CHASE's Group Project

1. Who collected the InsideAirbnb data?

The InsideAirbnb was collected by Murray Cox, Tom Slee, and a team of collaborators working to empower communities through data. Murray Cox is an Australian community artist, activist and photo- journalist who "uses data, media, and technology for social change" ('About' (no date)). (40)

2. Why did they collect the InsideAirbnb data?

Murray Cox and Tom Slee collected the InsideAirbnb data to critically assess the impact of Airbnb on housing markets, to provide unbiased independent publicly available data, and to facilitate the improved understanding of city authorities and regulatory bodies. Motivated by an observation of increasing entire-home listings and "multi-lister" hosts, Cox and Slee aimed to challenge Airbnb's portrayal as a platform for casual home sharing, revealing that much of its revenue comes from commercial operators who are pushing out local residents by raising house prices (Carville (2019)). (84)

3. How did they collect it?

Inside Airbnb's data is collected through web-scraping, using public information from Airbnb's website. There were two main stages of data collection: Identify listings for chosen set of coordinates. Collect the following information for each listing: listing type, approximate address, number of reviews and average review score, capacity, numbers of bedrooms and bathrooms, price, and coordinates. Data is periodically scraped for each location from the Airbnb website adamiak_airbnb_2019, ('Home' (no date)). ()

4. How does the method of collection (Q3) impact the completeness and/or accuracy of the InsideAirbnb data? How well does it represent the process it seeks to study, and what wider issues does this raise?

Inside Airbnb (IA) data is limited as scraping can only take place using publicly available data; that which is allowed in Airbnb's robots.txt file. Datasets are therefore only an approximation of the Airbnb market and might not be suitable for use by those requiring more detailed understanding of Airbnb's effect on housing markets eg. policymakers.

Using IA's data relies solely on the data of Airbnb which only provides an estimation of the short term rental market. Some listings may be booked directly with hosts to avoid

Airbnb's additional charges, and therefore might appear unavailable on Airbnb, but are actually booked; distorting the true effect of Airbnb on the housing market (Prentice and Pawlicz (2023)).

As acknowledged by IA, listings' geographic locations are not available, meaning that analysis must be aggregated to a higher level. This limits the ability to conduct detailed analysis of Airbnb's effect on the housing market, as would be the case when conducting price analysis using distance to points of interest as explanatory variables (Todd, Musah and Cheshire (2022)).

IA programmer, Slee, T. (n.d.), states that 'no guarantees are made about the quality of data obtained using this script, statistically or about an individual page,' encouraging researchers to check validity on their own. Furthermore, the script was last updated in 2019 (Slee (2024)), potentially resulting in inaccurate listing counts following changes to Airbnb's data structure, reducing the useability of the data to assess housing market impacts.

The IA data is therefore not 'raw', it is "verified, cleansed, analyzed and aggregated" 'Home' (no date), meaning the data is biased. Cleaning and aggregation removes detail and certain perspectives from the data. This erasure is especially significant when those working, processing and analysing the data are not aware of the context in which it was created (D'Ignazio and Klein (2020)).

Completeness and accuracy challenges raise the question of whether researchers should rely solely on data collected by one organisation, from one website, to analyse the impact of an industry. By focusing solely on the data provided by IA researchers will come to biased and partial conclusions that are influenced by the views of IA's creators. (345)

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

Terms of Service outline the contract through which users and Airbnb interact, specifying users must not scrape or use scrapers or crawlers to access or collect data ('Terms of Service - Airbnb Help Centre' (no date)).

From the perspective of an Airbnb user, having agreed to the Terms of Service, they expect that their data is protected. However, as InsideAirbnb demonstrates, these agreements do not guarantee that data will not be collected. Instead, Airbnb are relying on the conscience of the programmers to adhere to the Terms of Service and robot.txt files to guarantee privacy to their users.

The Terms of Service is contradictory to the robot.txt file- the former specifies not scraping data at all, the latter could be considered as permission to scrape certain data by explicitly prohibiting access to other data.

The robot.txt file is however non-binding, so relies on the programmer's adherence, which could cause harm to Airbnb's users and customers if not followed.

