The impact of Airbnb on residential property transaction prices in the Greater London residential property market

ABSTRACT. This thesis concerns an empirical analysis of the aggregated impact of Airbnb on the Greater London residential property market. Amongst in other cities, the presence of the home sharing economy platform opened a strong debate on affordability of residential properties in London. Airbnb is proxied as a density variable by measuring the number of active Airbnb listings per thousand inhabitants. Data between 2009 and 2017 is analyzed by using a fixed effect model approach. The results show that if Airbnb density increases with one percent, residential house prices will increase with 4.71 percent. These results could have strong implications for governmental policy makers.

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1. INTRODUCTION

During the past decade, the economy evolved from a manufacturing-based economy to a new economy which tends to be more focused on platforms that facilitate the sharing economy. Platforms such as Uber and Airbnb gained compelling traction on consumers which is proved by their disruptive force on traditional industries such as the taxi and hospitality industry. The power of these platforms lies in utilizing assets in a more efficient manner (Belk, 2014). Belk (2014) states that residential property is a perfect example to explain his theory. The efficiency of space-use can be increased in using platforms such as Airbnb by gaining an income while it is not in use by the owner-occupier. At the same time, housing affordability has become a significant issue in the world's major cities (Gurran et al., 2017) which increased the urge to regulate exogenous factors that increase residential property transaction prices. Since critics of Airbnb argue that the growth of the number of Airbnb listings in an area exacerbate profitability issues in high-demand urban areas this has become an important topic in national debates (Brousseau et al., 2015).

Through what mechanisms can the growth of Airbnb in a certain urban area lead to increased residential property transaction prices? Two theories are discussed in order to theorize the effect of Airbnb on transaction prices. These are the capitalization theory and the bid rent model. The capitalization theory highlights two mechanisms which are rental income and demanded return or ownership costs. In the capitalization theory increased rental income has a positive effect and increased ownership costs have a negative effect on asset values. With a fixed supply of housing in the short-term, an increase in demand for housing due to an increased popularity for Airbnb will cause rents to increase. At the same time, income for Airbnb hosts that is generated by letting their residential property can be viewed as normal income, but also as a form of negative expense meaning less ownership costs. In case ownership costs are lower, the demanded return can also be lower (Sheppard et al., 2018). The bid rent theory on the other hand values residential property based on location from the central business district (CBD) and based on this theory also two mechanisms can explain the effect of Airbnb on residential property transaction prices. At first, based on the bid rent theory it can be explained that when population increases also the bid rent curve shifts upward due to higher density and therefore cause higher rent values. A similar effect appears when household income increase. Increased income via Airbnb gives households more spending power on housing causing rents to rise. These four mechanisms based on the capitalization theory and bid rent theory will be further explained in chapter 2.

London has become the city with the most Airbnb-listings worldwide. Recent data on Airbnb show that 72,218 listings were available, of which 39,058 were entire houses (Cox, 2019). At the same time London is struggling with affordability. In England the average property value in March 2018 was £243.639 while in London it was £484.584 (gov.uk, 2018) and the amount of Airbnb listings in London grew with an average annual rate of 187 percent between 2011 and 2015. Although the growth rate is decreasing, the total amount of listings still increases (Cromarty et al., 2018). Several studies show a causal relationship between the number of Airbnb listings and increased house prices within different markets (Barron et al., 2018; Horn et al., 2016; Sheppard et al., 2016). Considered the continuing growth of Airbnb, the platform will remain a relevant topic in discussions around negative externalities such as decreased housing affordability.

The main research question of this study is as follows: What is the impact of Airbnb on residential property transaction prices in the Greater London area? This research question is answered by means of the following sub-questions:

1. Via what mechanisms can Airbnb affect resident residential property transaction prices?
2. To what extend does Airbnb affect resident residential property transaction prices?

The findings of this study can be considered as input for the local London government in their decision-making process regarding regulating Airbnb.

Although short-term rental market encompasses all possibilities and platforms to rent out properties it is known that Airbnb is the largest platform and driver that facilitates short-term renting. Horn et al. (2017) studied the externalities of Airbnb on transaction prices of residential property in Boston. Based on a dataset of property transactions and Airbnb listings they found evidence that each 12 Airbnb listings per census tract leads to an increase in the asking rents of 0.4 percent. Barron et al. (2018) created a data set for the US that combines house prices and rents from online real estate broker Zillow with Airbnb listings. They find that an increase of 10 percent in Airbnb listings in a ZIP code leads to a 0.42 percent increase in ZIP code rental prices and 0.76 percent increase in house prices. Furthermore, they find that the rent increase for Airbnb listings is even larger in ZIP codes with a larger share of nonowner-occupied housing. Another study on the effect of Airbnb density on transaction prices of residential property in New York City by Sheppard et al. (2018) showed similar results. Based on a hedonic model the authors found empirical evidence that doubling the total number or Airbnb properties within 300 meters of a house is associated with a six to nine percent increase in property values.

This thesis contributes to the existing academic literature by further exploring the effect of Airbnb on residential property transaction prices. The study area of current literature on Airbnb in relationship to transaction prices only focus on US housing markets. This study is the first examining the effect of Airbnb on house prices in the London residential property market. European housing markets are not covered on this subject in current academic literature. Furthermore, current literature applied empirical models focusing on individual property transactions. This is the first study that studies the effect of Airbnb on the housing market at an aggregated level. This adds value to current literature since it can serve as a test of robustness for results obtained in previous studies.

The remainder of this thesis proceeds as follows. Chapter 2 contains the literature review regarding the effect of Airbnb or other STR platforms on the housing market. After that, chapter 3 describes the research model used in the empirical analysis, followed by a discussion and description of the dataset in chapter 4. Finally, the results are presented in chapter 5, and are concluded in chapter 6.

2. THEORETICAL FRAMEWORK

In this section an overview of theoretical arguments is presented that could justify the preliminary hypothesis that an increase in the number of Airbnb listings in an area affect residential property prices. The number of Airbnb listings in an area is defined as Airbnb density in this thesis. First a brief overview of current literature on Airbnb will be provided. This overview is then followed by theorization of how an increase in Airbnb listings can influence residential property prices by means of the capitalization theory and the bid-rent theory developed by Alonso (2005). Finally, the hypothis will be presented, which is based on the theoretical perspectives as presented in this chapter.

Several previous studies found empirical evidence that the existence of Airbnb can affect residential property prices in urban areas. Horn et al. (2017) performed a study focusing on the effects of the growth of Airbnbs on the Boston rental market. Based on empirical analysis on individual rental transactions the researchers found evidence that twelve Airbnbs per census tract led to an increase in the asking rents of 0.4 percent. Barron et al. (2018) applied a broader perspective and focused on rental prices and house prices. Based on a dataset which covers the entire United States the authors found that an increase of ten percent in Airbnb listings within a ZIP code leads to a 0.42 percent increase in rents and 0.76 percent increase in house prices in that specific ZIP code. Finally, Sheppard et al. (2018) applied a hedonic model on the city of New York and found empirical evidence that doubling the number or Airbnb properties within 300 meters of a house is associated with a six to nine percent increase in property values. On the contrary, Koster et al. (2018) found empirical evidence that after the induction of regulation that restricts Airbnb use, rents decrease by three per cent in the New York metropolitan area.

