Effects of short-term rental markets on Lisbon's housing market – The Case of Airbnb

Catarina Santos

Dissertation written under the supervision of Professor Plamen Nenov

Dissertation submitted in partial fulfilment of requirements for the MSc in Economics at the Universidade Católica Portuguesa, September 13, 2019.

Abstract

Catarina Santos. Effects of short-term rental markets on Lisbon's housing market – The Case of Airbnb. Master in Economics (Major in Public Policy and Regulation). September, 2019

This research, aims to assess the impact of home-sharing platforms and short-term rental markets on Lisbon's housing market. The main question is if Airbnb listings impact house prices. Furthermore, if the impact on house prices differs with the type of Airbnb listings. The high demand for short-term rentals can lead homeowners to switch from supplying the long-term market to suppling the home-sharing market in response to increased demand, thus increasing house prices. Using data for Airbnb listings and data on the price per square meter of sales for the 24 neighborhoods that compose the city of Lisbon, I estimate a fixed effect model at the neighborhood level. The overall results of the investigation suggest that Airbnb presence affects local house prices. Specifically, I find that a 1% increase in Airbnb entire home listings increases house prices by 0,043%, controlling for time fixed effects and differential price trends across neighborhoods. This result is also consistent with the hypothesis that entire home listings may have a bigger impact on house prices than room listings.

Keywords: peer-to-peer markets, sharing economy, housing markets, Airbnb.

Resumo

Catarina Santos. Efeitos do mercado de arrendamento de curto-prazo no mercado imobiliário de Lisboa – O caso do Airbnb. Master in Economics (Major in Public Policy and Regulation). Setembro, 2019.

A presente investigação tem como objetivo avaliar o impacto das plataformas de partilha de alojamento e dos mercados de arendamento de curto-prazo no mercado imobiliário de Lisboa. A principal questão que se coloca é se os anúncios do Airbnb afetam os preços das casas. Além disso, se o impacto nos preços das casas diferem com o tipo de anúncio do Airbnb. A procura de alojamentos de curto-prazo pode levar proprietários a deixar de oferecer propriedades no mercado de longo-prazo para oferecerem no mercado de partilha de alojamento em resposta ao aumento da procura, aumentando os preços das habitações. Usando dados para os anúncios do Airbnb e para o preço por metro quadrado de vendas para os 24 bairros que compõem a cidade de Lisboa, eu estimo um modelo de efeitos fixos ao nível de bairro. Os resultados gerais da investigação sugerem que a presença de Airbnb influencia os preços das casa. Especificamente, um aumento de 1% nos anúncios de espaços inteiros aumenta o preço das casas 0,043%, controlando para efeitos fixos temporais e diferenças em tendência de preços nos vários bairros. Este resultado é também consistente com a hipótese de que anúncios de espaços inteiros possam ter um impacto maior nos preços das residências.

Palavras-chave: mercados peer-to-peer, economia partilhada, Mercado imobiliário, Airbnb.

Acknowledgements

Throughout this investigation I have received a continuous support and assistance. First and foremost, I would like to express my gratitude to my advisor Professor Plamen Nenov, for his support, patience and enthusiasm. His feedback and guidance helped me to be able to complete my dissertation.

My thanks and acknowledge also goes to my family. My mom, for supporting me even with the great distance between us, being always involved in every step of the way. My grandmother, for allowing me to reach this far in my academic studies. And my sister, for setting a great example of academic excellence.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

The quick growth of peer-to-peer markets through online platforms has been gaining policymakers' attention. Platforms such as Uber and Airbnb grew considerably in the past years and transformed service trade, with them the need to grasp their characteristics and impacts on the economy. Peer-to-peer markets, also called the sharing economy, facilitate trade between a large number of fragmented buyers and sellers, by matching buyers and sellers effectively while keeping search frictions low (Einav et al., 2016).

In the case of home-sharing, online platforms enabled the change in scope and scale of the usage of this market. Airbnb allows individuals to offer some available living space to people searching for accommodation over a short-term period (Horton and Zeckhauser, 2016). Although considered part of the sharing economy, Airbnb is a big business (Sharma, 2018). It is the largest home-sharing enterprise worldwide, valued at around 35 billion dollars. Founded in 2008, it has more than 6 million listings in more than 100 thousand cities and more than 191 countries, with a total of more than 500 million guests up to date.[1]

House prices in Lisbon have been steadily increasing since the first quarter of 2016, decreasing house affordability. Therefore, the evolution of the Lisbon housing market has become a big matter of concern for both residents and policymakers, since, anecdotally, people have been forced to move away from city borders in order to be able to afford housing. Residents can no longer afford to live in the more traditional neighborhoods, and this pattern is spreading to the rest of the city. These developments have motivated my research to understand the drivers of the increase in prices of properties in Lisbon and specifically the impact of home-sharing on property prices.

The Portuguese economy relies heavily on the tourism sector. It employs a significant portion of the working population, with a share of more than 9% of total employment in 2016[2], contributing significantly to GDP (8.2% in 2016)[3]. The increase in tourism exerts pressure in housing markets by both increasing demand for short-term rentals and thus contributing to the

[1] https://press.airbnb.com/fast-facts/
[2] https://travelbi.turismodeportugal.pt/pt-pt/Paginas/PowerBI/emprego-e-remuneracoes.aspx
[3] https://travelbi.turismodeportugal.pt/pt-pt/Paginas/PowerBI/Sustentabilidade/receitas-no-pib.aspx

contraction of supply for long-term housing, once a part of the housing stock moves from being supplied in the long-term housing market to the short-term tourist rental market (Elíasson and Ragnarsson, 2018). Given these, there is an increasing need to assess the impacts of the growing market for short-term rentals on the housing market in such a touristic city as Lisbon.

This research aims to assess the impact of home-sharing platforms and short-term rental markets on Lisbon's housing market. Airbnb listings are used as a proxy for this market due to its dominance, with more than 15 thousand listing in the city of Lisbon in December, 2018. The main question is if Airbnb listings impact house prices. Conceptually, the high demand for short-term rentals can lead homeowners to switch from supplying the long-term market to suppling the home-sharing market in response to increased demand, thus increasing house prices.

Through a regression analysis, I test if Airbnb presence has effects on house prices. To estimate this regression model, I use neighborhood level data on Airbnb listings and the price per square meter of sales, estimating a fixed effects model at the neighborhood level. Time fixed effects are also added to the model, to account for common time trends in the data. In addition to Airbnb listing, other indicators of Airbnb presence are used to test the impact of Airbnb, such as the decomposition of Airbnb listings into listings for entire homes vs. rooms.

