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Analysis of the Spatiotemporal Heterogeneity of Housing Prices' Association in China: An Urban Agglomeration Perspective

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Abstract: With the rise of urban agglomerations, regional divergence of China's real estate market has gradually intensified. City-specialized policies have become the main emphasis for promoting the healthy development of the regional real estate market. By adopting a gravity model, social net-work analysis, and impulse response analysis, this paper examines the spatial-temporal heterogeneity of housing prices' association in the Beijing-Tianjin-Hebei Urban Agglomeration (BTH-UA), the Yangtze River Delta Urban Agglomeration (YRDUA), and the Pearl River Delta Urban Agglomeration (PRDUA), which are the most developed urban agglomerations in China. Meanwhile, the formation mechanism of the housing prices' association network and spillover effect in urban agglomeration were theoretically analyzed. This paper found that (1) significant aggregation phenomena of housing prices were observed in the urban agglomerations; (2) characteristics of overall and individual networks were dynamically heterogeneous. In the BTHUA and the PRDUA, the associations of housing prices were polarized and sparse, while they were more linked and complex in the YRDUA; (3) polycentric network structure has been demonstrated in the urban agglomerations and the spillover effects of central cities varied in intensity and breadth on responding cities and persisted during the lag period. Accordingly, several policy recommendations have been made.

Keywords: housing prices; urban agglomeration; social network analysis; spillover effect; regional heterogeneity

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1. Introduction

In recent years, divergences in China's regional real estate market and soaring housing prices have drawn high attention from the central government. In the Outline of the 14th Five-Year Plan for National Economic and Social Development of the People's Republic of China and the Long-term Objectives for 2035, local governments are required to stabilize land prices, housing prices, and expectations for them by the central government. However, due to the enhancement of China's regional economic connections and the formation of urban agglomeration networks [1], the housing price connection between different cities has increased and become more diversified [2], which is associated with unbalanced and different regional development [3]. The high level of regional variability in China's housing prices can be attributed primarily to a broad urban distribution and regional economic imbalance [4]. Regional housing price fluctuations and spillover effects have had a significant impact on China's national economic development and social stability [1], including regional economy [3], population and labor [4], and entrepreneurship [5]. More importantly, "one-size-fits-all" real estate market regulation policy in the past appeared to have failed. "City-specific policy" and "one-city one-policy" have become the main concepts in real estate market regulation. Actually, the current policies have not resulted in the desired effects: housing prices in some cities are high, while the real estate market is sluggish in others. "City-specific policy" implementation is bottlenecked, and the regulation effect is restricted [3]. Solving this practical problem requires a thorough analysis of the divergence in spatial linkage and spillover effects of housing prices in different regions and determining central cities which have profound effects on the regional real estate market.

In a large number of studies, there is empirical proof of spatial linkages [6–8] as well as spillover effects [9–11] in different regional real estate markets. According to these findings, the linkage relationship between housing prices in cities no longer presents a simple geographical "close neighbor" effect, but rather a very complex multithreaded structure, namely a network [12]. Accordingly, housing price correlation between cities can also be considered as a complex network [13]. China has dozens of urban agglomerations of different development scales, and complicated housing price relationships occur among different regions. Existing attempts in the literature to model the dynamic characteristics of the real estate market include studying the spatial diffusion of centric price changes through single regional or national geographic unit networks, such as Beijing [14], Paris [15], and Seoul [9], but there are few studies that take metropolitan areas as research objectives to address the chain reaction of housing price changes [16]. Additionally, the existing research lacks a comparative analysis of different regional housing markets, so it cannot effectively reveal the dynamic heterogeneity and describe the diverse characteristics of regional housing markets and test the efficiency of housing price regulation policies.

