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ESTIMATING SPATIOTEMPORAL HETEROGENEOUS EFFECTS OF HAZE POLLUTION ON HOUSING RENTS IN CHINA

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Abstract. Severe haze pollution significantly affects urban life quality and employment location choices, which in turn impact rental housing demand and housing rents. While numerous studies have delved into the effects of haze pollution on the real estate market, with a particular focus on housing prices, there is a notable scarcity of research on its impact within China's rental housing market. This study employs spatial panel data encompassing 289 Chinese cities from 2015 to 2021 and applies a Geographically and temporally weighted regression (GTWR) model to investigate the spatiotemporal heterogeneous effects of haze pollution on housing rents in urban China. Our results indicate that the GTWR model's goodness-of-fit surpasses that of the OLS, GWR, and TWR models. The results of the GTWR model reveal that haze pollution has a negative effect on housing rents in China, with the eastern region experiencing a notably stronger negative impact than the western region. Moreover, this negative impact becomes increasingly stronger over time. In addition, population, economic, and social factors significantly impact housing rents in Chinese cities. These findings offer valuable insights into the relationship between haze pollution and housing rents, assisting policymakers in assessing the economic value of air pollution control in urban China.

Keywords: haze pollution, housing rents, GTWR model, spatiotemporal heterogeneous effects, China.

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1. Introduction

Since the initiation of economic reforms and the subsequent opening up to global trade in 1978, China's swift urbanization has catalyzed a significant surge in housing demand. This has, in turn, propelled the rapid expansion of the country's urban real estate market. Nevertheless, the extensive and prolonged process of urbanization has not only led to significant consumption of fossil fuels but has also given rise to severe air pollution challenges. Notably, this has been exemplified by the frequent occurrence of haze pollution, characterized by the presence of fine particulate matter known as $PM_{2.5}$ (Chen & Jin, 2019). Prior studies have demonstrated that $PM_{2.5}$ pollution not only diminishes social labor productivity but also influences the quality of urban life and the employment location choices of the migrant population (Smith et al., 2016). These factors may further impact the trajectory of the urban rental housing market and housing rents in China. In addition, the seventh national population census in 2020 showed that the floating population in China has surged to 376 million. These "new citizens", a diverse group encompassing individuals relocating to urban areas for employment or educational pursuits, are driving a significant demand for rental accommodations in large and medium-sized cities that are witnessing a net population increase. Accordingly, examining the correlation between haze pollution and rental housing prices in urban China is essential to reveal the economic benefits of mitigating haze and to emphasize the importance of preserving urban air quality. Such understanding can be instrumental in fostering the judicious management of housing rents and in bolstering the robust growth of the rental housing sector.

Haze pollution, recognized as a leading air contaminant in numerous countries and regions, is characterized by the presence of fine particulate matter with an aerodynamic equivalent diameter of 2.5 microns or less in the ambient air (Brook et al., 2010). This form of pollution has been conclusively linked to substantial health risks (Gu et al., 2019). It is widely recognized as a major contributor to various respiratory and cardiovascular diseases (Dales et al., 2010; Dauchet et al., 2018) and is correlated with increased rates of morbidity and mortality rates (Apte et al., 2015; Lim et al., 2012). In light of the detrimental health impacts of haze pollution, there has been a marked increase in urban residents' desire for a superior living environment and enhanced air quality in recent years (Li et al., 2020). This growing concern has led to a surge in the willingness of individuals to support initiatives aimed at improving air quality (Wang et al., 2006). Furthermore, an increasing number of people are opting to relocate to cities known for their better air quality when choosing their place of residence, thereby exerting a significant influence on the dynamics of the local real estate market (Liu et al., 2018).

The contributions of the current study are multifaceted. First, a plethora of existing literature has established the substantial adverse effect of air pollution on housing prices (Chen & Jin, 2019; Lan et al., 2020; Ou et al., 2022), and predominantly focus on national analyses in smaller economies or localized case studies (Gómez & Iturra, 2021; Liu et al., 2018). This study fills a significant gap by investigating the effects of haze pollution on urban rental housing markets across China at a national scale. This comprehensive analysis is particularly noteworthy for developing countries like China, where such nationwide investigations are scarce. Second, the distinct housing submarkets are subject to a variety of influencing factors, with the magnitude of their impact differing across various segments (Bangura & Lee, 2023). Therefore, a submarket analysis is indispensable when scrutinizing the housing market, especially for a housing market as large as China's. This study used the GTWR model to address the limitations of traditional regression methods employed in previous research (Wang & Lee, 2022), which can handle both spatial heterogeneity and temporal heterogeneity. Our investigation into the varying preferences for air quality among residents across different submarkets seeks to aid policymakers in crafting area-specific housing policies.

The remainder of this paper is organized as follows: Section 2 provides a summary of relevant research literature. Section 3 outlines data sources and research methods. Section 4 presents the empirical research findings. Sections 5 and 6 comprise the discussion and conclusion of the paper, respectively.

2. Literature review

With the influx of new citizens and the youth into cities, the burgeoning migrant populace has thrust urban housing rents into the spotlight, garnering significant interest from both society and government. Existing studies have confirmed that macro-level housing market prices are influenced by demographic and socioeconomic factors, such as population density, GDP per capita, proportion of tertiary industry output to GDP, city annual wage per worker (Bangura & Lee, 2022; Chen & Jin, 2019; Wang & Lee, 2022; Zou, 2019). Economically advanced and populous cities typically exhibit higher housing prices and rental costs (Bian & Gete, 2015; Choi & Jung, 2017; Li & Liang, 2022; Saiz, 2007). Beyond demographic and socioeconomic factors, the level of public service was considered an important factor affecting housing market prices, encompassing aspects such as transportation infrastructure, educational institutions, healthcare facilities, and the availability of green spaces (Bryant & Eves, 2014; Chen & Chen, 2023; Churchill et al., 2021; Kim et al., 2020; Li et al., 2019; Wen et al., 2014). Generally, there is a positive correlation between the enhancement of public service quality and the escalation of urban housing prices (Hu et al., 2023).