InsideAirbnb data is collected through web scraping, in contradiction to the Terms of Service, so despite the efforts taken by IA to anonymise the data, Airbnb users have not given their informed consent for any data to be collected in this way, nor have they consented to their data being used by third parties in this manner, raising ethical considerations over the use of data provided by Krotov, Johnson and Silva (2020).

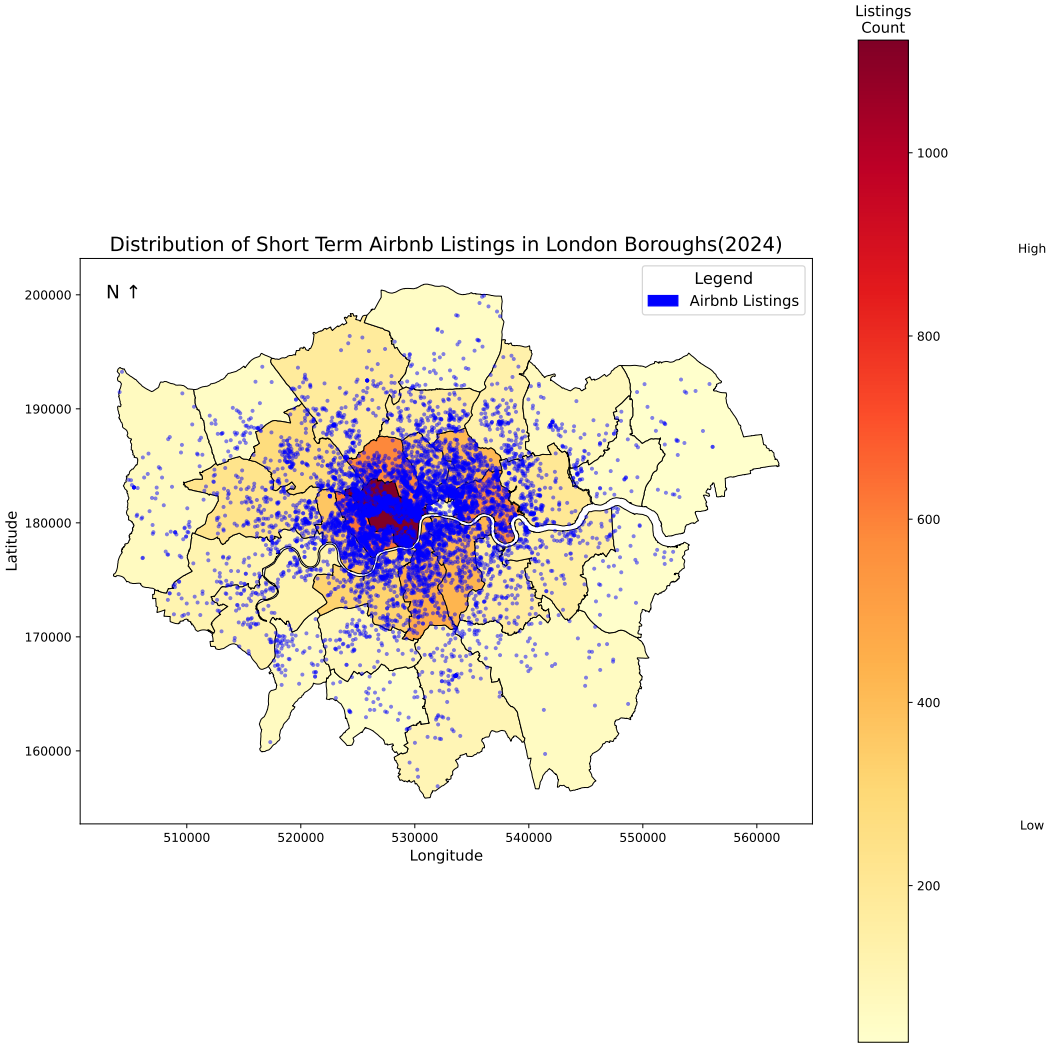
Another ethical issue is the accuracy of the data being provided. InsideAirbnb state that accuracy of the information compiled from the Airbnb site is not the responsibility of Inside Airbnb. Due care has been taken with any processing and analysis. - ('Home' (no date)).

