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Change Characteristics and Multilevel Influencing Factors of Real Estate Inventory—Case Studies from 35 Key Cities in China

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Abstract: High inventory is a common issue in urban real estate markets in many countries, posing a threat to the sustainable development of macroeconomics and society. This study built an analytical framework for the evolution of real estate inventory and its driving mechanisms and conducted an empirical study on 35 key cities in China. The findings show that, first, China has a huge real estate inventory with significant spatial heterogeneity. Second, the real estate inventory in China first rises and then falls, presenting an inverted U-shaped change trend; however, the spatial heterogeneity first falls and then rises, characterized by a U-shaped evolutionary change. Third, the present characteristics and evolutionary paths vary among different types of real estate inventory, mainly showing growth, stability, and inverted U-shaped changes. Fourth, the influencing factors of real estate inventory are increasingly diversified, and different factor pairs show bifactor-enhanced and nonlinearly-enhanced interaction effects, with a more intricate and complex driving mechanism. Fifth, four types of policy areas were divided according to the Boston Consulting Group Matrix, and it is recommended that the design of de-stocking policies should be dominated by "key factors" for cities in the stars and cows policy areas, while "important factors" and "auxiliary factors" should be equally emphasized for cities in the question policy area; the cities in the dogs policy area should keep the status quo as much as possible with avoidance of undesirable or excessive interventions.

Keywords: housing market; vacancy; spatial analysis; drive mechanism; China

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1. Introduction

1.1. Background

Commercial housing vacancy is a common phenomenon in most countries, and it is an important indicator reflecting the operational health of the real estate market, while being of much significance for government decision-making departments to know the allocation of housing resources, to decide the market and macroeconomic trends, and to analyze the wealth differentiation of residents' fixed assets [1,2]. High inventory is a huge risk that many countries must face in their real estate economic development for quite a long period of time. High inventory of commercial housing causes a serious waste of related resources and also weakens the driving force of the real estate for economic and social development. Inventory generally refers to the goods actually stored in the warehouse, including raw materials inventory and finished goods inventory. For real estate enterprises, inventory refers, in particular, to the houses that have been built but not sold or put into actual use. In real estate market statistics and research, the most direct and commonly used indicator to measure real estate inventory is the "area of business real estate for sale." Moderate inventory conforms to the law of business and market development, but too high a level will be a great danger to the real estate industry and macro economy. High inventory has become a core topic in the vacancy of commercial housing and has received attention from researchers in the fields of land management, spatial planning, human geography, and real estate economics [3].

After decades of rapid development, China's real estate has begun to face the issues of rising inventory and continued risk accumulation. Since 1994, when the Real Estate Annual Report of China began to turn the attention to vacant commercial properties, the issue of vacancy in Chinese real estate has been of great concern to all sectors. China's real estate market has been in a plight of increasing inventory since 2010, which has brought a great negative impact on the development of the national economy [4]. High inventory has become a bottleneck restricting the healthy development of China's real estate market and is also a huge burden, dragging down China's economic growth. To this end, the real estate de-stocking was listed as one of the five key tasks in 2015′s Central Economic Work Conference, marking that real estate de-stocking officially rose to the state-planned program.

Although the central government and local governments at all levels have implemented a number of real estate de-stocking policies since 2016, they failed to produce the desired effects. China has a large real estate inventory, characterized by significant regional differentiation and different types. Different cities and different types of real estate are under very uneven pressure of destocking, facing a complex and arduous task to achieve the goal. According to the *Market Size Report on Global Real Estate*, China has now grown into the fourth largest real estate market globally, with typical representation in the world. Therefore, it is of great theoretical significance and practical value to analyze the current characteristics and changing trends of China's real estate inventory for revealing the driving mechanism of the dynamic evolution of inventory and for providing a basis for the design of de-stocking policies in the real estate market.

1.2. Literature Review

The studies on the topic mainly involve three areas.

The first is about the vacancy chain model and the vacancy rate. Ferrari proposed a housing vacancy chain model [5], Emmi [6,7] further improved its prediction accuracy, and Ben-Shahar [8] analyzed the vacancy chains and mobility of the housing market. Miceli [9] explained the natural vacancy rate in the rental housing market based on the efficiency wage theory; Hagen [10] argued that there are significant differences in the natural vacancy rate across geographic regions; Vandell [11] studied the connection between the natural vacancy rate of commercial housing and taxation; and Gabriel [12] argued that rent changes have a significant impact on the housing vacancy rate, the natural vacancy rate, and the duration of housing vacancy in U.S. metropolitan cities. Tse [13] put forward a two-equation model of housing vacancy and rent adjustment, Zhang [14] and Suzuki [15] analyzed the factors influencing the postwar housing vacancy rate in Japan, Mcclure [16] and Vakili-Zad [17] argued that the coexistence of high rents and high vacancy rates is widespread, Wang [18] argued that vacancy rates inhibit the growth of housing rents in China, and Whitaker [19] argued that real estate vacancy helps lower the housing prices.

The second is about factors influencing housing vacancy. For example, Nam [20] and Nordvik [21] argued that factors such as an elderly population and construction permits are highly correlated with housing vacancy in Korea and the United States. Deng [22] conducted a multi-scale correlation analysis on the connection between housing vacancy and urban decay in the United States; Vanneste [23] analyzed the spatial structure of housing inventory in Belgium and its connection with social and economic inequality; Park [24] argued that homelessness in the U.S. is positively correlated with vacancy rates in the low-end housing market; Boessen [25], Jones [26], and Chen [27] analyzed the connection between housing vacancy and neighborhood crime (e.g., robbery and burglary);

and Wang [28] studied the connection between housing vacancy and urban growth in the United States.

The third is about empirical studies conducted in China and other countries. For example, Wang [29] and Pan [30] spatially identified housing vacancy in China, Li [31] estimated the vacancy rate of rural housing in China based on electricity consumption data, Shen [32] analyzed the correlation between urban government land supply and housing vacancy in China, and Chen [33] analyzed the performance of real estate de-stocking in China and its changing trends by the DEA method. In addition, Deilmann [34] made a prediction of housing vacancy in Germany in 2050, and Radzimski [35] found housing vacancy in Germany is closely associated with its urban contraction policies, while Olaya [36] and Immergluck [37] analyzed the dynamic characteristics of housing inventory and vacancy in Colombia and the United States.

There have been numerous valuable academic studies on real estate vacancy and inventory research in general, providing a multidimensional perspective and an important set of references for this article. However, the existing studies have certain shortcomings, mainly in the two areas below. First, in terms of the research object, there is a lack of comparative analysis studies of different types of real estate inventory. Most of the current studies focus on housing vacancy and total real estate inventory, including spatial identification and analysis of influencing factors. Real estate is a complex commodity with diversity, including many types such as buildings for residence, office, business, industrial, agricultural, special purposes, or mixed use. Office and business real estate in many cities is also under pressure from high inventory and vacancy compared to housing real estate. Besides, the inventory and vacancy dynamics of different types of real estate inventory such as buildings for residence and offices and businesses and their influencing factors are somewhat different, and a comparative study of their classification will help improve the reference value of research findings for housing market management and policy design at various levels of government. Unfortunately, the existing studies are still inadequate in this regard. Second, in terms of research methods, there is a lack of comprehensive research integrating economic, social, environmental, and other multi-dimensional influencing factors, and there is also a lack of sufficient attention to multi-factor interaction effects. Most of the current studies are based on classical research methods, such as remote sensing and GIS spatial analysis, interviews, and regression and correlation analysis. For example, Du [38] identified the housing vacancy rate in China and its correlation with socio-environmental factors based on nighttime remote-sensing data, and Bentley [39] analyzed the spatial distribution characteristics of vacant housing in Detroit in 1980, 1990, 2000, and 2010 and its correlation with race, unemployment, and class. Real estate inventory and vacancy are influenced by many factors, and there are complex interactions between these factors. There may be synergistic reinforcement or antagonistic constraints that arise from the combined action of multiple factors, eventually leading to the deformation or even denaturation of the driving force under the action of the factor alone. However, the existing studies neglect quantitative measurement and in-depth analysis in this regard.

1.3. Aim and Question

High inventory is an important indicator to determine overdevelopment of real estate, which will drain vital resources away from the real economy, squeeze the residents' consumption, and pose risks to the financial system and macroeconomic operations. The complexity of real estate de-stocking is beyond imagination, so it must be put in a broader economic, social, and environmental context for a holistic study. Only by determining the current characteristics, changing dynamics, evolutionary paths, spatial patterns, and influencing factors of different types of real estate inventory can we find the focus and key points for de-stocking. This study attempts to answer the following questions: (1) what are the current characteristics and changing trends of China's urban real estate inventory? It includes a comparative analysis of total inventory and different types of real estate inventory such as those for residence and offices and businesses. (2) What are the main driving forces behind the real estate inventory? It includes an exploration of the composition of the primary influencing factors on the changes of different types of real estate inventory and a quantitative measurement of the forces of different influencing factors. (3) How should the interaction effects between real estate inventory driving factors be quantitatively evaluated? It includes the calculation of interaction forces and the determination of interaction types. (4) How should adaptive policies for de-stocking different types of urban real estate based on the aforementioned research findings and in line with the laws of real estate market development and changing trends be developed? Therefore, this study is committed to analyzing the status and changing trends of different types of real estate inventory, quantitatively portraying the forces of their influencing factors and the intensity of their interactive effects based on case studies of 35 cities in China, with an attempt to further reveal the real estate inventory's driving mechanisms and to propose adaptive policy recommendations for real estate market de-stocking, so as to provide a reference for China and other countries such as the United States, Japan, and Mexico when making decisions on real estate inventory and vacancy management.

2. Research Design

2.1. Study Area: China

The study area was 35 key cities in mainland China, composed of municipalities directly under the central government, provincial capitals, and cities specifically designated in the state plan, dominated by provincial and sub-provincial cities, including a few prefecture-level provincial capitals (see Figure 1). There are several levels of administrative divisions in China's cities at present, with a total of 684 cities at all levels, including 4 municipalities directly under the central government (i.e., provincial cities), 14 sub provincial cities (including cities specifically designated in the state plan), 278 prefecture-level cities, and 387 county-level cities. Capital cities are home to the provincial or autonomous-region governments—a total of 28. Among the provincial capitals, 17 are prefecture-level cities, including Shijiazhuang, Taiyuan, Hohhot, and Hefei, while the rest are sub-provincial cities. The 35 cities hold an important position in the political, economic, social, and cultural development of China, and they are also the key cities for real estate market regulation with typical representation. The study area excluded Hong Kong and Macau, as well as cities in Tibet and Taiwan provinces, due to differences in the data statistics standards of Hong Kong, Macau, and Taiwan from that of mainland China and the massive data loss of cities in the Tibet Autonomous Region.

The total area of real estate for sale in all Chinese cities in 2019 was 498 million m^2, and the study area was 187 million m^2, accounting for about 37.59%. The total area of housing real estate for sale was 225 million m^2, and the study area was 67 million m^2, accounting for about 30.02%. The total area of office real estate for sale was 38 million m^2, and the study area was 24 million m^2, accounting for about 63.02%. The total area of business real estate for sale was 133 million m^2, and the study area was 44 million m^2, accounting for about 33.17%. The total real estate inventory and the housing and business real estate inventory experienced a fluctuating change from a decline to a rise during 2010–2019, while there was a steady and continuous growth in office real estate inventory. During the same period, the total real estate inventory and the inventory of housing, office, and business real estate in the study area accounted for 37.37%, 31.94%, 63.69%, and 35.10% of the country's average, respectively (see Table 1). In general, the real estate inventory in the study area was well represented in China, especially the office buildings. Therefore, an in-depth study of the current characteristics and evolutionary trends of real estate inventory in 35 cities, as well as an exploration of their main influencing factors and their interactive relationships, will help provide a decision-making basis for the design of de-stocking policies and real estate market regulation and will also help reveal the driving mechanism and evolutionary laws of real estate inventory development.