Amidst urban sprawl and economic growth, cities are grappling with severe environmental challenges, particularly air pollution. Consequently, a wealth of research has delved into the interplay between air pollution and the real estate market over time. The majority of existing studies have consistently demonstrated that the escalation in air pollution levels often correlates with a decline in local housing values (Huang & Skidmore, 2024; Nam et al., 2022). Amidst the grave air pollution crisis in Chinese cities, a growing number of empirical studies have focused on the associations of air pollution with housing prices in China, revealing its detrimental effects on residential property values (Zhang et al., 2019; Zou, 2019). For instance, Chen and Jin (2019) analyzed air pollution and housing price data from 286 cities in China, uncovering a negative correlation between the two. Their findings indicated that a 10% rise in haze pollution corresponds with a 2.4% decrease in housing prices. Likewise, Zhang et al. (2021) investigated the spatial spillover effects of air pollution on housing prices at the city level in China, estimating that a doubling of total imported air pollutants from neighboring cities within 100 km could potentially reduce local housing prices by 6%. While the existing studies have provided valuable insights into the relationship between air pollution and housing prices at a larger scale, several others have focused on this relationship within cities. Zhang et al. (2019) examined Handan and found a negative relationship between air pollution and housing prices. Conversely, Dai et al. (2020) investigated Nanjing and identified a significant positive correlation between $PM_{2.5}$ pollution and housing prices within the city.

The interplay between environmental quality and the housing market has been a focal point of extensive research, particularly concerning property values and the rental market dynamics. While numerous studies have scrutinized the effects of air pollution on real estate markets, with a predominant emphasis on housing prices (Chay & Greenstone, 2005; Wang et al., 2021), there is a notable scarcity of research exploring the impact of air quality on the rental housing market, especially in developing nations such as China. The swift urbanization in these regions has intensified environmental stressors, making this a critical area for further investigation (Gómez & Iturra, 2021; Liu et al., 2018). Nonetheless, most scholars have concentrated their analyses on the local scale, with only a few examining the national-scale impact of air pollution on urban housing rents in China. For instance, Wang and Lee (2022) explored the concerns of air quality improvement for both renters and homebuyers and found a significant negative impact of the air quality index on both housing prices and rents in China.

In terms of research methods, a multitude of prior investigations into housing values have relied on the hedonic model proposed by Rosen (1974) and have employed the Ordinary Least Squares (OLS) regression to assess the impact of air pollution. However, conventional OLS regression might fail to account for potential spatial dynamics, such as spatial autocorrelation and spatial heterogeneity, which are inherent in urban housing price patterns. To address this limitation, scholars have progressively adopted spatial hedonic models. Zou (2019) leveraged the OLS and Geographically Weighted Regression (GWR) models to investigate spatial variability in air pollution's impact on housing prices across 282 prefecture-level cities in China. His results demonstrated the GWR model's superior explanatory power and its adeptness at capturing spatial heterougeous effects of air pollution on housing values in different cities. Similarly, Lai et al. (2021) employed a GWR model to investigate the spatial heterogeneity of residents' marginal willingness to pay for clean air in Shanghai.

While the GWR model has shown superior goodness of fit in modeling real estate market prices compared to global OLS or spatial regression models, it traditionally neglects the temporal dimension, thus falling short in effectively modeling spatiotemporal data. To bridge this gap, Huang et al. (2010) extended the traditional GWR model to a GTWR model by integrating time non-stationarity, and investigated spatial-temporal heterogenous effects of various housing characteristic variables on housing prices in Calgary, Canada. In recent years, the GTWR model has been widely applied in social and economic research, yet its use to investigate the influencing factors of housing prices within urban areas has been relatively limited. As a result, studies specifically examining the spatiotemporal heterogeneity effects of haze pollution on real estate market prices at broader regional or national scales are still scarce.

In summary, prior research has exhibited two primary limitations. Firstly, while numerous studies have delved into the effects of air pollution on housing prices, there is a notable scarcity of evidence concerning the impact of haze pollution on urban housing rents at the national level, particularly within developing nations like China. Secondly, in terms of methodological approaches, the spatiotemporal variability in the influence of air pollution on urban housing rents in China has been largely overlooked when assessing the factors that determine rental prices. To fill these research gaps, this study leverages housing rent data from 289 prefecture-level cities in China, covering the period from 2015 to 2021. By utilizing the Geographically and Temporally Weighted Regression (GTWR) model, it investigates the spatial and temporal heterogeneity in the impact of haze pollution on urban housing rents.

3. Material and methods

3.1. Theoretical framework

Taking into account environmental, demographic, economic, and social determinants, this study constructs a theoretical framework for understanding the factors influencing housing rents in urban China, as depicted in Figure 1. Within this framework, environmental factor are proxied by $PM_{2.5}$ concentrations, while population factor is represented by the number of people per square kilometer. Economic factors encompass GDP to resident population per capita, the proportion of tertiary industry in GDP, and the year-end balance of RMB deposits in financial institutions. Social factors are represented by the number of ordinary primary schools per 10,000 people, the number of hospital beds per 10,000 people, the greening coverage of built-up areas, the capacity of buses or trams per 10,000 people. Finally, this research employs the GTWR model to identify the factors that significantly impact housing rents in urban China.

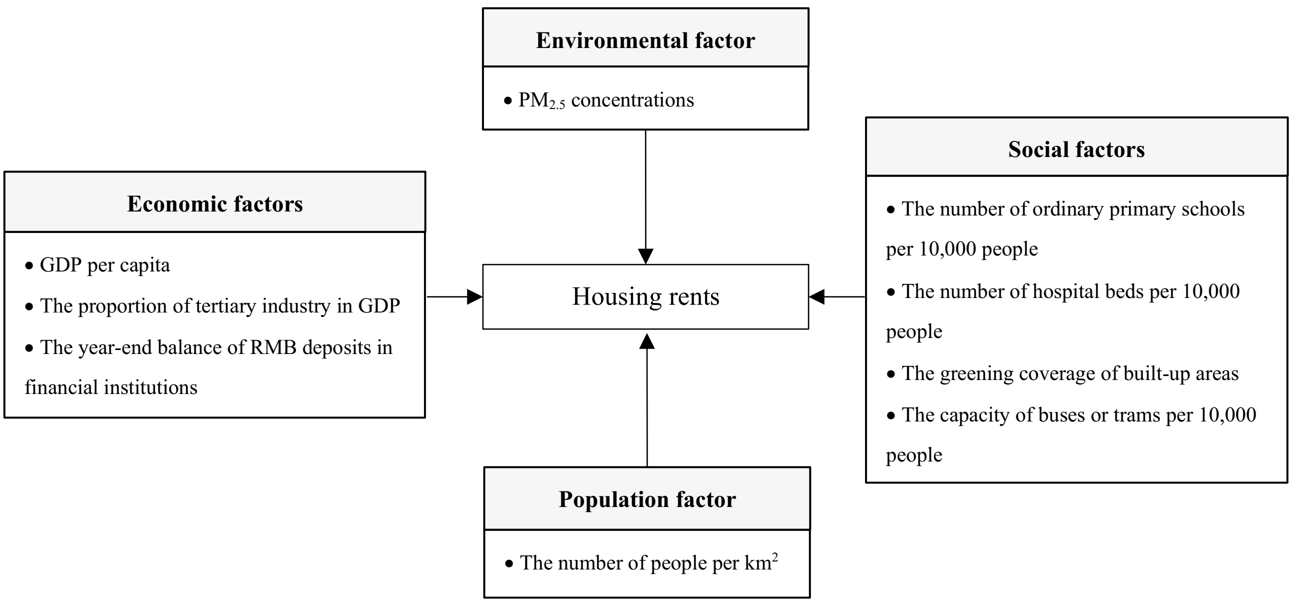

Figure 1. Theoretical framwork of the determinants of housing rents in urban China