The purpose of this paper is to develop a comprehensive understanding of the spatial-temporal heterogeneity of housing prices' associations in China's three urban agglomerations, which has not been analyzed previously. The rest of the paper is organized as follows: The second section reviews the research literature, both domestic and international. The third section theoretically analyzes the formation mechanism and spillover effect of the housing price association network in urban agglomeration. The fourth section introduces the research methods and data sources. The fifth section empirically analyzes the spatial-temporal heterogeneity of the housing prices' association networks and explores the spillover effects of central cities in three urban agglomerations. The sixth section is the conclusion and discussion.

2. Literature Review

Spatial correlation and spillover effect of housing prices have always been the academic focus of the spatial attribute of housing prices [3].

In terms of spatial correlation, a previous study has promoted that housing prices are spatial interdependent [17] and autocorrelated [18] between cities. The aggregated distribution of urban housing prices has been demonstrated by a number of studies [6,19,20]. In the real estate market of the United States [21], Paris [22], Taitung City [23], and Singapore [7], there is a spatial aggregation phenomenon and diffusion effect of housing prices in an urban area.

In terms of spillover effects, Drake was the first to prove that there were significant regional differences in housing price changes by comparing housing prices in different regions of the UK in 1995 [24]. Subsequent studies have revealed that there is a spillover effect of housing prices between cities [25]. On the one hand, this can happen between adjacent cities. De La Paz analyzed the characteristics of housing prices in Vega Baja country by applying an SAR-hedonic-based model, and the results showed that housing prices have spatial diffusion in the short distance [26]. Baltagi captured the neighborhood spillover effect of housing price of selling apartments in Paris from 1990 to 2003 by using a spatial lag model [15]. On the other hand, the spillover effect of housing price can extend to separate urban units, where the change in housing prices spreads from the beginning city to its neighboring cities and then to remote areas [27]. Yang et al. investigated how China's real estate boom was transmitted to another local market through spillover effects from 2003 to 2012 and showed that spatial spillover effects existed in both large and dense margins of China's neighboring markets [28].

The above literature has proven that the agglomerated distribution and spillover effect of urban housing prices is a reality that cannot be ignored. Meanwhile, with the profound changes in China's regional economic spatial structure, urban prosperity is gradually blending within urban agglomerations, which become important carriers of spatial structure and economic development [29]. Previous studies on the relationship between urban housing prices mainly focus on national geographical units, with few studying urban agglomerations, and the heterogeneity in the relationship between housing prices in different urban agglomerations lacks research, making it difficult to pinpoint the pattern of regional divergence in housing market development.

Furthermore, as socioeconomic factors such as population, information, money, and means of production continue to flow and concentrate in urban agglomerations, different spatial structures such as monocentric, polycentric, and networked [30] emerge in urban agglomerations. This led to a networked relationship of housing prices in urban agglomerations. Nevertheless, less research has been conducted on the network patterns constituted by housing prices' associations among urban agglomerations, and the social network analysis method is primarily used to analyze the mutual relationship and spatial interaction of urban housing prices between different cities as actors [31]. Drawing on social network analysis, Wang et al. identified that the interaction of housing prices among cities is in the form of a network structure in the Beijing-Tianjin-Hebei region in 2013 [32]. Wu et al. and Fang and Pei used the SNA method to investigate the structural characteristics of spatial correlation networks of housing prices of thirteen cities in China [13,33]. Additionally, Chen et al. and Quan et al. empirically examined the factors influencing the network structure of urban housing prices' associations by using the SNA method and QAP aggression [12,34]. These studies elucidate the connection formed by urban housing prices in urban areas from the perspective of network spatial structure.

Accordingly, existing studies mostly focus on the housing prices' associations within a region or urban agglomeration based on a singular spatial or temporal perspective. Few studies analyze spatial-temporal network relationships of housing prices in different urban agglomerations, consequently unable to reveal developmental divergence in the housing market. To fill this research gap, this paper took the Beijing-Tianjin-Hebei Urban Agglomeration (BTHUA), the Yangtze River Delta Urban Agglomeration (YRDUA), and the Pearl River Delta Urban Agglomeration (PRDUA), which are the most representative and maturely developed urban agglomerations in China, as research objects to investigate the divergent development patterns of housing prices' associations in the spatial-temporal dimension. Therefore, the formation of the housing prices' association network in urban agglomerations is analyzed in this paper, along with the spatial network characteristics, temporal spillover effects, and the determination and examination of central cities in a spillover scenario.

