land

MDPI

Article

Spatial Inequality in China's Housing Market and the Driving Mechanism

Sidong Zhao [1], Kaixu Zhao [2] and Ping Zhang [3,4,*]

1 School of Architecture, Southeast University, Nanjing 210096, China; 230189013@seu.edu.cn
2 College of Urban and Environmental Science, Northwest University, Xi'an 710127, China; zhao_kx@foxmail.com
3 College of Civil Engineering and Architecture, Jiaxing University, Jiaxing 314001, China
4 College of Architecture and Urban Planning, Lanzhou Jiaotong University, Lanzhou 730070, China
* Correspondence: ppqzhangp@zjxu.edu.cn

Abstract: Housing inequality is a widespread phenomenon around the world, and it varies widely across countries and regions. The housing market is naturally spatial in its attributes, and with the transformation of China's urbanization, industrialization, and globalization, the spatial inequality in the housing market is increasingly severe. According to the geospatial differences in the housing market supply, demand, and price, and by integrating the influencing factors of economic, social, innovation, facility environment, and structural adjustment, this paper constructs a "spatial–supply–demand–price" integrated housing market inequality research framework based on the methods of CV, GI, and Geodetector, and it empirically studies the spatial inequality of provincial housing markets in China. The findings show that the spatial inequality in China's housing market is significant and becomes increasingly serious. According to the study, we have confirmed the following. (1) Different factors vary greatly in influence, and they can be classified into three types, that is, "Key factors", "Important factors", and "Auxiliary factors". (2) The spatial inequalities in housing supply, demand, and price vary widely in their driving mechanisms, but factors such as the added value of the tertiary industry, number of patents granted, and revenue affect all these three at the same time and have a comprehensive influence on the development and evolution of spatial inequalities in the housing market. (3) All the factors are bifactor-enhanced or non-linearly enhanced in relationships between every pair, and they are classified into three categories of high, medium, and low according to the mean of interacting forces; in particular, the factors of GDP, expenditure, permanent resident population, number of medical beds, and full-time equivalent of R&D personnel are in a stronger interaction with other factors. (4) Based on housing supply, demand, price, and their coordination, 31 provinces are classified into four types of policy zones, and the driving mechanisms of spatial inequalities in the housing market are further applied to put forward suggestions on policy design, which provides useful references for China and other countries to deal with housing spatial inequality.

Keywords: housing market; spatial inequality; drive mechanism; real estate; China

Citation: Zhao, S.; Zhao, K.; Zhang, P. Spatial Inequality in China's Housing Market and the Driving Mechanism. *Land* **2021**, *10*, 841. https://doi.org/10.3390/land10080841

Academic Editor: Shiliang Su

Received: 25 July 2021
Accepted: 9 August 2021
Published: 11 August 2021

1. Introduction

Housing is a core issue in urban and rural planning and spatial governance, and one of the most important tasks of many subjects such as science of land administration, spatial planning, human geography, and real estate economics. The housing market is a vital element of the real estate economy, playing a pillar and leading role in the national economic system and having a fundamental and pioneering position in the development of social livelihood. In addition, the housing is represented by spatial fixity and diversity of supply and demand, with huge regional differences and prominent spatial inequalities. The immovability of housing determines that the housing market is regional, and there are significant differences in the level of housing market development in different regions. Housing plays a critical role in the transformation of local economic and social development, and it leads to a significant spatial heterogeneity and complexity of housing market development [1]. Therefore, the housing market dynamics and spatiotemporal patterns, housing inequality, and its driving mechanisms have been perennial themes of classical research and received long-standing attention from academic researchers, industry practitioners, and political administrators.

The housing inequality is a widespread phenomenon around the world, and it varies widely across countries and regions [2]. As a result of the rapid development of China's housing market and its huge scale, as well as the fact that housing is a matter of security and happiness for Chinese residents and the overall economic and social development, its importance, complexity, and sensitivity have become increasingly prominent with the development of the country's economic and social transformation, which determines its typical representation in the world. Since the reform and opening up of China, especially the housing monetization reform in 1998, the housing market has gained rapid development. According to the *China Real Estate Statistics Yearbook 2020*, from 1998 to 2019, the number of housing development enterprises in China increased by 4.1 times, the number of employees increased by 3.6 times, and the assets and profits of enterprises surged by 48.6 and 107.7 times respectively; during the same period, the average selling price of housing increased by 4.5 times, the annual area of housing sold increased by 14.1 times, and the annual investment in and sales amount of housing increased by 36.6 and 63.6 times, respectively. Meanwhile, the *Market Size Report on Global Real Estate* notes that China grew into the fourth largest real estate market in the world in 2018, surpassing Germany and trailing only the United States, Japan, and the United Kingdom.

The housing market is naturally spatial in its attributes [3], and with the transformation of China's urbanization, industrialization, and globalization, the housing market structure and management policies have entered a period of accelerated adjustment, and the problem of housing inequality, especially its spatiality, has become increasingly prominent. Exploring the spatial inequality of the housing market and its driving mechanisms in the new era provides a basis for housing market management, urban planning, and spatial governance, and it is highly valued by government, industry, academia, and the public. However, existing studies mainly focus on housing inequalities between different people groups, such as those from different classes, different ethnicities, different generations, different ages, different educational backgrounds, and different community environments, with a lack of in-depth exploration of inequalities in the housing market in the spatial dimension. Space and time are the two critical dimensions in understanding the world, and it is of great practical value and theoretical significance to reveal the characteristics of spatial inequality in the housing market and its development trend.

This paper aims to investigate the following questions: (1) If there were serious spatial inequalities in China's housing market, how do we quantitatively measure and determine their current characteristics and evolutionary trends? (2) How do we quantitatively measure the extent to which each factor affects spatial inequality in the housing market and further measure the interaction effects between different driving factors when the housing market development is influenced by a variety of factors? (3) What policy recommendations should we propose to address spatial inequality in the housing market based on the findings of the first two points and in line with the laws and trends of housing market development? To this end, this paper tries to quantitatively measure the spatial inequality of the housing market in 31 Chinese provinces (including municipalities directly under the central government and autonomous regions) and quantitatively represent the forces of their influencing factors and the interaction intensity between its driving factors, with an attempt to reveal the driving mechanism of spatial inequality in the housing market. It also further proposes adaptive regulatory measures and policy recommendations for the housing market, hoping to provide a policy reference for the healthy and sustainable development of the housing market in China and other similar countries.

2. Literature Review

According to a systematic review of the relevant literature, studies on housing inequality and its influencing factors mainly involve the following three areas from the academic evolution and research dynamics.

2.1. Study on Housing Inequality and Its Influencing Factors between Different Groups of People

First, the analysis of the characteristics of housing inequality among people of different races, ethnicities, and colors with the critical study of them [4] is the most discussed sub-topic in this field. DeSilva [5] noted in the study that the economic status, social conditions, demographic characteristics, immigration, and their spatial patterns have had different effects on housing inequality among white Asians, blacks, Puerto Ricans, Mexicans, and others in the United States; the analysis has led Medina to propose that the housing inequality between minorities and whites is quite significant in Salt Lake County, Utah (USA) [6]; Kriv [7] argues that immigrant characteristics have a significant impact on housing inequality for Hispanic and Anglo households in the United States; Uehara holds that race and gender affect the housing quality of people with mental illness [8].

Second, the study of housing inequality from a social class perspective is another popular sub-topic in this field. Filandri investigated housing inequality in Europe based on social stratification [9]; Lux [10], Soaita [11], and Bodnar [12] analyzed the impact of social stratification on housing inequality in post-socialist countries such as the Czech Republic, Romania, and Hungary; Zhao [13] proposed a model of urban housing inequality in China from a social stratification perspective; Sato [14] concluded that urban residents and migrant workers have huge differences in housing conditions, and a new type of housing poverty has emerged in migrant worker households.

In addition, some studies classify the studied population from more nuanced perspectives such as age, intergenerational relationships, and types of vulnerable groups to further investigate their housing inequalities and their influencing factors. Grander [15], Niu [16], and Coulter [17] analyzed housing inequality among the young people and the impact of income, education background, employment, household registration system, family, and other factors. For housing inequality in intergenerational populations, Hoolachan studied housing inequality between Baby Boomers and Millennials [18], Cui studied the intergenerational transmission of housing inequality in urban China [19]; Wah studied the characteristics and causes of housing inequality in vulnerable groups such as the elderly, single-parent families, women, and new immigrants [20].

Finally, in terms of studies on the root causes or influencing factors of housing inequality, there are representative findings that Goulden [21], Vesselinov [22], and He [23] concluded that institutional reforms (e.g., the transition from a centralized and planned economic system to a neoliberal economic system) are at the root of housing inequality in Syria, Bulgaria, and China, and that the changing role of the state in the housing market is its key factor. Hoekstra stated that the economic recession is a factor contributing to exacerbated housing inequality and that demographic and stratification policies have played a very complex role [24]; Gentile studied the impact of the "Soviet" factor on housing inequality in Donbas, Ukraine [25].

2.2. Study on Spatial Differences and Correlation Effects of Housing Market, Especially Housing Prices

The spatial differences and correlations of housing are studied based on spatial differences in housing prices to further reveal the spatial inequality of housing market development. They analyze the spatial differences and correlations of housing and their influencing factors with the housing price as a dependent variable, while extending and shifting the spatial scope and scale of the study from "intra-city" to "inter-city". In intra-city studies, the analysis of the spatial evolution of housing prices can be traced back to the studies of Alonso [26], Muth [27], Papageoriou [28], and Fujita [29], who analyzed the spatial pattern of housing prices from the center to the edge of monocentric and polycentric cities. The current studies focus on spatial correlation or autocorrelation of housing prices in large cities or metropolitan cities [30,31]. In inter-city studies, they aim to explore the spatial differentiation models and spatiotemporal variation patterns of housing prices among different cities in the region. For example, Bruyne analyzed the pattern of spatial differentiation of housing prices in Belgium [32], while Kim [33] and Tomal [34,35] found that housing price movements in metropolitan cities in the United States and Poland are distributed in a club-clustering pattern. The analysis had led Cook [36,37], Abbott [38,39], Holmes [40–42], Miles [43], Zhang [44], Churchill [45], Montanes [46], Sim [47], Blanco [48], and Zelazowski [49] to propose that housing prices in the UK, US, Australia, China, Korea, Spain, Poland, and the Eurozone are represented by spatial heterogeneity, convergence, and complexity.

In addition, some papers focus on the spatial effects of housing market development and its influencing factors, including spatial distribution, spatial agglomeration, spatial decision making, spatial influence, spatial correlation, and relevance of housing. For example, Moscone [50] and Mosciaro [51] discussed the spatial effects of housing markets in the United States, Brazil, Italy, and other countries, and they concluded that housing has become a productive tool to control urban space and finance. Lukas [52], Shatkin [53], Susewind [54], and Ramos [55] studied the role and impact of housing production and transformation in the process of urban growth, spatial competition, spatial segregation, and social and spatial inequality, and they noted that real estate has turned into a machine to drive urban growth. Dube [56] and Barreca [57] studied the spatial autocorrelation of the housing market and further explored the spatial factors affecting the development of the housing market. Jun [58], Iqbal and Wilhelmsson [59,60], and Aguirre [61] studied the impact of the spatial distribution of associated factors on housing, including the impact of greenbelt and crime hotspot spaces on house prices, and the impact of informal housing on urban development.

2.3. Research Analysis and Review

There have been many valuable academic achievements made on housing inequality in general, which provide a multidimensional perspective and an important reference for this paper to analyze spatial inequality in the housing market and its driving mechanisms in depth. However, there are certain inadequacies in the existing studies as below.

First, from the perspective of research scale, although the analysis of spatial inequality in the housing market from a geographical view has been concerned since the very early days [62], the research in this field has long been homogeneous in scale with overly microscopic or macroscopic extremes. Most of the current papers focus on the study of housing inequality in different groups of people in an urban interior space; for example, Akpinar [63], Koramaz [64], Huang [65], Liu [66], Symmes [67], and Cesaroni [68] et al. conducted case studies on housing inequality in large cities such as Ankara and Istanbul in Turkey, Beijing and Nanjing in China, Santiago in Chile, and Rome in Italy; a small number of papers have begun to focus on spatial inequalities in housing markets besides housing prices in the housing market across different countries and regions; for example, Norris analyzed the patterns of housing inequality between different countries in the EU, as well as its driving factors and effects [69], and Gu studied the time-varying conditional correlations and contagion effects in global housing markets [70]. The scale within cities is too small, while it is too large between countries. The study on spatial inequality in regional (e.g., interprovincial and intercity) housing markets enables a balance between micro and macro scales and helps improve the reference value of the findings for housing market management and policy design at all levels of government.

Second, from the perspective of research methods, there is a lack of comprehensive research on multiple dependent and independent variables, and there is also a lack of sufficient attention to multiple independent variable interaction effects. Most of the current papers are based on classical research methods, such as remote sensing and GIS spatial analysis, interview, and regression analysis. In recent years, there have also been papers based on new data, techniques, and methods; for example, Tan [71] investigated the spatiotemporal connections between public sentiment and housing prices based on Twitter data, Su [72] studied the impact of landscape amenities on housing prices based on semantic and sentiment analysis of online housing advertisement data, and Hu [73] conducted a spatial analysis of housing rental price dynamics in communities in Shenzhen based on a machine learning algorithm model. The current empirical studies are mainly conducted with housing prices or housing market size or attribute indicators of a certain area as dependent variables. However, it is often hard to accurately represent the actual level of housing market development by a single indicator. Therefore, it is urgent to take more indicators as dependent and independent variables for comprehensive research in the era of big data. In addition, as housing market development is influenced by many factors and there are complex interactions between these factors, there may be synergistic reinforcement or may be antagonistic constraints arising 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 papers neglect quantitative measurement and in-depth analysis in this regard.

3. Research Design

3.1. Study Area: China

The study covers 31 provinces, municipalities directly under the central government, and autonomous regions in mainland China, excluding Hong Kong, Macau, and Taiwan (see Figure 1). The release of the *Notice of the State Council on Further Deepening the Reform of the Urban Housing System and Accelerating Housing Construction* in 1998 and the *Notice of the State Council on Promoting the Sustainable and Healthy Development of the Real Estate Market* in 2003 marked the basic establishment of China's housing market-oriented system, which was followed by a growth spurt in China's housing market (see Figure 2). According to the needs of national transformation and local development, national and local governments have tightened macro control over the housing market since 2003, and they have promulgated a series of targeted policies successively to control dynamic changes in priorities. Specifically, the governments focused on controlling the scale of housing development in 2003–2005, focused on stabilizing housing prices in 2005–2008, especially controlling the rapid rise of housing prices in some cities, stimulated the recovery of the housing market and curbed speculative investment demand in parallel in 2009–2013, and have made efforts to cut excess inventory and crush foam since 2014. With the changes in policy orientation, the housing market in China is also undergoing significant structural and spatial adjustments, and the spatial heterogeneity and correlation of housing supply, demand, and prices in different regions and cities are becoming increasingly complex. In this context, an in-depth study of the characteristics and evolutionary trends of spatial inequality in the housing market across regions and cities in China and further analysis of the primary influencing factors and their interactions are of great theoretical significance and practical value for revealing the driving mechanisms of spatial inequality in China's housing market and promoting precise control of China's housing market.

