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Identifying Spatial Heterogeneity in the Effects of High-Tech Firm Density on Housing Prices: Evidence from Guangdong-Hong Kong-Macao Greater Bay Area, China

WANG Yang[1], WU Kangmin[2, 3], ZHANG Hong'ou[2, 3], LIU Yi[3, 4], YUE Xiaoli[2, 5]

(1. *Faculty of Geography*, *Yunnan Normal University*, *Kunming* 650500, *China*; 2. *Guangzhou Institute of Geography*, *Guangdong Academy of Sciences*, *Guangzhou* 510070, *China*; 3. *Institute of Strategy Research for Guangdong*, *Hong Kong and Macao Greater Bay Area*, *Guangzhou* 510070, *China*; 4. *Key Laboratory of Regional Sustainable Development Modeling*, *Institute of Geographic Sciences and Natural Resources Research*, *Chinese Academy of Sciences*, *Beijing* 100101, *China*; 5. *School of Architecture and Urban Planning*, *Guangdong University of Technology*, *Guangzhou* 510090, *China*)

Abstract: Innovation capitalization is a new concept in innovation geography research. Extant research on a city scale has proven that innovation is an important factor affecting housing prices and verified that innovation has a capitalization effect. However, few studies investigate the spatial heterogeneity of innovation capitalization. Thus, case verification at the urban agglomeration scale is needed. Therefore, this study proposes a theoretical framework for the spatial heterogeneity of innovation capitalization at the urban agglomeration scale. Examining the Guangdong-Hong Kong-Macao Greater Bay Area (GHMGBA), China as a case study, the study investigated the spatial heterogeneity of the influence of high-tech firms, representing innovation, on housing prices. This work verified the spatial heterogeneity of innovation capitalization. The study constructed a data set influencing housing prices, comprising 11 factors in 5 categories (high-tech firms, convenience of living facilities, built environment, the natural environment, and the fundamentals of the districts) for 419 subdistricts in the GHMGBA. On the global scale, the study finds that high-tech firms have a significant and positive influence on housing prices, with the housing price increasing by 0.0156% when high-tech firm density increases by 1%. Furthermore, a semi-geographically weighted regression (SGWR) analysis shows that the influence of high-tech firms on housing prices has spatial heterogeneity. The areas where high-tech firms have a significant and positive influence on housing prices are mainly in the Guangzhou-Foshan metropolitan area, western Shenzhen-Dongguan, north-central Zhongshan-Nansha district, and Guangzhou—all areas with densely distributed high-tech firms. These results confirm the spatial heterogeneity of innovation capitalization and the need for further discussion of its scale and spatial limitations. The study offers implications for relevant GHMGBA administrative authorities for spatially differentiated development strategies and housing policies that consider the role of innovation in successful urban development.

Keywords: innovation capitalization; high-tech firms; housing prices; spatial heterogeneity; semi-geographically weighted regression (SGWR); Guangdong-Hong Kong-Macao Greater Bay Area (GHMGBA)

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Corresponding author: WU Kangmin. E-mail: kangmwu@163.com

1 Introduction

In the era of globalization and knowledge economy, the rasing of innovation capability has become the core strategic of interregional competition (Boschma, 2022; Crescenzi et al., 2022; Moirangthem and Nag, 2022). Regions with strong innovation capability tend to have higher housing prices (Beracha et al., 2022). It shows that innovation factors may have a significant impact on housing prices that can not be ignored. At present, in the research of influencing factors of housing prices, scholars mainly focus on regional fundamentals such as population (Howard, 2020), income (Tita and Opperman, 2022), land (Duca et al., 2021), economic growth (Miller et al., 2011), or medium-micro factors such as public service accessibility (Rivas et al., 2019), public transport accessibility (Soltani et al., 2021), daily life service accessibility (Wilhelmsson and Long, 2020), and environment (Nicholls, 2019), *etc*. However, little attention was paid to innovation factors.

Wu et al. (2021a) confirmed that innovation factors have a significant influence on housing prices. Thus, the concept of 'innovation capitalization' was developed and verified recently in a case study in Guangzhou, China (Wu et al., 2021a). Innovation capitalization is the process through which 'innovation' is converted into property value (Wu et al., 2021a). According to that study, innovation factors (e.g., high-tech firms) had a significant positive influence on housing prices at the intra-city scale. The study represented important progress in the research on the relationship between innovation and housing prices at this scale. Moreover, for a wide range of regional scales, including national scales, studies have demonstrated the positive impact of innovation quality or innovation capacity on housing prices based on inter-city data (Yu and Cai, 2021; Beracha et al., 2022). However, case studies at the urban agglomeration scale (the regional scale) are still lacking. To further understand the relationship between innovation and housing prices, we need to verify innovation capitalization at the urban agglomeration scale. When we study housing price factors at this scale, we take into account both intra-city influencing factors (such as convenience and environment) and inter-city fundamental factors (such as population, income level, and economic level). These factors differentiate the urban agglomeration scale from the intra-city and national scales. Studying the impact of innovation on housing prices at the urban agglomeration scale can provide evidence to validate the theoretical framework of innovation capitalization.

The presence of high-tech firms is considered an important factor reflecting regional innovation capability (Wu et al., 2019; Liu et al., 2021). R&D investments by high-tech, small- and medium-sized enterprises enhance the speed and quality of innovation (Parida et al., 2012; Guo et al., 2020). There have been several case studies that focus on high-tech firms as an important evaluation perspective for regional innovation capability (Cowling et al., 2018; Lin et al., 2021). Therefore, analyzing the relationship between the distribution of high-tech firms and housing prices is an appropriate basis for assessing the capitalization effect of innovation.

The Guangdong-Hong Kong-Macao Greater Bay Area (GHMGBA) is a vital bay area, with concentrated factors of innovation (Liu, 2019;Chong and Pan, 2020). Hong Kong, Macao, and Shenzhen in the GHMGBA are cities with high housing prices globally (Kang et al., 2018; Li et al., 2021; Zhao et al., 2021). In addition, the innovation capacity within the GHMGBA varies greatly (Wu et al., 2021b), as do the housing prices. Tianhe District in Guangzhou and Nanshan District in Shenzhen are areas with a particularly high concentration of high-tech firms and high housing prices. This makes the GHMGBA a strong case study for the verification of the impact of high-tech firms on housing prices (i.e., innovation capitalization) at an urban agglomeration scale.

There are significant differences in innovation factors and capabilities across different GHMGBA regions (Feng et al., 2020; Fu, 2020; Ma et al., 2021). Housing prices also show large spatial heterogeneity (Huang and Song, 2019; Xu and Lin, 2020), reflecting a strong heterogeneity within the GHMGBA. Theoretically, the effects of high-tech firms on housing prices may also show spatial heterogeneity; that is, the effects may not appear in all areas in the GHMGBA. As such, the spatial heterogeneity of innovation capitalization needs to be considered; however, it has yet to receive sufficient attention.

