The relationship between short-term rental revenues and housing prices in the central parts of Sofia.

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Feb 21, 2024

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| Title | The relationship between short-term rental revenues and housing prices in the central parts of Sofia. |
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| Date | Feb. 21, 2024 |
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## ABSTRACT

This study investigates the relationship between short-term rental (STR) revenues and housing prices in Bulgaria's capital central area. We find a positive association between short-term rental performance, measured by Revenue per Available Room (RevPAR), and housing prices. Findings from the final main model reveal that an increase of the 3-month moving average of the market RevPAR by 1% is associated with 0.169% higher housing prices in the inner city and an almost three times larger effect when excluding the pandemic's influence in 2020. We find considerable heterogeneity in the estimate across housing submarkets, characterized by the number of bedrooms, emphasizing the dominance of specific segments in the Airbnb market. More specifically, studios' RevPAR influences the pricing of its own segment and causes a spillover effect on the housing prices of one and two-bedroom apartments. Similarly, the STR revenue performance of 1-bedroom properties is associated with heightened prices in both the studio and 2-bedroom segments. Finally, the study establishes that due to the influence of the STR revenue performance, homeowners pay a higher premium than investor buyers on housing purchases.

Keywords: housing prices, housing segments, spillover effects, central properties, short-term rentals, short-term rental revenue, RevPAR, Airbnb effect

# 1. INTRODUCTION

## 1.1 Motivation

Since the appearance of Airbnb in 2008, the sharing economy has created an opportunity for a new business model that allowed for the expansion of the short-term rental (STR) property sector. This has triggered a shift in the dynamics of residential property markets (Guttentag, 2015). On the one hand, Airbnb claims that it is a platform that offers local households an additional source of income by subletting and sharing their empty house rooms with guests (Dredge and Gyimothy, 2015). Second, scholars have highlighted the rising role of short-term rentals among real estate investors in the aftermath of the 2008 global economic crisis, as platforms like Airbnb[i] allow for attracting higher-income renters, thus increasing property investment returns. (Cocola-Gant and Gago, 2019; Janoschka et al., 2019). Hence, the STR markets offer a range of benefits for investors, including efficiency and ability to accumulate profits through renting properties for short to mid-term period, and then selling them tenant-free (Fields, 2019; Shaw, 2018). Overall, the option to convert residential properties into short-term rentals[ii] has provided property owners with flexibility and additional revenue sources for profit generation (Wachsmuth and Weisler, 2018; Yrigoy, 2018).

On the other hand, critics argue that Airbnb's influence contributes to the rising cost of living and potentially exacerbates societal issues. (Wachsmuth and Weisler, 2018). The proliferation of STRs, mainly concentrated in city centers and tourist hotspots, has been linked to the transformation of neighborhoods into tourist districts, leading to the displacement of long-term residents, housing affordability and societal issues (Barron et al., 2018; Garcia-López et al., 2020). Local lower-income tenants are displaced by existing landlords solely for subletting in the STR market (Cocola-Gant and Gago, 2019). Beyond that, another significant aspect to consider is the displacement of local homeowners, who prefer to move out and sell their houses in central city parts to real estate investors because of various negative effects caused by Airbnb such as safety, pollution, and traffic congestion problems (Pinkster and Boterman, 2017; Gallagher, 2017; Gurran & Phibbs, 2017). Those new-coming buy-to-let investors are attracted to acquiring inner-city properties for the same purpose of short-term renting, thus intensifying buying pressure in already competitive centrally located housing markets (Fuller and Michel, 2014; Pinkster and Boterman, 2017). Consequently, the soaring housing and rental prices create barriers for new local citizens, aggravating the challenges associated with the rising cost of housing.

This city-tourist-driven process has raised a discussion of the pros and cons of short-term rentals among different societal groups operating in urban areas. The concept has gained prominence in the societal and academic discourse as the Airbnb effect, encompassing the affordability issues caused by the rising housing and rental prices associated with STR activity in tourist and central neighborhoods. Regulators worldwide have been reacting to these impacts with all kinds of policies restricting the market; however, the sharing economy finds ways to overcome regulations, and no city so far has achieved the correct formula to reconcile the problem with the STR market (Nieuwland & Melik, 2018; von Briel & Dolnicar, 2020). As the issue remains, the impact on housing affordability, urban economics, and tourist activity concerns the interest of different agents, such as investors, local regulators, communities, and businesses (Gurran & Phibbs, 2017).

The focus of this paper in regard to the Airbnb effect is specifically on how STR revenue performance affects the housing market prices in the central area of Sofia, Bulgaria. By examining the STR phenomenon in a different approach and urban context this study extends beyond the scope of previous research to provide insights in understanding the nuanced dynamics of short-term rental activity and its consequences on housing markets.

### 1.2 Scientific Relevance

Academic research has been exploring the relationship between the STR channel and the housing markets. While prior studies conducted have provided valuable insights, the field encounters various research questions that could be further addressed and examined to gain an even deeper and more detailed understanding of the phenomenon.

Numerous studies have examined the effect of Airbnb and similar platforms on property prices and rentals. For instance, Barron et al. (2018) found that, on average, a 1% increase in Airbnb listings in the US boosts property prices by 0.026% and rents by 0.018%. The paper concludes that this is a result of landlords reallocating their housing stock from the long-term rental (LTR) markets to the STR platforms because of the potential for realizing higher profits. A similar study has been conducted by Garcia-López et al. (2020) in the city of Barcelona, where evidence has been found that for the average neighborhood, Airbnb activity has increased rents by 1.9% and housing transaction prices by 4.6%. Koster, van Ommeren and Volkhausen (2021) contributed to the literature by finding that since 2008 Airbnb contributed to a total average property increase of 3.6% for the whole of LA County. They also found that the properties in LA within 2.5 km of beaches rose by 5.8%, while central urban areas within 2.5km of Hollywood surged by 15%. Moreover, Bijl (2016) finds that for every 10,000 reviews posted within a 1,000-meter radius, twelve months prior to the transaction date of a property deal, there is a 0.42% increase in home prices. As already mentioned, previous scholars' literature arrives at the consideration that since Airbnb provides potentially higher revenues, the reason for housing affordability shrinkage is that landlords switch their tenants' leases to STR over time (Yrigoy, 2018; Weisler, 2018). Exploring the impact of homeownership ratio, Ayouba et al. (2019) find a controversial relationship between the Airbnb effect and the proportion of second-home owners to owner-occupiers. While for some central areas of cities in France a higher proportion of second-home buyers contributed to a diminishing Airbnb effect, for other cities the same setting indicated opposite results.

In general, findings so far have established the significant impact of the Airbnb effect on the housing market. This opens the field for further research on specific gaps to comprehensively grasp the phenomenon and gain more insights into it. To begin with, one thing worth noting is that the existing literature mostly contains findings about metropolitan areas from Western Europe, the US, and partially Australia and Asia. Nonetheless, other worldwide cities and regions that may differ in urban, regulation, and market specifics remain uninvestigated. By exploring the Airbnb effect in different cities with various market settings one can comprehend more clearly a broader picture of the underlying factors in play. Hitherto, researchers have been applying two common approaches to measure the impact of STR on housing transaction prices. The first method is by taking the density of listings on the platform for a certain region and calculating how it affects property sales prices. Such is the approach used by Barron et al (2018), Garcia-López et al. (2020), and Koster et al. (2021). Another similar approach for measuring Airbnb activity is implemented by Bijl (2016), who calculates how the increased density of Airbnb reviews impacts the residential real estate market. Naturally, in the lack of empirical data qualitative research methodologies have also been used to draw conclusions on the matter (Cocola-Gant and Gago, 2019). Furthermore, the existing research lacks conclusive findings on how the impact of STRs varies across separate housing submarket tiers and the differential influence it has on homeowner buyers compared to investors. Ayouba et al. (2019) illustrate that the Airbnb effect in central Paris is non-significant in areas with high rates of second homeowners, while in Montpellier the effect is the opposite. Hence, further exploration of different housing buyer types can be studied. With respect to the housing submarket segmentation - recent evidence suggests that the effects of Airbnb demand during the COVID-19 pandemic differed between full flats and shared flats (Bresciani et al., 2021), emphasizing the significance of comprehending the impact of STRs on different accommodation units.

This paper contributes to the existing literature, first, by examining a different housing market urban setting. The study focuses on the central region of the Bulgarian capital – Sofia. Similar to other large cities in Eastern Europe, the Bulgarian capital is a good representative of the urban development in the region in the last decades. In terms of urban environment, Eastern Europe tends to be less populated, less urbanized, and more dispersed; it follows a broader pattern of urban transition from socialist to capitalist regime change observed across the whole region (Taubenböck, 2019). As the paper unfolds, the research will go further into explaining certain market specifics of the city that make it distinctive among other worldwide metropolitan urban regions studied so far. Secondly, this study introduces a novel variable of interest to investigate the Airbnb effect, distinguishing it from the approaches utilized in prior research. Previous papers primarily focused on the density of listings, measuring the supply of Airbnb units as a proxy for the impact that STR activity has on housing prices. However, the growing supply of STRs discovered by the literature should be in response to the rising demand for shared accommodation services. If there was no value added for subletting short-term rentals for landlords, there wouldn't have been a market for such a service. Therefore, the demand factor that contributes to the Airbnb effect remains insufficiently explored so far. This research aims to explore the combination of both demand and supply factors, via which the STR is associated with housing price appreciation. The Revenue Per Available Room (RevPAR)[iii] is chosen as the key performance indicator due to its ability to capture the financial performance of the STR market. The RevPAR is actually the intersection point between supply and demand of the STR market. The daily rate, part of the calculation that produces the RevPAR, represents the demand and the travelers' willingness to pay for accommodation. The occupancy rate represents the supply of STR properties on the market, as the addition of each property in the market contributes to the expansion of accommodation available. By examining the RevPAR as a primary variable of interest, alongside the STR market supply, this study seeks to provide a comprehensive framework that examines the different factors on the STR market separately and aims to give insights into the impact of STRs' revenues on the real estate housing market. In sum, by considering the financial performance metric of the short-term rental (STR) market, this study contributes to the literature by proposing a more holistic framework exploring the impact of Airbnb activity on housing prices. This approach aims to reveal more about the demand in the Airbnb market. This fills a significant gap in existing research because, to the best of the author's knowledge, no paper has empirically examined the influence of the RevPAR on housing prices. The study hopes to provide valuable and useful insights into the complex dynamics of the Airbnb effect on the real estate housing market. Lastly, as noted above, existing research lacks definitive findings on how the Airbnb effect varies across separate housing submarket tiers, plus the differential influence it may exert on homeowner buyers compared to investors. With a focus on the latter, this study aims to bridge this gap by investigating the relationship between STR revenue and housing prices considering the buyer-type distinction of homeowners versus investors. By incorporating this differentiation, more insights may be gained into the decision-making processes of different real estate agents in the context of the STR market. With respect to housing segmentation, based on recent findings - it is plausible to consider that housing submarket apartment segments, defined by the number of bedrooms, may experience varying impacts from the STR market influence.

To the best of the author's knowledge, none of the abovementioned research gaps has been previously addressed. The aim of this study is to explore those gaps and contribute to the research topic by offering an expanded view of the influence of STR on the housing market. Besides, the study intends to stimulate further development in the field by opening new avenues of discussion.

### 1.3 Research Question

The central research question is: **"What is the relationship between STR revenue and housing prices in the central part of Sofia?"** In order to address this central research question, three sub-research questions have been outlined.

**RQ1: "What is the theoretical relationship between STR and housing prices in the central areas of cities?"**

This research question aims to investigate the theoretical relationship between STR and housing prices. Through an examination of relevant studies, theories, and models, insights will be gained into the potential connection and underlying mechanisms through which STR could impact housing prices. By delving into the existing literature[iv], this research seeks to develop a comprehensive understanding of the theoretical framework for exploring the relationship between STR and housing prices. The findings from this exploration will serve as a reference point for formulating hypotheses regarding the expected results for the subsequent empirical questions.

**RQ2: "What is the effect of STR revenue on the housing prices in the central part of Sofia?"**

The second research question seeks to measure the impact of STRs on property prices. To achieve this, a hedonic model equation will be used. It takes into account various control variables such as house characteristics and time-fixed effects. The focus then will be on examining the key variable of interest, more specifically the RevPAR, in order to establish the influence of Airbnb's financial performance on housing transaction prices in the central area of Sofia.

**RQ3: "To what extent does the presence of Airbnb in central Sofia impact housing prices across different housing segments and buyer types?"**

To gain a deeper understanding of the Airbnb effect on housing prices and obtain more detailed information, RQ3 is divided into two sub-questions that explore various aspects of the multifaceted presence of STR in the housing market.

In sub-question 3.1, the objective is to examine the impact of STR's financial performance on different housing submarket tiers in the central area of the city. The model in 3.1 will categorize apartment types based on the number of bedrooms into studios, 1-bedroom, 2-bedroom, and 3-bedroom units. It will incorporate an additional key explanatory variable, RevPAR by apartment type, which captures the revenue performance metric specific to each apartment type.

The goal is to analyze whether STR revenues, varying across apartment types, have differential impacts on separate housing segments.

The second sub-question, 3.2, aims to further investigate the relationship between STR revenues and housing prices by considering how different types of property buyers are influenced in their decision-making process by the impact of Airbnb revenues in the area. The extended hedonic model equation will include a dummy variable for the type of buyer, distinguishing between homeowner purchasers and investors.

The remainder of this paper is organized as follows. Section 2 describes the conceptual model and section 3 presents the summary statistics and the empirical approach. Section 4 showcases the results of the empirical exploration, and Section 5 presents the conclusion.

## 2. THEORY, LITERATURE REVIEW & HYPOTHESES

### 2.1 Theoretical explanation of housing prices

One of the most widely used theoretical frameworks for understanding house prices is rooted in the concept of hedonic price models, developed by Rosen (1974). The foundation of the theory lies in considering a good as a set of distinct components or features that collectively contribute to its utility. The theory defines goods and products based on their attributes or characteristics that enhance usefulness. Thus, when purchasing a product, buyers acquire a set of inherent qualities that they can utilize and consume. Applied to housing, a property is a multifaceted commodity embodying various features related to its locational and physical attributes.

To calculate the marginal implicit value of these attributes, hedonic models decompose and differentiate the price function for each feature (McMillan, Reid & Gillen, 1980). The hedonic model is often used to study how house qualities affect prices due to many factors that affect them (Chau & Chin, 2003). House type, age, number of bedrooms, additional rooms, and property amenities are common variables in these models. It is established that number of bedrooms, bathrooms, and floor space correlates positively with market price (Fletcher, Gallimore, & Mangan, 2000; Li & Brown, 1980; Garrod & Willis, 1992), while Kain and Quigley (1970) showed that property age lowers housing prices.

Moreover, researchers use hedonic price modeling to study the pricing effects that come with specific property locational attributes. Countless papers study all kinds of phenomena that impact housing prices; for instance, Adair, McGreal, Smyth, Cooper, and Ryley (2000) explore the relationship between housing prices and accessibility to a CBD, while Daams, Sijtsma and van der Vlist (2016) examine and discover a positive effect of natural space on nearby property prices. To achieve reliability of results and to reduce unobserved heterogeneity and omitted variable bias, isolating for time and location-fixed effects is a standard procedure (Turnbull & van der Vlist, 2020). Thus, the combination of physical attributes, location, and time-fixed effects into one hedonic model equation allows researchers to control for different components ingrained into housing value and focus on the exploration of only specific variables of interest.

When it comes to the Airbnb effect studies undertake different approaches. Unlike the traditional hedonic model, Barron et al. (2018) use macro-level data to understand how Airbnb supply affects housing market indices. Their method considers a variety of factors like owner-occupancy rates, and time-varying zip code characteristics that may affect housing prices to capture the general effect of Airbnb supply on housing and rent indices. So, instead of focusing on specific housing attributes and their effects on prices, they examine how Airbnb listings affect overall housing metrics across zip codes. However, in Garcia et al. (2020), it can be observed that the authors approach housing prices using a hedonic model, where they control for physical attributes, location and time-specific fixed effects to study the Airbnb effect of supply on housing prices in Barcelona.

Similarly, the study uses a hedonic model equation to examine whether short-term rental profitability affects housing prices. Just as factors like property size, amenities, and different location attributes add value to housing, the inclusion of short-term rental revenue can also contribute to explaining housing prices. Section 2 continues with the theoretical explanation of the Airbnb effect, whereas Section 3 goes into more detail on the construction of the hedonic model.

