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# The Relationship Between Airbnb and House Prices:

# Case Study on Airbnb in Amsterdam Post-Covid


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**Table of Contents**

## Abstract

Based on hedonic regression models, this paper examines the relationship between Airbnb and house prices in Amsterdam during the post-COVID period, specifically in 2022. Data on Airbnb intensity and average WOZ value at the district level are used to measure the association between Airbnb and house prices in Amsterdam. The findings indicate that a 1% increase in Airbnb intensity is associated with a 0.087% rise in house prices in 2022, controlling for other variables. Additionally, the study explores the interaction effect between Airbnb intensity and negative externalities on house prices, using data on nuisance caused by tourists as a proxy for negative externalities. The analysis shows an insignificant interaction effect on house prices. Consequently, it finds an insignificant difference in the magnitude of the association between Airbnb intensity and house prices after including the interaction term. The research findings highlight a positive association between Airbnb and house prices, providing information for policymakers to regulate the Airbnb market and the housing market.

## 1. Introduction

Person-to-person room sharing has gained a prominent role in the overnight tourist accommodation industry, with a majority of short-term rentals listed on a platform named Airbnb. Previous research has extensively analysed the impacts of Airbnb on rents and house prices. Horn and Merante (2017) found that a one standard deviation increase in Airbnb density is associated with a 0.4% rise in average asking rents in Boston neighbourhoods. Positive impacts of Airbnb on rent prices and property values have also been observed in geographical areas outside the United States. Garcia-López, Jofre-Monseny, Martínez-Mazza, and Segú (2020) found that neighbourhoods with average Airbnb listings experienced a 1.9% rise in rents and a 4.6% increase in house transaction prices in Barcelona. Extensive Airbnb research has been conducted in the United States and popular tourist cities, there is a lack of local Airbnb research examining the relationship between Airbnb and house prices in Amsterdam. Additionally, there is a lack of research focused on the negative externality effect through which Airbnb decreases house prices, as suggested by Sheppard and Udell (2016). Hence, this study aims to fill the research gaps and answer the research question of the relationship between Airbnb and house prices in Amsterdam in the post-COVID period. The year 2022 is chosen as the study period, as this was the year when self-quarantine travel restrictions were lifted (Government of the Netherlands, 2022). This research examines only the topic of house prices, as data on houses are more reliable compared to data on rents. Houses are openly traded, and the selling prices are more accurately recorded compared to rent prices. Data on rent prices are less representative of their true value due to the complexities of the renting market, such as illegal renting by landlords, student subletting, and subsidized social housing.

Amsterdam is selected for analysis due to the continuously increasing prices of existing owner-occupied dwellings. According to Statistics Netherlands (CBS) (2024b), prices of existing owner-occupied dwellings experienced a year-on-year increase ranging from 0.7% to 20.9% between May 2020 and January 2023. Given the circumstances in the Dutch housing market, investigating the association between Airbnb and house prices has policy implications. The studied association enables policymakers in Amsterdam to assess the impact of increased Airbnb activity on housing affordability for residents. Based on the findings on the association and the influence of negative externalities, policymakers can design and enforce relevant Airbnb and house regulations to mitigate the influence on rising house prices.

This paper first reviews the previous literature on the positive impacts of Airbnb on rent and house prices and the mechanisms behind the impacts. Then, three hypotheses for the association between Airbnb and house prices, the interaction effect of negative externalities, and the difference in the association effects are formulated. Subsequently, the paper introduces the hedonic price model developed by Rosen (1974) and the district-level data used in the research.

Based on the model, it shows that, on average, a 1% increase in Airbnb intensity is associated with a 0.087% increase in house prices, holding other variables constant. Additionally, the study does not find a negative interaction effect between Airbnb intensity and negative externalities on house prices. Consequently, there is no significant difference in the magnitude of the association after the inclusion of the interaction term. Following the analysis, the paper presents the robustness checks for the models and discusses the limitations and areas for future research. Lastly, the conclusion is presented.

## 2. Literature Review

### 2.1 The Impact of Airbnb on Housing Markets and Hypothesis

Previous research has focused on the impact of Airbnb on housing markets in specific cities. Horn and Merante (2017) studied the impact of Airbnb on the rental market in Boston neighbourhoods using weekly rental counts. Through hedonic regression estimation, they found that an increase of one standard deviation in Airbnb density is positively associated with a 0.4% rise in average asking rents. Similarly, through hedonic estimation, Sheppard and Udell (2016) demonstrated that doubling Airbnb listing is associated with a 6% to 11% rise in house values in New York City. Using an alternative difference-in-differences approach, Sheppard and Udell (2016) observed a 31.9% price increase in treated properties before and after Airbnb entered New York City in 2009. Likewise, Zou (2020) found that Airbnb increases single-family property prices by 0.66% to 2.24% in Washington, DC through hedonic estimation.

Numerous studies have derived a positive association between Airbnb and house and rent prices in U.S. cities (Horn & Merante, 2017; Sheppard & Udell, 2016; Zou, 2020). Research conducted in different geographical contexts using various methodologies has yielded similar outcomes. While Horn and Merante (2017) analysed Boston, Sheppard and Udell (2016) focused on New York, Barron, Kung, and Proserpio (2021) studied Airbnb listings across the entire United States. While Horn and Merante (2017) applied hedonic regression and a fixed effect model, Barron et al. (2021) employed an instrumental variables estimation strategy using Google search data for “Airbnb” as the instrument. They found that a 1% increase in Airbnb listings leads to a 0.018% increase in rental rates and a 0.026% increase in house prices. This instrument variable choice was also adopted by Garcia-López et al. (2020), who used “Airbnb Barcelona” and proximity to tourist amenities as instrument variables. Both Barron et al. (2021) and Garcia-López et al. (2020) demonstrated a positive and significant impact of Airbnb on housing prices and rents.

Based on previous findings that indicate a positive causal relationship and association between Airbnb and house prices (Barron et al., 2021; Garcia-López et al., 2020; Sheppard & Udell, 2016; Zou, 2020), the first hypothesis for the association between Airbnb intensity and house prices in this study is as follows:

*H0: There is no association between Airbnb intensity and house prices in Amsterdam.*

*H1: Airbnb intensity is positively associated with house prices in Amsterdam.*

In addition to studying the impacts of Airbnb on rents and house prices, research has focused on the heterogeneity of these impacts in different scenarios. Barron et al. (2021) examined the impact based on owner-occupancy, meaning the share of people living in their own homes. They found the effect to be stronger in zip codes with a lower share of owner-occupiers, as non-owner-occupiers are more likely to rent out homes for short-term rentals. Controlling for owner-occupancy and arbitrary city-level time trends, they discovered that a one standard deviation increase in Airbnb listings leads to a 0.54% increase in rents in the United States, similar to the 0.4% rise in rent in Boston neighbourhoods found by Horn and Merante (2017). In contrast to the owner-occupier research by Barron et al. (2021), Garcia-López et al. (2020) investigated the distribution of Airbnb activity in neighbourhoods. Using panel fixed-effect models, they found in Barcelona, neighbourhoods with average Airbnb listings experienced a rise in rents by 1.9%, house transaction prices by 4.6%, and house posted prices by 3.7%. Furthermore, Zou (2020) examined the impact of Airbnb on minority-populated regions in Washington, DC, and found that Airbnb increased house prices by 3.76% to 6.66% in areas with large shares of Hispanic and African American populations. As a consequence, the high house prices in these areas displace low-income minority house seekers and home buyers.