This study examines innovation capitalization by investigating the spatial heterogeneity of the relationship between high-tech firms and housing prices at the urban agglomeration scale. Specifically, we explore the degrees and directions of the influence of high-tech firms in the GHMGBA on housing prices and identify the local effects. Moreover, we use semi-geographically weighted regression (SGWR) technology to analyze the spatial heterogeneity of the directions and the degree of the influence of high-tech firms on housing prices. This study expands our understanding of the spatial limitations and spatial variability of innovation capitalization. Furthermore, it provides practical support for the GHMGBA in building international science and technology innovation centers.

2 Theoretical Framework

At the urban agglomeration scale, the explanation of the impact of high-tech firms on housing prices can be summarized into four theoretical perspectives; namely, local public goods, hedonic price theory, supply and demand theory, and neo-Marxism and space production. This differs somewhat from the theoretical interpretation of the process of innovation capitalization at the intra-city scale in Wu et al. (2021a). Spatial heterogeneity is an important feature of spatial data (Jiang, 2015). At the urban agglomeration scale, the housing market is a typical example with spatial heterogeneity and is composed of multiple regional submarkets. The distribution of innovation elements herein is also spatially heterogeneous (Wu et al., 2019); thus, the innovation capitalization in this context also has spatial heterogeneity. We can then explain the spatial heterogeneity of innovation capitalization at the urban agglomeration scale by examining the effects of high-tech firm density on housing prices. Fig. 1 shows the theoretical explanation of high-tech firms' effect on housing prices at the urban agglomeration scale.

First, from the theoretical perspective of local public goods, high-tech firms can provide more high-income employment opportunities for local citizens, attract more scientific and technological innovation talent to the local area, and contribute to local tax revenue, thus becoming an important driver of local economic development and regional vitality. Although the traditional conceptualizations of high-tech firms and local public goods are different, the agglomeration of high-tech enterprises creates a high-quality innovation space; this provides a large number of high-income employment opportunities that are exclusive at the urban agglomeration scale. In this sense, high-tech firms can be seen as high-quality local public goods. High-quality public goods attract more residents to an area (Tiebout, 1956) and accordingly increase property values through the capitaliation process (Oates, 1969). Therefore, as a type of high-quality public good, the density of high-tech firms increases housing prices in a local area. Some studies have shown spatial heterogeneity in the capitalization of local public goods (Fack and Grenet, 2010; Zheng et al., 2014). High-tech enterprises, which can be regarded as high-quality local public goods, also have spatial heterogeneity in their capitalization effects. This is because the employment demand of residents for these firms is spatially heterogeneous. If the distribution of the number of high-tech firms in an urban agglomeration is significantly different, the employment demand from these enterprises will also differ accord-

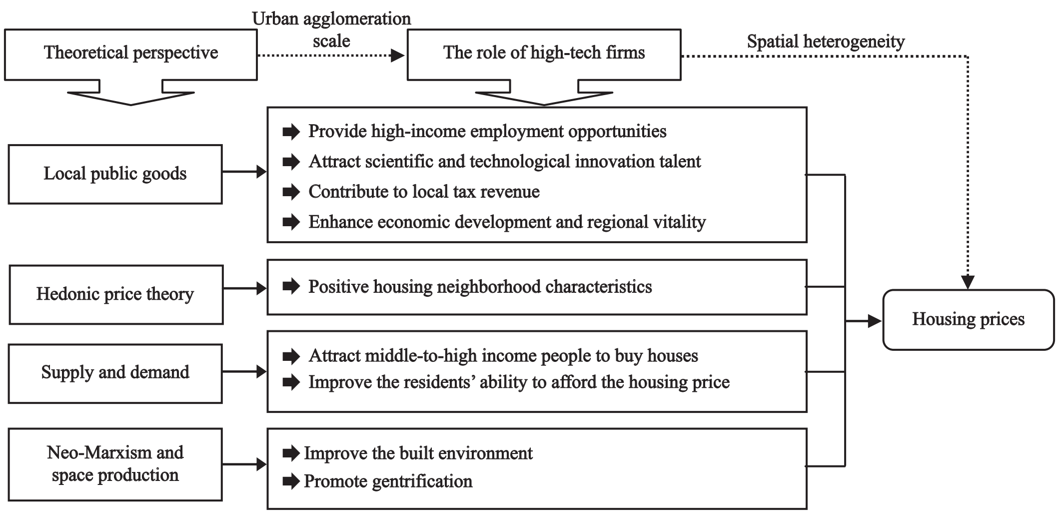

Fig. 1 Theoretical explanation of high-tech firms' effect on housing prices at the urban agglomeration scale

ingly. This results in spatial differences in the strength of the impact of high-tech firms on housing prices. In theory, the lower the density of high-tech enterprises, the smaller their impact on housing prices.

Second, from the perspective of hedonic price theory (Lancaster, 1966; Rosen,1974), the density of high-tech firms can be seen as an important component of neighborhood housing characteristics and an important variable for estimating housing prices. Along these lines, Wu et al. (2021a) proved that high-tech firms significantly influence housing prices. The spatial heterogeneity of innovation capitalization can be explained using the hedonic price theory of housing submarkets. According to this theory, different cities within the urban agglomeration scale are relatively independent housing submarkets. Thus, various housing characteristics have different degrees of influence on housing prices across these numerous submarkets (Feng and Han, 2021). As one characteristic that affects housing prices, high-tech firms may have differential effects on housing prices across different submarkets. This is because the impact of high-tech companies on housing prices differs in every city.

Third, from the perspective of supply and demand theory, an area where high-tech firms gather is more likely to attract homebuyers with middle-to-high incomes for its commuting convenience. Thus, high-tech firms will increase housing demand in their areas and improve the residents' ability to afford housing. Therefore, an area with a higher density of high-tech firms has more housing demand from the middle-to-higher income population. The spatial heterogeneity of innovation capitalization can be explained by the spatial heterogeneity of housing supply and demand. Both housing supply and demand vary in different areas. Generally, in areas with a high housing demand intensity or those with a low housing supply, residents are willing to pay higher premiums for certain public goods (i.e., a higher degree of capitalization of public goods) (Brasington, 2002; Zheng et al., 2014). In theory, high-tech firms also conform to this principal. Furthermore, unlike general public goods, high-tech firms create higher-income employment opportunities. Thus, regional differences in the density of high-tech firms result in regional differences in higher-income employment opportunities, which, in turn, will lead to spatial differences in housing prices. Therefore, in areas with a high density of high-tech firms, these enterprises will have a stronger effect on housing prices.

