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The Impact of Airbnb on Long-Term Rental Markets in San Francisco: A Geospatial Analysis Using Multiscale Geographically Weighted Regression

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Abstract: The rapid proliferation of peer-to-peer short-term vacation rentals has sparked a debate regarding their impact on housing markets. This study further investigates this issue by examining the effect of Airbnb on relative rent costs in San Francisco. The research addresses a critical gap in understanding whether Airbnb financially burdens local renters within different income groups. The authors also differentiated the effect of Airbnb accommodations with different levels of commercialization by categorizing Airbnb listings based on their level of commercialization. Using the multiscale geographically weighted regression technique, this study also considered spatial variations in the relationship between short- and long-term rental markets. The findings indicate that the density of Airbnb only affects the relative rent of renters with a yearly household income between USD 50,000 and USD 75,000. Furthermore, the density of Airbnb listings from more commercialized hosts that own between three and eleven showed a positive relationship with the relative rent cost. This study highlighted the variability in the impact of Airbnb on the local community by income group, listing characteristic, and geographic region. This finding underscores the need for differentiated regulation toward peer-to-peer accommodations, as the impact on rent affordability varies by host commercialization level and renter income group.

Keywords: Airbnb; short-term rentals; spatial analysis; geographically weighted regression; peer-to-peer accommodation; San Francisco

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1. Introduction

Peer-to-peer short-term rental accommodations have brought pivotal changes to the tourism industry [1]. Enabled by mutual trust grounded in the online platform [2,3], peer-to-peer accommodations are actively supplied and demanded in many cities around the world, bringing challenges to traditional accommodation sectors [4]. Traditional online distribution channels, such as Agoda, Booking.com, Expedia, and Hotels.com, now offer their users the option to host or book short-term vacation rentals on their website, along with conventional tourist lodgings. Some of the advantages short-term rental has over traditional accommodations include flexibility of supply and the ability to provide "live like a local" experiences [5–7]. However, peer-to-peer accommodations have also been criticized as a cause of negative impacts such as tourism-induced gentrification [8], conflicts between Airbnb guests and locals [5], illegal short-term rental activities [9], decreased tourism employment [10], and increased cost of living [11].

In particular, the purpose of this paper is to further examine the relationship between peer-to-peer short-term vacation rentals and the local long-term rental market. Although the demand for short-term rentals is driven by global tourists and long-term renters mainly consist of residents [12], the two demands rely on the same supply of renter-occupied housing units [11]. Scholars note that local tenants can be displaced and replaced by short-term renters if the landowner deems it more profitable [13]. Furthermore, the reallocation of the housing supply increases rent costs, which in turn leads to housing affordability problems for local renters [14,15].

However, we identified three areas where more detailed analysis is needed to investigate the nexus of short- and long-term rental markets. First, the prior literature only examined increases in *absolute* rent costs, assuming that all residents would be affected equally. On the contrary, the primary interest of this study is to establish whether vacation rentals affect the actual financial burden of residents by examining their impact on the *relative* rent costs of different income groups. Furthermore, studies tend to consider short-term rentals as a homogeneous entity, although their impact on locals varies significantly based on the level of commercialization [14]. Therefore, this study conducted a more detailed analysis of the effect of Airbnb on the long-term rental market by segmenting Airbnb listings based on the degree of commercialization. Finally, existing studies did not account for variations in the relationship between short- and long-term rental markets; that is, previous findings only portray the general effect of vacation rental activities. Considering the inherent spatial nature of the housing market, some regions may be more vulnerable to the negative impacts of short-term rentals, which would be underestimated in global models. Hence, this paper utilized the multiscale geographical weighted regression (MGWR) method, which reflects such spatial nonstationarity.

The present article is organized as follows. To begin with, this paper summarizes the extant literature on the impact of short-term rentals on the local housing market. Using this review as a foundation, this paper then outlines the limitations of previous work and presents specific research questions to address these shortcomings. Subsequently, the details of the analysis process and the results obtained from the statistical analysis are reported. This paper concludes with interpretations of the findings and their implications.

2. Literature Review

2.1. Peer-to-Peer Accommodation

Short-term rentals for vacation purposes are not an entirely new phenomenon, as noted by Yeager et al. [16]. The difference is that online technologies have lowered the barrier for both providers and demanders of short-term vacation rentals, making it possible for practically anyone to become a host or guest of peer-to-peer accommodation. Among several competitors in the peer-to-peer accommodation market, such as Vrbo and Flipkey, Airbnb has market dominance [17–19], to the point where it is synonymously associated with the peer-to-peer short-term rental platform [20].

Although peer-to-peer accommodation is generally contrasted with traditional lodging companies, the nature of short-term vacation rentals is also changing rapidly. For example, while it is true that various types of accommodation are offered on Airbnb, most of the supply, demand, and revenue are generated by listings that offer the rental of an entire home [21,22]. Furthermore, studies point to the professionalization and commercialization of peer-to-peer accommodation, in which hosts operate multiple units of accommodation exclusively for short-term rental purposes, diluting its nature as "sharing" or "collaborative" consumption [23,24].

2.2. Impact of Airbnb on the Local Community

The vast majority of academic discussion on Airbnb is centered on its users, both hosts and guests, while its impact on the host destination has received relatively less attention [25]. Further, most studies that examined peer-to-peer accommodation are revisits of well-established concepts related to tourism (e.g., motivation, satisfaction, behavior

intention, and loyalty) with marginalized use of Airbnb as a mere context [20]. On the contrary, the present study aims to address specific phenomena related to Airbnb and its effect on the local community.

Early studies of Airbnb focused primarily on its impact on the tourism industry, particularly the accommodation sector. However, there are conflicting viewpoints on whether Airbnb should be considered a threat to hotels. Some suggest that the targeted market of Airbnb differs from that of the traditional accommodation sector [1], supported by empirical studies that showed a insignificant relationship between hotel performance and the prevalence of Airbnb in the region (e.g., [26–28]). Others assert that short-term rentals and traditional accommodations should be considered substitutable goods [29], therefore hindering the performance of traditional lodging sectors (e.g., [30–33]).

