Analysis

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21/03/2022

Motivation

In 2017, a research review paper by Agnieszka Lisowska brought together several research experiments done on the subject of crime in tourism destination. Liowska (2017) believed this subject important as the large growth of the tourism industry world-wide is unevenly matched to a small amount of studies that observe this matter within urban tourist areas. Conceptually, she argues a logical relation between tourism and crime, as tourism leads to an increase inflow of strangers to unknown communities, thus increasing the risk of crime either done by or to tourists. It is concluded that while research on the negative aspects of tourism (such as impacts on nature, social or cultural environments) does exist, there is insufficient research on how criminalistic statistics are related to this phenomenon (Lisowska, 2017). A research paper done by Ke, O'Brien & Heydari (2021) aims to contribute to this issue by observing how Airbnb listings might enable or generate crime specifically in the city of Boston, United States. The usage of Airbnb is rather innovative and also logical, as Airbnb has become a major industry leader among hosting platforms as it has raised in value exponentially – being valued at \$113 billion in 2021 (Lock, 2022). The research categorizes crime as private conflict, public social disorder, and violence. Ultimately, the research suggests that Airbnb presence in a neighbourhood is significantly correlated only with increased violence. A concluding argument is that tourism may not have an effect on crime, rather the conversion of housing into short-term rental property undermines a neighbourhood's social organization, thus leading to increased crime (Ke, O'Brien & Heydari, 2021).

Having observed these research papers, this team is intrigued in conducting a similar analysis and further contributing to this field. The following research question is examined:

To what extent does the number of Airbnb listings affect crime rates within Amsterdam, and to what extent is this relationship different within different Amsterdam neighborhoods.

A major change is that this research will focus on the city and neighborhoods of Amsterdam, Netherlands, rather than Boston. This enables us to investigate whether the results are replicable or applicable for a different geographical location whilst contributing to a field lacking research. Naturally, available datasets are different between international geographical locations, which primarily implies that crime categorization will be different compared to previous research. Furthermore, it is transparent to note that some aspects of the analysis will be simplified – this will not only allow the team to conduct these analyses at their own level, but also account for other data absences not present in previous research.

The team believes this research is relevant on multiple levels. The academic benefits of this research extend beyond replication at different geographical parameters and contribution to a field that lacks research – it may enable a method of analyzing this phenomenon with more internationally readily available data. From a social perspective, this research can be particularly informative to homeowners (or prospective homeowners) who would like to stay informed on how services alike to Airbnb affect the neighborhood they live or would like to live in. Furthermore, this research can be of importance to policymakers (Ke, O'Brien & Heydari, 2021) and enforcement stakeholders (security businesses, police departments etc.), as it provides correlational evidence to whether Airbnb listings do or do not affect crime rates, and if they do, what changes can they expect so that security planning can be adjusted. Lastly, this research can be of relevance to Airbnb (as well as similar businesses), as it allows them to account for changes in local environments they might enable,

but are not be fully aware of. This is particularly important to Airbnb, as its previous enablement of pollution in Japan had cost the company \$10 million in compensation(McCurry, 2018) – there is always a possibility that another government may also do the same on the front of criminality enablement. Other possible stakeholders include hotels that rent to Airbnb users and tourism agencies that use/are partnered with Airbnb. It will enable them to stay informed of the changes in local environment caused by Airbnb and allow them to predict possible shortcomings or dangers.

Exploratory Analysis

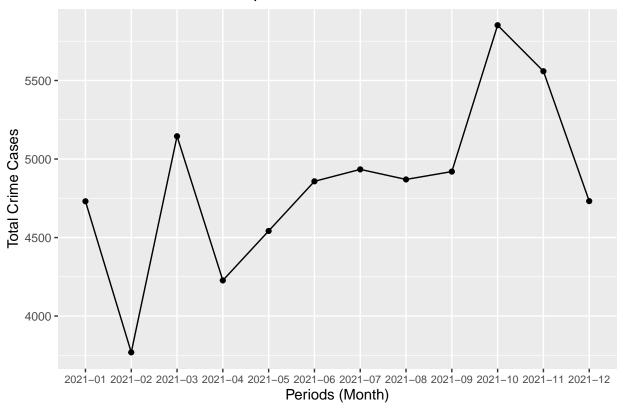
To begin this analysis, this report will first highlight some descriptive statistics about the dataset used. To begin with, the dataset contains 1680 rows worth of data, with each row highlighting the amount of listings and crimes (per type), the average listings price, and percentages per listing types based on an Amsterdam neighborhood and time period. The dataset features 20 unique Amsterdam neighborhoods and 12 unique time periods (from Januray 2021 to December 2021). The table below highlights all of the columns available in the dataset along with their descriptions.