Fourth, from the perspectives of neo-Marxism and space production (Harvey, 1973), differences in the built environment can form an unequal urban space, with local gentrification (Smith, 1987). The agglomeration of high-tech firms (characterized by high-density distribution of high-tech firms) can often improve the built environment in the region. The improvement of the built environment is a reflection of the production process of spatial value. In this process, there may be a spatial substitution of classes and gentrification. Gentrification often increases housing prices, and the area where such firms reside may become a space that only the middle class or a smaller number of people can afford. The spatial heterogeneity of innovation capitalization can be explained by the regional differences in improvements in the built environment along with gentrification. In other words, different cities have different built environment characteristics in their urban agglomeration (Wu et al., 2019). According to the theoretical perspectives of neo-Marxism and spatial production (Harvey, 1973), the agglomeration of high-tech firms improves the built environment and generates local spatial gentrification (Smith, 1987), which increases housing prices. However, this level of improvement is not the same in every area; specifically, there will be stronger and weaker differences in its influence in different areas. Innovation capitalization is only more significant in areas where the agglomeration of high-tech firms has a greater impact on the built environment.

Based on the above four theoretical explanations, in addition to high-tech firms as an innovation factor, other factors influencing housing prices at the urban agglomeration scale include the convenience of living facilities, the built environment, the natural environment, and the fundamentals of the region (e.g., population, income level, economic level, and service industry level). The impact of these factors on housing prices can be explained by different theoretical concepts.

3 Materials and Methods

3.1 Study area

The GHMGBA includes nine cities (Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Zhongshan, Huizhou, Jiangmen and Zhaoqing in the Pearl River Delta (PRD), the Hong Kong Special Administrative Region (HKSAR), and the Macao Special Administrative Region (Macao SAR)). It has an important strategic position in China and has become part of its general national development strategy. We looked at 585 subdistricts (including towns) as our basic research units (hereafter subdistricts). Among them, Macao was one research unit, while Hong Kong was divided into units according to the 'District Council'. Of the 585 subdistricts, we were able to obtain housing price data for 419 subdistricts. Therefore, we used these 419 units (Fig. 2) to analyze the influence of high-tech firms on housing prices. The research did not include the five mountainous counties (Guangning, Deqing, Fengkai, Huaiji, and Longmen) in the peripheral area of the PRD.

3.2 Research design

The research was designed to analyze spatial heterogeneity and the directions and intensity of the influence of high-tech firms on housing prices. The analysis process was as follows: first, based on the subdistrict scale, the spatial heterogeneity pattern of the density of high-tech firms in the GHMGBA and the spatial heterogeneity pattern of the housing price were analyzed. Second, taking the housing price as the dependent variable, the high-tech firms as the independent variable, and 10 control variables, a hedonic price model was constructed. Third, at the global level, using the ordinary least squares (OLS) model, we verified whether high-tech firms had a significant influence on housing prices and the direction of the influence. Fourth, a geographically weighted regression (GWR) model was used to conduct geographical variability tests of local coefficients. The purpose of this was to segment these into two categories, local variables and global variables. Fifth, SGWR was used to analyze the spatial heterogeneity of the influence of high-tech firms on housing prices. Last, we analyzed and discussed our results.

Since this study adopted subdistricts (including towns) as its basic research units, the design of the index system of influencing factors considers not only the convenience and environmental characteristics of the subdistricts themselves, but also the characteristics of the district (county) wherein the subdistricts are located. We constructed the index system of the influencing factors on housing prices based on 11 influencing factors in 5 categories (Table 1). In the system, the presence of high-tech firms was the explanatory variable and the other variables were control variables.

As stated, the presence of high-tech firms was used as the explanatory variable affecting housing prices. Studies have confirmed that high-tech firms are an important indicator of a regional innovation environment and innovation ability (Wu et al., 2021b). In this study, the density of high-tech firms is used as the evaluation index; theoretically, the higher the density of the high-tech firms, the higher the housing prices.

In terms of the convenience of the living facilities,

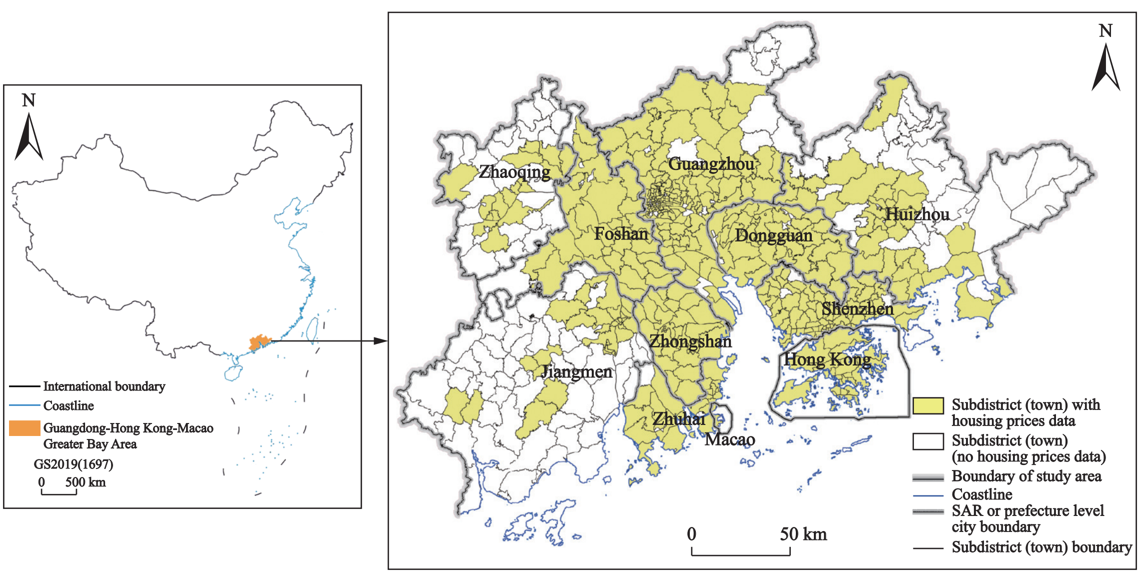

Fig. 2 The study area in the Guangdong-Hong Kong-Macao Greater Bay Area

Table 1 Index of impact factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Major categories of impact factors	Impact factors	Evaluation index / unit	Expected direction
High-tech firms (Explanatory Variable)	Density of high-tech firms	Density of high-tech firms / (activities/km^2)	+
Convenience of living facilities (Control Variables)	Public service convenience	Density of major public service facilities (schools, secondary schools, general hospitals, museums, general gymnasiums)/ (activities/km^2)	+
	Convenience of daily consumption	Density of daily consumption place (Dining and shopping venues) / (activities/km^2)	+
	Metro convenience	Density of subway station / (activities/km^2)	+
Built environment (Control Variables)	Density of road	Density of road / (km/km^2)	+
	Land use mix	Entropy of six types of land	+
Natural environment (Control Variables)	Air pollution	$PM_{2.5}$ concentration / (μg/m^3)	–
The fundamentals of the district (county) (Control Variables)	Newly-added population	The number of new permanent residents per square kilometer from 2016 to 2018 /(person/km^2)	+
	Income level	Average salary of on-the-job employees / (10^4 yuan (RMB)/mon)	+
	Economic level	GDP per capita / 10^4 yuan	+
	Service industry level	The added value of the tertiary industry as a percentage of GDP / %	+

public service convenience, daily consumption convenience, and metro convenience were adopted for the evaluation. First, public service convenience can be evaluated by the proximity of educational, medical, cultural, and sports facilities. Second, daily consumption convenience can be evaluated based on dining and shopping convenience, as dining and shopping are the two most common daily consumption activities. Third, metro convenience can be evaluated based on the density of subway stations in the subdistrict. Research has shown that convenience facilities mentioned above have significant positive effects on housing prices (Thompson, 2017; Yuan et al., 2018; Zhang et al., 2020; Yazdanifard et al., 2021).

