**): robbery, violence and sexual offences. - **Property** (**without force**): bicycle theft, burglary, criminal damage and arson, shoplifting, theft from the person, vehicle crime..

These three types of crime will be treated as dependent variables. Figure 2 shows the distribution of crime density per LSOA by type. Note that they take on a skewed distribution (Poisson distribution) for being based on count. We will treat this accordingly in our analysis while also not trimming any outlying values at this stage.

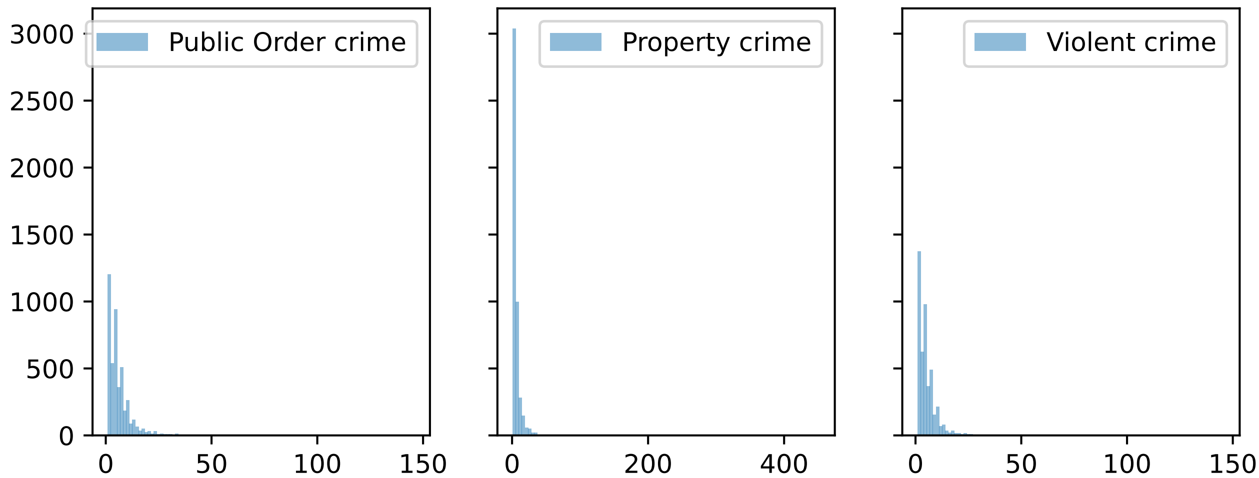

Figure 2a: Histogram of each crime category (LSOA level)