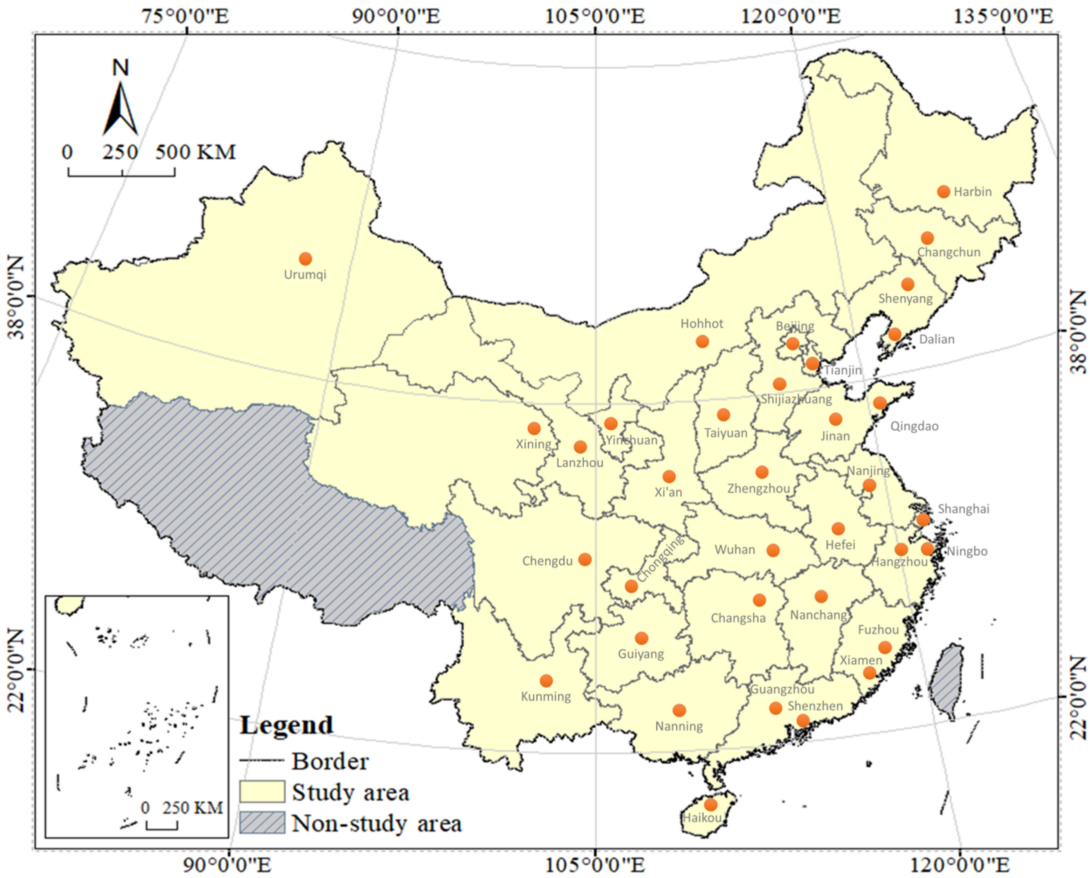


Figure 1. Study area.

Table 1. Analysis on the inventory of real estate in the study area.

	Inventory Area of Real Estate in 35 Cities (m^2)				Proportion in All Cities			
	Toal	**Housing**	**Office**	**Business**	**Toal**	**Housing**	**Office**	**Business**
2010	90,997,111	43,488,489	8,038,979	22,542,495	42.19	34.93	72.41	42.79
2011	119,260,155	66,209,859	8,155,959	25,482,230	41.54	36.60	64.51	41.81
2012	145,983,607	83,889,647	10,255,573	27,706,905	40.04	35.52	65.96	38.86
2013	183,513,635	106,843,431	12,423,014	32,942,628	37.23	32.97	63.56	35.25
2014	224,509,991	130,619,566	16,945,489	40,079,697	36.11	32.11	64.50	34.04
2015	248,084,372	137,834,412	19,872,050	46,676,604	34.53	30.46	60.66	31.83
2016	234,851,153	117,143,655	21,517,285	47,964,022	33.77	29.10	59.26	30.28
2017	205,203,992	87,253,836	22,026,674	47,042,107	34.83	28.93	60.11	30.94
2018	189,773,565	72,984,844	23,286,145	44,498,909	35.87	28.82	62.89	32.00
2019	187,251,148	67,459,957	23,9459,52	44,062,697	37.59	30.02	63.02	33.17

2.2. Research Methods

Common indexes for measuring the degree of variation in the spatial distribution of variables include the coefficient of variation, the Gini coefficient, the Theil index, the Herfindahl–Hirschman index, and the entropy index [40]. Common methods for analyzing the pattern of variation in the spatial distribution of variables include the kernel density, spatial hotspot clustering, the standard deviation ellipse, the nearest-neighbor index, spatial autocorrelation, and geographic connectedness [41]. Common methods for studying the driving mechanisms of variation in the spatial distribution of variables include the geodetector method, geographic-weighted regression, and the spatial panel model [42]. The spatial inequality in the housing market is mainly shown as the spatially differentiated distribution of the regional housing supply, demand and price, and their interconnections and dynamic changes. This study measured the spatial inequality of China's housing market based on the coefficient of variation and the Gini coefficient, visualized the spatial pattern by kernel density and spatial clustering methods, and determined the strength of the driving forces and their interaction effects based on the geodetector method.

2.2.1. Coefficient of Variation: CV

In classical statistics, the coefficient of variation (CV) is used for comparative analysis of the data dispersion degree, independent of the dimension and measurement scale. The coefficient of variation is equal to the ratio of the standard deviation of the source data to the mean. It is dimensionless, and a larger value represents a higher discrete degree and vice versa. According to Guan [43], Zhang [44], Ruan [45], Liu [46], Miyamoto [47], and She [48], dispersion is classified as weak, medium, and strong based on the CV values. That is, the dispersion is weak when the CV value is 0–0.15, indicating a low level of spatial inequality in the housing market; medium when the CV value is 0.16–0.35, indicating a high level of spatial inequality; and strong when the CV value is greater than 0.36, indicating a high level of spatial inequality.

2.2.2. Gini Index: GI

The Gini coefficient was first proposed by the Italian statistician and sociologist Corrado Gini in 1912 and redefined by the American statistician and economist Max Otto Lorenz in 1943 according to the Lorenz curve, which is used to determine the fairness of a national income distribution. It is a ratio value ranging between 0 and 1. A larger value indicates a larger difference and vice versa. According to studies by the United Nations Development Programme and the research proposal of Li [49], a Gini coefficient greater than 0.4 in this study indicates a large gap, which is used to characterize spatial inequality in the housing market; a Gini coefficient greater than 0.6 indicates a huge gap, used to characterize serious spatial inequality in the housing market.

2.2.3. Geodetector

The geodetector method, created by Professor Wang Jinfeng in 2010, is an emerging statistical method to detect spatial heterogeneity and reveal its influencing factors [50,51]. The geographically weighted regression is a linear model, while the geodetector is a nonlinear model. The geodetector method can quantify the interaction force between two independent variables and two dependent variables without considering multicollinearity. At present, the method has been widely used in geography [52,53], sociology [54,55], economics [56,57], ecology [58,59], environment science [60], landscape science [61], planning science [62,63], and even medicine [64] as well as many other natural sciences and humanities [65,66]. The geodetector is equipped with four functional modules responsible for factor detection, interaction detection, risk detection, and ecological detection. This study investigated the force and interaction of the influencing factors of spatial inequality in China's housing market depending on the two functional modules of factor detection and interaction detection. We assumed that the dependent variable is Y_i and the independent variable is X_i, and we used them to characterize the level of housing market development and its influencing factors, respectively. The q value of factor detection results, with a domain of (0, 1), can be used to measure the degree of spatial inequality of Y_i and the explanatory power of X_i for it. At some significance test level (typically 0.05), a larger value indicates that Y_i has a more significant spatial inequality and X_i has a stronger explanatory power for it. With the help of the interaction detection results it is possible to identify the interaction effect between X_i and X_j, that is, to determine whether X_i and X_j, when acting together, will enhance or diminish the explanatory power for the dependent variable Y_i, and, of course, their effects on Y_i may be independent of each other. The evaluation results fall into five overall categories based on the connections between q_{ij} and q_i, q_j under the interaction (see Table 2) [67,68].

Table 2. Interaction between explanatory variables.

Graphical Representation	Description	Interaction
	$q(X_i \cap X_j) < Min(q(X_i), q(X_j))$	Weaken, nonlinear
	$Min(q(X_i),q(X_j)) < q(X_i \cap X_j) < Max(q(X_i)), q(X_j))$	Weaken, uni-
	$q(X_i \cap X_j) > Max(q(X_i), q(X_j))$	Enhance, bi-
	$q(X_i \cap X_j) = q(X_i) + q(X_j)$	Independent
	$q(X_i \cap X_j) > q(X_i) + q(X_j)$	Enhance, nonlinear

Legend: ● $Min(q(X_i), q(X_j))$; ● $Max(q(X_i), q(X_j))$; ● $q(X_i) + q(X_j)$; ▼ $q(X_i \cap X_j)$.

2.3. Index Selection

Vacancy is a state in which the whole or part of real estate is not currently in use and is waiting to be rented or sold. Both new houses put in the market for the first time and those left by the current occupants due to migration are classified as vacant, as long as there are no new users (houses pending rental/sale). Real estate vacancy includes both stock vacancy and incremental vacancy. The real estate markets in developed countries and regions have become saturated, and their studies focus on stock vacancy. For China, the real estate market is still in a stage of rapid development, and there is still a very strong demand for real estate in these 35 cities in particular [69]. Therefore, studies of real estate vacancy in China, especially in the 35 cities, tend to focus on incremental vacancy, which is different from those in developed countries and regions. Inventory is the core of incremental vacancy, which can be measured by the "area for sale" of different types of real estate in the *China City Statistical Yearbook* and the *China Real Estate Statistics Yearbook*.

The area for sale is the part of the completed commercial properties available for sale or rent at the end of the reporting period of the statistical yearbook that has not yet been sold or rented, including the houses completed in previous years and those completed in the current year but not including houses built after demolition, houses built in a systematic or agential way, public-supporting buildings, or the real estate company's self-use housing or relocation housing that is not available for sale or lease. Commercial properties can be further subdivided according to the length of time they have been for sale into types such as for sale for less than 1 year, for sale for 1–3 years (including 1 year), and for sale for more than 3 years (including 3 years). Residential housing means real estate for residence, including villas, apartments, dormitories for families of workers and staff, and group quarters (including dormitories for single employees and student dormitories) but excluding unoccupied spaces in residential buildings such as basements used for civil air defense. Office real estate refers to office buildings, specifically all types of office space used by enterprises, institutions, agencies, groups, schools, hospitals, and other organizations. Commercial real estate refers to the houses used for business purposes by commercial, food, supply and marketing, food service, and other sectors, including resorts, restaurants, stores and supermarkets, hotels, bookstores, gas stations, etc.

In this study, the area of real estate for sale was used as the dependent variable, including the total area of real estate for sale and the areas of housing, office, and business real estate for sale, i.e., $Y_1 \sim Y_4$. Real estate inventory dynamics and spatial patterns are the result of a combination of factors, including the economy, finance, society, population, income levels, industrial structure, habitat environment, openness and innovation levels, and competition among real estate companies. The overlapping of different factors will produce a complex interactive effect. Therefore, with reference to the research of Bergeaud [70], Yan [71], Carrasco-Gallego [72], McMillan [73], Warsame [74], Oikarinen [75], Sun [76], and Hardie [77] et al., and based on the data accessibility, comparability, and completeness of the independent variables, this study explored the driving mechanisms of the evolution of different types of real estate inventory based on 20 indicators from 4 areas: the economic level, the social conditions, the habitat environment, and the competitive state of the real estate market itself as independent variables by the geodetector method (see Table 3).

Table 3. Model variable description.

Variable	Index	Code	Type
Dependent variable (Y_i)	Area of all real estate for sale (all)	Y_1	—
	Area of housing real estate for sale (housing)	Y_2	
	Area of office real estate for sale (office)	Y_3	
	Area of business real estate for sale (business)	Y_4	
Independent Variable (X_i)	Gross domestic product (GDP)	X_1	Economic driving force
	Per capita GDP	X_2	
	Expenditure of city government	X_3	
	Amount of bank loan	X_4	
	Added value of secondary industry	X_5	
	Added value of tertiary industry	X_6	
	Import and export quota of international trade	X_7	
	Foreign direct investment (FDI)	X_8	
	Number of permanent resident population	X_9	Social driving force
	Number of floating population	X_{10}	
	Average wage of residents	X_{11}	
	Total retail sales of consumer goods	X_{12}	
	Line length of urban rail transit (metro and light rail)	X_{13}	Living environment driving force
	Number stations of urban rail transit (metro and light rail)	X_{14}	
	Area of green coverage	X_{15}	
	Area of city park	X_{16}	
	Number of city parks	X_{17}	
	Number of real estate development enterprises	X_{18}	Market competition driving force
	Number of staff in real estate development enterprises	X_{19}	
	Average value of real estate price	X_{20}	

In the construction of the indicator system, we assumed that GDP and GDP per capita represent the stage of urban economic development [78,79]; that fiscal expenditure and loans reflect government support for real estate market development [80]; that the secondary industry represents the support of industrialization and the real economy [81]; that the tertiary industry reflects the supporting and service capacity of related industries; that import and export as well as foreign capital utilization represent the level of globalization and openness of the urban economy [82]; that the size of the resident and mobile population represents the real estate market demand and potential for de-stocking [83]; that the average wage reflects the income level of residents and real estate consumption capacity; that the retail sales of social consumer goods reflects the consumption vitality of the city; that public transportation and green space reflects the quality of the human living environment [84,85]; and that the number of real estate development enterprises, the number of employees, and housing prices represent the intensity of competition and dynamics of the real estate market.