Table 1 summarizes previous studies that examined the impact of Airbnb on long-term rental markets. The existing literature exhibited several notable limitations. Much of the previous research has focused on absolute rent increases without variations among renters, which fails to capture the actual financial burden on renters. Particularly, renters will experience a disproportionate impact based on their income. For example, the same USD 100 increase in rent would be more burdensome for lower-income renters because the proportional increase in rent cost is greater when the income is smaller. Although some studies used the number of bedrooms in housing to capture the heterogeneity of renters [13,34,35], it is far from direct measurement, requiring the inference that the number of bedrooms represents the renter's income level. Instead of proxy measures, this study proposes directly assessing the impact of Airbnb on *relative* rent using the income-to-rent ratio. Thus, the following research questions were formulated:

RQ1: *Is Airbnb density positively correlated with the relative rent costs of renters?*

RQ2: *Will the effect of Airbnb density on relative rent costs differ by income group?*

Additionally, previous analyses often treated Airbnb listings as a homogeneous entity, neglecting the significant differences between types of listings. The impact of renting out an entire home differs markedly from that of renting a single room [14,22]. Similarly, the level of commercialization of Airbnb listings—whether listings are managed by hosts with one property or multiple properties—can have varying effects on local rent prices [14,36,37]. This lack of differentiation can lead to inaccurate assessments of Airbnb's overall impact. A commonly used criterion is to differentiate between single- and multi-listing hosts, where Airbnb supplied by multi-listing hosts is considered more commercialized. Grouping multi-listing hosts together implies that Airbnb's commercialization level is dichotomous. Because there is still a great variation in the number of Airbnb listings among multi-unit hosts, the role of commercialization needs further clarification. A more plausible approach to modeling different spectrums of commercialization would be introducing additional segments within multi-unit listings. This led to the following research question:

RQ3: *Will the effect of Airbnb density on relative rent costs differ depending on the level of commercialization of Airbnb units' hosts?*

Lastly, all eight studies outlined in Table 1 did not account for the possibility that the relationship between Airbnb and rent prices can vary across different geographic areas. This oversight is significant, as ignoring spatial variations can obscure localized effects, leading to over- or under-estimated effects when using global-level analysis. Understanding this spatial nonstationarity is essential for a more nuanced and accurate depiction of Airbnb's role in housing markets, ultimately informing better policy decisions. Therefore, the following research question was formulated:

RQ4: *Will the effect of Airbnb density on relative rent differ by region?*

Table 1. Overview of literature on impact of short-term rental activities on long-term rent price.

Study	Dependent Variable	Study Area	Data Year	Heterogeneity of Renters	Heterogeneity of Airbnb	Estimation Method
Ayouba et al. [36]	• Rent	8 French cities	2014–2016	Yes (Move-in year)	Yes (Entire home or rented more than 120 days/year)	Spatial Autoregressive Combined (SAC)
Barron et al. [11]	• Housing price Rent • Price-to-rent ratio	US	2008–2016	No	No	2SLS (with instrument variable and fixed effects)
Benítez-Aurioles and Tussyadiah [13]	• Housing price • Rent	London, UK	2016–2019	Yes (# of bedrooms)	No	System GMM
Garcia-López et al. [38]	• Rent • Housing price	Barcelona, Spain	2007–2017	No	No	2SLS (with instrument variable and fixed effects)
Horn and Merante [34]	• Rent • Long-term rental supply	Boston, US	2015–2016	Yes (# of bedrooms)	No	Panel fixed effects
Lee and Kim [14]	• Rent • Housing price • % of households in relative poverty	New York City, US	2016–2019	No	Yes (Entire home and multi-listing host)	Dynamic Spatial Durbin Model
Ram and Tchetchik [35]	• Hotel occupancy rate Rent	Tel Aviv, Israel	2017–2018	Yes (# of bedrooms)	Yes (# of bedrooms)	System GMM
Shabrina et al. [37]	• Rent growth rate	London, UK	2015–2019	No	Yes (Entire home, rented more than 180 days/year, and multi-listing hosts)	OLS

3. Methodology

3.1. Data Collection

The city of San Francisco was chosen as the research area of the current study for the following reasons (see Figure 1). First, Airbnb was founded in 2007 in the apartment of three co-founders in San Francisco [39], making San Francisco the first and oldest city to be exposed to Airbnb and its adverse effects. Second, the level of income inequality is very high in San Francisco compared with other cities in the United States [40], but housing costs have been skyrocketing, resulting in signs of gentrification [41]. Lastly, the average cost of hotel rooms in the San Francisco area is one of the most expensive in the world [42], making peer-to-peer accommodation attractive for travelers.

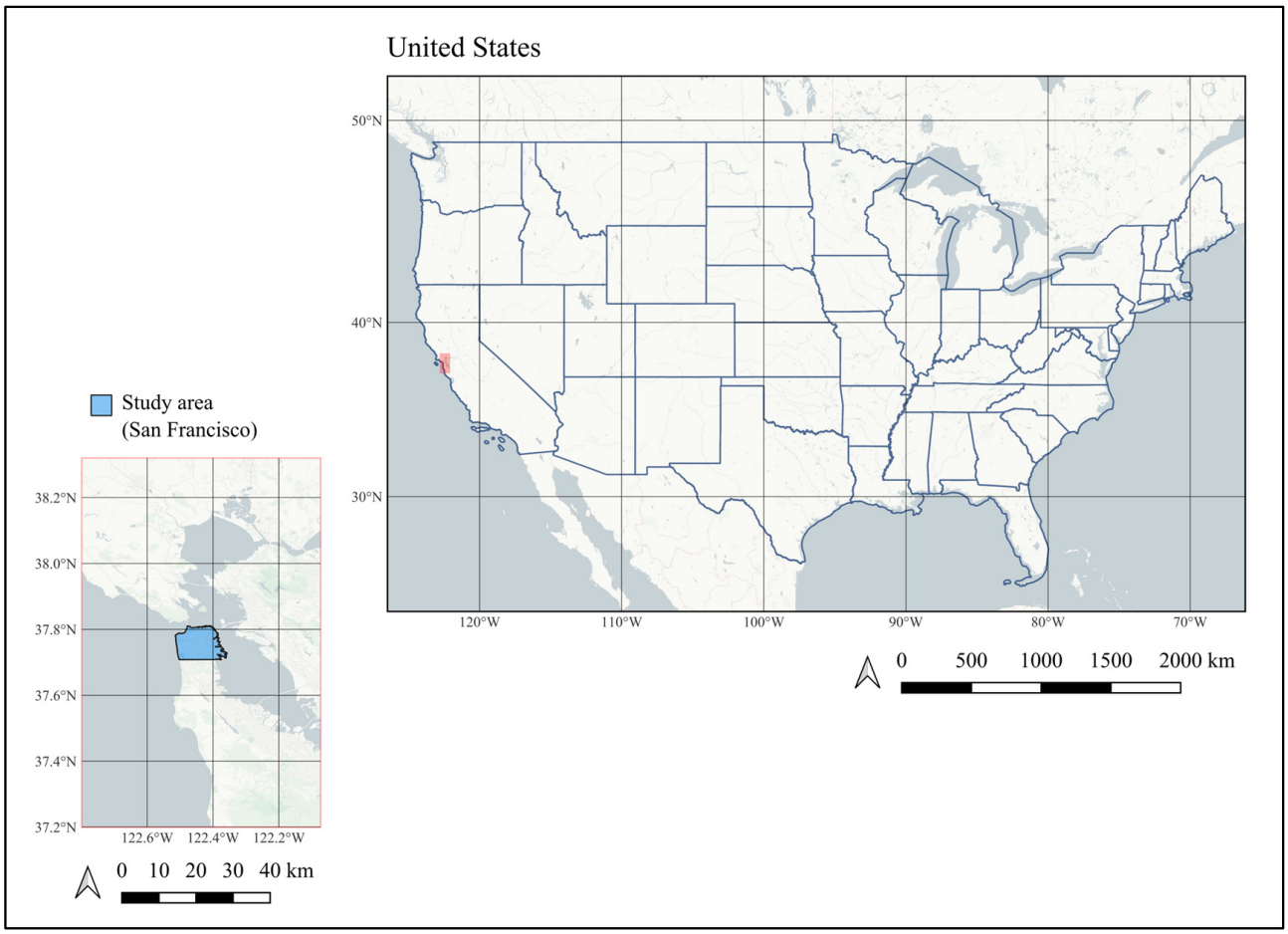


Figure 1. Overview of the study area.

