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Tourist proximity as a price determinant for short-term rental platforms in Buenos Aires, Argentina

Summary

Airbnb and other short-rental platforms have reshaped the tourism industry to an extent where it is becoming both an economic necessity to offer tourists while also affecting the local rental market and local urban life to an unprecedented degree. Understanding this phenomenon and its drivers is crucial for adequate planning and mitigation of negative externalities brought by this new rental format. This is true in cities with both developed and developing economies. Buenos Aires is a city that heavily promotes tourism to attract foreign currency and mitigate the national economic crisis and inflation. This situation has the added benefit of the town becoming very affordable and attractive for tourists. This investigation looks to measure to what extent STR pricing is determined by proximity to tourist locations in Buenos Aires. The land distribution of STRs in developing countries is subject to a heavy land bias. This is true in Buenos Aires, where most STRs are in neighbourhoods that cater to international expectations and have good safety conditions and connectivity. As a result, the extent to which proximity determines the price is low, only showing a marginal decrease in price as proximity values increase. Other internal variables regarding individual listings are shown to be much better predictors of Price than proximity. The areas where STRs are concentrated depend on economic prosperity, centrality and perceived safety. Areas of higher concentration are more vulnerable to the adverse effects of STRs; however, other areas show good potential to alleviate the higher numbers of STRs in one area.

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1) Introduction:

The phenomenon of short-term rental (STR) services, facilitated through platforms such as "Air BnB," has increased in popularity worldwide, accompanied by the recent rise of the sharing economy model. This unprecedented model allows tourists to reside in residential properties, allowing the traveller further to immerse themselves in the living spaces of the city as well as have more sustainable expenses through amenities provided in the properties many times at more reasonable prices than hotels. This, coupled with residents having the opportunity to capitalise on their properties and having a streamlined system to reach and interact with their clients, has reshaped the tourist and hospitality industries. Within the urban context, this has had mixed effects, with an improvement in the economy of neighbourhoods and an increase in property value (Benítez‑Aurioles & Tussyadiah, 2021; Tussyadiah et al., 2020) followed by displacement of citizens due to a gentrifying process that increases rent and property prices and reduces permanent residents (Gant, 2016; Picascia et al., 2019). With the model being largely unregulated, the topic of how beneficial STR platforms are and how to handle them has come into the scope of urban planning.

Latin American cities and other developing cities have been shown to have the highest degree of land bias regarding the distribution of STR, meaning the highest concentration of STR can be located in specific neighbourhoods (Quattrone et al., 2022). In contrast, others see considerably less activity in both the supply of offerings and demand by travellers. This can be attributed to safety indicators and the pronounced difference in living standards and wealth that Latin American cities experience. Property supply and demand are better distributed amongst neighbourhoods in developed western cities, where living conditions vary less (Quattrone et al., 2022). This means that the price of these rental properties will be highly dependent on locations that cater to the expectations of tourists.

Within this context, The Autonomous City of Buenos Aries (CABA) holds a particular position where the city has the predominant shape and design of a large European city but with the economic and social living conditions of a developing economy, corresponding to Latin American cities. The city is an important tourist location, with Argentina being the most visited country in South America, being visited by 7.4 million tourists annually, and Buenos Aires being the main entry point (World Bank, 2019). With tourists being the primary demand for STRs, CABA would benefit from understanding these properties' spatial distribution and dynamics to better accommodate the needs of hosts, tourists and residents within cities.

2) Research Problem

To further understand the distribution of listings in CABA, this investigation will aim to measure the relationship between the distance from prominent tourist locations and the STR price. This question estimates how much price is determined by the location of services offered to cater to the tourist experience.
The investigation's central question will be:

- To what extent does the proximity to popular tourist locations determine STR prices?

This analysis will portray the spatial distribution of where this tourist activity is occurring. Therefore, the following sub-questions relate to further investigation of this distribution. These sub-questions are as follows:

- How do other variables regarding the listing determine the price?
- What are the conditions of neighbourhoods where listings are mainly concentrated?
- Where should measures be taken to accommodate tourist and residential demands?

3) Theoretical framework

3.1) Study area

As the capital of Argentina and a metropolitan area with a population of more than 15 million people, the Autonomous City of Buenos Aries (CABA) is a separate administrative region consisting of the city's centre, where all main economic, tourist, and cultural activities occur.

CABA has a population of 3.5 million (Instituto Nacional De Estadística Y Censos [INDEC], 2022) and is surrounded by the city's suburbs. Buenos Aires has effectively adopted sharing economy platforms, including STR platforms. CABA receives about 1.5 million tourists per year (Instituto Nacional de Estadística y Censos [INDEC], 2022), and within its limits, more than 26,000 STR listings can be found (Inside Airbnb, 2023). Understanding the distribution of these listings can help urban planners and policymakers implement these new economic models efficiently and prepare and protect residents from the adverse effects the model can have on their livelihood. This is especially true for Latin American cities where land bias caused by differences in living standards can further exacerbate the issue through gentrification and displacement of the local population.

In the current context, Argentina is going through an economic crisis, with the annual inflation rate being 121% (International Monetary Fund, 2023). The Argentinian economy has both devalued the peso and has resulted in the country's reputation as a serial defaulter when paying their foreign debt. This has resulted in an informal dollarisation of the economy, with the dollar value increasing due to the financial stability individuals get from dollars and the scarcity of dollars held by the central bank. This means it is in the state's and people's best interest to attract dollars from abroad, tourism being a key industry to achieve this. Buenos Aires has become relatively cheap for tourists, while what the city offers in terms of attractions has stayed the same. Within this economic context, during the pandemic, there was a rental law reform that increased protections for long-term tenants in the context of evictions, deposits and dispute resolutions siding with the tenant. This has not been favourable for tenants since the risk of a long-term rental contract has increased, with tenants being less liable for their responsibilities. Therefore, short-term rentals, especially to tourists, have become a much more attractive alternative for landowners looking for passive income.