Variable	Description	Data Class	
neighborhood	The respective neighborhood in Amsterdam to which the data	Character	
listing_sum	pertains to. The total amount of listings in the respective neighborhood.	Integer	
average_price	The average price for listings in the respective neighborhood.	Integer	
percentage_home_apt	The percentage of listings that are home apartments out of the amount of total listings.	Numeric	
percentage_hotel_rool	The percentage of listings that are hotel rooms out of the amount of total listings.	Numeric	
percentage_private_room	The percentage of listings that are private rooms out of the amount of total listings.	Numeric	
percentage_shared_room	The percentage of listings that are shared rooms out of the amount of total listings.	Numeric	
periods	The periods of time to which crime data pertains to.	Character	
crime_type_category	The type of crime to which the data pertains to.	Character	
total_crime_sum	The amount of crime occurances of a certain type in a certain period.	Integer	

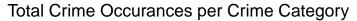
Based on the dataset, the area with the most amount of listings is Centrum-West with 59136 listings, while the area with the least is Bijlmer-Centrum with 420 listings. Furthermore, the most expensive area listings-wise is IJburg - Zeeburgereiland with 193.08888888889 average price, while the area with the least is Bijlmer-Centrum with 65 average price.

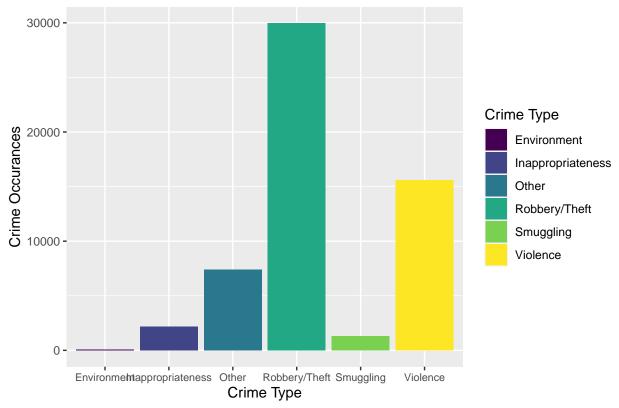
The graphs below visualize how the number of crimes has evolved throughout the available time periods, as well as the occurrences of crimes per type





As it can be seen from the Crime Occurrences per Month graph, the data exhibits no seasonality trend when viewed on a 12 month period. The lowest number of crime occurrences is on 2021-02 with 3769 crimes, while the highest is on 2021-10 with 5852 crimes.





When observing the distribution of Crime Occurrences per Crime Category graph, it is clear that crime occurrences are highly different in frequency. The graph clearly shows how the lowest number of crime occurrences is for Environment crimes with 86 occurrences, while the highest is Robbery/Theft crimes with 29962 occurrences.

Correlation Analysis

Before begging the analysis chapter, it is important to remember the hypothesis of this research:

To what extent does the number of Airbnb listings affect crime rates within Amsterdam, and to what extent is this relationship different within different Amsterdam neighborhoods.

To verify the validity of this hypothesis, the dataset will be used in a linear regression that takes the amount of crimes (total_crime_sum) as dependent variable, while taking the amount of listings(listings_sum) as independent variable and Amsterdam neighborhoods (neighborhood) as a categorical moderator. To make this possible the dataset has to be modified further - taking into account only the total crime figures (as in choosing only the rows where crime_type_category is "Total"). The regression formula used for this analysis is the following:

 $total_crime_sum = listings_sum + neighborhood$

The following table shows the results of the regression analysis:

##	# A tibble: 21 x 7						
##	term	estimate	std.error	statistic	p.value	$\verb conf.low $	conf.high
##	<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
##	1 (Intercept)	17.9	11.0	1.63	1.03e- 1	-3.64	39.4
##	2 listing_sum	0.489	0.0775	6.31	3.65e-10	0.337	0.641

```
## 3 neighborhoodBos en ~
                            -9.96
                                     13.1
                                               -0.759 4.48e- 1 -35.7
                                                                           15.8
## 4 neighborhoodBuitenv~
                            23.3
                                     14.7
                                                1.59 1.12e- 1
                                                                 -5.47
                                                                           52.1
## 5 neighborhoodCentrum~ -68.9
                                     20.6
                                               -3.34 8.62e- 4 -109.
                                                                          -28.4
## 6 neighborhoodCentrum~ -201.
                                     48.4
                                               -4.16 3.40e- 5 -296.
                                                                         -106.
## 7 neighborhoodDe Baar~ -163.
                                     36.2
                                               -4.51 6.97e- 6 -234.
                                                                          -92.1
## 8 neighborhoodDe Pijp~ -21.3
                                     15.4
                                               -1.38 1.67e- 1 -51.5
                                                                            8.93
## 9 neighborhoodGaasper~
                             4.48
                                     14.0
                                                0.320 7.49e- 1 -23.0
                                                                           32.0
## 10 neighborhoodGeuzenv~
                                     14.3
                                                4.66 3.39e- 6
                                                                           95.0
                            66.9
                                                                 38.7
## # ... with 11 more rows
```

Discussion

Conclusion

Sources

 $https://www.google.com/url?sa=t\&rct=j\&q=\&esrc=s\&source=web\&cd=\&ved=2ahUKEwjD_f2QuYn2AhUK7KQKHVp7Aurl=https\%3A\%2F\%2Fczasopisma.uni.lodz.pl\%2Ftourism\%2Farticle\%2Fdownload\%2F2208\%2F1864\&usg=AOvVaw33IzV3UaT7bLLU_4VKm4kH$

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