### 2.2 The STR Effect on The Supply Side in The Urban Center

*Impacts of STR on Long-Term Housing Dynamics and Central Area Supply Inelasticity*

To begin with, in the short term, the emergence of short-term rentals leads to a major outflow of buy-to-let owners of traditional long-term rental units transitioning into the short-term market. This results in a decline in the available stock of long-term rental apartments, while the rooms and properties on STR increase (Barron et al., 2018). Lee's findings support this argument, indicating a substantial withdrawal of housing units due to Airbnb (Lee, 2016). Consequently, if the vacancy rate of the long-term rented units drops below the structural LTR market vacancy rate, this will accelerate competition among renters to secure a living place, pushing LTR prices up (Gurran & Phibbs, 2017). This surge in rents due to the transfer of apartments is discovered by previous studies, illustrating how it impacts long-term rental prices (Horn and Merante, 2017; Zervas et al., 2017). This rise in rents is anticipated to exert upward pressure on housing prices (DiPasquale and Wheaton, 1992).

Looking at a broader perspective encompassing the long-term dynamics, a typical characteristic of a city's central area is the significant constraints imposed on the supply side. Considering Alonso (1960), the central business district is the area within one town, which is highly desirable due to its market functions. Therefore, the central locations are densely built-up areas, where businesses and residential functions compete on bidding higher prices for usage. In turn, this defines central locations as physically and geographically limited. Research by Hilber and Mayer (2009) underscores the main role of geographical factors in shaping the market's elasticity, amplifying inelastic supply for more constrained areas. Additionally, numerous cities have historical and cultural landmarks centrally situated (Segal, 1979). Hence, alongside stricter regulations because of geographical and physical scarcity, regulatory constraints due to cultural heritage, commonly observed in central areas, create an even higher barrier to fostering new development, and accelerate the capitalization effect of various factors on existing house prices (Hilber, 2017).

Overall, in the case of the city center, the more inelastic the supply, the stronger the mechanism that the housing market conveys an equilibrium through more volatile housing prices in reaction to changes in demand, and not by adding new supply.

*Real Option Theory*

The real option theory can give an additional explanation of the supply-side dynamics. The definition of a real option states that postponing an irreversible investment decision and waiting for additional market information before committing to a certain action holds an additional value (Titman, 1985). In the context of selling properties, a real option would bring the homeowner, or the investors, a strategic value to choose the optimal timing of selling a property. Qian (2013) explores the impact of this theory and demonstrates that real option theory influences the property investment decisions of individual households.

Barron et al. (2018) also emphasize on real options theory's relevance in boosting the value of empty housing capacity and influencing landlords' behavior. For one, there is the opportunity for higher returns in the STR market and an increase in the potential selling price. Even when STR is less profitable than the LTR, there is evidence that landlords may be affected by the option theory (Coles et al., 2017). This could be explained by the fact that in volatile housing markets, such as the central urban city areas, decent-quality properties tend to gravitate more towards investment values over consumption values (Hung and Tzang, 2021). This creates an inclination where the market is more prone to speculation (Janoschka et al., 2019). In such a scenario, Airbnb offers flexibility and an additional value incentive for property owners to postpone the time of a sale in the expectation of selling for a higher price later. Meanwhile, short-term rental agreements are less binding than long-term rental contracts, and any additional income from STR is beneficial (Cocola-Gant and Gago, 2019).

Hence, the STR markets provide an opportunity for homeowners to apply the real option theory. In an environment with sufficient demand from buyers, property owners have the option to postpone selling and decide to take advantage of Airbnb while waiting for higher market prices. This could contribute to a supply imbalance in the market between availability and demand, resulting in increased housing prices.

### 2.3 The STR Effect on The Demand Side in The Urban Center

Considering the explanation of the inelastic supply in the city center, the influx of new demand posed by Airbnb should influence a surge in housing prices in the downtown. The channel for short stays drives demand, mainly servicing the hospitality and tourism sector (Wachsmuth and Weisler, 2018; Yrigoy, 2018), as a lot of the main hotspots for sightseeing, shopping, and entertainment tend to be in the city center (Segal, 1979). This leads to STR revenues being correlated to the central city location to a high degree (Tong & Gunter, 2020). For landlords, the STR becomes an alternative to the LTR income, and if Airbnb's revenue surpasses the LTR, this would appreciate the value of housing prices, which can be viewed as purchasing the present value of future rental payments (Barron et al., 2018; Garcia-Lopez et al., 2018). Indirect evidence of this can be observed in previous studies stating that there are buy-to-let investors purchasing properties solely to rent them on Airbnb to exploit any excessive gains that can be made. In this way, there is new demand created in the central area by buy-to-let investors who are attracted by higher returns on investment (Gurran & Phibbs, 2017; Cocola-Gant and Gago, 2019). The new demand created by the STR will be more sensibly capitalized into the existing housing prices in the area (Hilbert, 2017).

*Housing Market Segmentation and Spillover Effects*

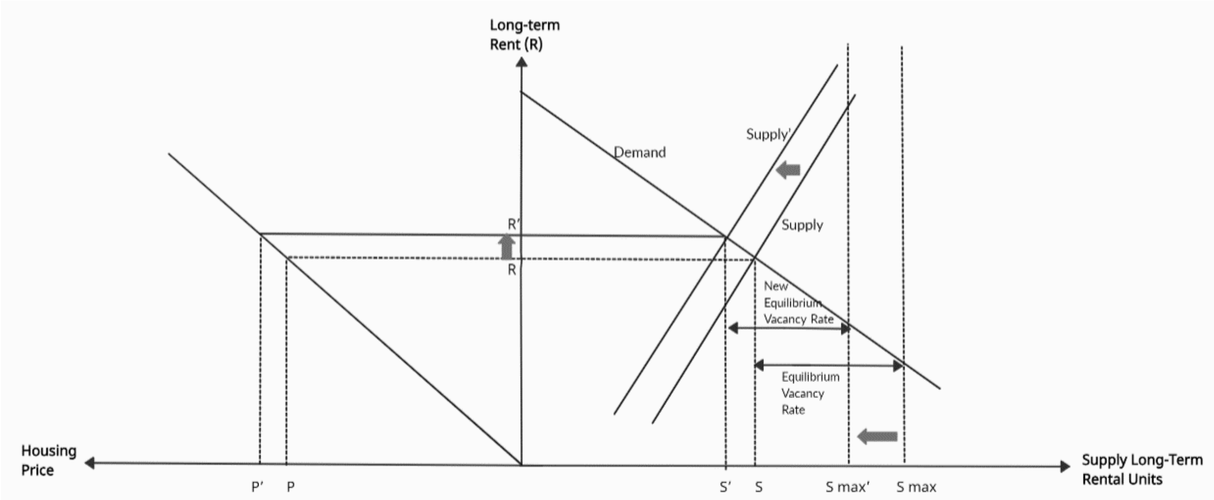
Previous literature has used different definitions for housing submarkets, stating that housing segments can vary based on various features such as location boundaries, regulation boundaries, and distinct housing attributes. At the core of the idea are the heterogeneous features of housing. Thus, the general housing market can be segmented into smaller submarkets with different elasticities of supply or demand-related factors. (Arnab Biswas, 2012; Goodman and Thibodeau, 1998). In this research, the central area location isolates the geographical and regulation boundaries. The research focuses on segmentation based on the number of bedrooms that an apartment, or a house, within the inner city possesses. Previous findings support the evidence of such segmentation for the Airbnb markets. Yin (2021) finds the count of bedrooms and homestay types as significant factors impacting the demand for Airbnb in China, while Bresciani et al. (2021) find evidence that demand during the COVID-19 pandemic differed by entire flats and shared flats.

The heterogeneous demand for Airbnb across different apartment-type segments can affect property prices differently. As this occurs, some segments experience a more expressed Airbnb effect than other apartment types. Another aspect of the submarket segments is their relation to the other submarkets that establish the housing market. Analogical to Biswas (2012), where adjacent to foreclosures properties sell at a discount, this research applies the same theory but in an opposite direction, where the premium caused by the spillover Airbnb effect on a given apartment segment impacts the housing prices of other segments in the city center. This study highlights the spillover effect not as a supply-side phenomenon like Biswas (2012), but rather as a demand-side dynamic caused by the heterogeneous tourist demand.

### 2.4 Conceptual Model and Hypotheses

With the help of the described literature, this subsection graphically illustrates the conceptual model with the expected relationship of Airbnb revenues in relation to housing prices and then follows to outline hypotheses. The conceptual model is similar to the 4Q framework of DiPasquale and Wheaton (1992). However, Figure 1 consists of only two quadrants and examines the dynamics in the short run between Airbnb and property values, only by observing a long-term rental supply shock, all other things being equal. The first quadrant represents the rental market. There is a total supply of LTR units fixed at $S_{max}$. Initially, the supply and the demand curve intersect at point $R$. There is also a total number of free vacant units ($S_{max} – S$), that shape the equilibrium vacancy rate for the market. The assumption is that a share of those free units is marketed as a potential sublet to new tenants. With the STR revenue alternative, there is an outflow of free unoccupied apartments from the LTR market to the STR market. Hence, the total stock is reduced to $S_{max}'$. The reduction of available units from $S_{max}$ to $S_{max}'$ moves the supply curve up and to the left because there is the same demand for LTR that is competing to secure a living place with fewer apartments available. The new point where demand intersects with the new supply curve is $R'$, where a new equilibrium vacancy rate is achieved ($S_{max}' – S'$). The price of the LTR increases from $R$ to $R'$. In the second quadrant, the boost in the income generation of housing is capitalized in the property value, as the price rises from $P$ to $P'$.

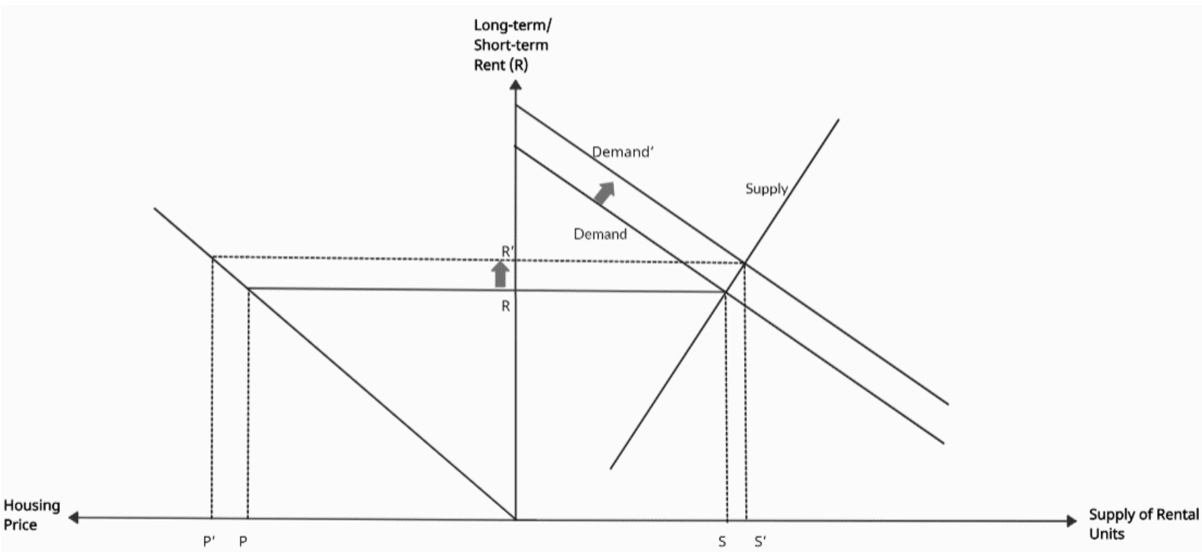
**Figure 1: Conceptual Model of the Airbnb Effect on the Supply Side**




Notes: Conceptual model illustrating the transitioning of long-term rental (LTR) apartments into the short-term rental (STR) market, causing a shock in the supply of LTRs, subsequently elevating rent and house prices. Adapted from DiPasquale and Wheaton's 4Q model (1992) to illustrate the supply side Airbnb effect on housing prices.

Figure 2 represents the evolving dynamics on the demand side, focusing primarily on longer-term effects. While the previous graph gives information on the initial supply shock, it's important to recognize that both supply and demand dynamics may influence housing prices over time. However, initially, Airbnb's introduction leads to a more expressed short-run supply change in big metropolitan areas. Over time, it is assumed that sustained growth in short-term rentals elevates demand, impacting housing markets in the longer time horizon. That is why in quadrant one in Figure 2, the assumption is that the STR revenue steadily becomes a substitute for the LTR among buy-to-let landlords. Starting from the balance point, where supply and demand intersect at *R*, the sustained growth in STR revenue moves the demand curve to the right and upward. Even though over time new supply stock can be produced to alleviate the rising prices, as has already been explained, the inelastic nature of the supply in the central areas limits the possibility of new LTR inventory entering the market. As a result, the new demand caused by Airbnb remains at a higher point. The demand curve and the supply curve now intersect at a higher point that is equal to the rental value of *R'* (*R'>R)*. Similarly to quadrant two in Figure 1, the surge in rental revenues is capitalized into the housing value, where *P* moves to *P'*.

**Figure 2: Conceptual Model of the Airbnb Effect on the Demand Side**



Notes: The conceptual model depicts the increased demand generated by short-term rentals, contributing to overall rental demand increase and consequent rent and house price appreciation. Adapted from DiPasquale and Wheaton's 4Q model (1992) to represent the demand side Airbnb effect on housing prices.

Overall, several hypotheses follow logically from the review of relevant theories, existing academic findings, and the conceptual model illustration. Those hypotheses offer the opportunity to advance the investigation of the Airbnb revenue effect on housing prices in Sofia's central housing urban area.

**Hypothesis 1: A positive association between STR revenue and housing prices**

With a strong foundation established in the literature regarding the positive correlation between short-term rental activity and escalating housing prices, it's hypothesized that the empirical analysis will align with the theoretical framework, indicating a positive relationship between STR performance (measured by RevPAR) and housing prices in the central region of Sofia.

**Hypothesis 2: The impact of Airbnb revenues on housing prices varies across housing submarkets, defined by bedroom type, and creates spillover effects into the other submarkets**

Given the existing literature highlighting the heterogeneous demand for short-term rentals (STRs), it's hypothesized that the impact of Airbnb revenue on housing prices will vary across different housing submarkets, which are defined by bedroom type. It is hypothesized that the variation in the STR revenue for the different apartment types would have a spillover effect on the other housing submarkets in the center.

**Hypothesis 3: The Influence of STR Revenues on Housing Prices Differs Based on Buyer Type**

Building upon the discussion surrounding the potential displacement of long-term residents and the gentrification pressure created by real estate investors, it's hypothesized that the influence of short-term rental (STR) revenues on housing prices in central areas will exhibit variations between homeowner purchasers and investors. Homeowner buyers may discount negative externalities like traffic congestion and pollution from the housing purchase price, while real estate investors may be motivated to pay a premium to capitalize on the Airbnb effect. The hypothesis emphasizes the varying reactions of homeowners and investors to STR revenues in the housing market.

## 3. DATA & METHODS

### 3.1 Context

This section goes into more detail to depict why Sofia should be considered a city with quite specific urban characteristics. In the context of other European countries, the Bulgarian residential market falls among the countries with a-high share of housing tenure at 84.9% homeownership rate for 2021 (Housing in Europe, 2021). According to the same statistics, other countries with a bigger than average share of homeownership are mainly located in Eastern and Central Europe, as well as the Baltic Region. In contrast, countries in Western Europe like the Netherlands and Belgium, have a homeownership rate of 70%. There are also more extreme exceptions such as Austria and Germany, where the share of homeownership drops to about 54% and 49% respectively (Housing in Europe, 2022).

Another specific feature of Sofia is the high percentage of empty housing stock in the residential housing market, which is caused by the declining population. According to the National Statistical Institute (NSI), in 2021, 229 370 housing units, equal to 30% of the total number of dwellings in the city, remain unoccupied (Appendix 1A). In this number, second homes and inherited properties are also included. Also, according to the last census conducted in 2021, there are 577,454 households and a total of 1,183,454 people living in the capital city, which is a drop of close to 20,000 people in the population from the previous census held in 2011. Despite this fact, there has been a substantial increase in the newly built homes that have been added to the housing stock in the last decade. Between 2011 and 2021 the total housing stock has risen from 608 426 units to 755 889 housing units (NSI, 2011; NSI, 2022). Although these numbers indicate the tendency for higher structural vacancy rates in the housing market, property prices in Bulgaria surged by more than 50% for the period between 2013 and 2021 (Housing in Europe, 2022). Part of this effect can be explained by the fact that there is a very active group of second-homeowner buyers of real estate. A large share of investors prefer to purchase properties for capital storage purposes or other reasons while keeping housing units vacant (Balgaranov, 2021). Overall, as illustrated, the active second-home housing market, combined with the interaction of high homeownership and vacancy rates results in a definitive urban real estate landscape in the capital city of Bulgaria.