3.2) Sharing Economy

The STR model is a derivative of a series of new advancements in the economy through the availability of digital platforms to connect users who offer a service or a product to the client; this is evident in food delivery, where platforms such as Rappi, Deliveridoo, and Thuisbesorg connects the client to both the restaurant and a delivery courier. An enhancement to this model was the introduction of the sharing economy, where the concept relies on users sharing assets. This provides the client with short-term use of an asset while allowing the owner to capitalise on their property. This is where STR platforms, Air BnB being the main one, have come in, with the products being offered being properties. These also include room rentals within a shared space but are mainly fully private residences varying from studio apartments to multiple-room houses. Mont et al. (2020) comprehensively analyse how to define and conceptualise the sharing economy and describe Airbnb and Uber (hospitality and transportation) as the main drivers of this economic model and the deregulated nature of these platforms. Because this model is digital and streamlined, authors writing on the topic, such as Adamiak (2019) and Quattrone, Kusek, and Capra (2022), also discuss the deregulated nature of the business being carried out and the clash against already established institutions such as taxi drivers, municipal regulators, and hotels.

3.2) STRs in Urban Planning

In their global scale analysis of Airbnb and the Sharing Economy, Quattrone, Kusek, and Capra (2022) provide a framework of concepts regarding STR analysis. In quantitative research, STR penetration is the level of STR activity in a particular location, measured through both growths in the offer of properties and increased travel demand. Land bias is explained as the preference for one area over another. It can be caused by geographic reasons such as conditions in the landscape, the presence of a beach, and socio-economic conditions such as safety and living standards. The findings of this analysis regarding Latin American cities having the highest rate of land bias are the primary justification for investigating the proximity of STRs to the primary tourist location as a main determinant for price in Buenos Aires.

Research regarding the STR economy revolves around measuring the benefits and drawbacks of the model. On the one hand, through a Qualitative analysis surveying residents in London, Tussyadiah, Liu, and Steinmetz (2020) conclude that the benefits perceived by the residents, such as an increase in economic activity and diversification of the cultural scene, outweigh the adverse effects. Adding to the benefits, Tussyadiah, Liu, and Steinmetz (2020) conclude that STRs increase property values. On the other hand, many authors, including (Adamiak, 2019; Del Castillo Klaufus, 2019; Gant, 2016; Picascia et al., 2019), all speak of the gentrifying effect that occurs with STR as rent prices increase and less space is made for the local population; the trend from residents being to leave these central locations. The cultural fabric that made the city attractive risks being lost. Research also shows that in many places, properties are being bought and administrated in bulk by companies rather than by individual landowners, as demonstrated by Ki and Lee (2019).

3.3) Price Determination

The price rates travellers pay per night vary depending on internal and external factors. Internal factors are type of residence, size, number of beds, amenities, or anything the property offers concerning the asset. All this information is available in the data; however, proximity to tourist spots is an external factor and is, therefore, the main focus of this investigation. External factors are broader and can vary between economic, geographical, and cultural aspects specific to each location. This includes connectivity to the property, neighbourhood popularity, Design/quality of neighbourhoods, and proximity to public areas and services. For example, Perez-Sanchez et al.(2018) researched pricing due to the proximity to a beach, and Wang and Nicolau (2017) compared STR prices to long-term rental accommodations. Ki and Lee (2019) researched spatial distributions of STRs in Seoul, considering the proximity to highways and commercial spaces.

3.4) Tourism and STRs

When considering the effects tourists and Airbnb have on a residential neighbourhood and its housing market, touristification addresses how the negative externalities caused by tourists displace residents. Cheung and Yiu (2022) state how visitors and residents compete for the areas with better connectivity and accessibility. Their research also says how the rent gap in an area decreases due to this competition, which is viewed as a positive externality of Airbnb rentals. The negative externality, however, comes from when an area is overcrowded and noisy due to the increase in tourist activities, which devalues the experience for residents, causing the touristifcation. This process is seen as a rift in interests between tourists and residents, where the economic benefits of tourism start outweighing the needs of those citizens who vote on issues regarding the city. The city officials' job is to balance these needs through regulations in their respective cities.

3.5) Legal Regulations

Regarding how different authorities have regulated the STR market in other cities, Nieuwland and Van Melik (2018) have researched the level of intensity when regulating STRS and the justification used to apply the regulation. These regulations can vary from more lenient ones, such as a limit on the number of days a person can stay in an STR, to entirely banning the service. Regulations can also vary between quantitative and qualitative. Quantitative, which imposes specific quotas in the number of guests, number of days that the service can be offered or any other attributes that can be numerically limited. On the other hand, qualitative regulations can refer to safety issues, noise regulations, and insurance requirements. The reasoning behind these regulations is also examined in this study, with the main line of thought being preserving residential liveability in neighbourhoods and protecting the housing market's affordability for residents. The authors also conclude that regulations are usually aimed at something other than limiting the original idea of home sharing but rather directed at a large-scale commercial model where rental companies buy multiple residences to use for Airbnb permanently.

4) Conceptual Model

The conceptual model shows how the statistical analysis will be produced by comparing how prices vary due to proximity. Proximity is the measurement of distance between a STR listing and tourist locations. The information will be used to answer the questions, and sub-questions can be found within the square. One is the spatial distribution of STRs and the penetration level in a particular area. Land bias will show which areas are favoured and which are not, and the analysis results will determine the relationship between an STR's proximity to tourist spots as a determinant for price. This is coupled with Demographic data and other factors relating to the properties listed, allowing ample information for discussion and analysis to answer the questions.