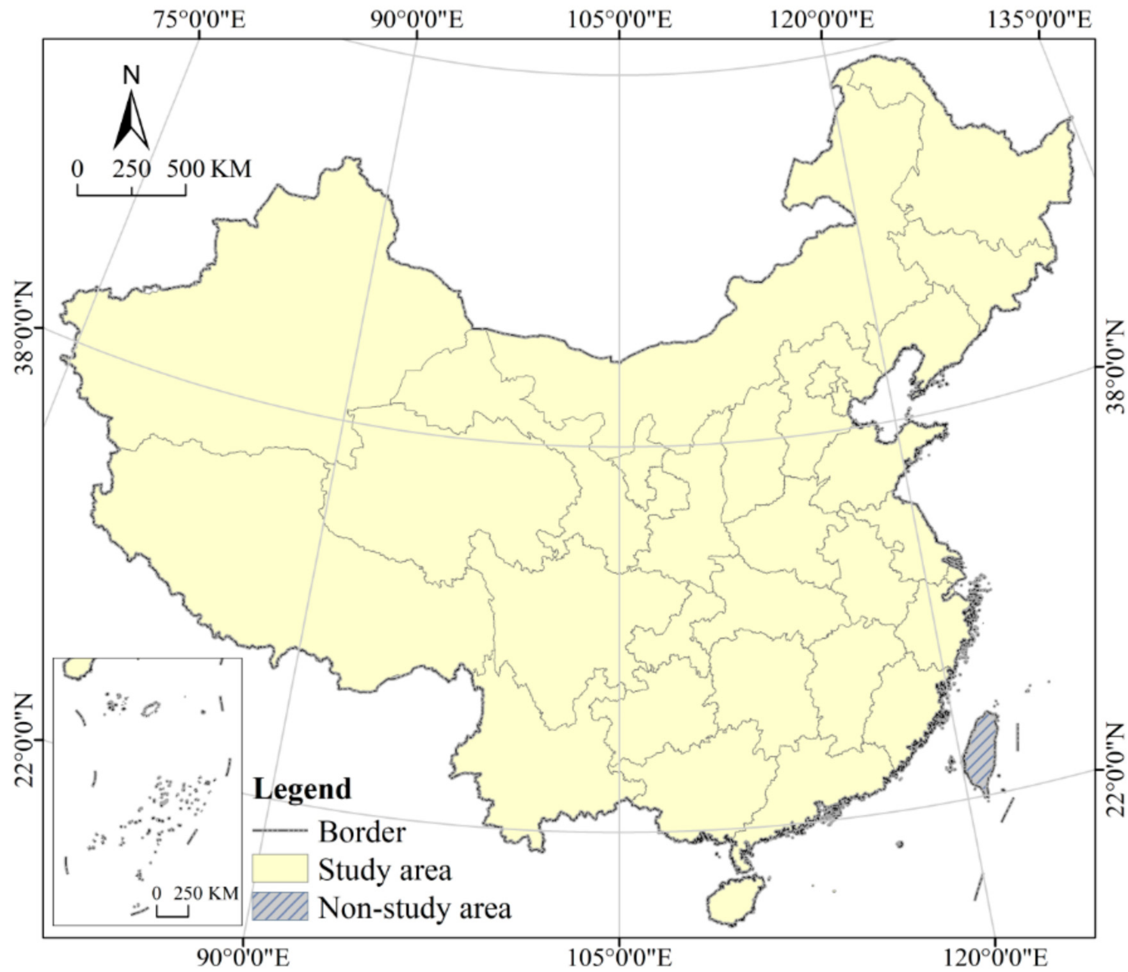

Figure 1. Study area.

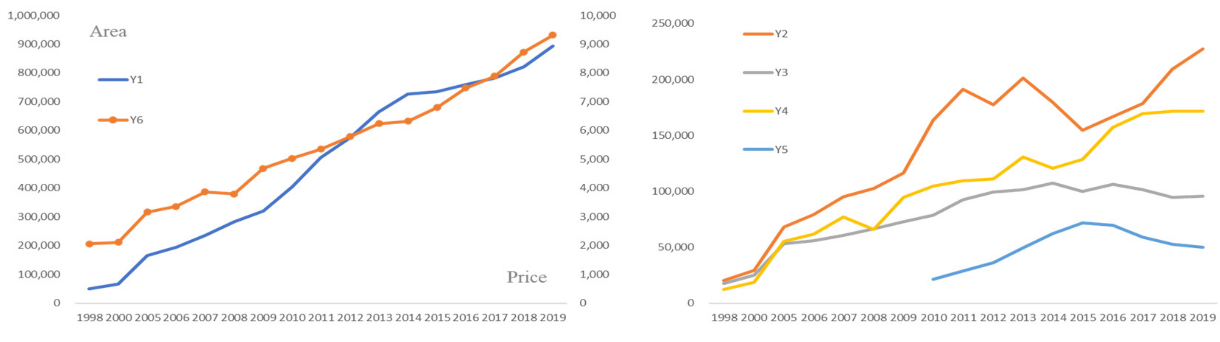

Figure 2. Analysis of changes in China's housing market.

3.2. Research Methods

Common indexes for measuring the degree of variation in the spatial distribution of variables include the coefficient of variation, Gini coefficient, Theil index, Herfindahl–Hirschman index, and entropy index [74], which are common methods for analyzing the pattern of variation in the spatial distribution of variables include kernel density, spatial hotspot clustering, standard deviation ellipse, nearest neighbor index, spatial autocorrelation, and geographic connectedness [75], and common methods for studying the driving mechanisms of variation in the spatial distribution of variables include Geodetector, geographic weighted regression, and spatial panel model [76]. The spatial inequality in the housing market is mainly shown as the spatially differentiated distribution of regional housing supply, demand and price, their interconnections, and their dynamic changes. This paper measures the spatial inequality of China's housing market based on the coefficient of variation and Gini coefficient, visualizes the spatial pattern by kernel density and spatial clustering methods, and determines the strength of the driving forces and their interaction effects based on the Geodetector method.

3.2.1. 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 [77], Zhang [78], Ruan [79], Liu [80], Miyamoto [81], and She [82], 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.

3.2.2. 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 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 [83], a Gini coefficient greater than 0.4 in this paper indicates a large gap, which is used to represent spatial inequality in the housing market; a Gini coefficient greater than 0.6 indicates a huge gap, which is used to represent serious spatial inequality in the housing market.

3.2.3. Cluster Analysis: ARCGIS

Clustering is a method to divide similar samples into different groups or more subsets by static classification or some rule set, so that the member samples in the same subset all have a similar property. This paper visualizes the spatial pattern of the geographic distribution of the dependent variable indicators based on the kernel density and cluster analysis methods of ARCGIS to show the characteristics of spatial inequality in the housing market.

3.2.4. Geodetector

Geodetector is an emerging analytical model for detecting the relationship between a geographic phenomenon and its explanatory factors [84], which is used to quantitatively measure the importance of independent variables relative to dependent variables based on the analysis of the overall differences between geospatial areas, and it has a clear advantage in handling mixed data [85]. The Geodetector is equipped with four functional modules for factor detection, interaction detection, risk detection, and ecological detection, respectively. This paper investigates 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.

Let us assume the dependent variable is Y_i and the independent variable is X_i, and use them to represent 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 1) [86,87].

Table 1. Interaction between explanatory variables (X_i and X_j).

Graphical Representation	Description	Interaction
	$q(X_i \cap X_j) < Min(q(X_i), q(X_j))$	Weaken, non-linear
	$Min(q(X_i),q(X_j)) < q(X_i \cap X_j) < Max(q(X_i)), q(X_j))$	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, non-linear

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

3.3. Index Selection

According to real estate economics, housing supply, demand, and price are the most essential areas for investigating the housing market development status and evolution trend. This paper constructs an integrated analysis framework of "space–supply–demand–price" in the housing market around spatial inequality. As the essential background and basis for analysis, space reveals the current characteristics and changing trends of spatial inequality in housing supply, demand, and price in the analysis of the spatial differences of 31 Chinese provinces based on the associated indicators. A total of six indicators are used as dependent variables in this paper, including three values of construction area, new construction area, and completed area for measuring the level of housing supply, two values of sales area and area for sale for measuring the state of housing demand, and the average selling price for representing housing prices. The housing market dynamics and spatial pattern are the result of a combination of factors, including economy, finance, society, population, income level, industrial structure, convenience and comfort of infrastructure and public service facilities, and openness. More complex relationships or changes will arise from the superposition of different factors. Therefore, with reference to the research experience of Bergeaud [88], Yan [89], Carrasco-Gallego [90], McMillan [91], Warsame [92], Oikarinen [93], Sun [94], and Hardie [95] et al., and based on the data accessibility, comparability, and completeness, we have explored the driving mechanisms of spatial inequality in the housing market (see Table 2) with 23 indicators as independent variables from four dimensions: economic level, social conditions, industrial structure, service, and infrastructure environment.

We assume in the construction of the indicator system that GDP and GDP per capita represent the stage of regional economic development [96,97], fiscal balance and loans reflect the potential and strength of government support for housing market development [98], population and urbanization represent the potential scale of housing demand [99], residents' income and consumption level reflect the ability and willingness to consume housing, the secondary industry represents the real economy [100], the tertiary industry and finance reflect the support capacity of intermediary services, import and export represent the development level of the open economy [101], health facilities and public transport conditions reflect the capacity and quality of infrastructure services [102], and the green land area and the number of parks reflect the quality of the ecological environment [103]. The analysis of independent and dependent variables based on the Geodetector method helps reveal the connections between the spatial inequality in the housing market and the stage of economic development, government support or policy orientation, urbanization, industrialization, globalization, infrastructure and public services, and environmental quality, and it provides the basis for policy design.

Table 2. Model variable description.

Variable.	Index	Code	Type
Dependent Variable (Y_i)	Construction Area	Y_1	Supply
	New Construction Area	Y_2	
	Floor Space Completed	Y_3	
	Sales Area	Y_4	Demand
	Area for Sale	Y_5	
	Average Selling Price	Y_6	Price
Independent Variable (X_i)	Gross Domestic Product (GDP)	X_1	Economic driving force
	Per Capita GDP	X_2	
	Revenue	X_3	
	Expenditure	X_4	
	Amount of Loan	X_5	
	Permanent Resident Population	X_6	Social driving force
	Floating Population	X_7	
	Urbanization Rate	X_8	
	Per Capita Disposable Income of Residents	X_9	
	Total Retail Sales of Consumer Goods	X_{10}	
	Added Value of Secondary Industry	X_{11}	Structural adjustment driving force
	Added Value of Tertiary Industry	X_{12}	
	Output Value of Financial Industry	X_{13}	
	Export	X_{14}	
	Import	X_{15}	
	Number of Medical Institutions	X_{16}	Service and Infrastructure driving force
	Number of Medical Beds	X_{17}	
	Number of Buses	X_{18}	
	Length of Bus Line	X_{19}	
	Urban Rail Transit Line Length (Metro and Light Rail)	X_{20}	
	Urban Green Area	X_{21}	
	Number of City Parks	X_{22}	
	City Park Area	X_{23}	

Unlike Western countries, China has experienced the intertwined processes of industrialization, urbanization, and globalization, which constitute the cardinal context and conditions shaping the spatial and temporal patterns of China's housing market and its evolution. According to the GDP and Chenery industrialization stage theory, per capita GDP, added value of the secondary industry, and added value of the tertiary industry become the essential independent variables. The level of urbanization is generally measured by demographic indicators, and in this paper, the urbanization rate is expressed as the proportion of urban population to the resident population. China is a highly mobile society with complex phenomenon of urbanization and semi-urbanization in different places, so floating population is another auxiliary indicator to measure the level of urbanization. China has been the world's top trading country for many years, and international imports and exports are key indicators to measure the level of globalization. Housing is a special commodity different from ordinary use goods, and people of all income classes have different preferences for it, including rigid demand (simply to solve the housing problem), improvement demand (non-first home purchased for the purpose of improving living conditions), investment, and even speculation demand. Therefore, it is necessary to select some indicators that can represent the social attributes and housing needs of the population from the perspective of the diversity and complexity of the population needs, including per capita disposable income of residents, number of medical institutions, number of medical beds, number of buses, length of bus line, urban rail transit line length (metro and light rail), urban green area, number of city parks, and city park area. As housing is the most important part of the consumer spending, it is necessary to clarify the relationship between housing market development and total retail sales of consumer goods in the context of the Chinese government's efforts to continuously expand domestic demand. Population is the basis for the development of the housing market, and with China's large population and prominent inter-regional mobility, the permanent resident population can better portray the impact of a province's population size on housing demand than the registered population. The regulation of the housing market in China involves acting subjects including governments, developers, and banks. Revenue, expenditure, amount of loan, and output value of financial industry are the key indicators reflecting their impact.

3.4. Research Steps

This study consists of four steps and nine key points (see Figure 3). The first step is 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 31 provinces into five categories by the percentile method to eliminate artificial influence (2–6). The second step is data processing. ③ Calculate the coefficient of variation and 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 is data review. Make a preferred choice among the alternatives in ②. ⑤ 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 is 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 driving forces to further reveal the driving mechanisms and policy insights of the spatial heterogeneity of the real estate economy.

3.5. Data Sources

In this paper, the dependent variable indicators are mainly from the *China Real Estate Statistics Yearbook*, the independent variable indicators are mainly from the *China Statistical Yearbook*, some indicators are from the *China Urban Construction Statistical Yearbook* and the *China City Statistical Yearbook*, and some missing data are collected from provincial statistical yearbooks and statistical bulletins. The study period was set to 2010–2019 for two main reasons: The first is to ensure the consistency of the statistical caliber of the data. In 2009, the National Bureau of Statistics adjusted the "vacant area" of commercial buildings to "area for sale", and the two indicators are not comparable, which will affect the accuracy of the conclusion by lengthening the research duration. The second is to keep the consistency of the policy background. China's housing market was generally under the severe control in 2010–2019, with anti-overheating, curtailment, reducing inventory, and housing residence instead of vicious speculation as the policy keynote.

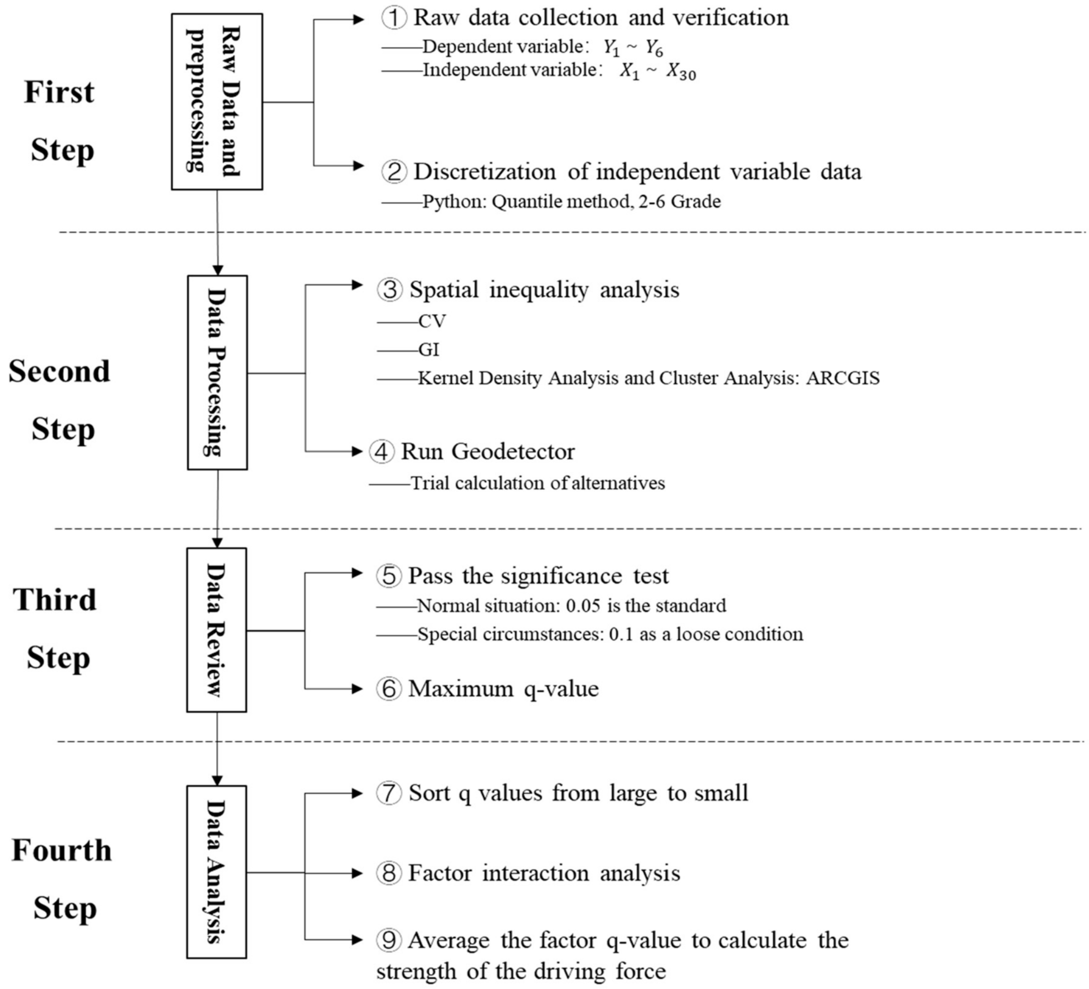

Figure 3. Research framework and steps.

