Impact of Urban Green and Blue Spaces on Gentrification in Vienna

By

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Author’s declaration

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Abstract

Urban green and blue spaces (UGBS) are getting popular in urban planning all around, including Vienna, the Austrian capital. Their benefits are not only limited to environmental and biodiversity impacts, but they also improve people's health and well being. However, those urban green and blue spaces can cause rising property values, and contribute to exclusion, marginalization and displacement of lower-income people, a concept defined as green gentrification. Although Vienna is considered as a city with high living standards via its distinctive social housing mechanism, social segregation through urban green and blue spaces can still exist, requiring an investigation. By using Airbnb data as a noisy proxy for real estate markets, and social status index, the impact of UGBS and social housing examined by using Ordinary Least Square. Even though the results suggested that proximity to UGBS did not significantly influence Airbnb prices, the type of UGBS has a statistically significant impact, signaling heterogeneous preferences of short-term visitors and residents. Moreover, it is found that there is positive correlation between the share of green areas and social status, indicating that people with higher socioeconomic levels tend to habit in greener neighborhoods, while this does not hold for blue areas for Vienna. The share of social housing was positively associated with both income and social status, proving the inclusive social housing model of Vienna and its possibility to mitigate some of the exclusionary dynamics of green gentrification.

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Introduction

Urban green and blue spaces (UGBS) are increasingly prioritized in city planning for their environmental and health benefits, but their development might bring unintended social consequences (Kronenberg et al., 2021). In Vienna, as in many global cities, investments in parks, waterfronts, and other natural amenities can lead to rising property values and the displacement of lower-income residents. By examining the spatial distribution of them, this thesis can provide insights for urban planners and policymakers seeking to balance ecological goals with social equity. It supports the creation of more inclusive strategies, such as rent regulation and targeted affordable housing measures, to ensure that the benefits of urban greening are shared by all residents, not just by the wealthy.

Although the definition of urban green and blue spaces can vary, most generically, they are natural areas that provide different social, environmental, and economic benefits in an urban context (Tate et al., 2024; McCord et al., 2024). Another concept that is widely associated with UGBS is green gentrification, which refers to the displacement of lower-income residents as a result of rising property values following the creation or amelioration of urban green or blue spaces. Green gentrification throughout this study is used to refer to the displacement of communities due to the development of both green and blue spaces. Even though the literature is mostly focused on the development of green spaces in this context, as different sources provide evidence, blue spaces might have a similar impact as well (Bockarjova et al., 2020; McCord et al., 2024). Displacement due to either green or blue gentrification affects both renters and homeowners participating in the real estate market (Bockarjova et al., 2020). Although UGBS development is not necessarily the root cause of affordability issues, it can intensify them by making neighborhoods more attractive and expensive.

As the city of Vienna is recognized with high living standards (The Economist Intelligence Unit, 2024; The Guardian, 2023; The New York Times, 2023) mostly through affordable housing provided by social housing policies (Kadi, 2025), it provides a unique opportunity to study green gentrification and the intersection of social and economic consequences. The social housing policy of Vienna distinguishes itself from many other cities for several reasons. First, it is considered highly decommodified, meaning that housing is seen mostly as a basic need, instead of a profit-motivated market element (Kadi, 2025). Second, in terms of size, all types of social housing were approximately 43% of all houses in 2020, demonstrating stability unlike the erosion of social housing policies in other European countries happening since the 1990s (Kadi and Lilius, 2024). Thus, it allows one to study whether, and to what extent, green gentrification occurs in a context where strong public housing systems exist while the city is aware of climate challenges (Vienna Municipal Administration, 2022).

Additionally, in Vienna, rising socio-spatial inequality is linked to uneven development across districts, with lower-status areas falling behind, which also affects access to essential infrastructure, as higher socio-economic status is associated with better access to services like healthcare and education (Riepl et al., 2025). As Neier (2023) explains, socio-spatial segregation describes the spatial separation of different groups, contributing to environmental and socioeconomic inequalities, such as unequal access to green spaces and the spatial concentration of disadvantaged groups. Hence, this thesis aims to shed light on the effect of UGBS on the socioeconomic level as well.

Although many other cities were examined in the green gentrification context with a focus on UGBS, housing prices, and socioeconomic level (Anguelovski et al., 2022; Bockarjova et al., 2020), the previous literature was concerned with exploring the individual effects of those variables separately. On the contrary, this thesis seeks to address and fill the gap in the literature by establishing a link between those variables. Due to the limited availability of data for Vienna, which is one of the reasons of the gap in the literature, I used Airbnb data as a proxy for real estate market prices while analyzing the impact of UGBS. Another two aspects of this thesis are the association of UGBS with socioeconomic status (using a census-based social status index) and the role of social housing policy in socio-spatial segregation. Those analyses are done by using Ordinary Least Squares.

The preview of results suggests that proximity to UGBS does not have a significant effect on explaining the variation in Airbnb prices in Vienna, indicating that short-term visitors may not value closeness to these amenities. However, the type of UGBS shows a small but significant impact, pointing to varying preferences based on the purpose of the visit. A second important result is the significant positive correlation between the share of green areas and social status index, suggesting that people with higher socioeconomic levels tend to habit in greener neighborhoods, while blue areas show a negative correlation. Lastly, the share of municipal estate housing negatively explains some part of the variation in income and social status, implying social housing is not only for marginalized groups and more inclusive (Macháč et al., 2022; Marquardt and Glaser, 2023).

The rest of this thesis is organized as follows. The next chapter discusses how this study fits into the recent literature about urban green and blue spaces and gentrification in the literature. Chapter 2 presents the data sets used for analysis and the methodology applied. Chapter 3 provides the results of the study with descriptive statistics and regression tables while Chapter 4 discusses the meaning of results with possible underlying meanings.

1 Literature Review

This chapter provides an overview of previous studies related to urban green and blue spaces (UGBS), housing markets, and socio-spatial inequality. It outlines the benefits and externalities of UGBS while focusing on how these spaces can influence desirability and property values. It also reviews the concept of green gentrification and the mechanisms that lead to displacement. Finally, it discusses Vienna's unique urban and housing context, focusing on its social housing policies, to situate this study within the broader academic and policy debate. Moreover, past studies on Airbnb and its possible application in gentrification studies are explained as well, since it takes part in my methodology.

Existing literature has investigated different aspects of urban green and blue spaces such as their ecological benefits (Žuvela-Aloise et al., 2016), their impact on resilience (Gorgol, 2024; Anguelovski et al., 2022), social cohesion (Saporito and Casey, 2015) for positive impacts, gentrification (Anguelovski et al., 2018 and distributional inequality (Wimmer et al., 2023) among the negative impacts. Reducing urban heat island effect (Žuvela-Aloise et al., 2016), and contributing to urban biodiversity (Palliwoda and Priess, 2021) are among ecological and health benefits.

By applying hedonic pricing, the method that allows to distinguish the impact of different (dis)amenities on real estate (Bockarjova et al., 2020), previous literature has looked at the impact of UGBS on property prices. Generally, as the distance from nature to properties decreases, there is an increase in property prices (Bockarjova et al., 2020). According to different empirical studies (Bockarjova et al., 2020; McCord et al., 2024), this relationship between proximity to nature and property prices includes a premium where for properties closer to nature effect is larger compared to the ones that are further away. However, since not every green and blue space has the same features, their impact on property prices varies as well (McCord et al., 2024).

These variations of UGBS include their type (e.g., park, cemetery, hunting area for green spaces, and river, pond, coastline for blue spaces), the size, and the amenities they offer (restroom, kindergarten, sports facilities) among other features (Macháč et al., 2022; McCord et al., 2024; Bockarjova et al., 2020). Furthermore, the heterogeneity in the real estate market (both for renters and homeowners) about UGBS is not only due to their features, but also the demographic attributes of people as well (Macháč et al., 2022). For instance, as Alves et al. (2008) shows in their study on the preferences of elderly people in Britain, key concerns were dog fouling, vandalism, presence of trees, and amenities, while water features and distance mattered less.