In contrast to research into the heterogeneity of the impact by neighbourhood characteristics (Barron et al., 2021; Garcia-López et al., 2020; Zou, 2020), Franco and Santos (2021) investigated the heterogeneity of the impact of Airbnb on house prices based on locations. Using the difference-in-difference approach, they found out that house price increased by 24.3% in 2015 and by 32.3% in the first quarter of 2016 in a high touristy parish compared to a low touristy parish before Airbnb expansion. Other studies have examined spatial heterogeneity at the city level. Ayouba, Breuillé, Grivault, and Le Gallo (2020) studied the impact of Airbnb density in eight cities in France through a hedonic model. They found significant positive impacts of Airbnb density on rents in Lyon, Montpellier, and Paris with increases of 0.385%, 0.398%, and 0.524%, respectively.

### 2.2 Airbnb Mechanisms and Hypotheses

Previous research has extensively analysed the mechanisms behind the relationship between Airbnb and house and rent prices. For instance, Horn and Merante (2017) studied the supply mechanism behind rental price increases caused by variations in short-term housing supply from shared accommodation, using a tract-level fixed effects model. Their study in Boston found a quantity reduction effect in available rental units, with a one standard deviation increase in Airbnb density correlating with a 5.9% reduction in the total number of rental units. In contrast, Barron et al. (2021) broke down the analysis of the supply mechanism into short-term and long-term rental units. They found that Airbnb increases the short-term rental supply and decreases long-term rental units in the United States, with the total housing supply remaining unchanged. This finding contrasts with Horn and Merante's (2017) finding that Airbnb correlates with a fall in the total number of rental units. Furthermore, Garcia-López et al. (2020) extended the analysis by showing the effect of Airbnb listings on reducing the number of resident households in Barcelona neighbourhoods, providing stronger support for the argument of the supply mechanism.

Besides the supply mechanism, research has also indicated an income mechanism through which Airbnb increases housing demand and house prices (Sheppard & Udell, 2016). Sheppard and Udell (2016) argued that increased demand for housing in New York City is attributable to rental income from Airbnb and house appreciation, thereby driving up house prices. Barron et al. (2021) also supported this income mechanism. They argued that shared accommodation enables owners to earn income from otherwise underutilized housing capacity, which in turn increases house prices by making owning more valuable compared to renting. Similarly, Cocola-Gant and Gago (2021) demonstrated the investment opportunities provided by Airbnb in Lisbon. They showed that Airbnb acts as an instrument for buy-to-rent financial investment opportunities, benefiting investors through its flexible and profitable business model.

Alongside the supply and income mechanisms driving rent and house prices, Sheppard and Udell (2016) proposed another mechanism through which Airbnb decreases property values. They suggested that the negative externalities created by Airbnb tenants, such as noise, crime, and increased demand for transportation, lead to a fall in property values. Filippas and Horton (2017) also criticized the negative externality issue of short-term rentals, emphasizing the unequal distribution of Airbnb benefits between neighbours who experience the noise and the host receives rent.

Based on the theory suggested by Sheppard and Udell (2016), this study zooms in on analysing the influence of negative externalities, through which Airbnb decreases house prices. This is examined by incorporating an interaction term between negative externalities and Airbnb intensity into the model. The second hypothesis is as follows:

*H0: There is no interaction effect between Airbnb intensity and negative externalities on house prices in Amsterdam.*

*H1: There is a negative interaction effect between Airbnb intensity and negative externalities on house prices in Amsterdam.*

If data support the negative externality mechanism, this explains that negative externalities negatively influence house prices. As such, the association between Airbnb intensity and house prices after incorporating the interaction term should be lower than the association obtained without incorporating the interaction term. Consequently, the third hypothesis is as follows:

*H0: There is no significant difference in the magnitude of the association between Airbnb intensity and house prices after the inclusion of the interaction term.*

*H1: The magnitude of the association between Airbnb intensity and house prices after incorporating the interaction term is significantly lower than the association obtained without incorporating the interaction term.*

### 2.3 Relevance

Most research on the impact of Airbnb on rents and house prices has been conducted in the United States and popular tourist cities. For instance, research has been undertaken in Boston by Horn and Merante (2017) and in Barcelona by Garcia-López et al. (2020). There is a need for more localized Airbnb research in other tourist cities. The city of Amsterdam is selected for this case study because of the annual growth in tourist numbers in recent years. According to CBS (2024a), the number of guests staying overnight in Amsterdam increased by 21% in 2023 compared to 2022. Based on the forecast by the Netherlands Board of Tourism and Conventions (2019), international incoming visitors will reach 29 million in 2030. Therefore, the city of Amsterdam deserves more research attention. The post-COVID period in the year of 2022 is studied, as the Netherlands lifted the self-quarantine travel restrictions for arrivals from February, 2022 (Government of the Netherlands, 2022). Consequently, in 2022, the number of overnight tourists in the Netherlands increased by 40 percent year-on-year, roughly reaching the level before the COVID outbreak (CBS, 2023a). Due to the revitalization of the tourism industry after the cancellation of COVID-19 travel regulations, research on the relationship between Airbnb and house prices during this specific time period in Amsterdam is needed.

Previous research has shown the impacts of Airbnb on rent and house price increases through the supply and income mechanisms (Barron et al., 2021; Garcia-López et al., 2020; Horn & Merante, 2017; Sheppard & Udell, 2016). There is a lack of research focused on the negative externality effect through which Airbnb decreases house prices, as suggested by Sheppard and Udell (2016). Apart from this being a research gap, it is also a prevalent social issue in Amsterdam that requires further investigation. According to the Living in Amsterdam survey conducted by Gemeente Amsterdam (2022), it was found that 20% of households in Amsterdam encountered varying degrees of nuisance due to room rentals in their building or neighbouring buildings in 2021.

Hence, this study aims to answer the research question of the relationship between Airbnb and house prices in Amsterdam during the post-COVID time period, specifically in 2022. The research findings have potential policy implications for Airbnb rentals and housing market regulations to control the rise in house prices. Additionally, the study of negative externalities provides policy makers with information to examine its influence on house prices and to enforce corresponding regulations to mitigate the influence. The research outcomes of this study are of interest to policymakers, local authorities, residents, real estate investors, and house buyers.

## 3. Data

### 3.1 Data Description

The data used in this study are extracted from two open-source datasets: one from CBS and the other from the Dataset Basic File Areas Amsterdam (BBGA). CBS publishes annual key figures regarding social, demographic, living, and economic information at district and neighbourhood levels across all municipalities in the Netherlands. The average WOZ value published by CBS (2023b) in 2023 at the district level is selected to represent house prices in 2022, measured in thousands of euros. According to Waarderingskamer (2024), the average WOZ value refers to the estimated selling price of a house if it had been sold on January 1st of the previous year. The value is calculated based on property characteristics and sale prices of all homes using an algorithm. The map of the average WOZ values in Amsterdam is presented in Figure 3 in Appendix 9.1. As shown on the map, the WOZ values are distributed throughout Amsterdam. In the latter part of the robustness check, the average WOZ values published in 2021 and 2022 from CBS (2021, 2022) are selected to measure house prices in 2020 and 2021, respectively. However, a limitation of this data is that no average WOZ value is determined for a district if there are fewer than 20 housing stocks or fewer than 85 per cent of homes in a district with this data.