As Mason (1986) explains, depending on how it is used, the data's accuracy can raise ethical concerns. InsideAirbnb's data is "used regularly over the last year by city analysts, journalists, academics and hospitality analysts" Cox and Slee (no date). The use of such data by city analysts will impact the lives of those that fall under the jurisdiction of the city authority, raising the ethical consideration of the data's accuracy due to the harm that may be caused from the use of Inside Airbnb's potentially misrepresentative data. This is of further concern when those analysing the data do not fully understand the process through which it has been collected and the limits this brings, causing potentially significant economic and societal impacts if InsideAirbnb's data is not used mindfully.

Mason (1986) argues that accessibility is also an ethical concern when it comes to using data. Not everyone has the technologies required to access the data, and even fewer have the intellectual skills to interpret and process the InsideAirbnb data. D'Ignazio and Klein (2020) explain that differential power has a silencing effect and that quantitative data can leave people out. Whilst InsideAirbnb's mission is to "work towards a vision where communities are empowered with data and information" ('Home' (no date)), its capability to do so is limited if the communities it seeks to empower lack the means to make use of the available data. The lack in transfer of data science skills and knowledge to the communities that InsideAirbnb seek to represent, and subsequent reliance on external researchers, mean that the imbalances in education and power will not be sufficiently addressed since the communities' reality will only ever be told through the partial perspective of said researchers. (540)

6. With reference to the InsideAirbnb data (*i.e.* using numbers, figures, maps, and descriptive statistics), what does an analysis of Hosts and the types of properties that they list suggest about the nature of Airbnb lettings in London? - Total 698

There is a possibility of making the base map of the airbnb density the price so that we save 150 words. So there wont be a bar graph of average price.



Calculating Percent of Short-Term Listings per Borough

Airbnb's short-term listings are clustered in boroughs surrounding the City of London. 14.4% of listings occur in Westminster, followed by 8.1% in Kensington and Chelsea, then 7.5% in Camden.

Boroughs with Airbnb Percentages:

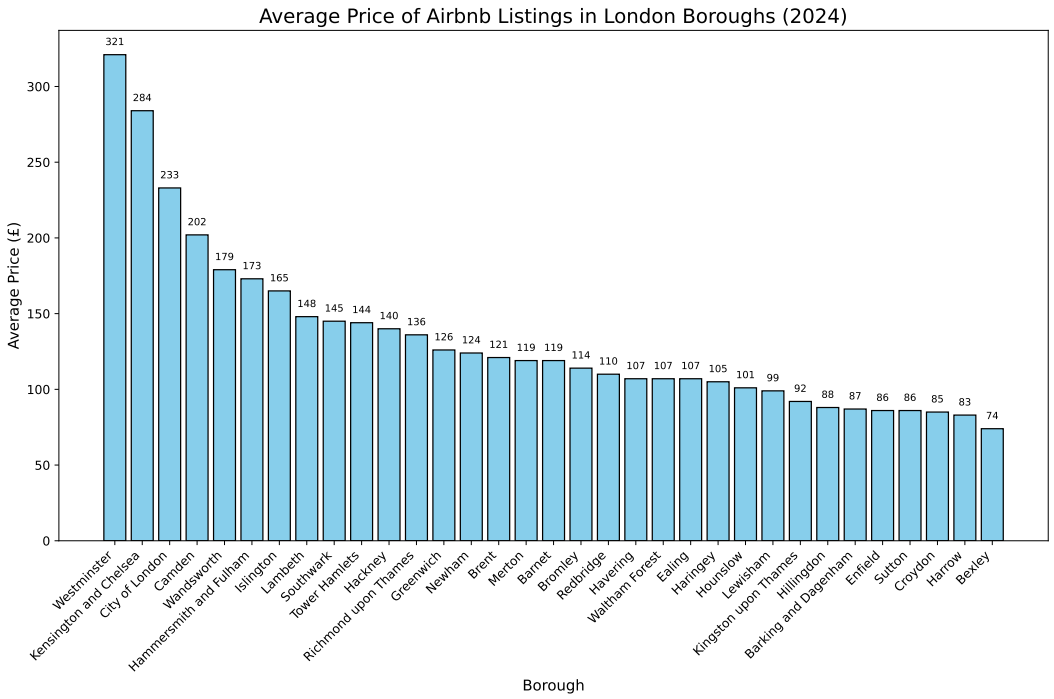
	NAME	Airbnb_Counts	Percentage
32	Westminster	1123	14.408519
19	Kensington and Chelsea	629	8.070310
5	Camden	586	7.518604
29	Tower Hamlets	578	7.415961
21	Lambeth	463	5.940467
27	Southwark	429	5.504234
11	Hackney	419	5.375930
12	Hammersmith and Fulham	367	4.708750
18	Islington	350	4.490634
31	Wandsworth	320	4.105722
3	Brent	279	3.579677
8	Ealing	233	2.989479