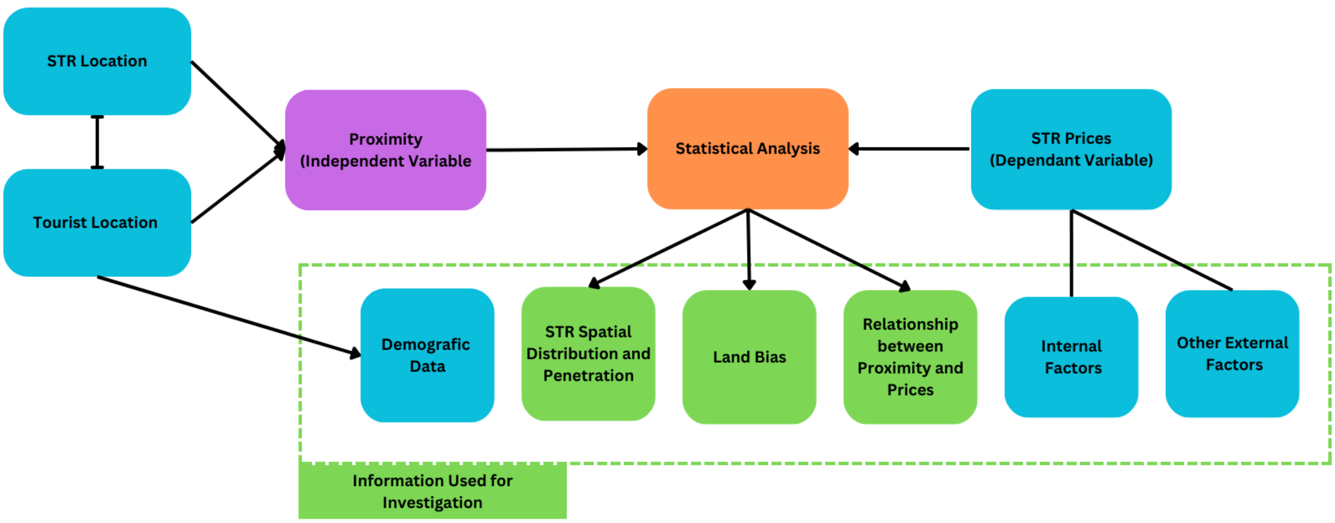
Legend

Blue: External Data

Purple: Measurement

Orange: Statistical Analysis

Green: Produced information

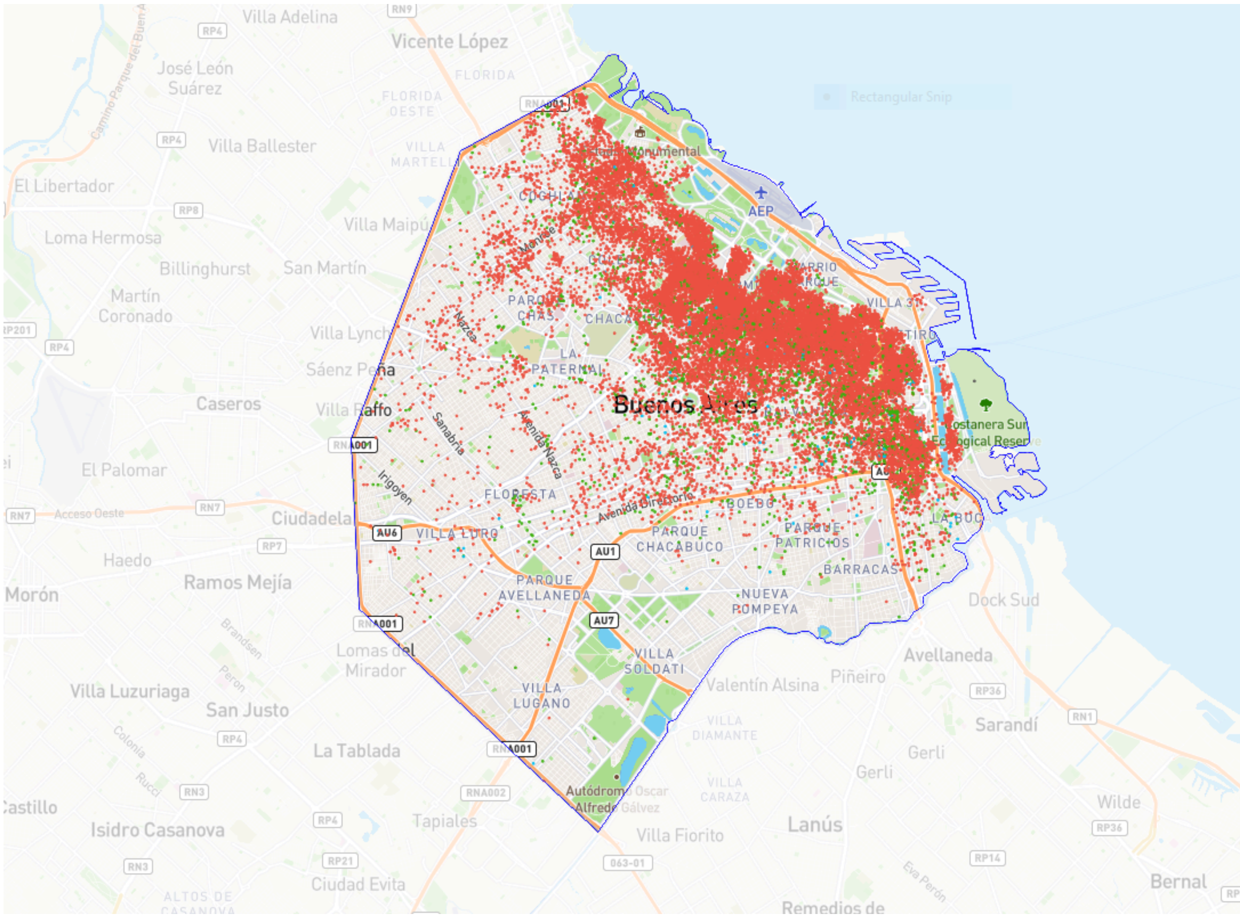


(Figure 1)

5) Hypotheses/Expectations:

Quattrone, Kusek, and Capra's (2022) conclusion on Latin American cities having a high concentration of STRs in a few districts due to socio-economic differences. The distribution of STRs in Buenos Aries will correspond with more STRs being in neighbourhoods closer to tourist destinations. Therefore, the effect of proximity on price determination will probably be low due to a higher concentration of most listings in tourist-friendly areas. However, Prices in areas with lower socio-economic conditions are determined less by proximity to tourist locations and more by the characteristics of the neighbourhood. It is important to note that since proximity value increases with distance, it should be inversely proportional to price.