In terms of the built environment, road density and land use mix were used for the evaluation; these are classic evaluation indices of the built environment (Cervero and Kockelman, 1997). Studies have noted that high road density (Ossokina and Verweij, 2015) and mixed use of land with 'positive functions' increase housing prices (Zhang et al., 2012).

In terms of the natural environment, air pollution is an important factor and the most intuitive embodiment of the natural environment. $PM_{2.5}$ concentration is a representative index of air pollution and has a noticeable negative influence on housing prices (Sun and Yang, 2020). In theory, the concentration of $PM_{2.5}$ would be negatively correlated with housing price.

Regarding urban agglomerations, besides the characteristics of the subdistricts that may influence housing prices, housing prices are likely to be influenced by area fundamentals on a larger scale (e.g., cities or counties). Studies have shown that the fundamental factors affecting housing price usually include population growth (Liew and Haron, 2013), income (Wang et al., 2017), the economy (Vogiazas and Alexiou, 2017), and the service industry (Shen and Liu, 2004), among others. Accordingly, we chose the newly added population, income level, economic level, and service industry level as the influential fundamental factors of the district; theoretically, these fundamental factors correlate positively with housing prices.

3.3 Data sources and processing

3.3.1 High-tech firm data

We obtained high-tech firm data for PRD from the list of high-tech firms announced by the Guangdong Provincial Department of Science and Technology in 2017 (http://gdstc.gd.gov.cn/). Using geocoding technology, the longitude and latitude coordinates of the enterprises were identified through the Baidu map application programming interface (https://lbsyun.baidu.com/). Then, coordinate transformation was carried out, outliers were eliminated, and a spatial database was constructed. There were 12 516 high-tech firms in the PRD (Wu et al., 2019). Most identified high-tech firms were newly founded small- and medium-sized enterprises (Wu et al., 2019). These enterprises also represented the latest technological development in this region (Hamidi and Zandiatashbar, 2019).

The data for high-tech firms in Hong Kong and Macao were from the point of interest (POI) database on the Amap (https://www.amap.com/). Our data screening method was as follows. In the enterprise data from Hong Kong, according to the enterprise name, we identified a total of 3034 firms with the keywords 'science and technology, network, technology, and high-tech'. Macao had relatively few enterprise data, so manual screening was adopted to judge whether the enterprises were high-tech firms according to their names; with six enterprises selected.

The final count included 15 556 high-tech firms in the GHMGBA. Their spatial distribution is shown in Fig. 3. The figure shows that the high-tech firms were mainly distributed in the area around the bay. Based on this, the density of high-tech firms in each subdistrict was calculated (firms/km^2).

3.3.2 Housing price dataset

The housing price unit in the study was yuan (RMB) / m^2. The housing price data for eight cities in the PRD (Guangzhou, Shenzhen, Zhuhai, Foshan, Huizuhou, Dongguan, Zhongshan, and Jiangmen) included the transaction prices for previously owned houses with elevators built since 2000 (the transaction period was January 1, 2018 to December 31, 2019). We obtained the data from the 'Beike House Finding Platform' (https://www.ke.com/city/). Some towns and subdistrict data in Jiangmen and Huizhou were supplemented based

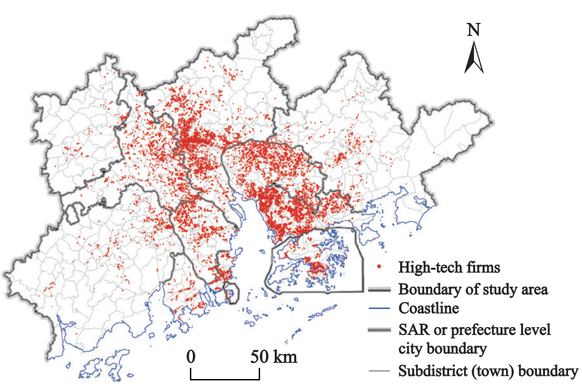

Fig. 3 The high-tech firms in the Guangdong-Hong Kong-Macao Greater Bay Area

on information in 'Fangtianxia' (https://www.fang.com/SoufunFamily.htm). Zhaoqing's housing price data included the sale prices of previously owned houses with elevators built since 2000. The data were acquired on May 13, 2021 from Fangtianxia (https://www.fang.com/SoufunFamily.htm). The housing price data for Hong Kong were the transaction prices of previously owned houses built since 2000 (the transaction period was from April 1, 2021 to May 30, 2019), and the data were from Centaline property (https://hk.centanet.com/findproperty/list/). The priceswere converted from HKD to RMB according to the average exchange rate from January to April 2021. The housing price data of Macao were the transaction prices of previously owned houses (the transaction period was from January 1, 2018 to December 31, 2019). The data were from Centaline property (https://mo.centanet.com/Transaction?FileType). The prices were converted from MOP to RMB according to the average exchange rate in 2019. Although the acquisition timeline of housing prices in Zhaoqing and Hong Kong differed from that in other cities, since the housing prices in Zhaoqing and Hong Kong had been relatively stable since 2018, the housing price data of these two cities were comparable with the prices in the other nine cities. The total sample of housing mentioned above was 55 670 units. According to the average calculation method, we obtained the average housing price of each subdistrict. There were 419 subdistricts with housing price data.

3.3.3 Control variable data

The evaluation index data for public service convenience, daily consumption convenience, metro convenience, and land use mix were from the POI data of the Baidu Map in January 2020. The land use mix was calculated according to the mix of six main land-use types (Liu et al., 2017). This included commercial, residential, industrial, institutional, transportation, and green space and squares. These six types were captured by POI data; the corresponding relationships between the types of land use and the types of POI data have been detailed by Wu et al. (2021b). Road data used to calculate road density were gathered from the Baidu Map. The $PM_{2.5}$ information for air pollution evaluation was from the Ministry of Environmental Protection of China, and was the annual average in 2017. The data on newly added population, income level, economic level, and service industry level were gathered from the *Digital Journal of*

Global Change Data Repository (https://doi.org/10.3974/geodb.2021.02.17.V1.) (Wang et al., 2021a). These included newly added 2016–2018 population data, and income level, economic level, and service industry level data from 2018.