Data for the current study were collected from two main sources: the US Census Bureau and Inside Airbnb. The 5-year estimate of the 2020 American Community Survey (ACS) was the latest census report available at the time of writing this article. Census tract-level estimates related to demographics, financial status, and housing conditions in San Francisco were obtained from ACS tables DP04, DP05, S2301, and S2503. There are 242 census tracts for San Francisco, excluding census tracts for the maritime area (tracts 9901 and 9902). Farallon Islands and Treasure Island (tracts 9804.01 and 179.03, respectively) were excluded because these areas are not adjacent to other areas. Furthermore, five census tracts (tracts 601, 604, 9802, 9803, and 9805.01) were excluded, since most of the land is covered by parks. Data for Airbnb listings in San Francisco were obtained from *Inside Airbnb*. Inside Airbnb regularly releases lists of Airbnb units in several major cities around the world. The Airbnb listing data used in this study were extracted and published on 4 December 2019. The initial dataset contained information for 8533 Airbnb listings in San Francisco. Airbnb units in the above-excluded census tracts (N = 49) were removed. Although several previous studies removed "inactive" Airbnb listings based on the number of reviews, empirical findings indicate that the bias caused by such inactive listings is negligible in practice [11,43]. Hence, all Airbnb listings were included in the analysis, regardless of their activity.

The broader literature on Airbnb commercialization has suggested categorizing Airbnb listings into quartiles based on the number of properties a given host manages within the same city [22,44]. An explorative analysis of our data also indicated that this is an effective way to differentiate between single- and multi-unit hosts while also accounting for different levels of commercialization among multi-unit hosts. Accordingly, the listings in San Francisco were divided into four mutually exclusive categories: Airbnb operated by hosts

who had one listing (quartile 1; N = 3238), two listings (quartile 2; N = 1285), three to eleven listings (quartile 3; N = 1858), and twelve or more listings (quartile 4; N = 2103) in San Francisco. The geographic locations of Airbnb listings are presented in Figure 2.

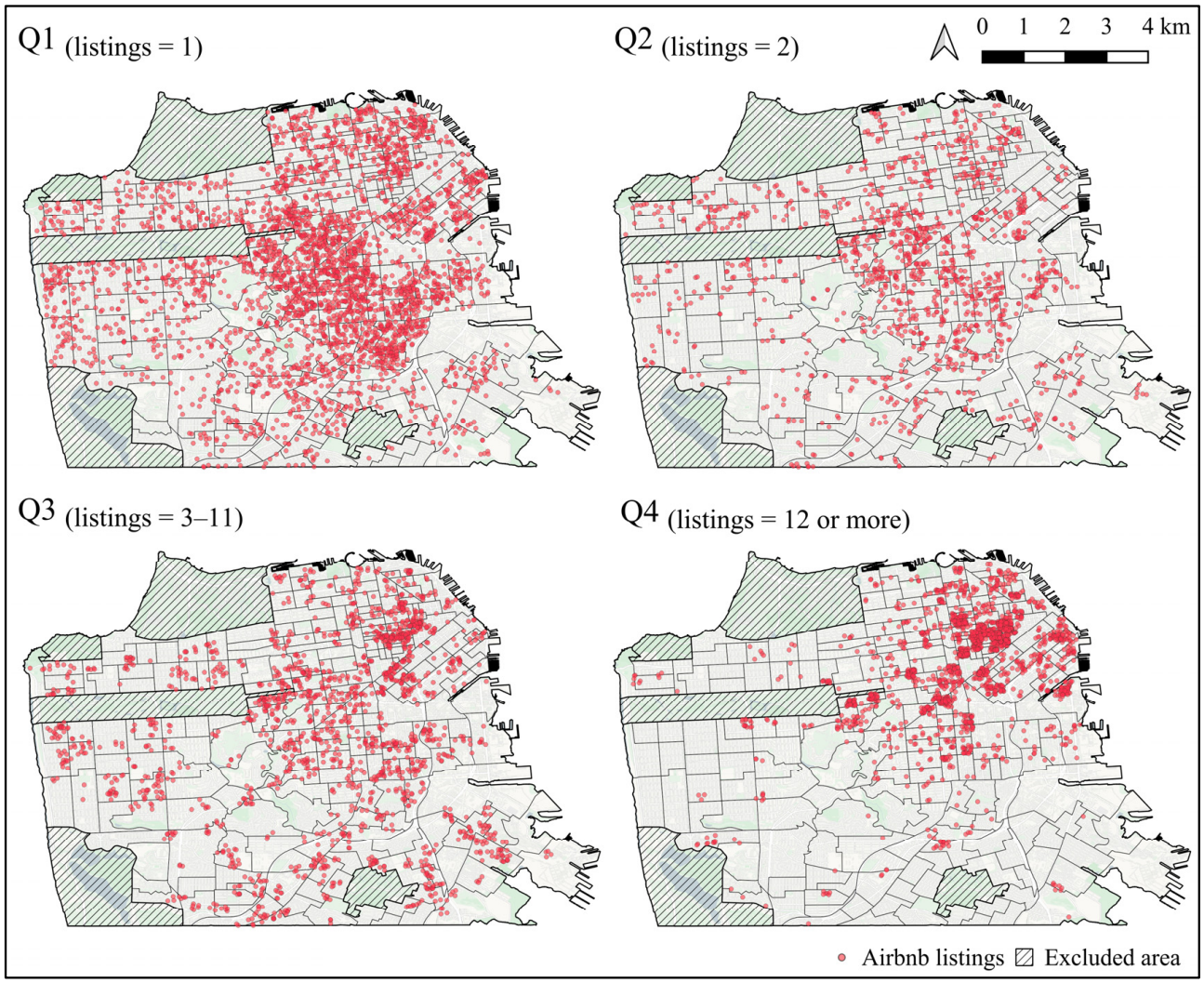


Figure 2. Airbnb listings by host categories.