Relationship between Airbnb listings and crime

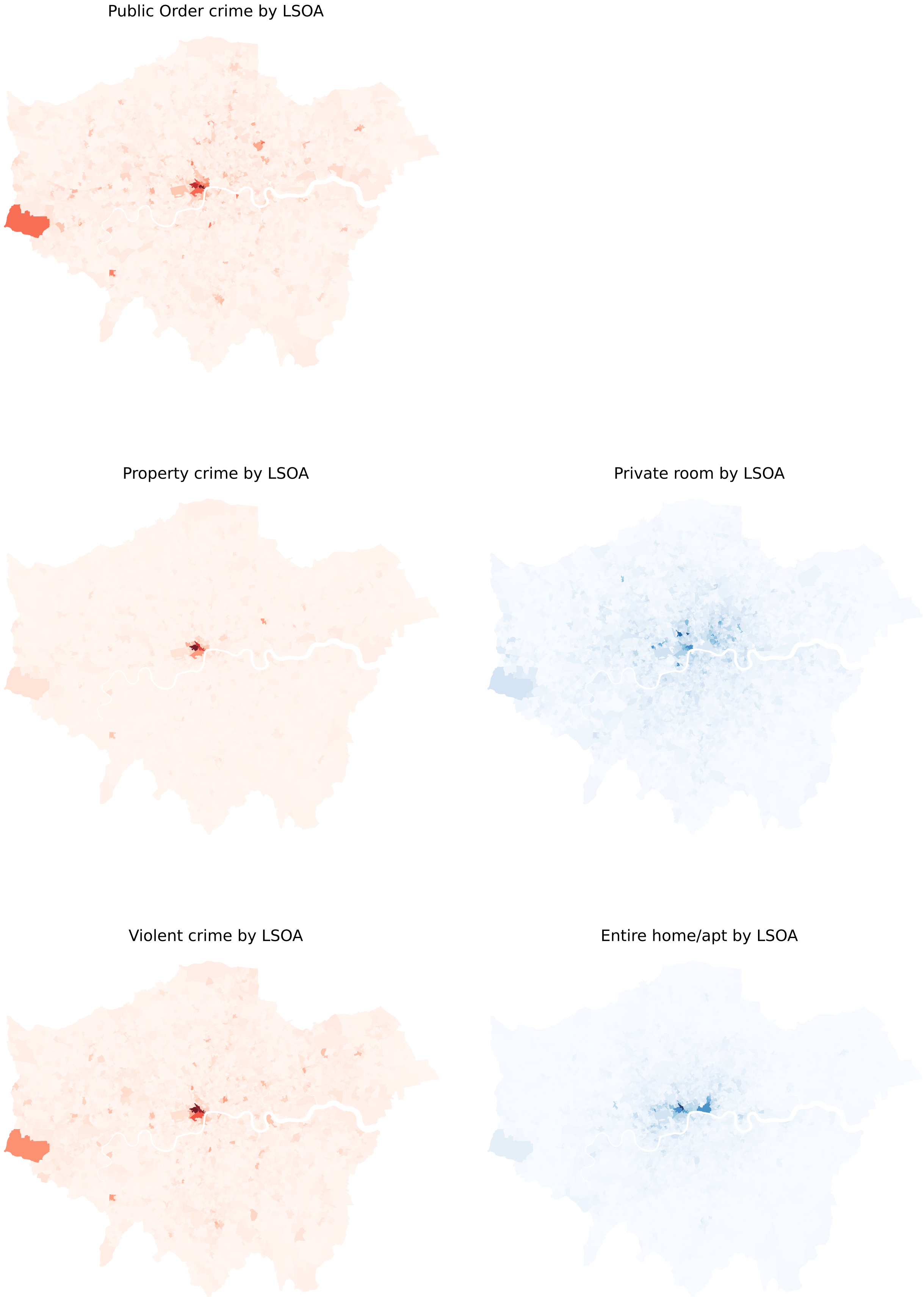

Figure 3: Density by LSOA

1. Spatial distribution

To start our spatial analysis of crime and listing patterns across LSOAs, distinct geographic concentrations emerge. Public order crimes are dispersed citywide, with notable pockets in Westminster and Hillingdon. Property crimes concentrate in central London, particularly in Westminster, while violent crimes exhibit a similar pattern, with Westminster and Hillingdon standing out. On the other hand, private rooms and entire homes exhibit citywide dispersal, with Westminster and Camden featuring prominently in Private room listing concentrations and the City of London emerging as a hub for entire homes.

2. Global Correlation and Spatial correlation

Zooming in to compare these variables among LSOAs via a correlation matrix with our variables of interest: We see that the correlation between **entire home** and **property crime** is the strongest (0.51). On the contrary, the correlation between private rooms and property crime is the weakest (0.284). Overall, it is interesting to see that entire home listings seem to be more exposed to crime, reinforcing the perception among opponents of Airbnb that not having live-in either engenders or is a magnet for crime.