3.4 Methods

3.4.1 Global regression based on the OLS model

The OLS model is the most commonly used global regression model. It can be applied to study the linear relationship between the housing price (dependent variable) and a series of influencing factors (independent variables). It can be expressed as follows (Wang et al., 2021b).

$$y_s = \beta X_s + \varepsilon_s, \left[\varepsilon_s \sim N\left(0, \delta^2 I\right)\right] \tag{1}$$

where s represents the subdistricts in the GHMGBA; y_s is the housing price of the sth subdistrict; X_s is the dimensional row vector (i = 1, 2, …, n) of the influencing factor i of the housing price, which represents the observed value of the ith influencing factor variable in the sth subdistrict; β is the dimensional column vector of i, which is the regression coefficient corresponding to these factor variables; ε is the error term of the model; $\varepsilon_s \sim N(0, \delta^2 I)$ indicates that the error term conforms to normal distribution and the variance is consistent, namely, the product of the error and the covariance matrix is 0; I represents the identity matrix. In this study, the independent variables (influencing factors) of vectors y_s (housing price) and X_s are standardized to obtain the natural logarithms. This can eliminate the influence of variables' dimensional differences on the results and facilitate the comparison of the influence degree of different factors on the housing price.

3.4.2 Local regression based on the SGWR model

The global multiple regression (GMR) model can capture the average intensity and significance of the statistical relationship between independent variables (influencing factors) and dependent variables (e.g., housing price) with just one equation for these variables (Wang et al., 2017). However, in the GMR model, this statistical relationship is assumed to remain stable everywhere. In fact, this statistical relationship often changes locally through different spatial positions. The local regression model represented by the GWR allows the relationship between independent variables and dependent variables to change locally in the whole space (Bitter et al., 2007; Hanink et al., 2012). The form of the GWR model is similar to that of the global regression model, but its parameters change with changes in spatial positioning (Brunsdon et al., 1996).

However, in some cases, not all regression coefficient in the model had local spatial changes. It is possible that global variables and local variables exist simultaneously. In this case, SGWR is more suitable for the analysis. The SGWR model proposed by Fotheringham et al. (2002) is a combination of the OLS model and the GWR model. Some parameters are set as fixed parameters and their corresponding variables are global. Others are set as variable parameters and their corresponding variables are local. The general form of the SGWR model is as follows (Mou et al., 2017; Wang et al., 2021b).

$$y_s = \sum_{i=1}^{m} \alpha_i x_{si} + \beta_0(u_s, v_s) + \sum_{i=m+1}^{n} \beta_i(u_s, v_s) x_{si} + \varepsilon_s, \left[\varepsilon_s \sim N(0, \delta^2 I)\right] \tag{2}$$

where α_i and β_i represent the global variable regression coefficient and local variable regression coefficient of the ith factor index of housing prices y_s, respectively; x_{si} is the observed value of ith influencing factor in the sth subdistrict; m is the number of influencing factor variables included in the global regression, and n is the number of all influencing factor variables. (u_s, v_s) are the geographical coordinates of subdistrict s; $\beta_0(u_s, v_s)$ is the constant term of the regression model of subdistrict s; and $\beta_i(u_s, v_s)$ is the regression coefficient of the ith variable in the regression model of subdistrict s, which varies with location; ε_s is the residual.

The global and local variables can be distinguished according to geographical variability tests of local coefficients in the classical GWR model. The results contain a 'DIFF of Criterion' value. If the value is positive, it suggests that there is basically no spatial variability in the variable's coefficient; thus, it should be regarded as a global variable; if it is negative, it should be regarded as a local variable (Wang et al., 2021b).

The elasticity coefficient of any housing (u_s, v_s) can be estimated generally by weighted least squares; its estimated value can be expressed as follows (Mou et al., 2017; Wang et al., 2021b).

$$\hat{\beta}(u_s, v_s) = \left(X^T W(u_s, v_s) X\right)^{-1} X^T W(u_s, v_s) y_s \tag{3}$$

where X is the matrix of the influencing factor variables on the housing prices y_s; T represents the transposition operation of the matrix; (u_s, v_s) is the location coordinates of subdistrict i; $W(u_s, v_s)$ is the spatial weight matrix, which is composed of monotonically decreasing function values of the geographical distance between subdistrict s and its surrounding subdistricts.

For the local variable factors, to determine which subdistrict should be selected for local regression, we need to define the spatial weight matrix (W_s). In this study, the fixed Gaussian kernel function is used to determine the spatial weight matrix. The spatial weight of the skth element in the spatial weight matrix (W_s) calculated from the fixed Gaussian kernel function can be expressed as follows (Shen and Yu, 2019).

$$w_{sk} = e^{-\frac{1}{2}\left(\frac{d_{sk}}{b_s}\right)^2} \tag{4}$$

where w_{sk} represents the positional spatial weight value between subdistrict s and subdistrict k; d_{sk} represents the distance between subdistrict s and subdistrict k; and b_s is the bandwidth.

As the spatial distribution of subdistricts is often uneven, subdistricts are more densely distributed in some areas (e.g., the core area of Guangzhou), and more sparsely distributed in others (e.g., Jiangmen, Zhaoqing, and Huizhou). Therefore, optimal bandwidth is needed. In this study, the adjusted value of the Akaike Information Criterion (AIC_C) is used to determine the optimal bandwidth (Fotheringham et al., 2002; Shen and Yu, 2019). The AIC_C can be expressed as follows (Mou et al., 2017; Wang et al., 2021b).

$$AIC_C = 2n\ln\hat{\sigma} + n\ln(2\pi) + \frac{n + tr(S)}{n - 2 - tr(S)'} \tag{5}$$

where $\hat{\sigma}$ represents the maximum likelihood estimation of the random error variance, and $tr(S)$ and $tr(S)'$ represent the trajectories of matrix S.

4 Results

4.1 Spatial heterogeneity of high-tech firms

We calculated the density of high-tech firms in each subdistrict as follows. According to the characteristics of data distribution, density can be divided into five grades from high to low: high density (> 3 activities/km^2), medium-high density (1.0–3.0 activities/km^2), medium density (0.5–1.0 activities/km^2), medium-low density (0.1–0.5 activities/km^2), and low density (0–0.1 activities/km^2). Using ArcGIS 10.0, we are able to see the spatial heterogeneity pattern of the density of high-tech firms in the GHMGBA, as shown in Fig. 4. We found spatial heterogeneity in the GHMGBA to be significant, and its subdistricts with high densities were mainly distributed in the urban areas of Guangzhou, the western part of Shenzhen, Hong Kong Island, and Kowloon. Medium-high density subdistricts were mainly distributed in the Panyu and Huangpu districts of Guangzhou, the urban area of Dongguan, western and northeastern parts of Shenzhen, the Xiangzhou district of Zhuhai, the Shunde district of Foshan, and northwestern and eastern parts of Zhongshan. Low-density subdistricts were distributed continuously in Jiangmen, Zhaoqing, Huizhou, the western part of Foshan, the western part of Zhuhai, and the northeastern part of Guangzhou.