Along with the economic and environmental benefits, urban green and blue spaces have social consequences as well. Contrary to their advantages, green spaces can paradoxically become 'GreenLULUs' (Locally Unwanted Land Uses). As Anguelovski et al. (2018) explain, locally unwanted lands describes traditionally undesired places, usually in neighborhoods where marginalized communities live. GreenLULUs, on the other hand, does not need to be undesired places, but instead, places that were created as public goods causing exclusion and polarization, becoming unwanted for marginalized communities. Hence, green gentrification and GreenLULUs happen along with each other. Although they are quite similar concepts, one should note that they are not the same, but instead Green LULUs concentrate more on social and racial aspect of green developments (Barcelona Lab for Urban Environmental Justice and Sustainability (BCNUEJ), n.d.). The mechanism of green gentrification can be describes as when particularly new green or blue infrastructure improves an area's attractiveness, leads to increased property values, ultimately forcing low-socioeconomic level people and marginalized communities to move out (Anguelovski et al., 2022; Anguelovski et al., 2018) over time (Kadi and Matznetter, 2022).

Gentrification does not have to be limited to horizontal space, but it can also take place as urban micro-segregation through vertical cities (Maloutas, 2024). Vertical segregation investigates how the social status of people changes within residential buildings (Maloutas and Karadimitriou, 2022) across different floors. The position of socio-economically powerful people in this vertical hierarchy of residential buildings can change depending on the existence of lifts, as Maloutas and Karadimitriou (2022) explain. It can happen dramatically by 'luxified skies' for wealthy people living in exclusive skyscrapers, like in New York, or in fenced verticality in regions where armed conflicts are taking place, like Beirut.

Social housing policies on the other hand can be a tool to prevent gentrification or micro-segregation. Vienna's social housing policy is characterized by a continuous and long-term state participation in the housing market, aiming to maintain a partly decommodified sector to secure the provision of affordable housing after the Second World War (Marquardt and Glaser, 2023). This policy is built on the assumption that housing needs cannot be met by markets alone and state intervention is needed to ensure affordable, high-quality housing. While social housing is used as an umbrella term (Kadi and Lilius, 2024), Vienna's social housing system includes three main types: i) municipal estates managed by the city, which has remained stable in terms of overall housing stock since the 1990s; ii) housing by Limited-Profit Housing Associations (LPHAs), which follow cost-rent principles and have been steadily expanding; and iii) subsidized private providers, which must follow similar regulations during the amortization period. Together, municipal and LPHA housing make up nearly half of Vienna's housing stock units (Kadi and Lilius, 2024; Marquardt and Glaser, 2023; City of Vienna – Wiener Wohnen, 2021). Additionally, recently SMART flats program, which offers compact, low-cost units with higher subsidies has been introduced to promote affordability and social mix within new developments (Marquardt and Glaser, 2023; City of Vienna – Wiener Wohnen, 2021). It should be noted that, as Novy et al. (2024) argue, through time, the housing policy of Vienna has weakened tenant protections and increased the power of the private actors, whether they are single-person landlords or institutional investors, however it is still considered as successful (Marquardt and Glaser, 2023).

As Marquardt and Glaser (2023) point out, the eligibility criteria for social housing in Vienna are comparatively more flexible than in some other European cities (e.g., Berlin). In addition to basic requirements such as age and minimum years of living in Austria, among others, the main requirement is an income threshold. The maximum of this threshold is considered relatively high and incorporates middle-income earners in addition to low-income earners to the system. The aim here is to allow not only marginalized people to stay in social housing but to ensure affordable housing for the majority, and hinder further alienation of people who stay in social housing units.

Finally I inquired previous literature on using Airbnb data in gentrification context, and its possible implications. Airbnb, a peer-to-peer marketplace for short-term rentals founded in

2008, allows homeowners to share their accommodation either as a single room or as an entire unit (Barron et al., 2018; Wyman et al., 2022). In the absence of long-term rental or real estate market data, Airbnb listings can serve as a noisy but useful proxy for capturing spatial and amenity-driven variations in housing demand—an approach that aligns with literature, referred to as ”nowcasting gentrification” (Glaeser et al., 2018; Jain et al., 2021). The granularity of Airbnb data and its nature as an ”early warning system” for gentrification are the benefits of using it when there is a lack of real estate data (Poorthuis et al., 2022). Not only Airbnb data but these types of platforms are seen as early warning systems for gentrification because of their possibility of reflecting changes in urban patterns and thus, signaling broader alteration in the urban fabric (Glaeser et al., 2018).

Despite the benefits of using Airbnb data, there is another side of the coin. As Reichle et al. (2023) argue, Airbnb data may underestimate the actual supply of shared housing due to the platform’s reliance on reviews for active properties, while it can also overestimate by including traditional tourist accommodations (e.g. hostels) and private rentals on the platform. Additionally, Jain et al. (2021) claim that analyses based solely on Airbnb users might provide skewed results since users of the platform are mostly educated, younger, and commonly wealthier people. This skewness is aligned with gentrification patterns, as those demographic groups are the ”in-movers” in the gentrification process. However, this skewness might cause potential biases, leading under or overestimation of gentrification in different districts.

2 Materials and Methods

2.1 Data

The main purpose of this study is to investigate the impact of urban green and blue spaces on property prices with a hedonic pricing method for Vienna. As a result, it required multiple sources. Additionally, to understand not only the effects of UGBS on property prices but also their connection to gentrification—specifically green gentrification—this thesis closely follows the recent study by Riepl et al. (2025). All used data sets are explained below, under their thematic divisions which are: i) city-scale data sets, ii) urban green and blue spaces datasets, iii) residential buildings, and finally iv) socioeconomic variables. In total, eight different data sets are used, all for the administrative boundaries of the city of Vienna.

2.1.1 City Scale Datasets

City-scale data sets allow to define the boundaries of the city and its districts. Austria has 9 states (Bundesländer), which one of them is Vienna, by itself as a city and a state. Vienna has 23 districts (Bezirke) in total, and they contain 250 census districts (Zählbezirke). Those data sets are found through Austria's data portal (City of Vienna, n.d.).

The city data is used to limit the study to the administrative boundaries of Vienna. The district data allows for indicating the boundaries of municipalities and also to assign other data sets (different socioeconomic variables) to their right geospatial coordinates. The district data contains the district code (BEZNR) of each, their name, and their area. Furthermore, the purpose of finding the census district boundaries data is to determine the boundaries of them correctly since socioeconomic variables were obtained in this scale. Census districts data is obtained by using Austria's data portal. It contains the district information that one census district lies within, its district and census district code(ZBEZ), and its area.

2.1.2 Urban green and blue spaces

The urban green spaces data was taken from Riepl et al. (2025), who used the data of the City of Vienna. The study included parks, gardens, green spaces, and forests as part of urban nature with their areas, circumference, name (such as Währinger Park), geometry, and location. The data set contains in total of 1936 urban green spaces. In total, these green areas are approximately 178 km^2, however, when this is limited to the parts that lie within the city boundary determined by census districts, it is around 127 km^2. Moreover, green spaces are divided into three categories: Limited traditional recreational purpose landscapes (L), restricted recreational urban greeneries (U), and public recreational areas (R). Limited traditional recreational landscapes contain cemeteries, sports fields, and transitional green areas, public recreational areas represent green areas fully designed for recreational purposes like Burggarten and Augarten, and restricted recreational urban greeneries include greeneries that has limited usability or restricted access large green spaces, such as vineyards and forestry close to the borders of the city.

Since urban nature consists of greeneries, but also blue spaces, which might have an impact on property prices (either rental or for sale), I included blue spaces as well. Although greeneries and blue spaces might coincide, this may not necessarily be the case. Thus blue spaces collected separately. I gathered urban blue space data from OpenStreetMap (n.d.) by querying features associated with water-related land use and hydrography. Specifically, I chose elements tagged as water and wetland from the natural category; river and canal among waterways; and pond, lake, reservoir, basin, and fish-pond from the water category. This classification captures a broad spectrum of both natural and anthropogenic aquatic environments relevant for assessing the spatial distribution of urban blue areas in Vienna. After filtering the blue spaces for those queries, 1014 different blue spaces are found in total. This combined geospatial data aided in mapping the urban nature within the boundaries of the city of Vienna for all 23 districts of the city, not only for green spaces but also for blue spaces as well.

Data provides blue spaces not only as areas (i.e. polygons and multi-polygons for their geometry), but also lines for canals, streams, and waterways, which needed to be addressed to ease of use. Initially, there were 939 blue areas and 72 blue lines: 40 canals and 32 rivers. The data does not contain much detail about their width. I buffered those lines in order to calculate the total areas of blue spaces. Although the average width indicated for rivers is 15 meters, and the maximum estimated width a river can be is 24 meters, I chose 10 meters as the buffering width. Choosing below the mean level for buffering is conservative, but it was safer to proceed as such for buffered spaces not to overlap. Even though this is done to ease analysis, its implications should be acknowledged. This arbitrary buffering caused an overestimation for some blue ’lines’ and an underestimation for others. The underestimated lines are all rivers, whereas it is not possible to say anything about canals since there is no information about their widths.