24	Newham	200	2.566076
1	Barnet	182	2.335130
13	Haringey	171	2.193995
22	Lewisham	163	2.091352
10	Greenwich	155	1.988709
30	Waltham Forest	135	1.732102
26	Richmond upon Thames	125	1.603798
17	Hounslow	118	1.513985
7	Croydon	104	1.334360
23	Merton	91	1.167565
25	Redbridge	72	0.923788
16	Hillingdon	70	0.898127
20	Kingston upon Thames	65	0.833975
4	Bromley	63	0.808314
6	City of London	56	0.718501
9	Enfield	54	0.692841
14	Harrow	52	0.667180
0	Barking and Dagenham	42	0.538876
2	Bexley	37	0.474724
28	Sutton	34	0.436233
15	Havering	29	0.372081

Calculating the Average Price of Airbnb Listings in London Boroughs

Average Price of Airbnb Listings per Borough:

	NAME	Average_Price
32	Westminster	321.0
19	Kensington and Chelsea	284.0
6	City of London	233.0
5	Camden	202.0
31	Wandsworth	179.0



Westminster, Kensington and Chelsea, and the City of London exhibit the highest average prices, while Bexley and Harrow have the lowest, reflecting significant variation in short-term rental costs across the city.

Properties Available for over 90+ Nights

A concern that Airbnb imposes in London is 'commercialisation'. The Greater London Authority (GLA) states that "it creates a risk of residential properties being used as letting businesses without the required planning permission and protections for neighbours" (Balogun *et al.* (2024), p.26). To avoid this issue, homeowners are required to obtain planning permission if they intend to use residential properties for short-term accommodation exceeding 90 nights. In the current 2024 analysis, we found that there is a total of 6254 listings available for over 90+ nights. Westminster has 15.7% of those listings, Kensington and Chelsea at 9%, and Tower Hamlets at 7.5%.

Airbnb Listings Available for 90+ nights by Borough (With Percentage):

	NAME	Airbnb_Counts	Percentage
0	Barking and Dagenham	31	0.495683
1	Barnet	153	2.446434
2	Bexley	26	0.415734
3	Brent	205	3.277902
4	Bromley	47	0.751519
5	Camden	465	7.435241
6	City of London	53	0.847458
7	Croydon	84	1.343140
8	Ealing	184	2.942117
9	Enfield	38	0.607611
10	Greenwich	131	2.094659
11	Hackney	325	5.196674
12	Hammersmith and Fulham	303	4.844899