It should be noted that there were only nine provinces having subways or light rails in 2010, and both quantiles and the classification results by natural breaks were obviously unreasonable. Therefore, according to the quantiles and the classification results by natural breaks, manual intervention was added to the 2010 classification schemes for X_{27} based on the data characteristics. The class 2 scheme is determined based on the presence of rail transit; in the class 3 scheme, the provinces without rail transit are listed separately, and 9 with rail transit are classified as high and low based on the value size; in the class 4 scheme, the provinces without rail transit are listed separately, and 9 with rail transit are classified as high, medium, and low based on the value size. As Geodetector requires at least two samples of each type, the class 5 and 6 classification schemes are abandoned.

4. Results

4.1. Inequality Analysis

The spatial inequality in China's housing market is very significant and already in an unreasonable state due to different development stages, resource endowments, and location conditions, and it is getting more serious with the development. The coefficients of variation of Y_1–Y_6 in 2019 were 0.73, 0.77, 0.89, 0.80, 0.74, and 0.66, respectively, all greater than 0.36, indicating that the spatial variability in the interprovincial housing market in China was highly significant. From 2010 to 2019, the coefficient of variation of Y_1–Y_4 gradually increased in fluctuations, and Y_3 achieved a rapid growth in particular, indicating that the spatial inequality in the housing market development supply and demand in China was increasing over time. On the contrary, the coefficient of variation of Y_5 and Y_6 declined by year in the fluctuation, indicating that the degree of spatial inequality in deinventory and housing prices in China's housing market was gradually decreasing, which showed convergence. In 2019, the Gini coefficients of Y_1–Y_4 were 0.41, 0.44, 0.47, and 0.47, all greater than 0.4, indicating that the level of inequality was beyond a reasonable range and in an urgent need for optimization and adjustment. Meanwhile, the Gini coefficients of Y_5 and Y_6 were 0.39 and 0.27, respectively, both less than 0.4, indicating that the inequality remains within a reasonable level. From 2010 to 2019, all the Gini coefficients of Y_1–Y_6 showed a tendency to go down first and then up, which was similar to the coefficient of variation in the change pattern but somewhat different in the fluctuation range and development trend. Specifically, the Gini coefficients of Y_1 and Y_6 decreased slightly and then increased, and generally, they remained stable; the Gini coefficients of Y_2–Y_4 decreased slightly and then increased significantly, showing a tendency of rapid increase in fluctuation in general; the Gini coefficients of Y_5 decreased significantly and then increased slightly, generally showing the tendency of rapid decrease in fluctuation (see Tables A1 and A2 and Figure 4).

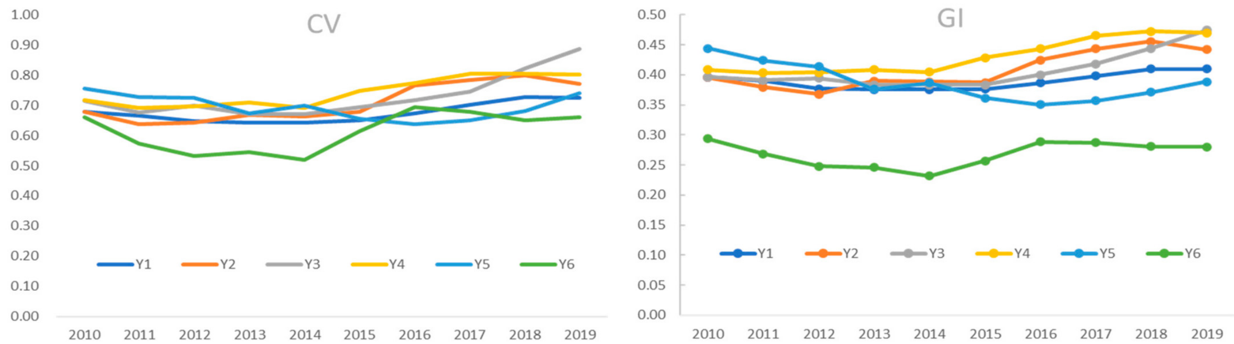

Figure 4. Analysis of the changing trend of CV and GI.

Based on the quantile spatial clustering analysis by ARCGIS 10.2, the study area is classified into three types of High, Medium, and Low. In 2019, Y_1, Y_2, Y_3, and Y_4 showed the similar geographical distribution pattern, with a gradient change in the direction of "east–central–west" in general, except a slight variation in local areas. For example, in Y_2, Hebei province is of high type, but it is of medium type in Y_1, Y_3, and Y_4; in Y_1 and Y_3, Fujian province is of high type, but it is of medium type in Y_2 and Y_4; in Y_1 and Y_2, Inner Mongolia is of medium type, but it is of low type in Y_3 and Y_4. The spatial distribution patterns of Y_5 and Y_6 are significantly different from the other dependent variables. For the former, the provinces of high type are mainly distributed in the Yangtze River Delta, Pearl River Delta, and Chengdu–Chongqing regions, and the provinces of medium type are concentrated in the northern and southwestern border regions and the central and southern regions in a contiguous distribution; for the latter, the provinces of high type are mainly distributed in the coastal region, Hubei, and Shaanxi regions, the provinces of medium type are concentrated in the northern coastal and central regions in a contiguous distribution, and the provinces of low type are mainly distributed in the southwest and northeast border regions. The spatial pattern was generally similar between 2010 and 2019, but there were some differences in some areas such as Heilongjiang, Jilin, and Hubei (see Figure 5). Based on the spatial autocorrelation analysis by GeoDa1.18, the Moran's I index of Y_1, Y_2, Y_3, Y_4, and Y_6 are greater than zero, indicating there is positive spatial correlation and dependence in their geographical distributions. In 2019, the Moran's I index of Y_1, Y_2, Y_3, Y_4, and Y_6 were 0.22, 0.22, 0.30, 0.27, and 0.26, respectively, at the significance level of 5%. In 2010, Y_1, Y_2, and Y_6 had the Moran's I indexes of 0.19, 0.17, and 0.31, respectively, and they could still pass the significance test of 5%; Y_3 and Y_4 had the Moran's I indexes of 0.15 and 0.13, respectively, but they could only pass the loose significance test of 10%. It should be noted that the Moran's I index of Y_5 in 2010 and 2019 were -0.106 and -0.002, respectively, both less than zero, but they failed the significance test, and therefore, it is impossible to determine whether there is negative spatial autocorrelation in their geographical distribution.

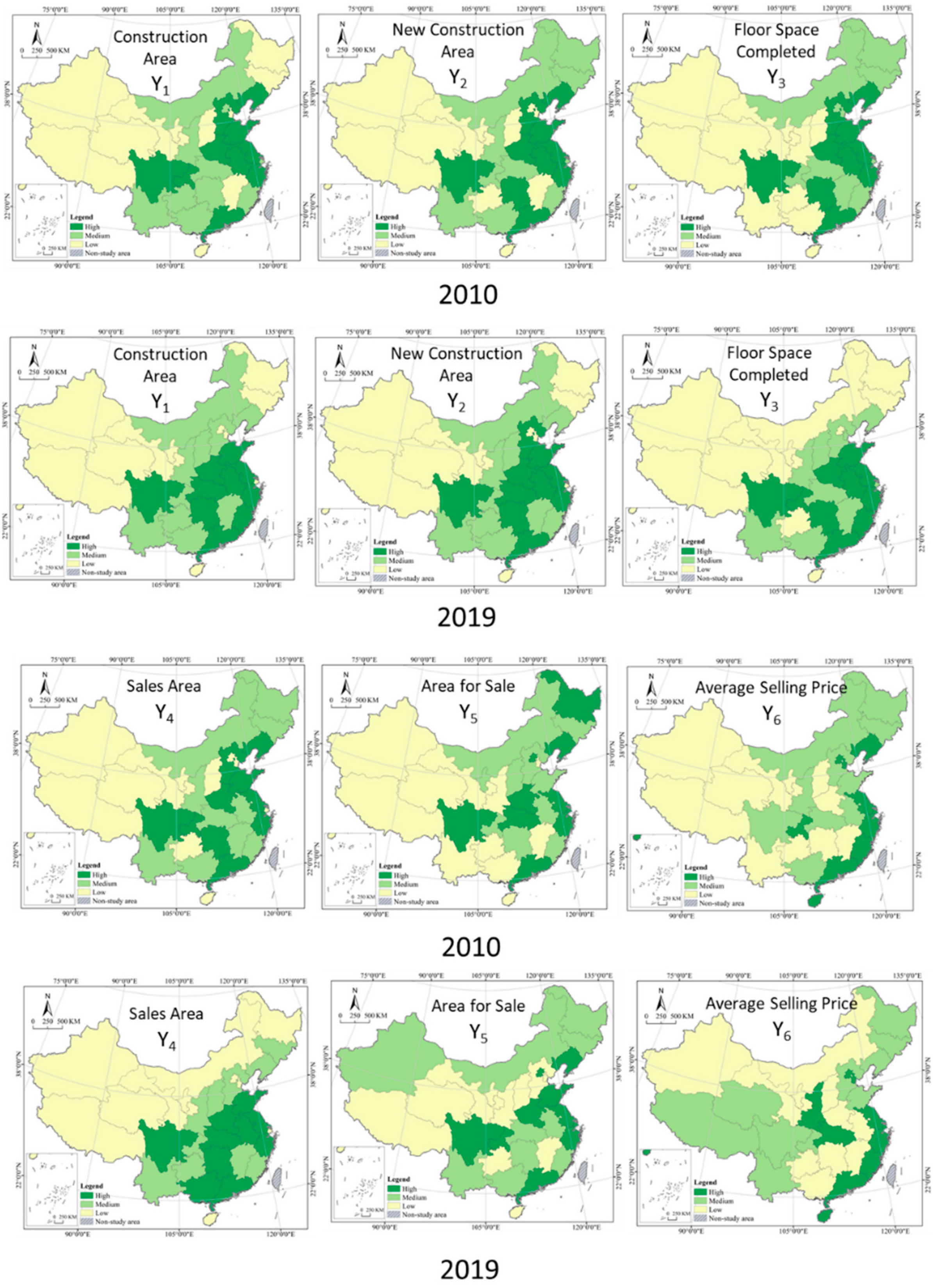

Figure 5. Cluster analysis of the housing market.

4.2. Factor Analysis

4.2.1. Construction Area

In 2019, X_8 failed to pass the significance test, and X_2 and X_9 could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Gross Domestic Product, Added Value of Secondary Industry, Number of Medical Beds, Expenditure, Permanent Resident Population, and Number of Buses are of the high type; Total Retail Sales of Consumer Goods, Number of City Parks, Length of Bus Line, Number of Medical Institutions, Added Value of Tertiary Industry, City Park Area, Urban Green Area, and Revenue are of the medium type; Output Value of Financial Industry, Exports, Floating Population, Imports, Amount of Loan, and Urban Rail Transit Line Length are of the low type. In 2010, X_8 and X_{20} failed to pass the significance test, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, Gross Domestic Product, Added Value of Secondary Industry, Number of Medical Beds, City Park Area, Total Retail Sales of Consumer Goods, and Expenditure are of the high type; Revenue, Amount of Loan, Permanent Resident Population, Added Value of Tertiary Industry, Output Value of Financial Industry, Length of Bus Line, Urban Green Area, and Number of City Parks are of the medium type; Per Capita GDP, Floating Population, Per Capita Disposable Income of Residents, Number of Medical Institutions, Imports, and Exports are of the low type.

There were nine factors that increased in force from 2010 to 2019, including X_{20}, X_{18}, X_{16}, and X_6 with a greater enhancement; and 13 decreased, including X_9, X_2, X_5, X_{23}, X_{21}, and X_3 with a greater fall. It should be noted that X_8 consistently failed the significance test, X_2 and X_9 degenerated to pass only the significance test of 10%, while X_{20} evolved to pass the significance test of 5%. There was a great difference in the ranking of driving factors between 2010 and 2019, with the former being Service and Infrastructure > Structural Adjustment > Economic > Social and the latter being Social > Economic > Service and Infrastructure > Structural Adjustment (see Tables A1 and A2 and Figures 6–8).

4.2.2. New Construction Area

In 2019, X_8, X_2, and X_9 failed to pass the significance test, and X_5 and X_{15} could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Gross Domestic Product, Expenditure, Permanent Resident Population , Added Value of Secondary Industry, and Number of Buses are of the high type; Total Retail Sales of Consumer Goods, Number of Medical Institutions, Number of City Parks, City Park Area, Added Value of Tertiary Industry, Revenue, and Urban Green Area are of the medium type; Output Value of Financial Industry, Floating Population, Export, and Urban Rail Transit Line Length are of the low type. In 2010, X_8 and X_{20} failed to pass the significance test, while the rest of the factors could pass the significance test of 5% and a more stringent level. There were 11 factors that increased in force from 2010 to 2019, including X_{20}, X_{18}, X_{16}, X_4, and X_6 with a greater enhancement; and 11 decreased, including X_9, X_2, X_5, X_{23}, X_{21}, and X_{15} with a greater fall. It should be noted that X_8 consistently failed the significance test, X_2 and X_9 degenerated to pass only the significance test of 10%, while X_{20} evolved to pass the significance test of 5%. At the significance level of 5%, Gross Domestic Product, City Park Area, Added Value of Secondary Industry, Number of Medical Beds, Total Retail Sales of Consumer Goods, and Urban Green Area are of the high type; Expenditure, Permanent Resident Population, Length of Bus Line, Number of City Parks, Revenue, Added Value of Tertiary Industry, Output Value of Financial Industry, and Number of Buses are of the medium type; Floating Population, Amount of Loan, Exports, Imports, Number of Medical

Institutions, Per Capita GDP, and Per Capita Disposable Income of Residents are of the low type. There was a great difference in the ranking of driving factors between 2010 and 2019, with the former being Service and Infrastructure > Economic > Structural Adjustment > Social, and the latter being Economic > Social > Service and Infrastructure > Structural Adjustment (see Tables A1 and A2 and Figures 6–8).