3. The Formation Mechanism of a Housing Price Association Network and Spillover Effect in an Urban Agglomeration

Social networks are a collection of social actors acting as nodes and their associated relationships [35], typically with a complex network structure and attributes. The housing prices' associations in an urban agglomeration share the same networked characteristics. During the process of urban development, regional differences in economic development levels and openness will encourage the flow of factors of production, investment, and trade between cities, and then cause a correlation of regional housing prices' fluctuations [20]. Due to the spatial interactions of housing prices, isolated cities with specific functions and structures essentially merge in the regional area [3]. As cities become more spatially integrated, agglomeration phenomena will intensify, creating a complex housing price association network within the urban agglomeration as the regional carrier. Figure 1 specifically describes the mechanism of formation of a housing price association network and spillover effect in an urban agglomeration.

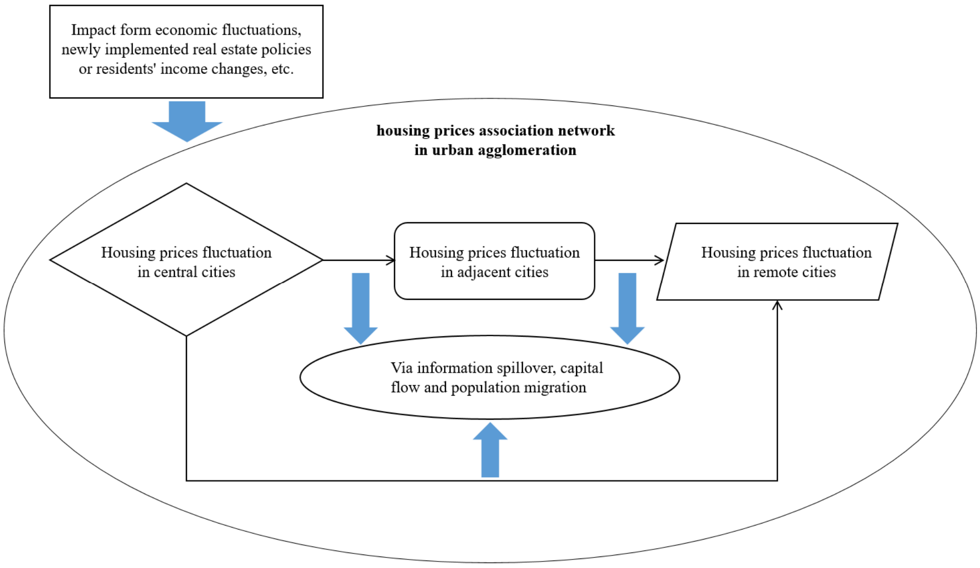

Figure 1. Mechanism of formation of a housing price association network and spillover effect in an urban agglomeration.

In Figure 1, each city is viewed as an actor and, through the continuous flow of capital, labor, and information, each city has economic connections with other cities, which create the spatial interaction of housing prices between cities, forming housing-price-associated relationships between them.

There is a "proximity" effect as well as a "spacing" effect in the spatial interaction of housing prices between cities. Since every city and its relationship to other cities are different and dynamically changed, cities in the network have different positions and roles at a certain time [36]. Therefore, cities serve as diversified nodes, and the spatial interactions between housing prices in cities serve as directed connections. Eventually, cities and their relationships will form a dynamic network for housing price association in an urban agglomeration.