Subsequently, the authors constructed independent and dependent variables using the two datasets. The descriptions of these variables are provided in Table 2. Independent variables used in this study are Airbnb densities per thousand housing units (*D*), which is calculated by dividing the number of Airbnb listings within a census tract by the number of occupied housing units and multiplied by 1000. Additionally, three control variables were included in the model based on previous studies [11,36]: population density (*Pp*), owner–occupancy ratio (*O*), and employment–population ratio (*E*). Although these variables are not the primary focus of this study, they represent characteristics of the housing market in a given region. For example, regions with dense populations would generally have high absolute rent costs due to high demand. By accounting for these factors, this study models the relationship between Airbnb density and relative rent cost, with these characteristics being equal. Lastly, dependent variables are the ratios of renter-occupied housing units with gross rent greater than 30% of household income (*R*). The average American spends 29.6% of their household income on rent, according to census data. For reference, this average rent–household income ratio is 32.2% in the state of California and 24% in San Francisco. Therefore, renters who spend more than 30% of their household income could consider that their rent cost relative to income is higher than average. The

assumption was that if R, the ratio of housing units with a rent–household income ratio of 30% or more in a certain region, increases (i.e., more people are spending a greater portion of their income as a rent cost), the relative rent cost in that region increases. The proposed regression model is as follows:

$$R_i = \beta_0 + \beta_1 \cdot D_{Q1} + \beta_2 \cdot D_{Q2} + \beta_3 \cdot D_{Q3} + \beta_4 \cdot D_{Q4} \\ [+ \beta_5 \cdot O + \beta_6 \cdot E + \beta_7 \cdot Pp] + \varepsilon_i \quad (1)$$

Table 2. Description of variables.

Variables	Notation	Description
Airbnb density (per 1000 housing units)	D	$\frac{No.\ of\ Airbnb\ listings}{Occupied\ housing\ units} \cdot 1000$
Q1 (Listings = 1)	D_{Q1}	
Q2 (Listings = 2)	D_{Q2}	
Q3 (Listings = 3–11)	D_{Q3}	
Q4 (Listings = 12 or more)	D_{Q4}	
Owner–occupancy ratio	O	$\frac{Owner\text{–}occupied\ housing\ units}{Occupied\ housing\ units}$
Employment rate (20 to 64 years)	E	$\frac{Employed\ population}{Population\ in\ labor\ force\ (20\ to\ 64\ years)}$
Population density	Pp	$\frac{Population}{Occupied\ housing\ units} \cdot 1000$
Ratio of housing units with gross rent greater than 30% of household income in the past 12 months (i = *household income*)		
$i <$ USD 50,000	$R_{<50}$	$\frac{Housing\ units\ (gross\ rent\ over\ 30\ percent\ of\ i\ )}{Housing\ units\ (i < 50{,}000)}$
USD 50,000 $\leq i <$ USD 75,000	$R_{50,75}$	$\frac{Housing\ units\ (gross\ rent\ over\ 30\ percent\ of\ i\ )}{Housing\ units\ (\$50{,}000 \leq i < \$75{,}000)}$
USD 75,000 $\leq i$	R_{75+}	$\frac{Housing\ units\ (gross\ rent\ over\ 30\ percent\ of\ i\ )}{Housing\ units\ (\$75{,}000 \leq i)}$

Note: ACS = American Community Survey.

The current study focused on identifying the impacts of Airbnb units on renters with relatively lower household incomes. Specifically, local renters were classified into three income groups: household income in the past 12 months less than USD 50,000, between USD 50,000 and USD 75,000, and USD 75,000 or more. The first income group has a household income of the past 12 months less than the US median of USD 64,994. For the second group, household income is lower than the median household income in California (USD 78,672). Hence, it can be stated that these two groups are in a state of relative income inequality. The household income of the last group is similar to or greater than the median California household income. For each income group, the authors calculated the ratio of housing units with gross rents greater than 30% of 12 months of household income ($R_{<50}$, $R_{50,75}$, and R_{75+}), which is visualized in Figure 3. We expected that the effect of Airbnb units on relative rent costs would be greatest for the lowest income group ($R_{<50}$), while those with household income greater than USD 75,000 would be less affected by Airbnb.

3.2. Geographically Weighted Regression (GWR)

Let us assume that there are regions h and i. Linear ordinary least squares (OLS) regression estimates a single regression coefficient *ß* through the observed relationship between X_h and Y_h and that between X_i and Y_i. However, this estimated relationship is a *global* estimate that does not reflect *spatial nonstationarity*, "[v]ariations in relationships over space" [45]. The geographically weighted regression (GWR) model aims to capture these local variations over space by estimating regression parameters for each location. Therefore, both Y_h and Y_i are functions of X_h and X_i because spatially adjacent regions can affect each other. In simplified form, this GWR model can be written as follows:

$$Y_i = \beta_0(u_i, v_i) + \beta(u_i, v_i) \cdot X_i + \varepsilon_i \quad (2)$$

where u and v are the coordinates of the individual observation point i.