The impact of an increased Airbnb density on local residential property prices can be explained via multiple mechanisms (Sheppard et al., 2018). The possibility to rent out residential property on the platform will generate a new income stream for residential property owners. This income can be viewed as income that could be assigned to several expenditures or for saving but can also be explained as negative ownership costs. The mechanism of how residential property appreciation due to an increase in income generated by Airbnb could be explained with the capitalization theory. The central expression in the capitalization theory is the following in which the value is based (*P*) on the income or rent generated (*R*) by an asset and the user cost of the asset (Sinai et al., 2005):

(1)

$$P = \frac{R}{u}$$

In this equation the user cost of the asset is defined by *u* which value is between zero and one. The user cost of an asset can also be defined as the yield demanded by the owner of the asset based on market circumstances and asset quality (Kuttner et al., 2012) and consists of several components:

$$u = r_{rf} + p + m - g + t_p - t_i(r_m + t_p) \tag{2}$$

This formula states that cost of ownership is a function of the market risk free rate (r_{rf}) which is the minimum return for a risk-free asset. However, renting out a house cannot be regarded as risk free investment and therefore an owner requires a risk premium (p). Furthermore, maintenance costs as a percentage of the property value (m) is required to obtain a certain value of utility from the property and since values can fluctuate over time, this should be reflected in the user cost of capital function (g). In case residential property prices increase these will decrease the cost of capital and vice versa. Finally, property tax (t_p) increases the cost to operate an asset, however this is partly tax deductible together with the mortgage interest rate (r_m).

From the above equation it becomes clear that all parameters increasing the user cost of the asset include a positive sign and all elements decreasing the asset costs have a negative sign. Income derived from renting out residential property on platforms such as Airbnb can be regarded as positive cash flows decreasing the cost of the asset corrected by any personal tax effects. This can be depicted in the following expression:

$$u = r_{rf} + p + m - g + t_p - t_i(r_m + t_p) - (1 - t_i) * A \tag{3}$$

This expression is comparable to equation 2 explaining the components of user cost of an asset but is now corrected for the after tax-effect of income raised by renting out a property on Airbnb. Assuming two equal residential properties with equal mortgage interest payments, maintenance costs and tax conditions one can expect an equal cost of ownership. However, if one property is at least partly rented out on platforms such as Airbnb and the other property is not, one can understand that the user cost between the two differs. Keeping the rent level constant, the lower cost of ownership as a result of income generated via Airbnb will result by means of equation 1 in a higher residential property value.

A second mechanism of how an increase of Airbnb can cause higher residential property values can be explained by an increase of demand. A lower cost of ownership cannot be ignored in explaining higher residential property values for houses that are (partly) rented out via Airbnb. However, equation 1 also acknowledges the impact of rental income as a parameter that can influence residential property values. The theoretical background of the mechanism how rental prices can alter based on a shift in housing demand is best explained by the DiPasquale-Wheaton model. This model graphically determines rental price, property price, construction cost and new supply of housing stock. This model defines the housing stock in the short term as fixed due to inelasticity of supply to demand (DiPasquale et al., 1994). It is not feasible to assume that it is possible to develop new residential property in the short term since construction of real estate is non-elastic with demand due to planning restrictions and (Evans, 2004). Above that it would also be not logical to demolish existing housing stock if the demand remains the same or increases. Therefore, it is assumed that the supply curve for residential property is a straight vertical line. In contrast to the supply curve, the demand curve is a downward sloping line since more space is demanded when rents are relatively low (Evans, 2004).

Current rent levels are based on the equilibrium rent prices were the demand curve intersects the short-term supply curve for space. But what happens if a demand shock in the housing market occurs due to an increased interest of investors in the housing market? The expected capital appreciation and extra rental income induces investors to acquire residential property and hold it for let in the short-term rental market. This speculative behavior of both individual owner occupier households and private investors result in an increase in demand for space (Sheppard et al., 2018). This will move the demand curve upwards and given a fixed supply of housing stock will increase the equilibrium rent price. As shown in equation 1 higher rent income will equal higher property values holding the cost of ownership constant.

The mechanisms through which Airbnb impacts residential property prices can also be demonstrated by a simple monocentric bid rent model. The bid rent model is developed by Alonso (2005) and based on the Von Thunen framework in which the land rent is a function of revenue, non-land payments and transport costs (McCann, 2013). The Von Thunen framework defines the rent for land as income minus resources spent on non-land consumption and transportation costs. Considering that all households work in the central business district (CBD), each must incur transportation costs to travel to their work. Since transportation costs are endogenously determined by the distance from the CBD, the disposable income that is available for land payments will decrease over distance. This means that the Von Thunen land-gradient is a downward sloping (McCann, 2013). Although this framework clarifies the households' decision-making process regarding space and consumption on other goods, it fails in considering substitution between the two inputs.

The bid rent model distinguishes itself on this flaw of the Von Thunen framework. In contrast to the Von Thunen framework, the bid rent model takes the effect of substitution between the land and other consumption into account (Alonso, 2005). This means that the relationship between the two inputs is not fixed but is described with a bid rent curve. This bid rent curve is not a straight line such as the Von Thunen land-gradient, but a curve that is convex to the origin where the CBD is located. The form of the curve implies that the transportation costs decrease with a decreasing rate over distance. In order to understand this negative convex slope, factor substitution should be considered which is explained by production theory. Standard economic production theory prescribes that all combinations of two input factors are depicted by an isoquant and that optimal production is determined at a point where the slope of the isoquant equals the slope of the budget curve. In this theory the budget curve represents all consumption possibilities based on the budget of a household. If for example labour becomes more expensive relative to capital, the firm rearranges its production so that less labour and more capital will be applied in the production process. The combination of all possible budget curves results in a decreasing convex bid-rent slope (McCann, 2013).

The effect of Airbnb on house prices in the light of the bid-rent theory can be explained by two parameters. First population and second an increase in income while holding the area constant. If the assumption is made that the city is constrained in spatial growth due to planning restrictions which could be a realistic assumption in the case of the Greater London area, the radius of the urban area can be viewed as constant meaning that the total radius of London starting from the CBD is fixed. When population increase, the demand for space increases resulting in a bid rent curve that shifts upward. As a result of this upward shift of the bid rent curve rents will unambiguously rise through the whole urban area (McCann, 2013; Sheppard et al., 2018). A similar effect will occur when income increases. When the income of households increases, they will spend more on space and other goods causing an increase in total utility. Due to the higher spending power on space the bid rent gradient will also shift upward (McCann, 2013).

Although the capitalization theory and the bid rent theory differ on several aspects from a technical perspective, the theories also show some similarities with respect to the parameters. The capitalization theory focused on a lower user cost or demanded return and higher rental income. These parameters show strong similarities with respectively higher income and population increase. This is because lower user cost can also be viewed as a form of income. At the same time higher rental income is caused by an increased demand assuming the supply as fixed. From an economic theoretical view, population increase can serve as a proxy for an increase in demand. With the help of the capitalization theory and the bid rent theory the following hypothesis can be formulated: "*A positive relationship exists between Airbnb density and the aggregated residential property transaction price in the Greater London area*". Airbnb density is defined in chapter 3 and 4 and is a measure for the number of listings corrected by the population in the urban area.