It is important to note that "area of green coverage" and "area of city park" are different indicators. The former refers to the vertical projection area of all plants such as trees, shrubs, and lawns in the city, including the vertical projection area of green plants in various green areas in the city, the vertical projection area of green plants on roofs, and the vertical projection area of scattered trees, reflecting more the natural attributes of green areas. The latter refers to parks and green areas open all year round for the public to visit; to enjoy; or to have a rest or organize scientific, cultural and leisure activities in, with full-equipped service facilities and favorable green environments and beautiful landscape, including comprehensive parks, children's parks, parks of cultural relics and monuments, monumental parks, scenic parks, zoos, botanical gardens, and strip parks, reflecting better the humanistic attributes of green areas. By analyzing the independent and dependent variables based on the geodetector method, this study attempted to reveal the connection between real estate inventory evolution and economic development stage, government support or policy orientation, urbanization, industrialization, globalization, habitat quality, and market competition intensity, so as to provide a basis for policy design.

2.4. Research Steps and Data Sources

This study consists of four steps and nine key points (see Figure 2). The first step involved raw data and preprocessing. ① Prepare a complete raw data table based on the data released by the concerned statistical websites; ② discrete the continuous data of the independent variables based on Python and classify the independent variables of 35 cities into 8 categories by the percentile method to eliminate artificial influence (2–9). The second step was data processing. ③ Calculate the coefficient of variation and the Gini coefficient of the dependent variable and conduct spatial analysis of the dependent variable by ARCGIS; ④ import the source data of the dependent variable and the discrete data of the independent variable into the geodetector application and calculate the analysis results. The third step was data review: make a preferred choice among the alternatives in ②; ⑥ use the significance test level as a basis for determining the credibility of the results; and ⑥ take the largest value of q while meeting the same or higher significance level as the final solution. The fourth step was the analysis and discussion of the results. ⑦ Determine the strength of the explanatory power of the independent variables based on the ranking of q values. ⑧ Analyze the interaction effects of the driving factors; ⑨ calculate the mean value of q for the independent variables that have passed the significance test and calculate the strength of the driving forces to further reveal the driving mechanisms and policy insights of the spatial heterogeneity of the real estate inventory [86].

In this study, the dependent variable indicators were mainly from the *China Real Estate Statistics Yearbook*, and the independent variable indicators were mainly from the *China City Statistical Yearbook*, while some indicators were from the *China Urban Construction Statistical Yearbook*; some missing data were collected from provincial statistical yearbooks and statistical bulletins. The study period was set to 2010–2019 for three reasons. The first was to ensure the same data statistics standards. The China National Bureau of Statistics changed the term "vacant area" to "area for sale" in 2009. The two indicators were not comparable, and lengthening the study period will affect the accuracy of the conclusions. The second was to keep the consistency of the policy background. China's housing market was generally under severe control in 2010–2019, with anti-overheating, curtailment, reducing inventory, and housing residences instead of vicious speculation as the policy keynotes. The third was to ensure the completeness of the data. Statistics on the area of real estate for sale in 2009 were missing for some cities in the study area, such as Shijiazhuang, Haikou, and Nanchang.

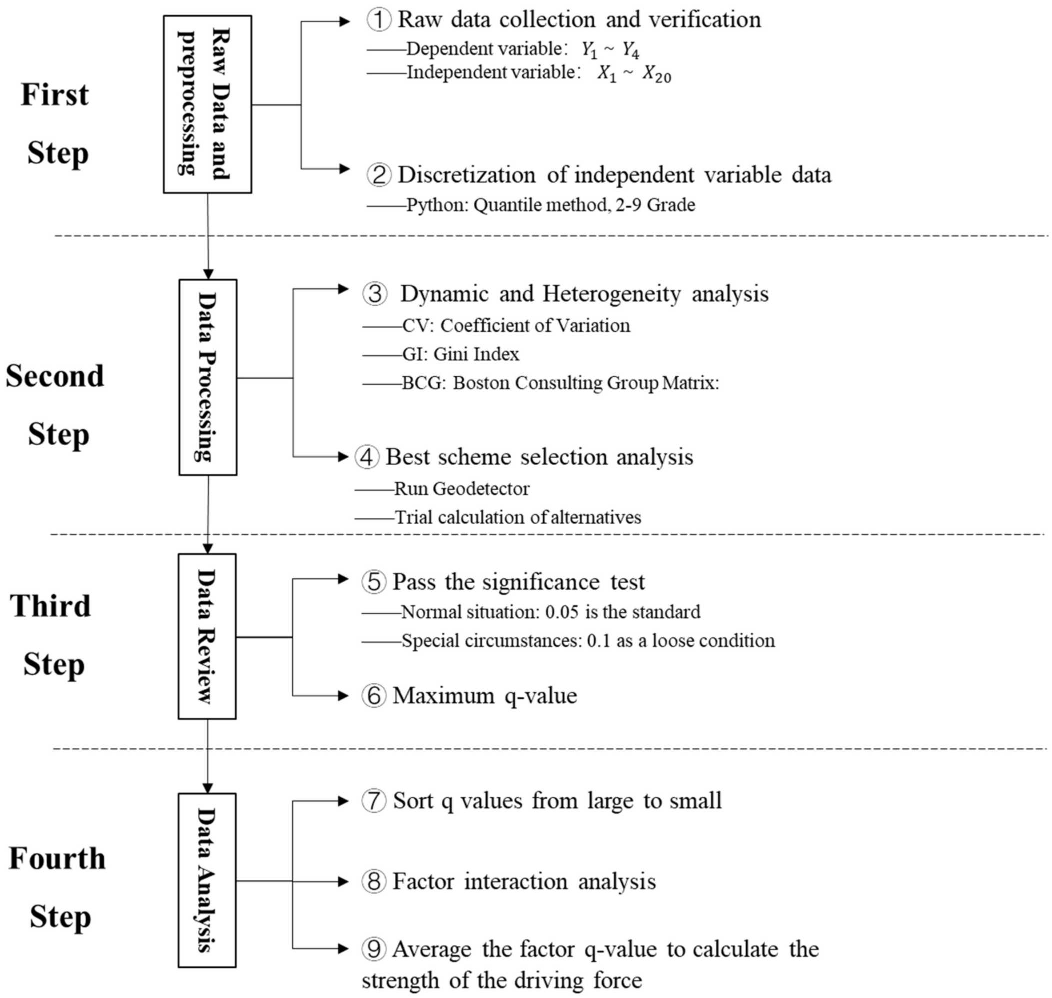


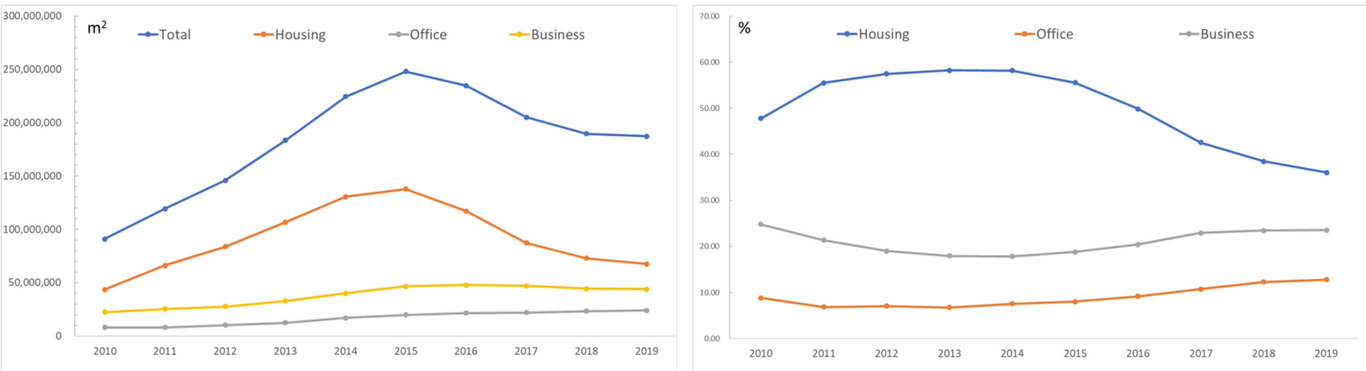
Figure 2. Research framework and steps.

3. Results

3.1. Dynamic Analysis

Factors such as the huge total real estate inventory, the trend of inverted U-shaped changes, the dominance of housing real estate inventory, and the medium-to-high growth of office and business real estate inventory are having an increasing impact on the real estate market inventory (see Figure 3). In terms of real estate inventory size, both total and housing real estate inventory experienced a rapid rise followed by a slow decline from 2010 to 2019, which is different from the office and business real estate, which has seen a continuous rise in inventory. In terms of real estate inventory structure, housing real estate inventory takes up the largest share, followed by the inventory of business real estate, with that of office real estate at the bottom. From 2010 to 2019, the share of housing real estate inventory rose slowly and then fell rapidly, staying above 40% for a long time and peaking at nearly 60%. During the same period, business real estate inventory fell slowly followed by a slow rise, stabilizing at around 20% in general. The share of office real estate inventory has been rising slowly for a long time and has remained stable at around 10% in general. In terms of the growth of real estate inventory, the annual average of total real estate inventory from 2010 to 2019 was 7.48%, with housing real estate inventory at the lowest rate (4.49%), office real estate inventory at the highest rate (11.53%), and business real estate inventory in between (6.93%).

According to the change in real estate inventory area from 2010 to 2019, the 35 cities can be classified into three types: growing, stable, and inverted U-shaped (see Figure 4). In terms of total inventory, Beijing, Shanghai, Changchun, Fuzhou, Xiamen, Zhengzhou, Guangzhou, Yinchuan, and Urumqi are growing cities; Hefei, Nanjing, Taiyuan, Hohhot, Wuhan, Nanning, and Changsha are stable cities; and Tianjin, Shijiazhuang, Shenyang, Dalian, Harbin, Hangzhou, Ningbo, Nanchang, Jinan, Qingdao, Shenzhen, Haikou, Chongqing, Chengdu, Kunming, Xi'an, Lanzhou, Xining are inverted U-shaped cities. In terms of housing real estate inventory, all cities are inverted U-shaped, with no growing or stable cities. In terms of office real estate inventory, Beijing, Tianjin, Shijiazhuang, Taiyuan, Dalian, Changchun, Shanghai, Hangzhou, Hefei, Qingdao, Zhengzhou, Shenzhen, Xi'an, and Yinchuan are growing cities; Haikou, Hohhot, Fuzhou, Xiamen, Jinan, Changsha, and Urumqi are stable cities; Shenyang, Ningbo, Nanchang, Wuhan, Guangzhou, Nanning, Chongqing, Chengdu, Guiyang, Kunming, and Xining are inverted U-shaped cities. In terms of business real estate inventory, Tianjin, Changchun, Shanghai, Hangzhou, Fuzhou, Xiamen, Nanchang, Qingdao, Zhengzhou, Guangzhou, Chengdu, Kunming, Lanzhou, and Urumqi are growing cities; Hohhot, Ningbo, Shenzhen, Guiyang, Xining, and Yinchuan are stable cities; Beijing, Shijiazhuang, Taiyuan, Shenyang, Dalian, Harbin, Nanjing, Hefei, Jinan, Wuhan, Changsha, Nanning, Haikou, Chongqing, and Xi'an are inverted U-shaped cities. It should be noted that total real estate inventory and office real estate inventory in Beijing and Shanghai have remained high for a long time and are still growing rapidly.



(**a**) (**b**)

Figure 3. Analysis of real estate inventory change from 2010 to 2019 in the study area (**a**) area; (**b**) proportion.