2.1.3 Residential Buildings

Apartments’ Prices and Features:

Statistics Austria made average property prices available for every state (Bundesländer) of Austria on an annual basis, including Vienna. This data is at district scale (Bezirke) from 2015 to 2023 (Statistik Austria, n.d.) enabling finer-scale correlation analysis with Airbnb data, which will be explained next, that is more granular. According to Statistics Austria, this data is based on purchases by private owners of houses, flats, and land (Statistik Austria, 2023). Prices are expressed per square meter, referring to indoor living space for houses and apartments, and to land area for plots. I chose to use solely apartment prices to not complicate the analysis with different types of properties, since it would have required more detailed data to control the impact of the types of properties on prices. This was done also because Airbnb data mostly contains flats, not other types. By choosing only apartments, I was also able to control their characteristics that might have an impact on property prices besides UGBS.

These different characteristics of properties include heating type and property ownership type (whether it belongs to a non-profit or private). This data is in census district (Zählbezirke) scale for Vienna. This data provided a larger sample since there are 250 census districts but 23 districts in Vienna and aid to differentiate the impact of UGBS from different attributes of properties. However, due to the absence of publicly available price data in the census or smaller scale, I used Airbnb prices as a proxy.

Airbnb Data:

The Airbnb dataset is sourced from Inside Airbnb (n.d.) and comprises 13,790 listings scraped on March 5, 2025, covering 48 distinct property types. I limited my analysis by including only the listings that include “Entire” in their property type, as they are more comparable to long-term rental units compared to shared-room Airbnb listings. This filtered subset forms the basis for further grouping, which was done to be able to use dummies to control the effect of property type characteristics' on Airbnb prices. Specifically, I grouped the subset into 3 categories: 'Entire Apartment', 'Entire House' (for stand-alone properties), and 'Other' for less frequent or ambiguous entries.

Due to the potential seasonality in Airbnb pricing — unlike the relatively stable nature of long-term rentals — three additional snapshots of listings were incorporated (scraped on June 15, September 11, and December 12, 2024). This allowed me to compute a 9-month average price, limited to properties that were continuously active during this period (8439 properties), thereby smoothing out short-term fluctuations. Similarly, average review scores over the same period were calculated, as guest feedback could influence per-night prices. Finally, using the latitude and longitude provided for each listing, all Airbnb units were geolocated within Vienna.

Before moving on, it is necessary to indicate the limitations of using the Airbnb data set instead of the long-term rental market or residential house prices. First, short-term and long-term rentals can have different pricing mechanisms due to people's different preferences in choosing those two different types of accommodation, and the intention of homeowners to lease their property as a short or long-term rental (Krause and Aschwanden, 2020). Second, as Wyman et al. (2022) point out, the increase in the number of short-term rentals may have diverse consequences on local residents, namely, a rise in the cost of living and displacement due to properties shifting from long-term rental to short-term Airbnb units. Finally, since gentrification is a concept related to permanent residency, one needs long-term rental data. Also, Airbnb data may overlook social dimensions that are more readily captured through long-term rental or residential housing market data that the former might have missed(Wyman et al., 2022). However, after acknowledging all these downsides, I used the Airbnb data set and complemented it with others for social dimensions which the former might have missed out.

Social Housing:

As explained in the Literature Review, the social housing system is an important phenomenon to consider in Vienna. Since they work as a type of rent control mechanism, their existence should be included in the methodology as well to control their effect on green gentrification. For this purpose, I gathered the municipal estate information by using Stadt Wien's search engine for municipal estates (Wiener Wohnen, n.d.-b). This data contains the name of the building, its address, and how many flats exist in that building or municipal estate unit.

There are 1636 buildings as municipal estates in Vienna, fully owned and controlled by the city of Vienna. Through their addresses, it is possible to locate them. There are no municipal estates in every census district, but 208 out of 250 contain at least one municipal estate within their boundaries, and those municipal estates are not equally distributed across census districts. Also, not every one of them has flats for people to accommodate. Some of the previously built estates turned into youth centers or laundry houses (Wiener Wohnen, n.d.-a). There are 11 estates without anyone living, resulting in the rest 1625 having at least one flat for living purposes. In total, these 1625 municipal estate buildings have 210,984 flats.

The minimum number of municipal estate buildings in any district (excluding those with zero) is found in District 0101, with just one building, while District 1505 has the maximum, totaling 31 municipal estate buildings. In terms of flat count, district 0101 again has the lowest number of municipal flats (18), whereas district 2105 has the highest, with 5,850.

2.1.4 Socioeconomic variables

The socioeconomic indicators were gathered to associate property prices with gentrification, all in census district scale (Riepl et al., 2025). This scale enables comparison of closer areas that might have different attributes within the same districts.

The socioeconomic variables are average income, university graduate share, unemployment rate, and social benefits recipient share, all for census districts of Vienna (Riepl et al., 2025). This data is gathered through the City of Vienna and Statistics Austria. Because there are 4 census districts with zero or very small numbers of inhabitants, the socioeconomic variable data set is finalized for 246 census districts. Income data is derived from the "Integrated Wage and Income Tax Statistics," which includes taxable earnings of employees, self-employed individuals, and pensioners while accounting for transfer payments such as unemployment benefits and childcare allowance. This ensures a detailed overview of income distribution and taxation for the reference year. The rates of social benefit recipients, unemployment, and university graduates are reported at the census district level for the year 2023, while average income data corresponds to the year 2020. All of them are standardized where above 0 means being higher than the city average. This goes the other way around as well with values below zero (Riepl et al., 2025).

Riepl et al. (2025) also calculated a social status index (SSI) following the method of Kadi et al. (2022). This index is based on a weighted average of those four standardized socioeconomic indicators explained above. Income and education each contribute one-third, while unemployment and social benefits are combined into a single measure of labor market exclusion due to their interdependence, making up the final third. The mechanism of this index works as after standardization of the values obtained, if an SSI score is above 0, it means that for that specific census district, the socioeconomic status is higher than the city average, similar to other social and economic variables (Riepl et al., 2025).

2.2 Methodology

The following hypotheses were tested in this study:

H1: The existence of urban green and blue spaces increases the property value nearby, correlating negatively with distance to it.

H2: Increased property prices lead lower social status communities further away from the UGBS, i.e. people with higher socioeconomic levels tend to habit in areas where more urban green and blue spaces exist.

In order to test these hypotheses, one should understand the impacts of different amenities on property pricing, both for rentals and sales. The hedonic pricing method is used to find out the impacts of different factors on the prices of different goods. In the case of the housing market, it is applicable through different features of real estate. These features can be internal or external in the sense that the former stands for the attributes of the property, eg. room numbers, heating type, and energy level, whereas the latter stands for the characteristics of the neighborhood such as crime rate, education quality and amenities close by, and the surrounding environment (Herath and Maier, 2010). As this thesis focuses on the impact of urban green and blue spaces on gentrification through property prices, it fits directly into the category of hedonic pricing.

After checking the correlation between Airbnb prices per night, and the average property price per square meter per district, I deem it appropriate to proceed to move on by using Airbnb rentals as a proxy. Excluding Innere Stadt (1st district) was necessary since first, historical city centers tend to have different property pricing due to their location in the old town, and second, as Anguelovski et al. (2022) point out, gentrification usually does not occur in the historical center, but instead outer districts of the city.

Following, all Airbnb units and municipal estates were located based on their coordinates. I computed their Euclidean distance (in meters) to the nearest green space (UGS), blue space (UBS), and their union (UGBS). A binary flag was created for Airbnb listings located within 300 meters of a UGBS, in line with WHO recommendations for urban green space proximity. World Health Organization (2017) guideline suggests that urban residents should have access to public green spaces of at least 0.5 to 1 hectare in size within 300 meters (approximately a 5-minute walk) from their homes.

I then estimated an Ordinary Least Squares (OLS) regression to test H1 and analyze how proximity to UGBS affects Airbnb pricing. Due to the ease of interpretability and skewness of the Airbnb prices, logarithm is applied for the dependent variable. Bockarjova et al. (2020) provides evidence that urban nature influences nearby housing prices, with the effect diminishing as the distance from nature increases. The quadratic distance term is included in the model to account for this non-linearity, in addition to linear distance term. Control variables are the average review score and the number of bedrooms and bathrooms, with missing values imputed using the mean within each property type group. Finally, property-type fixed effects are controlled through dummies. Robust standard errors were employed during this analysis to correct for potential non-constant variance in residuals, ensuring more reliable inference.