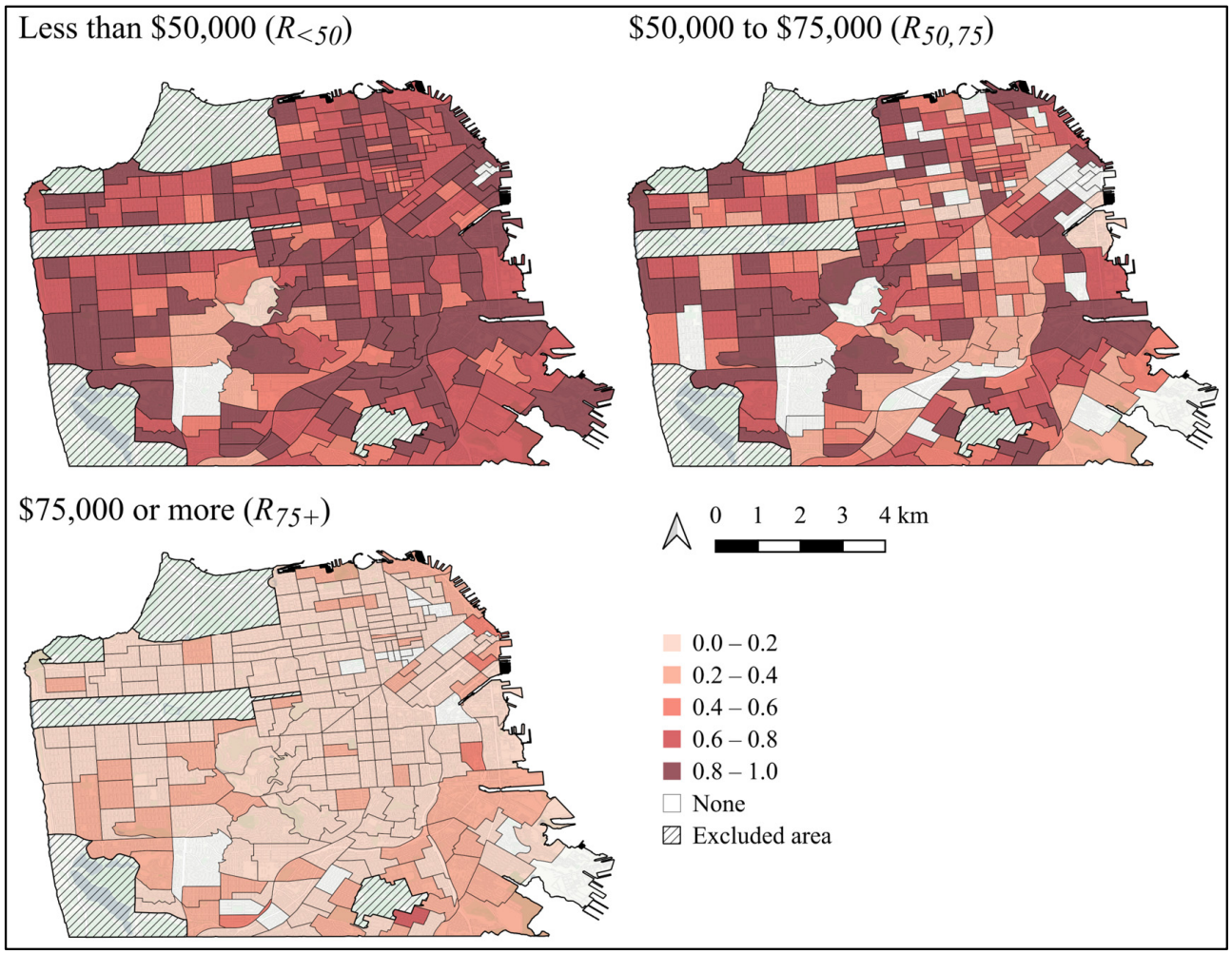


Figure 3. Ratio of housing units with gross rent greater than 30% of household income in the past 12 months.

However, one cannot assume that the strength of the effect of X_i on Y_i will be equal to that of X_h on Y_h. As the First Law of Geography suggests, closer things are more related than distant things [46]. The GWR model reflects this role of distance in the strength of relationships using spatial bandwidth and weight [47]. There are several spatial weighting functions, such as fixed Gaussian [48,49] and bisquare [50] functions, and adaptive Gaussian and bisquare functions, which attempt to mitigate exaggeration of the degree of nonstationarity [51]. The current study used the adaptive bisquare weighting function provided in the MGWR software [52]. If the weighting function determines the strength of the effect of variables in adjacent regions, the spatial bandwidth defines the range of nearby regions to be considered for estimation [53]. This article used the multiscale geographically weighted regression (MGWR) method, which does not use a fixed bandwidth for all variables but determines the bandwidths for each variable in the model [54]. The golden selection method was used to choose the optimal bandwidth for each variable, and the MGWR model was optimized using AIC scores. The visualization of the results was produced using the geographic information system (GIS) software QGIS [55]. Figure 4 summarizes the data analysis process.

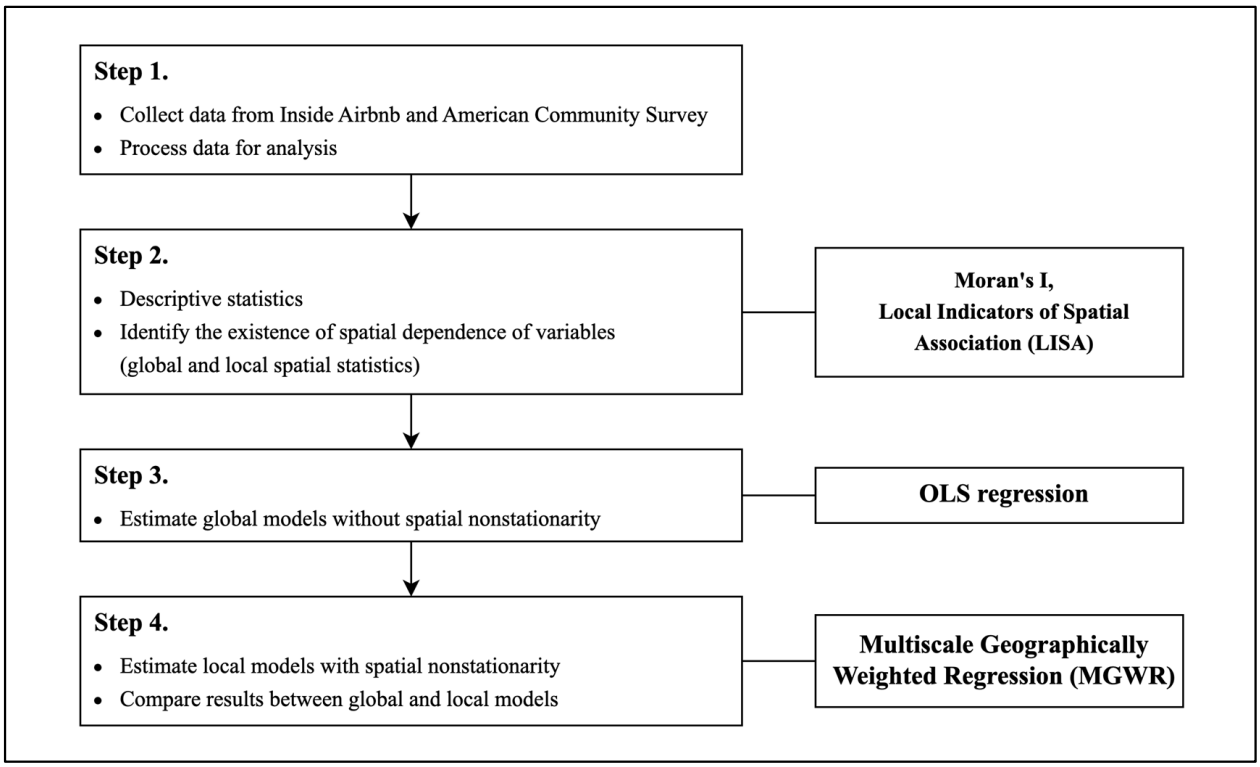


Figure 4. Summary of the analysis process.

4. Results

4.1. Characteristics of Variables

The descriptive statistics for the variables are presented in Table 3. Three variables (Airbnb density for Q3 and Q4 listings and employment–population ratio) violated the normality assumption [|Skewness| < 2 and |Kurtosis| < 7; [56]. Therefore, these variables were normalized using square root (D_{Q3} and D_{Q4}) and square transformation (E). The variance inflation factor (VIF) values of the predictor variables were below 5 [56], which means that multicollinearity is not a serious issue for the specified regression models.

Table 3. Descriptive statistics.