As to the STR, the Airbnb market in Bulgaria was not regulated until the end of 2019. As of 2020, a law regulation framework became active in response to the growing influence of short-term rentals and concerns about the tax collection from STR activities. The government considered a proposal from municipal authorities to create a register for STR apartments leased through STR channels like Booking, Airbnb, Expedia, and other platforms that prior to this had not been registered in any form. The amendments that have been made require property owners to register their properties before renting them through online platforms, and a categorization system for these properties, similar to hotels and guesthouses, was introduced (BNR, 2019). However, according to anecdotal expert sources and local media sources, the effectiveness of these regulations remains uncertain, as to this day there is no clear mechanism to prevent unregulated properties from continuing to operate on STR platforms illegally. One article discusses that the effectiveness of the new regulations in Bulgaria is questionable, stating that "Obviously, the change is of little value. Most apartment owners will not register their property anyway and unless municipalities actively pursue cooperation with AirBnB or Booking.com... The new regime will be short-lived because the European Court of Justice has ruled that Airbnb is an information service and as such it does not fall under EU property regulations." (Vateva, 2020). That is why although the Airbnb dataset contains information during both regimes, this research considers regulations negligent and doesn't anticipate that the change of the regulatory framework would interfere with results.

### 3.2 Data collection

For conducting the research, the study makes use of two datasets on Sofia's city center for the period 2019-2022. The first dataset comes from the largest brokerage agency in Bulgaria - Address. It contains information on housing sales and includes transaction price, sale month and year, as well as house characteristics such as the number of bedrooms, living area in square meters, construction year, construction material, floor level, buyer type, and whether the property was sold during construction stage. The location data for the property transactions is indicated to be in the inner city but further details are not disclosed. The map in Appendix 1B illustrates the area where sales transactions occurred. That is the reason why the paper's scope takes one step back and strives to explore findings that are related to the central area of the city on an aggregate level. It is important to note that the research has limitations in terms of establishing the location-fixed effect, as there is probably a heterogeneity discrepancy between properties, so the Airbnb effect may vary across the different parts of the central region. Additionally, the buyer type variable contains 244 observations because the dataset lacks information on it for the year 2020. Appendix 1C gives more information on the total number of housing sales realized in Sofia for the same period. The data comes from the official Register Agency in Bulgaria (n.d). The notes below Appendix 1C provide more information on the ratio between the number of observations in the sales dataset and the total number of actual housing transactions.

The second dataset contains the STR rental information, and it is provided by the largest short-term rental management company in Bulgaria called Flat Manager. Throughout the examined period, the company has collected data on the financial performance of its portfolio of STR-managed apartments in central Sofia that consists of around 100 individual listings monthly throughout the period between 2019-2022. The portfolio of apartments does not remain consistent over time, since there are properties that quit the company's services and there are new ones that also enter the business. However, there are no drastic changes in the number of properties managed throughout the period of the study. For each STR property under management, there is a monthly statistic with performance indicators containing average daily rates, occupancy rates, and RevPAR. Notably, the location of the apartment under management is in the inner city as well, so the area of the data overlaps with the location area for the sales transaction dataset.

### 3.3 Descriptive statistics/analysis

Both datasets with the transaction information and the STR data were merged into one constant sample. The final dataset sample consists of 321 observations of sales transactions spread throughout the period 2019-2022 (Appendix 1C). It contains the following descriptive statistics. Table 1 reports the descriptive statistics and variable definitions are given in Appendix 2. It can be observed that the properties in the sample have a mean size of 79.69 square meters, with a standard deviation of 24.70, indicating a moderate degree of variation in size. The housing prices exhibit considerable variability, ranging from 46,500 to 342,000 euros, with an average of 141,285 and a standard variation of 56,269. Furthermore, the variation in property values is once again confirmed by the price per square meter. In addition, the dataset encompasses the number of bedrooms per property sold, with the majority of units being one-bedroom and two-bedrooms, with a share of 46.42% and 40.81% of the total, respectively.

Regarding the distribution of transactions in time, it can be observed that they are relatively evenly spread throughout the years, except in 2022, which has a slightly smaller percentage share of 19.31%. There is an evident seasonality pattern observed in the data. Specifically, approximately 17.45% of sales occur in Q1, 22.43% in Q2, while Q3 and Q4 are quite close to each other, accounting for approximately 30% each. Furthermore, the construction age is segmented into four distinct construction periods: 1907-1945, the post-World War II era to almost the end of the communist regime (1946-1985), the transition into a market economy until 2010 marking the global housing crisis and its implications, and the period following 2010 with the economic recovery. It can be seen that the first two construction periods encompass more than two-thirds of the transacted homes. The building period of 2011-2023 has a share of 20.56, while 1986-2010 takes 10.09 percent of the observations. Additionally, the presale variable indicates transaction deals that occurred before the completion of the construction, which is only 10.09% of total observations.

Next, the most common level of the properties is not higher than the fifth floor, as this cumulatively accounts for approximately 67% of all observations in the dataset. The rest of the units are spread up to the $11^{th}$ floor. Moreover, the buyer type consists predominantly of homebuyers, constituting 69.01% of the observations, while investors account for 30.99%. It's also noteworthy that the observations for the buyer type are 242 because the information for this variable for 2020 is missing. As for the building material, almost 98% of the properties share a brick as a common construction material.

The main variable of interest in the dataset, the market RevPAR metric is calculated for each month from 2019 to 2022 using the aggregate portfolio performance of all the short-term rental units under management. The portfolio encompasses around 100 apartments, with modest fluctuations up and down in the total monthly number during the examined period. The RevPAR market ($RevPAR_{mkt\_t}$) variable is derived for each month within a given year *t* throughout 2019-2022. It's equal to the monthly average portfolio daily rate multiplied by the portfolios' monthly occupancy rate. RevPAR by apartment type ($RevPAR_{apt\_type\_t}$), defined by the number of bedrooms, is also derived using the same data, with the distinction that the calculation is done separately for each respective bedroom type. For instance, for the monthly RevPAR of studios, the formula is:

$$\text{Average Daily Rate Per Month}_{\text{studios\_t}} * \text{ Occupancy Rate Per Month}_{\text{studios\_t}} = \text{RevPAR}_{\text{studios\_t}}$$

The respective lagged variables of the $RevPAR_{\mathbf{t-1/t-2/t-3}}$ for three periods prior to a given property sale in month and year *t* for the RevPAR of both the general market and by apartment type are derived as well. With the help of lagged variables, simple moving averages (SMA), or just moving averages (MA), of the RevPAR are also calculated. The reasoning behind the SMA and the lagged variables is discussed in the following section, while here the focus is purely on the mathematical equation applied, using the formula from Johnston et al. (1999), where the MA calculated as a set of data points *y* over a specified number of periods *n*:

$$MA = (\frac{1}{n}) \sum_{i=0}^{n-1} y_{t-i} \qquad (\mathrm{i} = \ 0 \text{ to } \mathrm{n} - 1)$$

Hence, the calculation of the $RevPAR_{\mathbf{ma2}}$ and $RevPAR_{\mathbf{ma3}}$ is the following:

$$\text{RevPAR}_{ma2:} = \frac{\text{RevPAR}_t + \text{RevPAR}_{t-1}}{2}; \text{RevPAR}_{ma3} = \frac{\text{RevPAR}_t + \text{RevPAR}_{t-1} + \text{RevPAR}_{t-2}}{3}$$

The market RevPAR at time *t* shows an average of 21.55 and a standard deviation of 6.44, with a range between 4.79 and 36.22. The RevPAR for studio at *t* has an average of 14.97 and a standard deviation of 5.32, while the RevPAR for 1bd at *t* displays an average of 20.35 and a standard deviation of 5.91. RevPAR for 2bd and 3bd at *t* have an average of 22.89 and 27.84, with a standard deviation of 7.37 and 9.81, respectively. Additionally, the lagged RevPAR variables share the same minimum and maximum values with their corresponding variable at time *t*, with slight variations in the averages and standard deviations offering insights into the historical dynamics of revenue performance. Another notable observation is that the RevPARma2 and RevPARma3, along with the MAs of the RevPAR by apartment type, have the lowest standard deviations of all the other variations of the RevPAR for each separate category. Finally, the number of total monthly Airbnb listings, measuring the supply of the STR market, showcases an average of 1,732 listings for the whole city of Sofia and a standard deviation of 269.22 listings for the period 2019-2022.

Moreover, Appendix 3 gives further information on the distribution of the independent variable, the variables at interest, and the square meter area of the properties. We transformed into a natural logarithm to achieve a better natural distribution. Besides, the Appendix contains an illustration of the scatterplot between the natural logarithm of housing prices and the lagged t-1, t-2, MA2 and MA3 RevPAR variables, plus the development of the monthly RevPAR metric during the period.

**Table 1: Descriptive Statistics**

| | **Mean** | **Std. dev.** | **Min** | **Max** |
|---|---|---|---|---|
| ***Property characteristics*** | | | | |
| area (in m2) | 79.69 | 24.70 | 30 | 165 |
| price (in euro) | 141285.20 | 56269.02 | 46500 | 342000 |
| price (in euro per m2) | 1803.82 | 574.18 | 697 | 4013 |
| bedroom_type (%) | | | | |
| *studio* | 6.54 | | | |
| *1 bedroom (1bd)* | 46.42 | | | |
| *2 bedrooms (2bd)* | 40.81 | | | |
| *3 bedrooms (3bd)* | 6.23 | | | |
| sale_year (%) | | | | |
| *2019* | 27.23 | | | |
| *2020* | 24.61 | | | |
| *2021* | 28.35 | | | |
| *2022* | 19.31 | | | |
| sale_quarter (%) | | | | |
| *Q1* | 17.45 | | | |
| *Q2* | 22.43 | | | |
| *Q3* | 30.22 | | | |
| *Q4* | 29.91 | | | |
| Building_age_range (%) | | | | |
| *1907-1945* | 30.53 | | | |
| *1946-1985* | 38.01 | | | |
| *1986-2010* | 10.09 | | | |
| *2011-2023* | 20.56 | | | |
| Presale (1 = yes) | 0.081 | 0.27 | 0 | 1 |
| Floor (%) | | | | |
| *1* | 10.59 | | | |
| *2* | 19.94 | | | |
| *3* | 22.74 | | | |
| *4* | 19.94 | | | |
| *5* | 14.33 | | | |
| *6* | 8.10 | | | |
| *7* | 3.74 | | | |
| *9* | 0.31 | | | |

| | | | | |
|---|---|---|---|---|
| *11* | 0.31 | | | |
| buyer_type (0 = investor; 1 = homebuyer) | 0.69 | .46 | 0 | 1 |
| building_material (0 = brick; 1 = other) | .98 | 0.12 | 0 | 1 |
| ***STR Market characteristics*** | | | | |
| revpar$_{\mathbf{mkt_t}}$ | 21.55 | 6.44 | 4.79 | 36.22 |
| revpar$_{\mathbf{t-1}}$ | 20.97 | 6.45 | 4.79 | 36.22 |
| revpar$_{\mathbf{t-2}}$ | 20.33 | 6.24 | 4.79 | 36.22 |
| revpar$_{\mathbf{t-3}}$ | 19.92 | 6.45 | 4.79 | 36.22 |
| revpar$_{\mathbf{ma2}}$ | 21.26 | 6.13 | 5.55 | 34.90 |
| revpar$_{\mathbf{ma3}}$ | 20.95 | 5.81 | 6.94 | 33.90 |
| revpar$_{\mathbf{studio_t}}$ | 14.97 | 5.32 | 7.86 | 29.19 |
| revpar$_{\mathbf{studio_t-1}}$ | 14.66 | 5.18 | 7.86 | 29.19 |
| revpar$_{\mathbf{studio_t-2}}$ | 14.22 | 4.76 | 7.86 | 29.19 |
| revpar$_{\mathbf{studio_t-3}}$ | 14.11 | 4.94 | 7.86 | 29.19 |
| revpar$_{\mathbf{studio_ma2}}$ | 14.81 | 4.93 | 7.90 | 27.31 |
| revpar$_{\mathbf{studio_ma3}}$ | 14.62 | 4.54 | 8.89 | 26.43 |
| revpar$_{\mathbf{1bd_t}}$ | 20.35 | 5.91 | 5.99 | 32.38 |
| revpar$_{\mathbf{1bd_t-1}}$ | 19.88 | 6.00 | 5.99 | 32.38 |
| revpar$_{\mathbf{1bd_t-2}}$ | 19.35 | 6.00 | 5.99 | 32.38 |
| revpar$_{\mathbf{1bdt-3}}$ | 19.07 | 6.17 | 5.99 | 32.38 |
| revpar$_{\mathbf{1bd_ma2}}$ | 20.11 | 5.73 | 6.20 | 31.28 |
| revpar$_{\mathbf{1bd_ma3}}$ | 19.85 | 5.55 | 7.68 | 31.36 |
| revpar$_{\mathbf{2bd_t}}$ | 22.89 | 7.37 | 3.77 | 38.84 |
| revpar$_{\mathbf{2bd_t-1}}$ | 22.35 | 7.32 | 3.37 | 38.15 |
| revpar$_{\mathbf{2bd_t-2}}$ | 22.61 | 7.52 | 3.37 | 37.05 |
| revpar$_{\mathbf{2bd_t-3}}$ | 22.61 | 7.52 | 3.37 | 37.05 |
| revpar$_{\mathbf{2bd\ ma2}}$ | 22.61 | 6.95 | 5.23 | 38.50 |
| revpar$_{\mathbf{2bd_ma3}}$ | 22.35 | 6.51 | 6.00 | 37.64 |
| revpar$_{\mathbf{3bd_t}}$ | 27.84 | 9.81 | 1.94 | 53.83 |
| revpar$_{\mathbf{3bd_t-1}}$ | 26.90 | 9.90 | 1.94 | 53.83 |
| revpar$_{\mathbf{3bd_t-2}}$ | 25.83 | 9.48 | 1.94 | 53.83 |
| revpar$_{\mathbf{3bd_t-3}}$ | 24.92 | 9.59 | 1.94 | 53.83 |
| revpar$_{\mathbf{3bd_ma2}}$ | 27.37 | 8.91 | 1.97 | 44.42 |
| revpar$_{\mathbf{3bd_ma3}}$ | 26.86 | 8.31 | 4.24 | 41.30 |
| total monthly Airbnb listings (#) | 1732.20 | 269.22 | 1108 | 2371 |

Notes: The table provides key statistics describing the dataset used in this study, covering housing transactions and short-term rental (STR) data for the period from 2019 to 2022, merged into a constant sample. It outlines the transaction details and property characteristics, including housing size, sale price, bedroom distribution, temporal distribution, construction period, floor level, buyer type, and building material. The number of observations is 321, except for "buyer_type" dummy (N=242) because the information for this variable for 2020 is missing. The table also gives information about the STR market metrics, such as monthly market RevPAR (RevPARmkt_t) metrics for each month in a given year *t*, lagged RevPAR metrics (*t-1, t-2, t-3*), simple moving Average metrics (RevPAR*ma2*, RevPAR *ma3*), number of total monthly Airbnb listings during the period, as well as RevPAR_Apt_Type for each different apartment type defined by the number of bedrooms. In this classification, "1bd" denotes 1-bedroom apartments, "2bd" represents 2-bedroom apartments, "3bd" indicates 3-bedroom apartments, and "studio" refers to apartments with no bedrooms.