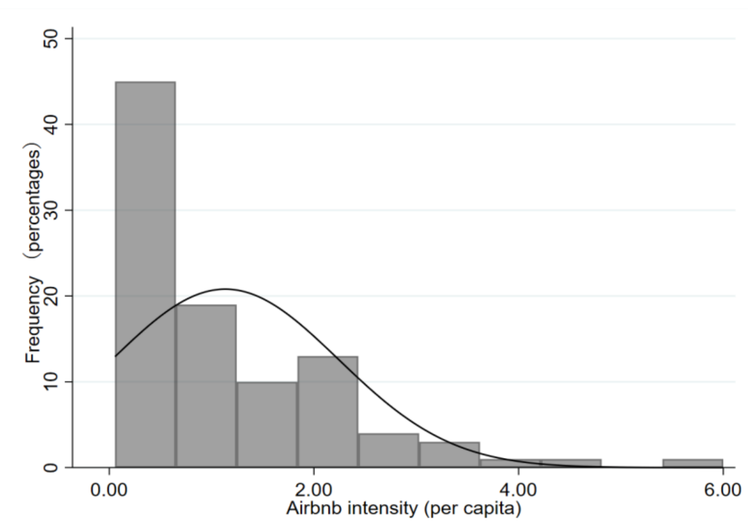
To isolate the association effect of Airbnb on house prices, characteristics that influence house prices are selected from CBS and BBGA dataset. First, social demographic characteristics at the district level are included. The total population number is selected, measured by thousands of inhabitants. Additionally, data on median private household wealth is selected, calculated by subtracting household debts from assets, measured in thousands of euros. Second, the percentages of houses with a construction year before 2000 in each district are selected to represent property characteristics. The percentages of construction years built in or after the year 2000 are not selected to circumvent the multicollinearity issue. Third, local amenities characteristics at the district level are included, including distances to GP practices, supermarkets, daycare centers, and schools, with all distances measured in kilometers. Fourth, data on tourism establishments at the district level are selected to represent tourist activity characteristics, measured by the number of companies and employees in accommodation, catering, passenger transport, and tourism-related companies. Data on the first three variables are obtained from CBS (2022), and data on tourism establishments are from Gemeente Amsterdam (2023).

District-level data for Airbnb listing numbers and negative externalities are extracted from BBGA dataset. This dataset contains various statistics on district and neighborhood levels in Amsterdam, scraped from different sources (Gemeente Amsterdam, 2023).

Data for Airbnb listings and negative externalities are only available for districts with at least 20 respondents and 50 respondents, respectively. The number of Airbnb listings in 2022 at the district level is selected, which is scraped from Housing Enforcement and Supervision (Gemeente Amsterdam, 2023). This value is then divided by the total population number in each district in 2022 to calculate Airbnb intensity at the district level, with district-level population data obtained from CBS (2022). In other words, Airbnb intensity represents the spread of Airbnb listings in residential neighborhoods, measured per capita. Figure 1 indicates that the distribution of Airbnb intensity values is right-skewed, with a large proportion of the values close to 0. The graph shows that almost 45% of districts in Amsterdam have a low spread of Airbnb listings, while few districts have a high spread of Airbnb listings. As shown on the map in Figure 2 on the next page, the central part of Amsterdam exhibits higher Airbnb intensity values than other areas, indicating a concentration of Airbnb listings in these regions.

**Figure 1**

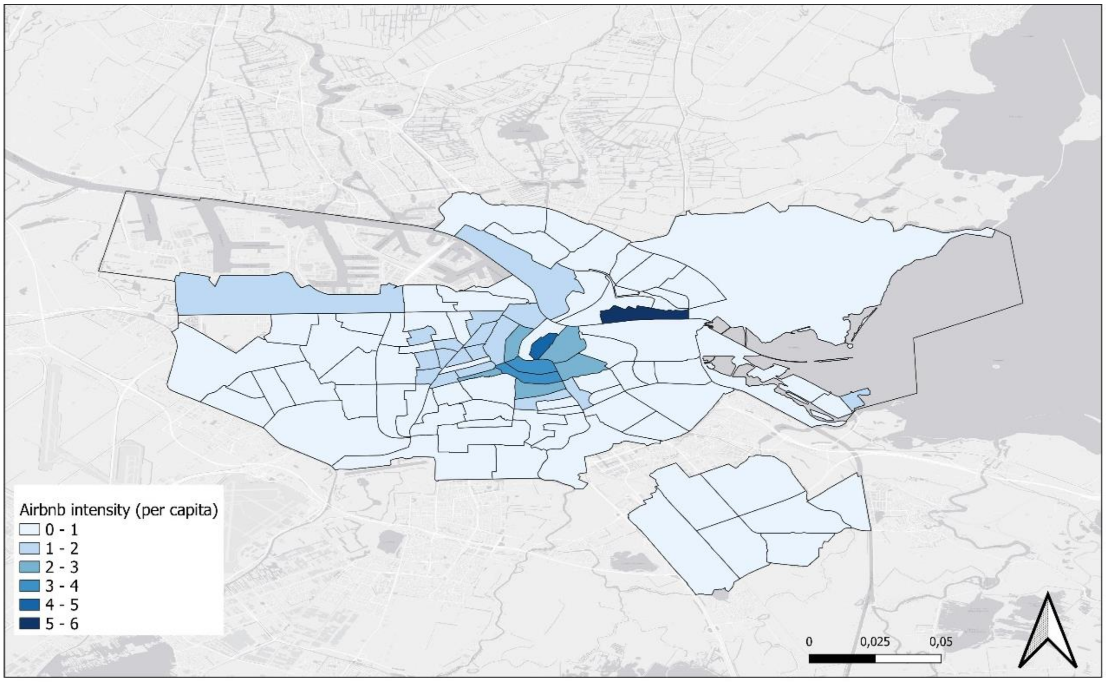
*Distribution of Airbnb intensity*




*Note.* Data from CBS (2022) and Gemeente Amsterdam (2023). Airbnb intensity is calculated by dividing Airbnb listing number by the number of inhabitants in each district.

**Figure 2**

*Airbnb Intensity in Amsterdam*




*Note.* This map contains the Airbnb intensity data in districts in Amsterdam. Airbnb intensity measures the number of Airbnb listings per inhabitant per district. The districts with darker shades of blue represent a higher Airbnb intensity in the district. Airbnb intensity data is from CBS (2022) and Gemeente Amsterdam (2023), developed in QGIS. Regions without color represent missing data. Map geometry data and map background are from PDOK (n.d.) and ESRI Netherlands, respectively.

The data of nuisance caused by tourists (% a lot) at the district level is selected from BBGA to represent negative externalities. This measures the percentage of people over 15 who report experiencing high levels of nuisance from tourists, based on the survey by the Safety Monitor (Gemeente Amsterdam, 2023). It is used as a proxied measure for the degree of noise from Airbnb tenants experienced by neighbours, representing negative externalities. The map of the nuisance data in Amsterdam is presented in Figure 4 in Appendix 9.1. As shown on the map, nuisance is highly concentrated in the central part of Amsterdam. The descriptive statistics of all the selected data for the analysis are presented in Table 5 in Appendix 9.2.

### 3.2 Data Transformation

Data at the district level in Amsterdam are selected for this research. According to CBS (2022), Amsterdam is divided into districts and neighbourhoods, with each district consisting of one or multiple neighbourhoods. Based on key figures from CBS (2022), there are a total 99 districts in Amsterdam (district code from WK036300 to WK036398). Each district code starts with the letter 'WK' followed by the 4 municipality codes and 2 district codes (CBS, 2022). District transformation is required because the CBS and BBGA datasets are recorded based on two different sets of area divisions in Amsterdam. Due to the change from the 2015 area division to the 2022 new area division in the Netherlands, different district names, area boundaries, and district codes are applied in the two datasets. This study uses the 2015 area division by CBS, as the majority of the data are recorded based on this division.

Data published by CBS in 2022 and the years before 2022 are based on the 2015 area division, whereas data published by CBS in 2023 are based on the 2022 area division. As such, data for all controlled variables in 2022 and average WOZ values in 2022 and 2021 do not require district transformation. However, the average WOZ value published by CBS in 2023 is recorded based on the 2022 area division. It therefore requires district transformation to the 2015 area division to ensure consistency in district names and codes. Data from the BBGA dataset also require district transformation to the 2015 area division. Districts with differences in their names between the 2015 and 2022 area divisions, along with their corresponding district codes based on the 2015 area division from CBS, are presented in Table 6 in Appendix 9.3. It needs to be noted that due to the merging of Weesp and Amsterdam municipalities based on the 2022 area division system, the four newly added Weesp districts are excluded from the data analysis based on the 2015 area division.