	Mean	SD	Max.	S	K	VIF	Transform	Moran's I	
Independent Variables									
D_{Q1}	9.14	7.12	39.68	1.41	2.70	1.96	-	0.546	***
D_{Q2}	3.66	3.45	19.48	1.48	2.55	1.79	-	0.294	***
D_{Q3}	5.52	5.44	43.30	2.50	11.04	1.31	Square root	0.188	***
D_{Q4}	6.18	14.01	173.21	7.96	87.43	1.64	Square root	0.533	***
Control Variables									
O	0.38	0.24	0.95	0.26	−0.95	1.82	-	0.670	***
E	0.80	0.11	1.00	−3.55	22.72	1.07	Square	0.121	***
Pp	2468.06	745.28	7065.18	1.56	5.44	1.60	-	0.631	***
Dependent Variables									
$R_{<50}$	0.74	0.20	1.00	−1.05	1.81	-	-	0.013	
$R_{50,75}$	0.52	0.31	1.00	−0.17	−0.95	-	-	0.078	*
R_{75+}	0.13	0.10	0.61	1.29	3.03	-	-	0.095	**

Note: SD = standard deviation, S = Skewness, K = Kurtosis, VIF = variance inflation factor, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In general, the spatial autocorrelation of variables is tested before performing the spatial analysis (e.g., [57–61]), using spatial dependency indicators such as Moran's I. Moran's I measures global-level spatial autocorrelation [62]. An I-value closer to −1

indicates a uniform distribution throughout the geographic area of the analysis, and an *I*-value closer to 1 indicates the presence of spatial autocorrelation. All variables except $R_{<50}$ showed the statistically significant presence of spatial dependence.

Moran's I is an indicator of the *presence* of spatial clustering at the global level. Local spatial patterns, even those that were not detected by global spatial indicators, can be identified using local indicators of spatial association (LISA; [63]). LISA statistics produce four types of clusters, categorized based on the values of the cluster and those of the neighboring region: high-high, low-low, high-low, and low-high. For example, the high-low type suggests a region with a high value that is surrounded by regions with low values. The current study calculated local Moran's I values to produce LISA statistics [63]. The resulting local Moran's I cluster map suggests the presence of local spatial autocorrelation (Figure 5). An interesting characteristic is that the density of Q4 Airbnb listings (D_{Q4}) showed a similar local spatial pattern to the owner–occupancy ratio (O), although the two showed inverse LISA statistics in most regions. For example, the high-high regions of D_{Q4} overlap with the low-low regions of O, and the low-low regions of D_{Q4} overlap with the high-high regions of O. This suggests that Airbnb Q4 listings (the most commercialized quantile) are densely populated in the regions where the proportion of renters is higher.

4.2. Regression Results

Table 4 presents the results of the OLS regression. The F-statistics of the regression models were insignificant except for the group with a household income of USD 75,000 or more (R_{75+}). For this income group, Airbnb density (D_{Q1} through D_{Q4}) did not show a statistically significant relationship with the ratio of housing units with gross rent greater than 30% of household income. The regression model also had very weak explanatory power (R^2 = 0.087). Furthermore, the Breusch–Pagan test suggests the heteroskedasticity of the residuals (BP = 17.65, p = 0.01), which suggests a violation of the assumption of homoskedasticity of the OLS. Therefore, all OLS regression models were rejected.

Table 4. Ordinary least squares (OLS) regression results.

	$R_{<50}$	$R_{50,75}$	R_{75+}
D_{Q1}	0.103	−0.085	−0.062
D_{Q2}	0.015	0.061	−0.132
D_{Q3}	0.080	0.154 *	0.081
D_{Q4}	0.031	−0.177 *	0.078
O	−0.083	−0.042	0.160
E	−0.028	−0.063	−0.019
Pp	0.138	−0.036	0.162 *
$ß_0$	<0.001	<0.001	<0.001
F	1.321	1.241	3.095 **
R^2	0.039	0.037	0.087
LL	−328.3	−328.5	−322.2
AIC	674.5	675.1	662.5
BIC	705.7	706.2	693.6
I_e	0.011	0.074 *	0.020
BP	29.28 ***	18.42 *	17.65 *

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, LL = log likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion, I_e = Moran's I for residuals, BP = Breusch–Pagan test.

However, the presence of global and local spatial autocorrelation suggests that linear OLS regression models may not be sufficient to reflect the spatial variability of variables. Therefore, MGWR models were constructed to reflect the spatial heterogeneity of the variables. The comparison between the OLS and MGWR models is presented in Table 5. In all models, the BIC score worsened, whereas the values of the log-likelihood and Akaike information criterion (AIC) suggest an improved model fit. Furthermore, the explanatory power of the models has improved. The regression model of $R_{50,75}$ showed the greatest improvement, and residuals no longer exhibit spatial autocorrelation.