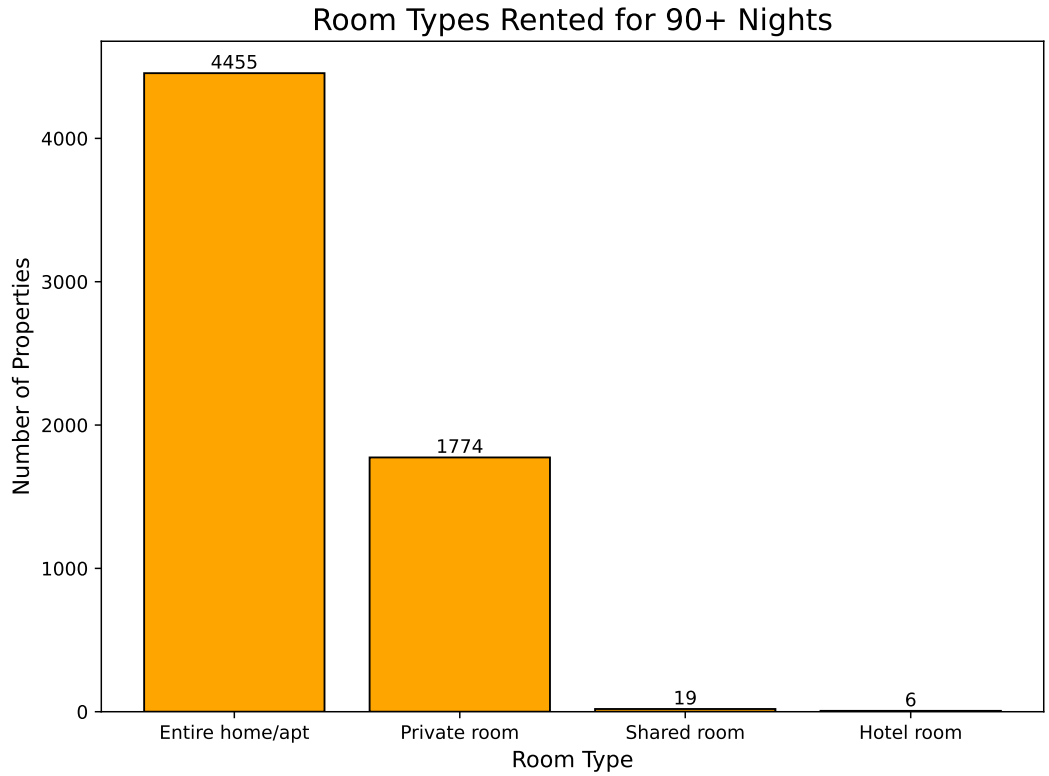
13	Haringey	137	2.190598
14	Harrow	42	0.671570
15	Havering	26	0.415734
16	Hillingdon	61	0.975376
17	Hounslow	87	1.391110
18	Islington	280	4.477135
19	Kensington and Chelsea	562	8.986249
20	Kingston upon Thames	47	0.751519
21	Lambeth	359	5.740326
22	Lewisham	110	1.758874
23	Merton	66	1.055325
24	Newham	157	2.510393
25	Redbridge	64	1.023345
26	Richmond upon Thames	77	1.231212
27	Southwark	329	5.260633
28	Sutton	28	0.447713
29	Tower Hamlets	469	7.499201
30	Waltham Forest	91	1.455069
31	Wandsworth	235	3.757595
32	Westminster	982	15.701951

Total Airbnb Listings Available for 90+ nights: 6254

Total Airbnb Listings Available for 90+ Nights: 6254

Room Types Available for 90+ Nights:

	Room Type	Count
0	Entire home/apt	4455
1	Private room	1774
2	Shared room	19
3	Hotel room	6



The most common ‘room types’ available for over 90+ nights are entire homes and apartments.

Hosts with Multiple Listings

GLA have discovered that hosts with multiple listings on Airbnb are more likely to be using the platform for commercial purposes (Balogun *et al.* (2024), 2024, p.25). The total number of hosts with two or more listings is 6253 with the average number of listings per host being 7.06. The maximum number of listings is 1253 that belong to Sykes Holiday Cottages. This shows that the Airbnb market in London is commercialised and does not adhere to the GLA 90-night policy limit.

```
Total number of hosts with more than 2 listings: 6253
Average number of listings per host: 7.06
Maximum number of listings: 1253
Minimum number of listings (2 or more): 2

Host(s) with the most listings:
                  host_name  total_listings
5518  Sykes Holiday Cottages            1253
```

7. Drawing on your previous answers, and supporting your response with evidence (*e.g.* figures, maps, EDA/ESDA, and simple statistical analysis/models drawing on experience from, e.g., CASA0007), how *could* the InsideAirbnb data set be used to inform the regulation of Short-Term Lets (STL) in London?

Insights from the previous section highlight the commercialized reality of Airbnb in London despite official regulations. Failure to limit Airbnb has the potential to exacerbate the affordable housing crisis in London by reducing the availability of long-term rentals. The impact of Airbnb is of particular concern with regard to deprived households, whereby increased housing costs can contribute to displacement, making it more difficult for these residents to remain in their communities.

Our analysis aims to answer the following questions: What wards are "at risk" of becoming an Airbnb hotspot? Of these wards, which are also the most vulnerable to the negative social impacts of Airbnb?

We filtered the Airbnb dataset to focus on listings most relevant to neighbourhood impacts:

- Minimum Nights: Excluded listings with a minimum stay over 30 nights to target short-term rentals.
- Recently Active: Included listings with reviews in the past six months for current relevance.
- Availability: Kept listings available at least 90 days annually to capture impactful activity.
- Room Type: Focused on "Entire home/apt" listings due to their greater effect on housing and neighbourhood dynamics.