3.2. Data sources

The dataset utilized in this study encompassed housing rents and socio-economic indicators for 289 cities classified as prefecture-level and above across China, spanning the years 2015 to 2021. Housing rent data were sourced from China Housing Network (http://www.fangchan.com/), haze pollution data were collected from the China Environmental Monitoring Station (http://www.cnemc.cn/), and the remaining explanatory variables were collected from the *China City Statistical Yearbook*, *China Urban Construction Statistical Yearbook* and *Statistical Communiqué of the People's Republic of China on National Economic and Social Development*. In this study, the dependent variable is urban housing rents, with haze pollution emerging as the key explanatory variable of interest.

Taking into account the findings of prior research (Zhai et al., 2018), this study has selected economic factors, population factors and social factors, in addition to environmental factors, as control variables to be included in the analysis (Table 1). For population factor, we selected the number of people per square kilometer (Popden), which represented by population density. Higher urban population density typically correlates with increased demand in the housing rental market. For economic factors, we selected three indicators, including GDP per capita, the proportion of tertiary industry in GDP, and the year-end balance of RMB deposits in financial institutions. Per capita GDP reflects regional economic development and the rental consumption capacity of a region, while the tertiary industry, known for its service sector, absorbs significant migrant employment, thereby becoming an important driver of urban rental housing demand. In addition, the year-end balance of RMB deposits in financial institutions reflects the region's economic activity and the accumulation of residents' wealth which are closely related to urban housing rents. For social factors, we selected the number of ordinary primary schools per 10,000 people (Sch), the number of hospital beds per 10,000 people (Hop), greening coverage of built-up areas (Green), and the capacity of buses or trams per 10,000 people (Bus). The quality of public service facilities significantly influences the livability of a city. Enhanced livability often draws a larger influx of migrants, drawn by the city's enhanced appeal, which in turn can drive up housing rents.

3.3. Spatial autocorrelation analysis

Spatial autocorrelation analysis encombasses both global spatial autocorrelation and local spatial autocorrelation. Globe spatial autocorrelation reflects spatial association intensity of one attribute value between a spatial object and its neighboring region in the entire study area, while local spatial autocorrelation is used to explore the spatial clustering degree of the selected attribute value for each spatial object at local space scale and to capture spatial clusters and spatial outliers among all the spatial objects. The local spatial autocorrelation measure can be expressed by Local Indicators of Spatial Association (LISA), and its specific formula is as follows:

$$I_i = \frac{\left(x_i - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right), \tag{1}$$

where: I_i represents the Local Moran's Index of the spatial object i; w_{ij} represents the spatial weight of the spatial objects i and j; n indicates the total number of spatial objects.

3.4. Geographically and Temporally Weighted Regression (GTWR)

The GTWR model diverges from the conventional GWR model by not only embracing the spatial dimension but also integrating the temporal dimension. This approach acknowledges the non-stationary nature of both time and space, enhancing the precision of estimations (Huang et al., 2010). The formula of GTWR model is calculated as follows:

$$Y_i = \beta_0\left(u_i, v_i, t_i\right) + \sum_k \beta_k\left(u_i, v_i, t_i\right) X_{ik} + \varepsilon_i, \tag{2}$$

where: Y_i is housing prices in the city i; $\left(u_i, v_i, t_i\right)$ represents the coordinates of the city i in space; $\beta_0\left(u_i, v_i, t_i\right)$ represents the intercept value; $\beta_k\left(u_i, v_i, t_i\right)$ represents a set of parameter values of the city i; X_{ik} represents the value of the k-th explanatory variable at the sample city i;

Table 1. Explanatory variable selection

Indicators	Variables	Description
Environmental factor	$PM_{2.5}$	The mass concentration of aerosol particles with a diameter of 2.5 μm or less in the air
Population factor	Popden	The number of people per km^2
Economic factors	Pgdp	GDP per capita
	Third	The proportion of tertiary industry in GDP
	Deposit	The year-end balance of RMB deposits in financial institutions
Social factors	Sch	The number of ordinary primary schools per 10,000 people
	Hop	The number of hospital beds per 10,000 people
	Green	The greening coverage of built-up areas
	Bus	The capacity of buses or trams per 10,000 people

ε_i represents the error term. The GTWR model provides an estimate of $\beta_k\left(u_i, v_i, t_i\right)$ for each variable and for each spatiotemporal position i by using the locally weighted least square method. The estimate of $\beta_k\left(u_i, v_i, t_i\right)$ can be expressed as follows:

$$\hat{\beta}\left(u_i, v_i, t_i\right) = \left[X^T W\left(u_i, v_i, t_i\right) X\right]^{-1} X^T W\left(u_i, v_i, t_i\right), \quad (3)$$

where: $W\left(u_i, v_i, t_i\right)$ represents the diagonal matrix of the weight of spatial and temporal distance of order n. The diagonal element W_{ij} can be expressed as follows:

$$W_{ij} = \exp\left(-\frac{d_{ij}^2}{h^2}\right), \quad (4)$$

where: h represents the bandwidth, which decays with distance; d represents spatiotemporal distance. Position and time are usually measured in different units, leading to different scale effects. A spatial distance, d^s, and a temporal distance, d^T, can be combined into a spatiotemporal distance, d^{ST}:

$$d^{ST} = d^s \otimes d^T, \quad (5)$$

where: $\otimes$ can represent different operators. If the "+" operator is used to measure the total spacetime distance d^{ST}, it is expressed as a linear combination of d^s and d^T, that is $d^{ST} = \lambda d^s + \mu d^T$. If $\mu = 0$, only the spatial nonstationary and spatial distances are included, the GTWR model is simplified as a GWR model; If $\lambda = 0$, the GTWR model is reduced to a TWR model. The cross-validation (CV) method is typically employed for the selection standard of bandwidth b. When a CV is the minimum value, the corresponding b is the optimal bandwidth. The expression in such a scenario is as follows:

$$CV = \sum_{i}^{n}\left[y_i - \hat{y}_i(b)\right]^2, \quad (6)$$

where: function $\hat{y}_i(b)$ indicates the predicted value y_i of the GTWR model; b represents bandwidth.