Therefore, I also test if the impact on house prices differs with the type of Airbnb listings. Is there a bigger impact on house prices in neighborhoods and periods where the presence of "entire home" listing is more prevalent? One can argue that, if Airbnb listings have an effect, it is exactly this type of accommodation that should have a greater impact on prices compared to room sharing. These properties could have been offered instead for sale in the housing market or has long-term rentals. In order to examine this, Airbnb listings are decomposed into two types: entire home listing and room listings, combining private rooms and shared rooms listings.

My findings are as follows. A 1% increase in Airbnb listing is associated with an increase of 0,66% in house price, significant the 1% level. This results only consider within neighborhood variation, with no association of average house price and listings differential between neighborhoods. When time fixed effects are added to the model, Airbnb listings loses statistical significance, however this seems to indicate that there is a significant house price and

Airbnb listings difference across different time periods that is common to all neighborhoods, with not enough neighborhood level time variation in my data to draw statistical inference from. Due to little within neighborhood and within time variation in my dataset, statistical inference cannot be also be drawn for the different Airbnb presence indicators. Notwithstanding, the results from Airbnb listings and particularly the decomposition of Airbnb into two groups are consistent with the hypothesis that entire home listings have an impact on house prices. Specifically, I estimate that a 1% increase in entire home listings is associated with a 0,16% increase in house prices per m^2, while a 1% increase in room listings is associated with a 0,13% decrease in the price per m^2. These results are robust to the inclusion of both neighborhood and time fixed effects, with the two coefficients significant at the 1% level. The inclusion of the lags of the dependent variable allows me to control for differential price trends across neighborhoods and give more confidence to the casual interpretation of the coefficient estimates of entire home listings. Specifically, I estimate that a 1% increase in Airbnb entire home listings increases by 0,043% house prices, when accounting for differential price trends across neighborhoods, while room listings have no effect on prices.

In summary, to gauge the impact of the short-term rental market on Lisbon's housing market I will address the following main questions:

RQ1: Do Airbnb listing affects the housing market? Do Airbnb listings impact house prices in Lisbon?

RQ2: Are all types of listing equal? Is there a bigger impact on house prices from "entire home" listings?

The dissertation proceeds as follows. The next section presents a summary of the existing literature on peer-to-peer markets, the effects of Airbnb, and the Regulatory Debate. Then, I describe the methodology adopted to test the hypothesis, along with the description of the data collected and descriptive statistics of the structure of the market. Next, the results are analyzed and the research questions addressed. Lastly, the conclusions of the investigation are drawn, as well as a brief discussion on the policy implications of the research.

Chapter 2: Literature Review

2.1 Peer-to-Peer Markets

The rise of peer-to-peer markets and the spread of the “sharing economy” companies such as Airbnb have become very important in the last few years (Quattrone et al., 2016). Peer-to-peer markets enable private individuals to enter a market as a small scale supplier (Sheppard and Udell, 2016) and have been highly facilitated by online services that leverage on information technologies (Quattrone et al., 2016), with the internet as a powerful tool in this process (Einav et al., 2016). Besides that, they lower market entry costs, which enables individuals and small businesses to compete with traditional firms (Einav et al., 2016).

Böckmann (2013) argues that societal, economical and technological factors drive the sharing economy and allow it to reach its global recognition. As these drivers become more integrated into peoples’ lives, so does the shared economy with peer-to-peer services helping to create this match in close surrounding, through the use of technology.

The trade off in these markets is, however, the balance between the market mechanisms that efficiently manage trade between the large number of fragmented buyers and sellers while at the same time minimizing costs. There are the additional market design problems of matching and maintaining low research frictions and organizing the market to set competitive prices, ensuring a safe and reliable relation between buyers and sellers (Einav et al., 2016)

2.2 Airbnb

The particular case of the sharing economy, home-sharing, has been receiving considerable attention from multiple segments of society. The generalized and growing adoption of home-sharing platforms as Airbnb, motivated a growing literature on the topic in an attempt to grasp the impacts of short-term listings.

Airbnb is a source of income for hosts. This can result in the capital appreciation of properties while generating income during ownership. The income and capital gains can increase house demand, resulting in an increase of property prices. Investors can be driven to purchase properties for personal use and to hold on to properties for longer because of a reduction in ownership costs (Sheppard and Udell, 2016).

Barron et al. (2018) argue that home-sharing increases property values through two main channels. The first is the reallocation of resources from locals to non-locals, once owners switch from supplying the long-term rental market to supplying the market for short-term rentals, which is then capitalized into house prices. The second channel works through the increase in ownership value due to income generated by excess housing supply that is then offered in home-sharing platforms. The increase in property values and the possibility of the shift to short-term rental markets can result in a lower supply of long-term housing and an increase of house prices.

An interesting analysis of the possible effects of home sharing when there is a premium on the short-term rental markets is conducted by Horn and Merante (2017). They find that there are five possible outcomes. First, that home sharing only affects its target market, however this would require complete market segmentation between the long-term and short-term rental market. Second, that home sharing prices could decrease to the prices of the long-term market, ending with the premium of the short-term rental market. Third, the premium could stimulate demand substitution[4]. Fourth, home-sharing could be focused only on vacant properties that are shifted for the home-sharing market. Finally, the premium could drop due to the increase of the price in long-term accommodations.

Different studies of the effects of Airbnb focus on different housing markets. The study of the effects on the rental market in Boston was carried out by Horn and Merante (2017) using a hedonic regression model; with the finding that a one standard deviation increase in Airbnb listings is associated with an increase in asking rents of 0,4% and that one standard deviation increase in Airbnb density is correlated with a 5,9% decrease in the number of rental units offered for rent. This supports the hypothesis that the increase of Airbnb presence works towards a lower supply of long-term rentals.

[4] This concern is also investigated by Zervas et al. (2017) whom study the impacts of Airbnb on the Hotel Industry.

Elíasson and Ragnarsson (2018) study the impacts of Airbnb growth on the Icelandic housing markets, they analyze the effects on house prices and the shift of properties to the short-term rental market. They estimate that Airbnb was responsible for a 6% accumulated growth of real house prices from the fourth quarter of 2014 through 2017 and for 1676 apartments being withdrawn from the residential housing segment through the end of 2017.