6) Data & Methodology



(Figure 2, Inside Airbnb)

6.1) Data

6.1.1) STR Data

For this research, only Quantitative data will be used. The data bank Inside Air BnB provides data on all STR listings in CABA. This includes internal factors regarding each property's location in coordinates, price, host attributes, how many people the listing accommodates, building and room type, number of beds and baths, Review scores and information, and other amenities and accessories offered in the property. Inside Airbnb states that their intention in publishing data is for investigations on the effects of STRs, and therefore, it is acceptable to use in this investigation. The data was published on the 22nd of September, 2023, making it a recent snapshot of listing information.

6.1.2) Proximity data (Independent)

A list of 15 popular tourist destinations with their coordinates was compiled to calculate the proximity using Tripadvisor publications.

Sites	Latitude	Longitude	Neighbourhood	Commune
Obelisco	-34.60374	-58.38158	San Nicolas	1
Plaza de Mayo	-34.60829	-58.37028	San Nicolas	1
Casa Rosada (Presidential Palace)	-34.60812	-58.37052	San Nicolas	1
Recoleta Cemetery	-34.58852	-58.39761	Recoleta	2
Teatro Colón	-34.59833	-58.38307	San Nicolas	1
La Bombonera (Boca Juniors Stadium)	-34.63554	-58.36454	La Boca	4
Caminito, La Boca	-34.63809	-58.36252	La Boca	4
Puerto Madero	-34.60993	-58.36206	Puerto Madero	1
Palermo Soho	-34.59092	-58.42477	Palermo	14
Malba (Museum of Latin American Art)	-34.57776	-58.42013	Palermo	14
Jardin Japonés (Japanese Garden)	-34.57157	-58.41609	Palermo	14
El Ateneo Grand Splendid (Bookstore)	-34.59592	-58.39443	Recoleta	2
Planetario Galileo Galilei	-34.56631	-58.41812	Palermo	14
Museo Nacional de Bellas Artes	-34.58954	-58.39721	Recoleta	2
Palacio Barolo	-34.60993	-58.39314	Montserrat	1

(Table 1)

The greater circle method was used to calculate the distance from each listing to each tourist destination, as it is an accurate method to calculate the total distance between two sets of coordinates on the globe. The method measures the distance as an arc of a circle that dissects the globe. To complete this step, the coordinates are converted to radiants. The greater circle method is expressed in the following formula:

- $d = R \cdot \mathrm{acos}(\sin(\phi 1) \cdot \sin(\phi 2) + \cos(\phi 1) \cdot \cos(\phi 2) \cdot \cos(\Delta\lambda))$

Although some locations are close to each other, this serves as a way to enhance the importance of these locations as famous tourist sights as areas with multiple are more attractive. Once the distance from each listing to each location is calculated, the 15 distances are averaged to give the proximity value used as the independent value in this investigation. If the resulting value increases, it implies a smaller proximity value.

6.1.3) STR Price (Dependent)

The price, representing nightly rates per listing, is based on a hedonic pricing scheme that is determined by internal factors such as listing: size, amenities, and type of building and offering (listing can be shared or private) and also determined by location regarding the neighbourhood and proximity, the latter being the focus of this investigation. The price shown in the data is represented in Argentinian Pesos, which poses a problem given the instability of the currency due to recent inflation rates, summed with the state controlling monetary policy issuing several exchange rates that depend on which industry the exchange is taking place and that overestimate the actual value of the peso. This effectively means that the Argentinean peso does not accurately represent pricing since its value constantly changes. To resolve this, the price was converted into dollars using the 'Dolar Blue' exchange rate on the date the data was published (22/09/23) at a rate of 740 ARS$ to 1 USD$ (Ámbito, 2023). The dollar blue can be understood as the 'informal' or 'free-floating' exchange rate found in the black market parallel to the official government rate. It is widely used and accurately represents market pricing and what tourists will pay. While there is a 'tourist dollar,' where tourists using foreign credit cards can get a beneficial exchange rate, this exchange rate is usually similar to the dollar blue as it looks to give an accurate representation of pricing for internationals. In the statistical regression, the natural log of the dollar price was taken and used as the dependent variable to normalise the price distribution (Iglesia, 2023) (Castillo Guillén, 2022) (Garita, 2023)

6.1.4) Demographic data

Socio-economic indicators of neighbourhoods in Buenos Aires can help understand why there are higher or lower concentrations of STR in particular neighbourhoods. This is important in a Latin American city or a developing country as areas with lower indicators are less transited by tourists for safety regions. The data is published either by the National Institute of Statistics and Census of Argentina (INDEC, 2022) or the General Directory for Statistics and Census of the government of the city of Buenos Aires (Dirección General de Estadística y Censos, 2022). This data is organised into different inquiries carried out during the 2022 census that determine other attributes of households per commune.

6.2) Methodology

6.2.1) Linear Regression:

For this research, only Quantitative data will be used. A linear regression model determines the relationship between price and proximity. Other numeric factors pertaining to internal aspects of the listing are also added in the regression to give a more robust model. These factors are the number of people the listing accommodates, the number of bedrooms, the number of bathrooms, average review scores, and the room type. For the room type, the data was coded to fit the different types where: a shared room is valued at ‘0.25’, a private room is ‘0.5’, a hotel room is ‘0.75’, and a complete home/apartment is ‘1’ because the data for the number of bathrooms and the number of bedrooms differentiated between shared and private values, a private bathroom or bedroom was coded as ‘1’ to convert this into a numeric value. In contrast, shared bathrooms or bedrooms were coded as ‘0.5’.