### 3.4 Methodology

In order to explore the effect of STR on house prices in the central area of Sofia, a hedonic model based on Rosen (1974) using a log-log regression equation is employed that is actually a measure of price elasticity (Brooks & Tsolacos, 2010). Taking the natural logarithm of transaction sales prices for the properties in the center as the dependent variable and RevPAR as the independent variables of interest. The control variables are time-fixed effects and property characteristics. The following baseline hedonic model equation 1 is used to regress the natural log of housing price against a set of independent variables:

$$\mathrm{Ln}(\mathrm{P}_{it}) = \beta_0 + \beta_1 * \mathrm{Ln}(\mathrm{RevPAR}_{\mathrm{mkt\_t}}) + \sum_{k=1}^{K} \beta_k Z_{k,i} + \sum_{y=1}^{Y} \delta_y \mathrm{Y}_y + \sum_{q=1}^{Q} \partial_q Q_q + \varepsilon_{it} \quad (1)$$

In this model, the dependent variable is the natural logarithm of the sales price of an individual property *i* at a specific time of the month and year *t*. First, the model includes an intercept $\beta_0$. The variable of interest is the natural logarithm of $\mathrm{RevPAR}_{mkt}$ at a specific month and year *t*, with its corresponding coefficient $\beta_1$. Given that real estate markets are to some degree inefficient and require processing time to assimilate any new information, as discussed by Evans (2004), it is anticipated that the influence of the revenue indicator of the STR activity will likely lag in time with respect to its influence on the housing market. Therefore, the model may incorporate the *t-1* lagged variable of $\mathrm{RevPAR}_{mkt}$ to analyze whether past monthly STR performance influences housing prices at time *t*. Theoretically, it is possible to explore further combination of lags (e.g., $\mathrm{RevPAR}_{mkt\_t-1}$, $\mathrm{RevPAR}_{mkt\_t-2}$, $\mathrm{RevPAR}_{mkt\_t-3}$) to find and incorporate in a model only the significant lagged variables that influence the housing market. Nonetheless, the addition of extra lags requires analysis of the autocorrelation function of the variable of interest - a procedure possible to conduct in time series models (Brooks & Tsolacos, 2010). This is out of the scope of this research because of limitations imposed by the current dataset. Alternatively, the model will examine results with the simple moving averages $\mathrm{RevPAR}_{ma2}$ and $\mathrm{RevPAR}_{ma3}$. One of the properties of MAs is that they are lagging indicators that also remove noise from data and help to discern trending patterns (Johnston et al., 1999; Ellis and Parbery, 2005). The reason why the 60-day, or 90-day, moving average RevPAR, respectively the $\mathrm{RevPAR}_{ma2}$ and the $\mathrm{RevPAR}_{ma3}$, could turn a robust way to explore the delayed effect of the STR performance is because the MAs encompass several lags within themselves and provide ways to test the reliability of the results for the best model fit (Ellis and Parbery, 2005). Moving forward, the model includes coefficients $\beta_k$ representing the effect of various property characteristics $Z_{k,i}$. Those coefficients capture the impact of each respective physical attribute *k*, such as size, construction year, and other relevant attributes, on the logarithm of the housing price of each individual property *i* sold. Additionally, the model incorporates time-fixed effects Y for the year, and Q for the quarter that a corresponding sale of property *i* at time *t* falls into, in order to capture and isolate the yearly market trend and the seasonality that affects property sales prices (Brooks & Tsolacos, 2010). Ideally, one shall seek an interaction between quarter and year, or even better – month and year. However, due to the lower number of observations in the dataset, such interactions won't produce any meaningful results, thus separate quarter and year time-fixed effects are selected as the best fit for the equation. The error term $\varepsilon_{it}$ captures the variability that cannot be explained by the model.

To dig deeper into the specification of the Airbnb effect on housing prices to obtain more detailed information on it and examine RQ3, two sub-questions aim to explore different aspects of the multifaceted STR presence in the housing market.

Sub-equation 2.1 goes beyond equation model 1 to further investigate the relationship between STR revenues and across different housing segments. The extended model, expressed as equation model 2.1, incorporates the following variables:

$$\mathrm{Ln}(\mathrm{P}_{it}) = \beta_0 + \beta_1 * \mathrm{Ln}(\mathrm{RevPAR}_{\mathrm{apt\ type}_t}) \times \mathrm{Bedrooms}_{\ i} + \sum_{k=1}^{K} \beta_k Z_{k,i} + \sum_{t=1}^{T} \delta_t \mathrm{Y}_t + \sum_{t=1}^{T} \partial_t Q_t + \varepsilon_{it} \qquad (2.1)$$

The model aims to discover how STR revenue for each housing segment, defined in this paper by the number of bedrooms, uniquely influences separate housing submarkets. The model introduces a main explanatory interaction variable between the number of bedrooms for each individual property *i* sold, and $\mathrm{RevPAR}_{apt\_type\_t}$. The number of bedrooms indicates the respective apartment type – studio, 1bd, 2bd, and 3bd. The $\mathrm{RevPAR}_{apt\_type\_t}$ is a continuous variable and captures the STR revenue performance metric corresponding to each respective segment at a specific time *t* of the year and month. Furthermore, the model would explore results with the lagged variables and moving average variables $\mathrm{RevPAR}_{apt\_type\_t-1}$, $\mathrm{RevPAR}_{apt\_type\_ma2}$, and $\mathrm{RevPAR}_{apt\_type\_ma3}$. This would allow for a more in-depth investigation of how different past revenue performance metrics of the STR market impact the pricing of separate housing segments. The final model allows for an analysis of how average STR revenue, given by the number of bedrooms may, to a higher or lesser extent, have an influence on its own segment and the different housing segments. The rest of the explanatory variables in the equation remain the same as in the basic model.

In the second sub-question, 2.2, the objective is to examine the impact of STR revenues on different buyer types in the central area of the city. The equation model, 2.2, is formulated as follows:

$$\mathrm{Ln}(\mathrm{P}_{it}) = \beta_0 + \beta_1 * \mathrm{Ln}(\mathrm{RevPAR}_{\mathrm{mkt}_t}) \times \mathrm{Buyer\_type}_{\ i} + \sum_{k=1}^{K} \beta_k Z_{k,i} + \sum_{t=1}^{T} \delta_t \mathrm{Y}_t + \sum_{t=1}^{T} \partial_t Q_t + \varepsilon_{it} \qquad (2.2)$$

In this expanded model, there is another primary interaction of interest - the natural logarithm of market RevPAR at time *t*, or its different lagged modifications, and the buyer type for each individual property *i*, represented by a binary choice. A value of 1 indicates an investor, while 0 indicates a homebuyer. The equation once again isolates for other property characteristics and the time-fixed effect of the quarter and the year of a sale at time *t*. By including this variable, the analysis aims to shed light on how the revenues generated from STR may impact the purchase behavior and the final price for an investor as opposed to a homebuyer purchaser.

## 4. RESULTS AND DISCUSSION

### 4.1 The Airbnb Effect in the Central Parts of Sofia

The main findings of this research, focusing on the relationship between Airbnb revenue and residential real estate values, are presented in the following section. The results are revealed through a series of Ordinarily Least Squares (OLS) regressions, where the main dependent variable is the natural logarithm of housing sales price.

Multiple regression computations were conducted with different variations of the market RevPAR to discover the most reliable model. As the previous chapter explained the inefficiency in the housing market, the information about the STRs' financial performance should require time to be processed by the residential market. That is why the RevPAR at *t* time alone can't explain the relationship with housing prices, although the variable produces significant results. The lagged *t-1* RevPAR variable was tested as well. It turned out to be significant at the 10 percent level. Following, the study tested the model using $RevPAR_{ma2}$ and $RevPAR_{ma3}$ as the main dependent variables. The $RevPAR_{ma3}$ model produces the best results of all the modifications. It achieves a slightly better adjusted R-squared of 0.6887 compared to 0.6882 for the $RevPAR_{ma2}$ model. Additionally, the MSE (mean square error) is something that studies testing different modifications of SMAs usually look at. In this case, the root MSE of the $RevPAR_{ma3}$ model is a bit lower than the $RevPAR_{ma2}$ model indicating a slightly higher level of accuracy of the former (Svetunkov and Petropoulos, 2017). No further information on the process of using SMA in relation to this study was found in the existing literature because the variable is mostly used for forecasting models rather than regressions. Hence, the research implements the natural logarithm of $RevPAR_{ma3}$ as the primary variable of interest used in the empirical research questions. Tables 3.1 & 3.2 in the Appendix lay the results of the testing process described above, and Table 4 below unveils the build-up to the final model for exploring the RQ2.

Column (1) provides the basic regression with the natural logarithm of RevPARma3 as the independent variable and residential real estate values as the dependent variable. The results suggest a positive relationship; a 1 percent increase in the 3-month moving average RevPAR results in a 0.424 percent increase in average residential real estate values in the city center of Sofia. The estimate is significant at the 1 percent level.

Next, column (2) introduces to the model the natural logarithm of square meters and the building period for each property examined. The coefficient for the size of the housing has a positive sign as expected, with a coefficient of 0.829 and a significance at the 1% level. Besides, the addition of the two variables boosts the adjusted R-squared up to 0.5951, as this effect is mostly driven by the natural log of the property size. For the construction age variable, the period between 1907-1945 is taken as a reference category. Then, the second period encompasses the years between the end of the Second World War almost until the end of the communist regime in Bulgaria. Next, the period 1985-2011 reflects the transition into the free market, while the last period explores the dynamics of housing constructed after the global financial crisis. It can be surprisingly seen that except for the second period, the last two building year ranges have a negative coefficient in comparison to the base category, as both periods 1985-2011 and 2011-2023 are significant at the 1 percent level. Part of the explanation could be the fact that the research focuses only on the central areas of Sofia, and it doesn't consider the location-fixed effects. This may impact and alternate results because with the advancement of the building periods, there was less space to build into the core parts of the center, and construction expanded into the broader areas of the CBD. Thus, this effect may be caused by the higher appreciation in value of old properties in the more favorable areas of the downtown, which offsets the depreciation of the housing stock in these areas. However, as this is not the focus of the paper, further investigation of the phenomenon is not conducted.

Column (3) further refines the model with the addition of the presale and building material variables. Notably, presold properties before completion exhibit a significant negative association with housing prices as opposed to already completed buildings, indicated by a coefficient of -0.252. Additionally, the coefficient for building material has significance at the 5 percent level with a positive number of 0.235, underscoring the favorable impact of construction with bricks in comparison to other types of building material.

Columns (4) and (5) build upon the model by incorporating floor and bedroom type variables. It can be observed that the floor variables, and more precisely up to the fifth level in reference to the ground floor in a building, demonstrate various positive significance on housing prices for column (4) and the onward columns. Moving to column (5), bedroom type is introduced as an additional variable. Although only two bedrooms show a significant result at the 5 percent level with a coefficient of 0.206, it may be due to the lack of a larger dataset. Apart from that, the data results are in line with expectations that the more rooms there are, the higher the housing price. In column (6), properties with one and two bedrooms show significance at the 5 and 1 percent level in comparison to studios. While one-bedroom properties demonstrate a coefficient of 0.162, a two-bedroom unit, on average, is associated with a price increase of 0.244 percent in price.

In column (6), the final model incorporates several new variables. First, the natural logarithm of the total number of monthly Airbnb listings is added to the model. By including the total Airbnb listings, alongside the RevPAR, the purpose is to disentangle the supply and demand effect. The total listings now present supply, while RevPAR, which typically encompasses both aspects, can be explored more as the demand-side effect of STR. The Airbnb supply variable does not exhibit statistical significance. For Sofia, this indicates that on the supply-side of the housing market, the Airbnb effect does not play a significant role. The reason perhaps is due to the high rate of empty housing stock in the city center and enough long-term rentals available in the market. Additionally, time variables are introduced, namely transaction sale year and sale quarter, with reference categories set as 2019 for the year and the first quarter for the season. Among these variables, only 2021 and 2022 show statistically significant impacts on housing prices compared to 2019, suggesting distinct trends or influences during these specific periods. Despite this, the inclusion of yearly and quarterly fixed effects improves the preciseness of the primary variable of interest - ln_revpar_ma3. The main variable of interest maintains a consistent significance throughout the model expansion, affirming its positive association with residential real estate values. When factoring in time-fixed effects, the coefficient changes from 0.353 at the 1% significance level in column (5) to 0.169 at the 5% significance level in column (6). It's worth noting that a more detailed time-fixed effects model, including interactions between quarters and years, or months and years, would have been ideal. Unfortunately, due to the limited dataset, such granularity was unattainable. Regardless, the adjusted R-squared value of 0.6887 in column (6) suggests that the included variables effectively capture a majority of factors influencing property values in Sofia's city center.

In column (7) the model includes the buyer-type dummy, where the reference category is for investors, and it is compared to homeowner purchasers. Because the variable lacks data for the buyer type for 2020 the number of observations drops down to 242. Although the results for buyer type are not significant, the gap in the data for 2020 excludes the initial year of the global pandemic crisis. Therefore, the table presents an opportunity to investigate the Airbnb effect in a setting where the substantial influence of the pandemic is factored out. The adjusted R-squared value of the model rises to 0.6993. The market $\text{RevPAR}_{\mathbf{ma3}}$ coefficient remains significant at the 5% level, while the magnitude of the coefficient rises to 0.478, almost three times larger than the coefficient of 0.169 ($p < 0.05$) in column (6). This indicates that the link between the STR revenue and the housing markets was weaker during the pandemic. The observation is in line with the argument that during COVID-19 housing buyers moved out of the city center and focused on more rural areas. Purchases of properties in the inner center appeared to be less influenced by short-term rental activity during this period. What's fascinating to observe is the results indicate a growing effect of the STR revenue on the housing market in the central area in recent years. Additionally, the table also presents another altered result. The total number of monthly Airbnb listings is now a significant factor at the 5% level with a coefficient of -0.492. Opposite to previous findings in the literature, the increase in the supply of Airbnb units in Sofia alleviates pressure on the housing market. As already stated, the reason should be that there are enough long-term rentals available in the city center and that new supply coming into the STR market successfully manages to apply downward pressure on the RevPAR, absorbing to an extent the increase in STR demand. The results in column (7) also reinforce the argument that the Airbnb effect in the city center of Sofia is driven by the demand side, and not by the reallocation of long-term rentals to the STR market.

Furthermore, a diagnostics check has been run on the final model. Based on these results, the regression model meets the assumptions of linear regression, including no severe multicollinearity, no significant heteroskedasticity, normally distributed residuals, appropriate specification, and functional form. The checks include Breusch-Pagan, VIF, Shapiro-Wilkes, and a test for appropriate functional form (Appendix 4).

TABLE 4: ESTIMATION RESULTS FOR PRICE MODELS, OLS ESTIMATES

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) | Model (7) |
|---|---|---|---|---|---|---|---|
| ln_revpar_ma3 | 0.424*** | 0.341*** | 0.328*** | 0.351*** | 0.353*** | 0.169** | 0.478** |
| | (0.0713) | (0.0483) | (0.0473) | (0.0468) | (0.0464) | (0.0703) | (0.188) |
| ln_aream2 | | 0.829*** | 0.826*** | 0.817*** | 0.698*** | 0.686*** | 0.707*** |
| | | (0.0469) | (0.0457) | (0.0451) | (0.0722) | (0.0680) | (0.0759) |
| Building Period 1946-1984 | | 0.0859** | 0.0830** | 0.109*** | 0.115*** | 0.100*** | 0.122*** |
| | | (0.0361) | (0.0352) | (0.0355) | (0.0353) | (0.0335) | (0.0358) |
| Building Period 1985-2011 | | -0.144*** | -0.134*** | -0.120** | -0.0799 | -0.0921* | -0.0325 |
| | | (0.0525) | (0.0513) | (0.0511) | (0.0528) | (0.0505) | (0.0550) |
| Building Period 2011-2023 | | -0.259*** | -0.166*** | -0.121** | -0.0924* | -0.111** | -0.127** |
| | | (0.0425) | (0.0486) | (0.0489) | (0.0503) | (0.0474) | (0.0530) |
| 1.presale | | | -0.252*** | -0.281*** | -0.272*** | -0.219*** | -0.194** |
| | | | (0.0653) | (0.0647) | (0.0641) | (0.0608) | (0.0872) |
| 1.building_material | | | 0.235** | 0.169 | 0.236* | 0.280** | 0.324** |
| | | | (0.118) | (0.129) | (0.129) | (0.122) | (0.134) |
| 2.floor | | | | 0.127** | 0.139** | 0.121** | 0.105* |
| | | | | (0.0544) | (0.0540) | (0.0507) | (0.0562) |
| 3.floor | | | | 0.214*** | 0.216*** | 0.207*** | 0.148*** |
| | | | | (0.0529) | (0.0525) | (0.0493) | (0.0540) |
| 4.floor | | | | 0.111** | 0.115** | 0.127** | 0.0951* |
| | | | | (0.0536) | (0.0530) | (0.0496) | (0.0545) |
| 5.floor | | | | 0.129** | 0.138** | 0.128** | 0.0611 |
| | | | | (0.0573) | (0.0568) | (0.0536) | (0.0592) |
| 6.floor | | | | 0.0522 | 0.0630 | 0.0619 | -0.00867 |
| | | | | (0.0663) | (0.0656) | (0.0615) | (0.0677) |
| 7.floor | | | | -0.000942 | 0.0274 | 0.0197 | -0.0821 |
| | | | | (0.0856) | (0.0853) | (0.0800) | (0.0974) |
| 9.floor | | | | -0.257 | -0.182 | -0.186 | -0.247 |
| | | | | (0.259) | (0.258) | (0.243) | (0.234) |
| 11.floor | | | | -0.128 | -0.0886 | -0.0609 | -0.127 |
| | | | | (0.287) | (0.284) | (0.269) | (0.266) |
| 1.bedroom | | | | | 0.100 | 0.162** | 0.174** |
| | | | | | (0.0690) | (0.0657) | (0.0735) |
| 2.bedrooms | | | | | 0.206** | 0.244*** | 0.241*** |
| | | | | | (0.0859) | (0.0811) | (0.0918) |
| 3.bedrooms | | | | | 0.118 | 0.162 | 0.134 |
| | | | | | (0.114) | (0.108) | (0.117) |
| ln_airbnblistings | | | | | | -0.147 | -0.492** |
| | | | | | | (0.160) | (0.234) |
| 2.sale_quarter | | | | | | 0.0447 | 0.0103 |
| | | | | | | (0.0441) | (0.0686) |
| 3.sale_quarter | | | | | | 0.0305 | -0.0337 |
| | | | | | | (0.0536) | (0.102) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 4.sale_quarter | | | | | | 0.0624 | -0.0117 |
| | | | | | | (0.0553) | (0.0988) |
| 2020.sale_year | | | | | | 0.00678 | - |
| | | | | | | (0.0548) | - |
| 2021.sale_year | | | | | | 0.118** | 0.0128 |
| | | | | | | (0.0556) | (0.0717) |
| 2022.sale_year | | | | | | 0.280*** | 0.121 |
| | | | | | | (0.0505) | (0.0861) |
| 1.buyer_type | | | | | | | -0.0354 |
| | | | | | | | (0.0331) |
| Constant | 10.50*** | 7.202*** | 7.021*** | 6.921*** | 7.208*** | 8.703*** | 10.36*** |
| | (0.215) | (0.247) | (0.273) | (0.275) | (0.323) | (1.262) | (1.808) |
| Observations | 321 | 321 | 321 | 321 | 321 | 321 | 242 |
| Adjusted R-squared | 0.0970 | 0.5951 | 0.6158 | 0.6349 | 0.6436 | 0.6887 | 0.6993 |