Sheppard and Udell (2016) estimate the impacts that Airbnb listings have on the value of residential properties in New York City. Their arguments suggest that Airbnb listings increase house prices, with a hedonic estimation that a doubling of Airbnb listings results in an estimated increase of 6% - 9% in property values.

Barron et al. (2018) perform a broader analysis of the impact of Airbnb. They study listings for the entire United States, assessing these impacts both on house prices and rents with an instrumental variable estimation and conclude that a 10% increase in Airbnb listings is associated with a 0,42% increase in rents and a 0,76% increase in house prices.

The finding from the mentioned studies show that an increase in Airbnb listings is associated with increases in house prices, both renting and selling prices. My findings are consistent with earlier works, with my results showing that a 1% in Airbnb listing for entire homes is associated with an increase of 0,043% in house prices. These results are very similar to the estimates from Barron et al. (2018), however they cannot be directly compared, once my investigation uses different regressors and datasets.

2.3 The Regulatory Debate

There is a discussion regarding which policies should be implemented, if any, to regulate the sharing economy. However, sharing economy platforms are different from each other and, therefore, they should not be all regulated the same; Quattrone et al. (2016) analyze Airbnb listings in the city of London, finding that they are related to neighborhood socio-economic conditions (Quattrone et al., 2016).

Due to the specifics of each city, it is important to understand and estimate the impact of platforms such as Airbnb on the specific cities.

Concerns about the growth of Airbnb also differ from sector to sector of the economy. Hotel owners state that Airbnb represents unfair competition to the hotel industry, since Airbnb hosts do not pay occupancy taxes and avoid other regulations. Tax authorities worry about a portion of host not reporting their incomes from Airbnb. Residents may have concerns about negative externalities associated with short-term visitors in residential areas. Finally, local authorities worry about the decrease in house supply available to residents by owners shifting to Airbnb rentals (Coyle and Yeung, 2016).

In addition, to the estimation of the effects of Airbnb, a growing literature strives to give policy recommendations. Lee (2016) assess short-term rentals in a regulatory perspective in an attempt to understand the negative effects on housing affordability in Los Angeles, through the evaluation of multiple reforms. In his view, the housing needs of residents should be prioritized over the needs of tourists. It recommends the adoption of a three-pronged strategy for short-term rentals: the city should prevent hotelization[5] and conversion of existing residential housing, ban year-round listing of apartments and set a hard cap on the number of units on a building that property owners and managers can list on Airbnb.

Quattrone et al. (2016) give recommendations on how policies should be set, addressing how, where, when and what to regulate, how the regulations could be enforced and refined. Along with the recommendations, it is advised that policies should be neighborhood specific due to the fact that Airbnb effects differ across geographical location. The authors explain that four main factors should be considered when regulating: the consequences of the adoption of regulation, development of local economies, sustainability of tourism and avoidance of the concentration of short-term rentals. Further, it recommends that listings of rooms and houses should be regulated differently.

With the growing concern about Airbnb, cities have already started tightening regulation on Airbnb. In Europe, the main objective, is not the collection of taxes, but to ensure that short-term rentals are offered in moderation and that the negative externalities are minimized (Interian, 2016).

[5] The author explains this mechanism as the phenomenon that as long as property owner or leaseholder can rent out a room on Airbnb for less than the price of a hotel room, while earning a substantial premium over the residential market or rent-controlled rent, there is an overpowering incentive to list each unit in a building on Airbnb rather than rent to Los Angeles residents.

Berlin has banned unregistered short-term rental, providing licenses only in the case of public interest or compensation for the permanent housing loss (Interian, 2016). Paris, to control the reduction of long-term house supply, requires the registration as commercial property rentals of Airbnb listings that are secondary residencies and limits primary residences to be offered as short-term rentals to a maximum of 120 days per year (Gyódi, 2019). In Barcelona, all types of listings require registration, and additional regulation has been added with a moratorium on the expansion of permits for short-term rentals, freezing the number for short-term rental in Barcelona (Segú, 2018).

As explained by Segú (2018) different cities have adopted different sets of measures to limit Airbnb, with some cities requiring some specific permits, others limiting the rental period, imposing rental taxes or even making it illegal under some circumstances.

The results from my study indicate that if housing affordability is an issue that policymakers want to address, then regulating home listings differentially from room listings may be a desirable approach.