4.2 Spatial heterogeneity of housing prices

As stated, we were able to gather housing price data for 419 of the 584 subdistricts. The values of the housing price in these 419 subdistricts differed significantly. We found the highest housing price in the Wanchai district of Hong Kong, at 166 282 yuan (RMB)/m^2, and the lowest in Sihui, at only 3471 yuan/m^2; about 48 times less. According to data distribution characteristics, the thresholds of housing price classifications were RMB 3471.00–10 000.00 yuan/m^2 (low housing price area), 10 000.01–25 000.00 yuan/m^2 (medium-low housing price area), 25 000.01–50 000.00 yuan/m^2 (medium housing price area), 50 000.01–100 000.00 yuan/m^2 (medium-high housing price area), and 100 000.01–

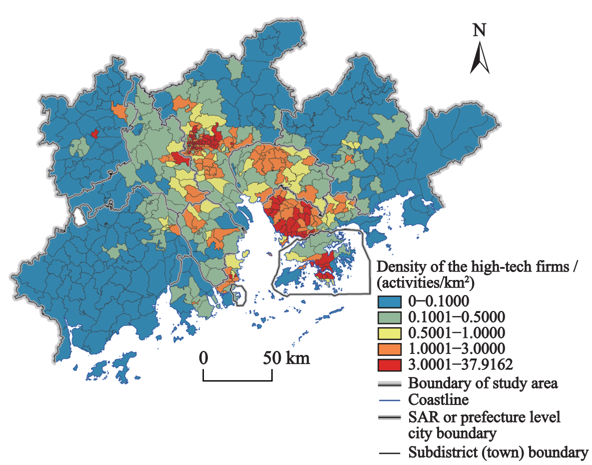

Fig. 4 Spatial heterogeneity pattern of the density of the high-tech firms in the Guangdong-Hong Kong-Macao Greater Bay Area

166 282.00 yuan/m^2 (high housing price area). The corresponding numbers of the subdistricts were 85, 140, 125, 58, and 11, respectively.

Fig. 5 shows the spatial heterogeneity of the GHMGBA plotted in ArcGIS 10.0. The high housing price area subdistricts were concentrated in Hong Kong Island, Kowloon, and the eastern part of the New Territories. The medium-high housing price areas were mainly in the western part of the New Territories in Hong Kong, the southwestern part of Macao and Shenzhen, and the core area of Guangzhou. The medium housing price areas were mainly in the northern part of Shenzhen, the urban area of Guangzhou and the Xiangzhou district of Zhuhai. In general, the three areas in the GHMGBA with relatively high housing prices were Hong Kong-Shenzhen, Guangzhou, and Macao-Zhuhai. The subdistricts with low housing price areas were mainly on the periphery of the GHMGBA, in areas such as Jiangmen, Zhaoqing, and Huizhou.

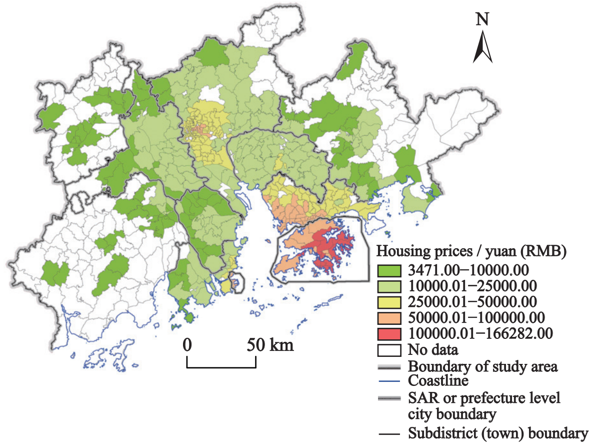

Fig. 5 The spatial heterogeneity pattern of housing prices in the Guangdong-Hong Kong-Macao Greater Bay Area

4.3 The Effects of high-tech firms on the housing price using the OLS Model

We used the OLS model to assess whether high-tech firms globally had a significant influence on housing prices, and the degrees and directions of that influence. First, all variables were tested for collinearity in SPSS 19.0 (Table 2), with the results showing that there was no collinearity among the 11 factors. Therefore, all 11 factors were included in the OLS model. Furthermore, the normalized residuals of the OLS model were tested through normal distribution. The results showed that the normalized residuals of the OLS model conformed to the normal distribution characteristics, indicating that the regression model had high accuracy.

The GWR 4.0.80 software was used to run the OLS model. The regression results showed that the values for the Adjusted R^2, Log likelihood, and AIC_C of the OLS model were 0.8725, –76.5194, and 179.9375, respectively. Among the 11 factors, 7 factors, namely, the density of high-tech firms, metro convenience, air pollu-

Table 2 Estimation results of the OLS model of impact factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Variable	Coefficient	SE	t	P	Tolerance	VIF
Intercept	13.9948	0.5626	24.8739	0.0000	–	–
Density of high-tech firms	0.0156**	0.0067	2.3446	0.0195	0.4798	2.0840
Public service convenience	–0.0105	0.0124	–0.8517	0.3949	0.3536	2.8283
Convenience of daily consumption	0.0205*	0.0123	1.6636	0.0970	0.3500	2.8573
Metro convenience	0.0288***	0.0036	7.9152	0.0000	0.4142	2.4145
Density of road	0.0357	0.0366	0.9755	0.3299	0.1884	5.3073
Land use mix	0.0061	0.0204	0.2994	0.7648	0.9407	1.0631
Air pollution	–1.5662***	0.1542	–10.1542	0.0000	0.5677	1.7616
Newly-added population	0.1006***	0.0146	6.8799	0.0000	0.2749	3.6383
Income level	0.7621***	0.1247	6.1134	0.0000	0.2031	4.9232
Economic level	0.1534***	0.0441	3.4773	0.0006	0.3820	2.6176
Service industry level	0.2457***	0.0555	4.4249	0.0000	0.4691	2.1318
R^2: 0.8761; adjusted R^2: 0.8725; log-likelihood: –76.5194; AIC_C: 179.9375						

Notes: ***, **, * represent the 0.01, 0.05, and 0.1 significance levels, respectively; VIF is variance inflation factor tion, newly added population, income level, economic level, and service industry level, were significantly correlated with housing price (with a significance of 0.05); and their influence direction was consistent with theoretical expectations (Table 2). We found that the housing price would increase by 0.0156% for every 1% increase in high-tech firm density. This suggests that on the global scale, the distribution of high-tech firms had a significant and positive influence on housing prices.

4.4 Impact of the spatial heterogeneity of high-tech firms on housing prices based on the SGWR model

As the spatial distribution of the housing prices in the GHMGBA was heterogeneous, we needed to analyze the spatial heterogeneity of the influence of these high-tech firms on housing prices using SGWR. The premise of using the SGWR model is to carry out geographical variability tests of local coefficients on the 11 independent variables to distinguish between the global and local variables. The GWR 4.0.80 software runs the GWR model. We used a projected coordinate type, a Gaussian model, and the fixed Gaussian geographic kernel. The golden section search was adopted to find the optimal bandwidth. The criterion for the optimal bandwidth was the AIC_C value. The results of the geographical variability tests of the local coefficients are shown in Table 3.