6.2.2) Neighborhood Comparison

Knowing the distribution of STRs divided amongst the districts of Buenos Aries can help understand if the city has a land bias when considering listing offerings to tourists. This, coupled with demographic data pertaining to the neighbourhood, can be used to contextualise the spatial distribution in a socio-economic context. The city's neighbourhoods are clumped into 14 numerically numbered communes used for administrative, statistical, and planning purposes.

Demographic data by INDEC is organised per commune, unlike the Inside Airbnb data, which shows each neighbourhood. Therefore, neighbourhood data was recoded into their corresponding communes. The boundaries of these communes were chosen for each to have similar populations to standardise administration; therefore, some are clusters of multiple neighbourhoods while others are singular neighbourhoods in one commune.

7) Results:

7.1) Linear Regression Model

7.1.1) Descriptive Statistics

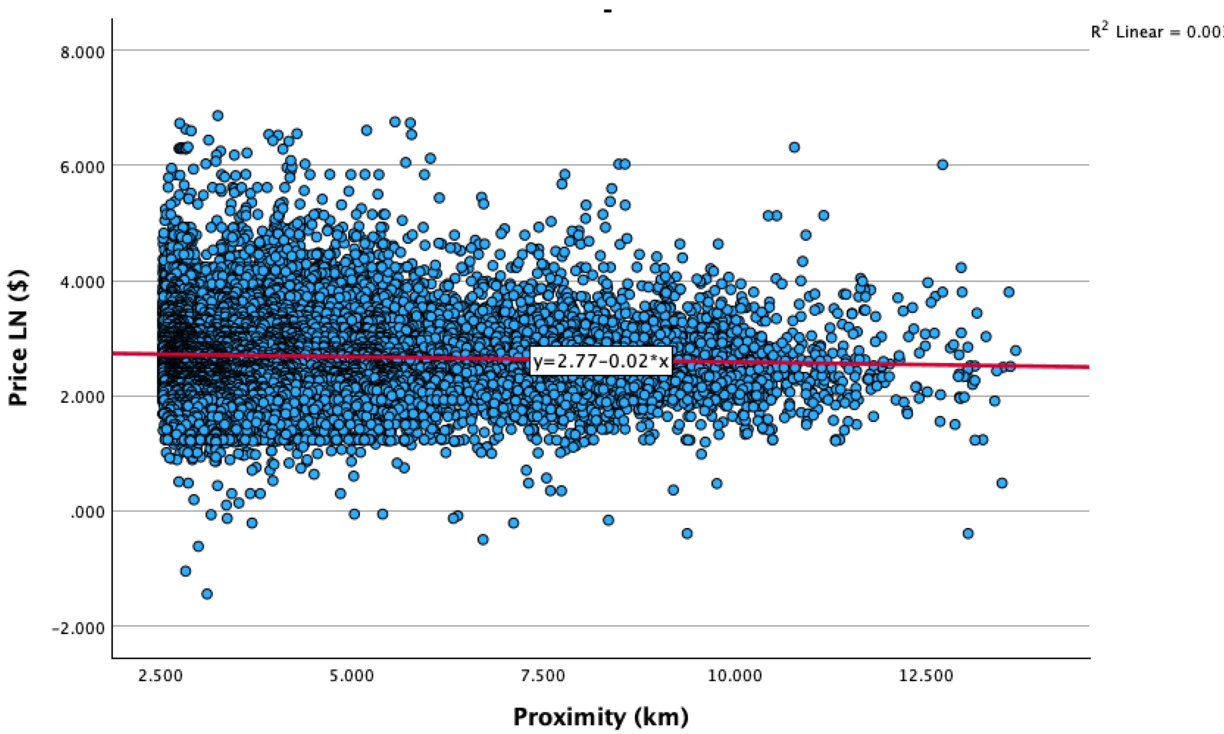
Descriptive statistics can give interesting information on how the data is composed. For one, the range of price values in US dollars is quite extensive. This can be due to several reasons regarding the data. For one, the minimum value of 24 cents and other similar values can be explained by inflation, where a listing has not changed its price in pesos for a long time, probably remaining inactive, making the value small with the more recent exchange rate. On the other hand, values that approach the maximum of almost 1000 dollars are explained by either an input error in the data set or, in the case of some listings, an abnormally large property like the one that accommodates 16 people. Nevertheless, the affordability of renting a property in Buenos Aires is shown by the affordable mean of 19.5 dollars per night. The proximity values show that, in general, the listing tends to be connected with the mean of 4.46 km, being close to the minimum value of 2.52 km. The mean of the room type (nominal value) being close to 1 shows that the majority of listings are complete homes or apartments.

	N	Minimum	Maximum	Mean	Std. Deviation
Proximity (km)	26177	2.524	13.676	4.46212	1.924162
Price ($)	26177	.24	959.04	19.4942	30.50040
Price LN ($)	26177	-1.442	6.866	2.68796	.648615
Accommodates	26177	1	16	2.88	1.480
Number of Bedrooms	26177	1.0	35.0	1.286	.7483
Number of Bathrooms	26154	.0	9.5	1.200	.5732
Room Type	26177	.25	1.00	.9485	.15591
Average Review Score	26177	.00	5.00	3.8821	1.90749

(Table 2)

7.1.2) Linear Regression

The linear regression output shows that price is inversely correlated to proximity by a small margin. The equation of the line of best fit is *y= 2.77 - 0.02x.* Quantity and price range of prices also decrease the more prominent the proximity value, meaning that there is more diversity of offerings near the tourist locations.



(Chart 1)

7.1.3) Model Summary

Both the model and the values were significant, thus rejecting the idea that price is not determined by the variables introduced into the model. The model was shown to have an R^2 of 0.338, meaning that 33.8 per cent of the fluctuation in the listing price can be explained by the variables included in the model.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.582[a]	.338	.338	.527389

a. Predictors: (Constant), Average Review Score, Accomodates, Proximity (km), Room Type, Number of Bathrooms, Number of Bedrooms

(Table 3)

7.1.4) Correlation

The model expresses a Pearson correlation coefficient of -0.053, resulting in a weak negative linear relationship, with the p-value showing the relationship to be significant. Other variables show much more substantial relationships, such as the number of baths, bedrooms, and people it accommodates, all having a higher coefficient than 0.4. Review scores are shown to have a negative correlation at a weak magnitude. This can be explained by some properties not having any review scores in the original data, as well as properties with higher prices being judged at higher standards by the clients.