3. METHODOLOGY

In order to test the hypothesis that an increase of Airbnb density positively affects residential property transaction prices, a fixed effect panel regression model is developed. This model defines the aggregated residential property transaction price which is specified per month and per borough as the dependent variable and is regressed on Airbnb density and multiple control variables. The empirical model is defined as follows:

$$PRICE = a + b1(AIRBNB) + b2(EARNINGS) + b3(POP\ GROWTH) + b4(INTEREST\ RATE) + \partial(BOROUGH) + \theta(MONTHS) + \varepsilon$$

where PRICE is the natural logarithm of the aggregated residential property transaction price per month and per borough. This average transaction price is log transformed due to non-normality of the variable. The main independent variable of this study is AIRBNB. AIRBNB is the density of the Airbnb listings within a borough and is measured by the number of listings per thousand inhabitants. This measure for the density of Airbnb listings is also applied in a study by Horn et al. (2017) which studies the effect of Airbnb listings on residential property values in Boston. EARNINGS is the average yearly income per resident in the borough. In previous studies, empirical evidence is found that income has a positive effect on residential property transaction prices (Boerassa et al., 2018; Fraser et al., 2012). Therefore, a positive causal relationship between income and aggregated transaction prices is expected. EARNINGS is measured per month and is also log transformed due to non-normality of the variable. POP GROWTH is the monthly percentage growth of the population that is measured on a borough scale. It is expected that population growth has a positive effect on transaction prices since it is a proxy for increased demand. INTEREST RATE is the monthly interest rate measured for the United Kingdom as a whole. Among other literature, Adams et al. (2009) and Boerassa et al. (2018) found a negative relationship between interest rates on loans and property prices. This is also supported by macro-economic theory. Based on literature and theory a negative relationship between interest rates and transaction prices is expected. et al.

By means of the Durbin-Wu-Hausman test it can be determined whether a fixed effects or random effects model should be applied (Durbin, 1954; Wu, 1973). A random effects model should be applied to panel data when the individual specific effects are not correlated with the independent variables. Conversely, a fixed effects model is applied when these individual specific effects are correlated with the independent variables (Greene, 2011). In the Durbin-Wu-Hausman test, the null hypothesis states that the random effects model is preferred and the alternative hypothesis that the fixed effects model is preferred. Since the null hypothesis is rejected, it can be concluded that the individual specific effects are correlated with the independent variables and therefore a fixed effect model should be applied on the panel dataset. In appendix A the output of the Durbin-Wu-Hausman test that was obtained from STATA can be found.

Before running a fixed effect panel model, it is necessary to test five assumptions that justify the use of such a model (Brooks et al., 2015). The required assumptions that should be reviewed and tested before running a fixed effect panel regression are the following:

1. There is a linear relation between the dependent and independent variables, the error term is equal to zero;
2. The variance of the error terms is constant (homoscedasticity);
3. The error terms are independent (no autocorrelation);
4. No multicollinearity exists among the independent variables;
5. The residuals are normally distributed.

Based on several tests it is concluded that most of the assumptions are met except for the assumption for no multicollinearity and autocorrelation. After running a correlation table and calculating variance inflation factor (VIF) values it can be concluded that high levels of multicollinearity exist causing biased regression coefficient values. However, it should be noted that only the coefficients of the multicollinear variables are biased. Airbnb density is not multicollinear and therefor this does not cause any issues regarding interpretation of the coefficient for this main variable. However, interpretation of control variables could lead to misleading findings. Appendix B includes an overview of all tests and results that have been performed for each assumption. The potential bias caused by autocorrelation is reduced by applying the Regression with Driscoll-Kraay standard errors method in Stata.

4. DATA AND SUMMARY STATISTICS

This chapter contains a description of the data that has been obtained and used for empirical analyses as described in the previous chapter. First a description of the different sources is provided followed by an overview of data transformations that have been performed. This is followed by a description of the statistics and a visualization of house prices and the development of Airbnb density in London. The scope of this thesis is studying the effect of Airbnb density on London residential property transaction prices between the years 2009 and 2017.

In total, four main sources of data have been used for this study: 1) Her Majesty's Revenue and Customs (HRMC) property transactions database, 2) InsideAirbnb, 3) London datastore and 4) the OECD. The property transactions database held by the HRMC and is the governmental body that is delegated to record all property transactions in the UK. Due to this delegated task the database can be regarded as complete and reliable. Although the reliability of this database can be assumed as high standard, the transactions database is checked on several potential data issues. Before aggregation of the transaction sales data, outliers have been removed from the database. 577 observations were dropped with sales prices above GBP 10.000.000 and 6.417 observations were dropped with sales prices below GBP 10.000. The dataset without outliers was then aggregated on a monthly scale for each borough. The HRMC property transaction database includes the borough in which each transaction is recorded. Since 32 boroughs are included (borough City of London was removed) for 108 timestamps this leaves 3456 observations. Appendix C contains a table of median aggregated transaction prices in the periods 2009 – 2011, 2012 – 2014 and 2015 – 2017. Over the whole period a strong upward trend in average aggregated house price per borough is visible, however in ten of the thirty-two boroughs the median aggregated house price between 2009 – 2011 and 2012 – 2014 show a decrease. A potential explanation of this decrease in some boroughs can be the aftermath of the financial crisis which has impacted house prices in the London housing market. Despite this, the median overall house prices increased with ten percent between these two sub-periods. Furthermore, in the borough Kensington and Chelsea, the median aggregated house price decreased between 2012 – 2014 and 2015 - 2017. This borough is characterized with residential properties with a wide range of transaction prices. Since no direct economic explanations can be found, a possible explanation for the decrease in median aggregated house price is that the frequency of houses sold in the higher transaction price range is right skewed.

Data on Airbnb listings in the Greater London Area are derived from Inside Airbnb. Inside Airbnb is an online open source data platform containing listings data of multiple cities which has been scraped from the Airbnb website. The London dataset contains various information on all listings that are or have been active in London since it launched in the city. Each listing contains the date of the first listing review, but also the date of the last listing review. Furthermore, the location of each Airbnb listing is recorded in the database which is used to join this with help of ArcGIS to the correct borough. The first and last review date contain valuable information for this research, since it can be used as a proxy to define the period in which the Airbnb was active. According to Brian Chesky, the founder and CEO of Airbnb, 72 percent of guests leave a review for hosts after their stay (Sheppard et al., 2018). Using first and last review date as a proxy to define Airbnb activity is also applied by Sheppard et al. (2018) in their study on the effect of Airbnb on house prices in New York. An Airbnb listing is regarded as active in a given month if this month lies between the month of the first and last review. For instance, if the first review data of a listing was on January 1st, 2016 and the last review on January 1st, 2017 the Airbnb is regarded as active in the twelve months during the given timespan. With a full listing of active and non-active Airbnbs a sum is made of all listings active in a certain month and spatially joined borough. The process of matching an Airbnb listing to the correct borough is performed with the spatial join tool which is built in into ArcGIS. This method of measuring Airbnb activity leaves the possibility of attenuation bias since there may be Airbnb hosts who make their property rarely available on the platform. By using this approach in determining the activity of Airbnb listings, it could be that the activity is overstated since it is only rarely available instead of continuously during the calculated period. This should be considered as a potential bias.

Figure 1 shows a self-created map of all active Airbnb's that are listed in the Greater London area as per December 2017 (Cox, 2019). Based on this map it can be concluded that Airbnb listings tend to aggregate in areas of high tourist visitation. For this reason, it could be expected that this would also lead to a higher Airbnb density in these areas of high tourist visitation while at the same time house prices in these areas are higher since these are closer located at the CBD. This should also be considered and discussed when interpreting the findings on Airbnb density on aggregated average house prices.