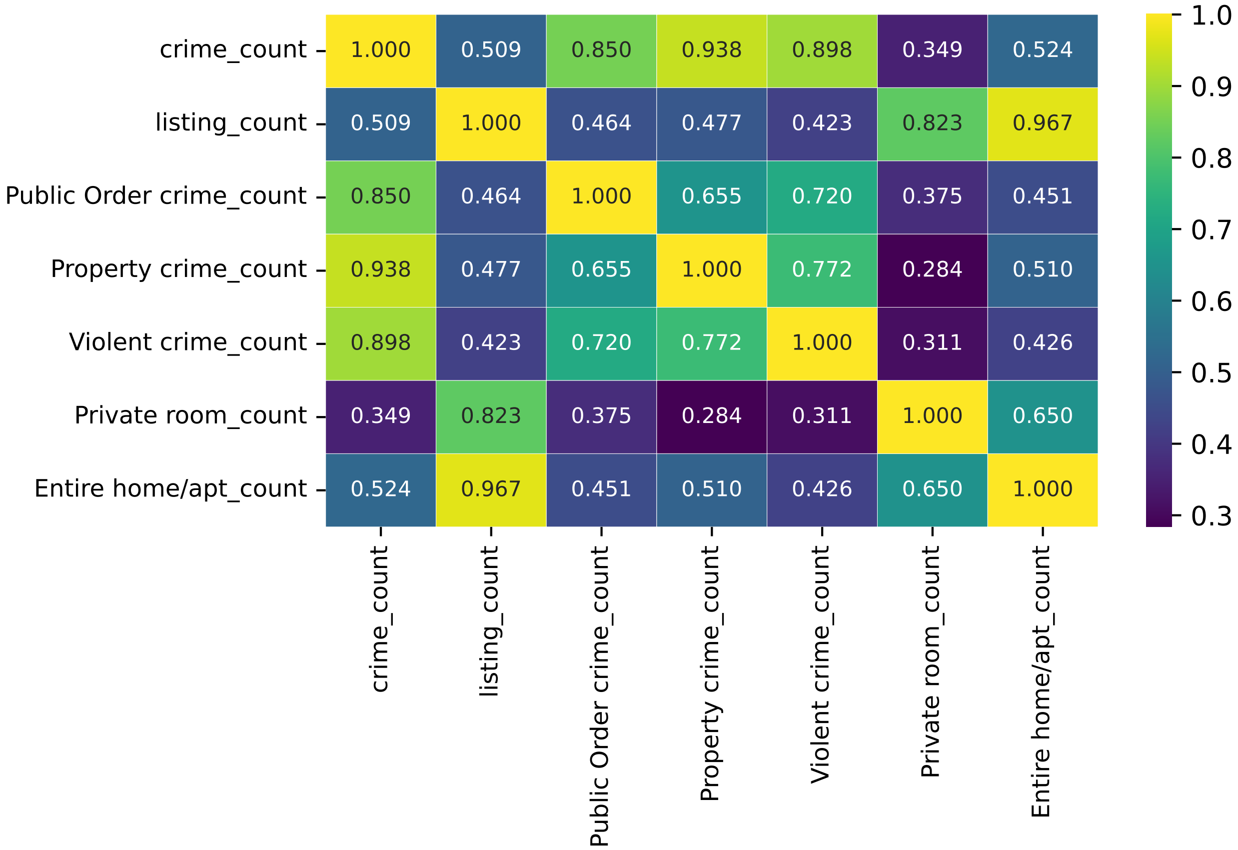

Figure 4: Correlation Matrix - Listing type vs Crime category

Beyond static correlation, when visualised on a map, more patterns emerge. Other notable areas outside of central London with a high concentration of crime incidents and Airbnb listings are **Hillington** (**Heathrow Airport**), **Richmond upon Thames, Croydon, Greenwich, Hounslow, etc.** Some are tourist destinations, while others, in contrast, seem to be in residential areas. This might allude to an underlying relationship between the concentration of Airbnb and crimes with tourism in general or population centres, and not between these variables alone.

Based on descriptive statistics so far, we can draw certain mixed conclusions about the relationship between crime and short-let. On the one hand, the distribution of Airbnb listings does align with the distribution of crime in many areas. More notably, we find correlations between Entire home/apt and Property crime. On the other hand, an underlying factor might shape this relationship across space (spatial dependence, confounding variables such as tourism attractiveness, etc.)

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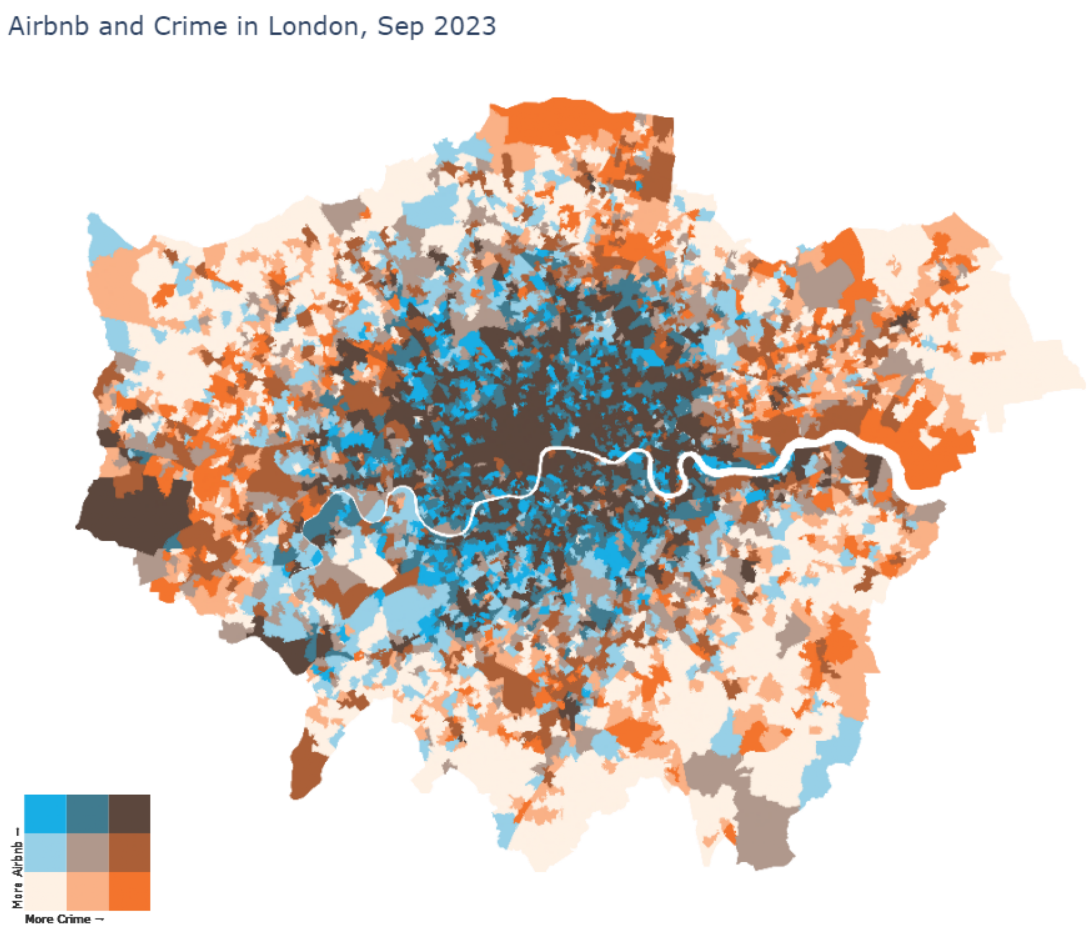

Figure 5: Bivariate Map of Airbnb and Crime in London*
(Interactive version available on the HTML output)

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7. Shortlet vs Crime and Policy recommendations

Variables

We will perform a regression analysis to determine whether different shortlet has an effect on crime, controlling for other relevant sociodemographic variables as much as possible. The chosen variables (calculated as proportions) are:

- population density,
- proportion of unemployed people among 16+
- proportion of young people (15-24 ages),
- proportion of household with a deprivation index of 3+
- proportion of people with qualification level 3 or higher
- proportion of tenanted household over all households

These control variables directly or indirectly provide a level of deprivation, which serves as a significant socioeconomic indicator linked to crime patterns (*Crimes recorded by neighbourhood income deprivation decile in London*, 2022). Meanwhile, for our target independent and dependent variables, we will also derive:

- proportion of Private and Entire home listings over total household, and
- proportion of property crime, public order crime, and violent crime over LSOA population ### Preparing Regression Data

Since we are using a simple linear regression to model this relationship to test our hypothesis, we must make sure the variables satisfy basic distribution requirements. Therefore we performed log transformations for select variable. Figure 7 shows the variables post-transformation.