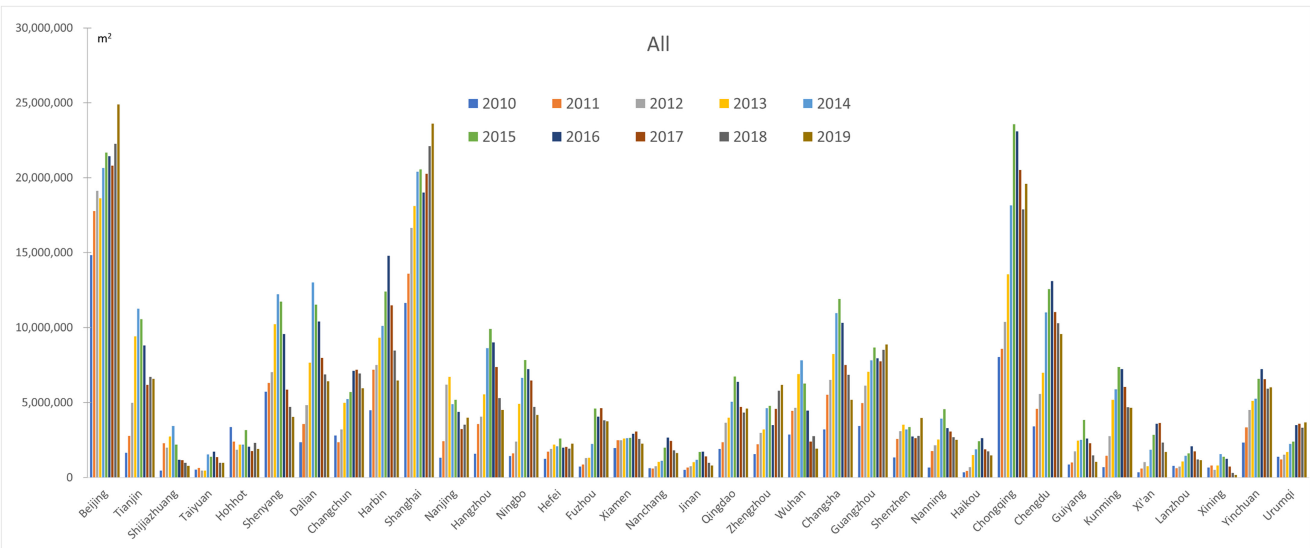


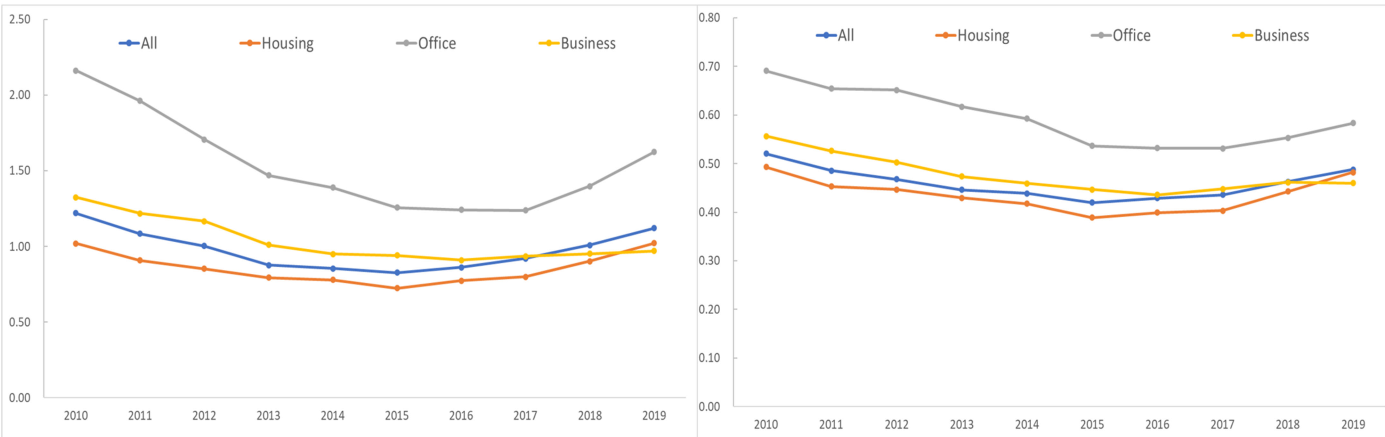
Figure 4. *Cont.*

Figure 4. Analysis of real estate inventory change from 2010 to 2019 in the 35 key cities.

3.2. Heterogeneity Analysis

Due to different stages of development, resource endowments, location conditions, and levels of real estate market development and competition, real estate inventory in the study area has very significant spatial heterogeneity, especially in the spatial variation of office real estate inventory. The coefficients of variation for total real estate inventory and housing, office, and business real estate inventory, for 2019 in the study area were 1.12, 1.02, 1.62, and 0.97, respectively, and the Gini coefficients were 0.49, 0.48, 0.58, and

0.46, respectively, which is much larger than 0.36 and 0.4, indicating that there is a very large variation in real estate inventory across the 35 cities, especially in office and total inventories. The spatial heterogeneity of the real estate inventory in the study area from 2010 to 2019 shows a decreasing and then increasing trend, with both convergence and divergence. A larger coefficient of variation in statistics represents a greater degree of dispersion in the data, and a value greater than 0.36 indicates highly significant spatial variation. According to the evolution and comparison of the coefficient of variation of real estate inventories from 2010–2019, the coefficient of variation of all types of real estate inventories in China is always much greater than 0.36, with a minimum value of 0.72 (housing in 2015) and a maximum value of 2.16 (offices in 2010). Studies by the United Nations Development Program and other organizations show that a larger Gini coefficient indicates greater spatial disparities, where 0.4 is a critical threshold. A value greater than it indicates a large disparity, and there is a need to take effective measures to deal with it, otherwise sustainable development will be compromised. The evolution and comparison of the Gini coefficient of real estate inventories from 2010–2019 shows that the Gini coefficient of all types of real estate inventories in China was generally greater than 0.4, with a minimum value of 0.39 (housing in 2015) and a maximum value of 0.69 (office in 2010). The overall ranking based on the coefficient of variation and the Gini coefficient is housing < all < business < office, with the coefficient of variation of business being surpassed by all and housing from 2018 and 2019, respectively. The trends in the total and housing real estate inventories were the same in general, with office real estate inventory falling and rising rapidly and business real estate inventory changing very slowly (see Figure 5). The evolutionary trends and comparative analysis of the coefficients of variation and the Gini coefficients from 2010–2019 in general show that there was significant spatial differentiation of real estate inventories in China, with serious inequality among cities. The ranking in severity was housing < all < business < office.



(**a**) (**b**)

Figure 5. Analysis of the changing trend of CV and GI (**a**) Coefficient of variation; (**b**) Gini index.

Based on the average of real estate inventory from 2010 to 2019, the 35 cities were classified into three types: high, medium, and low levels by nature breaks (see Figure 6). The cities with a total real estate inventory of more than 9 million square meters were of the high type; those with less than 4.6 million square meters were of the low type; and the rest were of the medium type. Those with a housing real estate inventory of more than 4.1 million square meters were of the high type; those with less than 1.5 million square meters were of the low type; and the rest were of the medium type; those with an office real estate inventory of more than 900,000 square meters were of the high type; those with less than 380,000 square meters were of the low type; and the rest were of the medium type. Those with a business real estate inventory of more than 1.79 million square meters were of the high type; those with less than 800,000 square meters were of the low type;

and the rest were of the medium type. In terms of the total inventory, Beijing, Shanghai, Chongqing, and Harbin were at a high level, with Chengdu, Shenyang, Guangzhou, Tianjin, Dalian, Changsha, and other cities at a medium level; Wuhan, Nanjing, Kunming, Qingdao, Zhengzhou, and other cities were at a low level. In terms of the housing real estate inventory, Beijing, Shanghai, Chongqing, Shenyang, Harbin, Dalian, and Changsha were at a high level, with Tianjin, Guangzhou, Changchun, Chengdu, Wuhan, and other cities at a medium level, and Shijiazhuang, Guiyang, Hohhot, Nanning, and other cities at a low level. In terms of the office real estate inventory, Beijing, Shanghai, and Hangzhou were at a high level, with Tianjin, Chongqing, Chengdu, Guangzhou, Zhengzhou, Wuhan, Changsha, Qingdao, and other cities at a medium level, and Yinchuan, Xiamen, Dalian, Guiyang, Kunming, Changchun, and other cities at a low level. In terms of the business real estate inventory, Beijing, Shanghai, Chongqing, and Harbin were at a high level, with Chengdu, Shenyang, Ningbo, Guangzhou, Hangzhou, Yinchuan, Tianjin, Qingdao, Changchun, Kunming, Dalian, Changsha, and other cities at a medium level, and Wuhan, Xiamen, Shenzhen, and Hefei and other cities at a low level.

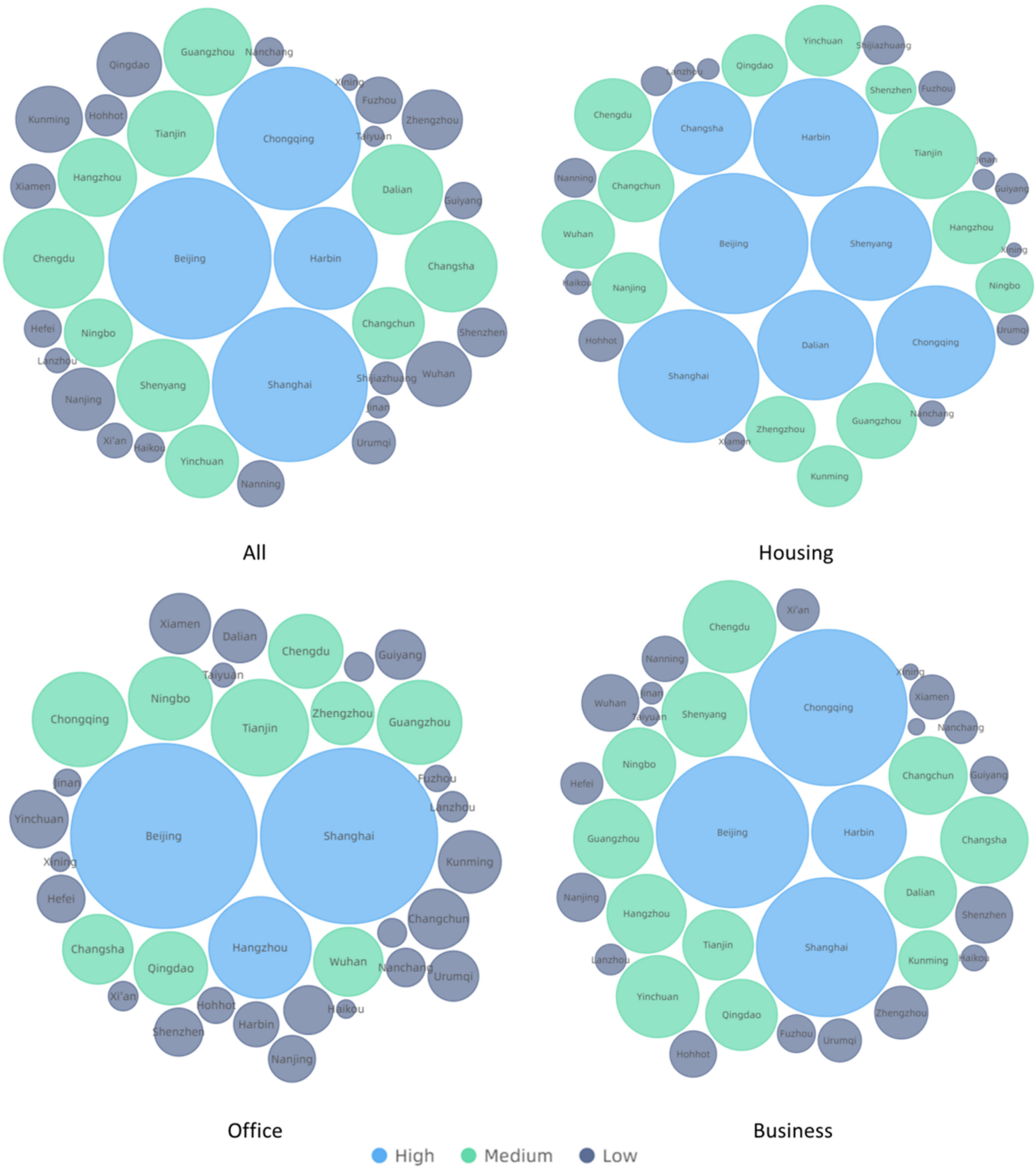


Figure 6. Real estate inventory classification based on 2010–2019 average.

3.3. Factor Analysis

3.3.1. All Real Estate

In 2019, X_2 and X_{20} failed to pass the significance test, while X_{11} and X_{16} could only pass the loose significance test of 10%. In 2010, X_{10}, X_{11}, and X_{20} failed to pass the significance test, while X_2 and X_{16} could only pass the loose significance test of 10%. At the significance level of 0.05, the driving factors of 2019 and 2010 were ranked in the order of intensity as $X_1 > X_{15} > X_{12} > X_{19} > X_9 > X_6 > X_{10} > X_8 > X_3 > X_{17} > X_{18} > X_5 > X_{14} > X_{13} > X_7 > X_4$, $X_{19} > X_{15} > X_{18} > X_9 > X_{14} > X_3 > X_{13} > X_8 > X_5 > X_1 > X_{12} > X_7 > X_4 > X_6 > X_{17}$. There were 12 factors that increased in force from 2010 to 2019, including X_1, X_6, X_{10}, X_{11}, X_{12}, and X_{17} with a larger rise; 7 decreased, including X_2, X_{13}, X_{14}, and X_{18} with a greater fall. It should be noted that X_{20} consistently failed the significance test; X_2 degenerated to fail the test; X_{10} and X_{11} evolved to pass the 5% and 10% significance tests, respectively; X_{16} consistently failed the significance test of 10%; and X_{20} consistently failed the significance test. The average force of the factor was 0.51 in 2010 and rose to 0.56 in 2019. There was a very large difference in the ranking of driving factors between 2010 and 2019, with the former being market competition > social > economic > living environment and the latter being social > market competition > living environment > economic (see Figures 7–9).