In this complex network, the fluctuations of housing prices in cities can be transmitted to the surrounding areas and other closely linked cities or regions through information spillover, capital flow, and population migration [20], leading to the fluctuation of housing prices in the adjacent cities. Chain reactions of regional housing price diffusion will lead in central cities, while in remote cities, price changes will lag behind, which is the spillover effect of regional housing prices [16]. Therefore, it can be illustrated in the network that when housing prices fluctuate, caused by economic fluctuations, newly implemented real estate policies or residents' income changes, and so on, central cities in the network will react at first, causing housing prices' fluctuations, which will be transmitted to other cities through the connections between cities, resulting in a global spillover effect of housing prices in the network. Accordingly, the following hypothesis is presented:

(1) Compared with a national network in China, the housing prices' associations will form a clustered spatial distribution in urban agglomerations, and this aggregation relationship exists not only between adjacent cities, but also throughout the entire network;
(2) Heterogeneity exists in terms of both spatial structure and spillover effects in different urban agglomerations.
(3) There will be multiple central cities that have significant spillover effects in urban agglomerations due to the increasing and profound associations between cities, and how to determine the central cities is also discussed in this paper.

4. Research Methods and Data Sources

4.1. Determination of Housing Prices' Association in an Urban Agglomeration

Social network analysis (SNA) studies the relationship between actors, so basically, the determination of relationships is particularly important [35]. Generally, two types of models can be used to determine the relationship between actors: the VAR model [12] and the gravity model [37]. However, the VAR model method is too sensitive to the choice of lag order, which affects the accuracy of describing network structure characteristics [38]. It can only describe network relationships for point sections, but cannot describe network relationships for time series, and the gravity model method can compensate for this deficiency.

The gravity model was first applied by Carey to the study of human activities [39]. Later, Zipf introduced the new gravity model into the extensive research in the economic and social fields [40,41]. At present, the gravity model has been widely used in urban network analysis, including urban spatial interaction [42], population and migration [43], transportation [44], business [36], pollution and ecology [45].

Studies of large-scale problems can be analyzed using the gravity model, which can be used to describe quantitative effects in economic activities [46]. Therefore, the gravity model can be used to quantitatively study the spatial interaction strength of housing prices' association between cities. Based on the modifications of the gravity model in previous studies [1,13], this paper constructs a modified gravity model to measure the strength of urban housing prices' association by considering geographical and economic distance between cities, and to be extended by the social network analysis method.

4.2. Measurement of Housing Prices' Association in an Urban Agglomeration

The spatial heterogeneity of the determinants that affect the urban real estate market results in a diversity of market activities and real estate values [47]. Therefore, when measuring the associations of urban housing prices, one has to consider the influence of differences in regional population, economy, and price on spatial interactions between cities, in order to objectively illustrate the heterogeneity of regional housing prices, as well as differences in correlations of housing prices and the dynamic evaluation of urban development.

When measuring the strength of housing prices' associations between cities, the gap between housing prices of sample cities represents the attraction of housing prices and serves as the gravitational coefficient in the gravity model. The permanent resident population at the end of the year, annual gross domestic product (GDP), and annual housing price ratio represent the housing price level, similar to the mass gravity model. The urban proximity is improved as well by this paper. Since urban proximity does not necessarily refer to spatial proximity, other distance measures can be used, such as economic distance [48,49] or social distance [50]. In a regional context, the proximity of one region to another depends on the transport infrastructure. Therefore, the ease of commuting between two regions may be a better indicator of economic interdependence than just physical closeness [27]. Thus, the urban proximity in this paper is composed of both geographical and economic distance. Since the majority of economic exchanges between cities are carried out by land transportation, the geographical distance is represented by the shortest geographical distance between cities. The economic distance is represented by the difference of annual growth rate of per capita GDP between cities, in order to reduce the unbalanced impact of accumulated economic aggregates. Combining the above factors, the association of urban housing prices can be quantitatively measured by a modified gravity model, and the variables are described as follows:

$$X_{ij} = k_{ij} \frac{\sqrt[3]{P_i G_i R_i} \times \sqrt[3]{P_j G_j R_j}}{{D^2}_{ij}} \quad (1)$$