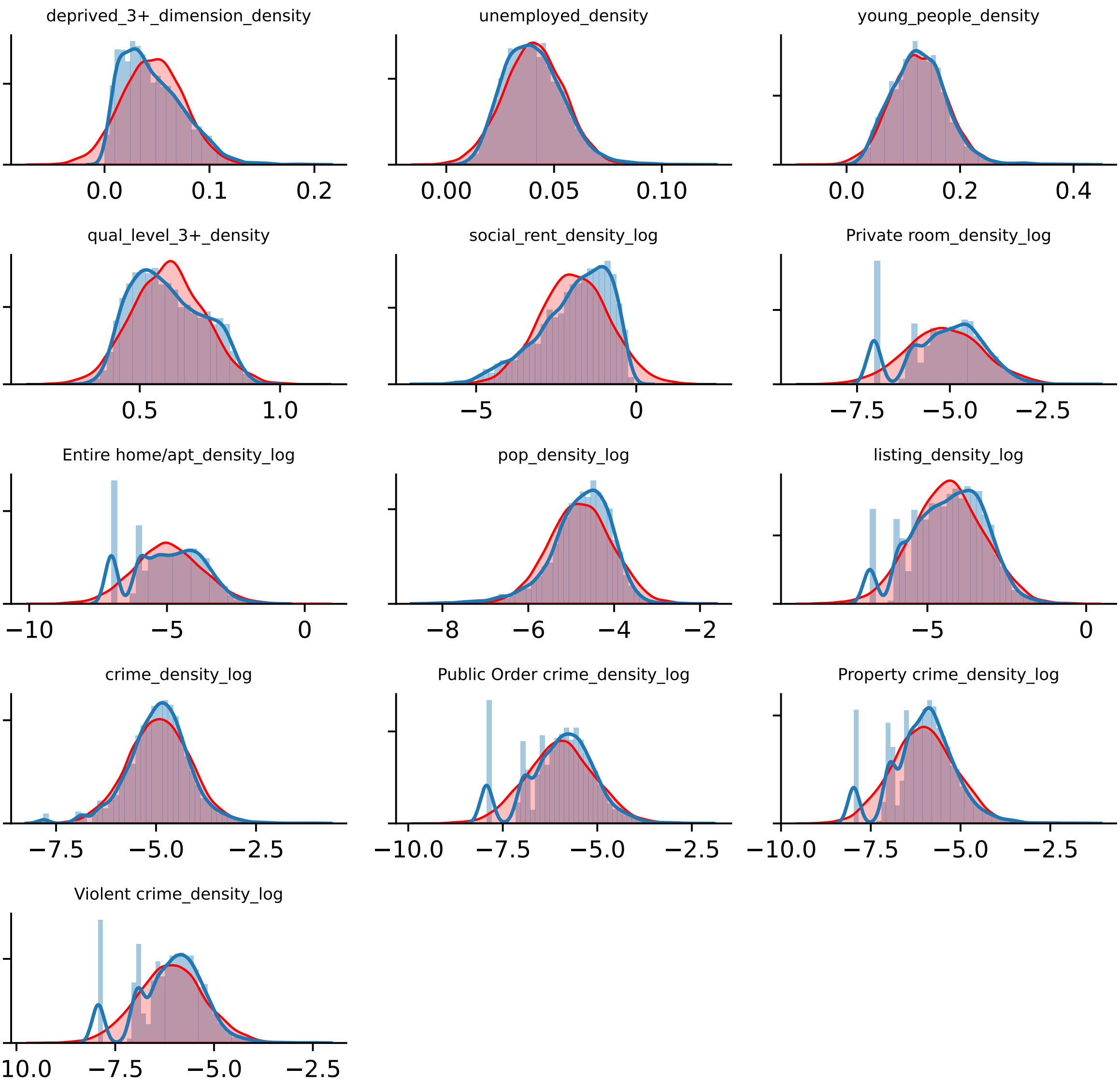

Figure 6: Regression dependent and indenpendent variables (post-log-transformation)

Regression Model Results

In analysing the factors affecting the density of each type of crime, we applied ordinary least squares (OLS) to construct a regression model. We found some key predictor variables to be statistically significant.