Chapter 3: Data

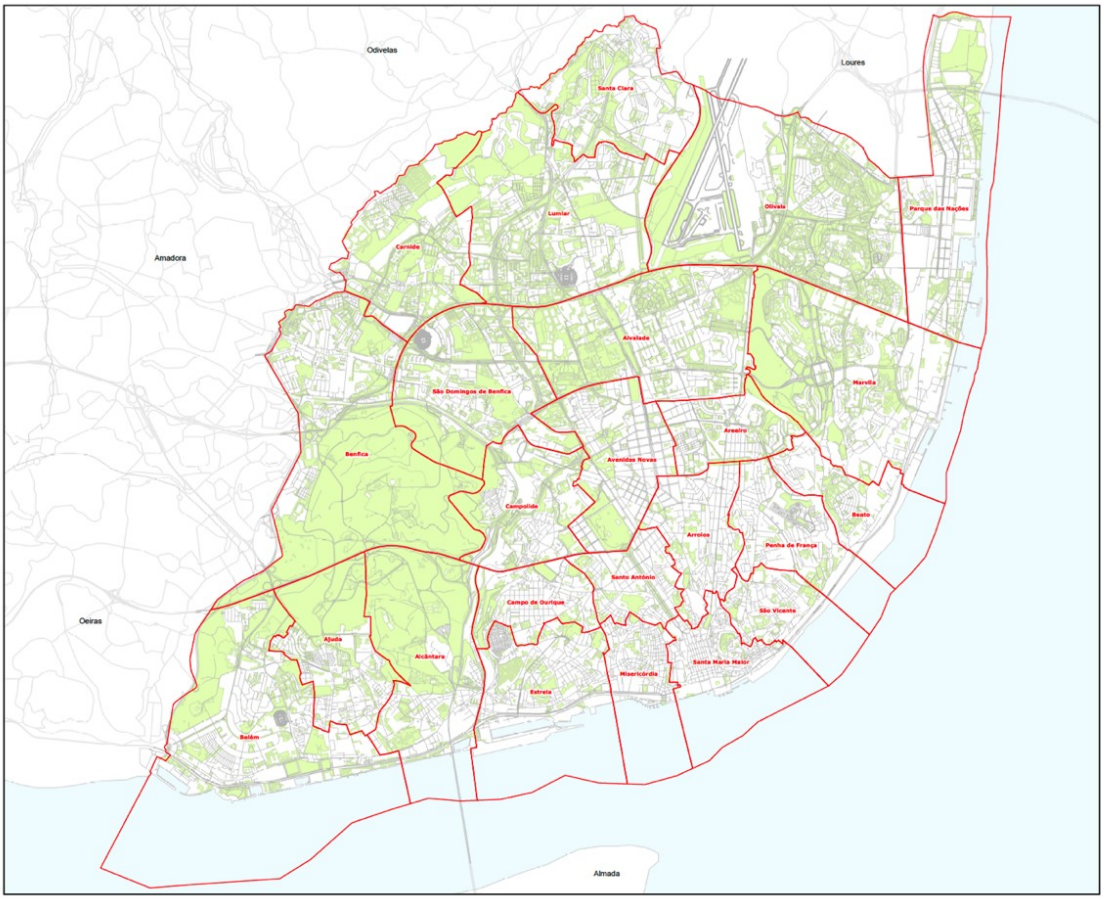
3.1. Airbnb Listings Data

The listings data for the analysis was obtained from the datasets created by Tom Slee, available on his website (tomslee.net) and from the datasets available on insideairbnb.com. All the data is publicly available for research purposes.

Lisbon was the chosen city of study, with a population of 547733 and an area of 85km²[6], the city is divided into 24 distinct neighborhoods, which are: Ajuda, Alcântara, Alvalade, Areeiro, Arroios, Avenidas Novas, Beato, Belém, Benfica, Campo de Ourique, Campolide, Carnide, Estrela, Lumiar, Marvila, Misericórdia, Olivais, Parque das Nações, Penha de França, Santa Clara, Santa Maria Maior, Santo António, São Domingos de Benfica e São Vicente. This area was selected to better gauge the effects of Airbnb in different areas and to understand its impact in areas with different Airbnb presence. It allows to perform a more detailed cross-sectional analysis within the city. Figure 1 presents the geographical map of the 24 neighborhoods that constitute the city of Lisbon.

[6] http://www.cm-lisboa.pt/investir/investimento/lisboa-em-numeros/retrato-de-lisboa

Figure 1: Neighborhood division of the city of Lisbon



Source: Câmara Municipal de Lisboa, retrieved from: http://www.cm-lisboa.pt/fileadmin/MUNICIPIO/Reforma_Administrativa/Mapas/NovasFreg_A1.pdf

With a total of 25 different dates, the data collected is for: March 18, 2015; March 20, June 2, September 12 and December 26, 2016; January 21, February 21, March 30, April 18, April 27, May 15, June 19, and July 27, 2017; April 18, May 22, July 29, August 20, September 16, October 17, November 19 and December 16, 2018; January 23, February 16, March 23 and April 22, 2019. They were merged and aggregated to obtain the number of listing for neighborhoods in the city of Lisbon, by type of listing. The final dataset assembled contains quarterly data on the daily number of Airbnb listings by listing types and neighborhood from Q1:2015 to Q2:2019 with missing values for the Q2:2015-Q4:2015, Q4:2017 and Q1:2018. In quarters with multiple daily observations, the average listings are used.

In Lisbon, Airbnb has been receiving guests since 2009. With almost 17,000 listings (based on data from Q2:2019), it can be considered a solid proxy for short-term rentals in the city of Lisbon. To take into consideration the difference in Airbnb density across neighborhoods, which is not achievable with the data on listings alone, the number of housing units were also considered[7]. Airbnb density was computed dividing the number of listings by the number of housing units per neighborhood. Table 1 illustrates the point, presenting Airbnb density across neighborhoods in the second quarter of 2019, ranging from 0,15% in Santa Clara to 33,29% in Santa Maria Maior.

Table 1: Airbnb listings in the city of Lisbon, daily listings; Housing units and Airbnb Density in Q2:2019

Neighborhoods	Airbnb Listings	Housing Units	Airbnb Density
Ajuda	159	8897	1,79%
Alcântara	289	8920	3,24%
Alvalade	265	18836	1,41%
Areeiro	377	12558	3,00%
Arroios	2193	21129	10,38%
Avenidas Novas	720	14532	4,95%
Beato	114	7793	1,46%
Belém	332	9477	3,50%
Benfica	84	21314	0,39%
Campo de Ourique	368	13815	2,66%
Campolide	189	9255	2,04%
Carnide	44	9310	0,47%
Estrela	1026	13144	7,81%
Lumiar	192	23382	0,82%
Marvila	87	16528	0,53%
Misericórdia	2889	10548	27,39%
Olivais	172	16965	1,01%
Parque das Nações	352	11527	3,05%
Penha de França	546	17820	3,06%
Santa Clara	16	10948	0,15%
Santa Maria Maior	3572	10729	33,29%
Santo António	1401	8583	16,32%
São Domingos de Benfica	164	19864	0,83%
São Vicente	1380	10918	12,64%
Total	16931	317315	