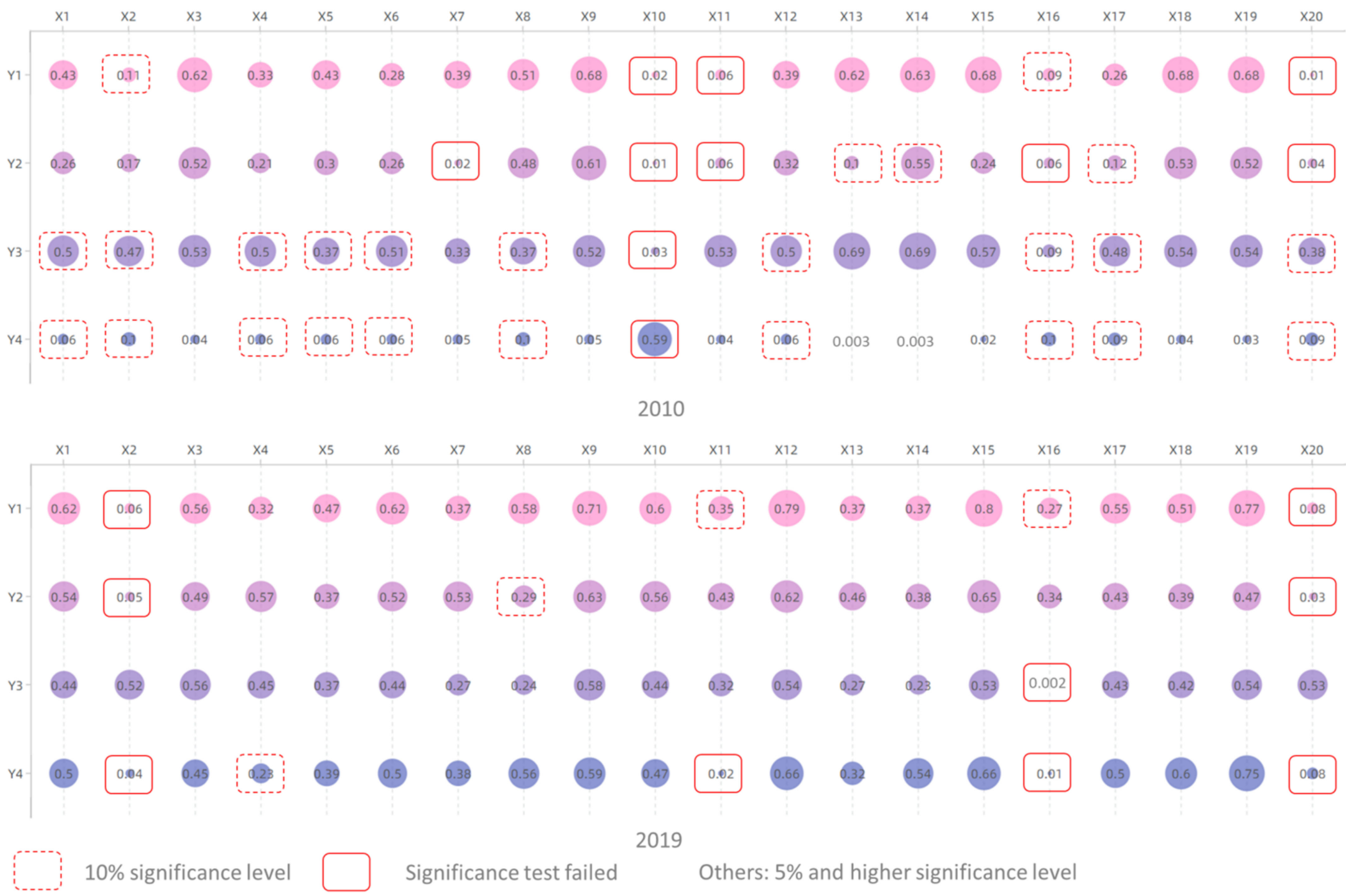


Figure 7. Analysis of factor detector.

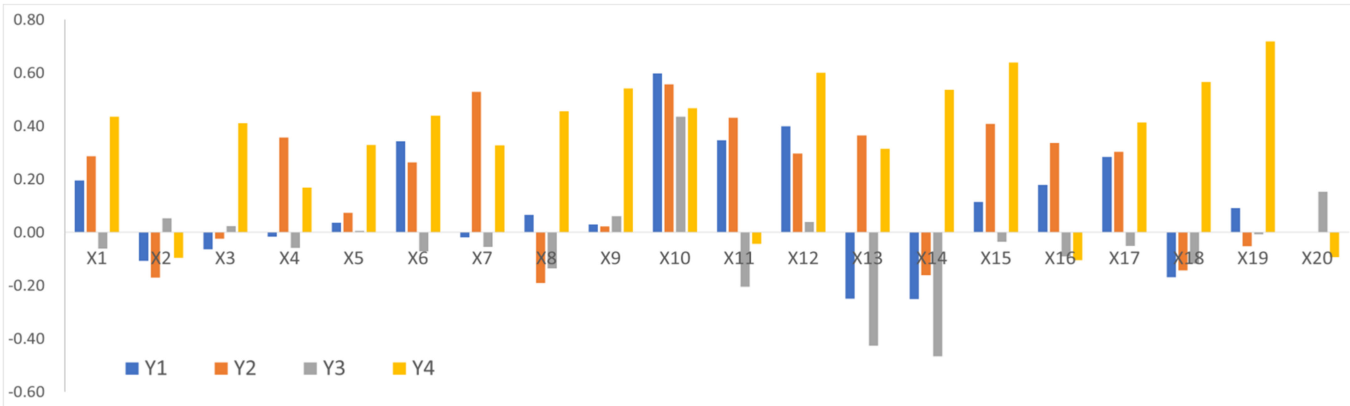


Figure 8. Change of factor influence from 2010 to 2019.

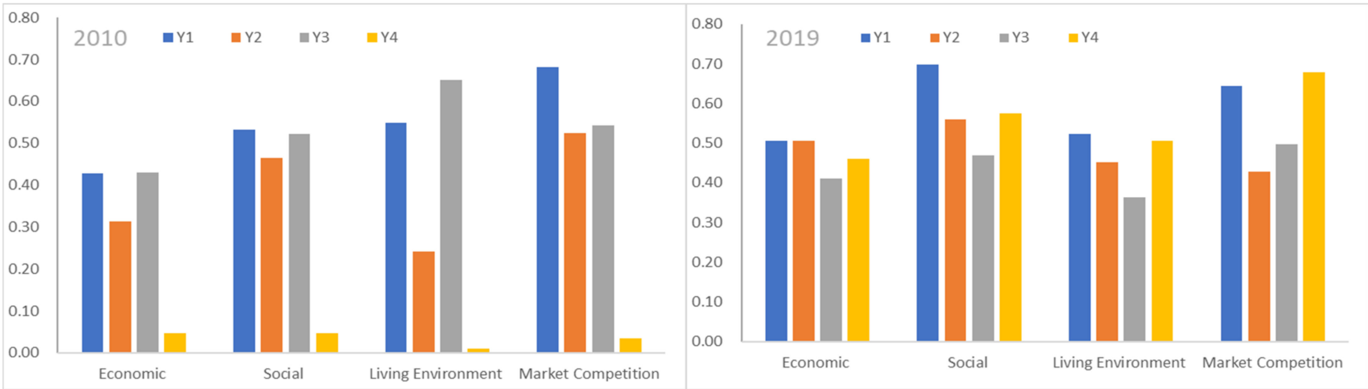


Figure 9. Analysis of driving force.

3.3.2. Housing Real Estate

In 2019, X_{20} and X_2 failed to pass the significance test, while X_8 could only pass the loose significance test of 10%. In 2010, X_7, X_{10}, X_{11}, X_{20}, and X_{16} failed to pass the significance test, while X_{14}, X_{17}, and X_{13} could only pass the loose significance test of 10%. At the significance level of 0.05, the driving factors of 2019 and 2010 were ranked in the order of intensity as $X_{15} > X_9 > X_{12} > X_4 > X_{10} > X_1 > X_7 > X_6 > X_3 > X_{19} > X_{13} > X_{11} > X_{17} > X_{18} > X_{14} > X_5 > X_{16}$, $X_9 > X_{18} > X_{19} > X_3 > X_8 > X_{12} > X_5 > X_6 > X_1 > X_{15} > X_4 > X_2$. There were 13 factors that increased in force from 2010 to 2019, including X_1, X_4, X_6, X_7, X_{10}, X_{11}, X_{12}, X_{13}, X_{15}, X_{16}, and X_{17} with a larger rise; 6 decreased, including X_2, X_8, X_{14}, and X_{18} with a greater fall. It should be noted that X_{20} consistently failed the significance test; X_2 degenerated to fail the test; X_8 degenerated to pass the 10% significance test only; while X_7, X_{10}, X_{11}, X_{16}, X_{13}, X_{14}, and X_{17} evolved to pass the 5% significance test. The average force of the factor was 0.37 in 2010 and rose to 0.49 in 2019. There is a very large difference in the ranking of driving factors between 2010 and 2019, with the former being market competition > social > economic > living environment and the latter being social > economic > living environment > market competition (see Figures 7–9).

3.3.3. Office Real Estate

In 2019, X_{16} failed to pass the significance test, while the rest of the factors could pass the significance test of 5% and a more stringent level. In 2010, X_{10} failed to pass the significance test, while X_6, X_4, X_{12}, X_1, X_{17}, X_2, X_{20}, X_8, X_5, and X_{16} could only pass the significance test of 10%. At the significance level of 0.05, the driving factors of 2019 and 2010 were ranked in the order of intensity as $X_9 > X_3 > X_{12} > X_{19} > X_{20} > X_{15} > X_2 > X_4 > X_1 > X_6 > X_{10} > X_{17} > X_{18} > X_5 > X_{11} > X_7 > X_{13} > X_8 > X_{14}$, $X_{13} > X_{14} > X_{15} > X_{19} > X_{18} > X_3 > X_{11} > X_9 > X_7$. There were 7 factors that increased in force from 2010 to 2019, including X_{10} and X_{20} with a larger rise; 13 decreased, including X_8, X_{11}, X_{13}, X_{14}, and

X_{18} with a greater fall. It should be noted that X_{16} degenerated to fail the significance test, while X_1, X_2, X_4, X_5, X_6, X_8, X_{10}, X_{12}, X_{17}, and X_{20} evolved to pass the 5% significance test. The average force of the factor was 0.55 in 2010 and decreased to 0.43 in 2019. There was a large difference in the ranking of driving factors between 2010 and 2019, with the former being living environment > market competition > social > economic, and the latter being market competition > social > economic > living environment (see Figures 7–9).