Looking directly at our target variables, **Entire home/apt** density has a notable effect on property crime incidents (coeff=0.183, p-value<0.05), followed by public order crime (coeff=0.169, p-value<0.05) and finally violent crime (coeff=0.101, p-value<0.05). Meanwhile, **Private room** density interestingly only has a notable and significant effect on public order crime (p-value<0.05) and violent crime (p-value<0.05)

Despite some signs of heteroscedasticity (see Figure 8), this has already been greatly accounted for after our log transformation)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      crime_density_log   R-squared:                       0.280
Model:                            OLS   Adj. R-squared:                  0.279
Method:                 Least Squares   F-statistic:                     242.8
Date:                Tue, 19 Dec 2023   Prob (F-statistic):               0.00
Time:                        02:11:59   Log-Likelihood:                -4973.7
No. Observations:                4994   AIC:                             9965.
Df Residuals:                    4985   BIC:                         1.002e+04
Df Model:                           8
Covariance Type:            nonrobust
=================================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                         -5.5693      0.190    -29.303      0.000      -5.942      -5.197
deprived_3+_dimension_density    1.6923      0.608      2.786      0.005       0.501       2.883
unemployed_density              3.9491      0.992      3.983      0.000       2.005       5.893
young_people_density            3.7466      0.229     16.349      0.000       3.297       4.196
qual_level_3+_density          -0.1408      0.128     -1.101      0.271      -0.392       0.110
social_rent_density_log         0.1554      0.014     11.251      0.000       0.128       0.182
Private room_density_log        0.0399      0.012      3.225      0.001       0.016       0.064
Entire home/apt_density_log      0.1645      0.013     13.115      0.000       0.140       0.189
pop_density_log               -0.2765      0.016    -17.471      0.000      -0.308      -0.245
==============================================================================
Omnibus:                      278.057   Durbin-Watson:                   1.812
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              633.030
Skew:                          -0.353   Prob(JB):                    3.46e-138
Kurtosis:                       4.595   Cond. No.                         983.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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                                OLS Regression Results
==================================================================================
Dep. Variable:     Property crime_density_log   R-squared:                       0.160
Model:                                    OLS   Adj. R-squared:                  0.158
```

```
Method:                        Least Squares   F-statistic:                     118.4
Date:                       Tue, 19 Dec 2023   Prob (F-statistic):          4.61e-182
Time:                               02:11:59   Log-Likelihood:                -6045.6
No. Observations:                       4994   AIC:                         1.211e+04
Df Residuals:                           4985   BIC:                         1.217e+04
Df Model:                                  8
Covariance Type:                   nonrobust
===================================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                          -7.3011      0.236    -30.995      0.000      -7.763      -6.839
deprived_3+_dimension_density    1.6626      0.753      2.208      0.027       0.186       3.139
unemployed_density              2.9107      1.229      2.368      0.018       0.501       5.320
young_people_density            3.3946      0.284     11.952      0.000       2.838       3.951
qual_level_3+_density           0.4430      0.159      2.795      0.005       0.132       0.754
social_rent_density_log         0.0795      0.017      4.646      0.000       0.046       0.113
Private room_density_log        0.0064      0.015      0.419      0.676      -0.024       0.036
Entire home/apt_density_log     0.1830      0.016     11.774      0.000       0.153       0.213
pop_density_log                -0.3090      0.020    -15.753      0.000      -0.347      -0.271
==============================================================================
Omnibus:                       95.493   Durbin-Watson:                   1.814
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              114.143
Skew:                          -0.278   Prob(JB):                     1.64e-25
Kurtosis:                       3.490   Cond. No.                         983.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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                                OLS Regression Results
=====================================================================================
Dep. Variable:     Violent crime_density_log   R-squared:                       0.221
Model:                                   OLS   Adj. R-squared:                  0.220
Method:                        Least Squares   F-statistic:                     176.6
Date:                       Tue, 19 Dec 2023   Prob (F-statistic):          1.94e-263
Time:                               02:11:59   Log-Likelihood:                -5650.3
No. Observations:                       4994   AIC:                         1.132e+04
Df Residuals:                           4985   BIC:                         1.138e+04
Df Model:                                  8
Covariance Type:                   nonrobust
===================================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                          -6.4194      0.218    -29.496      0.000      -6.846      -5.993
deprived_3+_dimension_density    0.3067      0.696      0.441      0.659      -1.057       1.670
unemployed_density              4.9426      1.135      4.353      0.000       2.717       7.168
young_people_density            3.9885      0.262     15.199      0.000       3.474       4.503
qual_level_3+_density          -0.7352      0.146     -5.020      0.000      -1.022      -0.448
social_rent_density_log         0.1929      0.016     12.200      0.000       0.162       0.224
Private room_density_log        0.0501      0.014      3.537      0.000       0.022       0.078
Entire home/apt_density_log     0.1012      0.014      7.047      0.000       0.073       0.129
pop_density_log                -0.2422      0.018    -13.363      0.000      -0.278      -0.207
```