4. Results

4.1. Analysis of temporal and spatial change in housing rents

Figure 2 maps the spatial distribution of housing rents across 289 Chinese cities from 2015 to 2021. The map illustrates the spatial variation in housing rents across China throughout the study period. Despite only minor temporal change in the various years, there is a pronounced east-west spatial gradient in the overall distribution. Notably, housing rents in first-tier cities and the eastern coastal regions are significantly higher compared to those in the central and western inland cities. Furthermore, during the period from 2015 to 2017, the regions with the highest housing rents, exceeding 50 yuan/month/m^2 in China, are predominantly concentrated in China's first-tier cities, such as Beijing, Shanghai, and Shenzhen. Over the subsequent years, from 2019 to 2021, Hangzhou and Guangzhou also emerge as the high-value areas with housing rents surpassing 50 yuan/month/m^2 in China.

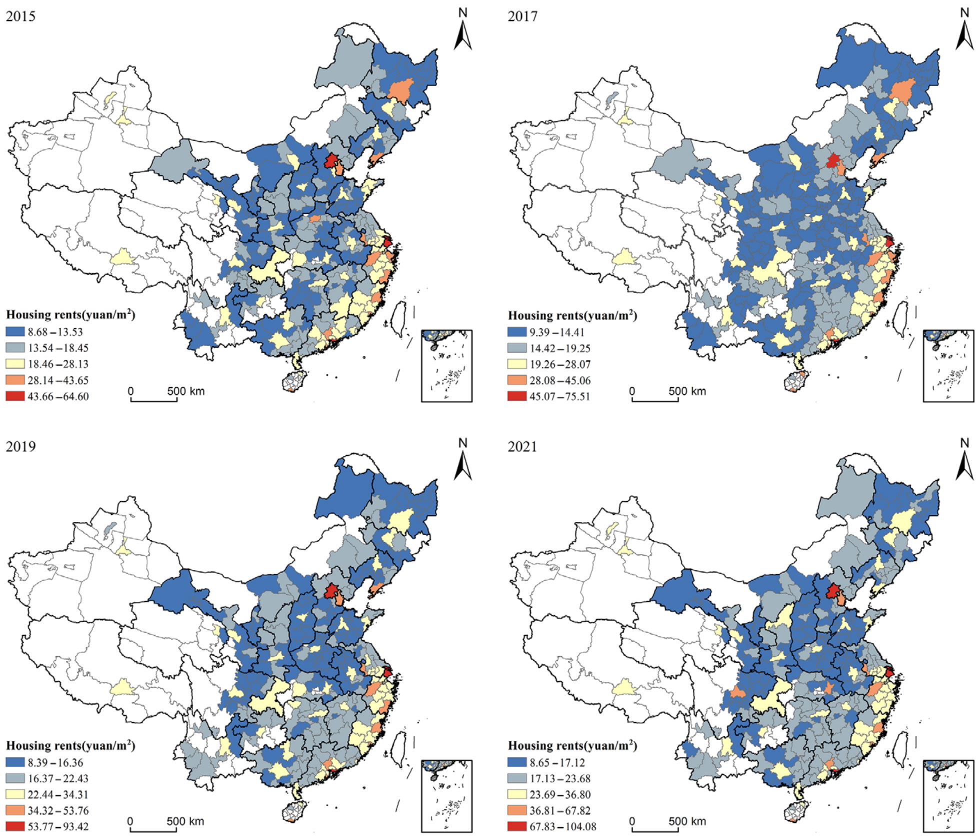

Figure 2. Spatial and temporal patterns of housing rents in China from 2015 to 2021

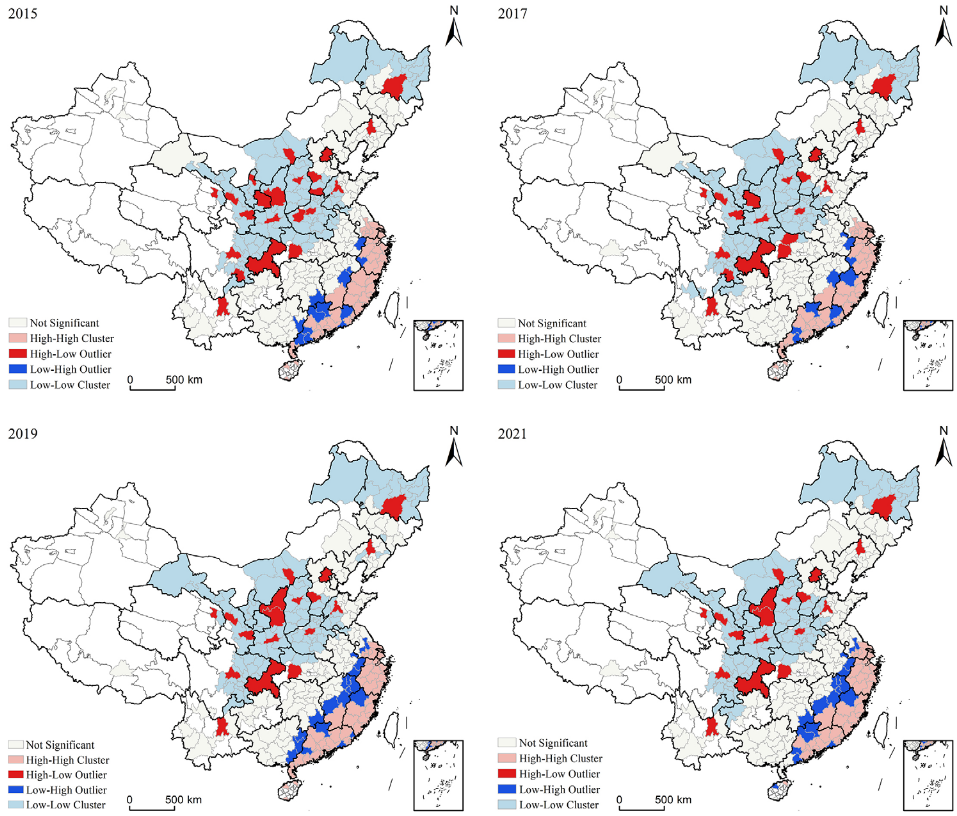

Figure 3. Local spatial autocorrelation of housing rents in China from 2015 to 2021

Figure 3 presents the local spatial autocorrelation results of housing rents in China from 2015 to 2021. The results illustrate spatial clusters and spatial outliers of housing rents in China at a local level. It is evident that there is an obvious spatial disparity in local spatial clusters among 289 Chinese cities during the study period. High-High Cluster areas of housing rents are stable in the Southeast, while Low-Low Cluster areas of housing rents are mainly distributed in several cities within central China and northeast China, such as Jiuquan, Hulunbuir, and Qiqihar. Regarding temporal shifts, Low-Low Cluster areas in China exhibite a stable presence from 2015 to 2017, with a consistent count of approximately 90 cities. However, in 2018, there was a notable increase, with the number of Low-Low Cluster areas rising to 144 cities. Subsequently, in 2021, this number experienced a decline, settling at 102 cities.