Data Reading and Wrangling

```
gdown is already installed. Skipping installation.
File already exists: London_Points_Of_Interest.gpkg. Skipping download.
File size: 129515520 bytes
```

Analysis

Decision Tree Model

We chose a decision tree methodology for this analysis due to its high interpretability, making it easy for policymakers to understand how each ward was classified as "at-risk" or "too late". Each classification decision the model makes can be easily traced in a simple, visual format.

The decision tree predicts whether a ward is likely to have high Airbnb density using ward-level characteristics of public transport accessibility, house prices, and point of interest density, which we then use to categorise each London ward into one of three groups:

Too Late: Wards already heavily impacted by Airbnb, that are in the top 5% of airbnb's per 1000 households.

At Risk: Wards predicted to have high Airbnb density but do not meet the threshold.

Neither: Wards that don't fall into either category.

We selected these variables as research has shown that higher-income neighborhoods, better transit access, and proximity to attractions significantly influence Airbnb activity Jiao and Bai (2020).

```
AirBnb Density 'Too-Late' Threshold: 5.63 per 1000 households

Average Ward AirBnb Density: 1.43 per 1000 households
Average Ward House Price: £434,979
Average Ward Point of Interest Density: 0.27
Average Ward Public Transport Accessibility Score: 3.78
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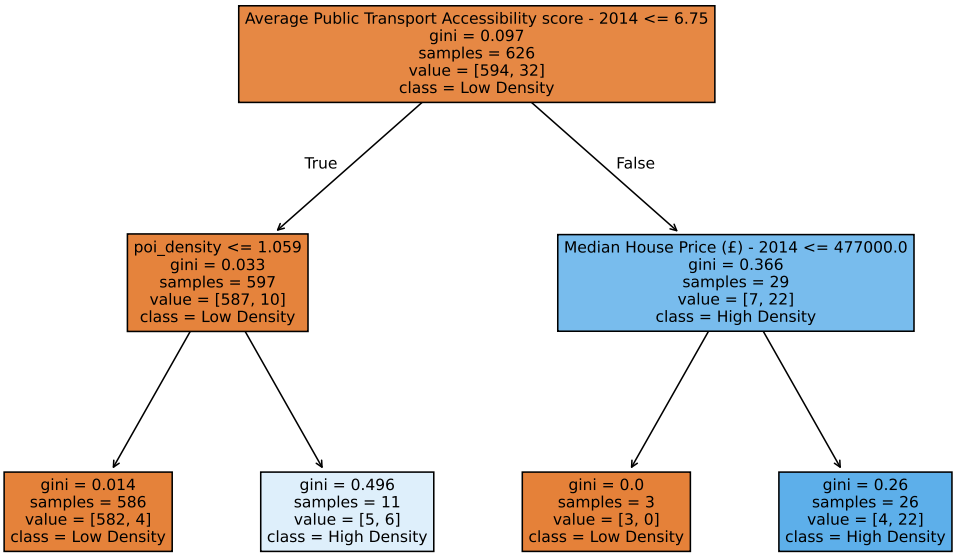


Interpreting the Decision Tree

The decision tree model identifies two scenarios where a ward is predicted to have a high Airbnb density:

- Transport Accessibility score of more than 6.75 and a Median House Price of more than £477,000

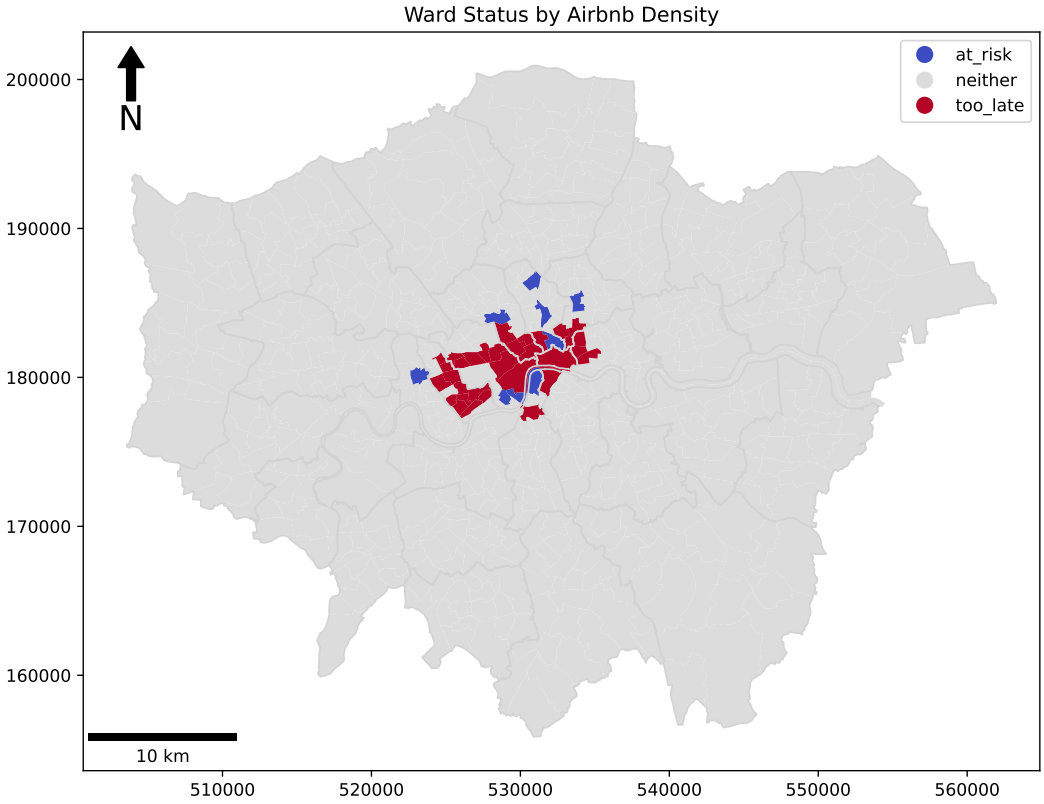
or

- Transport Accessibility score of less than or equal to 6.75 and a point of interest density of more than 1.059 per hectare.

The results suggest that high Airbnb density is linked to well-connected areas with above-average housing prices, though less connected areas can also attract Airbnb activity if they offer a high concentration of attractions and amenities.

There are 9 wards that meet either of these conditions but do not exceed the 'too late' Airbnb density threshold, so we have categorised them as 'at-risk'.