The estimated model is:

$$\begin{aligned}\log(Price_i) = \beta_0 + \beta_1 \cdot DistUGBS_i + \beta_2 \cdot DistUGBS_i^2 \\ + \beta_3 \cdot AvgReview_i + \beta_4 \cdot Bedrooms_i + \beta_5 \cdot Bathrooms_i \\ + \gamma_1 \cdot PropertyType_i + \gamma_2 \cdot UGBSType_i + \varepsilon_i \end{aligned} \tag{1}$$

where i indicates every Airbnb unit in the data set, and:

- Price_i is the average nightly price of that Airbnb unit in €
- DistUGBS_i is the distance from Airbnb unit i to the nearest UGBS in meters,
- DistUGBS_i^2 is included to capture potential non-linear effects of distance,
- AvgReview_i is the average review that the unit obtained over 9 months, and is from 0 to 5, where 5 indicates the best review,
- Bedrooms_i and Bathrooms_i are in numbers,
- PropertyType_i indicates the dummy variables for different property types, and finally,
- UGBSType_i indicates the dummy variables for different types of UGBS (L, U, R for green areas and blue spaces).

Moving on, to test H2, first, I investigated the correlation of district (Bezirke) level average property price per square meter with census level average incomes aggregated for districts and district-level social status index. Assuming rents follow the property prices, and affordability of rents is highly correlated with households' income and social status, they were tested. Another reason to examine these correlations can be the possible lagged effects of rental prices, and consequently earlier changes in wealth and social status in a neighborhood, compared to changes in average rental prices. After observing high correlations, the following two models are estimated:

$$\begin{aligned} AvgIncome_i = \beta_0 + \beta_1 \cdot GreenRatio_i + \beta_2 \cdot BlueRatio_i \\ + \beta_3 \cdot SocialHousing_i + \beta_4 \cdot CentralHeating_i + \beta_5 \cdot Ownership_i \\ + \beta_6 \cdot EmpRate_i + \beta_7 \cdot UnivShare_i + \beta_8 \cdot BenefitShare_i + \varepsilon_i \end{aligned} \tag{2}$$

$$\begin{aligned} SSI_i = \beta_0 + \beta_1 \cdot GreenRatio_i + \beta_2 \cdot BlueRatio_i \\ + \beta_3 \cdot SocialHousing_i + \beta_4 \cdot CentralHeating_i + \beta_5 \cdot Ownership_i \\ + \beta_6 \cdot EmpRate_i + \beta_7 \cdot UnivShare_i + \beta_8 \cdot BenefitShare_i + \varepsilon_i \end{aligned} \tag{3}$$

where i indicates each census district, and:

- SSI_i is the Social Status Index of census district i,
- AvgIncome_i is the average monthly income in € per capita for census district i,
- GreenRatio_i and BlueRatio_i represent the share of green and blue space area within the census district,
- SocialHousing_i is the share of municipal estates in the census district,
- CentralHeating_i is the proportion of apartments with central heating,
- Ownership_i is the share of privately owned apartments,
- EmpRate_i is the employment rate of the district's population,
- UnivShare_i is the share of university graduates,
- BenefitShare_i is the share of population receiving social benefits.

The OLS regressions above examine how the ratio of green and blue spaces to the area of a census district is associated with its average income level, and social status index, testing H2. I believe this might be due to low-income residents being priced out of these areas over time because of not being able to afford them. The dependent variable is the average income and SSI per census district, while the explanatory variables include the green space ratio, blue space ratio, social housing ratio, central heating rate, and private ownership rate. Regarding the ownership structure of apartments, in addition to privately owned and municipality-owned ones (municipal estates), there are non-profit ones as well. However, due to difficulty of interpreting data, I only focused on municipal estates (buildings and flats) and privately owned ones. To account for potential heteroskedasticity, robust standard errors were used.

The reason why I included social housing as an independent variable is that I believe social housing correlates with green gentrification. In other words, my expectation is for census districts with more social housing to have lower average income and lower social status, However, as Novy et al. (2024) argue, through time, the housing policy of Vienna has weakened tenant protections and increased the power of the private actors, whether they are as single-person landlords or institutional investors. While non-obligatory retrofitting initiatives of housing align with Vienna's environmental goals, they can be used by landlords to justify rent hikes, especially in the absence of preventative measures to secure affordability. This might hinder the preventative impact I expect social housing to display against green gentrification.

3 Results

Recalling that H1 states that the property values get higher as they get closer to urban green and blue spaces, showing a negative correlation with distance, Equation (1) is used to test it. Equations (2) and (3), on the other hand, are used to test H2 by using average income levels and SSI per census districts to test H2, rising property prices push lower-status communities further away from UGBS, with higher-income populations living closer to them, indicating a positive correlation between income/social status and the UGBS area share of a census district.

3.1 Relationship of distance to UGBS with Airbnb prices

3.1.1 Descriptive Statistics

As an initial validity check for using Airbnb prices instead of long-term rentals, I computed the correlation between the 9-month average of nightly Airbnb prices and average apartment prices, both in a district scale. The correlation was strong overall (0.89) and moderately strong when excluding Innere Stadt (0.675) as shown in Figure 1. Innere Stadt was excluded because of the low probability of gentrification happening at the historical city center (Anguelovski et al., 2022). This suggests that Airbnb price trends are broadly consistent with the rental housing market.

Figure 1: 9-month average Airbnb Prices - Apartment Prices Correlation

Note: Each dot represents a district. The plots display the correlation between district-level average Airbnb prices (2024–2025) and average apartment (building) prices (€/m²). The left panel includes all districts, while the right excludes Innere Stadt. The red line represents the linear fit with a 95% confidence interval shaded in pink.

Furthermore, as we can see in Table 1, the distribution of Airbnb units with distance to UGBS is tight. Almost 98% of Airbnb units included in this analysis are within 300 meters distance from any of the urban green spaces. Specifically, all Airbnb units lie within a maximum of 647 meters from urban green spaces (Table 1). These results are in line with Vienna's reputation as a green city (Vienna Tourist Board, 2020) and provide evidence that Viennese buildings follow the World Health Organization (2017) guideline. On the other hand, on average, blue spaces are farther away than green spaces to Airbnb units.

Moreover, as data indicates, green spaces are divided into three categories: Limited traditional recreational purpose landscapes, restricted recreational urban greeneries, and public recreational areas. The average size of different types of green spaces and the largest of each category is shown in Table 2. All values are provided in square meters. Based on the data, the green spaces included in this analysis mostly fall into the category of 'limited traditional recreational purpose landscapes' with 1,932 of 2,414 green spaces in all census districts labeled as such.

Table 1: Distance of Airbnb Units to Urban Green and Blue Spaces (in meters)

Distance to	Mean (m)	Max (m)
Green Space	120.79	646.28
Blue Space	496.32	1704.28
Urban Green and Blue Spaces	112.75	531.30

Table 2: Green area statistics per category (in m², census district code in parentheses)

Category	Count	Mean	Max (ZBEZ)
Restricted recreational	249	389,269.12	20,282,506.43(1310)
Public recreational	233	40,825.85	895,192.35 (1301)
Traditional greeneries	1932	10,612.97	656,508.93 (1112)

3.1.2 Regression Results

In order to capture the possible non-linear relationship of distance to UGBS and its impact on property prices, the squared distance term in Equation (1) is added to the regression. Since it would have been naive to include the impact of the proximity to an amenity as the only influencing factor of a housing unit's price, different control variables are added. These are the number of bedrooms and bathrooms a unit has, and the 9-month average of the reviews that unit obtained. Furthermore, two different dummy groups are added to capture: first, the impact of different property types on nightly Airbnb prices, and second, the specific impact driven by the type of green space. While applying Equation (1), in order to differentiate the sole effects of different variables on prices, the equation is regressed in four models, which can be seen as four different columns in Table 3.