[7] Number of housing units from the Portuguese Census 2011

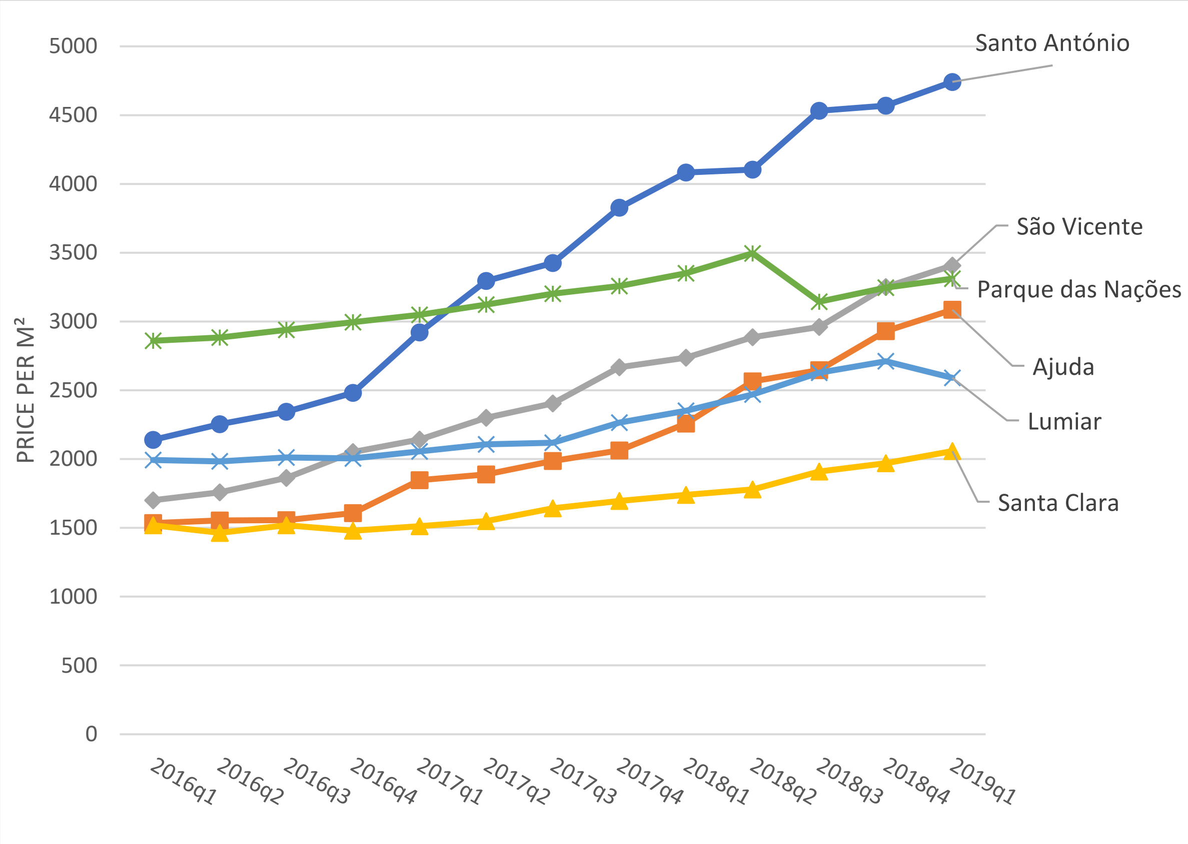
3.2. House Prices

For house prices, Statistics Portugal makes available neighborhood level data on median value per m^2 of dwelling sales[8]. The data is quarterly and it covers the period Q1:2016-Q1:2019. From the data, we can access the values for the city of Lisbon, showing that from the 1st quarter of 2016 the median value per m^2 of dwelling sales have increased around 66%. It is relevant to notice that the data on the house prices is divided into the same categories as the data on Airbnb listings, the 24 neighborhoods that compose the city of Lisbon.

Looking into the data across neighborhoods, we can assess the heterogeneity in evolution of house prices in the city of Lisbon. With the three neighborhoods that register the highest growth in house prices, Santo António, Ajuda and São Vicente, registering growth of around 122%, 101% and 100% respectively. While, the three neighborhoods with the lowest growth rate, Parque das Nações, Lumiar and Santa Clara register growth of around 16%, 30% and 26% respectively. The figure below illustrates the heterogeneity in house price evolution in the city of Lisbon. Interestingly, the neighborhoods with highest price growth in the figure are also the neighborhoods with high Airbnb density, while those with lowest growth have very low Airbnb density

[8] Dwelling is defined by Statistics Portugal as: "A separate and independent place which was built, rebuilt, enlarged or converted to be used as a private accommodation, and that is not totally occupied for other purposes during the reference period."

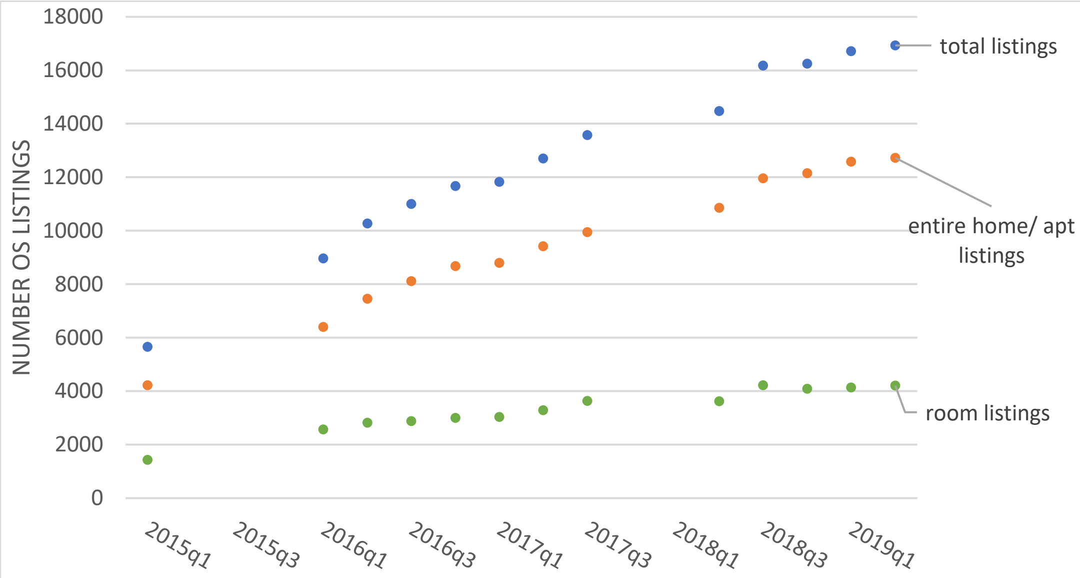
Figure 2: Median Value per m2 of dwelling sales in the neighborhoods Santo António, São Vicente, Parque das Nações, Ajuda, Lumiar and Santa Clara.



3.3. Descriptive statistics

Figure 3 illustrates the evolution of the total listings since 2015, as the evolution of the two types of listings considered in the analysis (entire home/apartment and rooms, that include private rooms and shared rooms). With the total Airbnb Listings registering an increase of 300% since 2015, entire home/ apartment listings an increase of 301% and rooms listings an increase of 294%-

Figure 3: Airbnb Listings over Time city of Lisbon



Looking into the more detailed data of the second quarter of 2019 we can access more precisely the structure of this market. Table 2 shows the distribution of listings into two types for the city of Lisbon in the second quarter of 2019. With the vast majority of listings (75,16%) being entire home/ apartments, whilst 24,84% are rooms, which include both private and shared rooms. This distribution illustrates the worries that underlie the debate, that Airbnb ends up taking properties from the long-term market that would otherwise be offered to residents.