After converting all district-level data according to the 2015 area division, all data are recorded based on 99 district codes. After removing missing values for the controlled variables, house prices, and Airbnb intensity, 97 district codes remain for the analysis of the first hypothesis. Subsequently, after removing missing data on nuisance caused by tourists, 73 district codes remain for the analysis of the second hypothesis. Regarding the data for the robustness check, after accounting for missing values for Airbnb intensity in 2022 and average WOZ values in 2021 and 2020, 95 districts remain.

In correspondence to the change in area division, data need to be averaged or summed for districts that were split into smaller districts. As shown in Table 6 in the Appendix 9.3, three districts in the 2015 area division have been subdivided into smaller districts in the 2022 area division: Bijlmer Centrum (D,F,H), Bijlmer Oost (E,G,K), and Slotermeer-Zuidwest. For each of these three districts, the average WOZ value based on the 2015 area division is calculated by averaging the values of the subdivided districts recorded based on the 2022 area division. To obtain values for Airbnb intensity, nuisance from tourists, and tourism establishments based on the 2015 area division, these values are summed for all the subdivided districts falling under each of the three districts in the 2022 area division.

## 4. Methodology

Hedonic price models developed by Rosen (1974) are applied in this research. This methodology aligns with previous research on the impact of Airbnb on rent and house prices by Ayouba et al. (2020), Horn and Merante (2017), Sheppard and Udell (2016), and Zou (2020). Rosen (1974) measured hedonic prices by utility functions that regress hedonic prices on the set of attributes tied to each product. Rosen (1974) also pointed out that hedonic price functions are subject to non-linear budget constraints. The mainstream methodology for addressing this issue involves a logarithmic transformation in hedonic regression, which can take a semi-log form or a log-log form (Herath & Maier, 2010). Taking logarithmic transformation on both sides is adopted since this study aims to investigate the elasticity of Airbnb intensity to house prices.

Two hedonic regression models are used to test the Hypothesis 1 and 2, as shown in Equations 1 and 2. Characteristics that influence house prices are controlled in the two equations to mitigate omitted variable bias and to prevent producing a biased relationship between Airbnb and house prices. Although it is impossible to control all omitted variables, this study controls for the important ones. Based on previous literature, characteristics related to neighborhood amenities such as crime rate, restaurants, building permits, and demographic attributes are controlled in the hedonic regressions (Barron et al., 2021; Horn & Merante, 2017). Therefore, factors reflecting neighborhood amenities and demographics are controlled in the models, in line with previous studies. In addition, property characteristics and tourist activity characteristics are controlled. The year of construction of a house impacts its selling price. Tourist activity characteristics, like tourism establishments, are positively correlated with Airbnb intensity and house prices, as Airbnb tenants tend to live close to places with tourist activities, and house prices are higher in such touristy areas.

$$ln(P_d) = \alpha + B_1 ln(Airbnb\ intensity_d) + \gamma X_d + \delta Y_d + \theta Z_d + \lambda U_d + \varepsilon_d \quad (1)$$

$$ln(P_d) = \alpha + B_1 ln(Airbnb\ intensity_d) + B_2 Nuisance_d + B_3 ln(Airbnb\ intensity_d) * Nuisance_d + \gamma X_d + \delta Y_d + \theta Z_d + \lambda U_d + \varepsilon_d \quad (2)$$

In Equation 1, the main variables of interest are the average WOZ value and Airbnb intensity at the district level, indicated by $P_d$ and Airbnb intensity$_d$, respectively. Coefficient $B_1$ measures the association effect between Airbnb intensity and house prices, testing Hypothesis 1. Vector coefficients γ, δ, θ, and λ are regression coefficients for the controlled social demographic characteristics $X_d$, property characteristics $Y_d$, neighbourhood amenity characteristics $Z_d$ , and tourist activity characteristics $U_d$ at the district level, respectively. The coefficient a is the constant term, and the variable $\varepsilon_d$ is the error term. Equation 2 tests the interaction effect stated in Hypothesis 2. Equation 2 includes an interaction term between the log of Airbnb intensity and nuisance caused by tourists at the district level, indicated by ln(Airbnb intensity$_d$)*Nuisance$_d$. The coefficient $B_3$ measures the interaction effect of these two variables on ln($P_d$). The variables *Airbnb intensity* and *Nuisance* are included separately in Equation 2 to isolate the effect of each variable on house prices. To test the equivalence of the association effect as stated in Hypothesis 3, the regression coefficients of Airbnb intensity from Equations (1) and (2) are tested using a Z-test.

The hedonic regression models are ordinary least squares regressions with log transformations. To obtain unbiased coefficient estimates, error terms need to conform to the following assumptions. First, there is no correlation between Airbnb intensity and the error term. The Variance Inflation Factor (VIF) is applied to test the strength of the correlation between all independent variables. If the VIF values are below the threshold of 5, there is no concern about multicollinearity. To address the issue of multicollinearity initially, only the total population number is included in the regression, as a higher population number in one group correlates with a lower population number in another. Second, the homoscedasticity assumption states that the error term has a constant variance. The Breusch-Pagan test is applied to test for homoscedasticity. Third, it is assumed that the error term follows a normal distribution, which the Shapiro-Wilk test is used to verify the normality assumption. Robust regressions are applied to Equations 1 and 2 to address concerns about the error term and to reduce the impact of outliers on the coefficient estimates. Following these assumptions and tests, statistical t-tests and Z-tests are used to assess the significance of the effects. Statistical software STATA is used to run the models and the tests. By comparing the corresponding p-value against the significance level thresholds, one can determine if the null hypotheses can be rejected.

Lastly, the robustness check is conducted by testing the reverse causality of house prices on Airbnb intensity. The reverse relationship is tested by regressing the log of Airbnb intensity in 2022 on the log of house prices in 2021 and 2020 at the district level, as shown in Equation (3). In addition, different model specifications are used to test the robustness of the results in Equations 1 and 2. As shown in Equations 4 and 5, logarithmic transformation is applied to the left side of the hedonic regression.

$$ln\left(Airbnb\ intensity_{d,2022}\right) = \alpha + B_1 ln\left(P_{d,2021}\right) + B_2 ln\left(P_{d,2020}\right) + \varepsilon_d \tag{3}$$

$$ln(P_d) = \alpha + B_1 Airbnb\ intensity_d + \gamma X_d + \delta Y_d + \theta Z_d + \lambda U_d + \varepsilon_d \tag{4}$$

$$\begin{gathered} ln(P_d) = \alpha + B_1 Airbnb\ intensity_d + B_2 Nuisance_d + \\ B_3 Airbnb\ intensity_d * Nuisance_d + \gamma X_d + \delta Y_d + \theta Z_d + \lambda U_d + \varepsilon_d \end{gathered} \tag{5}$$

## 5. Analysis

### 5.1 Baseline Results

**Table 1**

*Regression Results from Hedonic Regression Models*

| | Dependent variable: ln House price | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ln Airbnb intensity | | 0.087*** | 0.083** |
| | | (0.028) | (0.032) |
| Nuisance caused by tourists (% a lot) | | | 0.001 |
| | | | (0.005) |
| ln Airbnb intensity* nuisance: tourists | | | -0.001 |
| | | | (0.003) |
| Total population | -8.500*10^-6 | -1.270*10^-6 | -7.330*10^-6 |
| | (-5.160*10^-6) | (-5.200*10^-6) | (-4.780*10^-6) |
| Median private household wealth | 0.001*** | 0.001*** | 0.002*** |
| | (0.000) | (0.000) | (0.000) |
| Year of construction before 2000 | 0.001 | 0.000 | -0.001 |
| | (0.001) | (0.001) | (0.001) |
| Distance to GP practice | 0.013 | -0.026 | 0.005 |
| | (0.129) | (0.111) | (0.130) |
| Distance to large supermarket | -0.170 | -0.096 | -0.201 |
| | (0.106) | (0.100) | (0.152) |
| Distance to daycare center | -0.238 | -0.224 | -0.374 |
| | (0.181) | (0.175) | (0.207) |
| Distance to school | 0.013 | -0.006 | 0.197 |
| | (0.166) | (0.154) | (0.144) |
| Tourism establishments | 0.001** | 0.000* | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| Constant | 6.275 | 6.295 | 6.416 |
| | (0.127) | (0.121) | (0.123) |
| Observations | 97 | 97 | 73 |
| $R^2$ | 0.505 | 0.558 | 0.654 |

*Note.* Standard errors are in parentheses. This table contains the regression results from regressing the log of house price on the log of Airbnb intensity and the interaction term between the log of Airbnb intensity and nuisance. The variable *Airbnb intensity* measures the number of Airbnb listings per inhabitant per district. The variable *Nuisance caused by tourists (% a lot)* measures the percentage of people over 15 who report experiencing high levels of nuisance from tourists.