$$k_{ij} = \frac{P_i}{P_i + P_j} \tag{2}$$

$$D^2{}_{ij} = d^2{}_{ij} \times \left(g_i - g_j\right)^2 \tag{3}$$

Among them, X_{ij} represents the strength of housing prices' association of city I to city j. P_i and P_j represent housing prices of city i and city j. G_i and G_j represent the annual GDP of city i and city j. R_i and R_j represent the year-end resident population of city i and city j. D_{ij} represents the distance between cities i and city j, including geographical and economic distance. d_{ij} represents the minimum number of kilometers between city i and city j. g_i and g_j represent the annual growth rate of per capita GDP of cities i and city j. Variables are presented in detail in Table 1. According to the above formula, the value of housing prices' association of cities in the sample urban agglomerations is calculated.

Table 1. Variables in the modified gravity model.

Variable Name	Meaning of Variables
X_{ij}	X_{ij} represents the strength of housing prices' association of city i to city j
k_{ij}	k_{ij} is the gravity coefficient of housing prices of city i to city j
P_i, P_j	P_i and P_j represent the housing prices of city i and city j, respectively
G_i, G_j	G_i, and G_j represent annual GDP of city i and city j, respectively
R_i, R_j	R_i and R_j represent the total year-end resident population of city i and city j, respectively
D_{ij}	D_{ij} represents the distance between city i and city j
d_{ij}	d_{ij} represents the minimum number of kilometers between city i and city j
g_i, g_j	g_i and g_j represents the per capita gross domestic product growth rates of cities i and city j, respectively

In order to be further analyzed by the SNA method, the value of X_{ij} of cities in each urban agglomeration is processed to be a unique asymmetric matrix every year. Using the network analysis software UCINET, the social network analysis can be divided into three major categories: network characteristics of the overall network and individual network and network diagram, the core-marginal analysis, and the block modeling analysis.

4.3. Measurements of the Spatial Structure of the Housing Prices' Association Network

4.3.1. Overall and Individual Network Structure Characteristics and Network Diagram

The characteristics of the housing prices' association network in an urban agglomeration are generally divided into overall and individual network structure characteristics. The overall network is generally characterized by three parameters of network density, network connectedness, and network efficiency. The individual network is characterized by three parameters of degree centrality, closeness centrality, and betweenness centrality. The measurements of characteristics of the overall network and individual network are presented in Table 2.

Meanwhile, according to the degree centrality of cities, the dynamic network diagram of housing prices' association in each urban agglomeration at different times can be drawn by NETRAW and provide a visual representation of the locations and interconnectedness of cities in the network. Larger scope of the nodes shows a greater degree centrality, and increasing the size of the nodes demonstrates greater centrality and a greater impact on other cities in the agglomeration in terms of housing prices.

Table 2. Measurements of network structure.

Measurements for Overall Network Characteristics			
Parameters	Network Density	Network Connectedness	Network Efficiency
Purpose	Reflect the density degree of the network	Reflect the robustness and vulnerability of the network	Reflect the connection efficiency of the network
Formula	$D = \frac{L}{N \times (N-1)}$	$C = 1 - \left(\frac{V}{\frac{N \times (N-1)}{2}} \right)$	$E = 1 - \frac{M}{\max(M)}$
Variable interpretation	D: Network density; N: Number of nodes in the directed network; L: Actual number of associations among nodes	C: Network connectedness; V: Logarithm of the unreachable points in the network	E: Network efficiency; M: Number of redundant connections in the network; Max (M): Maximum number of redundant connections in the network
Measurements for Individual Network Characteristics			
Parameters	Degree Centrality	Closeness Centrality	Betweenness Centrality
Purpose	Reflect the central degree of cities in the network	Reflect the degree to which cities are not controlled by other cities in the network	Reflect the degree of control of the linkage between other cities
Formula	$C_{AD} = \frac{C_1 + C_2}{2N - 2}$	$C_{AP}^{-1} = \sum_{j=1}^{N} t_{ij}$	$C_{RB} = 2 \sum_{j}^{N} \sum_{k}^{N} \frac{b_{jk}(i)}{N^2 - 3N + 2}$
Variable interpretation	C_{AD}: Centrality degree C_1: Outdegree C_2: Indegree	C_{AP}^{-1}: Closeness degree t_{ij}: Number of lines contained in the shortcut distance between node i and j	C_{RB}: Betweenness degree $b_{jk}(i)$: The ability of node i to control the communication between node j and node k $g_{jk}(i)$: Number of shortcuts between nodes j and node k that exist through the third node i