Notes: Dependent variable is the natural log of transaction price. The variable of interest "ln_revpar_ma3" is the 90-day moving average of the market RevPAR. The reference categories include: Building Period 1907-1945, presale equal to 0 means "No", building material 0 equal to "other", floor equal to 0, bedroom type – studio, sale quarter is 1, sale year is 2019, and a buyer_type dummy, where 0 equals investor and 1 is homeowner. The absence of data for the buyer-type dummy variable in 2020 (N=242) results in the exclusion of reporting this year in column (7) of the table. All models include a constant term. Models (6) and (7) account for fixed effects for year and quarter, separately. Standard errors in parentheses with ***, **, * indicating significance at 1%, 5%, and 10%, respectively.

### 4.2 The Airbnb Effect in the Central Parts of Sofia on Different Housing Submarkets

Going forward, the paper examines different types of specifications for the market that are outlined in RQ3. So far, the research has found the average effect of short-term rental revenue performance on the prices of properties in the city center of Sofia. The aim of this subsection is to delve deeper into the unique effects of submarket-specific aggregate revenue performance (RevPAR$_{_apt_type}$) on its corresponding housing segments, characterized by the number of bedrooms. The STR effect may differ for the various subsegments of the housing market due to the heterogeneous tourist demand for accommodation. Furthermore, the Airbnb effect for one housing subsegment may trigger a domino effect and not only influence the increase of housing prices for its corresponding submarket but also create a spillover effect for other housing submarkets. For illustration, a surge in studio prices due to strong STR performance may prompt prospective buyers to reconsider the purchase of one-bedroom units. Consequently, this would influence the dynamics of the one-bedroom submarket. Conversely, those considering the acquisition of one-bedroom apartments might explore studios as an attractive option due to the studios' STR revenue. The spillover effect introduces an intricate supplementary layer to the housing landscape. Hence, the analysis seeks to disentangle the overall Airbnb effect for each submarket and to explore any presence of ripple effects on other housing segments, thus shedding more light on the multifaceted relationship between Airbnb and housing prices.

Table 5 below gives information on the results for different specifications. The main focus in Model 1 is on the interaction of each apartment type with its corresponding market performance metric (RevPAR$_{apt_type_ma3}$). All the coefficients are positive except for the negative interaction between the two-bedroom apartment type and its respective RevPAR metric. Besides, none of the results are significant predictors for housing prices, so the research moved on to further exploring. Following are the interaction terms between the number of bedrooms and the lagged STR revenue metric for each unit type. These interaction terms represent the impact of RevPAR's performance on the different segments in the market, testing in a different way for the STR impact on its corresponding submarket and any spillover effects. In Model 2, it is observed that there is a positive and statistically significant relationship at the 1% level between studios and studios' RevPAR (studio#ln_revpar_studio_ma3) with a coefficient of 0.443. Additionally, there is a statistically significant relationship at the 5% level between one-bedroom units and studios' revenue performance (1 bd#ln_revpar_studio_ma3) with a coefficient of 0.235. Furthermore, a statistically significant relationship at the 1% level is found between two-bedroom units and $RevPAR_{studio\_ma3}$ (2 bd#ln_revpar_studio_ma3) with a coefficient of 0.354. This suggests that a lagged STR revenue from the three-month moving average of studios has a positive influence on the prices of the described apartment types, indicating a spillover pricing effect from STR studios' performance to the corresponding property submarkets. In addition, in Model 2, the monthly supply of the STR market (ln_airbnblistings) is significant at the 10% level, with a coefficient of -0.285. In Model 3, the study investigates the interaction between the lagged RevPAR for one-bedroom apartments and the housing segment prices. The results indicate a positive relationship between studios and the three-month moving average of the 1-bedroom RevPAR, which is statistically significant at the 10% level with a coefficient of 0.254. For its segment, the interaction shows a positive relationship, but it is not statistically significant. Finally, for the two-bedroom apartments, the interaction demonstrates a positive and statistically significant relationship at the 5% level, with a coefficient of 0.190. In Model 4, the interaction term between the lagged three-month moving average of RevPAR for two-bedroom units and its submarket is observed to be positive. However, the relationship is not statistically significant, just as all the rest interactions with the 2-bd RevPAR moving average. In Model 5, the study examines the interaction between the unit types and the lagged three-month moving average of RevPAR for three-bedroom apartments. The results indicate a statistically significant positive relationship for the interaction with the one-bedroom units, resulting in a coefficient of 0.105 significant at the 10% level. This indicates that the STR performance of three-bedroom units may influence the prices of one-bedroom apartments. However, the relationships for studios, two-bedroom, and three-bedroom units are not statistically significant.

TABLE 5

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) |
|---|---|---|---|---|---|
| studio # $ln\_revpar\_studio_{ma3}$ | 0.422* | | | | |
| | (0.246) | | | | |
| 1bd # $ln\_revpar\_1bd_{ma3}$ | 0.531 | | | | |
| | (0.378) | | | | |
| 2bd # $ln\_revpar\_2bd_{ma3}$ | -0.583** | | | | |
| | (0.286) | | | | |
| 3bd # $ln\_revpar\_3bd_{ma3}$ | 0.395 | | | | |
| | (0.303) | | | | |
| studio # $ln\_revpar\_studio_{ma3}$ | | 0.443*** | | | |
| | | (0.170) | | | |
| 1 bedroom # $ln\_revpar\_studio_{ma3}$ | | 0.235** | | | |
| | | (0.116) | | | |
| 2 bedrooms # $ln\_revpar\_studio_{ma3}$ | | 0.354*** | | | |
| | | (0.116) | | | |
| 3 bedrooms # $ln\_revpar\_studio_{ma3}$ | | 0.233 | | | |
| | | (0.191) | | | |
| studio # $ln\_revpar\_1bd_{ma3}$ | | | 0.254* | | |
| | | | (0.139) | | |
| 1 bedroom # $ln\_revpar\_1bd_{ma3}$ | | | 0.141 | | |
| | | | (0.108) | | |

| | | | | | |
|---|---|---|---|---|---|
| 2 bedrooms # ln_revpar_1bd$_{ma3}$ | | | 0.190* | | |
| | | | (0.101) | | |
| 3 bedrooms # ln_revpar_1bd$_{ma3}$ | | | 0.225 | | |
| | | | (0.234) | | |
| studio # ln_revpar_2bd$_{ma3}$ | | | | 0.150 | |
| | | | | (0.110) | |
| 1 bedroom # ln_revpar_2bd $_{ma3}$ | | | | 0.0782 | |
| | | | | (0.0817) | |
| 2 bedrooms # ln_revpar_2bd $_{ma3}$ | | | | 0.0945 | |
| | | | | (0.0737) | |
| 3 bedrooms # ln_revpar_2bd $_{ma3}$ | | | | 0.181 | |
| | | | | (0.235) | |
| studio # ln_revpar_3bd $_{ma3}$ | | | | | 0.111 |
| | | | | | (0.0903) |
| 1 bedroom # ln_revpar_3bd $_{ma3}$ | | | | | 0.105* |
| | | | | | (0.0629) |
| 2 bedrooms # ln_revpar_3bd $_{ma3}$ | | | | | 0.0835 |
| | | | | | (0.0558) |
| 3 bedrooms # ln_revpar_3bd $_{ma3}$ | | | | | 0.327 |
| | | | | | (0.2423) |
| 1.bedroom_type | 0.668 | 0.713 | 0.496 | 0.382 | 0.177 |
| | (0.466) | (0.454) | (0.438) | (0.378) | (0.323) |
| 2.bedroom_type | 0.597 | 0.475 | 0.433 | 0.412 | 0.325 |
| | (0.448) | (0.447) | (0.423) | (0.363) | (0.310) |
| 3.bedroom_type | -0.109 | 0.709 | 0.248 | 0.0600 | -0.561 |
| | (0.893) | (0.632) | (0.780) | (0.806) | (0.847) |
| ln_aream2 | 0.709*** | 0.693*** | 0.682*** | 0.685*** | 0.694*** |
| | (0.0693) | (0.0679) | (0.0687) | (0.0689) | (0.0686) |
| 1946.constr_age_range | 0.0972*** | 0.0958*** | 0.100*** | 0.100*** | 0.102*** |
| | (0.0335) | (0.0335) | (0.0338) | (0.0340) | (0.0338) |
| 1985.constr_age_range | -0.102** | -0.0973* | -0.0957* | -0.0946* | -0.0919* |
| | (0.0510) | (0.0509) | (0.0513) | (0.0514) | (0.0510) |
| 2011.constr_age_range | -0.115** | -0.114** | -0.109** | -0.109** | -0.109** |
| | (0.0476) | (0.0476) | (0.0478) | (0.0480) | (0.0477) |
| 1.presale | -0.224*** | -0.220*** | -0.218*** | -0.215*** | -0.217*** |
| | (0.0608) | (0.0608) | (0.0614) | (0.0616) | (0.0613) |
| 2.floor | 0.115** | 0.120** | 0.122** | 0.123** | 0.119** |
| | (0.0507) | (0.0505) | (0.0510) | (0.0512) | (0.0511) |
| 3.floor | 0.202*** | 0.206*** | 0.213*** | 0.209*** | 0.203*** |
| | (0.0497) | (0.0491) | (0.0500) | (0.0503) | (0.0501) |
| 4.floor | 0.116** | 0.125** | 0.131*** | 0.131*** | 0.124** |
| | (0.0498) | (0.0496) | (0.0501) | (0.0505) | (0.0502) |
| 5.floor | 0.127** | 0.125** | 0.130** | 0.128** | 0.126** |
| | (0.0535) | (0.0534) | (0.0540) | (0.0541) | (0.0539) |
| 6.floor | 0.0584 | 0.0768 | 0.0670 | 0.0639 | 0.0492 |
| | (0.0626) | (0.0615) | (0.0621) | (0.0625) | (0.0626) |

| | | | | | |
|---|---|---|---|---|---|
| 7.floor | 0.00265 | 0.0144 | 0.0175 | 0.0202 | 0.0154 |
| | (0.0805) | (0.0803) | (0.0806) | (0.0809) | (0.0805) |
| 9.floor | -0.189 | -0.186 | -0.183 | -0.181 | -0.183 |
| | (0.243) | (0.242) | (0.245) | (0.246) | (0.244) |
| 11.floor | -0.200 | -0.126 | -0.0603 | -0.0422 | -0.0582 |
| | (0.272) | (0.269) | (0.270) | (0.271) | (0.270) |
| 1.building_material | 0.248** | 0.292** | 0.280** | 0.285** | 0.275** |
| | (0.123) | (0.122) | (0.123) | (0.124) | (0.123) |
| 2.sale_quarter | 0.0221 | -0.186 | 0.0465 | 0.0466 | 0.0624 |
| | (0.0567) | (0.159) | (0.0444) | (0.0446) | (0.0444) |
| 3.sale_quarter | -0.0486 | -0.0174 | 0.0338 | 0.0536 | 0.0498 |
| | (0.0666) | (0.0492) | (0.0555) | (0.0528) | (0.0514) |
| 4.sale_quarter | -0.0272 | -0.0285 | 0.0661 | 0.0910* | 0.0819 |
| | (0.0693) | (0.0610) | (0.0578) | (0.0538) | (0.0527) |
| 2020.sale_year | -0.0955 | -0.0555 | -0.0127 | -0.00970 | 0.00597 |
| | (0.0658) | (0.0493) | (0.0536) | (0.0571) | (0.0570) |
| 2021.sale_year | -0.00953 | 0.0837 | 0.0878 | 0.121** | 0.128** |
| | (0.0876) | (0.0563) | (0.0574) | (0.0565) | (0.0566) |
| 2022.sale_year | 0.0989 | 0.160** | 0.254*** | 0.304*** | 0.320*** |
| | (0.111) | (0.0720) | (0.0603) | (0.0493) | (0.0457) |
| ln_airbnblistings | -0.285* | -0.186 | -0.161 | -0.149 | -0.161 |
| | (0.167) | (0.159) | (0.161) | (0.163) | (0.161) |
| Constant | 8.896*** | 8.383*** | 8.592*** | 8.747*** | 8.905*** |
| | (1.333) | (1.292) | (1.302) | (1.303) | (1.269) |
| Observations | 321 | 321 | 321 | 321 | 321 |
| Adjusted R-squared | 0.6919 | 0.6919 | 0.6851 | 0.6829 | 0.6854 |

Notes: Dependent variable is the natural log of transaction price. All variables of interest “ln_revpar_apt_type_ma3” take the three-month moving average of the RevPAR for each respective apartment type, defined by the number of bedrooms. The reference categories include: Building Period 1907-1945, presale equal to 0 means “No”, building material 0 equal to “other”, floor equal to 0, bedroom type – studio, sale quarter is 1, and sale year is 2019. All models include a constant term, and fixed effects for year and quarter. Standard errors in parentheses with ***, **, * indicating significance at 1%, 5%, and 10%, respectively.

Overall, the empirical exploration of RQ 3.1 sheds light on the intricate relationship between the RevPAR of each apartment type and the housing prices of each segment in central Sofia. The analysis reveals the dominant influence of studios' STR performance on the housing market, with the lagged studio RevPAR variable showing a positive and statistically significant relationship with its own housing segment, the 1-bedroom, and the 2-bedroom housing market. One plausible explanation of the cascading effect of the STR performance of studio units on the pricing of the 1-bedroom and 2-bedroom housing segments could be that indeed the increased attractiveness of smaller properties created by an influx of Airbnb demand influences some potential buyers to reevaluate their decision-making and consider the purchase of larger properties in the city center, while other purchasers are just willing to pay higher prices because of increased competition. What’s more, the significantly negative coefficient of the total supply of Airbnb listings in Model 2 suggests that an increase in the total STR supply decreases the studio RevPAR Airbnb effect, and by extension creates a downward pressure on the overall Airbnb effect across the housing market. Moreover, it can be stated that to some degree the studio and the 1-bedroom STR markets are substitutes for one another, as both have a positive relationship with the studio housing prices. Spillover effects for the RevPAR of the other segments are observed as well. Changes in the STR performance of one-bedroom and three-bedroom units influence values in other apartment-type segments. The three-bedroom residential segment is the only one seemingly not affected by the Airbnb effect in any form. The observed spillover effects further contribute to the complexity of the relationship between Airbnb and housing prices, indicating that changes in the performance of one housing segment may ripple across others. These findings open a gap for further research into the specific demand and supply-side Airbnb effects on the pricing of separate housing segments. Future studies can offer valuable, specific insights on different urban markets worldwide into exactly which segments contribute to the Airbnb effect leading to housing appreciation. It is also essential to acknowledge the limitations imposed by the dataset, particularly the scarcity of observations for studios and 3-bedroom units, and the lack of specific location data. More comprehensive data can provide an improved understanding of the housing submarkets' dynamics.