```
==============================================================================
Omnibus:                      162.715   Durbin-Watson:                   1.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              182.026
Skew:                          -0.430   Prob(JB):                     2.98e-40
Kurtosis:                       3.369   Cond. No.                         983.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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                                OLS Regression Results
==========================================================================================
Dep. Variable:     Public Order crime_density_log   R-squared:                       0.229
Model:                                        OLS   Adj. R-squared:                  0.228
Method:                             Least Squares   F-statistic:                     185.1
Date:                            Tue, 19 Dec 2023   Prob (F-statistic):         9.29e-275
Time:                                    02:11:59   Log-Likelihood:                -5949.2
No. Observations:                            4994   AIC:                         1.192e+04
Df Residuals:                                4985   BIC:                         1.198e+04
Df Model:                                       8
Covariance Type:                        nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                        -6.1294      0.231    -26.528      0.000      -6.582      -5.676
deprived_3+_dimension_density    2.4954      0.739      3.379      0.001       1.047       3.943
unemployed_density            3.2818      1.205      2.723      0.007       0.919       5.645
young_people_density          3.7015      0.279     13.286      0.000       3.155       4.248
qual_level_3+_density        -0.3186      0.155     -2.049      0.041      -0.623      -0.014
social_rent_density_log       0.1499      0.017      8.926      0.000       0.117       0.183
Private room_density_log      0.0557      0.015      3.704      0.000       0.026       0.085
Entire home/apt_density_log    0.1685      0.015     11.052      0.000       0.139       0.198
pop_density_log              -0.2127      0.019    -11.054      0.000      -0.250      -0.175
==============================================================================
Omnibus:                      151.781   Durbin-Watson:                   1.859
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              165.629
Skew:                          -0.431   Prob(JB):                     1.08e-36
Kurtosis:                       3.231   Cond. No.                         983.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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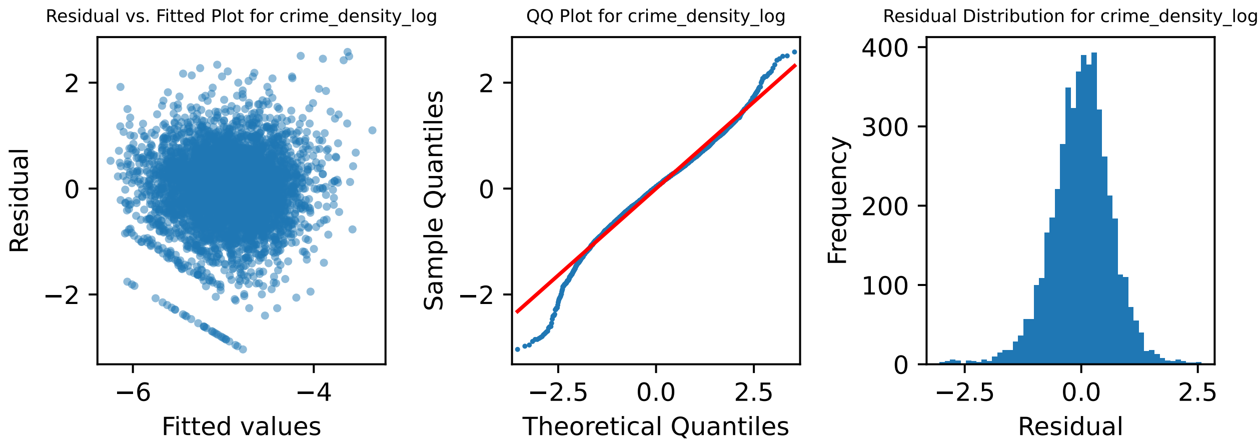

Figure 7: Residual Analysis to confirm OLS assumptions (All Crime)

Accounting for spatial autocorrelation

The fact that the crime observed in an LSOA affects crime observed in the neighbouring LSOAs results in spatial autocorrelation among the residuals. In fact, Moran's I test stats show that as a whole there is only a slight spatial autocorrelation among the residuals (Coeffs close to 0). Areas where our model might under-predict crime are in red (HH), whereas areas where our model might over-predict crime are in blue (LL). Fortunately, the Spatial Error Model below (introducing spatial component into our original OLS model for All Crimes) shows that it does not significantly affect the coefficients of our target variables. More specifically:

- **Private room** coeff=0.043 vs 0.040 originally (slightly stronger effect)
- **Entire home/apt** coeff=0.1473 vs 0.1645 originally (slightly weaker effect)

With this, we can conclude that there is a positive effect of the density of Airbnb listings on crime in a neighbourhood, especially for Entire home/apt listings.