*** p<0.01, ** p<0.05, * p<0.1

The regression results of the hedonic models are presented in Table 1. Column (1) shows the regression results of the log of house prices on all controlled district-level characteristics. Column (2) presents the regression results of the log of house prices on the log of Airbnb intensity while controlling for the factors in Column (1). The three assumptions of the error term in the hedonic model in Column (2) are tested. The results for all the tests are presented in Appendix 9.4. The VIP value of each variable is under the threshold of 5, and the P-values of the Breusch-Pagan test and the Shapiro-Wilk test are larger than the 5% significance level. Therefore, the results show that all the assumptions hold true. This indicates that the error term is not correlated with Airbnb intensity and that the homoscedasticity assumption and the normality assumption hold true. Column (3) adds the variable *Nuisance caused by tourists (% a lot)* and the interaction term between the log of Airbnb intensity and nuisance caused by tourists to the model in Column (2).

As shown in Column (1) of Table 1, among all regression coefficients, two variables have statistically significant relationships with house prices. At a 5% and a 1% significance level, tourism establishments and median private household wealth are positively associated with house prices, respectively. The R-squared value of the model in Column (1) is 0.505. By adding Airbnb intensity to the hedonic model, the R-squared increases to 0.558, as displayed in Column (2). Although the increase in R-squared value is not significant, this indicates that including Airbnb intensity improves the predictive power of the hedonic model.

First, Hypothesis 1 is assessed, which states that Airbnb intensity is positively associated with house prices in Amsterdam. This is tested by examining the regression coefficient of the log of Airbnb intensity and the p-value of the corresponding t-test in Column (2) of Table 1. As displayed in Column (2), the regression coefficient of the variable *Airbnb intensity* is 0.087. This indicates that on average, a 1% increase in Airbnb intensity is associated with a 0.087% increase in house prices, holding other variables constant. The p-value is less than 0.01, showing that this association is statistically significant at the 1% level. This provides strong evidence against the null hypothesis of Hypothesis 1 and the alternative hypothesis is not rejected. Therefore, it is found that Airbnb intensity is positively associated with house prices in Amsterdam. Comparing the regression coefficients of the controlled variables in Column (1) and Column (2) of Table 1, there are no significant change to the coefficients for the controlled variables.

Second, Hypothesis 2 is assessed, which states that there is a negative interaction effect between Airbnb intensity and negative externalities on house prices in Amsterdam. To test the interaction effect, the regression coefficient of the interaction term in Column (3) of Table 1 are examined. The coefficient for the interaction term between Airbnb intensity and nuisance caused by tourists is -0.001. Since the p-value of this regression coefficient is greater than 0.10, this negative interaction effect is statistically insignificant. This indicates no statistically significant difference in house prices between districts with the same level of Airbnb intensity experiencing nuisance and those not experiencing nuisance caused by Airbnb tenants. As such, it provides strong evidence not to reject the null hypothesis for Hypothesis 2, and the alternative hypothesis for Hypothesis 2 is rejected. The finding shows that there is no interaction effect between Airbnb intensity and negative externalities on house prices in Amsterdam. Comparing the regression coefficients of the controlled variables in Columns (2) and (3), there are no significant change to the coefficients for the controlled variables. To analyse the reason behind the insignificant interaction effect, the association between Airbnb intensity and negative externalities is examined. The magnitude of the association is 0.400, indicating that the two variables have a moderate association. This could possibly explain why an insignificant interaction effect is obtained in Column (3) in the first place.

Third, Hypothesis 3 is assessed, which states that the magnitude of the association between Airbnb intensity and house prices after incorporating the interaction term is significantly lower than the association obtained without incorporating the interaction term. The hedonic model in Column (3) of Table 1 produces a regression coefficient of 0.083 for the log of Airbnb intensity. This means that, on average, a 1% increase in Airbnb intensity is associated with a 0.083% increase in house prices, holding other variables constant. Compared to the coefficient for the log of Airbnb intensity in Column

(2), the regression coefficient decreases from 0.087 to 0.083 after including the interaction term and nuisance caused by tourists. To test the difference between the two regression coefficients, the Z-test is applied. The results of the Z-test are displayed in Table 2.

**Table 2**

*Z-test Results*

| Regression coefficient | Model 1 regression coefficient | Model 2 regression coefficient | Z-Statistic | P-value |
|---|---|---|---|---|
| ln Airbnb intensity | 0.087*** (0.028) | 0.083** (0.032) | -0.207 | 0.836 |

*Note.* This table contains the result of the Z-test, which tests whether the regression coefficients are equal across the two hedonic models presented in Equation (1) and Equation (2).

*** p<0.01, ** p<0.05, * p<0.1

As shown in Table 2, the Z-statistic for the difference of the two estimates is -0.207, and the corresponding p-value is 0.836. Since the p-value of the Z-statistic is greater than the 10% significance level, the null hypothesis of Hypothesis 3 is not rejected, and the alternative hypothesis for Hypothesis 3 is rejected. This indicates that there is no significant difference in the magnitude of the association between Airbnb intensity and house prices after the inclusion of the interaction term. In other words, the positive association between Airbnb intensity and house prices in Amsterdam is not influenced by the interaction term between Airbnb intensity and negative externalities.

### 5.2 Robustness Checks

To test the robustness of the regression coefficients, this section examines reverse causality and tests the association effects using a different form of the hedonic regression model. This research investigates the association between Airbnb and house prices. House prices could, in turn, influence Airbnb through rental income from Airbnb. Homeowners who perceive house prices as expensive might seek additional income by renting their rooms on Airbnb. As such, the rental income from Airbnb also explains the increase in Airbnb listings caused by high house prices. The increase in Airbnb listings contributes to a higher Airbnb intensity, as Airbnb intensity is measured by the number of Airbnb listings per inhabitant per district. This therefore raises the issue of endogeneity and biased estimated coefficients in the hedonic models. Although the study does not intend to investigate the causal relationship of Airbnb on house prices, the reverse relationship of house prices on Airbnb still needs to be addressed. This is tested by regressing Airbnb intensity in 2022 on lagged data of house prices from 2021 and 2020, applying log-log transformations on both sides.

**Table 3**

*Regression Results for Reverse Causality*

| | Dependent variable: ln Airbnb intensity |
|---|---|
| ln House price in 2021 | -3.342 |
| | (2.870) |
| ln House price in 2020 | 3.796 |
| | (2.728) |
| Constant | -3.008 |
| | (2.267) |
| Observations | 95 |
| $R^2$ | 0.085 |

*Note.* Standard errors are in parentheses. This table contains the regression results from regressing the log of Airbnb intensity on the log of house prices for the years 2021 and 2020. The variable *Airbnb intensity* measures the number of Airbnb listings per inhabitant per district.