4.3.2. Core-Marginal Analysis

According to the core-marginal analysis, cities in the urban agglomeration are categorized into core and marginal cities. Core cities greatly influence housing prices in other areas, whereas cities in the margins are subordinated, unable to affect the network, and in turn are greatly influenced by the core cities.

4.3.3. Block Model Analysis

The block model analysis, based on the CONCOR clustering method and the role of different blocks in the network, can reveal and depict the internal structure state of the housing prices' association network in an urban agglomeration from dimensions such as the number, composition, and relationship in clusters [51].

Cities in an urban agglomeration are classified into four types of blocks based on their role position in the block model: (1) Spillover block. Cities in this block generate more spillover relations to cities in other blocks than receive spillover relations from them and generate less spillover relations to internal cities. Thus, cities in this block have the most competitive influence in a spillover scenario so they are considered to be central cities in the urban agglomeration. (2) Broker block. Cities in this block generate as much spillover relations to cities in other blocks as receive spillover relations from them, but few spillover relations are generated internally. (3) Bidirectional spillover block. Cities in this block generate more spillover relations to both internal and external cities. (4) Beneficial block. Cities in this block receive more spillover relations from cities in other blocks than generate spillover relations to them.

4.4. Measurements of the Spillover Effect of the Housing Prices' Association: Generalized Impulse Response Function

The impulse response function (IRF) describes the response of a variable to the impact of a unit change from another variable, which can more directly reflect the dynamic interaction between the variables and their effects. The IRF method has been widely adopted in recent studies on the associations between economic variables in housing prices. By establishing an IRF analysis with a lag of ten years, Liu and Ren observed the heterogeneity between cities with high and low housing prices to income ratios [52]. In a study by He et al., an IRF analysis with twelve lagging periods has been performed to study the dynamic movements in housing prices, interest rates, bank credit, mortgages, and real estate development loans [53]. Duan et al. traced the responses of housing prices over ten periods to a one standard deviation shock in money supply, mortgage rates, and inflation by an IRF method [54].

The Cholesky decomposition method proposed by Sims is the most commonly used method [55], but the results estimated by the Cholesky decomposition primarily depend on the ranking relationship of variables. Therefore, this paper uses the generalized impulse response function (GIRF) method proposed by Pesaran and Shin [56] for the analysis. The results obtained by this method are unrelated to the variable ranking, so it is more reliable [57]. Recent studies on the dynamic association between housing prices and economic factors have also confirmed the reliability and applicability of the GIRF method [58–63].

The linear error correction equations for housing prices fluctuations in the sample cities over T time are as follows:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B x_t + \varepsilon_t \tag{4}$$

where y_t is the vector of the time series variables as $y_{1t}, y_{2t}, \ldots, y_{kt}$. $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ are the lag vector of phase 1 to phases p of y_t. x_t is the d-dimensional exogenous variable vector. $A_1, A_2, \ldots, A_p$ are the coefficient matrix of k by k. B is the coefficient matrix of k by d. t is the K-dimensional perturbation vector.

If Equation (4) is stationary, the following equation is obtained:

$$y_t = \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \ldots + \Psi_p \varepsilon_{p-t} + \ldots \tag{5}$$

where $\Psi_p = (\Psi_{p,ij})$ is the coefficient matrix, $\Psi_{o,ij}, \Psi_{1,ij}, \ldots, \Psi_{p,ij}$ is the impulse response function to y_j.

Impulse cities, responding cities, and the number of lag periods need to be carefully considered when analyzing the housing prices' spillover effects using the GIRF method.