### 4.3 Is There a Difference of the Airbnb Effect Among Different Buyer Types?

In the context of Equation Model 2.2, Table 6 provides insights into the differentiation among buyer types regarding the influence of STR revenue on housing prices in Sofia's city center. For Model 1, the interaction term between buyer type (0 for investors, 1 for homebuyers) and the lagged revenue metric, ln_revpar_ma3, is statistically significant at the 5% level for homebuyers, with a coefficient of 0.501, while the effect for investors has the same significance but a lower coefficient of 0.435. Results indicate that the revenue performance of short-term rentals is positively associated with the purchase prices that both homeowners and investors pay, as the effect is slightly higher for homebuyers. The distinction in how Airbnb impacts property prices for homeowners versus investors might stem from varying priorities; homeowners could be more subjective when purchasing a property, while investors can leverage purchase deals and have a higher risk tolerance. They can acquire depreciated properties at discount prices and increase their value through renovation and short-term subletting for higher returns. Results are in line with the expectation that investors are driven by Airbnb's revenue performance when purchasing a property. Homeowners are even paying a higher premium for housing when demand for STR is increasing. Once more, dataset restrictions are recognized, and more extensive data can reveal different outcomes and shed more light on the relationship between buyer types.

TABLE 6

| | (1) Model Buyer Type |
|---|---|
| investors # $ln\_revpar_{ma3}$ | 0.435** |
| | (0.207) |
| homeowners # $ln\_revpar_{ma3}$ | 0.501** |
| | (0.193) |
| 1.buyer_type (0 = investors; 1 = homeowners) | -0.239 |
| | (0.406) |
| ln_aream2 | 0.704*** |
| | (0.0762) |
| 1946.constr_age_range | 0.124*** |
| | (0.0360) |
| 1985.constr_age_range | -0.0301 |
| | (0.0553) |
| 2011.constr_age_range | -0.129** |
| | (0.0532) |

| | |
|---|---|
| 1.presale | -0.191** |
| | (0.0875) |
| 1.building_material | 0.329** |
| | (0.134) |
| 2.floor | 0.104* |
| | (0.0564) |
| 3.floor | 0.147*** |
| | (0.0541) |
| 4.floor | 0.0952* |
| | (0.0546) |
| 5.floor | 0.0597 |
| | (0.0594) |
| 6.floor | -0.0101 |
| | (0.0679) |
| 7.floor | -0.0820 |
| | (0.0976) |
| 9.floor | -0.246 |
| | (0.234) |
| 11.floor | -0.116 |
| | (0.267) |
| 1.bedroom_type | 0.176** |
| | (0.0737) |
| 2.bedroom_type | 0.244*** |
| | (0.0922) |
| 3.bedroom_type | 0.139 |
| | (0.117) |
| ln_airbnblistings | -0.506** |
| | (0.236) |
| 2.sale_quarter | 0.0143 |
| | (0.0692) |
| 3.sale_quarter | -0.0302 |
| | (0.102) |
| 4.sale_quarter | -0.00822 |
| | (0.0993) |
| 2021.sale_year | 0.00748 |
| | (0.0726) |
| 2022.sale_year | 0.120 |
| | (0.0863) |
| Constant | 10.60*** |
| | (1.875) |
| Observations | 242 |
| Adj. R-squared | 0.6983 |

Notes: Dependent variable is the natural log of transaction price. The variable of interest is the interaction term between “ln_revpar”, which is the natural logarithm of the 3-month moving average of the market RevPAR, and the “buyer_type” dummy, where 0 equals investor and 1 is homeowner. The reference categories include: Building Period 1907-1945, presale equal to 0 means “No”, building material 0 equal to “other”, floor equal to 0, bedroom type – studio, sale quarter is 1, and sale year is 2019. All models include constant term, and fixed effects for year and quarter. Standard errors in parentheses with *** , **, * indicating significance at 1%, 5% and 10%, respectively.

### 4.4 Discussion

The intersection between the Airbnb market and housing markets unveils a controversial set of externalities that have been discussed in prior literature. Critics point to the fact that Airbnb fosters gentrification, which refers to the process of urban neighborhoods experiencing an inflow of wealthier residents, leading to the displacement of lower-income social groups by higher-income tourists (Cocola-Gant, 2019). In the case of STRs, existing criticism points to the notion that Airbnb fosters a form of gentrification unique to the tourism-driven influx of short-term travelers, distinguishing it from conventional urban gentrification (Lee, 2016). This transformation shifts the local community landscape without necessarily introducing permanent residents, altering urban landscapes.

The positive impact of externalities manifests through increased demand from the sharing economy, concentrating capital in tourist-centric areas, subsequently reflected in escalated housing prices (Wachsmuth and Weisler, 2018). However, residents experience various negative effects caused by Airbnb rentals and opt to move out, as this creates a self-reinforcing local community deterioration and displacement (Pinkster and Boterman, 2017; Gallagher, 2017; Gurran & Phibbs, 2017).

The study cannot exclude external impacts or distinguish between positive and negative externalities. The Airbnb effect in Sofia may have negative externalities that affect housing values, but they are not significant enough to outweigh the positive effects of the STR RevPAR alongside other beneficial externalities.

What is interesting to note in addition to the main finding is that the significance of the RevPAR coefficient is consistent with the explanation of a real option effect, which is discussed above in the theoretical section. The results are in line with the expectation from the real option theory because it is the lagged variable $RevPAR_{ma3}$ that has an impact on housing prices. One could suspect that market agents are aware of the STR market performance and use it as an option to postpone a sale and achieve a higher selling price later. However, results are only indicative, as no earlier literature has been found to support the statement, so further exploration of the real option theory and its relationship to the Airbnb effect is required.

It is also worth mentioning that this article examines a 4-year effect of Airbnb, and long-term consequences may vary. Along with market externalities, the housing market cycle plays a role in pricing. As demonstrated by Lin (1993) house prices tend to rise at the peak of a cycle, and then deflate in the following years, as this can alter the Airbnb effect.

## 5. CONCLUSION

This study set out to explore the relationship between Airbnb revenue and housing prices in the central region of Sofia, Bulgaria. By integrating theories, concepts, and empirical analyses, the three hypotheses are not rejected. The empirical analyses affirm some of the established findings so far and add new insights.

The research contributes to the current literature on the Airbnb effect by exploring a new variable of interest – the STR revenue performance metric, called the RevPAR. Incorporating the RevPAR as a main independent variable enables to conduct research that distinguishes between the supply-side and demand-side Airbnb effects on the housing prices in Sofia's city center, where the demand-side effect is expressed by the RevPAR. The main result of the paper exhibits a positive association between short-term rental revenue performance, measured by the RevPAR, and housing prices. The main model reveals a coefficient of 0.169 at a 5% level of significance for the three-month market moving average of RevPAR. Interestingly, excluding the major influence of the pandemic during 2020, the coefficient of the RevPAR almost triples to 0.478 ($p < 0.05$). This demonstrates an increasing Airbnb effect on housing prices during recent years in central Sofia. Also, unlike findings from studies in other cities, Sofia experiences a negative supply-side effect of Airbnb due to its surplus of vacant housing stock. Furthermore, the segmentation analysis conducted highlights nuanced cascading effects of the STR revenue by unit type across separate housing submarkets. Notably, the demand-side Airbnb effect on studios is the most expressed one, as it affects the housing prices for its own segment and spills over to the 1-bedroom and the 2-bedroom housing prices. The one-bedroom RevPAR also causes some cascading effects impacting the studios and the two-bedroom housing segments. The other specification analysis in section 4.3 finds that, in the city center, the increased demand due to the Airbnb effect affects homeowner purchasers more than investor buyers.

Future research can employ a similar approach to explore the STR relationship with the long-term rental market, along with the housing market prices. This could bring even more understanding of the Airbnb effect that can help urban planners and regulators mitigate its impact. In the case of Sofia, the aggressive demand for studios, and to some degree for 1-bedrooms, creates most of the pressure on the housing market. If regulators and urban planners aim to decrease the overall Airbnb effect in Sofia, they could think of strategic ways to incentivize the development, or the subletting of more studios and 1-bedrooms into the STR market, fostering a better balance among the STR, LTR, and the housing markets. Although findings for other cities show that an increase in STR supply is positively associated with house price appreciation, Sofia's unique urban setting reveals the need for further exploration of the Airbnb demand effect. It is plausible that the strong STR revenue performance due to high demand could be a more dominant factor for other cities as well in driving the Airbnb effect rather than the transitioning of units from the long-term rental market to the short-term rental market. Moreover, it could be that only one or two submarket segments are responsible for most of the Airbnb effect, and effective measures against it can be taken. Additionally, future studies could focus on the externalities created by the STR market. Understanding the effect of both negative and positive externalities can be valuable. In the inner-city of Sofia, the larger premium that homebuyers pay on housing due to the Airbnb effect when compared to investor purchasers may signal the presence of external factors such as gentrification influencing the housing market. In response to these findings, policymakers should consider policies safeguarding homeowner buyers. Some buyers unnecessarily face an additional investment value premium paid for properties due to the Airbnb effect. Preferential tax rates or subsidies for first-time homebuyers experiencing the Airbnb effect in Sofia can be applied. Enhancing affordability and accessibility can mitigate some of the adverse effects of rising property prices and promote socio-economic balance within urban neighborhoods. Lastly, the indication that the delayed effect of the moving average RevPAR variable affects housing prices also opens avenues for future research on the matter.

In conclusion, this research provides nuanced insights into the varying impacts of the Airbnb phenomenon. However, the findings are constrained by dataset limitations. More comprehensive and detailed datasets providing extensive information would allow for the isolation of location-fixed effects and the application of more specific time-fixed effects into the empirical models. This approach promises further robustness in results, facilitating even deeper exploration and understanding of the topic of interest.

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## APPENDIX

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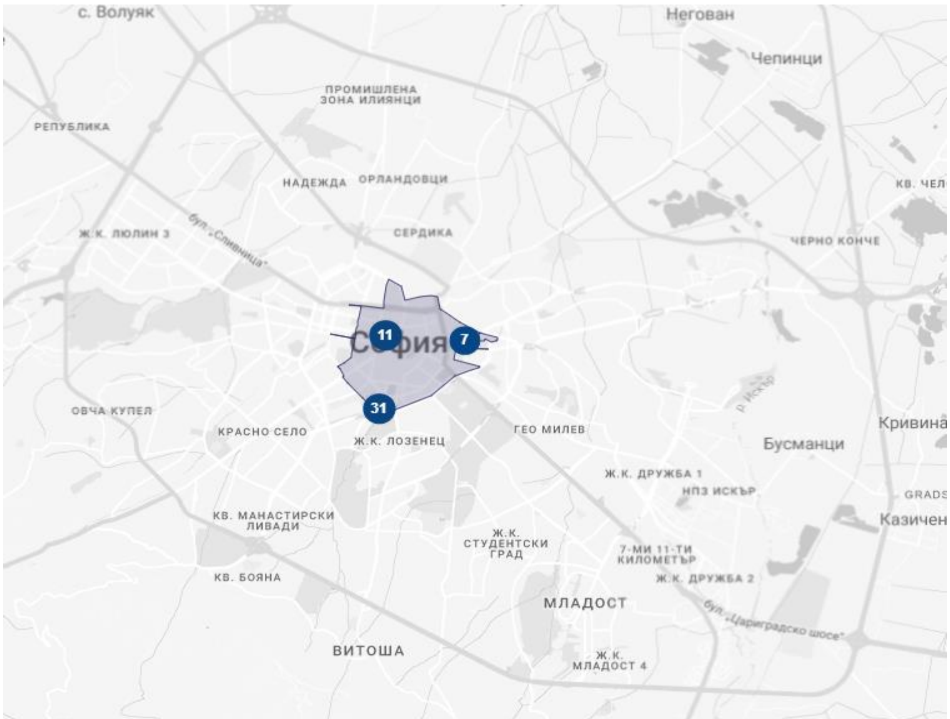
## FIGURES & TABLES

**Appendix 1A:** Vacant dwelling units in Bulgaria, 2021

| | Total dwellings | # of occupied dwellings | # Uninhabited or “vacant” dwellings | % Uninhabited or “vacant” dwellings |
|---|---|---|---|---|
| **Sofia Capital** | 755 889 | 526 519 | 229 370 | 30,34% |

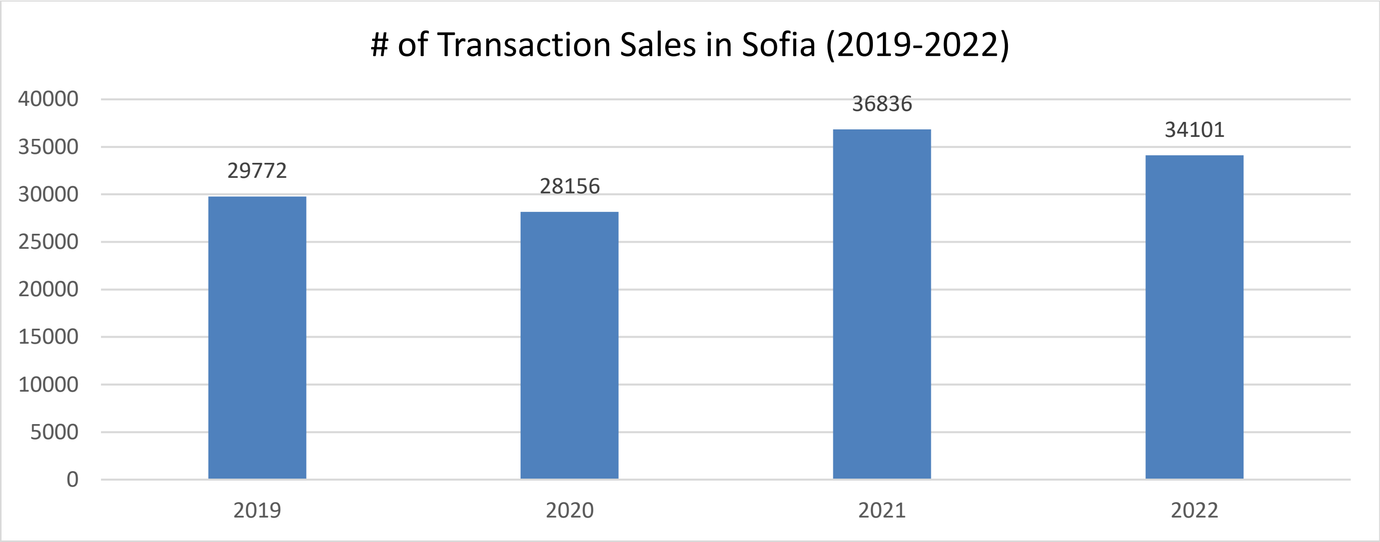
Source: 2021 Census, National Statistical Institute

**Appendix 1B: Inner-city area map**




Notes: The inner-city is defined by the blue shape on the map. It has an approximate area of 7 km squared.

**Appendix 1C: Number of Yearly Transaction Sales in Sofia (2019-2022)**




Notes: Based on data from the Register Agency Bulgaria (n.d.), Sofia, with a total area of 492 square kilometers, witnessed an average of 32,216 transactions per year between 2019 and 2022, translating to roughly 65.5 transactions per square kilometer annually. The research dataset comprises 321 observations for the same period, covering an area of 7 square kilometers, leading to an estimated average of approximately 11.5 transactions per square kilometer per year in the city center. This suggests a ratio of dataset transactions per $km^2$ and total sales transactions per $km^2$ of around 0.175%. Even with a reduced observation count of 242, lacking data for 2020 and requiring division by three, but not by four years, the ratio remains similar.