*** p<0.01, ** p<0.05, * p<0.1

Table 3 presents the regression results using lagged house prices. As shown, the regression coefficients for house prices in 2021 and 2020 both have p-values greater than 0.10. This indicates that past house prices do not have statistically significant effects on values of Airbnb intensity in 2022. Given that no evidence is found for the reverse causality between Airbnb and house prices, this reinforces the robustness and reliability of the estimated association effect found in the Baseline Results Section. Consequently, this supports the finding of a positive association between Airbnb intensity and house prices in this study.

To further examine the robustness of the obtained positive association, a different hedonic model specification is used, applying the logarithmic transformation only to house prices. The regression results of semi-log form hedonic models are presented in Table 4.

**Table 4**

*Regression Results from Hedonic Regression Models in Semi-log Form*

| | Dependent variable: ln House price | |
|---|---|---|
| | (1) | (2) |
| Airbnb intensity | 0.072 | 0.142*** |
| | (0.046) | (0.033) |
| Nuisance caused by tourists (% a lot) | | 0.003 |
| | | (0.005) |
| Airbnb intensity*nuisance: tourists | | -0.002** |
| | | (0.001) |
| Total population | -3.540*10^-6 | -6.370*10^-6 |
| | (-5.280*10^-6) | (-4.390*10^-6) |
| Median private household wealth | 0.001*** | 0.002*** |
| | (0.000) | (0.000) |
| Year of construction before 2000 | 0.001 | -0.001 |
| | (0.001) | (0.001) |
| Distance to GP practice | -0.029 | 0.033 |
| | (0.116) | (0.135) |
| Distance to large supermarket | -0.085 | -0.183 |
| | (0.104) | (0.140) |
| Distance to daycare center | -0.198 | -0.382 |
| | (0.173) | (0.178) |
| Distance to school | -0.031 | 0.158 |
| | (0.000) | (0.115) |
| Tourism establishments | 0.000 | 0.001 |
| | (0.000) | (0.000) |
| Constant | 6.179 | 6.233 |
| | (0.129) | (0.130) |
| Observations | 97 | 73 |
| $R^2$ | 0.541 | 0.690 |

*Note.* Standard errors are in parentheses. This table contains the regression results of the hedonic model, applying the logarithmic transformation to house prices.

*** p<0.01, ** p<0.05, * p<0.1

As shown in Column (1) of Table 4, the association between Airbnb intensity and house prices is insignificant at the 10% significance level, contrasting with the positive significant association obtained through the log-log form hedonic model. However, as shown in Column (2) of Table 4, the association between Airbnb intensity and house prices becomes significant at the 1% significance level after incorporating the interaction term, aligning with the significant association displayed in Column (3) of Table 1. Moreover, the negative interaction effect between Airbnb intensity and nuisance is statistically significant at the 5% significance level, as shown in Column (2) of Table 4. This contrasts with the insignificant interaction effect obtained through the log-log form hedonic model. Based on the differences in the significance of these relationships, it can be speculated that the positive association and insignificant interaction effect in the Baseline Result Section are influenced by the choice of the model. Despite this, the log-log form hedonic model is adopted to analyse the relationship between Airbnb intensity and house prices, as taking logarithmic transformations on both sides allows for investigating the elasticity of change and overcoming the non-linear budget constraint of hedonic prices.

## 6. Discussion

### 6.1 Interpretations

The finding of a positive association between Airbnb intensity and house prices in Amsterdam aligns with previous research results from Barron et al. (2021), Garcia-López et al. (2020), Sheppard and Udell (2016), and Zou (2020). This study shows that in Amsterdam in 2022, a 1 % increase in Airbnb intensity is associated with a 0.087% rise in house prices. In New York City, it was found that doubling Airbnb listings is positively associated with a 6% to 11% rise in house values (Sheppard & Udell, 2016). Similarly, in the United States, a 1% increase in Airbnb listings leads to a 0.026% rise in house prices (Barron et al., 2021). Moreover, this research indicates that Airbnb intensity and negative externalities do not jointly influence house prices in Amsterdam. This finding contradicts with the negative externality mechanism proposed by Sheppard and Udell (2016). Consequently, the study demonstrates that there is no significant difference in the magnitude of the association between Airbnb intensity and house prices after including the interaction term. The study obtains valid findings through hedonic regression analysis. However, the research has certain limitations, primarily biased estimators and data, which are further discussed in Section 6.2.

### 6.2 Limitations

The hedonic regression models presented in Equations (1) and (2) may produce biased regression estimators due to negative outliers and omitted variable bias. This study applies the log transformation to both Airbnb intensity and house prices, as the aim is to determine the elasticity of the change. A significant proportion of Airbnb intensity values are close to zero, as shown in Figure 1. This results in producing extremely negative outliers for Airbnb intensity values after the log transformation, which distorts the association effect between Airbnb intensity and house prices and weakens the model's predictive power. This issue is less concerning for house price values after the log transformation, given that the minimum average WOZ value is 204 (measured by 1,000 euros). To mitigate the impact of negative outliers, robust regression methods are employed in the study. Alternatively, the Instrumental Variable Estimation method could have been adopted to address this issue. Based on previous research by Barron et al. (2021) and Garcia-López et al. (2020), they used Google search data for “Airbnb” and “Airbnb Barcelona” respectively as the instrumental variables. Similarly, Google search data for “Airbnb Amsterdam” could have been used as the instrumental variable to conduct the research.

Biased regression estimators also arise from omitted variable bias. The hedonic regressions partially control for omitted variable bias by including demographic characteristics, property characteristics, neighbourhood amenity characteristics, tourist activity characteristics at the district level. However, other confounding factors such as the convenience of transportation and the distance to city centers, are positively correlated with Airbnb intensity and house prices. These factors are not included in the research due to data unavailability. The exclusion of these factors is likely to overestimate the association effect between Airbnb intensity and house prices. Future Airbnb research should involve detailed data on these confounding factors.

Data limitations are another main area of limitation in this research. The findings are based on district-level data for Airbnb intensity and average WOZ value. More accurate conclusions about the relationships could be drawn using individual house prices and Airbnb intensity within a short radius of each house. However, only aggregate district-level data is available at the time of the research.

Furthermore, the three main variables used in the study have their weaknesses, which reduce the accuracy of the estimated relationships. Firstly, the Airbnb listing data from the BBGA dataset does not provide exact occupancy rates. A more accurate relationship can be found if Airbnb listing data distinguishes between vacant and active rooms. Secondly, house prices are represented by the average WOZ value at the district level from CBS. As mentioned in the Data Section, the average WOZ value is calculated based on an algorithm that compares all sold houses and property characteristics (Waarderingskamer, 2024). Taking that into consideration, using the average WOZ value to represent house prices is less effective in capturing the true effect of Airbnb on house prices.

Thirdly, reported nuisance data from a survey is used as a proxy to represent negative externalities. This data measures the percentage of people who report experiencing high levels of nuisance from tourists, but it does not fully capture noise and other forms of negative externalities generated by Airbnb tenants, such as street pollution, congested public traffic, and criminal activities. To address this limitation, future research could use more comprehensive measures of negative externalities beyond nuisance data. Additionally, the data is not representative of nuisance generated solely by Airbnb tenants, as hotel tenants can also generate nuisance to residents. Data on the number of hotels in each district should be included in the regression, as it influences the level of nuisance, the number of tourists staying overnight at Airbnb, and house prices. However, this data is not included as a controlled variable due to data unavailability.