Table 3: Ordinary Least Squares Model of Airbnb Price and Distance to Green/Blue Spaces

	(1) (Only Distance)	(2) (except UGBS type)	(3) (All UGBS)	(4) (Full Model)
Distance to UGBS	-0.0001	-0.0000	0.0000	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Distance^2	0.000	0.0000**	0.0000	-0.000
	(0.000)	(0.000)	(000)	(0.000)
Average review		0.028*		0.0318**
		(0.0161)		(0.0162)
Traditional UGBS			-0.2872***	-0.2786***
			(0.0272)	(0.0239)
Restricted UGBS			-0.3332***	-0.3109***
			(0.0666)	(0.0583)
Recreational UGBS			-0.0886***	-0.0899***
			(0.0329)	(0.0287)
Property: Entire House		0.0491		0.048
		(0.0504)		(0.051)
Property: Other		0.1071		0.151
		(0.1432)		(0.1436)
Bedroom count		0.233***		0.2319***
		(0.0087)		(0.0085)
Bathroom count		0.2243***		0.223***
		(0.0323)		(0.0314)
R^2	0.0001	0.2396	0.0319	0.269
Adjusted R^2	-0.0002	0.2388	0.0312	0.268
Observations	6920	6920	6920	6920

Note: Column (1) includes only distance-related variables. Column (2) adds review scores and Urban Green and Blue Space dummies, where blue spaces serve as the reference category. Column (3) introduces property type and size characteristics, where the entire apartment is the base category. Column (4) combines all controls and provides the best model fit (Adjusted R² = 0.268). Coefficient significance is denoted by * p<0.1, ** p<0.05, *** p<0.01 with robust standard errors in parentheses.

The number of bedrooms and bathrooms are the only control variables that have a significant impact on Airbnb prices, according to this model. Also, the model has a very low R^2 value, indicating that this model does not effectively explain how Airbnb pricing is done in Vienna for the average of 9 months of 2024-2025. The result for distance to UGBS not having a significant impact aligns with the limitation of using Airbnb data since pricing for short and long-term rentals indicates different preferences. As the existing literature suggests, UGBS are not counted among the features that affect Airbnb prices, but instead physical characteristics (e.g., number of bedroom and bathrooms), proximity to touristic destinations, and hosting factors (Krause and Aschwanden, 2020).

Moreover, it should be noted that there is no statistically significant correlation (neither positive nor negative) between distance to UGBS and Airbnb prices, suggesting that short-term rental prices are not affected by the distance to UGBS. This may also indicate that visitors of the city (e.g., tourists and businesspeople) who rent these short-term units do not value being closer to UGBS. H1, on the other hand, is a hypothesis concerning the residents of the city.

Although Airbnb prices highly correlate with residential unit prices, as Table 1 illustrates, their pricing does not follow this correlation.

The type of UGBS, on the other hand, has a small but statistically significant impact on Airbnb prices. This signifies the preferences of short-term rental unit users. In contrast to the impact of distance, different UGBS types that have different impacts may be associated with the purpose of the visit. For instance, a tourist visiting the city might prefer staying closer to Votivpark, a park categorized as recreational in the data, staying within the boundaries of the historical center, and close to many tourist attractions. However, a resident might prefer larger parks categorized as restricted recreational in order to benefit from their social and environmental impacts (e.g., larger cooling effect and partial recreational) in the longer run at a larger extent. This type of difference is associated not with the distance, but with the impact of the type of UGBS, according to the regression.

Finally, the observed negative impact of all categories of UGBS on Airbnb pricing may be driven by a combination of spatial, behavioral, and modeling factors. First, a peripheral bias could be at play, as larger green spaces (categorized mostly as restricted recreational) are often located in less central and historic districts where Airbnb demand and prices are expected to be lower due to limited tourist demand. In other words, short-term visitors typically prioritize access to historic centers, nightlife, and commercial hubs over tranquil natural environments (Krause and Aschwanden, 2020; Reichle et al., 2023). In Vienna for instance, being distant to the historical city center has a negative impact on Airbnb prices, as Gunter and Önder (2018) proved. Additionally, mere proximity to parks or waterfronts does not guarantee accessibility or desirability — especially if these areas are not well-connected by public transport or lack nearby amenities. Thus, not controlling for those different preference sets, district fixed effects, and closeness to different amenities and transportation possibilities, might be causing omitted variable bias, which further distorts results.

3.2 Relationship of the area of UGBS with socioeconomic level

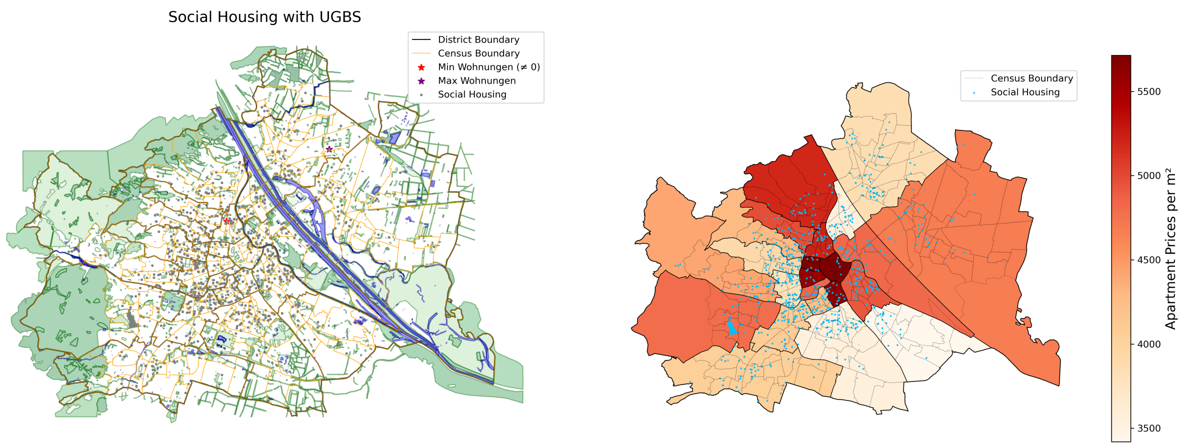
3.2.1 Descriptive Statistics

The correlation analysis (Figure 2) of apartment prices with average income and SSI, showed that both socioeconomic indicators are highly correlated with apartment prices, suggesting that lower-income and lower social status people are priced out of districts with higher apartment prices. This might be due to the unaffordable prices of housing units in those districts. The correlation coefficient was moderately high when Innere Stadt was included (0.78 for average income-apartment price, and 0.77 for SSI-apartment price), but if it is excluded, we observe an even stronger correlation, both becoming 0.83, as shown in Figure 2.

Figure 2: Apartment Price Correlation with Average Income and Social Status Index
Note: Each point represents a district (excluding Innere Stadt). The left panel shows the correlation between standardized average income and apartment(building) prices (€/m²), while the right panel illustrates the relationship between the Social Status Index (SSI) and apartment prices. The red lines represent linear trend lines, with 95% confidence intervals shaded in pink.

As one might expect for a census district with a higher ratio of municipal estates to have lower SSI, and less UGBS according to H2, the existence of municipal estates is important. In order to be entitled to social housing, one should satisfy criteria about social and economic status as explained in the Literature Review. Figure 3 displays how municipal estates were distributed in Vienna with respect to UGBS (Fig 3a) and average apartment prices per district (Fig 3b).

Table 4 presents descriptive statistics on green and blue areas per census districts, and municipal estates (information about both buildings and flats). They are presented as counts because the data provides the number of municipal estate buildings and flats, but not the exact area they cover. All descriptive statistics reported here are calculated at the census district level



(a) Municipal estates with urban green and blue spaces

(b) Municipal estates with average apartment prices

Figure 3: Location of municipal estate buildings in Vienna

Note: The left panel maps the spatial distribution of municipal housing alongside urban green and blue spaces (UGBS), highlighting proximity relationships. The right panel shows average apartment prices across Vienna per m², with darker shades indicating higher prices; blue dots represent the location of municipal (social) housing buildings. District and census boundaries are overlaid for spatial reference.

rather than as aggregated city-wide figures. For each variable (e.g., green area, blue area, number of municipal housing units), the values represent the corresponding measure within each individual census district. Mean values represent the average across all districts, treating each district equally regardless of its size or population. Area variables (green and blue areas) are reported in square kilometers. Ratios indicate the proportion of green/blue space to the total area of a census district and the ratio of municipal estate flats relative to the total number of flats within a census district, and are expressed as percentages or decimal shares.