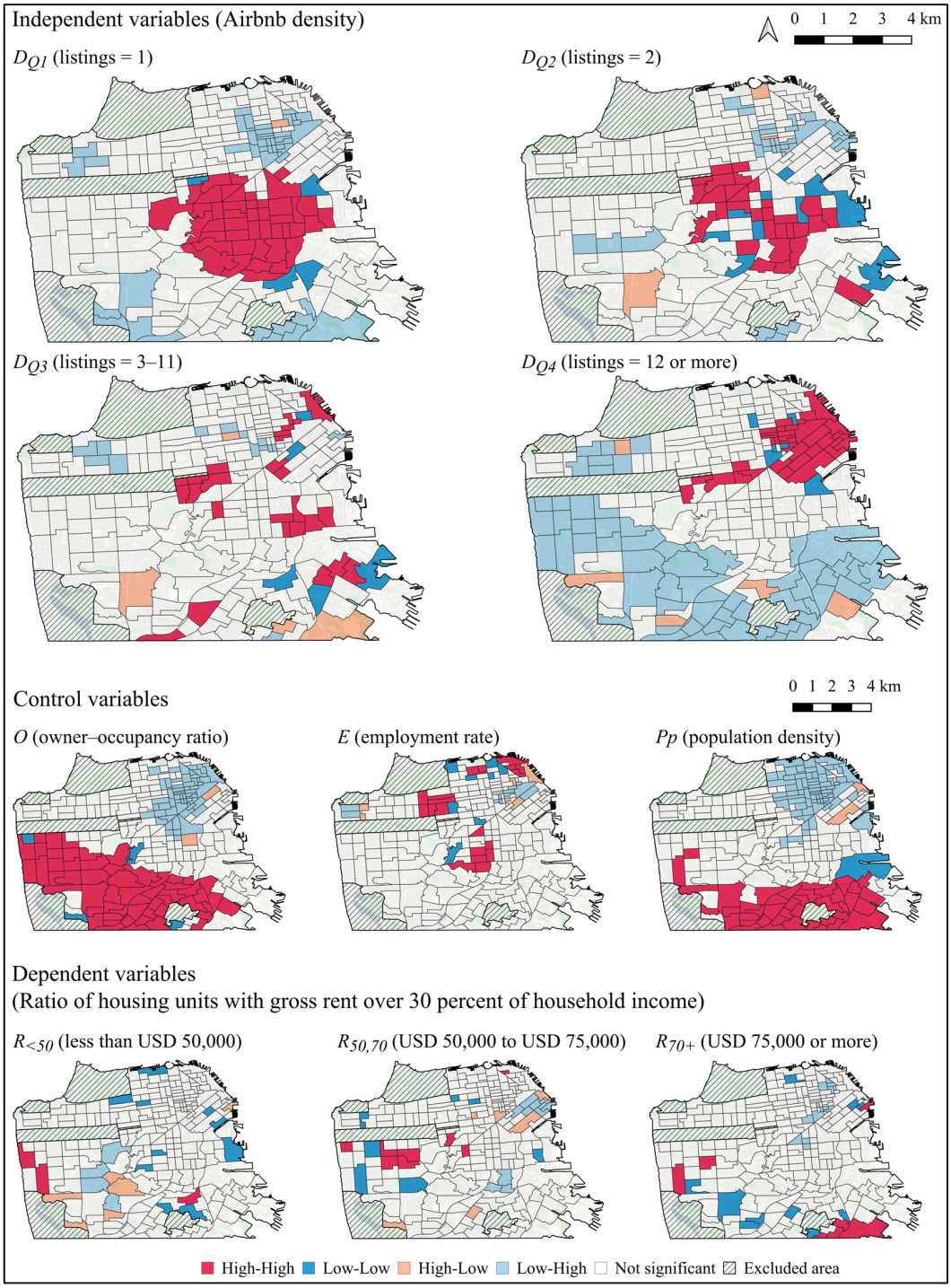


Figure 5. Local Moran's I cluster map.

Since MGWR calculates the coefficients for each region of analysis, the individual local coefficients and their statistical significance must be examined. Using adjusted *T*-values as critical thresholds [64], local coefficients that did not show statistical significance were identified and filtered out. The MGWR model of $R_{<50}$ had zero significant local coefficients, and the model of R_{75+} showed 77 statistically significant local relationships for the control variable *O* (Min. = 0.207, Mean = 0.227, Max. = 0.253). Therefore, details of these two models are not included in the current paper. The regression model of $R_{50,75}$ exhibited 11 significant β for D_{Q2}, 95 for D_{Q3}, and 13 for *Pp* (Table 6). A visualization of local coefficients is presented in Figure 6. Both D_{Q2} and D_{Q3} were positively correlated with $R_{50,75}$ (mean β = 0.608 and

β = 0.189, respectively). That is, if Airbnb density for Q2 and Q3 listings increases in these regions, the proportion of housing units with gross rent over 30% of household income increases for the USD 50,000 to USD 75,000 income group. The GWR bandwidth suggests that the effect of D_{Q2} is more local than that of D_{Q3} (bandwidth = 55 vs. 233).

Table 5. Comparison between OLS regression and MGWR models.

	$R_{<50}$		$R_{50,75}$		R_{75+}	
	OLS	**MGWR**	**OLS**	**MGWR**	**OLS**	**MGWR**
LL	−328.3	−311.6	−328.5	−291.2	−322.2	−314.4
AIC	674.5	671.9	675.1	642.7	662.5	661.0
BIC	705.7	756.1	706.2	747.1	693.6	716.8
R^2	0.039	0.166	0.037	0.299	0.087	0.146
I_e	0.011	−0.039	0.074 *	−0.046	0.020	0.014

Note: LL = log likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion, I_e = Moran's I for residuals. * $p < 0.05$.

Table 6. Multiscale geographically weighted regression (MGWR) result for household income between USD 50 k and USD 75 k.

	Sig. β	**Mean**	**Min.**	**Max.**	**SD**	**BW**	**Adj. *T* (95%)**
D_{Q1}	n.s.	—	—	—	—	233	2.102
D_{Q2}	11	0.608	0.466	0.705	0.085	55	2.854
D_{Q3}	95	0.189	0.175	0.199	0.005	233	2.236
D_{Q4}	n.s.	—	—	—	—	233	2.138
O	n.s.	—	—	—	—	226	2.219
E	n.s.	—	—	—	—	190	2.386
Pp	13	−0.605	−0.745	−0.347	0.123	74	2.718
$ß_0$	n.s.	—	—	—	—	182	2.274
R^2							0.299
LL							−291.2
AIC							642.7
BIC							747.1
I_e							−0.046

Note: Sig. β = number of significant coefficients, n.s. = not significant, BW = bandwidth, LL = log likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion, I_e = Moran's I for residuals.

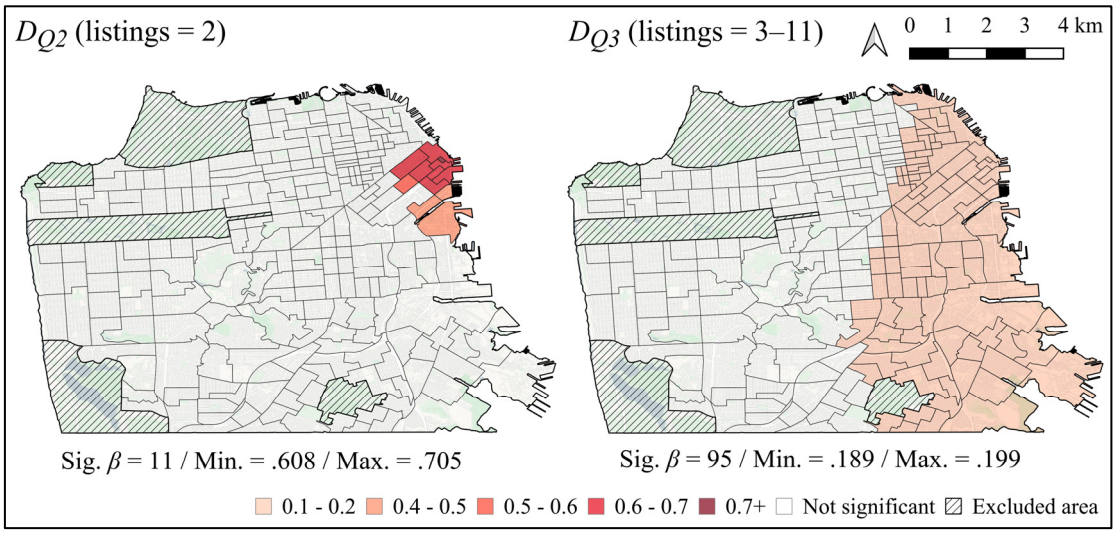


Figure 6. Map of MGWR coefficients. Note: Sig. β = number of significant coefficients.