Table 2: Airbnb listings by listing type (second quarter of 2019)

Listing Type	Frequency	%
Entire home/ apartment	12725	75,16%
Rooms	4206	24,84%
Total	16931	100,00%

Table 3 shows the summary statistics for the variables in the final data set. Looking at the table, significant properties of the data can be observed. We can see that there is a high variation in Airbnb listings, with a standard deviation of 746,96 listings and a mean of 532,69 listings per neighborhood. When we consider the different type of listings, we identify that most of the variation in listings is due to variation on entire home/ apartment listings, with a mean number of 395,17 with a standard deviation of 638,13. Rooms listings, which include the listings of private rooms and shared rooms, have a standard deviation of 164,06, with a mean of 137,50 listings. The Airbnb density, calculated by diving the number of listings of the specific neighborhood by the housing units in the same neighborhood, has a mean value of 0,0449, so on average Airbnb listings represent 4.49% of the housing units of the neighborhood. The price per m² has a mean of 2030,85€, with a standard variation of 701,21.

The last part of the table presents the summary statistics for the log transformation of the same variable presented at the top part. Worth to notice is that due to the fact that Airbnb

Table 3: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Airbnb Listings	312	532.69	746.96	3	3572
Entire home/ apartment listings	312	395.17	628.13	0	3155
Room listings	312	137.50	164.06	3	956.67
Airbnb density	312	.0449	.0683	.0003	.3329
Price per m2	312	2430.85	701.21	1244	4742
Log Airbnb Listings	312	5.44	1.34	1.10	8.18
Log entire home/ apartment listings*	311	5.01	1.41	1.61	8.056
Log room listings	312	4.27	1.22	1.10	6.86
Log price per m2	312	7.76	.28	7.13	8.46

Chapter 4: Methodology

In this chapter the specific methodology adopted to investigate if Airbnb affects the long-term housing market is explained below.

To estimate the impact of Airbnb on the housing market, I start by estimating the following regression:

$$\log ppm2_{it} = \alpha + \beta \log listings_{it} + \varepsilon_{it} \ , \tag{1}$$

where i indexes each neighborhood and t represents time (in quarters). Log $ppm2_{it}$ is the log of the price per square meter in neighborhood i at the time period t, α an intercept and $\log listings_{it}$ represents the log of Airbnb listings in neighborhood i at time period t. Finally, ε_{it} is a mean zero error term.

For this pooled specification to be consistent, the data must have neither significant cross-sectional (between neighborhoods) nor significant common temporal effects. If that is the case, the model can be estimated with an ordinary least squares (OLS).

In case of presence of significant cross-sectional effects, then neighborhood fixed effects need to be accounted for. Anticipating neighborhood fixed effects and to control for this, the following fixed effects model is also estimated:

$$\log ppm2_{it} = \alpha_i + \beta \log listings_{it} + \varepsilon_{it}. \tag{2}$$

This is a log-log regression where the intercept term differs for the different neighborhoods and where all the other terms have the same interpretation as in (1). This fixed effect regression controls for time-invariant characteristics between neighborhoods, which ensures that the estimated coefficient is not biased due to omitted time-invariant characteristics.

In addition to neighborhood fixed effects, there is the possibility of existence of a common time trend. To deal with it, the following fixed effects model with both neighborhood and time effects is estimated:

$$\log ppm2_{it} = \alpha_i + \beta \log listings_{it} + \gamma_t + \varepsilon_{it}, \tag{3}$$

where a full set of time dummy variables is added to regression (2).[9]

To test if the cross-sectional and/ or time fixed effects are significant and to determine which model specification is the appropriate both fixed effects are tested for through a poolability test comparing $R^2's$ of models (2) and (3) with model (1).

Airbnb listing present an uneven distribution across the different neighborhoods of Lisbon. For that reason, it is expected that Airbnb density will have a higher explanatory power over house prices and represent better the Airbnb presence. Airbnb density is also a regressor to account for the impacts of Airbnb in Horn and Merante (2017). Therefore, I examine the impact of Airbnb presence formally with:

$$\log ppm2_{it} = \alpha_{(i)} + \beta Airbnbdensity_{it}(+\gamma_t) + \varepsilon_{it} , \tag{4}$$

where Airbnb$density_{it}$ is the Airbnb listings density in a given neighborhood at a given time period, calculated by dividing the number of Airbnb listings by the housing units stock at that neighborhood.

Three specifications of equation (4) are estimated, following the same structure, explained and adopted for regressions (1), (2) and (3). First, a pooled specification with no fixed effects; secondly, I consider neighborhood fixed effects; and lastly, both neighborhood and time fixed effects.

[9] A log-log model specification was adopted to have a more intuitive analyses of the results.

A similar three specification analysis can be made to consider the price adjustment process in the housing market, through the use of the one period lag of Airbnb listings as regressor. Formally, I estimate the equation:

$$\log ppm2_{it+1} = \alpha_{(i)} + \beta \log listings_{it} \, (+\gamma_t) + \varepsilon_{it} \ , \qquad (5)$$

where $\log ppm2_{it+1}$ is the log of price per square meter in a given neighborhood in the time period after the observed Airbnb listings.

Finally, to investigate how the different types of listings impact house prices and to test whether the entire home listings are associated with a higher increase in house prices, I estimate:

$$\log ppm2_{it} = \alpha_{(i)} + \beta_1 \log entire_{it} + \ \beta_2 \log rooms_{it} \, (+\gamma_t) + \varepsilon_{it} \, , \qquad (6)$$

where Airbnb listings are decomposed into two variables: $\log entire_{it}$, the log of Airbnb listings of the type entire home/ apartment and $\log rooms_{it}$, the log of Airbnb listings of the type private rooms and shared rooms.

This categorization into entire home listings and rooms listings of the Airbnb groups entire home/ apartment listings, private and shared rooms listings, fits the argument that only the last two group can be considered a part of sharing economy, while the first does not fall into the definition of this market (Gyódi, 2019).

The estimation of the three specifications of the model with different independent variables as indicators of Airbnb presence allows for a better understanding of how the housing market is being affected by the presence of Airbnb and to determine if there is unobserved neighborhood heterogeneity and time heterogeneity, and if so, to account for it.

All the analysis and results interpretations carried out in the next chapter assume that the following assumption hold: Gauss Markov assumptions and orthogonality between regressors and error term conditional on controls.