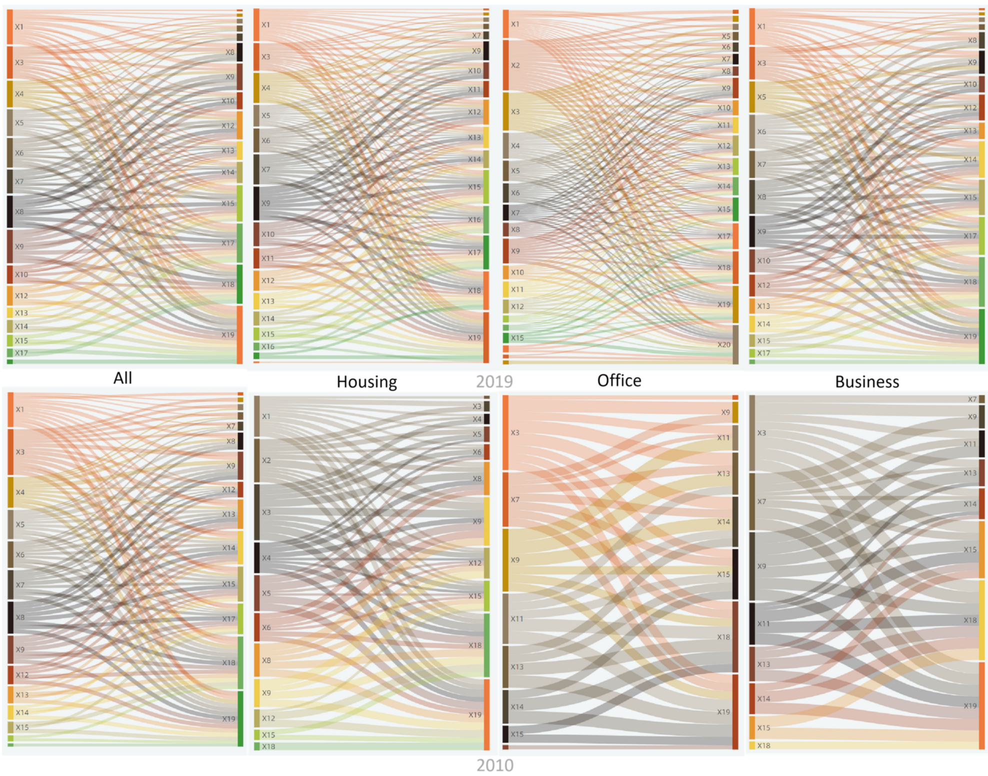
3.3.4. Business Real Estate

In 2019, X_2, X_{11}, X_{16}, and X_{20} failed to pass the significance test, while X_4 could only pass the loose significance test of 10%. In 2010, X_{10} failed to pass the significance test, while X_{16}, X_8, X_2, X_{20}, X_{17}, X_1, X_{12}, X_4, X_5, and X_6 could only pass the loose significance test of 10%. At the significance level of 0.05, the driving factors of 2019 and 2010 were ranked in the order of intensity as $X_{19} > X_{15} > X_{12} > X_{18} > X_9 > X_8 > X_{14} > X_{17} > X_1 > X_6 > X_{10} > X_3 > X_5 > X_7 > X_{13}$, $X_7 > X_9 > X_{11} > X_3 > X_{18} > X_{19} > X_{15} > X_{14} > X_{13}$. There were 16 factors that increased in force from 2010 to 2019, including X_1, X_3, X_6, X_9, X_{10}, X_{12}, X_{14}, X_{15}, X_{18}, and X_{19} with a larger rise; 4 decreased, including X_2 and X_6 with a greater fall. It should only be that X_4 could consistently pass the significance test of 10% only, and X_2, X_{11}, X_{16}, and X_{20} degenerated to fail the significance test, while X_1, X_5, X_6, X_8, X_{12}, and X_{17} evolved to pass the 5% significance test. The average force of the factor was 0.03 in 2010 and decreased to 0.52 in 2019. There is a very large difference in the ranking of driving factors between 2010 and 2019, with the former being social > economic > market competition > living environment, and the latter being market competition > social > living environment > economic (see Figures 7–9).

3.4. Interaction Analysis

In 2019, at the significance level of 5%, Y_1 formed a total of 120 factor pairs, all bifactor-enhanced with a mean interaction force of 0.79. The factor pair $X_{12} \cap X_{17}$ had the largest interaction force (0.98), while $X_{13} \cap X_4$ had the smallest (0.41). The factor pairs can be classified into three types by nature breaks, including 35 pairs at a high level, 41 at a medium level, and 44 at a low level. Y_2 forms a total of 136 factor pairs, with a mean interaction force of 0.75. The factor pair $X_{11} \cap X_9$ had the largest interaction force (0.98), while $X_5 \cap X_{16}$ had the smallest (0.46). There were 29 pairs at a high level, with 62 at a medium level, and 45 at a low level. The factor pairs were predominantly bifactor-enhanced, while $X_{16} \cap X_{14}$ and $X_{16} \cap X_{18}$ were nonlinearly-enhanced. Y_3 formed a total of 171 factor pairs, with a mean interaction force of 0.64. The factor pair $X_2 \cap X_{17}$ had the largest interaction force (0.97), while $X_{13} \cap X_{14}$ had the smallest (0.30). There were 24 pairs at a high level, with 61 at a medium level, and 86 at a low level. The factor pairs were predominantly bifactor-enhanced, while $X_2 \cap X_5$, $X_2 \cap X_7$, $X_9 \cap X_{11}$, and $X_{19} \cap X_{11}$ were nonlinearly-enhanced. Y_4 formed a total of 105 factor pairs, all bifactor-enhanced with a mean interaction force of 0.79. The factor pair $X_{12} \cap X_{14}$ had the largest interaction force (0.99), while $X_{13} \cap X_5$ had the smallest (0.43). There were 54 pairs at a high level, with 28 at a medium level, and 23 at a low level. It should be noted that some influencing factors were strongly interacted with others, including X_{19}, X_{18}, X_{17} of Y_1, X_{18}, X_{19}, X_{16} of Y_2, X_2, X_3, X_{18}, X_{11} of Y_3, X_{19}, X_{18}, X_{17}, and X_8 of Y_4 (see Figure 10 and Table 4).

In 2010, at the significance level of 5%, Y_1 formed a total of 105 factor pairs, with a mean interaction force of 0.74. The factor pair $X_{13} \cap X_{18}$ had the largest interaction force (0.96), while $X_6 \cap X_4$ had the smallest (0.41). The factor pairs can be classified into three types by nature breaks, including 43 pairs at a high level, 42 at a medium level, and 20 at a low level. Except the factor pair $X_{17} \cap X_8$ in a nonlinearly-enhanced relationship, all the rest are bifactor-enhanced. Y_2 formed a total of 66 factor pairs, all bifactor-enhanced with a mean interaction force of 0.58. The factor pair $X_3 \cap X_{19}$ had the largest interaction force (0.90), while $X_{15} \cap X_1$ had the smallest (0.28). There were 18 pairs at a high level, with 28 at a medium level and 23 at a low level. Y_3 formed a total of 36 factor pairs, all bifactor-enhanced with a mean interaction force of 0.79. The factor pair $X_9 \cap X_{11}$ had the largest interaction force (0.9964), while $X_3 \cap X_7$ had the smallest (0.57). There were 12 pairs at a high level, with 21 at a medium level, and 3 at a low level. Y_4 formed a total of 36 factor pairs, with a mean interaction force of 0.79. The factor pair $X_7 \cap X_9$ had the largest interaction force (0.9964), while $X_{13} \cap X_{14}$ had the smallest (0.36). There were 22 pairs at a high level, with 9 at a medium level, and 5 at a low level. The factor pairs were predominantly bifactor-enhanced, while $X_9 \cap X_{11}$, $X_{11} \cap X_{18}$, $X_{19} \cap X_{11}$, and $X_{13} \cap X_{14}$ were nonlinearly-enhanced. It should be noted that some influencing factors were strongly interacted with others, including X_{19}, X_{18}, X_3 of Y_1, X_{18}, X_{19}, X_9, X_3 of Y_2, X_{19}, X_3, X_{18}, X_7, X_9 of Y_3, and X_{19}, X_{18}, X_{15}, X_9, X_3, X_7, and X_{11} of Y_4 (see Figure 10 and Table 4).



Legend		2019				2010			
Type	Line	All	Housing	Office	Business	All	Housing	Office	Business
Low	Thin	⩽0.7221	⩽0.7059	⩽0.5900	⩽0.6549	⩽0.5576	⩽0.3848	⩽0.5771	⩽0.5231
Medium	Medium	others	others	others	others	others	others	others	others
High	Thick	⩾0.8832	⩾0.8220	⩾0.7523	⩾0.8197	⩾0.7696	⩾0.6840	⩾0.7378	⩾0.8105

Figure 10. Analysis of interaction detector.

Table 4. Statistical analysis of factor pairs and interaction forces.

		Number of Factor Pairs				Strength of Interaction Effect		
		Total	**High**	**Medium**	**Low**	**Min**	**Max**	**Average**
2019	Y_1	120	35	41	44	0.4117	0.9816	0.7908
	Y_2	136	29	62	45	0.4640	0.9805	0.7513
	Y_3	171	24	61	86	0.3001	0.9679	0.6440
	Y_4	105	54	28	23	0.4343	0.9895	0.7872
2010	Y_1	105	43	42	20	0.3809	0.9646	0.7409
	Y_2	66	18	28	20	0.2832	0.8968	0.5771
	Y_3	36	12	21	3	0.5653	0.9964	0.7884
	Y_4	36	22	9	5	0.3627	0.9964	0.7945

4. Discussion

4.1. Drive Mechanism

At the significance level of 5%, the common mean values of the influencing factor forces of Y_1~Y_4 were 0.54, 0.44, 0.46, and 0.37, respectively, in 2010 and 2019. With TOP3 and mean values as thresholds, the driving factors can be classified into three categories, that is, "key factors," "important factors," and "auxiliary factors" (see Figure 11). "Key factors" are mainly directly exerting effects, and their direct forces were ranked TOP3. "Important factors" act in the form of both direct and interaction factors at the same time. The direct factors of such factors are generally greater than the average, and, if less, it indicates they have a very strong interaction force. The other factors that pass the significance test are "auxiliary factors," and they are weak in both direct and interaction forces. In terms of the ranking of driving forces, Y_1 and Y_4 are the same, that is, market competition > social > living environment > economic, and the driving forces of Y_2 are ranked in the order of social > market competition > economic > living environment, while the driving forces of Y_3 are ranked in the order of market competition > living environment > social > economic. The number of factors passing the significance test in 2019 was significantly larger than that in 2010, with more significant factor interaction effects, indicating that the factors influencing real estate inventory in Chinese cities are increasingly diversified and that the driving mechanisms are more intricate and complex.

The primary influencing factors for different types of real estate inventory vary in general. The degree of greening of the build-up environment, the real estate market and enterprise competition intensity, and the population size have the strongest influence on total inventory, while city government support, consumption vitality, and foreign investment also play an important role. In terms of housing real estate inventory, population size and international trade are the key influencing factors, but the influence of government financial support, the availability of public transport, the real estate market, and enterprise competition cannot be ignored. In terms of the office real estate inventory, the degree of greening of the build-up environment and government support are key influencing factors, but the influence of the city's economic development stage and consumption vitality, housing prices, and rail transit availability cannot be ignored. In terms of business real estate inventory, urban consumption vitality and foreign investment scale are key influencing factors, but the impact of urban economic scale, industrial structure, and mobile population cannot be ignored.

Some findings in this study have testified partial content from existing articles. Yoo [87] argued that green space affects the dynamics of real estate inventory in Gyeonggi-do, South Korea, and this study also found that "area of green coverage (X_{15})" is a key factor affecting total real estate inventory and office real estate inventory in China, while the "number of city parks (X_{17})" is a key factor influencing business real estate inventory. Tan argued that population, GDP, and housing prices are negatively correlated with China's real estate inventory and positively correlated with industrial structure [88]; Zhang [89] pointed out that income inequality is positively correlated with China's housing vacancy rate; Pan [90] argued that the a community living environment has a great influence on housing vacancy; and Newman [91], Reyes [92], and Couch [93] argued that land area, population and urbanization, and the level of economic development are the primary driving factors of housing vacancy in the cities of the US, Mexico, and the UK. Their conclusions are generally in agreement with the findings in this study, where we found that the "number of permanent resident population (X_9)" has a great impact on office real estate inventory and the "number of floating population (X_{10})" has a strong impact on business real estate inventory, and they have a vital effect on both the total real estate inventory and the housing real estate inventory. In addition, the "average value of real estate price (X_{20})" and the "per capita GDP (X_2)" have a major influence on office real estate inventory, while the "gross domestic product (X_1)" and the "added value of tertiary industry (X_6)" have a major influence on the business real estate inventory. The "average wage of residents (X_{11})" and the "added value of secondary industry (X_5)" were below the average in forces, but their influence cannot be ignored.

Besides, Liu [94] empirically examined the effects of promoting urbanization and lowering housing prices on real estate inventory destocking based on the panel data from 2001 to 2013 and concluded that, in general, promoting urbanization and lowering housing prices indeed can help to effectively digest the current excess real estate inventory; however, they showed obvious regional differences, with a significant role in promoting urbanization but a limited role in lowering housing prices in the eastern region and a significant role in lowering housing prices but a limited role in promoting urbanization in the central and western regions. Moreover, Liu argued that raising per capita income also has a positive impact on real estate destocking. These conclusions are roughly consistent with the findings of this study. Li [95] empirically studied the impact of real estate destocking on housing prices in the context of new urbanization based on the panel data from 2007 to 2016 and concluded that real estate destocking in the context of new urbanization is spatially dependent on housing prices in different regions, but the impact is not the same. It has a negative impact on the stability of housing prices in first- and second-tier cities, while it has no fixed impact on the stability of housing prices in third- and fourth-tier cities. Wang [96] constructed a housing inventory pressure index based on the panel data from 2000 to 2014 and a random effects model and analyzed the regional differences of real estate inventory pressure and its influencing factors in Chinese cities from many perspectives such as housing supply, demand, and equilibrium price, concluding that there are obvious differences in inventory pressure in different regions, as evidenced by a "convergent" housing price curve between equilibrium and actual housing prices in the eastern region, a "breakaway" housing price curve in the central region, and an "escape" housing price curve in the western region. Additionally, he pointed out that the different economic development levels and the real estate market management levels are key factors affecting the degree of urban real estate inventory pressure. The conclusions of the above studies are generally in agreement with the findings of this study in different dimensions, and they are mutually verified.