Table 3 shows that public service convenience, daily consumption convenience, metro convenience, road density, and land use mix had positive values (greater than two). Thus, these five variables were suitable to be included in the SGWR model as global variables. The other six variables were negative; therefore, they were considered suitable as local variables. It is worth noting that the presence of high-tech firms represented a local variable; meaning that the influence of high-tech firms on housing prices had spatial variability.

We established the SGWR model according to the above test results. The best bandwidth was 12 694.288. Compared with OLS, the GWR, and the SGWR models (Table 4), the adjusted R^2 and log-likelihood of the

Table 3 Geographical variability tests of local coefficients of impact factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Variable	F	DOF for F test	Diff of criterion	Local or global coefficients
Intercept	–12804.7126	–253.619	–9203.2767	Local
Density of high-tech firms	3.3444	7.4090	–5.4921	Local
Public service convenience	2.2261	5.4990	3.7353	Global
Convenience of daily consumption	1.6874	8.5140	11.6346	Global
Metro convenience	2.1627	5.2910	4.0327	Global
Density of road	2.5147	6.8140	2.0890	Global
Land use mix	0.6647	6.929	18.8676	Global
Air pollution	5.2850	6.2720	–19.8618	Local
Newly-added population	4.1739	5.9500	–10.7302	Local
Income level	4.2845	4.8260	–9.5054	Local
Economic level	3.9866	4.0830	–6.5585	Local
Service industry level	13.4612	4.0370	–52.9797	Local

Notes: DOF, Degree of freedom; Diff of criterion, Difference of criterion

Table 4 Comparison of the OLS, GWR, and SGWR models of impact factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Regression model	R^2	Adjusted R^2	AIC_C	Log-likelihood
OLS	0.8761	0.8725	179.9375	–76.5194
GWR	0.9609	0.9419	–30.5749	165.2568
SGWR	0.9652	0.9489	–80.2256	189.2970

SGWR were the highest, while the AIC_C was the lowest, indicating that the SGWR was the optimal model; this model was most suitable for explaining the relationship between high-tech firms and housing prices.

In the SGWR model, there were 377 subdistricts with a local R^2 of influence on housing price higher than 0.6, accounting for 89.98% of the sample. There were 318 subdistricts with a local R^2 higher than 0.7, accounting for 76.08% of the sample. This indicates that the local regression models of most subdistricts had strong explanatory powers. The coefficient statistics of local variables in the SGWR model are shown in Table 5. The maximum value of the local regression coefficient of the density of high-tech firms was 0.4010, the median value was 0.0394, and the minimum value was –0.1781. There were 207 subdistricts whose high-tech firm density had a significant positive influence on housing price, accounting for 49.40% of the sample; this value was the highest among the six local factor variables (Table 6). This means that of the local factors, high-tech firm density had a significant influence on housing prices in the greatest number of subdistricts (in line with the theoretical expectation).

Using ArcGIS 10.0, we plotted a spatial distribution map of the local regression coefficient of high-tech firm density (Fig. 6). The map shows that the areas where high-tech firms had a significant positive influence on housing price (consistent with theoretical expectation) were mainly: 1) Guangzhou-Foshan urban areas, 2) the western part of Shenzhen-Dongguan, and 3) the northeastern part of the Zhongshan-Nansha district of Guangzhou. These areas were concentrated, and most were located in the core area of the GHMGBA. Among them, subdistricts with local parameter estimates of high-tech firm density greater than 0.1 and with significance were distributed mainly in Foshan, Dongguan, and the western part of Guangzhou.

5 Discussion

The global regression analysis results show that high-tech firm distribution has a significant positive influ-

Table 5 Statistics of the local coefficients of the SGWR model of impact factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Variable	Mean	STD	Min.	Median	Max.
Intercept	14.1917	10.7416	–28.8071	13.7609	106.9685
Density of high-tech firms	0.0507	0.0653	–0.1781	0.0394	0.4010
Air pollution	–1.5102	2.9722	–22.7096	–1.1963	3.8898
Newly-added population	0.1057	0.1498	–1.1189	0.0947	0.7130
Income level	0.3960	1.0486	–5.8148	0.2201	4.6669
Economic level	0.1708	0.5804	–4.5475	0.0885	4.6764
Service industry level	0.0871	0.5958	–5.5125	0.1289	4.5732

R^2: 0.9652; adjusted R^2: 0.9489; log-likelihood: 189.2970; AIC_C: –80.2256

Table 6 Statistical significance of the parameters of the local variables based on the SGWR model of six factors on housing price in the Guangdong-Hong Kong-Macao Greater Bay Area

Variable	Proportion of subdistricts with $P < 0.05$ / %	Significant and positively correlated proportion of subdistricts / %	Significant and negatively correlated subdistricts proportion / %
Density of high-tech firms	52.98	49.40	3.58
Air pollution	45.11	3.10	42.00
Newly-added population	45.11	44.39	0.72
Income level	22.20	21.48	0.72
Economic level	32.46	31.03	1.43
Service industry level	23.87	18.14	5.73

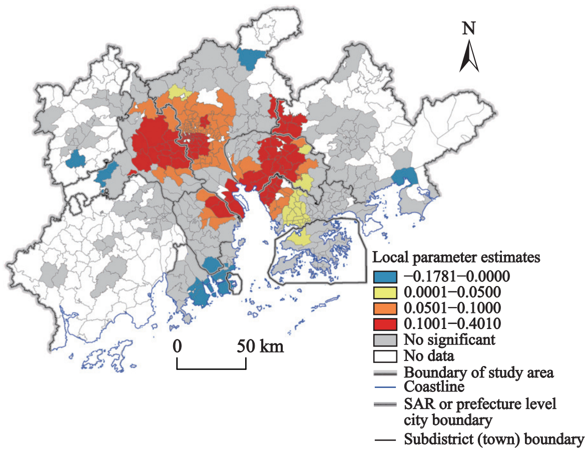

Fig. 6 The spatial heterogeneity pattern of local parameter estimates of high-tech firms in the Guangdong-Hong Kong-Macao Greater Bay Area based on the SGWR model

ence on housing prices in the GHMGBA. These results validate, globally, the theoretical framework of the impact of high-tech firms on housing prices at the urban agglomeration scale proposed earlier in this study. High-tech firms can be viewed as both a local public good and an important component of the housing hedonic model as they boost local housing demand, enhance residents' purchasing power, and improve the local built environment. Generally, the denser the distribution of high-tech firms, the higher the housing prices of a given area. For example, the urban areas of Guangzhou, western Shenzhen, Hong Kong Island, and Kowloon have a relatively high density of high-technology firms, with their housing prices also being relatively high within the wider GHMGBA. This verifies the capitalization effect of innovation at an urban agglomeration scale and extends research by Wu et al. (2021a), who used Guangzhou as a case study. Generally, the denser the distribution of high-tech firms, the stronger the innovation ability and development vitality of the region.