4.2. Model comparison

To assess the GTWR model's applicability and precision, Table 2 compares the goodness of fit from Ordinary Least Squares (OLS), Geographically and Temporally Weighted Regression (GWR), Temporally Weighted Regression (TWR), and the GTWR models. In contrast to the OLS, GWR, and TWR models, which reported R-squared values of 0.547, 0.626, and 0.494 respectively, the GTWR model exhibited a significantly higher R-squared value of 0.699. This comparison underscores the GTWR model's enhanced explanatory capability, as it adeptly accounts for the complexities of spatiotemporal heterogeneity.

Table 2. Comparison of model results

Model	R^2	Adjusted R^2	AICc
OLS	0.547	–	61.265
GWR	0.626	0.613	32.126
TWR	0.494	0.492	200.648
GTWR	0.699	0.698	–632.003

As shown in Table 3, the GTWR model observes an R-squared value of 0.699, indicating that it can explain 69.9% of the variance of housing rents across 289 Chinese cities. The model's supplementary fit indices, including Residual-Squares, Sigma, and AICc, are reported at 76.412, 0.194, and –632.003, respectively. These metrics collectively imply that the GTWR model achieves a higher goodness of fit for investigating the impact of haze pollution on housing rents within the Chinese context.

Table 3. Goodness of fit measures of the GTWR model

Statistics	Parameters
Residual-squares	76.412
Sigma	0.194
AICc	–632.003
R^2	0.699
Adjusted R^2	0.698
Spatiotemporal distance ratio	0.269

Table 4. Regression coefficients results of the GTWR model

Variable	Minimum	Lower quartile	Median	Upper quartile	Maximum
$PM_{2.5}$	–0.6174	–0.4181	–0.2938	–0.2096	0.0693
Popdens	–0.1036	0.0197	0.0417	0.0734	0.1403
Pgdp	–0.0664	–0.0095	–0.0025	0.0078	0.0352
Third	–0.3034	–0.0783	–0.0385	0.0381	0.5521
Deposit	0.0196	0.0518	0.0781	0.1153	0.3613
Sch	–0.1885	–0.1247	–0.0884	–0.0488	0.0938
Hop	–0.1327	–0.0184	0.0350	0.0795	0.2434
Green	–0.1324	–0.0815	–0.0428	–0.0156	0.0489
Bus	–0.0052	0.0288	0.0529	0.0726	0.1210

Table 4 displays the regression coefficients from the GTWR model, highlighting the varied impacts of eight explanatory variables on housing rents in 289 Chinese cities over the entire time periods. The results reveal that $PM_{2.5}$ concentrations, the number of ordinary primary schools per 10,000 people, the greening coverage of built-up areas, the proportion of tertiary industry in GDP, GDP per capita have negative effects on housing rents in most of cities in China, while the year-end balance of RMB deposits in financial institutions, the capacity of buses or trams per 10,000 people, the number of hospital beds per 10,000 people, and the number of people per km^2 have positive effects. It is noteworthy that $PM_{2.5}$ has the greatest impact on housing rents compared to other factors.

4.3. Temporal evolution of influencing factors of housing rents

To elucidate the temporal evolution of the GTWR model's estimated parameters, Figure 4 presents a boxplot analysis for each explanatory variable. Regarding the impact of haze pollution, the regression coefficient demonstrates a consistent downward trend. The boxplot of this coefficient reveals a transition from a more compact to a more dispersed range, indicating a growing spatial heterogeneity in the impact of haze pollution from 2017 to 2020. Furthermore, the distribution of the regression coefficient, exhibiting a modest leftward skew, implies that haze pollution predominantly exerts a negative influence on housing rents in the majority of cities. This is likely attributable to the toll that haze pollution takes on urban environments, resources, and human health, consequently resulting in diminished housing rents.

In terms of population characteristics, the result is displayed in Figure 4b. The regression coefficient for population density shows a gradual increase over time. The boxplot displays a slight right-skewed distribution from 2015 to 2020 and a slight left-skewed distribution in 2021, suggesting that population density predominantly exerts a positive influence on housing rents in the majority of cities during this period. This may be attributed to the stimulation of urban resources and public services by higher urban population densities, resulting in increased housing rents. Moreover, numerous outliers in the boxplot suggests that spatial imbalances in the development of the housing rental market in China may lead to a spatial varying effects of population density.

In terms of economic characteristics, the results are shown in Figure 4c to Figure 4e. The regression coefficient for per capita GDP exhibits a trend of initially decreasing and then increasing. The median lies mostly in the middle to lower part of the boxplot, indicating a right-skewed or normal distribution. This indicates that per capita GDP exerts a predominantly positive effect on housing rents, with the boxplot's extension over time suggesting a growing dispersion of the data. This trend may be attributed to increased spending on housing rents with economic development. The regression coefficient for the tertiary industry structure displays a trend of initially decreasing and then increasing. The boxplot shows a slight right-skewed trend from 2016 to 2019, indicating a predominantly positive impact of this variable on housing rents in most areas. The boxplot initially shortens and then lengthens, indicating centralized distribution from 2016 to 2019. This trend may stem from rapid commercialization and traffic development associated with the high-level development of the tertiary industry, leading to increased housing rents. The regression coefficient for the year-end balance of RMB deposits in financial institutions gradually increases over time. The boxplot lengthens and becomes more discrete, indicating increasing instability in the coefficient. Numerous outliers suggest fluctuations in investment behavior influenced by bank-rate policies and consumer spending habits.