It is important to note that there are also some new ideas and findings in this article with the in-depth study of some influencing factors, which are of great value to complement and improve the driving mechanisms and evolutionary laws of real estate inventory. This study found that the "FDI (X_8)" and the "import and export quota of international trade (X_7)" that represent the level of globalization of the urban economy have long played an important role in the total real estate inventory and the housing real estate inventory; in addition, the "number of real estate development enterprises (X_{18})," the "number of staff in real estate development enterprises (X_{19})," and the "average value of real estate price (X_{20})" that represent the intensity of the real estate market and enterprise competition are increasingly influential on China's total real estate inventory. According to a subdivision study of the impact of economic openness of cities, "FDI (X_8)" has a much stronger effect on the total real estate inventory and the business real estate inventory than the "import and export quota of international trade" (X_7). However, they have the opposite effect on the ranking of the housing real estate inventory's influencing factors, and both have a weak influence on the office real estate inventory. The "number of city parks (X_{17})" has a much greater impact on real estate inventory than the "area of city parks (X_{16})," indicating that increasing the number of city parks is a more effective measure for de-stocking than expanding park area. Rail line length and the number of stations vary widely in their impact on real estate inventory. The "number stations of urban rail transit (X_{14})" has a greater impact on total real estate inventory and business real estate inventory than the "line length of urban rail transit (X_{13})," but they have the opposite impact on housing and office real estate inventory.

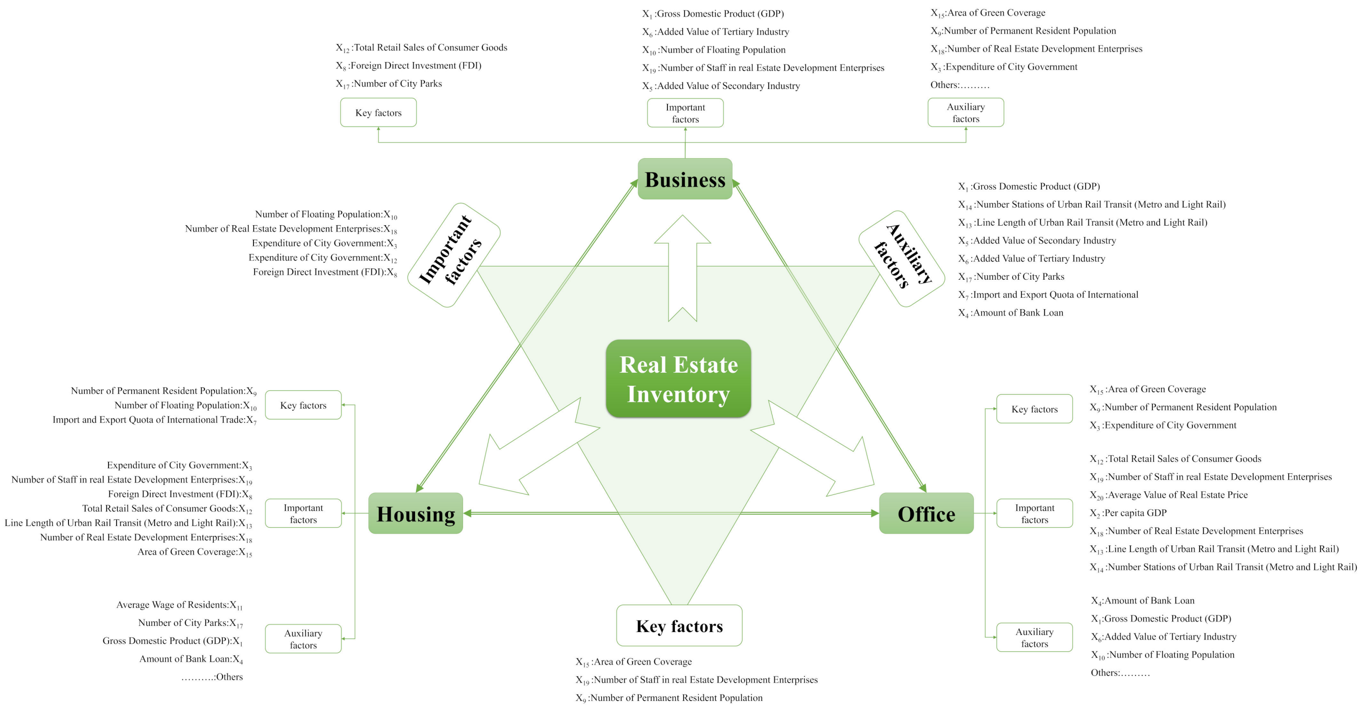


Figure 11. Driving mechanisms of spatial inequalities in the housing market.

4.2. Policy Implication

In recent years, China's central and local governments have introduced a series of de-stocking policies and have stepped up regulatory measures for the real estate market. However, these policies have not been implemented with good results. A major reason is the lack of awareness among policymakers of the complexity of the factors influencing the evolution of different types of real estate inventory and their driving mechanisms, thus resulting in poorly directed and synergistic de-stocking measures and policies. In view of the development trend, the idea of "adapting measures by classification and implement control by city" has become the consensus of the government and the society, and there is an urgent need for differentiated policy design and policy supply based on real estate inventory influencing factors and their interaction. The average growth rates of total real estate inventory and housing, office, and business real estate inventories in the study area from 2010 to 2019 were 7.85%, 4.67%, 15.14%, and 9.72%, respectively, and the average value of the absolute proportion of real estate inventory (i.e., the area of inventory in each city/total area of inventory in 35 cities $*$ 100%) in 35 cities was 2.86%. In view of the relative balance of the number of cities in each type, the 35 cities were divided in this study into four policy areas of stars, cows, questions, and dogs based on the Boston Consulting Group Matrix with 3% and 10% as the thresholds of the absolute proportion and the growth rate, respectively (see Figure 12).

The policy area of stars refers to cities with a high absolute proportion and a growth rate of real estate inventory, which are under great pressure to de-stock and where more precise and diversified policy measures must be taken to slow the growth rate of inventory and to reduce inventory size. Total inventory in Dalian, Chengdu, Hangzhou, Guangzhou, and Tianjin; housing real estate inventory in Nanjing, Tianjin, and Dalian; office real estate inventory in Hangzhou, Tianjin, Qingdao, Ningbo, and Chongqing; and business real estate inventory in Chengdu, Changsha, Ningbo, and Changchun are all in this policy area.

The policy area of cows refers to cities with a high absolute proportion of real estate inventory but a low growth rate. Although their growth rate has been under effective control, generally with slower or even negative growth, they are still facing a high pressure of de-stocking, and they should improve the synergy and interaction between different policies and measures for de-stocking in the future. Total inventory in Shenyang, Changsha, Harbin, Chongqing, Shanghai, and Beijing; housing real estate inventory in Guangzhou, Hangzhou, Changchun, Chengdu, Changsha, Chongqing, Harbin, Shenyang, Shanghai, and Beijing; office real estate inventory in Shanghai, Guangzhou, Beijing, and Chengdu; and business real estate inventory in Shanghai, Chongqing, Beijing, Harbin, Hangzhou, Guangzhou, and Shenyang are all in this policy area.

The policy area of question refers to cities with a low absolute proportion of real estate inventory but a high growth rate. These cities may face greater pressure to de-stock in the future with the growth at a high rate, although they currently do not have a large inventory. Additionally, it shows that there are great defects in current de-stocking policies, without good accuracy or coordination. Total inventory in cities including Kunming, Fuzhou, Xi'an, Haikou, and Zhengzhou; housing real estate inventory in cities including Nanning, Kunming, Shenzhen, and Ningbo; office real estate inventory in cities including Zhengzhou, Kunming, Shijiazhuang, Yinchuan, Dalian, and Nanchang; and business real estate inventory in cities including Xi'an, Nanchang, Qingdao, Taiyuan, and Tianjin are all in this policy area.

The policy area of dogs refers to cities with a low absolute proportion and growth rate of real estate inventory but under less pressure to de-stock now and in the future. Total inventory in cities including Xining, Hohhot, Wuhan, and Guiyang; housing real estate inventory in cities including Xining, Xiamen, Lanzhou, and Hefei; office real estate inventory in cities including Haikou, Jinan, Shenyang, and Urumqi; and business real estate inventory in cities including Xining, Nanjing, Hefei, Jinan, and Dalian are all in this policy area.