Our study contributes to existing research by extending innovation capitalization from the urban scale (Wu et al., 2021a) to the urban agglomeration scale. We expounded on the theoretical basis and path of the impact of innovation factors represented by high-tech enterprises on housing prices at the urban agglomeration scale and verified the phenomenon of innovation capitalization at this scale by using the GHMGBA as a case study. The urban agglomeration scale falls between a city scale and a national scale. Different theoretical explanations of the factors influencing housing prices have varied impacts across regional scales; at the urban agglomeration scale, innovation factors represented by high-tech enterprises have a significant and positive impact on housing prices. This validates and deepens the innovation capitalization theory in terms of spatial scale.

More importantly, our study found that the influence of high-tech firms on housing prices reflected significant spatial heterogeneity based on the results of a local regression analysis; namely, innovation capitalization showed spatial heterogeneity. This has rarely been mentioned in previous studies. This validates the theoretical explanation for the spatial heterogeneity of the impact of high-tech firms on housing prices at the urban agglomeration scale as proposed in this study. Since the real estate market's characteristics vary widely across subdistricts within the GHMGBA, this creates a housing submarket that is formed based on the different subdistricts. Furthermore, the value of high-tech firms as high-quality local public goods varies across subdistricts. From the perspective of the hedonic price model, different subdistricts often have their own hedonic price models; therefore, the implied prices of high-tech firms in the hedonic price models of different housing submarkets would then differ. Similarly, the supply and demand situation in the housing market differs across subdistricts, with the ability of high-tech firms to shape the built environment also varying, indicating that the degree of impact of high-tech firms on housing prices differs. The results of our study show that the influence of high-tech firms on housing prices is concentrated in some areas rather than in all areas of urban agglomeration. These areas are often core cities where high-tech enterprises gather, such as Guangzhou, Shenzhen, Dongguan, and Foshan. The impact of high-tech firms on housing prices is strong only in specific areas of these cities. In areas where high-tech enterprises are generally concentrated and distributed, innovation vitality and capability are relatively strong (Wu et al., 2021b). This also shows that innovation capitalization can only occur in regions with strong innovation ability. We explain and verify the spatial heterogeneity of innovation capitalization at the urban agglomeration scale by taking high-tech enterprises as an example. This point has not been emphasized in previous studies.

It is worth noting that, although in the city-by-unit results, cities with greater high-tech firm density have more significant innovation capitalization, in the subdistricts as a unit, the relationship between high-tech firm density and the degree of innovation capitalization in some subdistricts is not completely consistent in space. This is due to the logistical nature of the GWR regression. Another reason may be that areas with the highest density of high-tech firms transmit innovation capitalization effects to adjacent areas due to the strong spatial correlation of urban housing markets between subdistricts.

In addition, due to the institutional boundary between Hong Kong and Macao and the Pearl River Delta, the innovation capitalization effect is not significant in these cities. Although the density of high-tech enterprises is higher on Hong Kong Island, Kowloon, and the southern New Territories, the impact of high-tech enterprise density on housing prices is not significant in these areas. The reason is that the housing prices in Hong Kong are very high, and the characteristics of the housing market in that area are quite different from those in the nine cities in the Pearl River Delta, such that the capitalization effect of innovation is not obvious in Hong Kong. Due to the low density of high-tech enterprises in Macao, coupled with the influence of institutional boundaries, the capitalization effect of innovation is also not obvious in Macao.

The significance of our study is fourfold. First, we explain and verify the innovation capitalization effect at the urban agglomeration scale, using high-tech firms as an example. Second, our results offer a reference value for understanding the spatial limitations of innovation capitalization. Third, based on our findings, global research on innovation capitalization can progress from the perspective of spatial differentiation. When studying the innovation capitalization of a region (or city) (e.g., the influence of high-tech firms on housing prices), we need to pay attention to regional differences. Last, we provide a basis for policymakers to formulate innovative development strategies and housing policies based on spatial differentiation.

This study contributes to the literature in the following ways. In terms of its theoretical contributions, it expands our understanding of the spatial limitations and spatial variability of innovation capitalization (i.e., the effects of high-tech firms on housing prices). Moreover, our findings explain the spatial heterogeneity of innovation capitalization from four theoretical perspectives: local public goods, hedonic price theory, supply and demand theory, and neo-Marxism and space production, which then enriches the current theoretical framework outlining the effects of high-tech firms on housing prices at the urban agglomeration scale. In terms of contributions to future case studies and policy, the results can help relevant administrative authorities establish spatially differentiated innovative development strategies and housing policies.

6 Conclusions and Policy Implications

This study examined housing prices in 419 subdistricts in the GHMGBA and their influencing factors (especially high-tech firms). We used SGWR technology to analyze the spatial heterogeneity of these factors' influences on housing prices. Our conclusions are as follows. 1) There was significant spatial heterogeneity in the distribution of high-tech firms in the GHMGBA. Generally, the density of high-tech firms in the 'Science and Technology Corridor' formed across Guangzhou-Dongguan-Shenzhen-Hong Kong was relatively high. Similarly, the housing prices in the GHMGBA also showed spatial heterogeneity. Hong Kong-Shenzhen, Guangzhou, and Macao-Zhuhai had higher housing prices. 2) High-tech firms in the GHMGBA had a significant positive influence on housing prices, and the direction of influence was in line with theoretical expectations. Every 1% increase in the density of high-tech firms caused a 0.0156% increase in the housing price. 3) There was spatial heterogeneity in the influence of high-tech firms in the GHMGBA on housing prices. The subdistricts where high-tech firm density had a significant and positive influence on housing price accounted for 49.40% of the sample. These areas included Guangzhou-Foshan urban areas, the western part of Shenzhen-Dongguan, the northeastern part of the Zhongshan-Nansha district of Guangzhou, reflecting the spatial heterogeneity and spatial limitations of innovation capitalization in the GHMGBA. In areas with densely distributed high-tech firms, the phenomenon of innovation capitalization was more significant. In sum, at the urban agglomeration scale, we can theoretically infer that the density of high-tech enterprises has a positive impact on housing prices, and that this impact has spatial heterogeneity; that is, innovation capitalization has spatial heterogeneity.

The findings of this study could provide decisionmaking support for the innovation-driven development and urban function enhancement strategies of the GH-MGBA. First, in the areas wherein innovation elements are concentrated, stakeholders should build high-quality innovation spaces (e.g., high-tech firm parks) to create ideal conditions for the spatial concentration of high-tech firms, as well as support the development of high-quality public service resources and the building of high-quality houses in innovation spaces. This will then result in the formation of high-quality innovation spaces within new urban growth poles and the development of the highest-quality areas possible, which, in turn will lead to the improvement of the competitiveness of the city as a whole. Second, in terms of relatively under-developed areas, their overall value can be enhanced through the strategic method of either introducing high-tech firms or nurturing local ones in order to grow them into high-tech firms, which will in turn attract the inflow of talent and improve the built environment, thereby promoting the virtuous circle of regional development. Finally, in the older area of a given city, the capitalization effect of high-tech firms needs to be fully utilized, with the introduction of high-tech firms being undertaken as an important way in which to renew these older urban areas so as to promote their renewal and improve their overall value, thus helping them to regain their original vitality and attractiveness.

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