Chapter 5: Results

This chapter presents the regression results of the analysis implemented by using the models and specifications presented in the last chapter

Table 4: Regression result. Log price per m²on log listings

Variable	(1)	(2)	(3)
loglisting	.1357***	.6623***	-.0110
	(0.0102)	(0.0833)	(0.0840)
N	264	264	264
R^2	.3789	.6518	.8936
Neighborhood Fixed Effects		X	X
Time fixed Effects			X

Note: Robust standard errors in parentheses
legend: * p<.1; **p<.05; *** p<.01
X denotes inclusion of the respective fixed effect

Table 4 presents the results for the regression of models (1) – (3) used to estimate the impact or Airbnb listing on house prices. The first column displays the results for the simple pooled OLS regression of log house prices on Airbnb listings. the second the fixed effects model, and the third the fixed effects model with time fixed effects.

The results for equation (1) in the first column show that a 1% increase in Airbnb listings is associated with an increase of 0,14% in house prices. The coefficient is highly significant at the 1% level.

Column 2 reports the results for equation (2) that includes the individual neighborhood effects, through a fixed effects model in order to control for unobservable neighborhood characteristics. The results show that a 1% increase in listings is associated with a 0,66% increase in house prices. This regression also gives significant estimates at the 1% level. The adjusted R^2 increases significantly once only the within neighborhood variation of the data is used. The fixed effects model removes the effect of static house price and listings differential between neighborhoods.

In the third column both neighborhood fixed effects and time fixed effects are accounted for with the estimation of equation (3). When time fixed effects are added to the model the explanatory variable loses statistical significance. There appears to be a significant house price and Airbnb listings difference across the different periods, common to all neighborhoods. Therefore, periods with higher listings are also periods with higher house prices for all neighborhoods. Furthermore, there is not enough neighborhood level time variation in my data to draw statistical inference from. There is an increment of 0,2418 in adjusted R^2 against the first fixed effects model, with time effects being significant in general.

The estimates from table 4 are consistent with the hypothesis that the pooled OLS estimation of the model with Airbnb listings as the explanatory variable presents biased estimates. The results are also consistent with higher Airbnb listings driving prices. However, the correlation between listings and prices may also be due to a common factor driving both.

The Airbnb listing have an uneven distribution across neighborhoods, to control for this difference, I test the hypothesis that the Airbnb density better explains the evolution in house prices with three specifications of equation (4). I regress log house prices on Airbnb density using simple pooled OLS, neighborhood fixed effects and both neighborhood fixed effects and time fixed effects.

Table 5: Regression results. Log price per m² on Airbnb Density

Variable	(1)	(2)	(3)
Airbnbdensity	2.34***	8.40***	1.1391
	(0.1607)	(2.3832)	(0.9255)
N	264	264	264
R^2	.3044	.3684	.8982
Neighborhood Fixed Effects		X	X
Time fixed Effects			X

Note: Robust standard errors in parentheses
legend: * p<.1; ** p<.05; *** p<.01
X denotes inclusion of the respective fixed effect

The first column of table 5 shows the simple pooled OLS estimation of equation (4) that gives the coefficient estimate of 2,34, significant at 1% level, which means that with a one standard deviation increase in Airbnb density is associated with an increase of around 0,16% in house prices.

With the incorporation of neighborhood fixed effects, the coefficient estimate is also significant at the 1% level and takes the value of 8,4. This can be interpreted by a 0,57% higher house prices with one standard deviation increase of Airbnb density.

When the neighborhood fixed effects and time fixed effects are added to the model, the explanatory variable coefficient estimate is 1,14. This coefficient loses significance when both fixed effects are included, however.

In line with the argument that housing markets take time to adjust, and to address the possible delays in the effects of Airbnb listings, I estimate equation (5). Again, the first column presents the simple pooled OLS regression, the second the fixed effects estimation of the model, and the third the fixed effects model with time fixed effects.

Table 6: Regression Results. Log price per m² on lag of log listings

Variable	(1)	(2)	(3)
loglisting			
L1.	.1384***	.6550***	.02963
	(0.0103)	(0.0795)	(0.0877)
N	240	240	240
R^2	.4099	.6726	.8951
Neighborhood Fixed Effects		X	X
Time Fixed Effects			X

Note: Robust standard errors in parentheses
legend: * p<.1; **p<.05; *** p<.01
X denotes inclusion of the respective fixed effect

The estimates are in line with those from the model with contemporaneous Airbnb listings, suggesting that periods with higher listings are also followed by periods with higher house prices for all neighborhoods. The explanatory variable still loses statistical significance when time fixed effects are added to the model.

Finally, to address the question of whether the different types of listings have different effects on house prices, the log of house prices is regressed on the log of entire house listings and on the log of room listings (both private and shared listings); equation (6).

Table 7: Regression Results. Log price per m² on log entire home/ apartment listings and log room listings

Variable	(1)	(2)	(3)	(4)
logentire	.1640***	.6328***	.1561***	.0430*
	(0.0184)	(0.1332)	(0.0321)	(0.0237)
logrooms	-.0445**	.0452	-.1254***	.0008
	(0.0221)	(0.1173)	(0.0422)	(0.0128)
logprice				
L1.				1.0206***
				(0.0872)
L2.				-.2766**
				(0.1252)
Neighborhood Fixed Effects		X	X	X
Time Fixed Effects			X	X
N	264	264	264	216
R^2	.4052	.6499	.9129	.9679

Note: Robust standard errors in parentheses
legend: * p<.1; **p<.05; *** p<.01
X denotes inclusion of the respective fixed effect

The first column with pooled OLS shows that an increase of 1% in entire home/apartment listings is expected to result in a 0,16% increase in house prices, at a 1% significance. In spite of a 1% increase in room listings it is expected a 0,045% decrease in house prices, with a 5% significance level.

When neighborhood unobservable characteristics are added in column 2, the variable log of rooms loses statistical analysis, and if the number of entire home/ apartment listings goes up by 1%, house prices are expected to increase by 0,63%. These effects are comparable to the estimated effect from table 4.

The regression of equation (6) on the third column, with both fixed effects, shows that the coefficient estimates on the two independent variables are significant at the 1% level. An increase of 1% in entire home/ apartment listings is associated with an increase of 0,16% and an increase of 1% in room listings with a decrease of 0,13% in house prices respectively, ceteris paribus.

In the fourth column, a two-period lag of the price per m² is added to the regression, to account for differential price trends across neighborhoods as suggested by Figure 2. When these two variables are introduced, the coefficient for log of room listings loses significance, while the coefficient for log of entire home listings remains significance, but at the 10% level. Therefore, a 1% increase in entire home listings is associated with a 0,04% increase in house prices. This addition, allows to control for different trends in house prices and the fact that the coefficient for room listings loses significance is consistent with the neighborhood-specific time trends being the main driver for changes in the house prices, with the difference in prices being correlated with the different evolution in listings.