Table 4: Green/Blue Space and Municipal Housings Descriptive Statistics by Census District

Feature	**Mean**	**Max** (Subdistrict Code)
Green Area (km²)	0.334	17.169 (1412)
Blue Area (km²)	0.061	2.695 (0208)
Green Area Ratio (%)	0.109	0.844 (1412)
Blue Area Ratio (%)	0.025	0.504 (2001)
Municipal Estates Buildings (count)		31 (1505)
Municipal Estates Flats (count)		5850 (2105)
Municipal Estates Flat Ratio (%)	0.502	77.462 (2130)

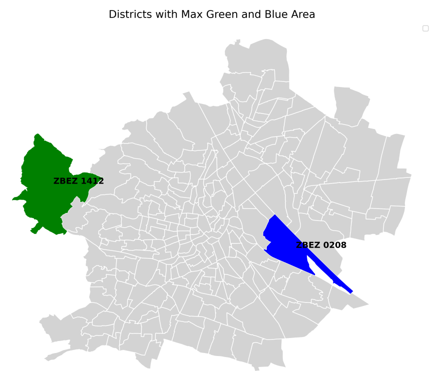


Figure 4: Census districts with maximum green and blue areas

Note: ZBEZ is an abbreviation for census district codes.

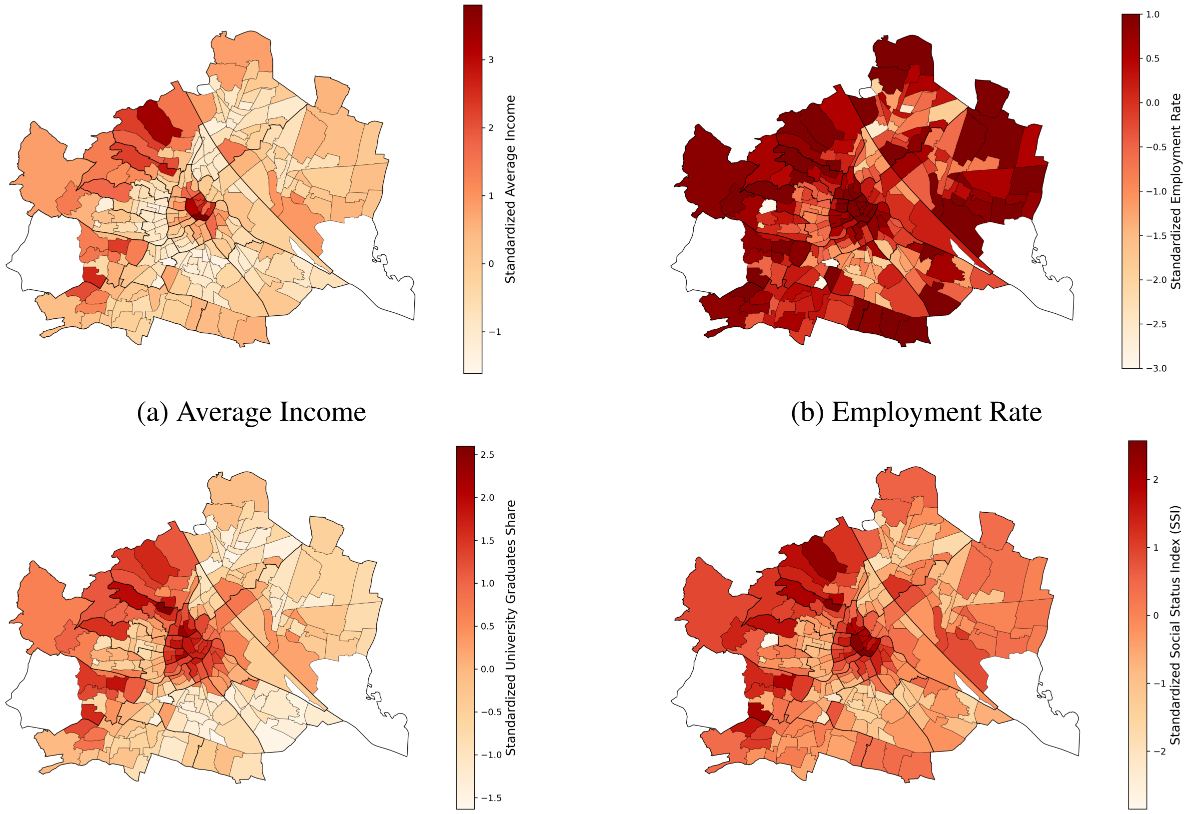
There are 90 census districts with no blue area at all. In addition to this, two census districts have no green area at all. Both of them are located on the left bank of the Danube, one in Floridsdorf (Shuttleworthstraße, 2120), and one in Donaustadt (Industriegebiet Erzherzog Karl Straße, 2231). For this reason, there has been no information given in Table 4 about the minimum values.

On the other hand, there are four census districts without any inhabitants and fully covered by green areas. Two of these census districts are again located in Floridsdorf (Industriegebiet Strebersdorf, 2130) and Donaustadt (Lobau, 2230) districts. One of them is located in the Leopoldstadt (Freudenauer Hafen, 0210), the island between two sides of the Danube, and one is at the southeastern side of the city in Hietzing (Lainzer Tiergarten, 1310). The area that these four census districts covered with only green spaces is approximately 48 km². However, the green areas these four districts cover are not distributed evenly. While two of them (one in Leopoldstadt and one in Floridsdorf) are quite small, contributing approximately 4% of this 48 km² total. This means that almost one-third of the green areas within the census districts in Vienna are in these four census districts where no one lives, predominantly in two of them. The census district numbered 2230 has the maximum amount of green area within its boundaries at 22.4 km².

If we look at only census districts where people live (excluding the four without inhabitants), the census district that has the highest green area is 1412 with slightly more than 17 km². Figure 4 illustrates the census districts with the highest green and blue areas among the ones with people residing. Green colored one shows the census district with the highest green area, and the blue for the census district with the highest blue area.

For social indicators distributed across census districts, I present the distribution of average monthly income (5a), employment rate (5b), university graduates share (5c) and social status index (5d) across all 250 census districts together in Figure 5. The reason for three out of four of these indicators (except SSI) to be chosen is, as explained in Chapter 2, that they contribute to the generation of the social status index (SSI) created by Kadi et al. (2022). In addition to these three, the share of benefit recipients was also included in the creation of SSI, but as explained in Riepl et al. (2025), unemployment and benefit recipients follow each other closely. Thus, its distribution across census districts was not provided here on a map due to similarity.

All indicators are normalized, and above-mean values are positive, indicating a higher level than the average. The census districts that are not colored are the ones without any residents. They help to visually examine observe the relationship of socioeconomic indicators with UGBS within the city.



(a) Average Income

(b) Employment Rate

(c) University Graduate Share

(d) Social Status Index

Figure 5: Different socioeconomic variables across Vienna census districts

Note: Each map displays the standardized distribution of a key socioeconomic variable across Vienna's census districts. Darker shades represent higher values relative to the citywide mean.

3.2.2 Regression Results

The main variables of interest are the green area ratio and the blue area ratio, to explain the association between UGBS and the socioeconomic variables. For control variables, the ratio of municipal estate flats among all flats in that given census district, the ratio of the number of flats that have central heating compared to all, and lastly, the share of privately owned apartments among total apartments are added. I also included employment rate, university graduate share, and share of social benefit recipients in a given census district as further controls, since they affect SSI directly by creation.

Unlike the OLS models presented in Table 3, which did not establish any significant relationship with distance to UGBS, here, in Table 5, the green area ratio of a census district has a statistically significant positive impact on both average income level and SSI, which proves that H2 holds for green areas. In other words, the higher the share of green area compared to the overall area of a census district, the higher the average income and the SSI. This correlation is highly observable in Figure 5. They clearly show higher income, higher university graduate share, more employment, and higher social status in the northwestern corner of the city (upper left corner of the figures). As Neier (2023) points out, these peri-urban areas at the northwestern corner of the city, characterized by high vegetation cover and relatively easy access to the city center, have become attractive to higher-income and higher-status groups seeking improved environmental amenities. As a result, these areas reinforce socio-economic segregation by leaving more marginalized or lower-income and lower social status groups in less vegetated districts. The move of prosperous populations toward the indicated areas explains the positive sign in front of the green area ratio in Table 5. On the other hand, H2 is rejected for blue areas, meaning that, unlike what H2 states, the observed correlation between the blue area ratio and both average income and SSI is negative. This situation is discussed in Chapter 4.

Recalling that this regression also displays the correlation between the municipal estate flats and dependent variables, it is noted that in both cases the correlation is negative for the first three models (3 columns) while the variable of interest changes sign in column 5, when the all independent variables are regressed on the dependent variable. Wondering which variable is responsible for this change of sign, both average income and SSI are regressed in five more different ways. In each of these five new models, green area ratio, blue area ratio, and social housing rate are kept, while all the other variables (i.e., central heating rate, private ownership rate, employment rate, benefit share, and university graduates share) are included in the regression one by one. The results of these models can be found in the Appendix, Table **??**,. The variable that changes the sign of the social housing rate when the dependent variable is SSI (Panel B), is the benefit share. This might be due to the fact that, unlike other social indicators, benefit share moves in another direction from others. In other words, as the employment rate rises, benefit share decreases, as it indicates the share of people who receive benefits from the state.