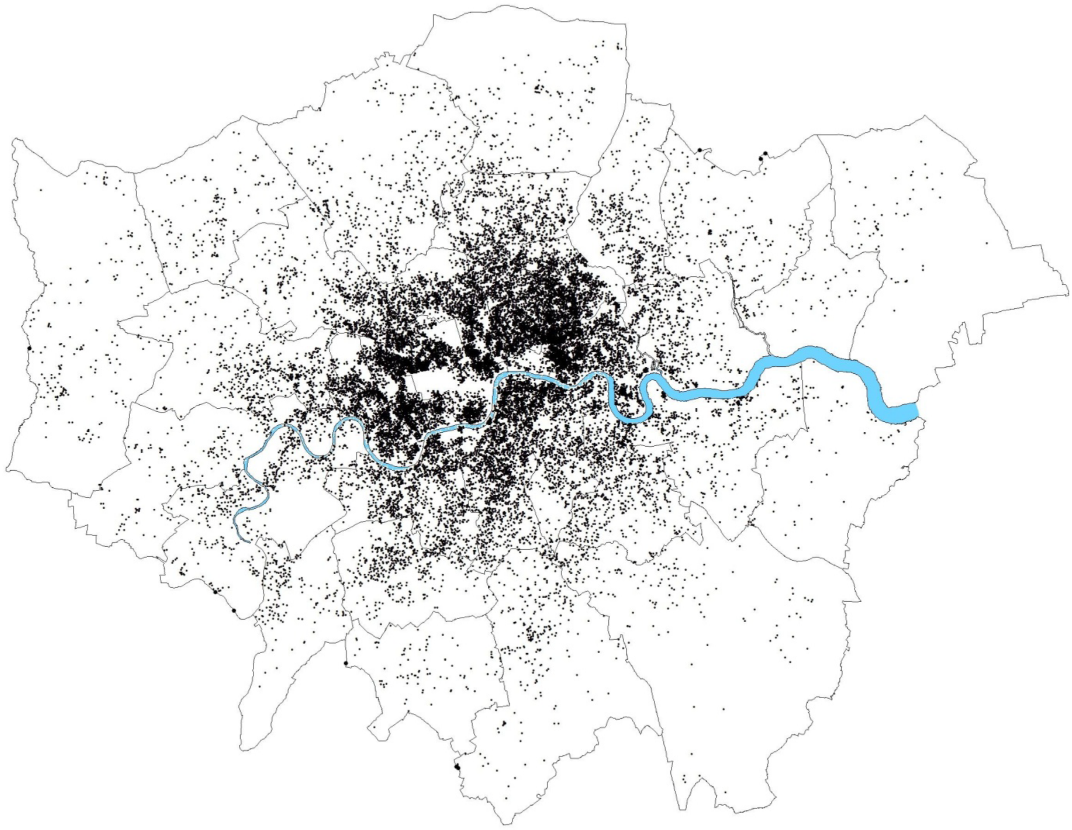

***FIGURE 1** – Airbnb listings per December 2017 in Greater London (source: own production created with ArcGIS based on InsideAirbnb data)*

The dataset of Airbnb consists of 30.691 listings in 33 boroughs between the period of 2009 and 2017. Since the borough City of London is excluded due to data availability, 151 listings have been

TABLE 1 – Airbnb dataset showing number of listings first review and last review per year (source: own production based on InsideAirbnb data)

OF REVIEWS	*FIRST REVIEW*	*LAST REVIEW*	*ACTIVE AIRBNBs*
2009	1	-	1
2010	25	-	26
2011	116	2	140
2012	704	18	827
2013	1.056	43	1.844
2014	2.066	142	3.781
2015	5.237	1.284	7.889
2016	8.633	2.800	13.791
2017	12.702	5.295	21.497
2018	-	7.187	-
2019	-	13.920	-

deleted resulting in a final dataset of 30.540 listings. Table 1 shows the descriptive statistics of the Airbnb dataset. Since only Airbnb listings with a first review date between 2009 and 2017 have been selected for this study, no observations are visible for the first review in the years after 2017. In addition to this table, figure 2 depicts the number of active Airbnb listings per timestamp. The graph shows that in the first 40 months (as of January 2009) little Airbnb activity was visible, followed by a period of rapid increase up until the December 2017.

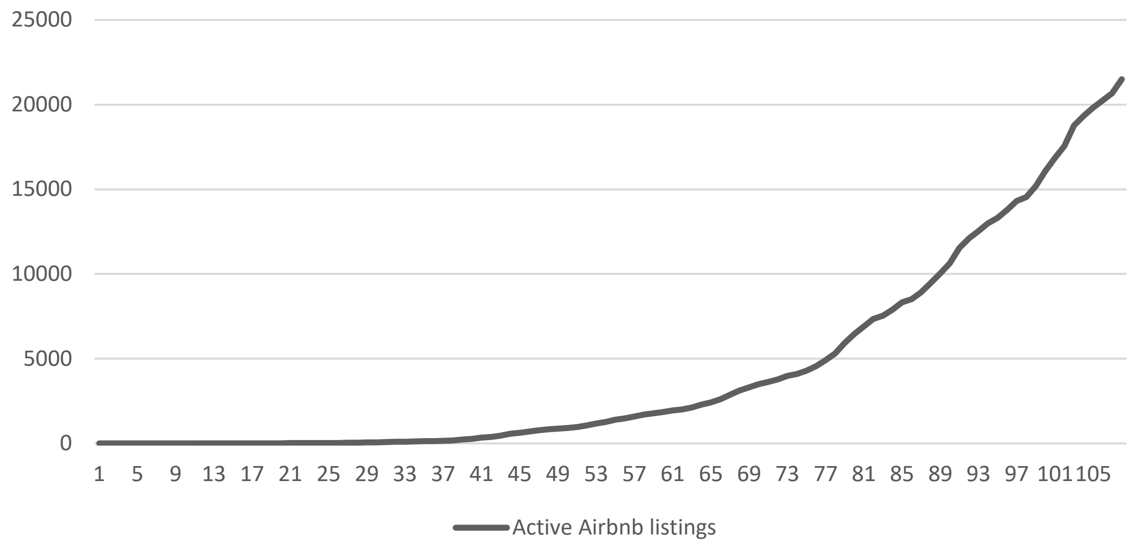

FIGURE 2 *– Active Airbnb listings (source: own production based on InsideAirbnb data)*

The third dataset that has been used is the London datastore. The London datastore contains open source data on their website including statistics on income, health, housing and other topics. Since the data is collected by the local London government it can be regarded as reliable. From this source, data on two control variables have been gathered. The first control variable is population growth and the second control variable is earnings. Population growth is calculated based on data on population per month and per borough with the use of STATA. Another control variable for which data is taken from the London datastore is annual earnings. The London datastore has data available on yearly earnings per borough. Yearly earnings data shows that for each London borough, the earnings increase per year. Based on the assumption that earnings tend to always increase with for example inflation, the yearly earnings are interpolated so that yearly earnings are measured per month. Finally, the open source datastore of the Organization for Economic Co-operation and Development (OECD) is used to obtain monthly data on interest rates in the UK.

TABLE 2 *– Descriptive statistics independent parameters*

Variable	Observations	Mean	Std. Dev.	Min	Max
Average price	3,456	440,976.90	255,938.00	153,051.30	1,823,648.00
Yearly earnings	3,456	27,821.48	3,842.30	19,229.60	42,523.44
Airbnb density	3,456	0.5359	1.1917	0	9.8256
Interest rate	3,456	2.4141	0.9197	0.7421	4.1007
Population growth	3,456	0.0014	0.0022	-0.0022	0.0249
Boroughs	3,456			0	32

Table 2 describes the dependent and independent variables that are included in the empirical model specification. It becomes clear that for each of the variables the standard deviation is relatively high which is also reflected in the minimal and maximum values. Due to this fact a more insightful tool is needed to describe the behavior of each variable. Appendix D contains graphs for each independent variable and how it relates to the development of the level of aggregated average house price. Looking into appendix D shows that Airbnb density, yearly earnings and population growth tend to move upward while interest rate shows a clear downward trend over time

5. RESULTS

This chapter reports the empirical results of the different evaluated fixed effects models on aggregated average transaction price. First the different models that have been applied are explained followed by a discussion on the final model. The final model is used to interpret regression coefficients of Airbnb density and the control variables on aggregated average transaction price. After this, the robustness of the final model will be discussed in order to verify the reliability of the coefficients and the significance levels per independent parameter.