Chapter 6: Discussion and Conclusions

In this chapter the key findings from this investigation will be presented along with its limitations, connecting them with the regulatory debate on this issue.

This study aimed to study the impact of short-term rentals on house prices through the use of data on Airbnb listings, while also studying if different types of listings affect the market differently.

The overall results suggest that Airbnb presence affects house prices. However, there is substantial common time variation across all neighborhoods in both prices and listings, so that when the time fixed effects are included there is too little within neighborhood and within time variation for statistical inference.

The most interesting result of this study concerns the effects of Airbnb listings when these are decomposed into two categories. I find that both groups of listings are statistically significant and have opposite effects. Specifically, the result suggests that a 1% increase in entire home listings leads to a 0,16% increase in house prices per m², while a 1% increase in room listings (both private and shared rooms combine), is associated with a 0,13% decrease in the price per m². These findings are consistent with my hypothesis that entire home listings have a bigger impact on the increase on house prices and confirming that not all Airbnb listings are the same. Nevertheless, the negative coefficient estimate on room listings is puzzling.

Specially, although significant results are found whether both cross sectional and time fixed effects are considered, other biases cannot be completely rejected. The negative impact of room listings on prices can be better understood and explained by a higher growth of room listings in neighborhoods that experience relatively low-price growth compared to the average for Lisbon. Similarly, the positive effect of entire home listings could also be due to such listings growing more in neighborhoods experiencing faster growth in house prices than the Lisbon average.

With the inclusion of lags of the dependent variable, the coefficient for log of room listings loses significance, while the coefficient for log of entire home/ apartment listings remains significance, but at the 10% level. These results, when the lags are added, confirm my explanation. The negative coefficient associated with the room listings, when both neighborhoods and time fixed effects are included, is due to neighborhoods experiencing relative lower house price growth also having relatively more room listings. While neighborhoods experiencing relatively higher price growth have relatively more entire home listings. However, there appears to be an independent positive effects of entire home listings on house prices, controlling for the different house prices trends across neighborhoods. The inclusion of the lags of the dependent variable gives more confidence to the coefficient estimate of entire homes listings having a casual explanation, with a 1% increase in Airbnb entire home listings leading to an increase of 0,043% of house prices.

This investigation contributes to the literature of the effects of short-term rentals on long-term housing market by presenting estimates of the effects with detailed data at the neighborhood level for the city of Lisbon, with the use of short interval data and the introduction of decomposed Airbnb listings variable into two types.

The findings from this investigation are connected with the regulatory debate surrounding Airbnb. Further analysis, however, would be necessary for a complete understanding of home-sharing platforms, as a broader estimation of Airbnb impact on welfare. The increase of home-sharing can have positive externalities on the economy with the increase of tourism or negative externalities, such as noise, traffic and safety concerns (Sheppard and Udell, 2016). However, the present analyses contribute to the debate with new evidence that Airbnb listings affect house prices.

Taking a casual interpretation of my estimates suggests that regulation of Airbnb listings for entire homes might alleviate unaffordability issues in Lisbon. Some policies are already in place in the city of Lisbon. A mandatory registration of Airbnb listings as local accommodations, requiring licensing and a suspension of new local accommodation licenses for certain areas of the city with higher local accommodation house units ratio.[10]

The limitations of this study revolve around the fact that the investigation focuses only on the city of Lisbon and, therefore, the generalization of the results should not be made to

[10] The suspension was published on August 22, 2019 in the Portuguese "Diário da República" and takes effect from October 22, 2019.

other cities. In addition, I do not utilize any natural experiment or quasi-random variation, so the results cannot be given a definitive casual interpretation. The data used did not include control variables that drive changes in house prices at the neighborhood level. The adoption of hedonic regressions in this study, with the inclusion of different Airbnb property characteristics and neighborhood indicators could provide a sharper conclusion on this topic. I leave such investigation for future research.

REFERENCES

BARRON, K., KUNG, E. & PROSERPIO, D. 2018. The sharing economy and housing affordability: Evidence from Airbnb.

BÖCKMANN, M. 2013. The Shared Economy: It is time to start caring about sharing; value creating factors in the shared economy. *University of Twente, Faculty of Management and Governance*.

COYLE, D. & YEUNG, T. 2016. Understanding Airbnb in fourteen European cities. *The Jean-Jacques Laffont Digital Chair Working Papers*.

EINAV, L., FARRONATO, C. & LEVIN, J. 2016. Peer-to-Peer Markets. *Annual Review of Economics,* 8**,** 615-635.

ELÍASSON, L. & RAGNARSSON, Ö. P. 2018. Short-term renting of residential apartments: Effects of Airbnb in the Icelandic housing market.

GYÓDI, K. 2019. Airbnb in European cities: Business as usual or true sharing economy? *Journal of Cleaner Production,* 221**,** 536-551.

HORN, K. & MERANTE, M. 2017. Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics,* 38**,** 14-24.

HORTON, J. J. & ZECKHAUSER, R. J. 2016. Owning, using and renting: some simple economics of the" sharing economy". National Bureau of Economic Research.

INTERIAN, J. 2016. Up in the air: Harmonizing the sharing economy through Airbnb regulations. *BC Int'l & Comp. L. Rev.,* 39**,** 129.

LEE, D. 2016. How Airbnb short-term rentals exacerbate Los Angeles's affordable housing crisis: Analysis and policy recommendations. *Harv. L. & Pol'y Rev.,* 10**,** 229.

QUATTRONE, G., PROSERPIO, D., QUERCIA, D., CAPRA, L. & MUSOLESI, M. Who benefits from the sharing economy of Airbnb? Proceedings of the 25th international conference on world wide web, 2016. International World Wide Web Conferences Steering Committee, 1385-1394.

SEGÚ, M. 2018. Do short-term rent platforms affect rents? Evidence from Airbnb in Barcelona.

SHARMA, S. 2018. *IMPACT OF SHORT TERM RENTALS ON THE RENTAL AFFORDABILITY IN SAN FRANCISCO – THE CASE OF AIRBNB.* University of Illinois at Urbana.

SHEPPARD, S. & UDELL, A. 2016. Do Airbnb properties affect house prices. *Williams College Department of Economics Working Papers,* 3.

ZERVAS, G., PROSERPIO, D. & BYERS, J. W. 2017. The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of marketing research,* 54**,** 687-705.