Moreover, nuisance data is not available for every district. It is only available if there are more than 50 respondents in a district, which results in only 73 districts in the analysis containing nuisance data. Missing nuisance data in some districts does not imply that noise issues are absent in those districts. Therefore, this might explain why this study does not find a significant interaction effect between negative externalities and Airbnb, as some residents may not report their noise experiences from Airbnb tenants in the survey. Finally, the last issue with nuisance data is that the level of nuisance in one district is dependent on the level of nuisance in surrounding districts, as nuisance can spread to neighboring districts. As shown on the map in Figure 4 in Appendix 9.1, the central part of Amsterdam is concentrated with high nuisance. This partially illustrates the special correlation of nuisance data, indicating that nuisance data are correlated across districts. As a result, the interdependency of nuisance data across districts affects the accuracy of the estimated interaction effect.

### 6.3 Recommendations

As aforementioned, it is suggested to use alternative instrumental estimation strategies and to include alternative, detailed data at the individual level to study the relationship between Airbnb and house prices. Additionally, several recommendations are proposed for future research and policy design.

First, this study shows that the negative externality mechanism behind the change in house prices does not hold in Amsterdam. Future research should investigate other mechanisms behind the house price increases, such as supply and income mechanisms, Second, this research estimates the mathematical association between Airbnb and house prices in 2022. More research is needed on the exact causal effect of Airbnb on house prices in Amsterdam in subsequent years, as the effect may change due to the rapid growth of tourism. Third, this study focuses on the general association effect of Airbnb intensity on house prices in Amsterdam. Future local Airbnb research could narrow down the scope of the research by analyzing the heterogeneity of this effect based on factors such as house ownership, house locations, and demographic compositions in districts. Fourth, although this study does not find evidence of negative externalities influencing house prices, misbehaved Airbnb tenants do negatively influence residents’ well-being. More qualitative research is needed on the impact of Airbnb tenants on residents' quality of life across Amsterdam's districts. This will enable authorities to assess the impact and develop relevant regulations to enhance residents’ living experiences.

Lastly, a unidirectional positive association between Airbnb and house prices is found in the study. This finding is of interest to several stakeholders, including policymakers, local authorities, residents, real estate investors, and house buyers. The finding helps policymakers and authorities consider the direction of intervention to mitigate rising house prices and design relevant policies, such as enforcing stricter legislation for Airbnb rental permits and limiting the maximum number of days for short-term rentals. The finding also informs residents, real estate investors, and house buyers about Airbnb's influence on housing affordability. Further research on the causal relationship between Airbnb and house prices is necessary to design regulations for Airbnb rental and housing markets, reducing Airbnb's impact on rising house prices.

## 7. Conclusion

This research aims to examine the relationship between Airbnb and house prices in the post-COVID period. Previous studies have found a positive causal relationship between Airbnb and rent and house prices in various regions (Barron et al., 2021; Franco & Santos, 2021; Garcia-López et al., 2020; Sheppard & Udell, 2016; Zou, 2020). Researchers have provided explanations of the mechanisms behind this impact (Barron et al., 2021; Horn & Merante, 2017; Garcia-López et al., 2020; Sheppard & Udell, 2016). This study conducts local Airbnb research studying the relationship between Airbnb and house prices in Amsterdam in the year 2022. Three hypothesises are put forward in the research. Based on hedonic regression analysis, the first hypothesis is proven, showing a positive association effect between Airbnb intensity and house prices. It is found that a 1% increase in Airbnb intensity is positively associated with a 0.087% rise in house prices, which aligns with previous research outcomes. The second hypothesis is not proved by the analysis, in which an insignificant interaction effect between Airbnb intensity and negative externalities on house prices in Amsterdam is found. This finding does not align with the negative externality mechanism proposed by Sheppard and Udell (2016). The third hypothesis is also not supported by the analysis, in which there is no significant difference in the magnitude of the association between Airbnb intensity and house prices after the inclusion of the interaction term.

The chosen methodology and available data present constraints to the research, which reduce the accuracy of the estimated relationship. Considering these limitations, alternative instrumental estimation methodology and individual-level and detailed data are suggested for future research. To further contribute to the research field, it is suggested to investigate areas such as other mechanisms underlying the relationship, the heterogeneity of the effects, and the impact on residents' quality of life. This research highlights the issue of Airbnb positively correlating with higher house prices, providing policymakers with information to examine Airbnb's influence on house prices and to enforce corresponding regulations. Further research on the causal relationship between Airbnb and house prices is necessary to design regulations for Airbnb rental and housing markets.

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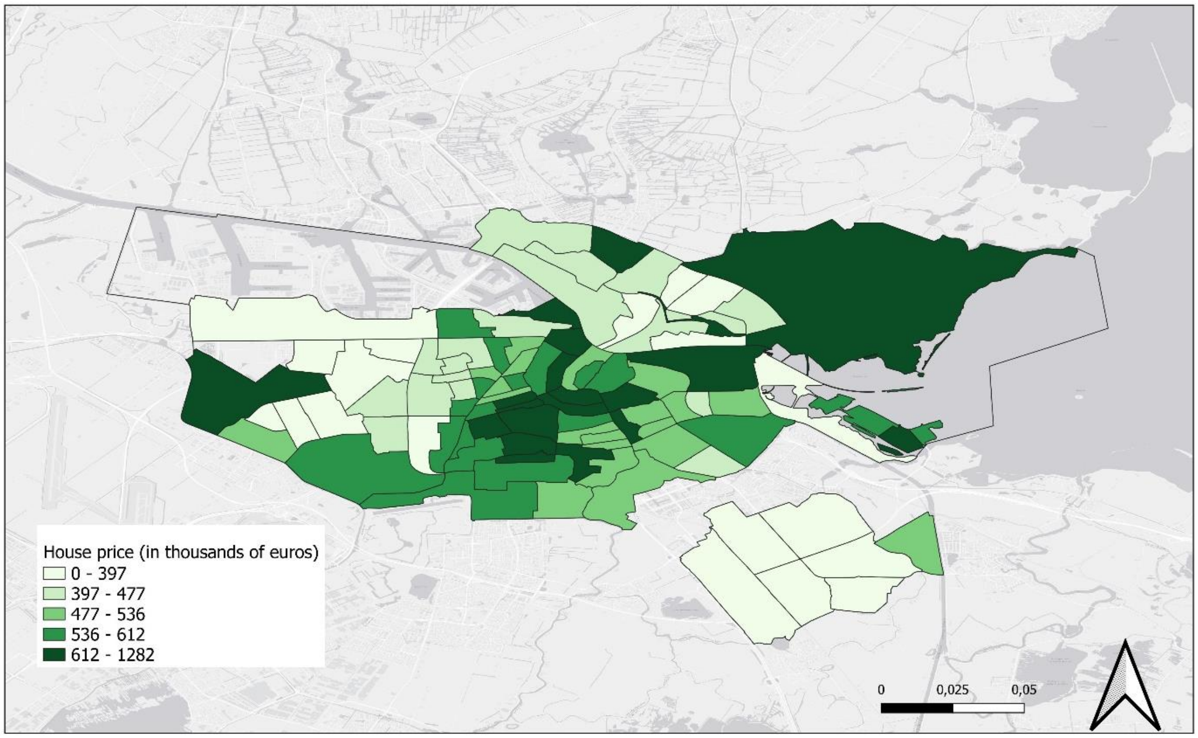
# 9. Appendix