The final note on this regression is the high R^2 observed every time when social indicators are included in the regression. This is because SSI is created by using those variables and the average income. Thus, in other words, Panel B in Table 5 presents the variation in average income and what is the rest afterward that affects SSI.

Table 5: Ordinary Least Squares Model for Monthly Average Income and Social Status Index

	(1) (UGBS only)	(2) (+ Social Housing)	(3) (Property attributes)	(4) (SSI contributors)	(5) (Full Model)
Panel A - Dependent Variable: Average Income					
Green area ratio	2.498***	2.449***	1.677***		1.328***
	(0.505)	(0.513)	(0.344)		(0.262)
Blue area ratio	-1.982***	-1.942***	-1.387***		-0.788***
	(0.567)	(0.56)	(0.371)		(0.291)
Social housing ratio		-0.375*	0.063		0.183**
		(0.225)	(0.216)		(0.072)
Central heating rate			22.089***		12.55***
			(1.99)		(1.92)
Private ownership rate			3.281***		1.112***
			(0.249)		(0.239)
Employment rate				0.543***	0.292***
				(0.143)	(0.087)
University graduate rate				0.408***	0.359***
				(0.058)	(0.04)
Benefit recipients share				-0.095	0.026
				(0.09)	(0.069)
R^2	0.146	0.168	0.622	0.713	0.834
Adjusted R^2	0.138	0.158	0.614	0.71	0.828
Panel B - Dependent Variable: Social Status Index (SSI)					
Green area ratio	1.785***	1.707***	0.997***		0.491***
	(0.478)	(0.495)	(0.346)		(0.72)
Blue area ratio	-1.708***	-1.644***	-1.089***		-0.292***
	(0.606)	(0.578)	(0.4)		(0.108)
Social housing ratio		-0.595**	-0.163*		0.068**
		(0.303)	(0.265)		(0.027)
Central heating rate			18.231***		4.643***
			(1.73)		(0.71)
Private ownership rate			3.551***		0.411***
			(0.239)		(0.088)
Employment rate				0.386***	0.293***
				(0.053)	(0.032)
University graduate rate				0.521***	0.503***
				(0.021)	(0.015)
Benefit recipients share				0.15***	0.195***
				(0.033)	(0.026)
R^2	0.068	0.119	0.57	0.965	0.9797
Adjusted R^2	0.06	0.108	0.561	0.9646	0.979
Observations	239	239	239	239	239

Note: Column (1) and (2) present baseline models with only green and blue area ratios, and the addition of social housing ratio. Column (3) introduces housing characteristics, while column (4) adds socio-economic controls. Column (5) includes all variables, offering the most comprehensive specification with the highest explanatory power (Adjusted R^2 = 0.828). Coefficient significance is denoted by * $p<0.1$, ** $p<0.05$, *** $p<0.01$ with robust standard errors in parentheses.

4 Discussion

In the case of Vienna, the findings of this thesis raise important questions about equity and access: Are lower-income populations pushed out far away from urban nature? What explains the negative correlation between blue space availability and the Social Status Index (SSI)? And to what extent do Vienna's inclusive social housing policies protects residents from the displacement pressures that might be associated with the development of UGBS? Finally, I try to discuss the potentially bidirectional causal relationship between urban greening and gentrification.

First of all, about greeneries, one implication of highly vegetated areas owned by higher socioeconomic status owners might be the population concentration in the suburbs of the city. According to Hatz (2008), those areas immediately surrounding the city of Vienna include an additional 2.2 million inhabitants approximately. This might be explained by lower-income people being priced out of suburbs, where a life closer to nature can be afforded only at the cost of longer commuting times to the city center, which provides employment and other benefits. However, with this data set used in this thesis, this idea cannot go further than being an assumption. Testing this assumption requires demographic data of people who live just outside the border of the city, property prices there, and knowledge about their commuting reasons.

Second, contrary to expectations, the correlation of the blue area ratio with SSI (and also with average monthly income) in OLS regression is negative, unlike the observed positive sign with green areas. This might be due to the fact that quantitative aggregate data is not able to present the nuances of case-specific differences. For instance, living by the Donaukanal means not just living by blue infrastructure but also close to a heavily used 3-lane road, which can be detected from satellite images of the neighborhood. This might cause residents to not enjoy the benefits of blue spaces as much as they can because of the noise and pollution caused by the road. As Maloutas and Karadimitriou (2022), quantitative data in census district scale will not be enough to differentiate micro-segregation in cities across streets and even within buildings as the case with Donaukanal shows.

Further explanation for the negative correlation of blue spaces with social status can be based on the effect of the type of blue spaces, which is not known in the data of this thesis.

As McCord et al. (2024) point out, based on their study on Belfast Metropolitan, Northern Ireland, walking distance to rivers indicated a negative impact on property prices, similar to what is observed in Table 5. This might be due to unmanaged riparian areas, pollution, and hardened banks. The study provides evidence for heterogeneous preferences across different blue infrastructures. They argue and prove that expensive properties place more value on being within walking distance from the coastlines or lakes, while urban rivers are seen as a dis-amenity and negatively affect prices across all property levels (McCord et al., 2024). These findings align with Macháč et al. (2022), which highlights inconsistent preferences for different forms of blue and green infrastructure through broad literature, often shaped by demographic factors and contextual characteristics of the landscape. Because of that, further research focusing on the demography and the type of blue space Vienna has should be conducted to understand the exact reason of the negative correlation of blue areas on property prices.

Another point that requires attention is that Table 5 also proves that the municipal estates explain the variation in average income and SSI positively correlating at 5% significance level for model 5. Although it may sound counterintuitive for average income and social status to be positively correlated with the social housing ratio, this might be due to the city's inclusive public housing model as explained in the literature review. The significance only appears after including socioeconomic indicators (specifically employment and benefit share, see Appendix), which capture the socioeconomic level of people. Vienna's municipal housing is not limited only to low-income groups; it accommodates a socially mixed population, including middle-income residents as well. In appendix, the results of more regressions to indicate the variable that changes the sign of social housing can be found. Additionally, municipal estates are not thrown away only to the outer districts of the city, but instead also situated in desirable locations with infrastructure and access to nature that is visible in Figure 3a.

Regarding the historical progress of the social housing system of Vienna, what Novy et al. (2024) discuss is that weakened tenant protections and increased power of the private actors over time might cause rent hikes in the absence of preventative measures to secure affordability. This creates another risk, another type of gentrification where ecological upgrades intended to enhance urban quality of life may instead contribute to "low-carbon" gentrification, again pushing out lower-income and/or low socioeconomic level people (Novy et al., 2024). Future research should be aware of how environmental policies affect housing possibilities, including but not limited to social housing.

Finally, the next step in the discussion is to consider the challenges of estimating the causal impact of UGBS even within a dynamic framework, particularly when accounting for the fact that social planners may endogenously respond to residents' preferences. In other words, as Sharifi et al. (2021) argues, the causal relationship between greeneries and gentrification is hard to detect. The question boils down to understanding whether changes in urban greenness drive shifts in neighborhood income status (gentrification), whether gentrification induces increased greening efforts in higher socioeconomic areas, or whether the two processes are jointly and endogenously shaped.

What Sharifi et al. (2021) found out by using spatial autoregressive models and instrumental variables to explore the causality is that gentrification — measured as rising suburban income — can lead to increased greening, but there is no significant evidence that greening causes gentrification. This suggests the relationship is context-dependent and influenced by other urban factors, such as proximity to the city center or transportation access. Hence, it is safe to indicate that, even with dynamic models and time-series data, it might not be possible to argue a causal relationship between the development of urban nature and gentrification. What can be pointed out is that the correlation they have, which is also one of the findings of this thesis, supporting the previous literature.

4.1 Limitations

This study is subject to several limitations, primarily stemming from data availability and scope constraints. One significant limitation is the granularity of the housing price data. While district-level average prices per square meter were obtained, this provides only 23 data points — one for each district in Vienna. More fine-grained data, ideally per flat or at street level, would enable a more precise spatial analysis of housing affordability. Having this smaller-scale data would have enabled to explain the socioeconomic impacts of UGBS within a subdistrict, across streets, and even across buildings. Not just the impact of distance, but the impact of the type of

UGBS could also be discovered more precisely, with a more detailed data set. This would allow not only to look across census districts, which are already large, but also in a vertical sense, how different floors of buildings were affected by UGBS. Unfortunately, such detailed data is not publicly available, limiting the extent of gentrification analysis.