	Variable	Price LN ($)	Sig. (1-tailed)
Pearson Correlation	Price LN ($)	1.000	.000
	Proximity (km)	-.055	.000
	Accommodates	.479	.000
	Number of Bedrooms	.449	.000
	Number of Bathrooms	.437	.000
	Room Type	.286	.000
	Average Review Score	-.074	.000

(Table 3)

7.1.5) Coefficients

By looking at the coefficients, accommodation, number of bedrooms, number of bathrooms and room type are shown to be moderate predictors for the price change. In contrast, proximity and average ratings are relatively weaker predictors. No variable is shown to have a strong effect on the price, yet all values are significant. Once again, this shows that the effect proximity has on price is marginal compared to other internal properties that each listing has.

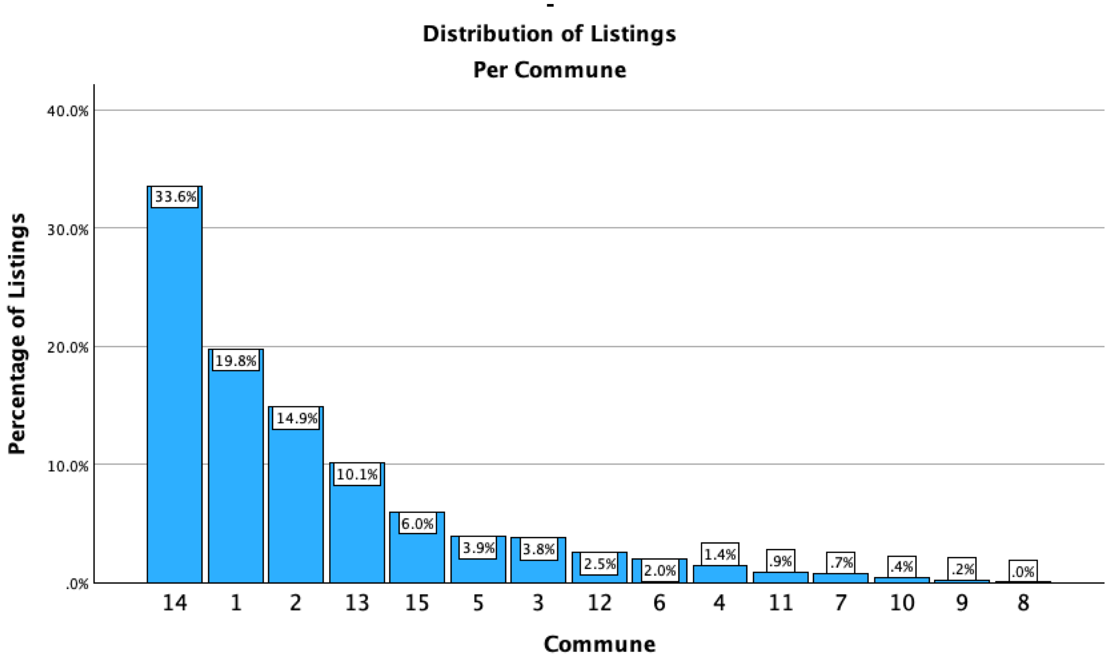
		Unstandardised		Standardised		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.470	.023		63.705	<.001
	Proximity (km)	-.018	.002	-.053	-10.452	<.001
	Accommodates	.091	.003	.208	29.511	<.001
	Number of Bedrooms	.114	.004	.186	27.514	<.001
	Number of Bathrooms	.221	.007	.196	31.058	<.001
	Room Type	.870	.021	.209	40.529	<.001
	Average Review Score	-.029	.002	-.085	-16.659	<.001

a. Dependent Variable: Price LN ($)

(Table 4)