5. Discussions

The present paper extensively examines the effect of peer-to-peer rentals on local renters. In general, the findings of the present article align with the results of previous studies that Airbnb density is positively related to rent cost (e.g., [11,14]). However, in light of the findings from the literature that identified heterogeneous characteristics of affecters (Airbnb listings) and affected (local renters), the current study has revealed the differential effect of Airbnb density on local renters. In summary, *not all Airbnb accommodations affect the relative rent cost, and not all renters are affected.* The authors used the ratio of housing units with gross rent greater than 30% of household income as an indicator of an increase in relative rent cost within the geographic unit of analysis. The results of the OLS regression and the MGWR models suggest that the relative rent costs of renters with household income in the past 12 months of less than USD 50,000 and more than USD 75,000 are not affected by Airbnb density. Although the authors of this study anticipated that households earning similar to or more than median household income would not be affected by Airbnb density, it was unexpected that renters at the lowest end of the income spectrum did not show a statistically significant relationship. There are at least two possible explanations for this finding. One scenario is that Airbnb density is not a major factor that influences the relative rent cost of tenants with less than USD 50,000 in household income. The other possibility is that some low-income renters who could not afford to spend a larger portion of their income were displaced to a different region, therefore reducing the number of housing units with a high percentage of rent costs.

Regarding the differential effect among Airbnb listing subdivisions, the OLS and MGWR models consistently predicted that Airbnb units from hosts who only have one listing (Q1; the least commercialized quartile) did not affect the relative rent cost. In contrast, the Q3 Airbnb units (hosts with 3–11 listings) showed a statistically significant positive relationship in both the OLS and the MGWR models. Additionally, Airbnb units in Q2 also exhibited a positive relationship, but only in the MGWR model. When comparing the impacts of D_{Q2} and D_{Q3}, D_{Q2} showed higher standardized coefficients than D_{Q3}. However, areas with a statistically significant effect of D_{Q2} on relative rent costs are mainly concentrated in areas near the Financial District neighborhood, while the effect of D_{Q3} is significant in wider regions that cover the east side of San Francisco. To summarize, the least commercialized Airbnb listings had no impact on the relative rent cost, while more commercialized listings are positively related to the relative rent cost, and the affected area increases along with the level of commercialization. Nevertheless, this study could not reveal why the most commercialized Airbnb units (12 or more listings) did not show a statistically significant relationship in the MGWR model.

The current paper contributes to the scarce literature on the relationship between short-term vacation and long-term residential rental markets by addressing key gaps in previous research. Unlike previous studies, which often assumed uniform effects among renters, this study identifies significant income-based disparities, showing that renters face a disproportionate financial burden from Airbnb activity. Additionally, the study differentiates the impacts of Airbnb listings by the degree of commercialization, revealing that there are differences in the negative impact of Airbnb even among multi-unit listings. Methodologically, the use of the multiscale geographically weighted regression (MGWR) model allowed for capturing the understanding of Airbnb's region-specific impact.

These insights, taken together, call for multifaceted regulatory frameworks that address income-based vulnerabilities, regulate commercialized Airbnb activities, and consider spatial heterogeneity. This nuanced perspective can be beneficial for regional governments that attempt to strike a balance between the positive impact of peer-to-peer accommodations for tourism and its negative impact on the housing supply for residents. Tourism destination policymakers are imposing regulations on peer-to-peer short-term accommodations, some stricter than others, to amend their negative impacts [65]. But clearly, as the findings of this study also suggest, a one-size-fits-all regulatory approach would not be effective [14,66]. Unlike the current regulatory framework for short-term rentals, the

authors suggest imposing differentiated regulations based on the level of commercialization of Airbnb hosts. For example, stricter regulations could be imposed on Airbnb hosts who own several listings within the city compared with hosts who own single Airbnb units. Miller [67] and Wegmann and Jiao [68] similarly concluded that "mom-and-pop" hosts and commercial operators should be distinguished. Our quantitative findings provide support for their proposals, since only Airbnb units from professional hosts (with multiple listings) significantly impacted relative rent, while private individual hosts (with single listings) had an insignificant effect. In addition, regulators could collaborate with the Airbnb company, as detecting the impact of short-term rentals and imposing direct regulation through peer-to-peer accommodation platforms would be one of the most effective methods. Countries all over the world already collect taxes related to short-term rental accommodation directly from the Airbnb platform [20], effectively blocking the possibility of tax evasion.

6. Limitations and Future Studies

Most of the limitations of current research are related to the constraints of data accessibility. First, as mentioned in the Methods section, the unit of analysis of the current study was housing units. Although absolute rent costs may not vary significantly between tenants of the same housing units, their income levels can differ, resulting in variations in relative rent costs within the same building. For a similar reason, the current study was unable to directly calculate the rent–income ratio for each income group; therefore, the proportion of housing units with a high rent–income ratio (over 30%) was used instead. Future research could use household or individual-level data to verify the applicability of the findings. Additionally, the ACS Census data are an estimation based on sampling, whereas the Airbnb listings dataset is a near-perfect snapshot of the Airbnb units supplied in San Francisco. A methodological limitation of this study is that unlike spatial econometric models that distinguish direct and indirect effects [69], the GWR model does not differentiate the two. The Airbnb density within the same region (direct effects) and the "spillover" effects of the adjacent region (indirect effects) may exhibit different impacts on the relative rent cost. Lastly, the research area of the current study is a highly urbanized city with a high population density. Short-term accommodation in less urbanized or rural areas can have different effects on long-term renters, as the characteristics of the housing market differ significantly.

7. Conclusions

In conclusion, the research underscores the need to consider the differentiated and localized impacts of Airbnb on long-term renters. Specifically, the research demonstrated that Airbnb density significantly increased the proportion of rent spending for middle-income renters but had negligible effect on the lowest and highest income groups. The effect also varied by Airbnb commercialization, where listings managed by hosts who own only one Airbnb in San Francisco did not significantly influence relative rent costs. In contrast, Airbnb managed by hosts who own three to eleven listings had a notable impact on middle-income renters that was widespread throughout the city. The spatial analysis revealed that the impact of commercialized Airbnb listings is more pronounced in specific neighborhoods, like city centers, indicating localized effects of Airbnb on the rental market.

The implication of these findings is that policymakers should consider differentiated and localized strategies rather than uniform city-wide regulations to effectively manage the impact of Airbnb. Regulatory frameworks should account for the varying impacts of Airbnb across different income groups and neighborhoods. Implementing targeted regulations could mitigate adverse effects on middle-income renters while preserving the economic benefits of short-term rentals for other stakeholders. Our findings can also inform urban planners about the potential displacement effects caused by short-term rentals, enabling them to design more equitable policies that balance the benefits of tourism with the needs of residents.

Either explicitly or implicitly, Airbnb has often been portrayed as a singular entity that affects the lives of locals. This study showed that not all Airbnbs are equal; so are local renters affected by Airbnb. Now the question is not *whether* short-term rentals impact renters, but *who* is impacted by *which* Airbnb and *where*. Unraveling this complex nexus between short- and long-term rentals will inform more targeted and effective decision-making that balances the interests of hosts, renters, and cities, ultimately shaping a more inclusive and sustainable future for tourism destinations.

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