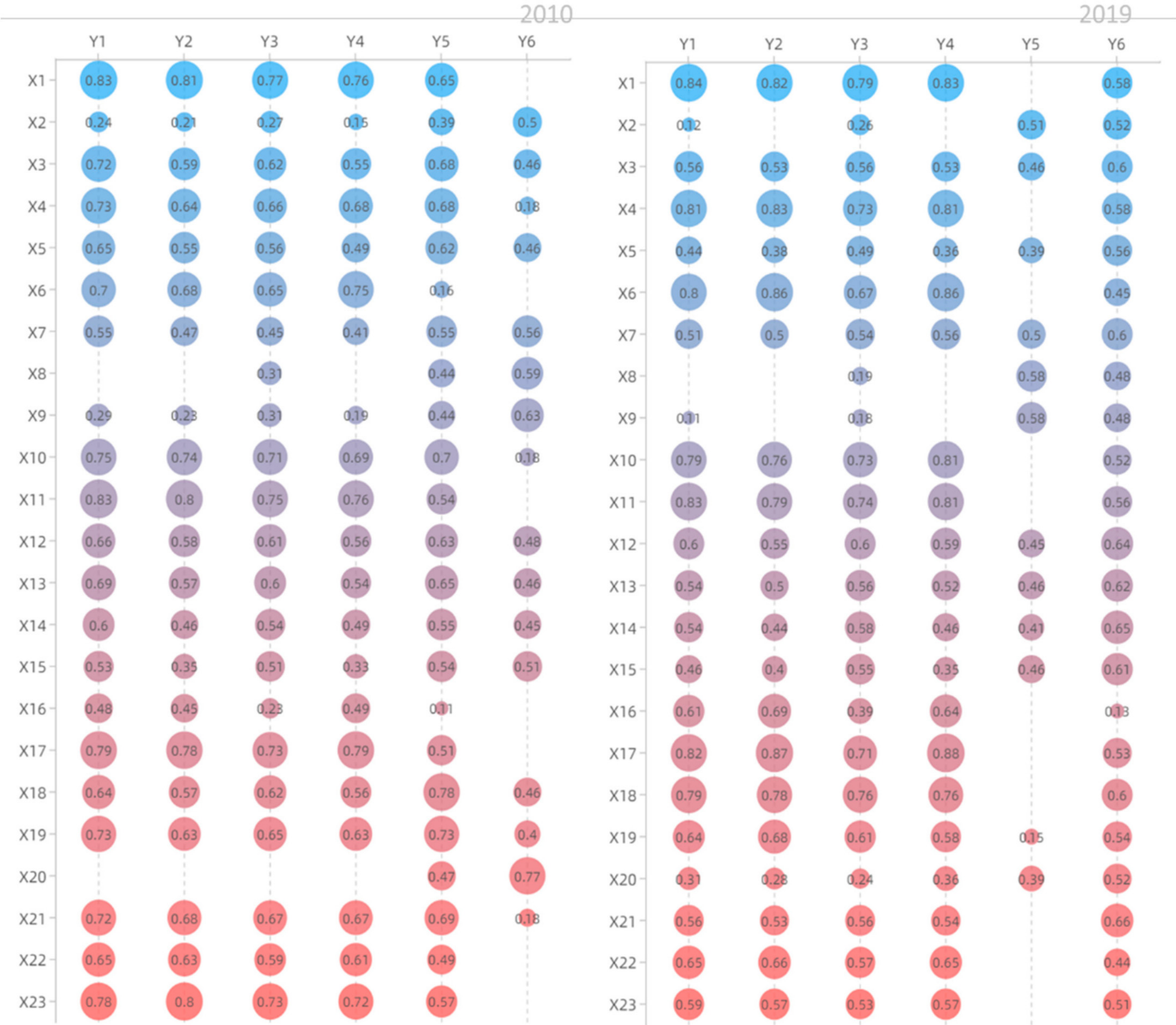

Figure 6. Analysis of factor detector.

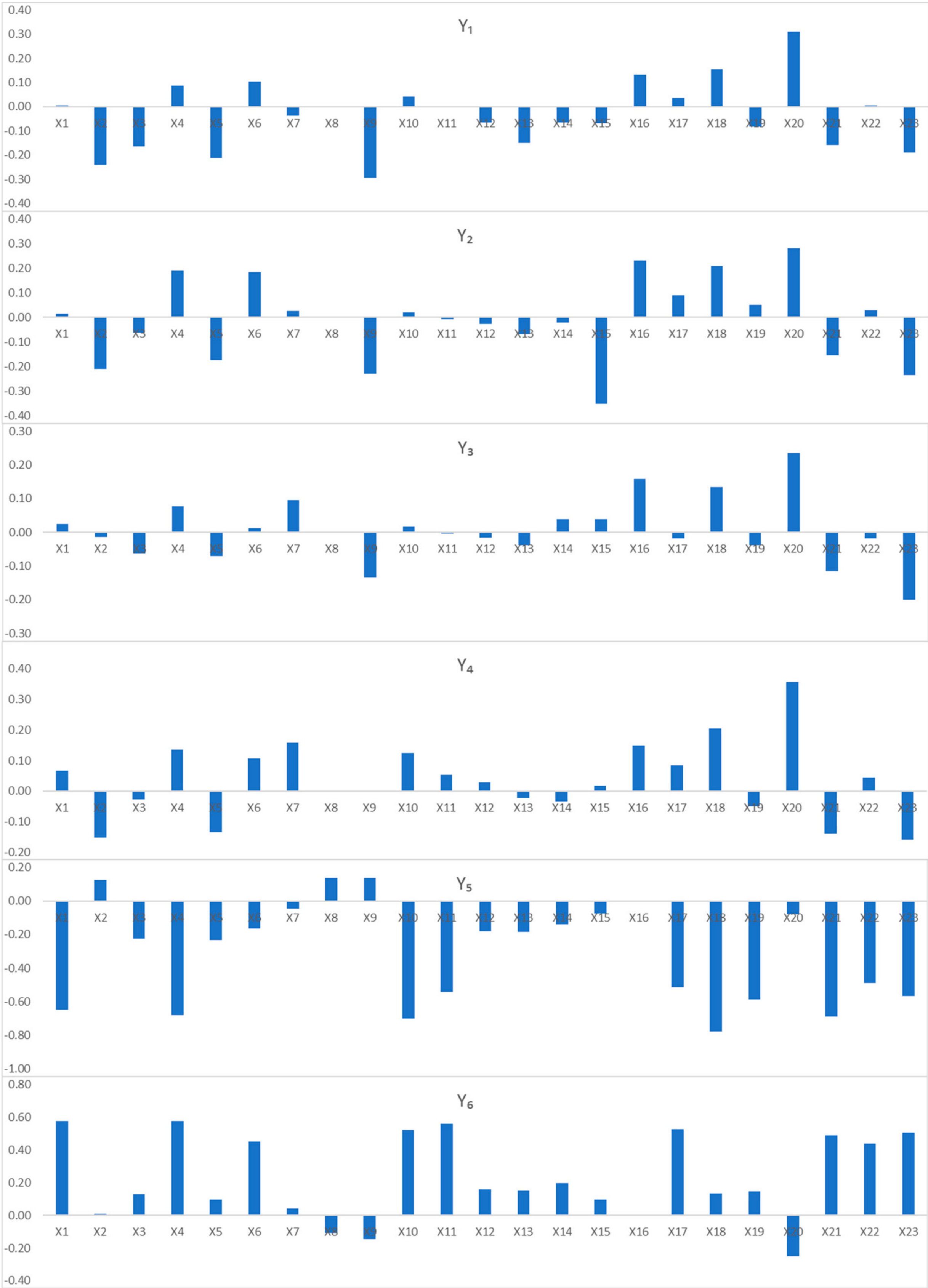

Figure 7. Change of factor influence from 2010 to 2019.

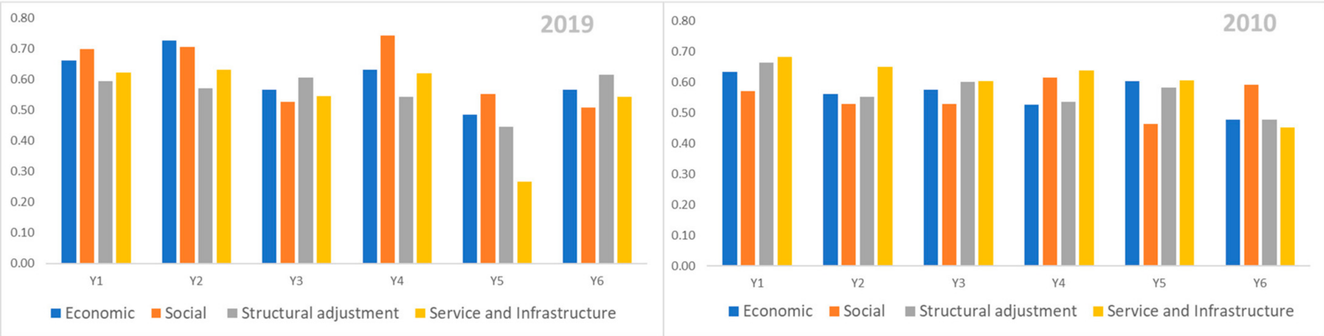

Figure 8. Analysis of driving force.

4.2.3. Floor Space Completed

In 2019, X_8 could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Gross Domestic Product, Expenditure, Permanent Resident Population, Total Retail Sales of Consumer Goods, Added Value of Secondary Industry, Number of Medical Beds, and Number of Buses are of the high type; Revenue, Floating Population, Added Value of Tertiary Industry, Output Value of Financial Industry, Exports, Imports, Length of Bus Line, Urban Green Area, and Number of City Parks are of the medium type; Per Capita GDP, Amount of Loan, Per Capita Disposable Income of Residents, Number of Medical Institutions, Urban Rail Transit Line Length, and City Park Area are of the low type. In 2010, X_{20} failed to pass the significance test, and X_8 could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, Gross Domestic Product, Added Value of Secondary Industry, Total Retail Sales of Consumer Goods, Number of Medical Beds, Urban Green Area, and City Park Area are of the high type; Expenditure, Amount of Loan, Permanent Resident Population, Revenue, Added Value of Tertiary Industry, Output Value of Financial Industry, Number of Buses, Length of Bus Line, and Number of City Parks are of the medium type; Per Capita GDP, Floating Population, Per Capita Disposable Income of Residents, Exports, Imports, and Number of Medical Institutions are of the low type. There were 10 factors that increased in force from 2010 to 2019, including X_{20}, X_{18}, X_{16}, X_7, and X_4 with a greater enhancement; and 12 decreased, including X_{23}, X_{21}, and X_9 with a greater fall. It should be noted that X_8 could always only pass the significance test of 10%, while X_{20} evolved to pass the significance test. There was a large difference in the ranking of driving factors between 2010 and 2019, with the former being Service and Infrastructure > Structural Adjustment > Economic > Social, and the latter being Structural Adjustment > Economic > Service and Infrastructure> Social (see Tables A1 and A2 and Figures 6–8).

4.2.4. Sales Area

In 2019, X_8, X_2, and X_9 failed to pass the significance test, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Gross Domestic Product, Number of Medical Beds, Permanent Resident Population, Added Value of Secondary Industry, Total Retail Sales of Consumer Goods, and Total Retail Sales of Consumer Goods are of the high type; Number of Buses, Number of Medical Institutions, Number of City Parks, Added Value of Tertiary Industry, Length of Bus Line, City Park Area, Urban Green Area, and Floating Population are of the medium type; Revenue, Output Value of Financial Industry, Exports, Amount of Loan, Urban Rail Transit Line Length, and Imports are of the low type. In 2010, X_8 and X_{20} failed to pass the significance test, and X_9 could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, Gross Domestic Product, Permanent Resident Population, Total Retail Sales of Consumer Goods, Added Value of Secondary Industry, Number of Medical Beds, and City Park Area are of the high type; Expenditure, Revenue, Added Value of Tertiary Industry, Output Value of Financial Industry, Number of Buses, Length of Bus Line, Urban Green Area, and Number of City Parks are of the medium type; Per Capita GDP, Amount of Loan, Floating Population, Exports, Imports, and Number of Medical Institutions are of the low type. There were 13 factors that increased in force from 2010 to 2019, including X_{20}, X_{18}, X_{16}, and X_7 with a greater enhancement; and eight decreased, including X_{23}, X_{21}, X_5, and X_2 with a greater fall. It should be noted that X_8 consistently failed the significance test, X_2 and X_9 degenerated to fail the significance test, while X_{20} evolved to pass the significance test of 5%. There was a large difference in the ranking of driving factors between 2010 and 2019, with the former being Service and Infrastructure > Social > Structural Adjustment > Economic, and the latter being Social > Economic > Service and Infrastructure > Structural Adjustment (see Tables A1 and A2 and Figures 6–8).

4.2.5. Area for Sale

In 2019, X_1, X_4, X_6, X_{10}, X_{11}, X_{16}, X_{17}, X_{18}, X_{21}, X_{22}, and X_{23} failed to pass the significance test, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Urbanization Rate, Per Capita GDP, and Per Capita Disposable Income of Residents are of the high type; Revenue, Floating Population, Added Value of Tertiary Industry, Output Value of Financial Industry, and Imports are of the medium type; Amount of Loan, Exports, Length of Bus Line, and Urban Rail Transit Line Length are of the low type. In 2010, X_{16} could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, Gross Domestic Product, Revenue, Number of Buses, Length of Bus Line, Total Retail Sales of Consumer Goods, and Urban Green Area are of the high type; Expenditure, Amount of Loan, Floating Population, Output Value of Financial Industry, Added Value of Tertiary Industry, Exports, City Park Area, Added Value of Secondary Industry, and Imports are of the medium type; Number of Medical Beds, Number of City Parks, Urban Rail Transit Line Length, Per Capita Disposable Income of Residents, Urbanization Rate, Per Capita GDP, and Permanent Resident Population are of the low type. There were three factors that increased in force from 2010 to 2019, including X_8 and X_9 with a greater enhancement; and 19 decreased, including X_1, X_4, X_{10}, X_{11}, X_{18}, X_{19}, and X_{21} with a greater fall, which is primarily due to the degradation of most of them to fail significance tests. There was a great difference in the ranking of driving factors between 2010 and 2019, with the former being Service and Infrastructure > Economic > Structural Adjustment > Social, and the latter being Social > Economic > Structural Adjustment > Service and Infrastructure (see Tables A1 and A2 and Figures 6–8).

4.2.6. Average Selling Price

In 2019, X_{16} could only pass the loose significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, the factors were classified into high, medium, and low types according to the classification principle of "3:4:3" based on the strength of the direct force of the factors. Among them, Gross Domestic Product, Urban Green Area, Exports, Added Value of Tertiary Industry, Output Value of Financial Industry, and Imports are of the high type; Floating Population, Revenue, Number of Buses, Expenditure, Amount of Loan, Added Value of Secondary Industry, Length of Bus Line, Number of Medical Beds, and Total Retail Sales of Consumer Goods are of the medium type; Urban Rail Transit Line Length, Per

Capita GDP, City Park Area, Urbanization Rate, Per Capita Disposable Income of Residents, Permanent Resident Population, and Number of City Parks are of the low type. In 2010, X_1, X_{18}, X_{19}, X_{20}, X_{21}, X_{22}, and X_{23} failed to pass the significance test, and X_{16} and X_{17} could only pass the significance test of 10%, while the rest of the factors could pass the significance test of 5% and a more stringent level. At the significance level of 5%, Per Capita GDP, Revenue, Expenditure, and Amount of Loan are of the high type; Permanent Resident Population, Floating Population, Urbanization Rate, Per Capita Disposable Income of Residents, Total Retail Sales of Consumer Goods, and Added Value of Secondary Industry are of the medium type; Added Value of Tertiary Industry, Output Value of Financial Industry, Exports, and Imports are of the low type. There were 19 factors that increased in force from 2010 to 2019, including X_1, X_4, X_6, X_{10}, X_{11}, X_{17}, X_{21}, X_{22}, and X_{23} with a greater enhancement, primarily because most of them evolved to pass the significance test; and three decreased, including X_{20} with a greater fall. It should be noted that X_{16} evolved to pass the significance test of 10%. There was a great difference in the ranking of driving factors between 2010 and 2019, with the former being Social > Structural Adjustment > Economic > Service and Infrastructure, and the latter being Structural Adjustment > Economic > Service and Infrastructure > Social (see Tables A1 and A2 and Figures 6–8).

4.3. Interaction Analysis

The value of the interaction force is 0–1, and a larger value indicates a stronger force. At the significance level of 5%, there were a total of 1142 factor pairs in 2010 with a mean interacting force of about 0.79, a minimum of 0.29, and a maximum of 0.98; there were a total of 1061 factor pairs in 2019 with a mean interacting force of about 0.81, a minimum of 0.28, and a maximum of 0.99. Based on the mean values of factor interacting forces in 2010 and 2019, the factor pairs were classified as high, medium, and low with a threshold of 0.8 and 0.9 according to the maximum and minimum values and the balance of the distribution of the number of factor pairs. It needs additional explanation that Y_5 in 2019 uses 0.55 and 0.65 as the threshold. Since it has a small number of factor pairs, if the classification criteria of 0.8 and 0.9 are followed, the high and medium will be missing. It should be noted that there are strong interaction effects of X_1, X_4, X_6, X_{17}, and X_{22} in 2019 and X_1, X_6, X_{17}, X_{22}, and X_{23} in 2010 with other factors (see Table 3 and Figures 9 and 10).

Table 3. Statistical analysis of factor pairs and interaction forces.