In terms of public service level, the results are shown in Figure 4f to Figure 4i. The regression coefficient for the number of ordinary primary schools per 10,000 people initially declines and then ascends. The distribution of this coefficient is skewed, with a normal distribution pattern from 2015 to 2017, shifting to a rightward bias from 2018 to 2021. This result indicates that, in the majority of cities, the presence of more primary schools per capita tends to have a predominantly negative effect on housing rents. This is because that, in big cities, the number of ordinary primary schools per 10,000 people is typically lower due to a significant influx of migrants, which in turn boosts the demand for rental housing. The regression coefficient

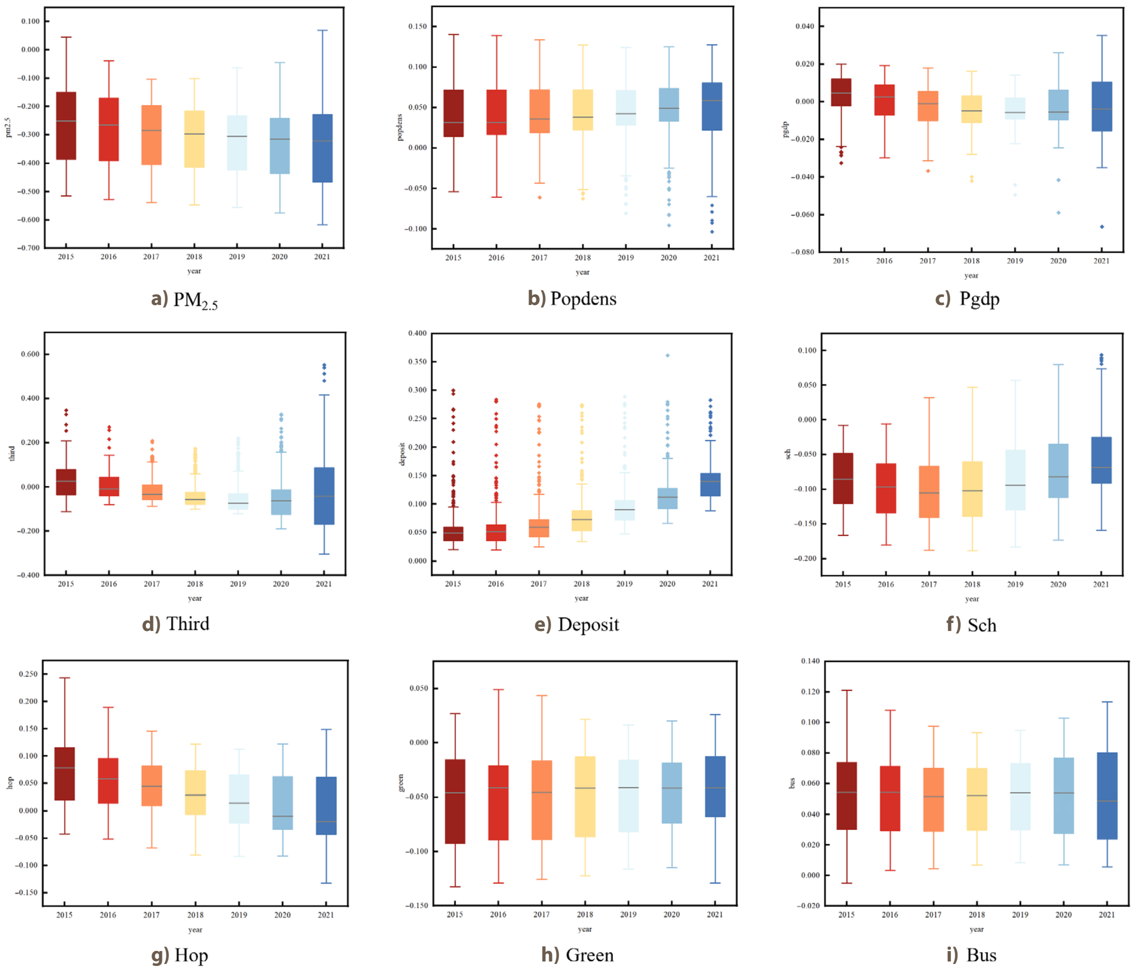

Figure 4. Temporal trends of estimated coefficients in the GTWR model

for the number of hospital beds per 10,000 people gradually decreases over time. The boxplot displays a left and middle-skewed distribution from 2015 to 2016 and a slight right-skewed distribution from 2017 to 2021, suggesting a predominantly positive impact of this variable on housing rents across most cities. This may be attributed to the attractiveness of areas with good medical facilities for residential purposes. The regression coefficient for the greening coverage of built-up areas remains relatively stable over time, indicating a predominantly negative impact on housing rents in most cities. The boxplot length remains consistent, suggesting a stable change in the coefficient. This may be due to the fact that green space development and conservation may limit economic development and rental housing demand enhancement. The regression coefficient for the capacity of buses or trams per 10,000 people remains relatively stable over time. The boxplot shows a slight right and middle deviation distribution, indicating a predominantly negative impact on housing rents in most cities. The boxplot length initially shortens and then lengthens, indicating stable changes in the coefficient over time.

4.4. Spatial heterogeneity of the influencing factors on housing rents

Figure 5 displays the spatial heterogeneity of the regression coefficients for nine explanatory variables. In terms of environmental factor, as shown in Figure 5a, haze pollution exerts a significant negative impact on housing rents in China, with the regression coefficients diminishing progressively from northwest to southeast China. The impact of haze pollution on housing rents varies across different submarkets. In the eastern coastal areas, a one-unit rise in $PM_{2.5}$ concentration correlates with a decrease in rental prices ranging from 0.5046 to 0.6173 yuan. In contrast, in the western and northeastern regions, a similar increase in $PM_{2.5}$ leads to a decrease in rental prices of less than 0.1966 yuan, and in some locales, rental prices may paradoxically rise. The cities that experience the most pronounced negative impacts are predominantly situated in the southeast coastal areas, including Wenzhou, Taizhou, and Fuzhou. The possible reason is that inhabitants in the eastern coastal regions typically exhibit a heightened awareness of environmental issues and exhibit greater concern for air quality, thereby heightening their sensitivity to haze pollution. Furthermore, the eastern coastal areas are characterized by a dense population and robust housing demand, which amplifies the effect of air quality on rental prices.

In terms of population factor, as shown in Figure 5b, the regression coefficients for population density exhibit a gradient decline from the eastern to the western regions of China. The possible reason is that China's eastern regions boast a robust economy, which draws a multitude of job opportunities and a significant influx of migrants, consequently resulting in elevated population density. With the rise in population density, the demand for housing escalates, driving up rental prices. Conversely, the western regions are characterized by a less advanced economy, exerting less pull on the population and exhibiting a comparatively subdued demand for rental properties. Generally, there is a positive correlation between population density and housing rents, with the effect being especially pronounced in southeastern Chinese cities, including Zhuhai, Shenzhen, and Shantou.