As stated in the research method in chapter 3, the dependent variable is the natural logarithm of the aggregated average monthly price and the main independent variable of this study is Airbnb density which is measured as the number of listings per thousand inhabitants. Since these are the main variables of these study, these are included in each fixed effect model. As a result, the first and basic model (model 1) includes the aggregated price as dependent variable and Airbnb density as main independent variable. In order to verify the statistical power of this model the R-squared is evaluated. The R-square shows the percentage of variance that is explained by the model. In the case of model 1 the R-square is 30,9 percent. This first model is used as a basic model and is enriched by adding more control variables. Table 3 shows that the R-squared of each model increases by adding a new control variable up until the final model which is defined by model 4. This model has a final R-squared value of 55.4 percent and has the strongest statistical power. Because of this, model 4 should be evaluated for empirical analysis. Table 3 contains the coefficients, t-values and R-squared values for each model. Table 3 shows that all independent variables that which are included in the final model are significant at the one percent level. The first and second lagged aggregated price variables are both significant at a one percent level and show positive signs. This is in line with the expectation that current dates' aggregated house prices are dependent on previous house prices. Above that the results show that the first lag coefficient is larger than the second lag coefficient meaning that the first lag coefficient's effect on current dates house prices is larger than the second lag. The positive coefficients are in line with literature on the sales comparison method which states that current transaction prices are partially dependent on previous transaction prices (Brueggeman et al., 2015; Schram, 2006).

__TABLE 3__ – Regression results full dataset

	Model 1 Aggregated Price	**Model 2** Aggregated Price	**Model 3** Aggregated Price	**Model 4** Aggregated Price
Airbnb Density	0.098^{***}	0.089^{***}	0.085^{***}	0.046^{***}
	(6.40)	(10.40)	(8.92)	(5.17)
Earnings Yearly		1.147^{**}	1.163^{***}	0.624^{***}
		(2.71)	(2.84)	(2.09)
Population Growth			60.357^{***}	22.993^{**}
			(3.21)	(2.03)
Interest Rate				-0.102^{***}
				(-11.89)
Fixed Effects				
Boroughs	X	X	X	X
Months	X	X	X	X
Constant	12.827^{***}	1.104	0.881	6.695^{***}
	(1567.64)	(0.26)	(0.21)	(2.18)
N	3,456	3,456	3,456	3,456
Adj. R^2	30.9%	35.3%	38.3%	55.4%

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficient for population growth is positive while the coefficient for interest rate is negative. This in line with studies of Adams et al. (2009) and Boerassa et al. (2018). The final control variable in this model is yearly earnings and the coefficient shows a positive relation between income within a borough and the house transaction prices. This result is in line with results found by Boerassa et al. (2018) and a study of Fraser et al. (2012) on the effect of income shock effects on UK house transaction prices. Finally, the coefficient of the main independent variable, Airbnb density, shows a positive sign and the coefficient is significant at a one percent scale. Based on this coefficient, it can be concluded that on an aggregated level house prices will increase with 4.71 percent if the number of listings per thousand inhabitants increase with one percent *ceteris paribus*. Based on this result it can be preliminary stated the null-hypothesis that '*an increase in the density of Airbnb listings does not increase residential property transaction prices'* can be rejected. This positive effect of Airbnb listings on house prices is in line with other recent studies (Horn et al., 2017; Barron et al., 2018; Sheppard et al., 2018).

In order to verify the reliability of the coefficient and significance for Airbnb density on aggregated residential house prices, a robustness test is performed. Robustness tests can contribute to empirical analysis since it allows to examine how certain main regression coefficients behave when the empirical model is modified (Lu et al., 2014). A way to test the robustness of the results is to verify

TABLE 4 – *Regression results robustness check*

	Model 4A Aggregated Price	**Model 4B** Aggregated Price
Airbnb Density	0.050***	0.053***
	(15.79)	(11.09)
Earnings Yearly	0.404***	0.813***
	(4.25)	(9.19)
Population Growth	57.790***	7.973**
	(7.13)	(1.63)
Interest Rate	-0.085***	-0.104***
	(-14.14)	(-32.24)
Fixed Effects		
Boroughs	X	X
Months	X	X
Constant	9.029***	4.718***
	(9.16)	(5.22)
N	1,080	2,376
Adj. R^2	61.2%	52.9%

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

if the results hold among different locations. A common distinction in the Greater London area is the distinction between inner and outer London. This distinction is legally formalized in the London Government Act that was enacted in 1963. Appendix E contains an overview of this categorization in two sub-areas. Table 4 contains the results of the full empirical model that has been run on inner and outer London boroughs, resulting in respectively model 4a and model 4b. The findings of the robustness test show that in model 4a all coefficients are significant at the one percent level and the coefficients contain the expected sings that were also found in the full final model. Similarly, the findings of model 4b show also the expected signs and except for the coefficient for population growth, all coefficients are significant at the one percent level. The findings for the models for each of the sub-areas also show that the coefficient for Airbnb Density is similar to the coefficient of the full model. Based on the coefficient of Airbnb Density in model 4a it can be concluded that aggregated average house prices will increase with 5.13 percent if the number of listings per thousand inhabitants increase with one percent *ceteris paribus* in inner London. Similarly, the coefficient for Airbnb Density in model 4b shows that the aggregated house prices will increase with 5.44 percent if the number of listings per thousand inhabitants increase with one percent *ceteris paribus* in outer London. The differences between these findings can be regarded as small and indicate that the findings concerning the contribution of Airbnb Density on residential house prices are robust.

6. CONCLUSION AND DISCUSSION

The main goal of this thesis is to study the effect of Airbnb listings on the transaction price of residential property in the Greater London area for the period 2009 – 2017. This is an interesting period for research since it covers the start of Airbnb in London up to the data for which data is available. Other research did not study the effect of Airbnb on the Greater London residential property market and used different models to study the effect of Airbnb on residential property prices. Therefore, the findings of this research can be valuable either to have a better understanding on the Greater London residential property market as well as a robustness test for previous study results.

The hypothesis of this thesis is as follows: "*A positive relationship exists between Airbnb density and the aggregated residential property transaction price in the Greater London area*". Based on a panel dataset and a fixed effects model that regresses Airbnb density on aggregated residential property transaction prices empirical evidence for this hypothesis is found. Rejecting the null hypothesis indicates that empirical evidence exists that there is a significant causal relationship between the number of Airbnb listings and aggregated residential property transaction prices. The results of this study show empirical evidence that a one percent increase of Airbnb density cause a 4.71 percent increase of aggregated residential property transaction prices in the Greater London area. The magnitude of the effect of Airbnb density on residential property prices is small, but also in line with previous studies performed on this topic. Furthermore, a robustness check is performed and shows that the coefficients for inner and outer London are also significant and correspond to a transaction price effect of 5.13 and 5.44 percent respectively. Since these effects are similar to the main effect for the Greater London area it can safely assumed that the main result for the full research area is robust.

The results obtained from this study add valuable information to the current literature and affirm previous results obtained from previous studies. Above that it can help policy makers in the London local government to further understand the effects of rapidly growing home-sharing platforms such as Airbnb on important topics such as housing affordability.