## 9.1 Maps

**Figure 3**

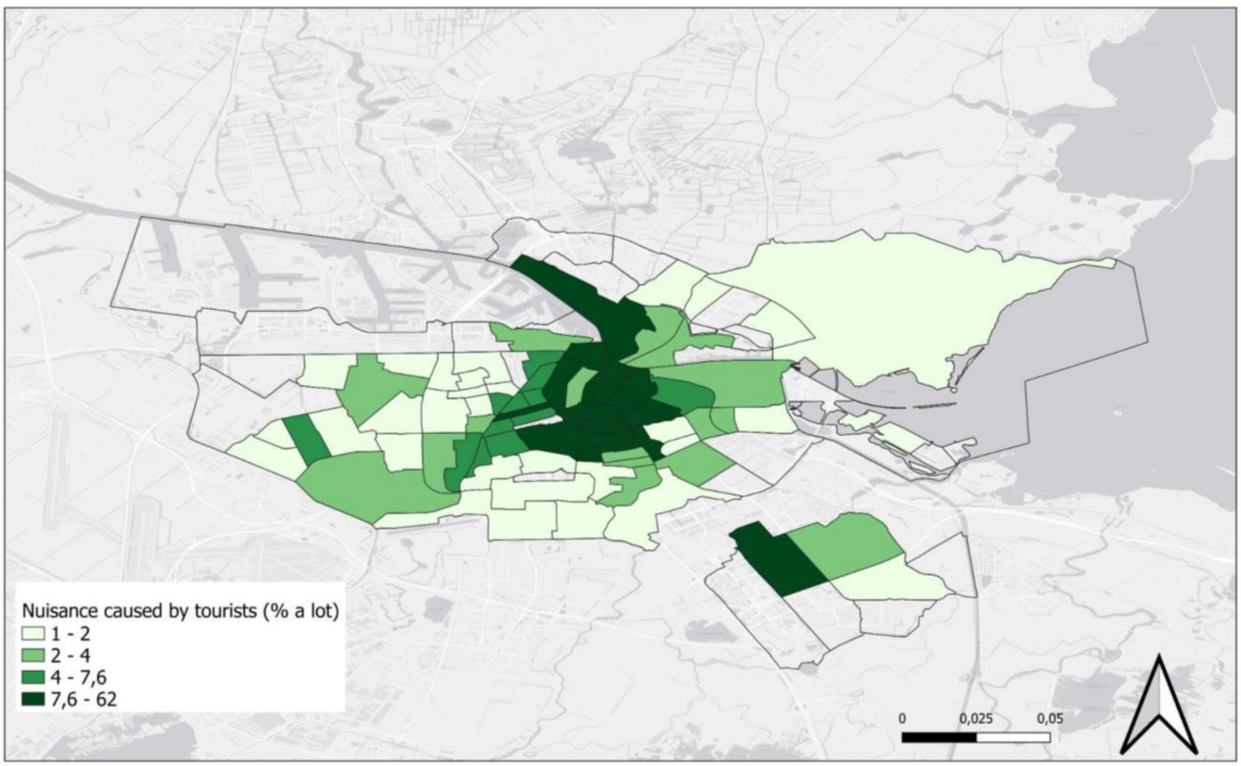
*House Price in Amsterdam*




*Note.* This map contains data on average WOZ values in districts in Amsterdam. Average WOZ value represents the estimated selling prices of houses. The districts with darker shades of green represent a higher house price in the district. House price data is from CBS (2023b), developed in QGIS. Regions without color represent missing data. Map geometry data and map background are from PDOK (n.d.) and ESRI Netherlands, respectively.

**Figure 4**

*Nuisance Caused by Tourists in Amsterdam*




*Note.* This map contains the reported nuisance data in districts in Amsterdam. Nuisance caused by tourists measures the percentage of people over 15 who report experiencing high levels of nuisance from tourists. The districts with darker shades of green represent a higher level of nuisance experienced by inhabitants in the district. Nuisance data is from Gemeente Amsterdam (2023), developed in QGIS. Regions without color represent missing data. Map geometry data and map background are from PDOK (n.d.) and ESRI Netherlands, respectively.

## 9.2 Descriptive Statistics

**Table 5**

*Relevant Descriptive Statistics*

| Variable | Observations | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|---|
| Average WOZ value | 97 | 204 | 1282 | 544.99 | 203.71 |
| Airbnb intensity | 97 | 0.06 | 6 | 1.13 | 1.11 |
| Nuisance caused by tourists (% a lot) | 73 | 1 | 62 | 7.14 | 11.13 |
| Total population | 97 | 230 | 29895 | 9062.89 | 5554.27 |
| Year of construction before 2000 | 97 | 0 | 100 | 78.16 | 29.93 |
| Median private household wealth | 97 | 0 | 821.20 | 69.30 | 166.48 |
| Distance to GP practice | 97 | 0.30 | 2.50 | 0.66 | 0.40 |
| Distance to large supermarket | 97 | 0.20 | 2.90 | 0.64 | 0.42 |
| Distance to daycare center | 97 | 0.10 | 1.90 | 0.44 | 0.26 |
| Distance to school | 97 | 0.30 | 2 | 0.64 | 0.28 |
| Tourism establishments | 97 | 2 | 514 | 114.06 | 97.18 |

*Note.* Data from CBS (2022, 2023b) and Gemeente Amsterdam (2023). The variable *average WOZ value* represents the estimated selling prices of houses. The variable *Airbnb intensity* measures the number of Airbnb listings per inhabitant per district. The variable *nuisance caused by tourists (% a lot)* measures the percentage of people over 15 who report experiencing high levels of nuisance from tourists.

## 9.3 Difference in District Names in 2015 and 2022 Area Division System

**Table 6**

*District Names and Corresponding District Codes in Amsterdam*

| District name in the 2015 area division | District name in the 2022 area division | District code based on the 2015 area division from CBS |
|---|---|---|
| Sloterdijk | Sloterdijk West | WK036336 |
| Bedrijventerrein Sloterdijk | Sloterdijk Nieuw-West | WK036311 |
| Kinkerbuurt | Bellamybuurt | WK036318 |
| Vondelbuurt | Vondelparkbuurt | WK036322 |
| Middelveldsche Akerpolder | De Aker | WK036384 |
| Sloter-/Riekerpolder | Sloten/Nieuw-Sloten | WK036388 |
| Noord | Weesp-Noordwest | WK045702 |
| Binnenstad | Weesp Binnenstad/Zuid | WK045700 |
| Aetsveld | Aetsveld/Oostelijke Vechtoever | WK045704 |
| Westelijk Havengebied | Havens-West | WK036310 |
| Bijlmer Centrum (D,F,H) | Venserpolder | WK036393 |
| - | Amsterdamse Poort e.o | WK036393 |
| - | H-buurt | WK036393 |
| Bijlmer Oost (E,G,K) | Ganzenhoef e.o | WK036394 |
| - | Geerdinkhof/Kantershof | WK036394 |
| - | Bijlmermuseum | WK036394 |
| - | K-buurt | WK036394 |
| Slotermeer Zuidwest | Slotermeer-West | WK036377 |
| - | Slotermeer-Zuidoost | WK036377 |

*Note*. Adapted source from Bicknese et al. (2022).

### 9.4 Tests for the Assumptions of the Error Term

**Table 7**

*Variance Inflation Factors*

| Variable | VIF value |
|---|---|
| Distance to GP practice | 4.36 |
| Distance to daycare center | 3.77 |
| Distance to large supermarket | 3.17 |
| Distance to school | 2.40 |
| ln Airbnb intensity | 1.52 |
| Total population | 1.50 |
| Median private household wealth | 1.35 |
| Year of construction before 2000 | 1.23 |
| Tourism establishments | 1.22 |
| Mean VIF | 2.28 |

*Note.* This table contains the results of the Variance Inflation Factors for each variable. The Variance Inflation Factors is used to test the correlation between Airbnb intensity and the error term.

**Table 8**

*Breusch-Pagan Test Results*

| Variable | Chi-Square statistic | Difference | P-value |
|---|---|---|---|
| Error term | 1.15 | 1 | 0.28 |

*Note.* This table contains the results of the Breusch-Pagan Test, which tests the presence of heteroskedasticity in the error term.

*** p<0.01, ** p<0.05, * p<0.1

**Table 9**

*Shapiro-Wilk Test Results*

| Variable | Observations | W | V | Z | P-value |
|---|---|---|---|---|---|
| Error term | 97 | 0.99 | 0.84 | -0.40 | 0.65 |

*Note.* This table contains the results of the Shapiro-Wilk test, which tests the normality of the error term.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$