In terms of economic factors, the results are shown in Figure 5c, Figure 5d, and Figure 5e. For GDP per capita, the majority of cities exhibit an inverse relationship with housing rents, suggesting that elevated GDP per capita can result in diminished housing rents. The underlying reason might be that in cities with higher GDP per capita, a greater number of individuals opt to purchase homes instead of renting, thus diminishing the demand for rental properties and leading to lower housing rents. Nevertheless, in certain cities in southern China, there is a positive correlation between GDP per capita and housing rents, with coefficient values ranging from 0.0091 to 0.0352. The possible reason is that these cities are predominantly driven by labor-intensive service industries and tourism, which attract a substantial migrant population and consequently create a high demand for rental housing. Notably, southeast coastal cities such as Sanya, Haikou, and Zhanjiang are among those most significantly affected. Regarding the proportion of tertiary industry in GDP, the majority of Chinese cities experience a decrease in housing rents as the proportion of tertiary industry in GDP increases. The possible reason is that the tertiary sector, encompassing industries like services, finance, and technology, tends to offer higher income levels. Affluent groups often favor homeownership over renting, thus reducing the demand for rental properties and resulting in lower rents. However, in northeastern China and certain cities in the central and western regions, there is a positive correlation between the proportion of tertiary industry in GDP and housing rents, with the most pronounced positive impact observed in northeastern cities such as Hulunbuir, Shenyang, and Baicheng.

With respect to the year-end balance of RMB deposits in financial institutions, its coefficient exhibits a gradient decline from the western to the eastern regions, varying from 0.0883 to 0.2827. This variable is predominantly positively associated with housing rents, indicating that an uptick in RMB deposits within financial institutions correlates with an increase in housing rents. Notably, cities in Western China, including Wuwei, Tianshui, and Jiuquan, demonstrate the most substantial positive influence from this factor. This is because that the balance of RMB deposits in financial institutions is indicative of residents' propensity and capacity to allocate funds towards housing expenses. A higher deposit level may prompt more individuals to opt for renting over buying property, consequently boosting the demand within the rental market and leading to an increase in rental prices.

In terms of social factors, the results are presented in Figure 5f, Figure 5g, Figure 5h, and Figure 5i. For the number of ordinary primary schools per 10,000 people, the spatial distribution of regression coefficients increases from the central and northern regions of China towards the peripheral areas. This variable shows a significant negative correlation with housing rents, indicating that augmenting the number of ordinary primary schools per 10,000 people may mitigate the escalation of housing rents. The possible reason is that a greater number of ordinary primary schools per 10,000 people does not necessarily equate to superior educational quality. In the wake of population migration, certain cities, particularly smaller and medium-sized ones, have experienced a decline in population. However, the number of ordinary primary schools has not been reduced accordingly, resulting in an increased ratio of ordinary primary schools per 10,000 people. For the number of hospital beds per 10,000 people, the spatial distribution of regression coefficients exhibits a decreasing trend from the southern to the northern regions of China. In the southeastern region of China, the number of hospital beds per 10,000 people is positively correlated with housing rents, suggesting that an increase in hospital beds promotes growth in housing rents, with cities in Southeast China such as Guangzhou, Jiangmen, and Zhanjiang showing the most significant positive impact. In contrast, in northern Chinese cities, there is a negative correlation between the number of hospital beds per 10,000 people and housing rents. The likely explanation is that the southeastern coastal areas boast a more favorable living environment and superior medical resources, which draw an influx of residents, especially the elderly, to settle in these regions. This migration consequently boosts the demand within the rental market, leading to increased housing rents.

Regarding the greening coverage of built-up areas, the regression coefficients with lower values are predominantly located in central China. There is a pronounced negative correlation between greening coverage and housing rents in the Bohai Rim region, encompassing cities such as Yangquan, Langfang, and Cangzhou. This result could be attributed to the fact that an elevated green coverage rate implies a greater allocation of land to parks, green spaces, and landscaping amenities, thereby reducing the amount of land available for urban development and economic activities. Consequently, these regions tend to draw fewer immigrants, which in turn leads to a diminished demand for rental properties. Regarding the capacity of buses or

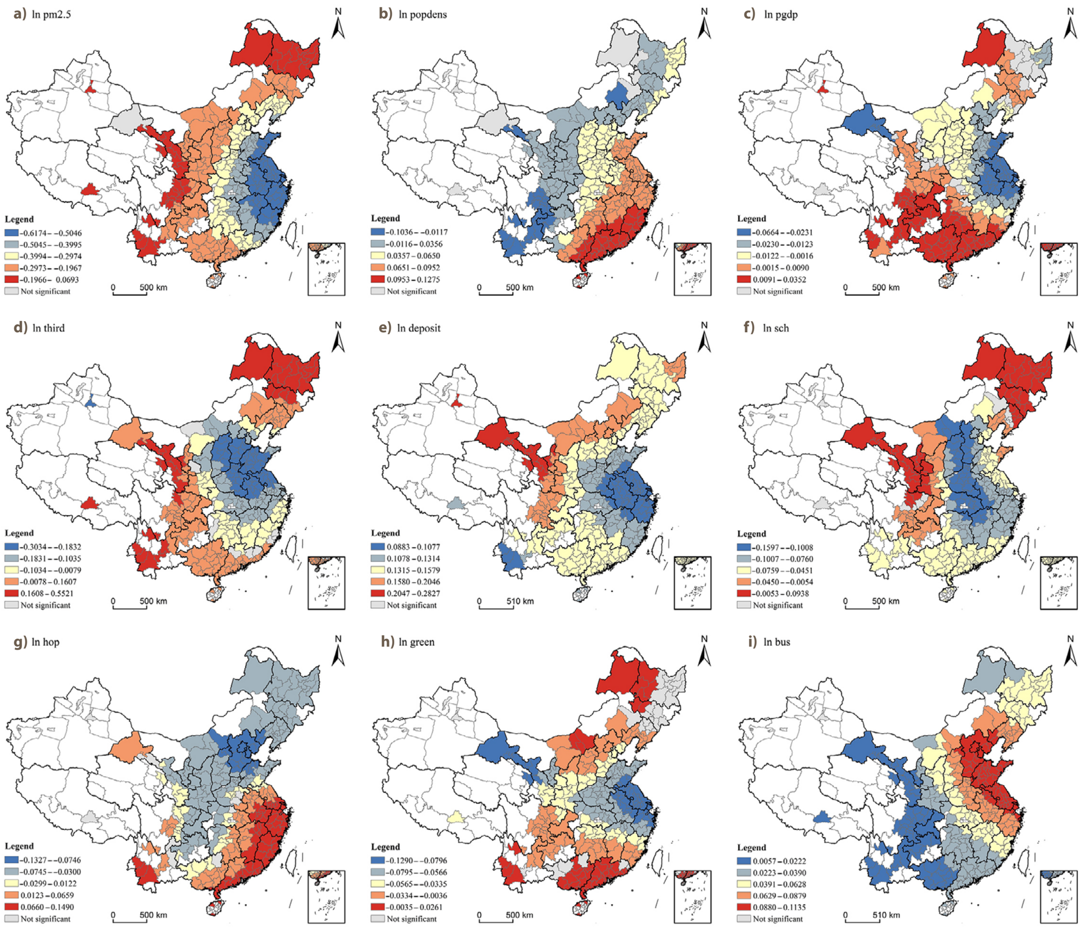

Figure 5. Spatial distribution of regression coefficients for explanatory variables across China in 2021

trams per 10,000 people, the spatial distribution of regression coefficients reveals a progressive increase from eastern to western China. This variable exhibits a robust positive correlation with housing rents, suggesting that an augmentation in transportation capacity is likely to stimulate an increase in housing rents, with particularly pronounced effects in the Bohai Rim region. This correlation can be explained by the fact that a higher density of buses or trams per 10,000 people signifies superior transportation accessibility, which in turn heightens a city's appeal. Such enhanced accessibility draws more immigrants to the city, resulting in a surge in rental demand and consequently driving up rents.