		Number of Factor Pairs				Strength of Interaction Effect			Factors with Significant Interaction
		Total	**High**	**Medium**	**Low**	**Min**	**Max**	**Average**	
2019	Y_1	190	89	53	48	0.59	0.98	0.85	$X_1, X_4, X_6, X_{11}, X_{16}, X_{18}, X_{22}$
	Y_2	153	67	59	27	0.56	0.97	0.86	$X_1, X_4, X_6, X_{11}, X_{16}, X_{17}$
	Y_3	231	49	118	64	0.28	0.98	0.82	$X_1, X_4, X_6, X_{17}, X_{22}$
	Y_4	190	83	64	43	0.45	0.99	0.85	$X_1, X_4, X_6, X_{17}, X_{18}, X_{22}$
	Y_5	66	17	26	23	0.41	0.70	0.59	$X_2, X_3, X_5, X_7, X_{20}$
	Y_6	231	12	90	129	0.59	0.98	0.76	$X_2, X_6, X_9, X_{17}, X_{20}, X_{22}$
2010	Y_1	210	86	74	50	0.34	0.98	0.86	$X_1, X_6, X_{11}, X_{17}, X_{22}, X_{23}$
	Y_2	210	41	85	84	0.29	0.97	0.80	$X_1, X_6, X_{11}, X_{17}, X_{22}, X_{23}$
	Y_3	210	12	95	103	0.38	0.94	0.78	$X_1, X_6, X_{11}, X_{17}, X_{22}, X_{23}$
	Y_4	190	20	94	76	0.41	0.97	0.80	X_1, X_6, X_{22}, X_{23}
	Y_5	231	8	96	127	0.53	0.98	0.78	$X_2, X_8, X_9, X_{17}, X_{18}, X_{21}, X_{22}$
	Y_6	91	2	18	71	0.49	0.93	0.67	$X_2, X_3, X_5, X_7, X_8, X_9, X_{20}, X_{21}$

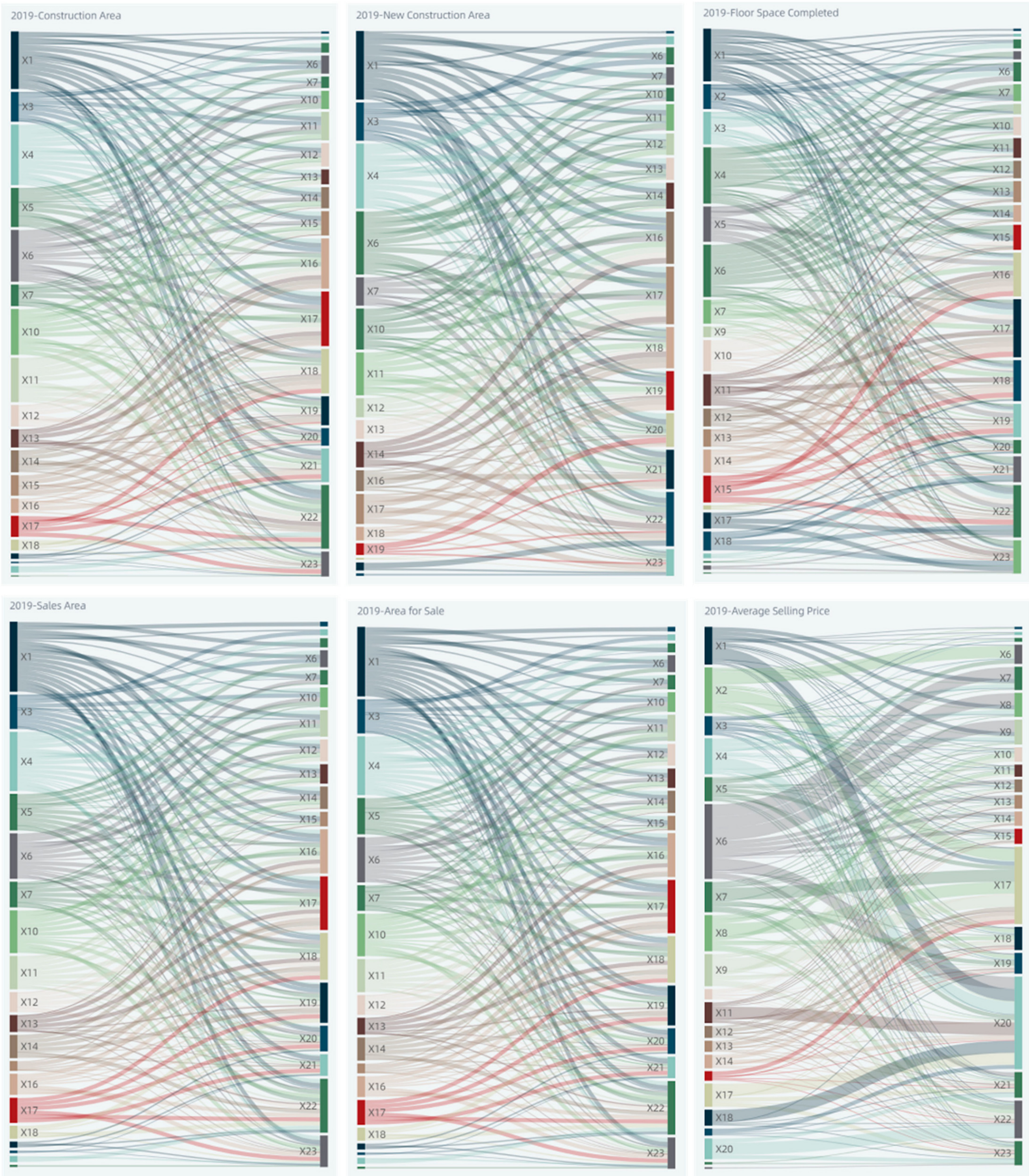

Figure 9. Analysis of interaction detector in 2019.

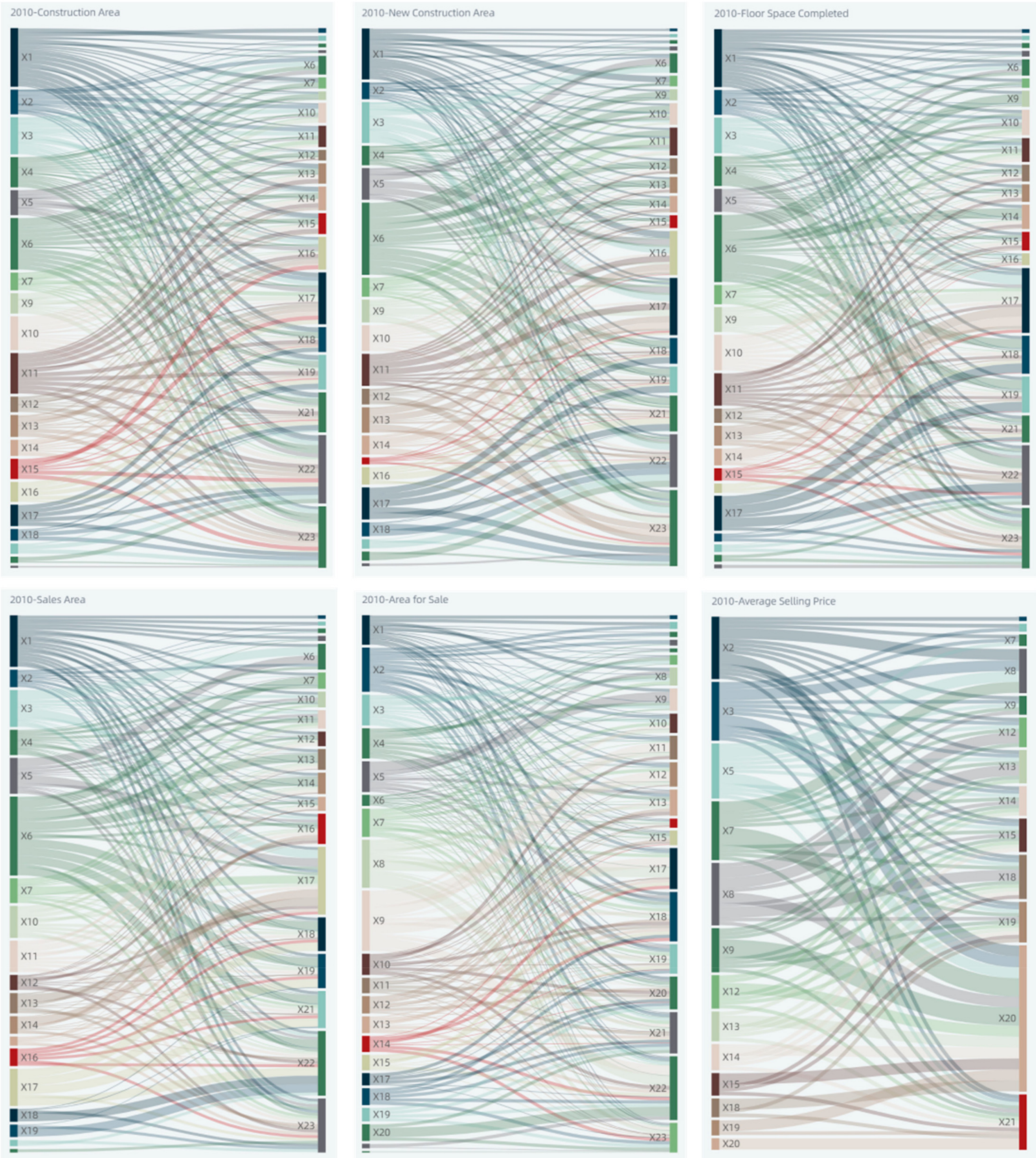

Figure 10. Analysis of interaction detector in 2010.

All of the factor pairs were bifactor-enhanced or non-linearly enhanced with each other in 2010–2019, and there were no independent or asymptotic relationships. The factor pairs were predominantly bifactor-enhanced and supplemented by non-linear enhancement, with less than 1% of the factor pairs non-linearly enhanced. There were eight factor pairs non-linearly enhanced in 2019, accounting for about 0.75%. Y_1, Y_4, and Y_5 had no factor pairs non-linearly enhanced, the non-linearly enhanced factor pair of Y_2 was $X_5 \cap X_{20}$, the non-linearly enhanced factor pairs of Y_3 included $X_2 \cap X_{16}$, $X_9 \cap X_{19}$, $X_9 \cap X_{22}$, and the non-linearly enhanced factor pair of Y_6 was $X_6 \cap X_8$. There were nine factor pairs non-linearly enhanced in 2010, accounting for about 0.79%. Y_3 and Y_6 had no factor pairs non-linearly enhanced; the non-linearly enhanced factor pairs of Y_1 included $X_2 \cap X_{16}$, $X_9 \cap X_{16}$ the non-linearly enhanced factor pairs of Y_2 included $X_6 \cap X_9$, $X_9 \cap X_{16}$, the non-linearly enhanced factor pair of Y_4 was $X_2 \cap X_{16}$, and the non-linearly enhanced factor pairs of Y_5 included $X_2 \cap X_6$ and $X_6 \cap X_{20}$.

5. Discussion

5.1. Drive Mechanism

At the significance level of 5%, the mean of the corresponding factor forces (q) of Y_1, Y_2, and Y_3 can be calculated to measure their influence on housing supply; the mean of the corresponding factor forces of Y_4 and Y_5 can be calculated to measure their influence on housing demand; and the corresponding factor forces of Y_4 can be used to represent their influence on housing market prices. In terms of housing supply, the mean influence of the 22 factors was 0.58 in 2019, and the mean influence of the 21 factors was 0.60 in 2010. In terms of housing demand, the mean influence of the 23 factors was 0.60 in 2019, and the mean influence of the 23 factors was 0.56 in 2010. In terms of housing prices, the mean influence of the 22 factors was 0.56 in 2019, and the mean influence of the 14 factors was 0.49 in 2010. Based on the ranking and the mean values of the factor forces, the driving factors can be classified into three categories, that is, "Key factors", "Important factors", and "Auxiliary factors" (see Figure 11 and Table 4). "Key factors" are dominated by the direct force, with the interaction between factors balanced. They are determined on two bases, which must be satisfied at the same time. One is that they should be TOP5 factors in 2019, and the other is that their q-values in 2010 must be greater than the mean. "Important factors" act on both direct and factor interaction forces at the same time. They are determined on two bases, and at least one of them must be satisfied. One is that they should have a q-value greater than the mean in both 2010 and 2019; and the other is that they should have a q-value less than the mean in 2010, but they must be in the TOP5 in 2019. "Auxiliary factors" have a very weak direct force and are dominated by interactions, and most of them are factors with significant interactions. It should be noted that the driving factors such as X_3, X_7, X_{12}, X_{13}, X_{14}, and X_{19} can work together on housing supply, demand, and prices in China.

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

	Supply				Demand				Price			
	2019		2010		2019		2010		2019		2010	
1	X_1	0.82	X_1	0.80	X_{17}	0.88	X_1	0.70	X_{21}	0.66	X_{20}	0.77
2	X_{17}	0.80	X_{11}	0.79	X_6	0.86	X_{10}	0.69	X_{14}	0.65	X_9	0.63
3	X_4	0.79	X_{23}	0.77	X_1	0.83	X_{21}	0.68	X_{12}	0.64	X_8	0.59
4	X_{11}	0.79	X_{17}	0.76	X_{11}	0.81	X_{19}	0.68	X_{13}	0.62	X_7	0.56
5	X_{18}	0.78	X_{10}	0.73	X_{10}	0.81	X_4	0.68	X_{15}	0.61	X_{15}	0.51
6	X_6	0.78	X_{21}	0.69	X_4	0.81	X_{18}	0.67	X_7	0.60	X_2	0.50
7	X_{10}	0.76	X_6	0.68	X_{18}	0.76	X_{17}	0.65	X_3	0.60	X_{12}	0.48
8	X_{19}	0.65	X_4	0.67	X_{22}	0.65	X_{11}	0.65	X_{18}	0.60	X_{13}	0.46
9	X_{22}	0.63	X_{19}	0.67	X_{16}	0.64	X_{23}	0.65	X_1	0.58	X_5	0.46
10	X_{12}	0.58	X_3	0.65	X_9	0.58	X_3	0.62	X_4	0.58	X_3	0.46

Table 4. *Cont.*

	Supply				Demand				Price			
	2019		2010		2019		2010		2019		2010	
11	X_{16}	0.56	X_{13}	0.62	X_8	0.58	X_{12}	0.60	X_5	0.56	X_{18}	0.46
12	X_{23}	0.56	X_{22}	0.62	X_{23}	0.57	X_{13}	0.59	X_{11}	0.56	X_{14}	0.45
13	X_{21}	0.55	X_{12}	0.62	X_{21}	0.54	X_5	0.56	X_{19}	0.54	X_{19}	0.40
14	X_3	0.55	X_{18}	0.61	X_7	0.53	X_{22}	0.55	X_{17}	0.53	X_{21}	0.18
15	X_{13}	0.53	X_5	0.59	X_{12}	0.52	X_{14}	0.52	X_{10}	0.52		
16	X_{14}	0.52	X_{14}	0.54	X_2	0.51	X_{16}	0.49	X_{20}	0.52		
17	X_7	0.52	X_7	0.49	X_3	0.49	X_7	0.48	X_2	0.52		
18	X_{15}	0.50	X_{15}	0.46	X_{13}	0.49	X_{20}	0.47	X_{23}	0.51		
19	X_5	0.47	X_{16}	0.39	X_{14}	0.43	X_6	0.46	X_9	0.48		
20	X_{20}	0.28	X_9	0.28	X_{15}	0.40	X_9	0.44	X_8	0.48		
21	X_2	0.26	X_2	0.24	X_5	0.37	X_8	0.44	X_6	0.45		
22	X_9	0.18			X_{20}	0.37	X_{15}	0.43	X_{22}	0.44		
23					X_{19}	0.36	X_2	0.27				

Figure 11. Analysis diagram of the driving mechanisms of spatial inequalities in the housing market.