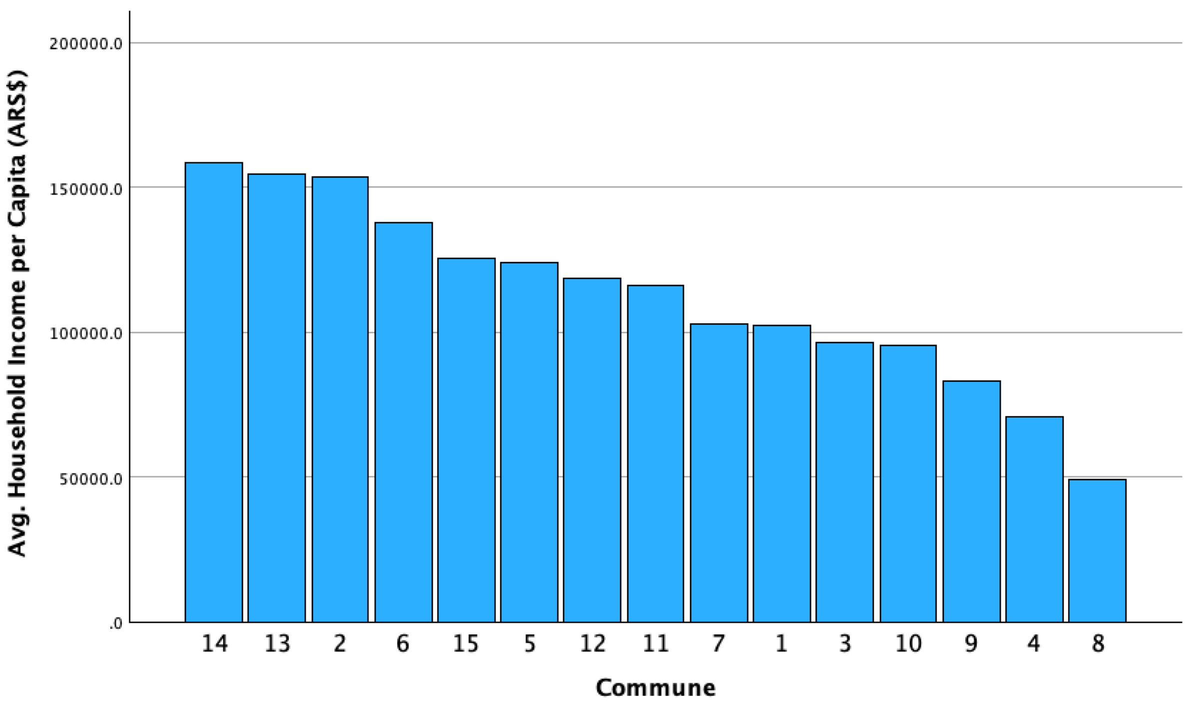
7.2) Neighborhood comparison

When looking at how the STR listings are distributed amongst the communes of Buenos Aries, there is a clear land bias, with a majority of listings concentrated in particular areas. Commune 14, consisting of the Palermo neighbourhood, has 33.6% of all listings. This is unsurprising as it is known for its parks, restaurants, and vibrant scene, including four tourist locations from the list used to calculate proximity. Commune 1, which includes the city's historical centre, where most government buildings and monumental attractions are found, follows with 19.8% of listings. Commune 2, consisting only of the neighbourhood of Recoleta, is an upper-class, mixed-use, and residential area known for its Parisian architecture and is third with 14.9% of listings. These three communes contain 13 out of the 15 tourist locations used for this investigation. The outlier in this pattern is Commune 4, which contains, among other neighbourhoods, La Boca, where the last two tourist locations are located, but only 1.4% of listings can be found. La Boca is known for being a working-class neighbourhood popularised by the football team and for its humble yet colourful architecture. The communes with the fourth and fifth highest listings, 13 and 15, respectively, are known for consisting of multiple middle-class residential areas.



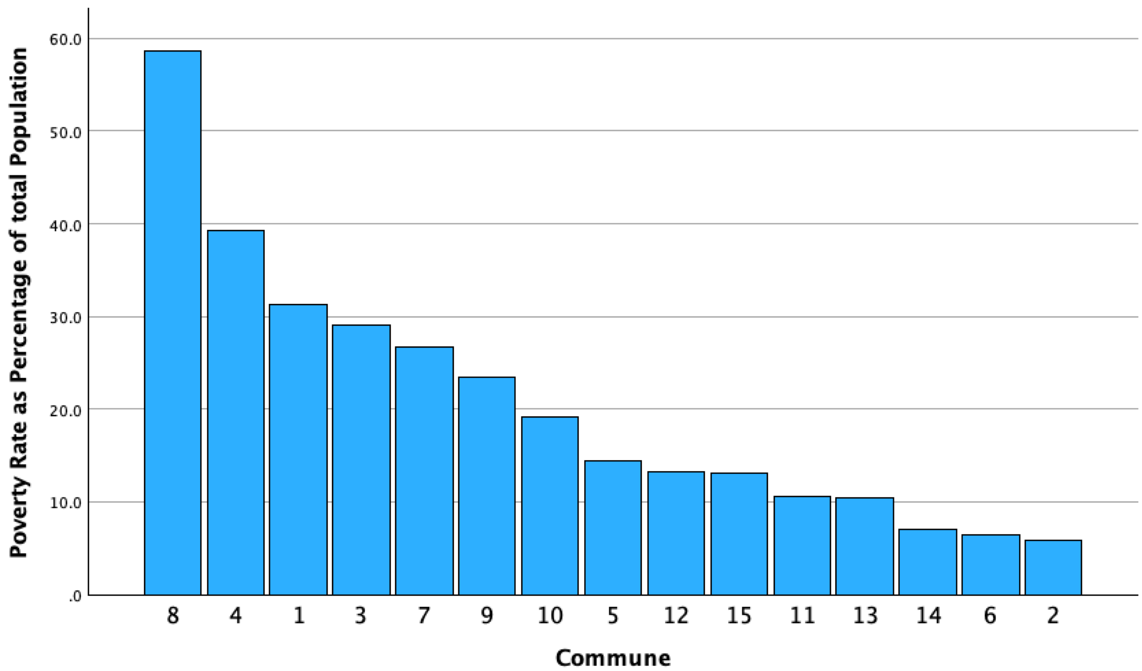
(Chart 2)

When looking at demographic data corresponding to each commune, some patterns emerged to explain the distribution. Considering the hypothesis of land bias, in Latin American countries being higher in the specific neighbourhoods that cater to international expectations of higher pricing, we can see that the concentration of STRs somewhat corresponds to what neighbourhoods have the highest household income per capita. Commune 14 is once again the highest value, and communes 2, 13, and 15 are still in the top five. The exception here is the historical centre Commune 1, which has, on average, a lower income. This can be explained by the historical centre being primarily where one finds offices and businesses, with busy streets making the area undesirable to live in. However, tourists might find the centrality more appealing as it is only a temporary measure. Commune 6, however, seems to have the opposite effect where the neighbourhood is shown to have the fourth highest income, but due to its residential nature and distance from tourist locations, it does not figure in having a significant amount of STRs located in it. Commune 8, where La Boca neighbourhood is located, is shown to have the lowest income out of the 15 communes, further explaining why many STRs are not located in this area regardless of its tourist attractions.