Despite that the results of this study seem robust, this study deals with some limitations. One important limitation of this research is the assumptions made in order to categorize an Airbnb listing as active or non-active. As mentioned in chapter 4 of this study, this is done with scraped data on reviews that have been submitted by Airbnb visitors. Although 72 percent of Airbnb visitors leave a review after their stay, it gives not an exact measure of all actual stays in a listing. Above that a possibility for a certain level of attenuation bias exists caused by hosts that make their property rarely available on the Airbnb platform. This can be explained with the following example. If an owner-occupier rents out a residential property and obtains a review from a guest in January 2012 and afterwards delists the property from the platform, no possibility for attenuation bias exists. However, if the same host again lists the same residential property on the Airbnb platform in January 2016 and obtains a review, the method of measuring Airbnb activity measures four years of Airbnb activity. This is an overstatement of Airbnb activity and could bias the results from the fixed effects model.

Another limitation of this study is the possible existence of endogeneity. Endogeneity exists when one or more independent variables non-stochastic. This means that these regressors are correlated with the error term of the estimated equation. In this study a certain level of endogeneity is expected since it can be assumed that in areas where aggregated residential property transaction prices are high, also the density of Airbnb listings is high. When endogeneity exists, it can bias coefficients of the variables that are non-stochastic and therefore must be considered while interpreting results (Brooks et al., 2015).

A final limitation of this study is the possibility of omitted variable bias. Omitted variable bias can cause coefficients to be biased which has an impact on the interpretation of the main result (Brooks et al., 2015). The research model in this study is based on an aggregated residential property transaction price using a panel regression. Multiple studies found different variables that can have a significant effect on residential property prices and that the statistical significance of a variable can differ across different real estate markets (Bourassa et al., 2017; Grum et al., 2016; Akbari et al., 2012). This means that it is possible that due to data availability some variables have not been included which have a potential significant effect on aggregated residential property transaction prices. Omitted variable bias is a common issue in a lot of studies but should be considered when interpreting the findings of this study.

Although this study adds valuable information to the existing literature and can help local authorities, there is still room for further research on the effect of Airbnb on the Greater London residential property market. First it would be valuable to apply a different research strategy and model to the study area. This study was limited with little data on each residential property transaction that could be used to control for housing specifics such as square meters, number of bedrooms or the presence of a garden. In case a property transaction dataset including these specifics can be obtained, a more in-depth hedonic study can be performed including distance parameters. By including multiple dummy variables for distance, valuable information can be obtained on to what extend Airbnb listings affect residential property transaction prices for different distances. A second suggestion for further research is studying the effect of regulation on the effect of Airbnb listings in the Greater London housing market. The local London authorities regulated Airbnb use by setting a limit of renting out of maximum 90 nights per listing as per January 2017 (Airbnb, 2019). Due to data limitations of several control variables the scope of this study is too short to study the actual effect. et al.

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APPENDIX A: DURBIN-WU-HAUSMAN TEST

By means of the Durbin-Wu-Hausman test it is decided whether an fixed effects or random effects model can be used (Durbin, 1954; Wu, 1973). The null hypothesis states that the random effects model is preferred and the alternative hypothesis that the fixed effects model is preferred. The following syntax in STATA is used for this test:

quietly xtreg $ylist $xlist, fe
estimates store fixed
quietly xtreg $ylist $xlist, re
estimates store random
hausman fixed random

This gives the following output:

	— Coefficients —			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lnprice_L1	.4395257	.6226064	-.1830806	.0007938
lnprice_L2	.1802716	.2880139	-.1077423	.
airdensity	.0149499	.0063305	.0086193	.
lnearnings	.2834473	.2348171	.0486302	.0444697
pop_growth2	14.30054	-.8932227	15.19376	2.155874
InterestRate	-.0427719	-.0118945	-.0308774	.0010632

```
                 b = consistent under Ho and Ha; obtained from xtreg
  B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

              chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                      =      786.62
            Prob>chi2 =      0.0000
            (V_b-V_B is not positive definite)
```

Since the null hypothesis is rejected, it can be concluded that the individual specific effects are correlated with the independent variables and therefore a fixed effect model should be applied on the panel dataset.

APPENDIX B: REGRESSION ASSUMPTIONS

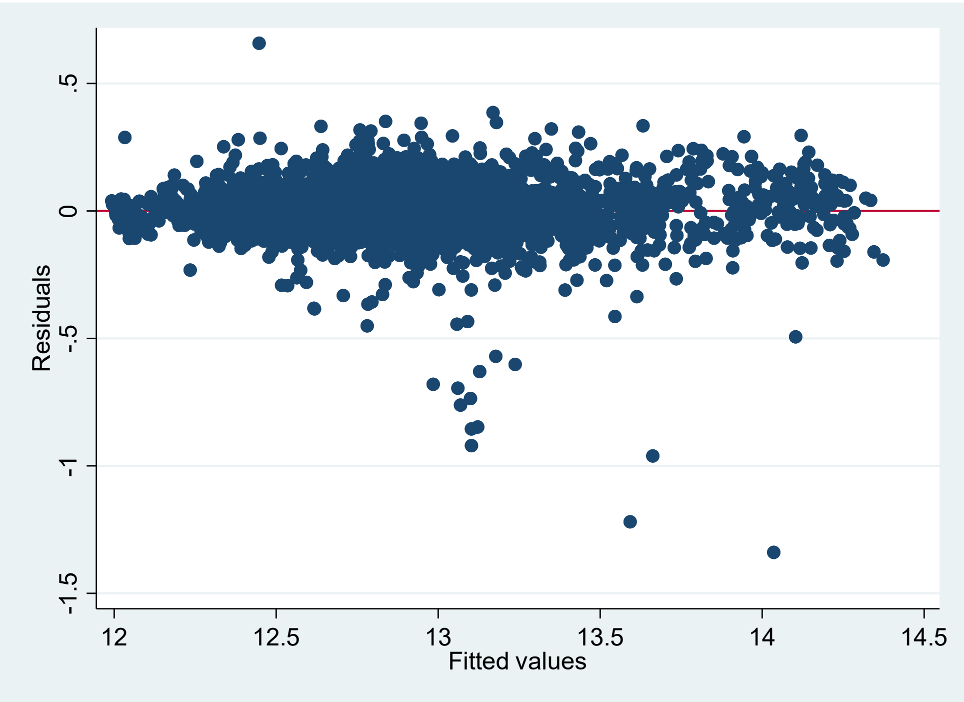
Obtaining reliable results in panel regression analysis, requires the regression to meet the following assumptions:

1. A linear relation exists between the dependent and independent variables, the error term is equal to zero;
2. The variance of the error terms is constant (homoscedasticity);
3. The error terms are independent (no autocorrelation);
4. No multicollinearity exists among the independent variables;
5. The residuals are normally distributed.

Assumption 1: A linear relation exists between the dependent and independent variables, the error term is equal to zero

This assumption can be tested by creating a residual-versus-fitted plot. The below plot shows the residuals including a horizontal line through y = 0. This visualization of the residuals makes clear that the residuals have a mean value that is equal to zero.

rvfplot, yline(0)



Furthermore, the residuals are summarized using the following command in STATA:

summarize residuals

This results in the following table from which can be concluded that the mean of the residuals is
- 4.67e-12 which is approximately equal to zero.