The findings in this paper have corroborated some conclusions in the existing papers, although there are differences or even contradictions between them. The new findings made in this study are of great value in complementing and refining the driving mechanisms and evolutionary patterns of the housing market inequality. Yi [104], Liu [105], Zhang [106], and Lin [107] argue that there are significant spatial inequalities in housing in urban and provincial regions in China; Zhou [108], Chen [109], Tuofu [110], Dube [111], Liu [112], and Su [113,114] believe that the factors such as level of economic development, city size, industrial structure, blue and green space, landscape, public transportation, and rail transit have a significant impact on housing inequality in China; Zaniewski [115] holds that industrialization driven by the rapid development of the secondary industry is the dominant mechanism leading to housing inequality in socialist countries; Wang [116], Wilhelmsson [117], Cerutti [118], Golob [119], and Bates [120] propose that finance, especially loans, is in a complex causal relationship with housing and even macroeconomic development, which is largely in agreement with the findings in this paper. However, Zhang [121] argues that urbanization is closely related to housing inequality, Liu [122] argues that the pattern of interaction between urbanization and real estate varies across regions and that urbanization has a Granger effect on real estate investment, and Logan [123] argues that income is the core factor affecting housing inequality in China, all of which are different from the findings in this paper. We find in the study that urbanization and income mainly affect housing prices and inventories to some extent, while they have a very weak effect on housing supply and demand. Hansen [124] concluded in the study that there is significant spatial inequality in U.S. housing, which agrees with the case in China as analyzed in this paper; however, he also noted that spatial inequality in U.S. housing is decreasing, which is contrary to the findings in this paper. According to Tsai, the spatial differentiation in the Eurozone real estate market is decreasing [125], which is clearly different from the Chinese housing market trends found in this paper. As these differences may be subject to the influence of the scale, geographical characteristics of the study area, and research method errors, they still required further exploration and analysis based on more empirical studies, case studies, and comparative studies.

In addition, in this paper, we have further subdivided and deepened the study of some known views and found some interesting things. On the one hand, a small number of sister factors have essentially equivalent influence, such as imports and exports; on the other hand, most sister factors are quite different in forces between each other, which provides a more refined basis for the design of housing market management policies and the implementation of spatial governance measures. In terms of the connections between macroeconomic development and the housing market, many studies have found a complex interaction between the two. This paper finds that the total GDP, fiscal expenditure, and secondary industry have a greater influence on the degree of spatial inequality in the housing market than the GDP per capita, fiscal revenue, and tertiary industry. In terms of social development, many studies point out there is a dynamic interaction between housing markets and population size, structure, and migration [126,127], and according to the further study in this paper, we find that mobile populations have a greater influence on spatial inequality in housing markets than resident populations. In terms of service facilities, beds are stronger drivers than hospitals; rail transit is weaker than bus operating mileage, and the number of parks is stronger than park area and green space in impact.

5.2. Policy Implication

In recent years, China has stepped up its regulatory measures for the housing market, as evidenced by a series of frequent central and local policies issued on real estate development and control. However, the implementation of these policies has not achieved good results in general, and we believe a key reason is that the existing regulatory measures and policies fail to effectively reach the spatial contradiction facing the development of the housing market. At present, the inadequate understanding by policy makers of the complexity of the spatial inequality of supply, demand, and price in the housing market has led to a weak spatial directionality of housing market regulation measures and a lack of precision and synergy in regulation. In view of the development trend, the idea of "tailoring measures and zoning control" has become a consensus of the government, industry, and society, and it is urgent to carry out differentiated policy design based on the characteristics of spatial inequality in the housing market and its driving mechanism. In this paper, the dependent variable data are standardized by the "Max-Min normalization" method. The mean value of Y_1, Y_2, and Y_3 is calculated to measure the supply state of the housing market, the mean value of Y_4 and Y_5 is calculated to measure the demand state of the housing market, Y_4 is used to represent the price level of the housing market, and the sum of supply, demand, and price is calculated to measure the overall state of the housing market. By creating a ternary diagram according to the shares of supply, demand, and price in the housing market as well as the source values of the housing market, the 31 provinces can be classified into four types of policy areas (see Figure 12).

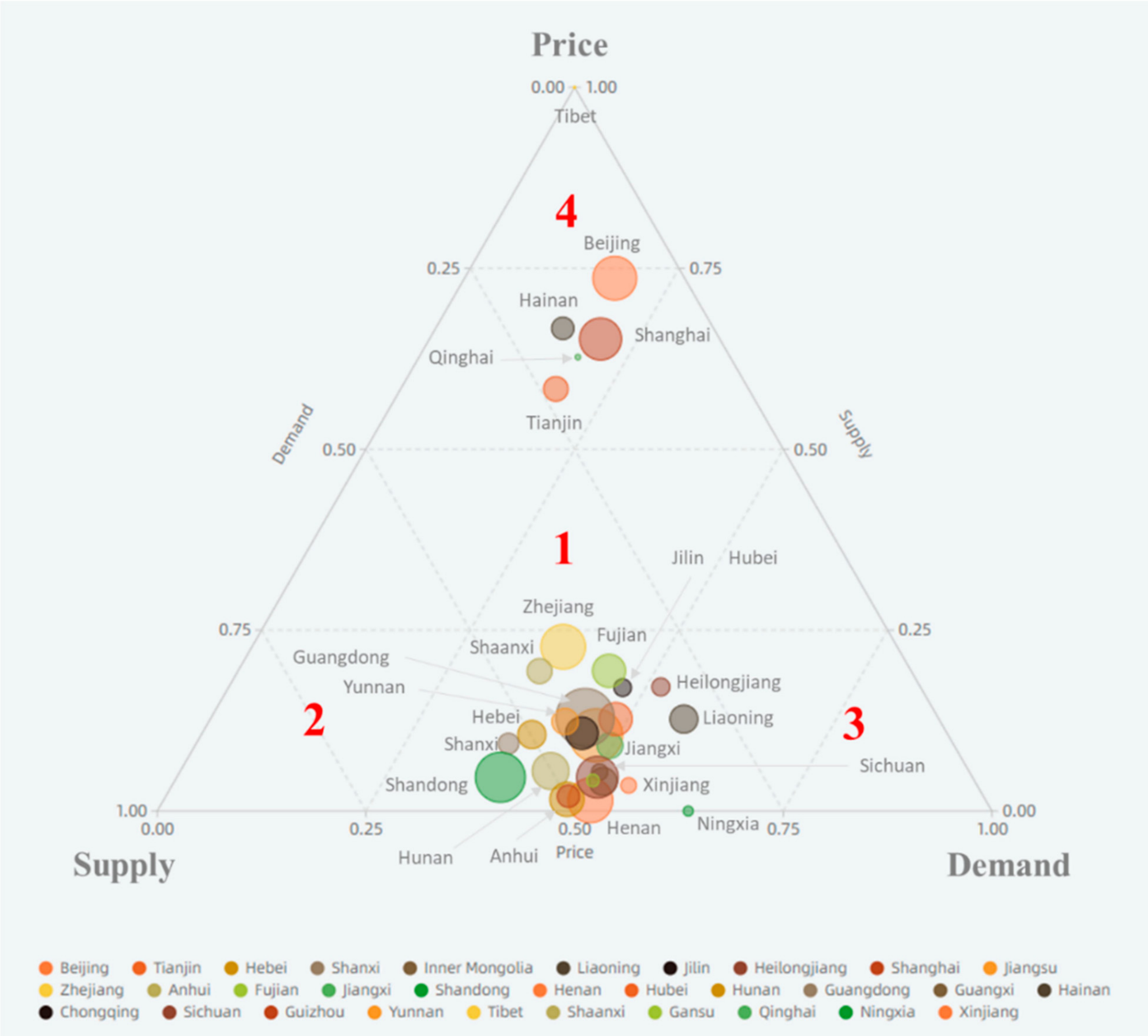

Figure 12. Zoning map of housing market management policies.

Members of the first type of policy area include Zhejiang, Fujian, Shaanxi, Guangdong, Jilin, Hubei, Jiangsu, Chongqing, and Yunnan, where the housing supply, demand, and price are relatively balanced, and the policy design and implementation of regulatory measures should highlight comprehensive driving factors, such as X_3, X_7, and X_{12}. Members of the second type include Shandong, Anhui, Guizhou, Hunan, and Shanxi. Members of the third type include Ningxia, Xinjiang, Sichuan, Heilongjiang, Liaoning, and Henan, where there is a serious imbalance between supply and demand. Most of them are in the northwest and northeast regions, they are influenced by the stage of development and geographical conditions, and their housing price is on the low side. Therefore, they should highlight the balance of supply and demand in policy design and take regulatory measures around the factors such as X_1, X_4, X_{11}, X_{10}, and X_{18} to put up their prices reasonably and achieve a balanced development of the housing market. Members of the fourth type include Beijing, Shanghai, Tianjin, and Hainan, where the housing price is on the high side with abnormal supply and demand. They should design regulatory policies around factors such as X_{12}, X_{13}, X_{15}, and X_7 in the future, to achieve the maximum satisfaction of social needs.

6. Discussion

Housing is available for consumption and investment in its attributes, and housing inequality has become a major element of modern social inequality. Housing inequality is multidimensional in nature, and different conclusions or new findings can be acquired from different dimensions such as economy, society, culture, geography, and planning. Based on the geographical and spatial differences of supply, demand, and price in the housing market, this paper integrates the economic, social, innovation, facility environment, and structural adjustment factors to construct a new incorporate framework of "space–supply–demand–price" for the housing market inequality research and empirically investigates the spatial inequality in China's provincial housing market.

A key finding of this paper is that the problem of spatial inequality in China's housing market is quite serious, showing dynamic changes in the past decade toward a more and more serious situation in general, with little possibility of seeing any convergence in the short term. Based on the study, we have also confirmed the findings as below. First, the influence of different factors on the housing market varies greatly. Based on the ranking and the mean value of their forces and the development trend over the past decade, the influencing factors can be classified into three types, that is, "Key factors", "Important factors", and "Auxiliary factors". "Key factors" are dominated by the direct driving forces, "Important factors" are based on the combination of direct and interactive forces, and "Auxiliary factors" mainly depend on the indirect forces. Second, for different segments in the housing market, the dominant drivers vary considerably in composition. Specifically, Gross Domestic Product (GDP), number of medical beds, expenditure, added value of the secondary industry, and other factors mainly affect housing supply and demand; added value of the tertiary industry, output value of the financial industry, imports, and other factors mainly affect the price; added value of the tertiary industry, revenue, and other factors affect housing supply, demand, and price at the same time, and they have a comprehensive influence on the development and evolution of spatial inequality in the housing market. Third, all the factor pairs are bifactor-enhanced or non-linearly enhanced with each other. X_1, X_4, X_6, X_{17}, and X_{22} are in a strong interaction with other factors. The factor pairs can be classified as high, medium, and low based on the mean interacting force of the factors. Fourth, according to the level of housing supply, demand, and price as well as their coordination degree, the 31 provinces are divided into four types of policy areas, and adaptive policy design is recommended according to the spatial inequality in the housing market and its driving mechanism.

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 study the characteristics of spatial inequality in the housing market and its evolution trends, and it helps to reveal the dynamics of the housing market development and its spatial governance mechanisms. Practically, this study helps urban policy makers and decision makers identify a scientific and reasonable housing supply pattern, provides a necessary decision basis for the government to conduct housing management and policy regulation, and offers valuable references for urban planners and real estate managers to carry out housing and land use planning and spatial planning design. Housing is the material basis for people's survival and development in any country or region, city, or countryside. Both large countries such as the United States, Russia, Germany, India, and Iran, and small nations such as Singapore, Vietnam, the United Arab Emirates, Oman, Mexico, and Morocco are all faced with various housing inequalities. The research methods and findings in this paper will provide valuable references for them to solve the problem. However, there are some shortcomings in our study. For example, there are no comparative studies on spatial inequality in housing markets across different dimensions, such as cities and countries, which may produce some impact on the precision and applicability of some of the findings in this paper. In the end, we sincerely call for more researchers to join us to provide more accurate knowledge to academia and society.

Author Contributions: Conceptualization, S.Z. and P.Z.; methodology, P.Z. and S.Z.; software, S.Z. and K.Z.; validation, P.Z. and K.Z.; formal analysis, P.Z. and S.Z.; investigation, S.Z., P.Z. and K.Z.; resources, P.Z.; data curation, S.Z., K.Z. and P.Z.; writing—original draft preparation, S.Z. and P.Z.; writing—review and editing, P.Z.; visualization, S.Z. and K.Z.; supervision, P.Z.; project administration, P.Z.; funding acquisition, P.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This paper and the related research are financially supported by the National Natural Science Foundation of China (Project Number: 51768029), National Natural Science Foundation of China (Project Number: 51768030).

Data Availability Statement: The data used in this paper mainly come from the China Statistical Yearbook and China Real Estate Statistical Yearbook. Most of the data can be obtained by visiting the following links: http://www.stats.gov.cn/tjsj/ndsj/ (accessed on 16 March 2021), https://data.cnki.net/yearbook/Single/N2021010050 (accessed on 16 March 2021).

Acknowledgments: All authors are very grateful to reviewers and academic editors, thank them for their creative and practical suggestions. At the same time, we must thank the assistant editors, especially Wang and Tian.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Analysis of factor detector in 2019.

	Y_1		Y_2		Y_3		Y_4		Y_5		Y_6	
	q	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**
X_1	0.84	0.00	0.82	0.00	0.79	0.00	0.83	0.00	0.10	0.11	0.58	0.00
X_2	0.12	0.08	0.06	0.22	0.26	0.04	0.05	0.23	0.51	0.01	0.52	0.01
X_3	0.56	0.00	0.53	0.00	0.56	0.01	0.53	0.00	0.46	0.03	0.60	0.00
X_4	0.81	0.00	0.83	0.00	0.73	0.00	0.81	0.00	0.17	0.11	0.58	0.00
X_5	0.44	0.04	0.38	0.08	0.49	0.02	0.36	0.10	0.39	0.03	0.56	0.01
X_6	0.80	0.00	0.86	0.00	0.67	0.00	0.86	0.00	0.24	0.11	0.45	0.03
X_7	0.51	0.02	0.50	0.02	0.54	0.00	0.56	0.01	0.50	0.01	0.60	0.00
X_8	0.12	0.22	0.06	0.42	0.19	0.09	0.05	0.51	0.58	0.00	0.48	0.01
X_9	0.11	0.09	0.05	0.23	0.18	0.04	0.07	0.18	0.58	0.00	0.48	0.02
X_{10}	0.79	0.00	0.76	0.00	0.73	0.00	0.81	0.00	0.10	0.11	0.52	0.00
X_{11}	0.83	0.00	0.79	0.00	0.74	0.00	0.81	0.00	0.07	0.75	0.56	0.01
X_{12}	0.60	0.00	0.55	0.00	0.60	0.00	0.59	0.00	0.45	0.03	0.64	0.00
X_{13}	0.54	0.00	0.50	0.01	0.56	0.01	0.52	0.01	0.46	0.03	0.62	0.00
X_{14}	0.54	0.01	0.44	0.04	0.58	0.00	0.46	0.03	0.41	0.02	0.65	0.00
X_{15}	0.46	0.03	0.40	0.07	0.55	0.01	0.35	0.01	0.46	0.03	0.61	0.00
X_{16}	0.61	0.00	0.69	0.00	0.39	0.03	0.64	0.00	0.05	0.27	0.13	0.07

Table A1. *Cont.*

	Y_1		Y_2		Y_3		Y_4		Y_5		Y_6	
	q	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**
X_{17}	0.82	0.00	0.87	0.00	0.71	0.00	0.88	0.00	0.06	0.23	0.53	0.01
X_{18}	0.79	0.00	0.78	0.00	0.76	0.00	0.76	0.00	0.10	0.11	0.60	0.00
X_{19}	0.64	0.00	0.68	0.00	0.61	0.00	0.58	0.00	0.15	0.05	0.54	0.00
X_{20}	0.31	0.02	0.28	0.03	0.24	0.05	0.36	0.01	0.39	0.05	0.52	0.00
X_{21}	0.56	0.01	0.53	0.01	0.56	0.01	0.54	0.01	0.08	0.15	0.66	0.00
X_{22}	0.65	0.00	0.66	0.00	0.57	0.00	0.65	0.00	0.03	0.34	0.44	0.04
X_{23}	0.59	0.00	0.57	0.00	0.53	0.01	0.57	0.00	0.00	0.74	0.51	0.01

Table A2. Analysis of factor detector in 2010.