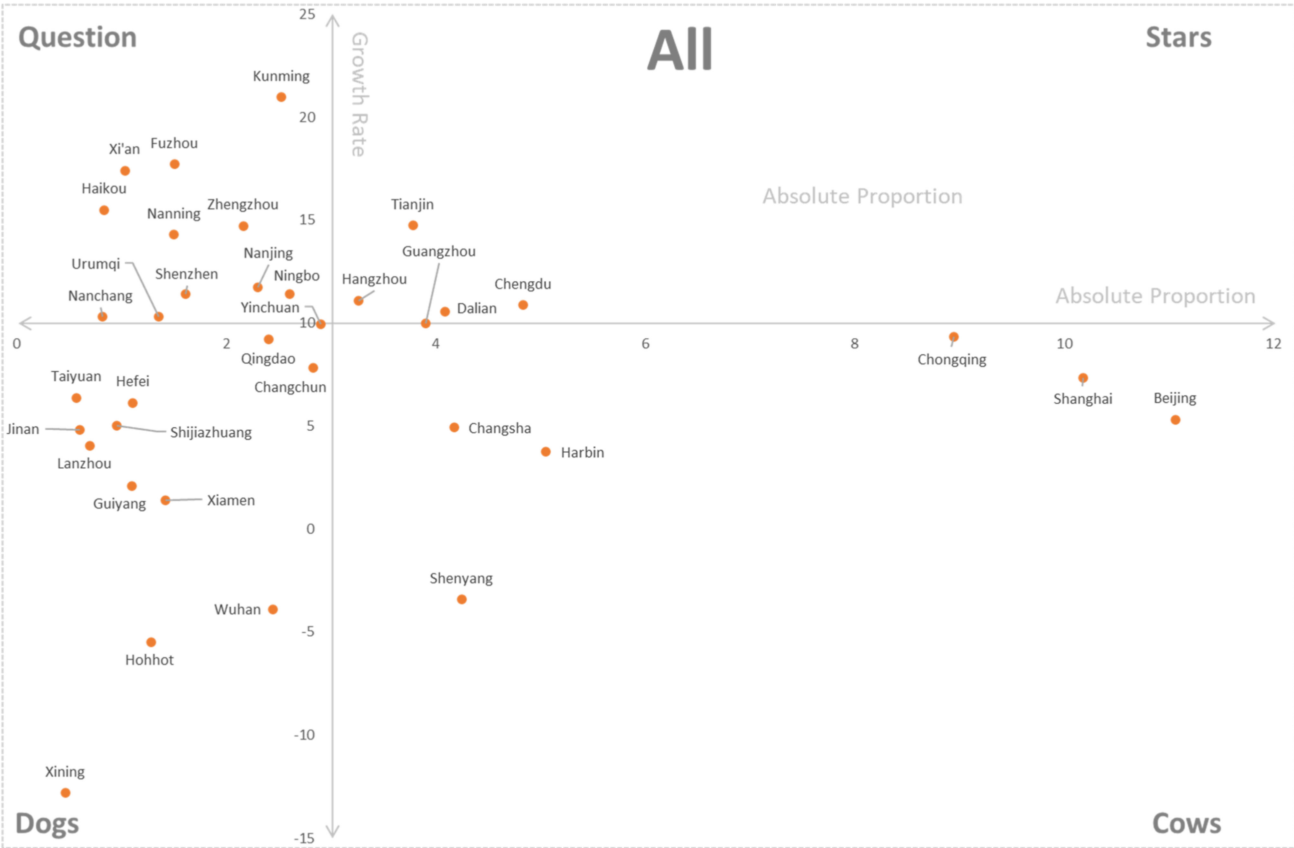


Figure 12. *Cont.*

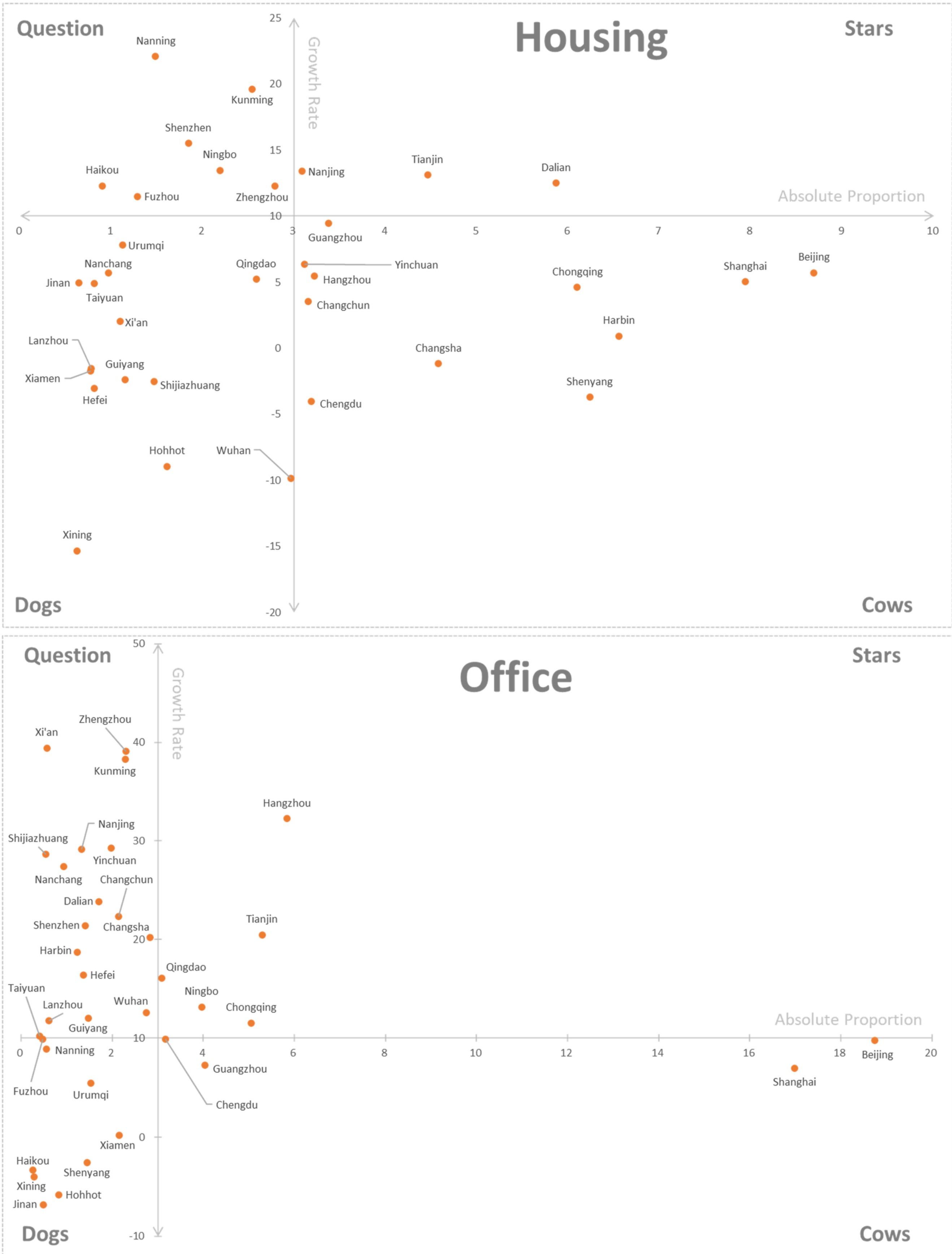


Figure 12. *Cont.*

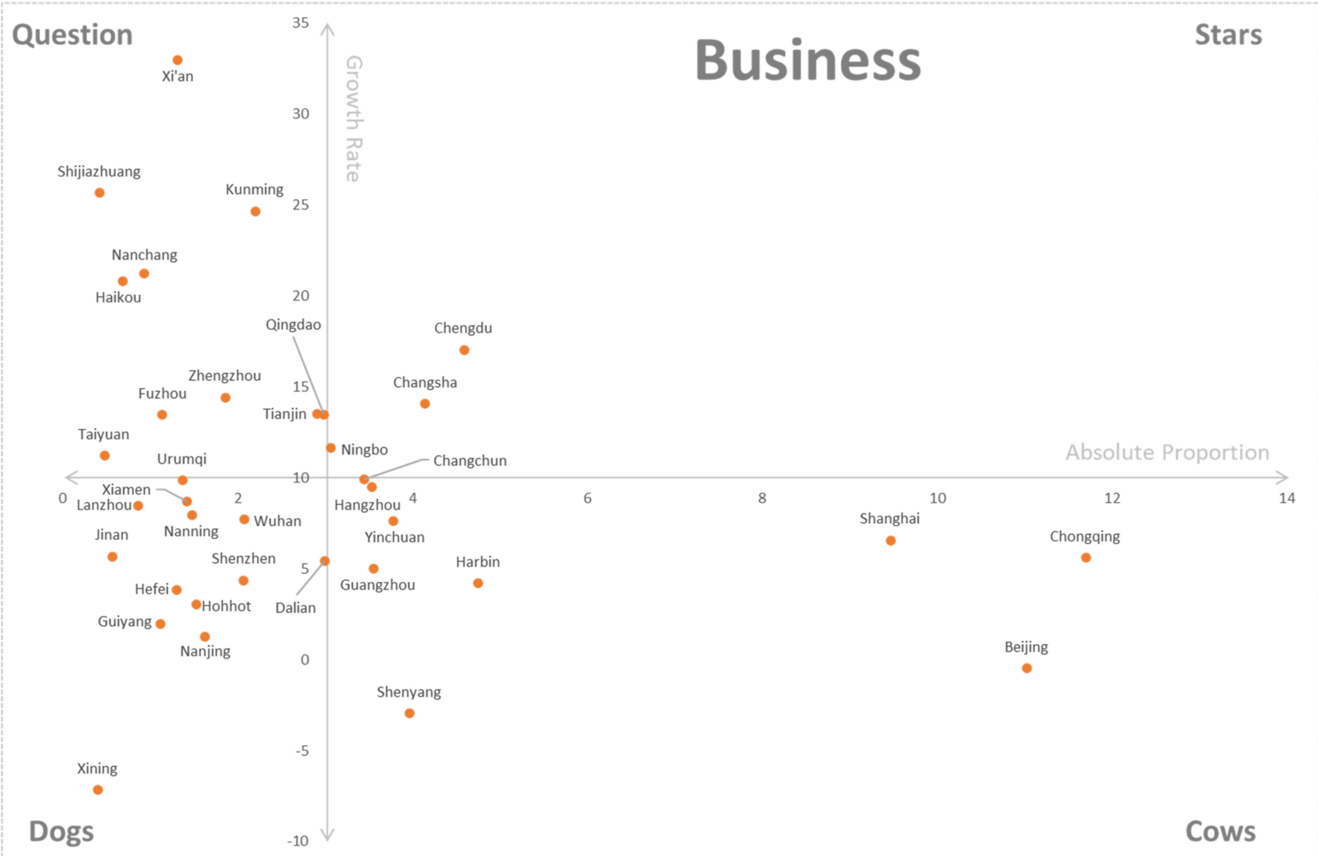


Figure 12. Policy zoning of urban real estate inventory pressure.

The cities in the policy area of stars are key ones, and those in the policy area of cows are major ones for real estate de-stocking, for which efforts should be made to accelerate the optimization of policy design, taking a variety of measures in combination to promote the achievement of the goal. Their de-stocking policies should be designed under the guidance of "key factors," including the "area of green coverage (X_{15})," the "number of staff in real estate development enterprises (X_{19})," the "number of permanent resident population (X_9)," the "import and export quota of international trade (X_7)," the "area of green coverage (X_{15})," the "expenditures of city government (X_3)," the "total retail sales of consumer goods (X_{12})," and the "FDI (X_{13})," which should be combined scientifically with the interaction effects between factors to bring about the maximum policy effectiveness. Cities in the policy area of question are currently under little pressure to de-stock, but they should prepare for the inevitable. They should design de-stocking policies around "important factors" and "auxiliary factors," including the "number of floating population (X_{10})," the "expenditure of city government (X_3)," and "per capita GDP (X_2)" and make full use of the indirect influence and interaction of the factors to intervene in the real estate market. With less pressure to de-stock, the policy area of dogs should maintain its current policies to promote the healthy development of the real estate market with avoidance of excessive intervention.

5. Conclusions

Cities in China, the United States, Japan, South Korea, Germany, and other countries and regions are currently facing varying degrees of real estate inventory and vacancy. High inventories and vacancies affect the healthy operation of the real estate market and also threaten the sustainable development of the macroeconomy and society, so reducing inventory and vacancy has become a major economic and social issue. There are many factors affecting real estate inventory and vacancy, and they exist in a complex interaction.

In addition, the factors affecting different types of real estate inventory and vacancy vary widely. Therefore, a "one-size-fits-all" solution should be avoided in the design and supply of real estate de-stocking policies; instead, it is required to take measures in the light of local conditions and to implement the policies by classification. Based on the spatial differences of real estate inventory in cities and the integrated influencing factors such as economic, social, habitat environment, and the competitive state of the real estate market itself, this study built an analytical framework for the evolution of real estate inventory and its driving mechanisms and conducted an empirical study on 35 key cities in China. The main conclusions we reached are as follows.

The first is the analysis of the current status and evolutionary characteristics of China's real estate inventory. There is a huge real estate inventory in the study area, changing in an inverted U-shaped trend of a rapid rise followed by a slow decline. Residential inventory still dominates the leading position but with a decrease in its importance in general. Office and business real estate have maintained a medium-to-high growth in inventory, which has an increasingly significant impact on real estate market inventory. Based on the average of real estate inventory from 2010 to 2019, the 35 cities were classified into three types: high, medium, and low levels by nature breaks. There were three types of real estate inventory trends from 2010 to 2019, that is, growing, stable, and inverted U-shaped, with varying trends in housing, office, and business real estate inventory. Due to different stages of development, resource endowments, location conditions, and levels of real estate market development and competition, real estate inventories in the study area had very significant spatial heterogeneity, especially in the spatial variation of office real estate inventory. The change trend of the total real estate inventory was generally the same as that of the housing real estate inventory in spatial heterogeneity from 2010 to 2019, with rapid convergence and then slow divergence. During the same period, the spatial heterogeneity of the office real estate inventory experienced a rapid decline and increase, while the spatial heterogeneity of the business real estate inventory remained stable.

The second is that the primary influencing factors of China's real estate inventory and their interaction were revealed. According to the average value and ranking order of influencing factors in 2010 and 2019, the driving factors were divided into "key factors," "important factors," and "auxiliary factors," and, based on the interaction effects among the factors, the driving mechanisms were put forward for different types of real estate inventory. "Key factors" were mainly directly exerting effects, with direct forces ranked as the top three, such as the "area of green coverage (X_{15})," the "number of staff in real estate development enterprises (X_{19})," the "number of permanent resident population (X_9)," and the "number of floating population (X_{10})." "Important factors" act in the form of both direct and interaction factors at the same time, which are factors with direct forces greater than the average or with very strong interaction forces, such as the "number of floating population (X_{10})," "expenditures of city government (X_3)," and "per capita GDP (X_2)." The other factors passing the 5% significance test are "auxiliary factors," which have less direct forces than the average with weak interaction forces. Factor interactions are dominated by bifactor enhancement and supplemented by a small portion of nonlinear enhancement, with no attenuated or independent relationships. The market competition driving force affects all types of real estate inventory incrementally, and the social driving force mainly affects housing and business real estate inventories, while the living environment driving force has more influence on the office real estate inventory. There was an increasing number of factors affecting the real estate inventory from 2010 to 2019, and their interaction effects were becoming more significant, indicating that the driving mechanisms of the real estate inventory evolution are becoming increasingly intricate and complex.

The third is that the policy advice of "adapting measures by classification and implement control by city" is put forward. The 35 cities were divided in this study into four policy areas of stars, cows, questions, and dogs based on the Boston Consulting Group Matrix with 3% and 10% as the thresholds of the absolute proportion and the growth rate, respectively. It was recommended that city policy makers carry out differentiated policy design and policy supply based on real estate inventory influencing factors and their interaction. Cities in the policy areas of stars and cows are under the biggest pressure to de-stock, and their policies should be designed around "key factors." That is, based on the direct forces of factors and the interaction effects between factors, they are combined in an appropriate manner with various measures taken to achieve the maximum policy effectiveness. Cities in the policy area of question should plan ahead and design de-stocking policies around "important factors" and "auxiliary factors" to improve the accuracy and synergy of de-stocking policies to the utmost. Cities in the policy area of dogs should maintain their current policies to achieve healthy development of the real estate market, with avoidance of excessive or undesirable interventions.

Theoretically, this study provides a new research framework and methodology for researchers in real estate economics, land management, human geography, spatial economics, and spatial planning to analyze the dynamic characteristics of real estate inventories and their evolutionary trends. Moreover, it helps to reveal the laws of real estate inventory development and their governance mechanisms. Practically, this study helps urban policy makers and decision makers to find a scientific and reasonable model of real estate inventory governance and provides a necessary decision basis for government management and policy regulation; it is applicable to China and also provides a decision reference for countries such as the United States, Korea, Japan, Mexico, Germany, the United Kingdom, and Italy to solve the real estate inventory and vacancy problems.

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