```
These at-risk wards are: Lambeth - Bishop's, Hammersmith and Fulham -
Shepherd's Bush Green, Westminster - Vincent Square, Westminster -
Warwick, Camden - Camden Town with Primrose Hill, Islington -
St. Mary's, Islington - Bunhill, Islington - Finsbury Park, Hackney -
Dalston
```



“At-Risk” Wards and Deprivation

To assess potential social impact of Airbnb in London, we analyzed the relationship between our Airbnb decision tree classifications and deprivation rank in wards. Deprivation rank is a relative measure comparing the level of deprivation across London wards. The lower the deprivation rank, the greater the deprivation score in the ward.

EDA

```
Mean Deprivation Rank for 'at-risk' wards: 200
Mean Deprivation Rank for 'too-late' wards: 319
Mean Deprivation Rank for 'neither' wards: 315
```

We begin with an exploratory data analysis of deprivation and ward classifications. The results shows the average deprivation rank between classification types. We see that the mean deprivation of “at-risk” wards is lower than “too-late” wards. This suggests that “at-risk” wards are not only desirable to Airbnb letters based on our classification, but are also particularly vulnerable to the negative impacts of Airbnb due to these areas being more deprived on average.

Spatial Autocorrelation Analysis

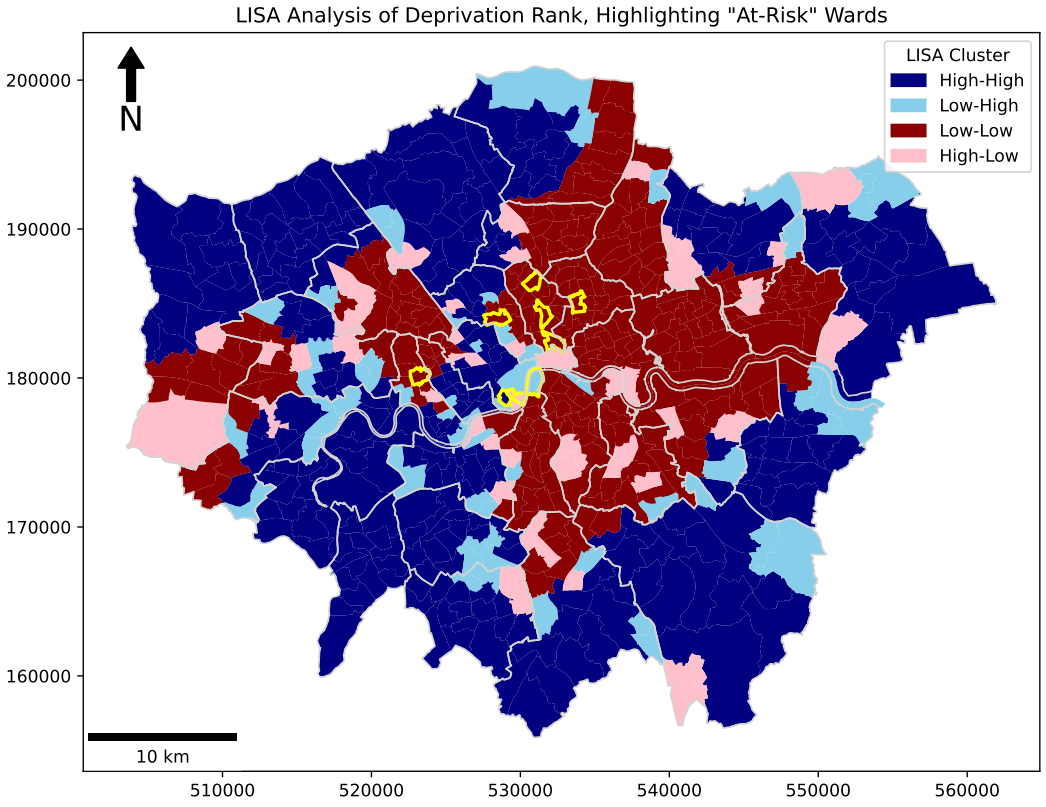
The question of remains where overlaps between “at-risk” wards and high deprivation occur. Spatial autocorrelation analysis of deprivation in London wards was employed to assess the spatial distribution of deprived wards and examine which “at-risk” wards lie within high deprivation clusters. Cluster analysis improves the generalizability of the study by identifying patterns of deprivation beyond individual wards with arbitrary boundaries.

Moran’s I:

```
Global Moran's I: 0.6888600665914413
p-value: 0.001
```

A Moran’s I test is conducted to establish that deprivation is not randomly distributed across wards in London. A Global Moran’s I statistic of 0.689 with a p-value less than 0.05 indicates there is statistically significant clustering of deprivation in London wards.

LISA:



Local indicators of spatial autocorrelation (LISA) statistics allow us to visualize the clustering of deprivation in London. Outlining “at-risk” wards in yellow, we see an overlap of deprivation clustering and “at-risk” classification for three wards in Islington, one in Hackney, one in Camden, and one in Hammersmith and Fulham.

Conclusion

The study concludes there are 9 wards “at-risk” of becoming heavily saturated by Airbnb. Furthermore, six of these wards are located within clusters of high deprivation. City policy should focus on better regulating and limiting Airbnbs in the the boroughs of Islington,

Hackney, and Hammersmith and Fulham to mitigate the negative impacts of Airbnb on vulnerable populations.

Limitations

Significant limitations to this study remain. We chose to use data from the 2014 London Ward Atlas in order to incorporate public transit accessibility into our analysis. However, this approach means that all other variables used from this dataset (i.e. house price and deprivation rank) are equally 10+ years outdated. Results from this study should be verified when updated accessibility scores for current wards become publicly available. Additionally, a purely quantitate analysis cannot comprehensively capture lived experience and local context. Qualitative work in our specified wards would be valuable for gaining better insights to the impact of Airbnb in these areas.

Sustainable Authorship Tools

Using the Terminal in Docker, you compile the Quarto report using `quarto render <group_submission_file>.qmd`.

Your QMD file should automatically download your BibTeX and CLS files and any other required files. If this is done right after library loading then the entire report should output successfully.

Written in Markdown and generated from Quarto. Fonts used: Spectral (mainfont), Roboto (sansfont) and JetBrains Mono (`monofont`).

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