	Y_1		Y_2		Y_3		Y_4		Y_5		Y_6	
	q	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**	**q**	**p**
X_1	0.83	0.00	0.81	0.00	0.77	0.00	0.76	0.00	0.65	0.00	0.10	0.11
X_2	0.24	0.04	0.21	0.02	0.27	0.03	0.15	0.05	0.39	0.02	0.50	0.01
X_3	0.72	0.00	0.59	0.00	0.62	0.00	0.55	0.00	0.68	0.00	0.46	0.02
X_4	0.73	0.00	0.64	0.00	0.66	0.00	0.68	0.00	0.68	0.00	0.18	0.09
X_5	0.65	0.00	0.55	0.00	0.56	0.00	0.49	0.02	0.62	0.00	0.46	0.02
X_6	0.70	0.00	0.68	0.00	0.65	0.00	0.75	0.00	0.16	0.04	0.05	0.24
X_7	0.55	0.00	0.47	0.00	0.45	0.02	0.41	0.03	0.55	0.00	0.56	0.00
X_8	0.09	0.12	0.09	0.13	0.31	0.10	0.06	0.19	0.44	0.02	0.59	0.00
X_9	0.29	0.02	0.23	0.05	0.31	0.05	0.19	0.08	0.44	0.04	0.63	0.00
X_{10}	0.75	0.00	0.74	0.00	0.71	0.00	0.69	0.00	0.70	0.00	0.18	0.10
X_{11}	0.83	0.00	0.80	0.00	0.75	0.00	0.76	0.00	0.54	0.00	0.00	0.83
X_{12}	0.66	0.00	0.58	0.00	0.61	0.00	0.56	0.00	0.63	0.00	0.48	0.02
X_{13}	0.69	0.00	0.57	0.01	0.60	0.00	0.54	0.01	0.65	0.00	0.46	0.02
X_{14}	0.60	0.00	0.46	0.03	0.54	0.01	0.49	0.02	0.55	0.00	0.45	0.01
X_{15}	0.53	0.01	0.35	0.01	0.51	0.01	0.33	0.01	0.54	0.01	0.51	0.01
X_{16}	0.48	0.02	0.45	0.03	0.23	0.02	0.49	0.02	0.11	0.10	0.21	0.14
X_{17}	0.79	0.00	0.78	0.00	0.73	0.00	0.79	0.00	0.51	0.01	0.05	0.26
X_{18}	0.64	0.00	0.57	0.01	0.62	0.00	0.56	0.01	0.78	0.00	0.46	0.02
X_{19}	0.73	0.00	0.63	0.00	0.65	0.00	0.63	0.00	0.73	0.00	0.40	0.03
X_{20}	0.09	0.23	0.07	0.29	0.14	0.14	0.06	0.30	0.47	0.03	0.77	0.00
X_{21}	0.72	0.00	0.68	0.00	0.67	0.00	0.67	0.00	0.69	0.00	0.18	0.04
X_{22}	0.65	0.00	0.63	0.00	0.59	0.00	0.61	0.00	0.49	0.01	0.01	0.61
X_{23}	0.78	0.00	0.80	0.00	0.73	0.00	0.72	0.00	0.57	0.00	0.01	0.61

Table A3. The CV of China's housing market from 2010 to 2019.

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
2010	0.6786	0.6780	0.7146	0.7183	0.7565	0.6609
2011	0.6649	0.6383	0.6757	0.6907	0.7278	0.5738
2012	0.6480	0.6427	0.6983	0.6962	0.7260	0.5308
2013	0.6428	0.6686	0.6716	0.7102	0.6735	0.5455
2014	0.6422	0.6638	0.6713	0.6915	0.6989	0.5191
2015	0.6508	0.6772	0.6941	0.7483	0.6542	0.6131
2016	0.6732	0.7665	0.7159	0.7744	0.6366	0.6937
2017	0.7007	0.7832	0.7451	0.8032	0.6495	0.6790
2018	0.7281	0.7986	0.8227	0.8049	0.6799	0.6495
2019	0.7260	0.7715	0.8873	0.8022	0.7389	0.6600
Average	0.6755	0.7088	0.7296	0.7440	0.6942	0.6125

Table A4. The GI of China's housing market from 2010 to 2019.

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
2010	0.7052	0.7042	0.7060	0.7117	0.7271	0.6587
2011	0.7020	0.6962	0.7030	0.7086	0.7174	0.6458
2012	0.6964	0.6921	0.7047	0.7087	0.7137	0.6359
2013	0.6952	0.7013	0.6993	0.7111	0.6964	0.6352
2014	0.6948	0.7005	0.6994	0.7085	0.7013	0.6285
2015	0.6954	0.7011	0.6999	0.7204	0.6898	0.6412
2016	0.7007	0.7193	0.7078	0.7272	0.6845	0.6565
2017	0.7063	0.7273	0.7158	0.7372	0.6870	0.6559
2018	0.7122	0.7330	0.7287	0.7396	0.6936	0.6526
2019	0.7119	0.7268	0.7436	0.7386	0.7026	0.6523
Average	0.7020	0.7102	0.7108	0.7212	0.7013	0.6463

References

1. Montagnoli, A.; Nagayasu, J. UK house price convergence clubs and spillovers. *J. Hous. Econ.* **2015**, *30*, 50–58. [CrossRef]
2. Tan, S.K.; Wang, S.L.; Cheng, C.H. Change of Housing Inequality in Urban China and Its Decomposition: 1989–2011. *Soc. Indic. Res.* **2016**, *129*, 29–45. [CrossRef]
3. Evans, B.P.; Glavatskiy, K.; Harre, M.S.; Prokopenko, M. The impact of social influence in Australian real estate: Market forecasting with a spatial agent-based model. *J. Econ. Interact. Coord.* **2021**, 1–53. [CrossRef]
4. Ratcliffe, P. Housing inequality and 'race': Some critical reflections on the concept of 'social exclusion'. *Ethn. Racial Stud.* **1999**, *22*, 1–22. [CrossRef]
5. De Silva, S.; Elmelech, Y. Housing Inequality in the United States: Explaining the White-Minority Disparities in Homeownership. *Hous. Stud.* **2012**, *27*, 1–26. [CrossRef]
6. Medina, R.M.; Byrne, K.; Brewer, S.; Nicolosi, E.A. Housing inequalities: Eviction patterns in Salt Lake County, Utah. *Cities* **2020**, *104*, 102804. [CrossRef]
7. Krivo, L.J. Immigrant characteristics and Hispanic-Anglo housing inequality. *Demography* **1995**, *32*, 599–615. [CrossRef]
8. Uehara, E.S. Race, Gender, And Housing Inequality—An Exploration of The Correlates of Low-Quality Housing among Clients Diagnosed with Severe and Persistent Mental-Illness. *J. Health Soc. Behav.* **1994**, *35*, 309–321. [CrossRef]
9. Filandri, M.; Olagnero, M. Housing Inequality and Social Class in Europe. *Hous. Stud.* **2014**, *29*, 977–993. [CrossRef]
10. Lux, M.; Sunega, P.; Katrnak, T. Classes and Castles: Impact of Social Stratification on Housing Inequality in Post-Socialist States. *Eur. Sociol. Rev.* **2013**, *29*, 274–288. [CrossRef]
11. Soaita, A.M. Overcrowding and 'underoccupancy' in Romania: A case study of housing inequality. *Environ. Plan. A Econ. Space* **2014**, *46*, 203–221. [CrossRef]

12. Bodnar, J.; Borocz, J. Housing advantages for the better connected? Institutional segmentation, settlement type and social network effects in Hungary's late state-socialist housing inequalities. *Soc. Forces* **1998**, *76*, 1275–1304.
13. Zhao, W.; Ge, J.H. Dual institutional structure and housing inequality in transitional urban China. *Res. Soc. Stratif. Mobil.* **2014**, *37*, 23–41. [CrossRef]
14. Sato, H. Housing inequality and housing poverty in urban China in the late 1990s. *China Econ. Rev.* **2006**, *17*, 37–50. [CrossRef]
15. Grander, M. The inbetweeners of the housing markets—Young adults facing housing inequality in Malmo, Sweden. *Hous. Stud.* **2021**, 1–18. [CrossRef]
16. Niu, G.; Zhao, G.C. State, market, and family: Housing inequality among the young generation in urban China. *J. Hous. Built Environ.* **2021**, *36*, 89–111. [CrossRef]
17. Coulter, R.; Bayrakdar, S.; Berrington, A. Longitudinal life course perspectives on housing inequality in young adulthood. *Geogr. Compass* **2020**, *14*, e12488. [CrossRef]
18. Hoolachan, J.; McKee, K. Inter-generational housing inequalities: 'Baby Boomers' versus the 'Millennials'. *Urban Stud.* **2019**, *56*, 210–225. [CrossRef]
19. Cui, C.; Huang, Y.Q.; Wang, F.L. A relay race: Intergenerational transmission of housing inequality in urban China. *Hous. Stud.* **2020**, *35*, 1088–1109. [CrossRef]
20. Wah, C.K. Excluding the disadvantaged—Housing inequalities in Hong Kong. *Third World Plan. Rev.* **2001**, *23*, 79–96. [CrossRef]
21. Goulden, R. Housing, Inequality, and Economic Change in Syria. *Br. J. Middle East. Stud.* **2011**, *38*, 187–202. [CrossRef]
22. Vesselinov, E. The continuing 'wind of change' in the Balkans: Sources of housing inequality in Bulgaria. *Urban Stud.* **2004**, *41*, 2601–2619. [CrossRef]
23. He, S.J.; Liu, Y.T.; Wu, F.L.; Webster, C. Social Groups and Housing Differentiation in China's Urban Villages: An Institutional Interpretation. *Hous. Stud.* **2010**, *25*, 671–691. [CrossRef]
24. Hoekstra, M.S.; Hochstenbach, C.; Bontje, M.A.; Musterd, S. Shrinkage and housing inequality: Policy responses to population decline and class change. *J. Urban Aff.* **2020**, *42*, 333–350. [CrossRef]
25. Gentile, M. The "Soviet" factor: Exploring perceived housing inequalities in a midsized city in the Donbas, Ukraine. *Urban Geogr.* **2015**, *36*, 696–720. [CrossRef]
26. Alonso, W. *Location and Land Use: Towards a General Theory of Land Rent*; Harvard University Press: Cambridge, MA, USA, 1964.
27. Muth, R.F. *Cities and Housing: The Spatial Pattern of Urban Residential Land Use*; University of Chicago Press: Chicago, IL, USA, 1969.
28. Papageorgiou, G.J.; Casetti, E. Spatial Equilibrium Residential Land Values in a Multicenter Setting. *J. Reg. Sci.* **1971**, *11*, 385–389. [CrossRef]
29. Fujita, M.; Ogawa, H. Multiple Equilibria and Structural Transition of Non-Monocentric Urban Configurations. *Reg. Sci. Urban Econ.* **1982**, *12*, 161–196. [CrossRef]
30. Morali, O.; Yilmaz, N. An Analysis of Spatial Dependence in Real Estate Prices. *J. Real Estate Financ. Econ.* **2020**, 1–23. [CrossRef]
31. Wong, S.K.; Yiu, C.Y.; Chau, K.W. Trading Volume-Induced Spatial Autocorrelation in Real Estate Prices. *J. Real Estate Financ. Econ.* **2013**, *46*, 569–608. [CrossRef]
32. De Bruyne, K.; Van Hove, J. Explaining the spatial variation in housing prices: An economic geography approach. *Appl. Econ.* **2013**, *45*, 1673–1689. [CrossRef]
33. Kim, Y.S.; Rous, J.J. House price convergence: Evidence from US state and metropolitan area panels. *J. Hous. Econ.* **2012**, *21*, 169–186. [CrossRef]
34. Tomal, M. House Price Convergence on the Primary and Secondary Markets: Evidence from Polish Provincial Capitals. *Real Estate Manag. Valuat.* **2019**, *27*, 62–73. [CrossRef]
35. Tomal, M. Spillovers Across House Price Convergence Clubs: Evidence from the Polish Housing Market. *Real Estate Manag. Valuat.* **2020**, *28*, 13–20. [CrossRef]
36. Cook, S. The convergence of regional house prices in the UK. *Urban Stud.* **2003**, *40*, 2285–2294. [CrossRef]
37. Cook, S. β-convergence and the Cyclical Dynamics of UK Regional House Prices. *Urban Stud.* **2012**, *49*, 203–218. [CrossRef]
38. Abbott, A.; De Vita, G. Pairwise Convergence of District-level House Prices in London. *Urban Stud.* **2012**, *49*, 721–740. [CrossRef]
39. Abbott, A.; De Vita, G. Testing for long-run convergence across regional house prices in the UK: A pairwise approach. *Appl. Econ.* **2013**, *45*, 1227–1238. [CrossRef]
40. Holmes, M.J.; Grimes, A. Is there long-run convergence among regional house prices in the UK? *Urban Stud.* **2008**, *45*, 1531–1544. [CrossRef]
41. Holmes, M.J.; Otero, J.; Panagiotidis, T. Investigating regional house price convergence in the United States: Evidence from a pair-wise approach. *Econ. Model.* **2011**, *28*, 2369–2376. [CrossRef]
42. Holmes, M.J.; Otero, J.; Panagiotidis, T. A Pair-wise Analysis of Intra-city Price Convergence within the Paris Housing Market. *J. Real Estate Financ. Econ.* **2017**, *54*, 1–16. [CrossRef]
43. Miles, W. House price convergence in the euro zone: A pairwise approach. *Econ. Syst.* **2020**, *44*, 100782. [CrossRef]
44. Zhang, H.Y.; Chen, J.; Wang, Z. Spatial heterogeneity in spillover effect of air pollution on housing prices: Evidence from China. *Cities* **2021**, *113*, 103145. [CrossRef]
45. Churchill, S.A.; Inekwe, J.; Ivanovski, K. House price convergence: Evidence from Australian cities. *Econ. Lett.* **2018**, *170*, 88–90. [CrossRef]
46. Montanes, A.; Olmos, L. Convergence in US house prices. *Econ. Lett.* **2013**, *121*, 152–155. [CrossRef]