5. Discussion and implications

Drawing upon housing rents data across 289 Chinese cities at the prefecture level and above from 2015 to 2021, this study investigates the spatiotemporal distribution characteristics of housing rents in urban China and employs a GTWR model to estimate the spatiotemporal heterogeneous effects of haze pollution on housing rents. Our contributions to existing literature are twofold. First, this study demonstrated the superiority of the GTWR model over the OLS and GWR models in revealing the spatial and temporal relationship between haze pollution and housing rents. The reason is that the GTWR model accounts for spatial heterogeneity overlooked by OLS model and incorporates the temporal dimension ignored by the GWR model. This methodological advancement offers valuable insights for modelling the determinants of housing values. Second, our findings not only contribute to the understanding of housing rent dynamics in China at a national scale, but also offer insights for policymakers in designing effective real estate market policies in response to air pollution concerns.

Numerous studies have found the negative impact of haze pollution on the real estate market. Echoing the findings of prior studies (Chen & Jin, 2019; Gómez & Iturra, 2021; Ou et al., 2022; Zhang et al., 2021), this study finds that haze pollution is negatively correlated with housing rents in China. Moreover, this study reveals significant spatiotemporal heterogeneity in the effects of haze pollution on housing rents. The negative impact of haze pollution on housing rents is greater in the eastern region of China than in the western China, as residents in the eastern region tend to have a stronger environmental awareness and are thus more willing to pay for better air quality. This is consistent with a previous study in China (Wang & Lee, 2022), which found that different housing submarkets have varying sensitivities to haze pollution. However, inconsistent with previous studies that leveraged traditional econometric models to elucidate the relationship between haze pollution and housing rents (Lai et al., 2021; Rosen, 1974; Zou, 2019), this study introduces a comparative analysis with the OLS, TWR and GWR models, demonstrating that the GTWR model offers the superior goodness of fit. The results of the GTWR model, which accounts for both the temporal dimension and spatial heterogeneity, reveal an intensifying negative effect of haze pollution on housing rents over time. Moreover, consistent with previous literature (Saiz, 2007; Wang & Lee, 2022), this study also highlights the significant spatiotemporal heterogeneous effects of population factors, economic factors and social factors, such as per capita GDP, population density, and per capita urban park green space area, on housing rents in China. Specifically, per capita GDP exhibits a stronger positive effect in Southern China, population density shows a stronger positive effect in Eastern China, and per capita urban park green space area demonstrates a stronger positive effect in Northeast China.

The findings of this study have several policy implications. Firstly, governments should adopt policies or strengthen regulations to improve air quality, as it significantly impacts housing rental market prices. Tailored air pollution control measures should be implemented based on local conditions to attract talent and floating populations, thereby fostering green and high-quality economic development. Secondly, policymakers should focus on addressing the haze pollution issues in eastern China, where its detrimental impact on housing rents is particularly severe. The eastern region should focus on implementing stricter measures to improve air quality. For example, it can strengthen regulations on industrial emissions, promote green building standards, and increase investments in public transportation and renewable energy to reduce pollution sources and enhance air quality. Additionally, the government can encourage the development of green spaces, such as expanding urban greenery and parks, to help reduce haze pollution. Lastly, for the western and northeastern regions of China, although haze pollution has a limited direct impact on rental prices, improving air quality is still essential for residents' health and quality of life. Policymarkers in the western and northeastern regions should adopt measures to gradually limit the expansion of high-pollution industries, promote clean energy and environmentally friendly technologies, and enhance overall air quality, laying a foundation for the healthy development of the economy and rental housing market in the future.

This study also has several limitations that should be acknowledged. First, due to data constraints regarding housing rents at the national level, our analysis is limited to the period from 2015 to 2021. Future research could extend this timeframe for a more comprehensive understanding. Second, the study focuses on 289 prefecture-level cities in China, excluding certain regions within Tibet, Qinghai, Xinjiang, Inner Mongolia, and Guizhou provinces or autonomous regions. Future research could broaden the geographical scope and spatial scale of the analysis. Third, while we examine the direct impact of haze pollution on housing rents, further studies could investigate the mediating effects of factors such as labor productivity, urbanization, and population flow on housing rents in China.

6. Conclusions

Drawing on housing rents data across 289 Chinese cities at the prefecture level and above from 2015 to 2021, this study employs descriptive statistics and spatial autocorrelation analysis to investigate the spatiotemporal distribution characteristics of housing rents. Furthermore, it utilizes the GTWR model to estimate spatial heterogeneous effects of haze pollution on housing rents in China. This study not only offers empirical evidence for the national-scale relationship between air pollution and housing rents in China, but also provides valuable policy insights for evaluating the economic implications of air pollution control measures for Chinese cities.

This study has several findings. First, this study finds that the GTWR model surpasses OLS, TWR, and GWR models in the model goodness of fit, achieving an R^2 of 0.699. Second, this study reveals that haze pollution is significantly negatively correlated with housing rents in China, and this negative relationship becomes increasingly strong over time. The results emphasize the growing importance that residents place on air quality in their residential areas and highlights the significance of strengthening environmental governance for the future real estate market. The submarket analysis shows that haze pollution has varying impacts on housing rents across different cities. The impact of haze pollution on housing rents gradually decreases from the southeast to the northwest and northeast regions of China, showing that haze pollution has a significant negative impact on the housing rental market in southeastern China due to local air quality preferences and socioeconomic levels. Moreover, other variables, such as population, economic, and social factors, also have a significant impact on housing rents. Among then, the year-end balance of RMB deposits in financial institutions and the capacity of buses or trams per 10,000 people predominantly exhibit a positive impact on housing rents in China. GDP per capita, the proportion of tertiary industry in GDP, the number of ordinary primary schools per 10,000 people, the greening coverage of built-up areas have a negative impact on housing rents in most cities in China. The number of hospital beds per 10,000 people exhibits a positive correlation with housing rents in southeastern China, whereas in northwestern China, a negative correlation is observed.

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