Variable	Obs	Mean	Std. Dev.	Min	Max
residuals	3,454	-4.67e-12	.10426	-1.339273	.657843

Assumption 2: The variance of the error terms is constant (homoscedasticity)

In order to test if the homoscedasticity assumption holds the Breusch-Pagan / Cook-Weisberg test should be performed by using the following STATA syntax:

estat hettest

This results in the following output:

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lnprice

         chi2(1)      =   493.13
         Prob > chi2  =   0.0000
```

The null hypothesis of the Breusch-Pagan / Cook-Weisberg test states that there is no heteroskedasticity. Since this null hypothesis can be rejected based on the above output, it can be concluded that heteroskedasticity exists. In order to correct for this the ‘robust’ option is added to the final regression specification in STATA.

Assumption 3: The error terms are independent (no autocorrelation)

Since the dependent variable is aggregated residential property transaction price, it can be expected that autocorrelation exists. This should be considered when interpreting the results of the regression analysis. Therefore the fixed effect regression with Driscoll-Kraay standard errors is applied which reduces autocorrelation bias.

xtreg $ylist $xlist, fe robust
est store fe_robust
xtscc $ylist $xlist, fe

Assumption 4: No multicollinearity exists among the independent variables

This assumption is tested by means of a VIF-table which shows the variance inflation factors among the regressors. In case the VIF is lower than 5 it can safely assumed that no multicollinearity exists for the regressor (Brooks et al., 2015). The following syntax in STATA is used:

vif, uncentered

This gives the following output:

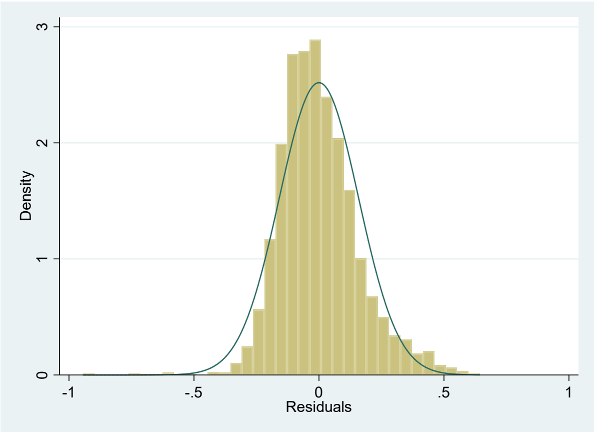
Variable	VIF	1/VIF
lnprice_L1	13680.45	0.000073
lnprice_L2	13539.54	0.000074
lnearnings	2262.55	0.000442
InterestRate	10.45	0.095710
pop_growth2	2.74	0.365251
airdensity	2.00	0.500797
Mean VIF	4916.29	

The table shows that the VIF of Airbnb density and population growth is well below the threshold value of 5. However other control variables have a VIF much higher than 5 which can result in biased regression coefficients. Since these are control variables this does not cause any issues because the main variable does not suffer from multicollinearity.

Assumption 5: The residuals are normally distributed