47. Sim, S.-H. Investigating the Convergence of Regional House Sales-Prices in Korea. *J. Korean Data Anal. Soc.* **2015**, *17*, 53–67.
48. Blanco, F.; Martin, V.; Vazquez, G. Regional house price convergence in Spain during the housing boom. *Urban Stud.* **2016**, *53*, 775–798. [CrossRef]
49. Zelazowski, K. Price Convergence in the Regional Housing Markets in Poland. *Real Estate Manag. Valuat.* **2019**, *27*, 44–52. [CrossRef]
50. Moscone, F.; Tosetti, E.; Canepa, A. Real estate market and financial stability in US metropolitan areas: A dynamic model with spatial effects. *Reg. Sci. Urban Econ.* **2014**, *49*, 129–146. [CrossRef]
51. Mosciaro, M. The real estate/financial complex in Brazil and Italy: Tools for the financial production of urban space. *Scr. Nova-Rev. Electron. Geogr. Cienc. Soc.* **2021**, *25*, 59–81. [CrossRef]
52. Lukas, M.; Lopez-Morales, E. Real estate production, geographies of mobility and spatial contestation: A two-case study in Santiago de Chile. *J. Transp. Geogr.* **2018**, *67*, 92–101. [CrossRef]
53. Shatkin, G. The real estate turn in policy and planning: Land monetization and the political economy of peri-urbanization in Asia. *Cities* **2016**, *53*, 141–149. [CrossRef]
54. Susewind, R. Spatial Segregation, Real Estate Markets and the Political Economy of Corruption in Lucknow, India. *J. South Asian Dev.* **2015**, *10*, 267–291. [CrossRef]
55. Ramos, G.C.D. Real Estate Industry as an Urban Growth Machine: A Review of the Political Economy and Political Ecology of Urban Space Production in Mexico City. *Sustainability* **2019**, *11*, 1980. [CrossRef]
56. Dube, J.; Legros, D. A spatio-temporal measure of spatial dependence: An example using real estate data. *Pap. Reg. Sci.* **2013**, *92*, 19–30. [CrossRef]
57. Barreca, A.; Curto, R.; Rolando, D. Urban Vibrancy: An Emerging Factor that Spatially Influences the Real Estate Market. *Sustainability* **2020**, *12*, 346. [CrossRef]
58. Jun, M.J. The effects of Seoul's greenbelt on the spatial distribution of population and employment, and on the real estate market. *Ann. Reg. Sci.* **2012**, *49*, 619–642. [CrossRef]
59. Ceccato, V.; Wilhelmsson, M. Do crime hot spots affect housing prices? *Nord. J. Criminol.* **2020**, *21*, 84–102. [CrossRef]
60. Iqbal, A.; Wilhelmsson, M. Park proximity, crime and apartment prices. *Int. J. Hous. Mark. Anal.* **2018**, *11*, 669–686. [CrossRef]
61. Aguirre, C.; Marmolejo, C. Polycentrism impact on the spatial distribution of values Real estate: An analysis for the metropolitan area of Barcelona. *Rev. Constr.* **2011**, *10*, 78–88. [CrossRef]
62. Zaniewski, K.J. Housing Inequalities Under Socialism—A Geographic Perspective. *Stud. Comp. Communism* **1989**, *22*, 291–306. [CrossRef]
63. Akpinar, F. Class Dimension of Housing Inequalities in The New Era of Liberalization: A Case Study in Ankara (1). *METU J. Fac. Archit.* **2008**, *25*, 39–69.
64. Koramaz, T.K.; Dokmeci, V. Spatial Determinants of Housing Price Values in Istanbul. *Eur. Plan. Stud.* **2012**, *20*, 1221–1237. [CrossRef]
65. Huang, Y.Q.; Jiang, L.W. Housing Inequality in Transitional Beijing. *Int. J. Urban Reg. Res.* **2009**, *33*, 936–956. [CrossRef]
66. Liu, Y.T.; He, S.J.; Wu, F.L. Housing Differentiation Under Market Transition in Nanjing, China. *Prof. Geogr.* **2012**, *64*, 554–571. [CrossRef]
67. Symmes, L.R.; Salinas, A.C.; Cabello, F.C. Normative Inequality in Verticalized Areas in Santiago De Chile. Transit Towards the Conformation of a Public Space Deducted from The Real Estate Business? *Andamios* **2019**, *16*, 127–149.
68. Cesaroni, G.; Venturini, G.; Paglione, L.; Angelici, L.; Sorge, C.; Marino, C.; Davoli, M.; Agabiti, N. Mortality inequalities in Rome: The role of individual education and neighbourhood real estate market. *Epidemiol. Prev.* **2020**, *44*, 31–37. [CrossRef]
69. Norris, M.; Shiels, P. Housing inequalities in an enlarged European Union: Patterns, drivers, implications. *J. Eur. Soc. Policy* **2007**, *17*, 65–76. [CrossRef]
70. Gu, H.Y.; Liu, Z.X.; Weng, Y.L. Time-varying correlations in global real estate markets: A multivariate GARCH with spatial effects approach. *Phys. A Stat. Mech. Its Appl.* **2017**, *471*, 460–472. [CrossRef]
71. Tan, M.J.; Guan, C.H. Are people happier in locations of high property value? Spatial temporal analytics of activity frequency, public sentiment and housing price using twitter data. *Appl. Geogr.* **2021**, *132*, 102474. [CrossRef]
72. Su, S.L.; He, S.J.; Sun, C.X.; Zhang, H.; Hu, L.R.; Kang, M.J. Do landscape amenities impact private housing rental prices? A hierarchical hedonic modeling approach based on semantic and sentimental analysis of online housing advertisements across five Chinese megacities. *Urban For. Urban Green.* **2021**, *58*, 126968. [CrossRef]
73. Hu, L.R.; He, S.J.; Han, Z.X.; Xiao, H.; Su, S.L.; Weng, M.; Cai, Z.L. Monitoring housing rental prices based on social media:An integrated approach of machine-learning algorithms and hedonic modeling to inform equitable housing policies. *Land Use Policy* **2019**, *82*, 657–673. [CrossRef]
74. He, S.J.; Liu, L.; Yang, G.B.; Wang, F.L. Housing differentiation and housing poverty in Chinese low-income urban neighborhoods under the confluence of State-market forces. *Urban Geogr.* **2017**, *38*, 729–751. [CrossRef]
75. Wang, J.; Kuffer, M.; Pfeffer, K. The role of spatial heterogeneity in detecting urban slums. *Comput. Environ. Urban Syst.* **2019**, *73*, 95–107. [CrossRef]
76. Zhao, S.; Zhang, C.; Qi, J. The Key Factors Driving the Development of New Towns by Mother Cities and Regions: Evidence from China. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 223. [CrossRef]

77. Guan, X.Y.; Wang, S.L.; Gao, Z.Y.; Lv, Y.; Fu, X.J. Spatio-temporal variability of soil salinity and its relationship with the depth to groundwater in salinization irrigation district. *Acta Ecol. Sin.* **2012**, *32*, 198–206.
78. Zhang, R.F. *Theory and Application of Spatial Variability*; Science Press: Beijing, China, 2005; pp. 13–14.
79. Ruan, B.Q.; Xu, F.R.; Jiang, R.F. Analysis on spatial and temporal variability of groundwater level based on spherical sampling model. *J. Hydraul. Eng.* **2008**, *39*, 573–579.
80. Liu, X.N.; Huang, F.; Wang, P. *Spatial Analysis Principle and Method of GIS*; Science Press: Beijing, China, 2008; pp. 199–206.
81. Miyamoto, S.; Chacon, A.; Hossain, M.; Martinez, L. Soil salinity of urban turf areas irrigated with saline water I. Spatial variability. *Landsc. Urban Plan.* **2005**, *71*, 233–241.
82. She, D.L.; Shao, M.A.; Yu, S.G. Spatial Variability of Soil Water Content on a Cropland-grassland Mixed Slope Land in the Loess Plateau, China. *Trans. Chin. Soc. Agric. Mach.* **2010**, *41*, 57–63.
83. Li, S.M. Housing inequalities under market deepening: The case of Guangzhou, China. *Environ. Plan. A* **2012**, *44*, 2852–2866. [CrossRef]
84. Wang, J.F.; Li, X.H.; Christakos, G.; Liao, Y.-L.; Zhang, T.; Gu, X.; Zheng, X.-Y. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127. [CrossRef]
85. Wang, J.F.; Xu, C.D. Geodetector: Principle and prospective. *Acta Geogr. Sin.* **2017**, *72*, 116–134.
86. Zhao, S.; Yan, Y.; Han, J. Industrial Land Change in Chinese Silk Road Cities and Its Influence on Environments. *Land.* **2021**, *10*, 806. [CrossRef]
87. Wang, J.F.; Hu, Y. Environmental health risk detection with GeogDetector. *Environ. Model. Softw.* **2012**, *33*, 114–115. [CrossRef]
88. Bergeaud, A.; Ray, S. Adjustment Costs and Factor Demand: New Evidence from Firms' Real Estate. *Econ. J.* **2021**, *131*, 70–100. [CrossRef]
89. Yan, Z.L. Empirical Researches on Macroeconomic Influence factors in Real Estate Based on Data Mining (DM). *Agro Food Ind. Hi-Tech* **2017**, *28*, 2729–2732.
90. Carrasco-Gallego, J.A. Real Estate, Economic Stability and the New Macro-Financial Policies. *Sustainability* **2021**, *13*, 236. [CrossRef]
91. McMillan, A.; Chakraborty, A. Who Buys Foreclosed Homes? How Neighborhood Characteristics Influence Real Estate-Owned Home Sales to Investors and Households. *Hous. Policy Debate* **2016**, *26*, 766–784. [CrossRef]
92. Warsame, A.; Wigren, R.; Wilhelmsson, M.; Yang, Z. The Impact of Competition, Subsidies and Taxes on Production and Construction Cost: The Case of the Swedish Housing Construction Market. *ISRN Econ.* **2013**, *2013*, 868914. [CrossRef]
93. Oikarinen, E.; Falkenbach, H. Foreign investors' influence on the real estate market capitalization rate evidence from a small open economy. *Appl. Econ.* **2017**, *49*, 3141–3155. [CrossRef]
94. Sun, L.J.; Zhang, S.X. External dependent economy and structural real estate bubbles in China. *China World Econ.* **2008**, *16*, 34–50. [CrossRef]
95. Hardie, I.W.; Narayan, T.A.; Gardner, B.L. The joint influence of agricultural and nonfarm factors on real estate values: An application to the Mid-Atlantic region. *Am. J. Agric. Econ.* **2001**, *83*, 120–132. [CrossRef]
96. Franses, P.H.; De Groot, B. Do commercial real estate prices have predictive content for GDP? *Appl. Econ.* **2013**, *45*, 4379–4384. [CrossRef]
97. Jin, Y.; Leung, C.K.Y.; Zeng, Z.X. Real Estate, the External Finance Premium and Business Investment: A Quantitative Dynamic General Equilibrium Analysis. *Real Estate Econ.* **2012**, *40*, 167–195. [CrossRef]
98. Pan, J.N.; Huang, J.T.; Chiang, T.F. Empirical study of the local government deficit, land finance and real estate markets in China. *China Econ. Rev.* **2015**, *32*, 57–67. [CrossRef]
99. Ren, H.H.; Folmer, H.; Van der Vlist, A.J. What role does the real estate-construction sector play in China's regional economy? *Ann. Reg. Sci.* **2014**, *52*, 839–857. [CrossRef]
100. Bischoff, O. Explaining regional variation in equilibrium real estate prices and income. *J. Hous. Econ.* **2012**, *21*, 1–15. [CrossRef]
101. Zhang, H.; Li, L.J.; Chen, T.T.; Li, V. Where will China's real estate market go under the economy's new normal? *Cities* **2016**, *55*, 42–48. [CrossRef]
102. Bashar, O.H.M.N. An Intra-City Analysis of House Price Convergence and Spatial Dependence. *J. Real Estate Financ. Econ.* **2020**. [CrossRef]
103. Zalejska-Jonsson, A.; Wilkinson, S.J.; Wahlund, R. Willingness to Pay for Green Infrastructure in Residential Development—A Consumer Perspective. *Atmosphere* **2020**, *11*, 152. [CrossRef]
104. Yi, C.D.; Huang, Y.Q. Housing Consumption and Housing Inequality in Chinese Cities During the First Decade of the Twenty-First Century. *Hous. Stud.* **2014**, *29*, 291–311. [CrossRef]
105. Liu, T.Y.; Su, C.W.; Chang, H.L.; Chu, C.C. Convergence of Regional Housing Prices in China. *J. Urban. Plan. Dev.* **2018**, *144*, 04018015. [CrossRef]
106. Zhang, F.; Morley, B. The convergence of regional house prices in China. *Appl. Econ. Lett.* **2014**, *21*, 205–208. [CrossRef]
107. Lin, R.; Zhang, X.; Li, X.T.; Dong, J.C. Heterogeneous convergence of regional house prices and the complexity in China. *Zbornik Radova Ekonomskog Fakulteta u Rijeci Proc. Rij. Fac. Econ.* **2015**, *33*, 325–348. [CrossRef]
108. Zhou, Q.; Zhang, X.L.; Chen, J.; Zhang, Y.Y. Do double-edged swords cut both ways? Housing inequality and haze pollution in Chinese cities. *Sci. Total. Environ.* **2020**, *719*, 137404. [CrossRef] [PubMed]

109. Chen, J.H.; Wu, Y.; Li, H.J. Vocational Status, Hukou and Housing Migrants in the New Century: Evidence from a Multi-city Study of Housing Inequality. *Soc. Indic. Res.* **2018**, *139*, 309–325. [CrossRef]
110. Tuofu, H.; Qingyun, H.; Dongxiao, Y.; Xiao, O.Y. Evaluating the Impact of Urban Blue Space Accessibility on Housing Price: A Spatial Quantile Regression Approach Applied in Changsha, China. *Front. Environ. Sci.* **2021**, *9*, 696626. [CrossRef]
111. Dube, J.; Abdel-Halim, M.; Devaux, N. Evaluating the Impact of Floods on Housing Price Using a Spatial Matching Difference-In-Differences (SM-DID) Approach. *Sustainability* **2021**, *13*, 804. [CrossRef]
112. Liu, G.W.; Wang, X.Z.; Gu, J.P.; Liu, Y.; Zhou, T. Temporal and spatial effects of a 'Shan Shui' landscape on housing price: A case study of Chongqing, China. *Habitat Int.* **2019**, *94*, 102068. [CrossRef]
113. Su, S.L.; Zhang, J.Y.; He, S.J.; Zhang, H.; Hu, L.R.; Kang, M.J. Unraveling the impact of TOD on housing rental prices and implications on spatial planning: A comparative analysis of five Chinese megacities. *Habitat Int.* **2021**, *107*, 102309. [CrossRef]
114. Su, S.L.; Zhang, H.; Wang, M.; Weng, M.; Kang, M.J. Transit-oriented development (TOD) typologies around metro station areas in urban China: A comparative analysis of five typical megacities for planning implications. *J. Transport. Geogr.* **2021**, *90*, 102939. [CrossRef]
115. Zaniewski, K.J. Housing Inequalities Under Socialism—The Case of Poland. *Geoforum* **1991**, *22*, 39–53. [CrossRef]
116. Wang, F.Y.; Ran, G.H. Excessive Financial Support, Real Estate Development and Macroeconomic Growth: Evidence from China. *Emerg. Mark. Financ. Trade* **2019**, *55*, 2437–2447. [CrossRef]
117. Wilhelmsson, M. What role does the housing market play for the macroeconomic transmission mechanism? *J. Risk Financ. Manag.* **2020**, *13*, 112. [CrossRef]
118. Cerutti, E.; Dagher, J.; Dell'Ariccia, G. Housing finance and real-estate booms: A cross-country perspective. *J. Hous. Econ.* **2017**, *38*, 1–13. [CrossRef]
119. Golob, K.; Bastic, M.; Psunder, I. Analysis of Impact Factors on the Real Estate Market: Case Slovenia. *Inz. Ekon. -Eng. Econ.* **2012**, *23*, 357–367. [CrossRef]
120. Bates, L.J.; Giaccotto, C.; Santerre, R.E. Is the Real Estate Sector More Responsive to Economy-Wide or Housing Market Conditions? An Exploratory Analysis. *J. Real Estate Financ. Econ.* **2015**, *51*, 541–554. [CrossRef]
121. Zhang, L.; Ye, Y.M.; Chen, J. Urbanization, informality and housing inequality in indigenous villages: A case study of Guangzhou. *Land Use Policy* **2016**, *58*, 32–42. [CrossRef]
122. Liu, T.Y.; Su, C.W.; Chang, H.L.; Chu, C.C. Is urbanization improving real estate investment? A cross-regional study of China. *Rev. Dev. Econ.* **2018**, *22*, 862–878. [CrossRef]
123. Logan, J.R.; Bian, Y.J.; Bian, F.Q. Housing inequality in urban China in the 1990s. *Int. J. Urban Reg. Res.* **1999**, *23*, 7–25. [CrossRef]
124. Hansen, J.L.; Formby, J.P.; Smith, W.J. The Measurement and Trend of Housing Inequality in the United-States, 1978–1985. *Appl. Econ.* **1994**, *26*, 1021–1028. [CrossRef]
125. Tsai, I.C. House price convergence in euro zone and non-euro zone countries. *Econ. Syst.* **2018**, *42*, 269–281. [CrossRef]
126. Fernandez, M.D.; Marron, M.L.; Rodriguez, P.M. Does the population determine the dynamics of the real estate activity? An analysis of cointegration for the Spanish case. *Investig. Econ.* **2016**, *75*, 103–124. [CrossRef]
127. Wang, X.R.; Hui, E.C.M.; Sun, J.X. Population Aging, Mobility, and Real Estate Price: Evidence from Cities in China. *Sustainability* **2018**, *10*, 3140. [CrossRef]