## Appendix 1D: Sales Count Per Month

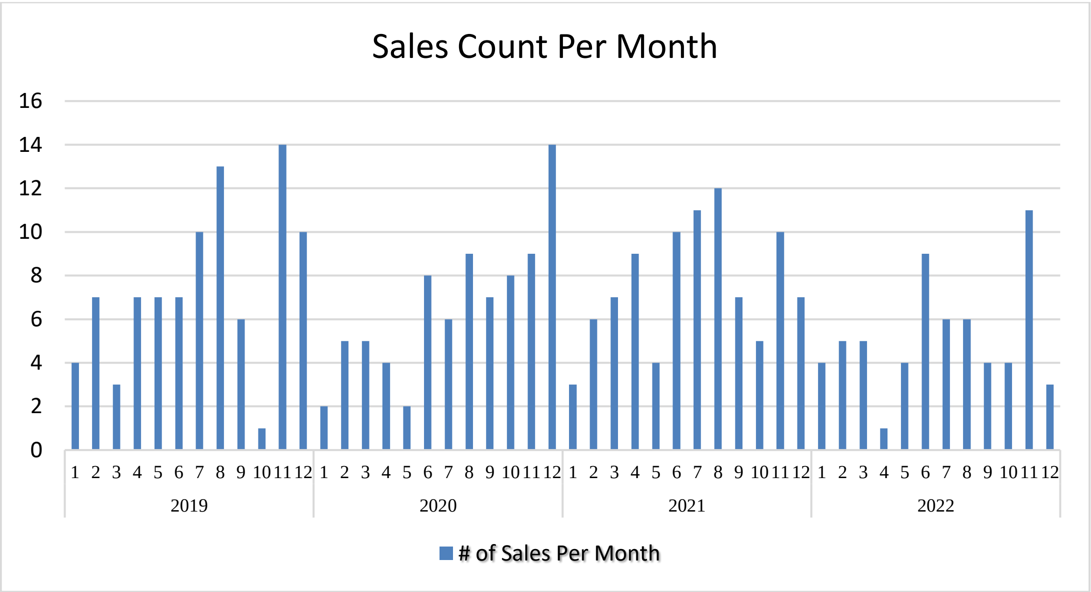


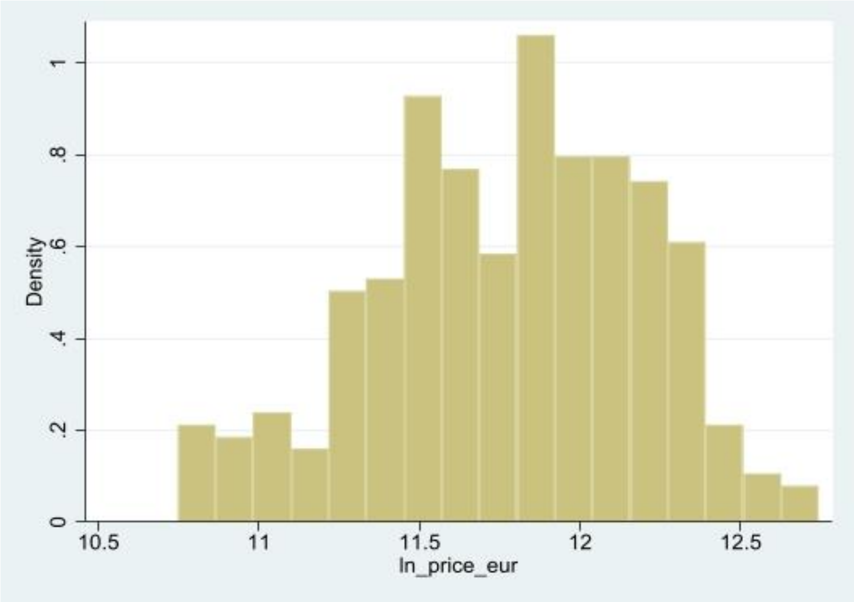

**Table 2: Variables Definition**

| Variables | Definition |
|---|---|
| price_eur | Price of the property sold in EUR |

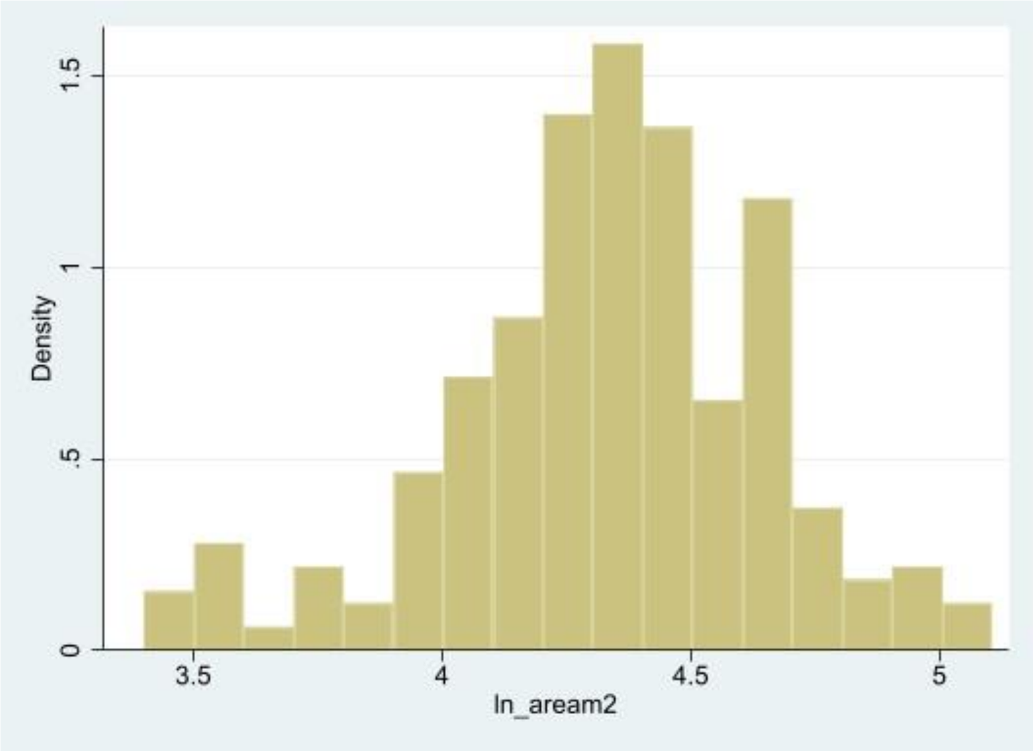
| | |
|---|---|
| pricem2 | Price per square meter in EUR |
| aream2 | Area of the property sold in square meters |
| sale_year | The corresponding year of the sale |
| sale_quarter | The corresponding quarter of the sale |
| building_age_range | Period of construction of the building |
| Presale | Dummy variable that indicates whether the apartment was sold before the completion of the construction (0=no; 1=yes) |
| Floor | The respective floor level |
| revpar_studio/1bd/2bd/3bd_t | The corresponding average aggregate RevPAR for the given bedroom type of the property sold in the respective month and year of the sale |
| revpar_studio/1bd/2bd/3bd_t_minus1/2/3 | The corresponding average aggregate RevPAR by bedroom type of the property sold one, two, or three months prior to the sale |
| revpar_mkt_t | The corresponding average overall market RevPAR in the corresponding month and year of the sale |
| revpar_mkt_t_minus1/revpar_mkt_t_minus2/revpar_mkt_t_minus3 | The corresponding average overall market RevPAR one, two or three months prior to the sale |
| Airbnblistings | Number of total homes in Sofia in the Airbnb platform for the given month and year t |
| buyer_type | Dummy variable that indicates the motivation of the buyer for the purchase, where 0 = investment purpose and 1 = living purpose |
| bedroom_count | Categorical variable for the type of the apartment, where 0 = studio, 1 = 1 bedroom; 2 = 2 bedroom; 3 = 3 bedroom |
| building_material | Indicates the construction material, where 1 = brick and 0 = other (e.g. wooden joinery, precast concrete) |

**Appendix 3: Natural Distribution of Dependent and Main Independent Variables**

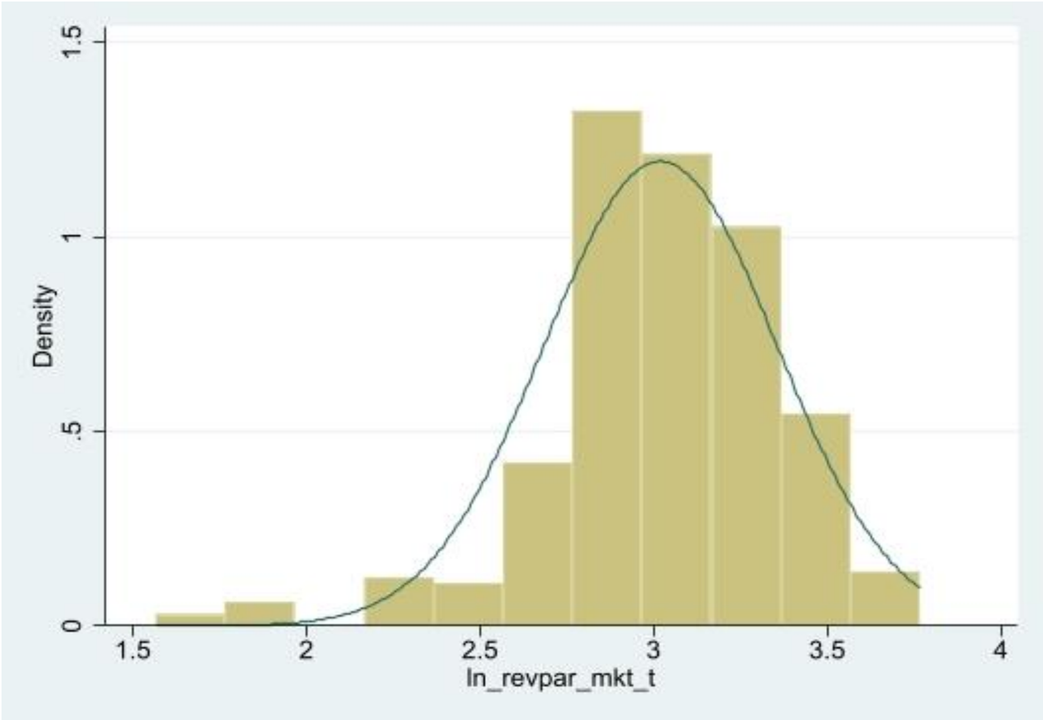
- Hist by sales price:



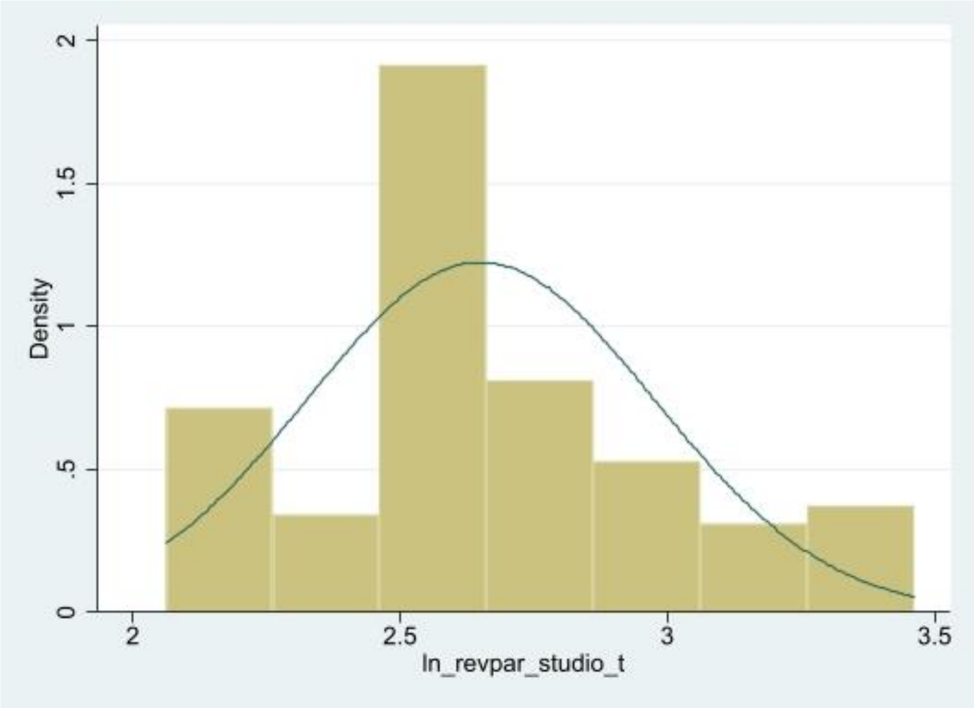

- Hist by aream2:



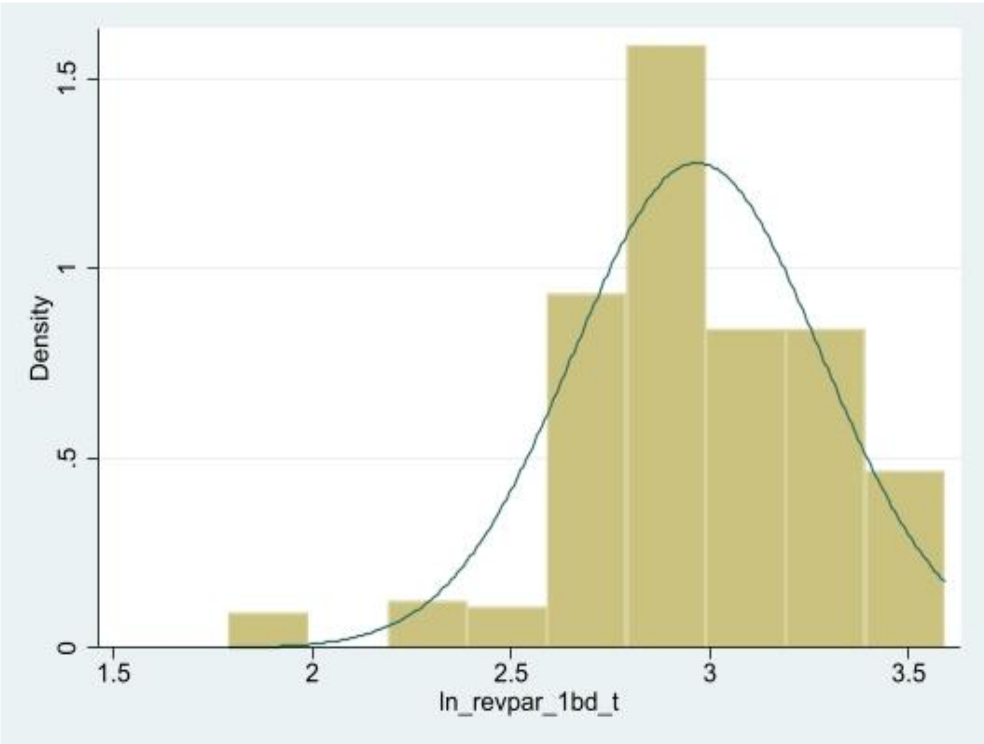

- Hist RevPAR market average aggregated monthly for 2019-2022:



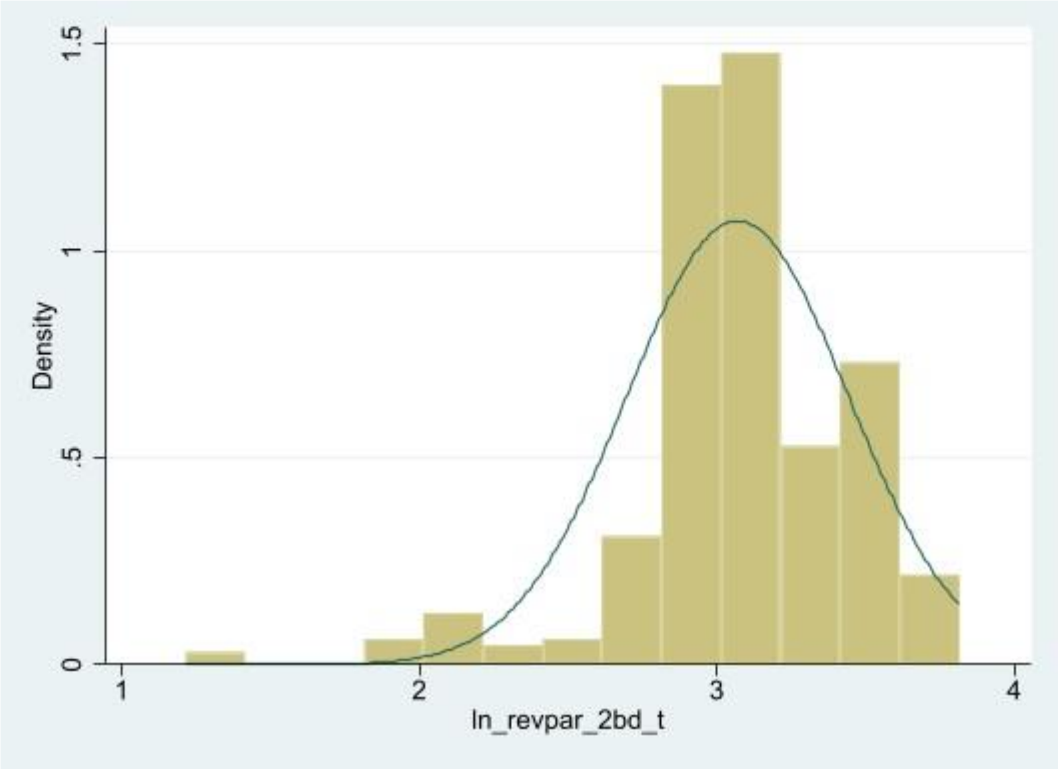

- Hist by RevPAR studio:



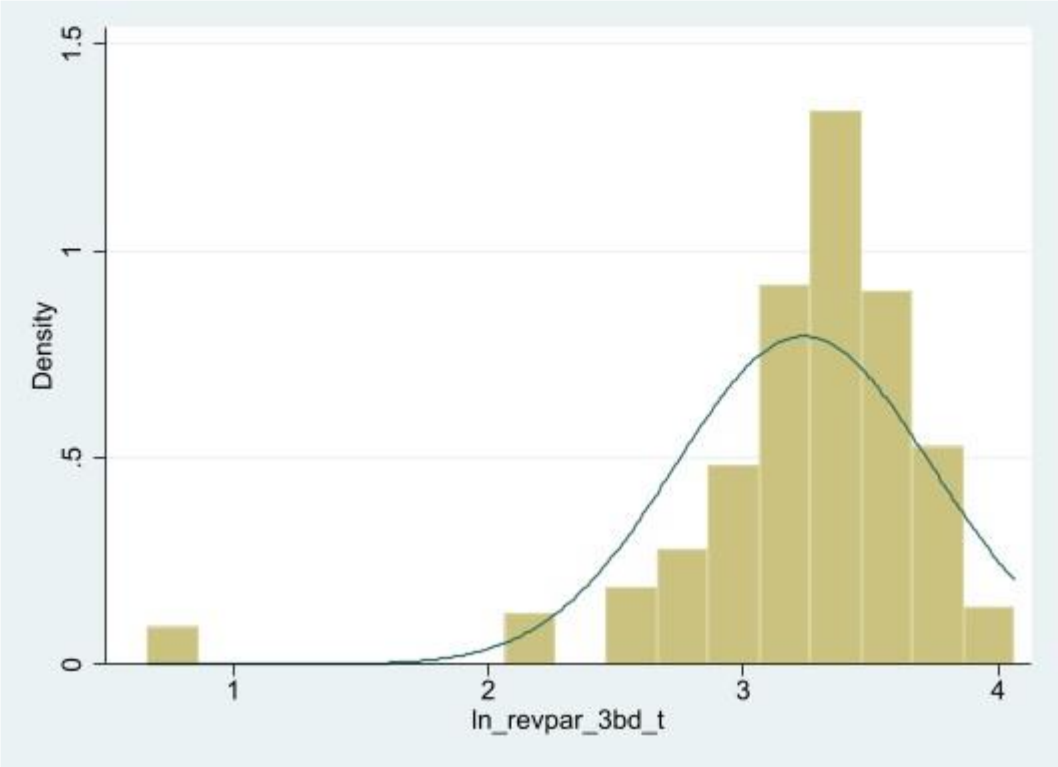

- Hist by RevPAR 1-bedroom:



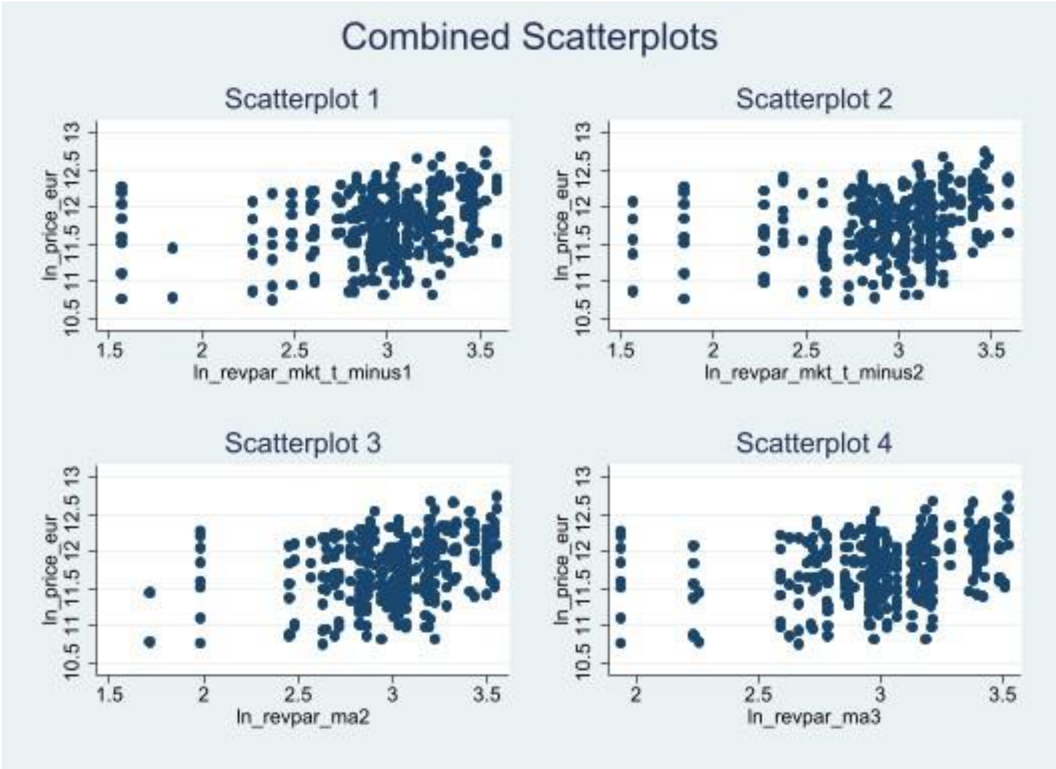
- Hist by RevPAR 2-bedroom:




- Hist by RevPAR 3-bedroom:



- Scatterplot ln_housing price & ln_RevPAR$_{mkt_t-1}$ / ln_RevPAR$_{mkt_t-2}$ / ln_RevPAR$_{ma2}$ / ln_RevPAR$_{ma3}$:




- Monthly RevPAR graph 2019-2022:

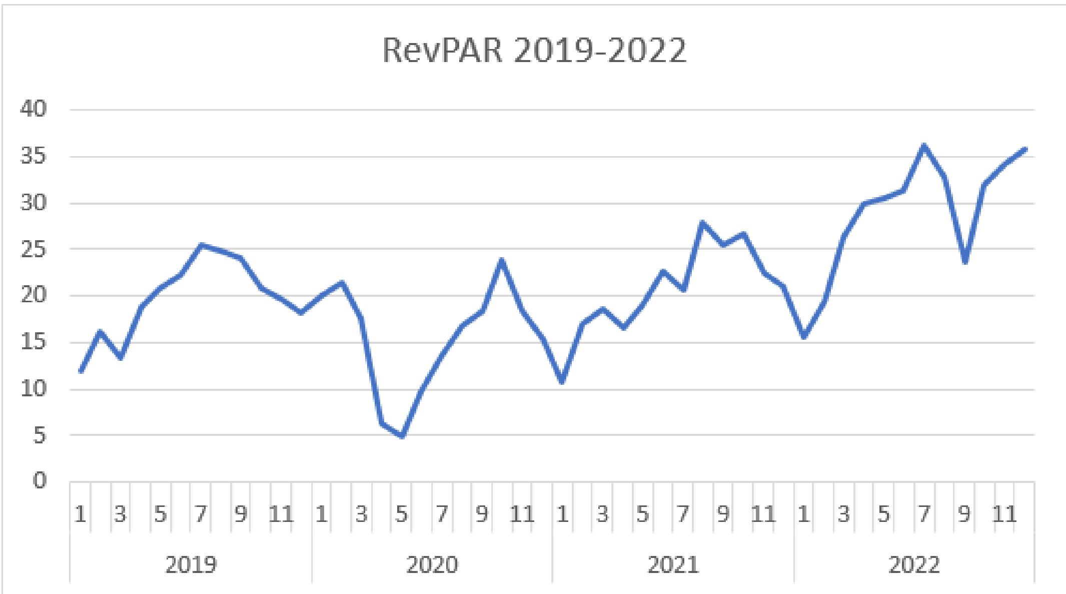


TABLE 3.1: ESTIMATION RESULTS FOR PRICE MODELS, OLS ESTIMATES

| | Model RevPAR t | Model RevPAR t-1 | Model RevPAR ma2 |
|---|---|---|---|
| ln_revpar_mkt_t | 0.159** | - | - |
| | (0.0654) | - | - |
| ln_revpar_mkt_t_minus1 | - | 0.0907* | - |
| | - | (0.0521) | - |
| ln_revpar_mkt_t_ma2 | - | - | 0.157** |
| | - | - | (0.0678) |
| ln_aream2 | 0.680*** | 0.687*** | 0.683*** |
| | (0.0681) | (0.0683) | (0.0681) |
| Building Period 1946-1984 | 0.103*** | 0.0998*** | 0.102*** |
| | (0.0336) | (0.0337) | (0.0336) |
| Building Period 1985-2011 | -0.100** | -0.0914* | -0.0942* |
| | (0.0505) | (0.0508) | (0.0506) |
| Building Period 2011-2023 | -0.119** | -0.113** | -0.117** |
| | (0.0475) | (0.0476) | (0.0475) |
| 1.presale | -0.207*** | -0.214*** | -0.209*** |
| | (0.0610) | (0.0611) | (0.0610) |
| 1.building_material | 0.288** | 0.287** | 0.285** |
| | (0.122) | (0.123) | (0.122) |
| 2.floor | 0.128** | 0.123** | 0.125** |
| | (0.0507) | (0.0510) | (0.0508) |
| 3.floor | 0.209*** | 0.205*** | 0.209*** |
| | (0.0493) | (0.0495) | (0.0493) |
| 4.floor | 0.132*** | 0.128** | 0.129** |
| | (0.0496) | (0.0499) | (0.0497) |
| 5.floor | 0.132** | 0.132** | 0.133** |
| | (0.0536) | (0.0540) | (0.0537) |
| 6.floor | 0.0696 | 0.0625 | 0.0645 |
| | (0.0615) | (0.0618) | (0.0615) |
| 7.floor | 0.0126 | 0.0167 | 0.0149 |
| | (0.0800) | (0.0804) | (0.0801) |
| 9.floor | -0.173 | -0.188 | -0.184 |
| | (0.243) | (0.244) | (0.243) |
| 11.floor | -0.0507 | -0.0547 | -0.0583 |
| | (0.269) | (0.270) | (0.269) |
| 1.bedroom | 0.158** | 0.167** | 0.160** |
| | (0.0659) | (0.0660) | (0.0659) |
| 2.bedrooms | 0.241*** | 0.244*** | 0.241*** |
| | (0.0812) | (0.0815) | (0.0812) |
| 3.bedrooms | 0.153 | 0.166 | 0.158 |
| | (0.108) | (0.108) | (0.108) |
| ln_airbnblistings | -0.314* | -0.156 | -0.214 |
| | (0.168) | (0.161) | (0.160) |
| 2.sale_quarter | 0.0543 | 0.0490 | 0.0480 |
| | (0.0439) | (0.0442) | (0.0440) |
| 3.sale_quarter | 0.0527 | 0.0476 | 0.0368 |

| | | | |
|---|---|---|---|
| | (0.0506) | (0.0531) | (0.0529) |
| 4.sale_quarter | 0.106** | 0.0866 | 0.0810 |
| | (0.0492) | (0.0538) | (0.0523) |
| 2020.sale_year | -0.0315 | -0.0170 | -0.0125 |
| | (0.0500) | (0.0532) | (0.0521) |
| 2021.sale_year | 0.0716 | 0.117** | 0.0986* |
| | (0.0583) | (0.0558) | (0.0560) |
| 2022.sale_year | 0.259*** | 0.306*** | 0.273*** |
| | (0.0551) | (0.0482) | (0.0525) |
| Constant | 9.992*** | 8.975*** | 9.244*** |
| | (1.254) | (1.257) | (1.232) |
| Observations | 321 | 321 | 321 |
| Adjusted R-squared | 0.6858 | 0.6858 | 0.6882 |

Notes: Dependent variable is log of transaction price. The reference categories include: Building Period 1907-1945, presale equal to 0 means "No", building material 0 equal to "other", floor equal to 0, bedroom type – studio, sale quarter is 1, and sale year is 2019. All models include constant term, and fixed effects for year and quarter. Standard errors in parentheses, coefficients with *** , **, * indicating significant at 1%, 5% and 10%, respectively.

TABLE 3.2 Root Mean Square Error (RMSE) Comparison of RevPARma2 and RevPARma3 Models

| | Model RevPAR ma2 | Model RevPAR ma3 |
|---|---|---|
| Root MSE | .23251 | **.23234** |

Notes: The table provides Root Mean Square Error (RMSE) values for both the RevPARma2 and RevPARma3 models. In this instance, the RevPARma3 model exhibits a slightly lower root MSE compared to the RevPARma2 model, suggesting marginally improved accuracy or predictive performance (Svetunkov and Petropoulos, 2017).

## Appendix 4: Regcheck Test for OLS Assumptions Violations

| **Regression assumptions:** | **Test:** | **We seek values** |
|---|---|---|
| 1) **no heterokedasticity problem** | **Breusch-Pagan hettest**<br>Chi2(1): 0.127<br>p-value: 0.721 | **> 0.05** |
| 2) **no multicollinearity problem** | **Variance inflation factor**<br>ln_revpar_ma3 : 2.82<br>5.floor : 2.82<br>6.floor : 1.57<br>7.floor : 1.48<br>9.floor : 2.18<br>11.floor : 1.64<br>1.building_material : 2.44<br>1.bedroom_type : 2.53<br>2.bedroom_type : 2.34<br>3.bedroom_type : 2.10<br>ln_airbnblistings : 1.67<br>ln_aream2 : 1.37<br>2.sale_quarter : 1.09<br>3.sale_quarter : 1.33<br>4.sale_quarter : 1.37<br>2020.sale_year : 6.39<br>2021.sale_year : 9.45<br>2022.sale_year : 4.03<br>1946.constr_age_range : 3.55<br>1985.constr_age_range : 2.01<br>2011.constr_age_range : 3.60<br>1.presale : 3.81<br>2.floor : 3.31<br>3.floor : 3.73<br>4.floor : 2.36 | **< 5.00** |

| | | |
|---|---|---|
| 3) residuals are normally distributed | Shapiro-Wilk W normality test<br>z: 0.664<br>p-value: 0.253 | > 0.01 |
| 4) no specification problem | Linktest<br>t: 0.890<br>p-value: 0.374 | > 0.05 |
| 5) appropriate functional form | Test for appropriate functional form<br>F(3,292):1.155<br>p-value: 0.327 | > 0.05 |

[i] Due to Airbnb's widespread use, this paper uses the company's brand name as a synonym for all the rest short-term vacation rental marketplaces and platforms.

[ii] In this paper, the term "short-term rentals" is used to encompass both short-term and mid-term rentals. These rentals refer to accommodation options that are available for reservations ranging from one day up to a few months. They serve diverse user groups such as tourists, business travelers, and digital nomads. The common characteristic among these groups is their perception of the accommodation as temporary, indicating that they do not have the intention to establish long-term residency at the rental property. It is worth noting that Airbnb and other online platforms cater to all these different user types mentioned above.

[iii] RevPAR is a key performance metric used in the hospitality industry to assess the financial performance of a hotel or accommodation establishment. In the context of short-term rentals, the room is equivalent to one unit listing, and the monthly RevPAR is calculated as follows:

RevPAR = Average Daily Room Rate * Monthly Occupancy Room Rate;

[iv] Keywords such as "housing prices", "Airbnb effect", "short-term rentals", "sharing accommodation", "sharing economy", "hedonic pricing housing", "hedonic price attributes", "housing prices and rent", "property prices", "Airbnb gentrification", "tourist gentrification", "housing spillover effects", "property submarkets spillover effects", "real-estate cycle", "real option theory", "real options and housing prices", " Simple Moving Average", "Simple Moving Averages in regression models" were used in searches across various academic search engines including RUG SmartCat, JSTOR, University of Groningen and University of Amsterdam repositories, Google Scholar, SSRN, Springer, and EconPapers.