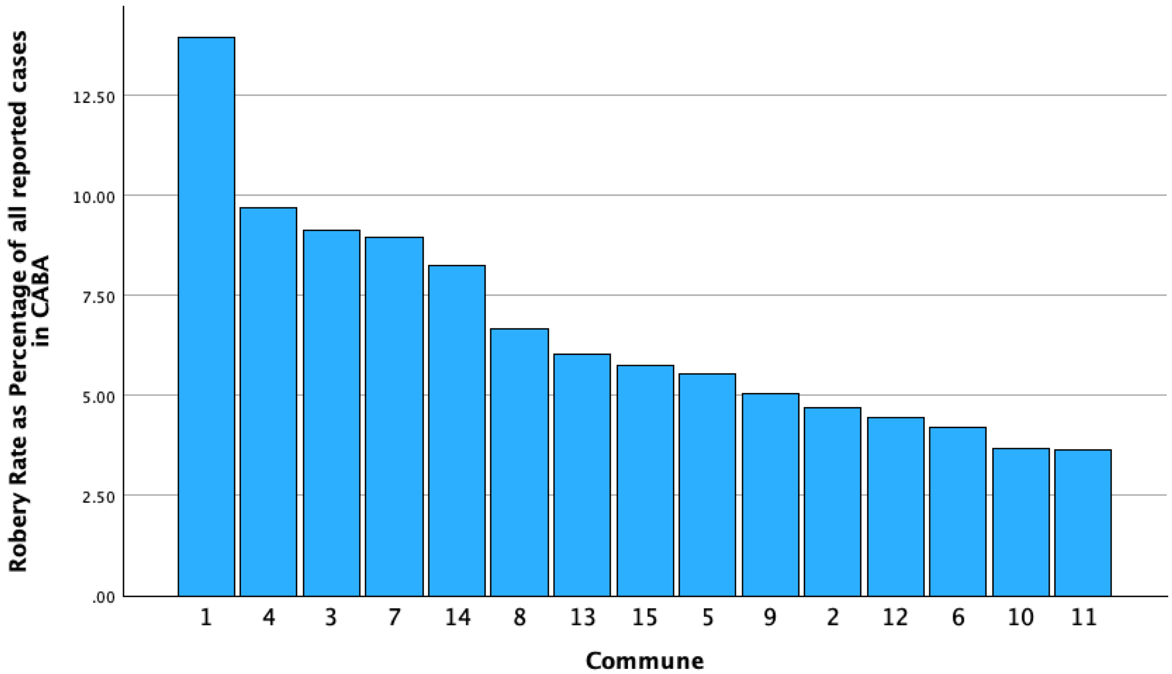
(Chart 3)

This pattern is repeated when looking at the poverty rate per commune. Commune 8 is shown to have the highest, with 14, 6 and 2 being the lowest. Commune 1 is also placed high on the list because the available housing in the city centre is for lower-income families.



(Chart 4)

When postulating the hypothesis, the idea of safety being a main driver for land bias seemed logical. However, this does not seem to be shown when comparing the distribution of STRs to robbery rates. Commune 1 is shown to have the highest, once again a consequence of the labural activity that occurs during the day. Commune 14 (Palermo) is shown to have a higher rate than commune 8 (la Boca) despite the economic indicators of the area. Commune 2 (Recoleta), an upper-class neighbourhood, has a relatively low crime rate, which could be attributed to private security in the area. Once again, Commune 6 is also shown to have a low crime rate despite having low numbers of STRs. This can be explained by tourist and hosts not making their decisions based on actual crime data but rather by a perception of safety. Commune 8 is out of bounds because it is considered a poor neighbourhood, while Commune 1 is seen as central and monumental to the city and thus considered safe. Despite its high crime rate, commune 14 is regarded as a wealthy, vibrant area. There could also be a data bias since institutions tend to work better in wealthier and central locations, and crime is reported more consistently than in poorer neighbourhoods.



(Chart 5)

8) Conclusions

The results show that the proximity value elaborated in this model is not a good indicator for determining the price of a short-term rental listing. This is due to the high concentration of STRs around the same area with a similar proximity offer. With increased competition amongst listings in the same neighbourhood, price determinants have more to do with internal rather than location-based external factors.

When considering the investigation by Quattrone, Kusek, and Capra (2022), it is evident that there is a significant land bias, mainly concentrated around Commune 1, 2 and 14. Tourist locations are also concentrated along the northern zone by the estuary Bank, providing a somewhat radial distribution of STRs from the north coast into the interior of CABA. Therefore, it can be assumed that the specific distribution and land bias condition the city's structure to be centralised where proximity impacts price determination less. These are the areas with the highest level of STR penetration and that cater to the expectations of tourists. Given the higher income of these areas or, in the case of Commune 1, the amount of business activity found there, one can expect that the gentrification caused by tourists is going to have a lower effect given the similarities of spending habits and prices that they would share with their temporary neighbours.

This does not mean, however, that it is not occurring, and neighbourhoods like Palermo are the most vulnerable, given the magnitude of STR penetration in that particular neighbourhood. It is recommended that regulatory measures be taken to somewhat limit and control the number of STRs to protect the residents from tourism, especially considering the monetary crisis, which is reducing the similarities between residents and tourists at a rapid rate. On the other hand, these regulations could also spread the number of STRs amongst neighbourhoods with good conditions but less fame, such as those found in Commune 6 that enjoy a high-income level, wealth and low crime rates. Since proximity to tourist locations does not heavily affect the pricing of listings, these neighbourhoods have a large economic potential to attract more tourists.

9) Reflection

This investigation has established a vivid picture of how and where STRs are distributed in Buenos Aires. Although one can have basic logical predictions of what is to be expected, results show that the reality of the city makes it more complicated to assume these conclusions to be true. This is especially true for a Latin American city, which shows drastic demographic differences in socio-economic levels and is in the middle of a financial and monetary crisis. Due to these conditions, Argentina is currently experiencing a radical government change that will inevitably change the conditions that were present when the data was produced. This constantly changing situation can easily make the observations of this investigation obsolete.

Moreover, the investigation had room to expand its scope. However, it was mentioned that public transport was not addressed as a contributing factor to the proximity to tourist locations. Instead, the proximity measure was based on linear distances and not on how a tourist would move around the city. Also, comparison to other similar cities either in Argentina, Latin America or another part of the world would have given legitimacy to the methods used in this investigation as it would have provided a more comprehensive view of the positives and negatives of the methodology.

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