In order to overcome this, Airbnb data is used. While Airbnb data served as a practical proxy for housing market activity, its use introduces important limitations that shape how the results should be interpreted. The findings may primarily reflect short-term housing pressures rather than long-term affordability or displacement risks. This distinction is important when considering green gentrification, as the mechanisms driving change in short-term versus long-term housing markets may differ significantly. Consequently, while Airbnb data provides valuable insight, it likely captures only part of the overall housing impact of urban green and blue spaces.

In terms of the granularity of data, aggregating variables at the census district level may hide critical variations within districts that are not visible due to the large scale of the data. Socio-spatial inequality might be observed on a smaller scale—across streets, between adjacent buildings, or even vertically (Musil and Kaucic, 2024; Maloutas and Karadimitriou, 2022). Micro-level data for flats, or at least for buildings, would have been better to distinguish inequality within census districts.

Another issue is the static nature of the data. This study uses a cross-sectional dataset, capturing a snapshot in time. As such, it cannot assess how changes in urban green and blue spaces influence housing prices dynamically. Incorporating time-series data for both property prices and UGBS developments would allow to try identifying causal relationships. Not only identifying the causality but also investigating the realization of green gentrification requires continuous data. As Hatz (2008) reveals the history of gentrification in Vienna, it is a process stretched over decades. Future research should prioritize the collection and use of such continuous datasets to evaluate temporal effects.

Moreover, this study includes only municipal estates as a representation of the social housing program. However, Vienna's affordable housing system also includes subsidized cooperative housing and other non-profit models. The omission of these categories may lead to an underestimation of the availability and distribution of affordable housing across the city, while also not adequately explaining the variation in average income and SSI. Further research should consider these other types of social housing as well.

As highlighted in Chapter 1, Literature Review, the impact of UGBS on property prices and social dynamics is not only influenced by their presence but also by their size, quality, and the recreational and environmental benefits they offer. Although these features were controlled to some extent by UGBS type dummies, they still vary widely within each group in terms of not only size but also their features, such as having a playground, dog zone, availability of restrooms, and many more. Likewise, the existence of a park or blue space does not inherently ensure usability, attractiveness (negative correlation of blue spaces with social status), or meaningful recreational opportunities. For lack of usability and recreational opportunities, one can thing of the greeneries that are categorized as restricted recreational. Those places are not fully closed to public, but not every part is open for recreational purposes. Attributes such as cleanliness, biodiversity, available facilities, and perceived safety play a significant role in determining the social and economic value of these spaces (Palliwoda and Priess, 2021), where the latter indicates how much UGBS influences property prices or local investment. However, this thesis focuses on the spatial distribution and proximity of UGBS and does not incorporate their qualitative characteristics, which may limit the extent of the conclusions reached.

Conclusion

This thesis examined the social and economic consequences of urban green and blue spaces (UGBS) in Vienna, with particular attention to their impact on housing prices and social status. By analyzing spatial data on public green and blue spaces alongside prices of Airbnb units available for 9 months in 2024-2025, social status indices, and the distribution of municipal housing, the study aimed to reveal whether and how UGBS contributed to patterns of inequality in the city, and the impact of social housing policies.

The results suggested that proximity to UGBS did not significantly influence Airbnb prices, implying that short-term visitors may not strongly value closeness to these amenities when selecting accommodation. This is opposed to hypothesis 1, which suggested a significant negative correlation between distance to UGBS and property prices. The reason for rejecting this hypothesis might be because of the Airbnb data does not reflect the same preferences as the rental or homeowners market in real estate. Unlike this first result, the type of UGBS—whether different types of green or blue—had a modest yet statistically significant effect, indicating heterogeneous preferences even among temporary users, depending on the features of the environment.

In contrast, a stronger association emerged between UGBS and social status. Areas with higher shares of green space were positively correlated with higher socioeconomic indices, implying that more affluent residents tended to live in greener neighborhoods, not rejecting the second hypothesis for green spaces. Blue spaces, however, showed a negative correlation with social status, a surprising result that may reflect the preferences for the type of blue space, following McCord et al. (2024). Because blue space data did not have the differentiation that the literature suggested, testing the impact of different blue area types was not possible within the scope of this thesis.

Additionally, the share of municipal estates was positively associated with both income and social status after controlling for socioeconomic indicators, suggesting that Vienna's social housing model may not only serve marginalized communities and provide affordable housing more inclusively. These findings underscored the distinctive nature of Vienna's housing policy, where public housing appears to mitigate some of the exclusionary dynamics of green gentrification, proving the fame of Viennese social housing policy. However, it requires city comparison analysis to determine whether Vienna has a better social housing policy against green gentrification or not.

This research contributed to the growing literature by establishing links between different concepts discussed in UGBS literature. While much of the prior work focused on i) the benefits of UGBS with a focus on environmental, health, and social aspects; ii) social housing policies, or iii) green gentrification, this thesis provided evidence from a city where housing is partially decommodified and heavily regulated. The analysis bridged multiple dimensions—real estate pricing (via Airbnb), spatial equity, and social housing policy—offering a more integrated understanding of how environmental and social planning intersect in Vienna. The use of Airbnb data as a proxy for property prices, despite its limitations, also demonstrated a creative methodological approach in the data-scarce context of Vienna.

Nevertheless, several limitations constrained the findings. The analysis relied on aggregated data at the district and census district levels, which may have veiled micro-level segregation. The reliance on cross-sectional data also limited the ability to capture dynamic changes in the real estate market and neighborhood composition over time. Future research would benefit from time-series datasets to better understand how the creation or improvement of UGBS affects housing affordability and social change by using more granular data for housing prices.

In sum, this thesis provided evidence that while Vienna's social housing model may buffer some of the adverse effects of green gentrification, socio-spatial inequality still persists. These findings call for a more nuanced approach in urban greening strategies, one that not only prioritizes ecological goals but also seeks social equity through more inclusive design of policies.

Appendices

Table 6: OLS results with robust standard errors for average income and SSI

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Dependent Variable: Average Income						
Green area ratio	2.449***	2.339***	2.306***	1.678***	1.768***	1.765***
	(0.513)	(0.504)	(0.452)	(0.475)	(0.339)	(0.428)
Blue area ratio	-1.942***	-1.903***	-1.751***	-0.906*	-1.149***	-1.309***
	(0.560)	(0.561)	(0.505)	(0.479)	(0.379)	(0.433)
Social housing ratio	-0.375*	-0.338	-0.238	0.035	-0.076	0.223***
	(0.225)	(0.240)	(0.159)	(0.091)	(0.086)	(0.063)
Central heating rate		4.941***				
		(1.685)				
Private ownership rate			1.658***			
			(0.225)			
Employment rate				0.665***		
				(0.084)		
University graduate rate					0.638***	
					(0.041)	
Benefit recipients share						0.658***
						(0.052)
R^2	0.168	0.191	0.347	0.661	0.622	0.630
Adjusted R^2	0.158	0.177	0.336	0.655	0.616	0.624
Panel B - Dependent Variable: Social Status Index (SSI)						
Green area ratio	1.707***	1.714***	1.516***	0.762**	0.822***	0.830***
	(0.495)	(0.492)	(0.391)	(0.345)	(0.267)	(0.278)
Blue area ratio	-1.644***	-1.647***	-1.389***	-0.373	-0.614*	-0.832***
	(0.578)	(0.578)	(0.495)	(0.359)	(0.315)	(0.311)
Social housing ratio	-0.595**	-0.597**	-0.412*	-0.092	-0.205**	0.173***
	(0.303)	(0.299)	(0.222)	(0.112)	(0.105)	(0.063)
Central heating rate		-0.324				
		(2.024)				
Private ownership rate			2.211***			
			(0.238)			
Employment rate				0.816***		
				(0.071)		
University graduate rate					0.830***	
					(0.031)	
Benefit recipients share						0.845***
						(0.039)
R^2	0.119	0.119	0.403	0.781	0.804	0.798
Adjusted R^2	0.108	0.104	0.393	0.778	0.801	0.795
Observations	239	239	239	239	239	239

Note: Column (1) includes the base green and blue area ratios and the social housing ratio. Columns (2)–(6) introduce housing and socioeconomic variables incrementally. Robust standard errors in parentheses. Significance levels are indicated with stars: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

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