This assumption can be tested based on a histogram of the residuals. Based on the histogram it can be stated that the residuals are normally distributed. The histogram is obtained with the following syntax in STATA:

histogram residuals, normal

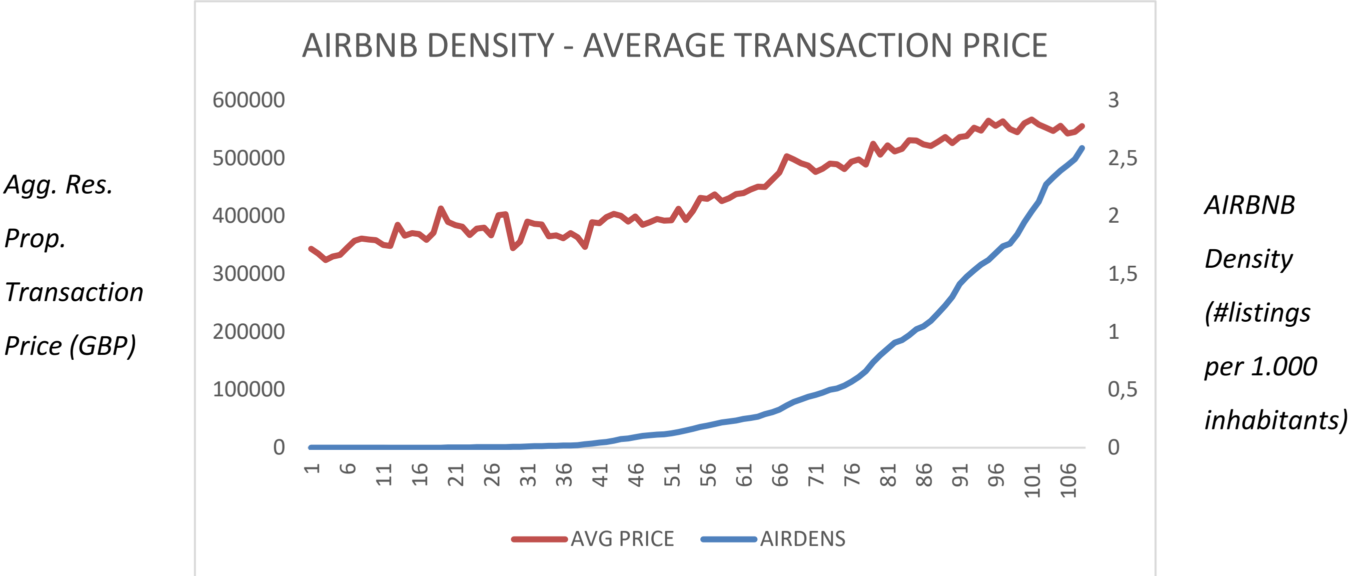


APPENDIX C: MEDIAN AGGREGATED RES. PROPERTY TRANSACTION PRICE PER PERIOD

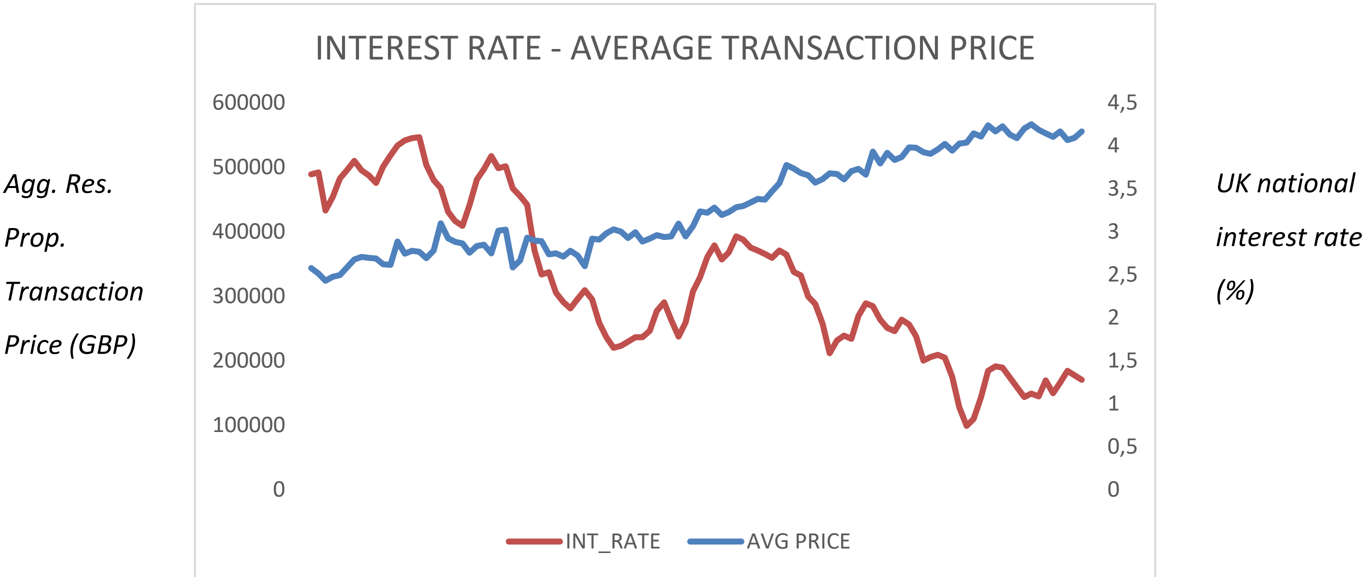
	2009-2011	2012-2014	2015-2017
Barking and Dagenham	169.162	169.451	250.430
Barnet	425.321	486.659	491.344
Bexley	213.918	200.818	295.475
Brent	317.189	378.630	425.442
Bromley	317.828	310.699	444.918
Camden	619.318	701.526	832.516
Croydon	250.323	226.004	316.232
Ealing	310.664	398.001	442.698
Enfield	269.449	252.098	362.983
Greenwich	289.949	272.612	391.820
Hackney	341.439	378.198	556.126
Hammersmith and Fulham	599.161	649.050	803.526
Haringey	371.540	413.262	544.483
Harrow	325.050	317.496	406.176
Havering	241.050	220.027	309.407
Hillingdon	267.242	256.241	399.406
Hounslow	320.064	332.124	449.236
Islington	445.613	511.385	640.104
Kensington and Chelsea	990.842	1.441.404	1.319.231
Kingston upon Thames	321.575	341.565	494.293
Lambeth	360.145	365.894	529.800
Lewisham	257.684	262.146	387.370
Merton	456.500	414.313	499.768
Newham	208.429	209.491	319.619
Redbridge	256.453	269.238	384.635
Richmond upon Thames	494.825	597.072	670.824
Southwark	357.892	384.102	570.843
Sutton	258.285	287.469	350.146
Tower Hamlets	352.726	348.298	533.273
Waltham Forest	222.077	235.576	366.996
Wandsworth	460.238	477.574	672.155
Westminster	784.921	979.247	1.364.122

APPENDIX D: GRAPHS OF REGRESSORS IN RELATION TO DEPENDENT VARIABLE

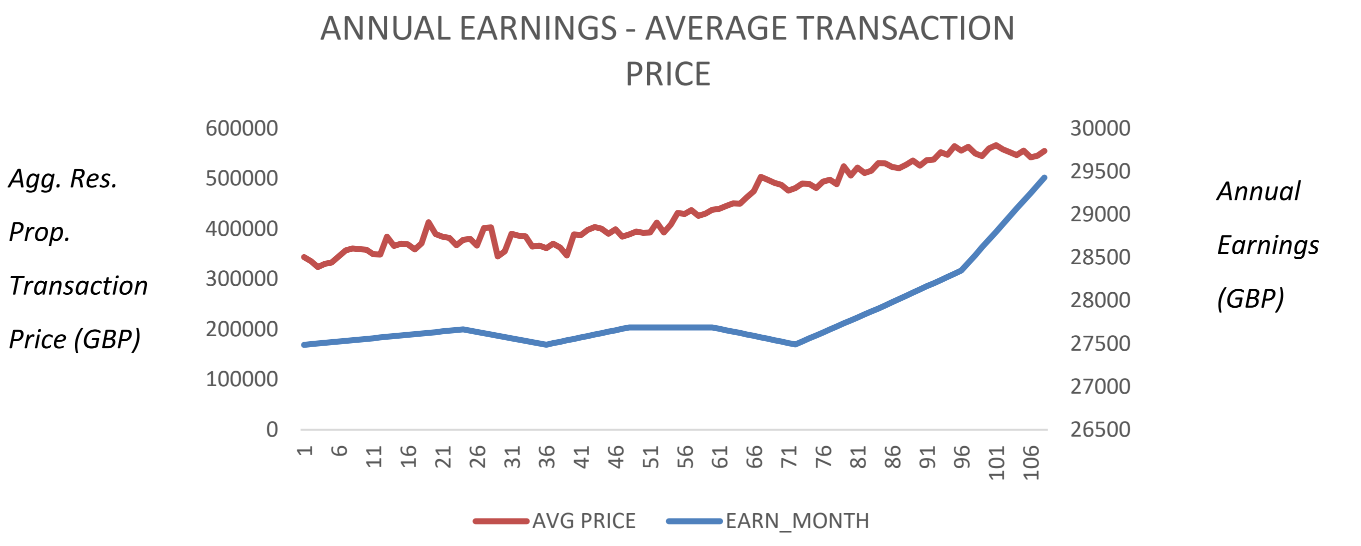
GRAPH 1: AIRBNB DENSITY



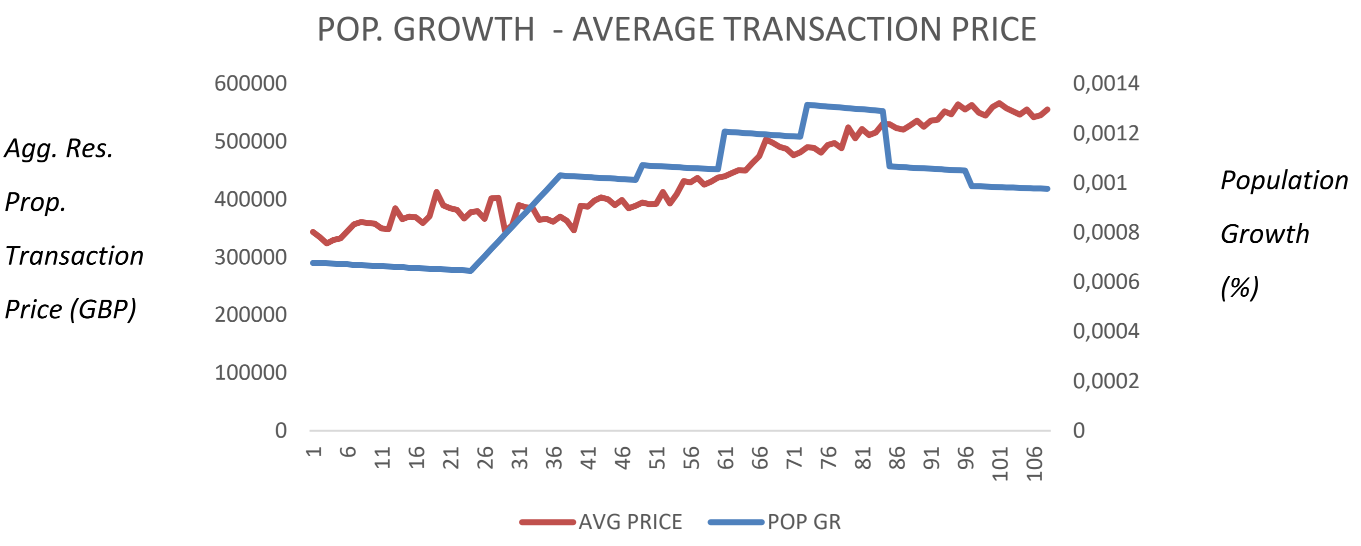
GRAPH 2: INTEREST RATE



GRAPH 3: ANNUAL EARNINGS



GRAPH 4: POPULATION GROWTH



APPENDIX E: CLASSIFICATION BOROUGHS IN THE GREATER LONDON METROP. AREA

A common distinction in the Greater London area is the distinction between inner and outer London. This distinction is legally formalized in the London Government Act that was enacted in 1963.

Inner London boroughs	**Outer London boroughs**
Camden	Barking
Greenwich	Barnet
Hackney	Bexley
Hammersmith	Brent
Islington	Bromley
Kensington and Chelsea	Croydon
Lambeth	Ealing
Lewisham	Enfield
Southwark	Haringey
Tower Hamlets	Harrow
Wandsworth	Havering
Westminster	Hillingdon
	Hounslow
	Kingston upon Thames
	Merton
	Newham
	Redbridge
	Richmond upon Thames
	Sutton
	Waltham Forest