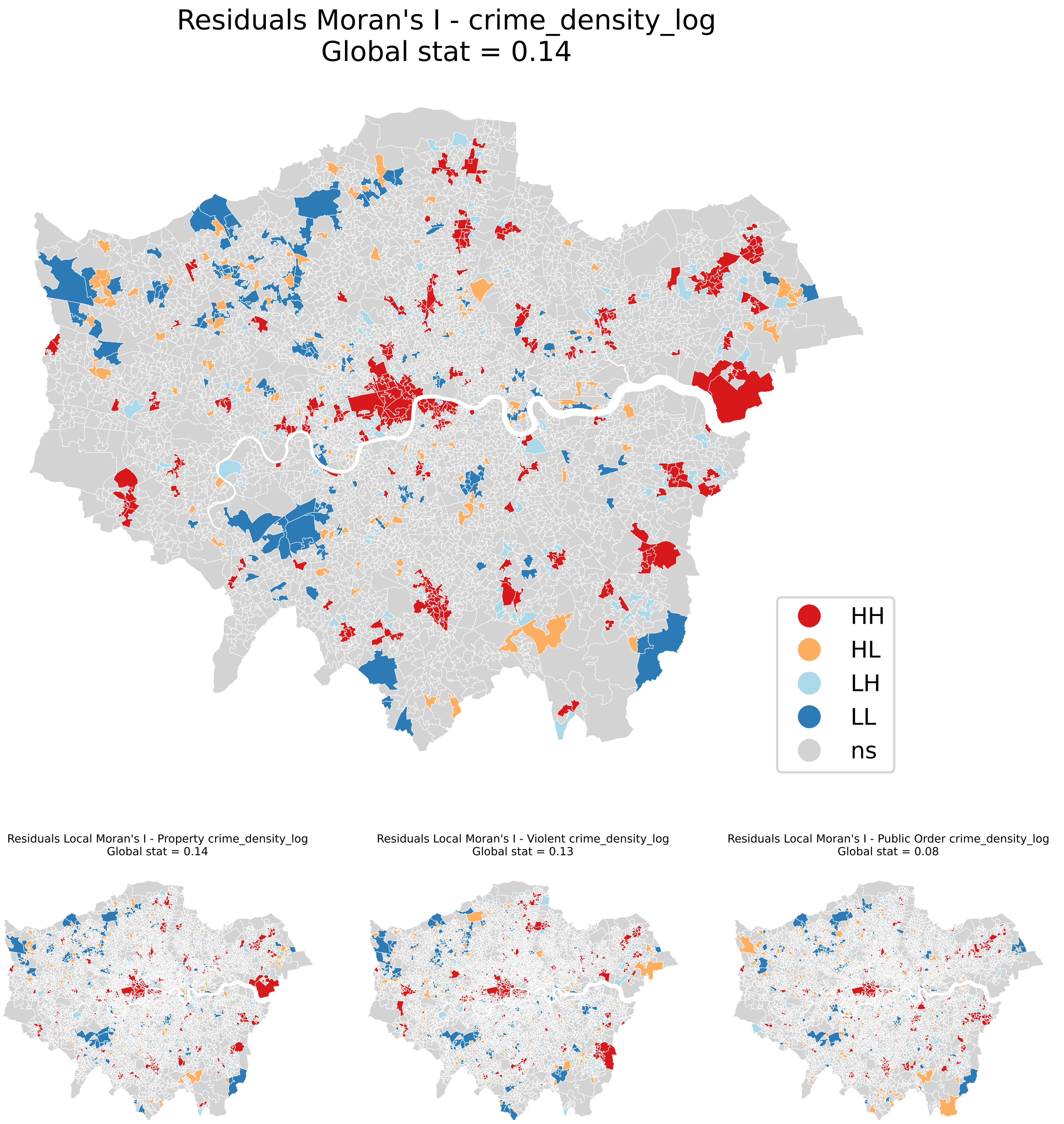

Figure 8: Residual Morans I - by crime category

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REGRESSION
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SUMMARY OF OUTPUT: SPATIALLY WEIGHTED LEAST SQUARES (HET)
---------------------------------------------------------
Data set            :     unknown
Weights matrix      :     unknown
Dependent Variable  :crime_density_log                Number of Observations:        4994
Mean dependent var  :     -4.9364                Number of Variables    :           9
S.D. dependent var  :      0.7723                Degrees of Freedom     :        4985
Pseudo R-squared    :      0.2793
N. of iterations    :           1                Step1c computed        :          No

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-----------------------------------------------------------------------------------
           CONSTANT      -5.9655501       0.2044357     -29.1805674       0.0000000
deprived_3+_dimension_density       1.8324987       0.6020768       3.0436297       0.0023374
  unemployed_density       4.6903925       1.0099169       4.6443352       0.0000034
young_people_density       3.8837126       0.3005917      12.9202271       0.0000000
qual_level_3+_density       0.0832843       0.1452991       0.5731923       0.5665145
social_rent_density_log       0.1472213       0.0146169      10.0720046       0.0000000
Private room_density_log       0.0427652       0.0128661       3.3238801       0.0008877
Entire home/apt_density_log       0.1473091       0.0134343      10.9651657       0.0000000
     pop_density_log      -0.3004990       0.0189553     -15.8530249       0.0000000
             lambda       0.3381210       0.0198324      17.0489488       0.0000000
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Do short-lets in different areas have a different effect on crime?

Using a Geographically Weighted Regression, we can further visualise where precisely the effect of short lets on crime is statistically significant. The results show that:

- **Private Room** presence has a particularly strong effect on crime (including property crime) in East and Southeast London (City, Boroughs of Tower Hamlets, Bermondsey, Southwark, etc.)
- **Entire Home** presence has a particularly strong effect on crime (including Property Crime) in Central London (Boroughs of Westminster, Camden, South Islington)

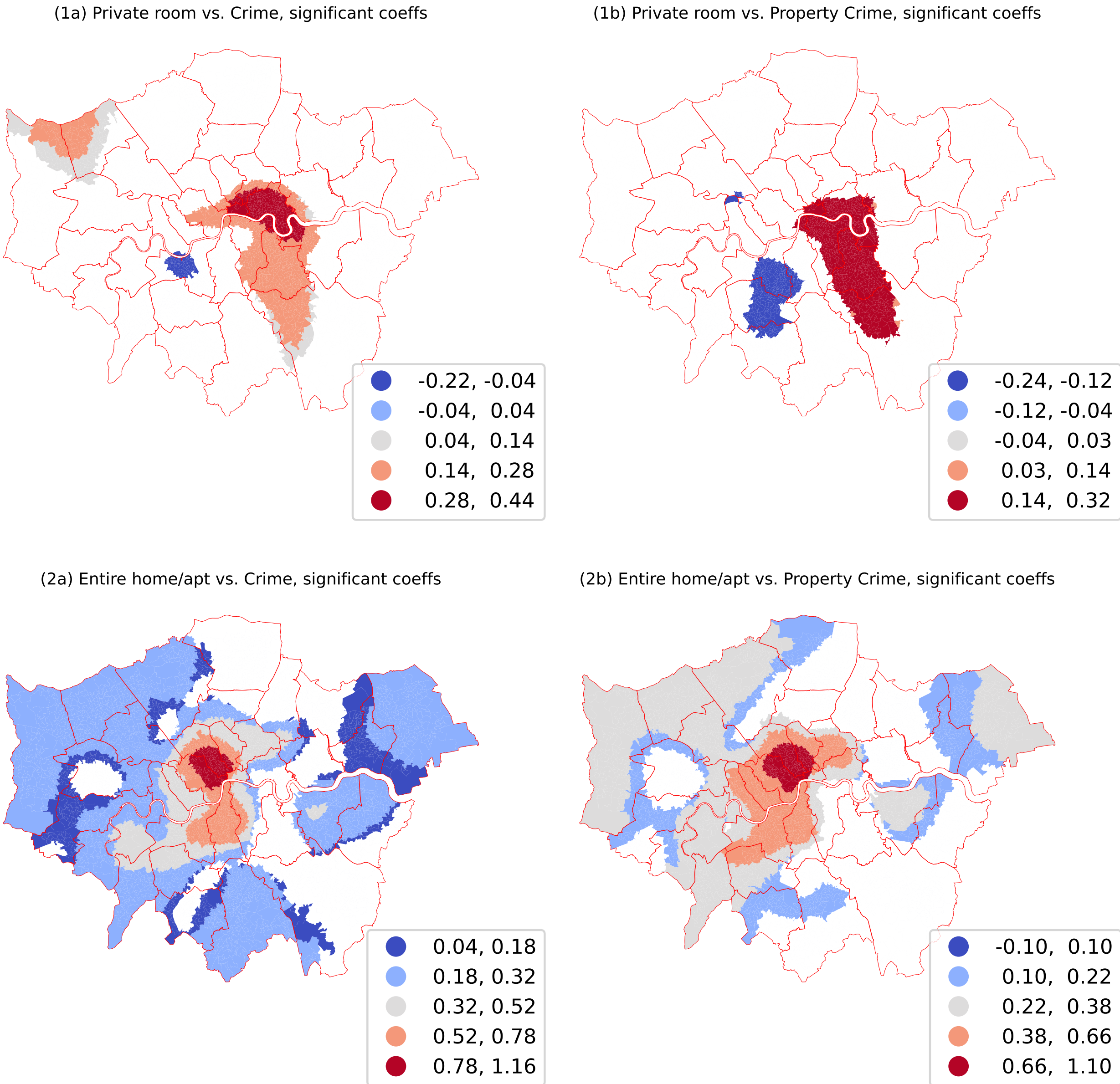

Figure 9: Geographically weighted effect of short-lets on crime

Reflection and Recommendations

After the public consultation on the policy in 2022, the government will require landlords to register and will conduct random checks on some listings or require landlords to upload legal documents to prove the safety of their listings (Consultation on a registration scheme for short-term lets in England, 2023). While this will allow for better listing management and tenants' safety, we recommend further actions based on our analysis thus far:

First, for **property crime**, *entire home* shortlets are at particular risk, especially in central London, and *private room* listings in East London, whether shortlet tenants are committing theft or disturbances against neighbours or being targeted. We suggest that Airbnb should strengthen the background checks of tenants (Barron, Kung, and Proserpio, 2018) and choose whether to ban the use of the Airbnb platform according to the number of tenants with criminal property records. If permitted, Airbnb needs to provide relevant information to the landlord and keep records synchronised with local police departments. In the property security protection of tenants, Airbnb needs to strengthen the door lock management, such as encouraging the landlord to replace the smart door lock as much as possible and allowing each group of tenants to reset their password.

Second, there is an impact of shortlets on **violent crime and public order crime**. Since our crime data cannot be detailed into whether or not the offence occurred within the listing, the following recommendations will encompass all stakeholders:

- **a**) **For Airbnb**, more regulations on tenants' behaviour are needed. For example, while Airbnb currently states the required quiet time for tenants on its booking interface, it does not specify penalties. For tenants reported for taking drugs, disturbing residents, committing crimes against neighbours or listings, or violating Airbnb's rules, Airbnb shall block the tenant's Airbnb account based on the severity. Moreover, Airbnb should set up efficient channels to ensure responsive security measures, making it easier for tenants or landlords to file complaints against each other. Especially after receiving safety reports about the listings, Airbnb should consider taking the listings offline (Grind and Shifflett, 2019).
- **b**) **For the government**, there are benefits to strictly regulating shortlets, e.g. enforcing owner-occupied residences, a cap on the number of renters, and neighbour notifications (Vande Bunte, 2014). Moreover, we could refer to San Francisco's approach, which imposes strict rules on the duration each landlord can rent out a property each year, effectively controlling the number of short-rental properties (Cromarty, 2023), reducing the transient population (Mburu and Helbich, 2016). Besides, a conscious effort should be made to increase police presence in places where Airbnb is particularly dense.
- **c**) **For tenants**, both Airbnb and the government should encourage them to understand and comply with local laws and regulations regarding short-term rentals like the New York State Multiple Dwelling Law (Schneiderman, 2014) through various channels, such as news pop-ups and educational publicity programs. Improving public awareness is essential to reducing crime and creating a safe environment (Felson et al., 2019).

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Use of Github Copilot AI within Visual Studio Code IDE in parts.