Firstly, based on the dynamics of the housing prices' association network and the spillover effect of central cities in an urban agglomeration, cities in the spillover block are considered impulse cities, and the other cities are considered as responding cities to measure the spillover effect of housing prices in an urban agglomeration.

Secondly, for the choice of the number of lag periods, short-term observations have been shown to be valid in empirical studies of housing prices' dynamics based on GIRF. Zhen et al. constructed a GIRF model with different lag periods to investigate the long-term contagion mechanism of real estate bubbles. The results indicate that the model with a 6-year lag period performs the best [58]. By adopting a GIRF method of an 8-lag period, Chien estimated the long-run relationship between global liquidity and housing prices in both advanced and developing economies [59]. Wang et al. used GIRF to analyze the response of macroeconomic variables over periods 1 to 12 under the impact of a positive shock by housing prices' fluctuation [60]. Han constructed a GIRF with a lag period of 10 to investigate the dynamic response of household loan interest rate and household loan to unit changes in housing prices [61]. In an analysis of the impulse response of consumer demand to housing prices by Zhang and He, a GIRF model was constructed with a lag period of 13 years [62]. By using a GIRF model with a lag period of 10 years, Jeong explores the dynamic interactions between the Greek real estate and stock markets [63].

Therefore, short lag periods will be considered in this study in order to examine the spillover effect of housing prices' fluctuations from impulse cities to responding cities in three urban agglomerations.

4.5. Data Sources

By using the modified gravity model, the social network analysis method, and the impulse response function above, this paper takes the BTHUA, the YRDUA, and the PRDUA as the research objects to investigate the spatial-temporal heterogeneity of housing prices' association in an urban agglomeration from 2010 to 2020. The annual GDP, total year-end resident population, and per capita GDP growth rates of cities were compiled by the National Statistical Yearbook of China. The minimum number of kilometers between cities were geographically measured by Gaode Map. In order to fully reflect the real situation of urban housing prices, transaction commodity housing prices data were used as housing prices of cities from the Anjuke Database, which contains comprehensive data on China's macro and micro real estate markets. The unit of housing prices was one RMB per square meter; the unit of GDP was one billion RMB; the unit of population size was ten thousand people; the unit of geographical distance was one kilometer. To eliminate the heteroscedasticity effect of data, the above variables were logarithmic.

5. Results

5.1. Strength of Housing Prices' Associations in the Urban Agglomerations

Figure 2 shows the arithmetic mean of housing prices' association strength in sample urban agglomerations from 2010 to 2020. Generally speaking, urban housing prices were becoming more closely correlated, of which the strength value reached the highest in 2019 (2.48 of the PRDUA, 2.54 of the YRDUA, and 2.51 of the BTHUA), indicating that urban housing prices were increasingly aggregated regionally. Whereas, in 2020, the all-round association strength declined, which may have been due to the shock of the national property market caused by COVID-19 and the adjustment of national policies on the housing market in 2020, which inhibited the rapid growth of housing prices and weakened the attraction of housing prices between cities. Specifically, the strength value in the PRDUA was generally higher than that in the BTHUA and YRDUA, proving a strong attraction effect of housing prices among cities, probably due to the growing population size and industrial clusters in the past ten years in the PRDUA, and led to stronger intercity economic linkages. The growth rate of the strength value in the YRDUA was relatively stable, while it fluctuated more in the BTHUA, which dropped significantly in 2011, 2015, and 2018, showing an unstable attraction relationship of housing prices among cities.

Figure 3 specifically demonstrates the association strength of every city in each urban agglomeration from 2010 to 2020. The higher the value, the stronger the association of housing prices to cities in the urban agglomeration. The strength distribution in the YRDUA was fairly uniform, and the proportion of cities with higher association strength was rising significantly, while in the BTHUA and the PRDUA, it was increasing slowly, and the strength distribution was obviously divergent. In particular, Beijing, Tianjin (in the BTHUA), Guangzhou, and Shenzhen (in the PRDUA) had considerably higher strength values than other cities within their urban agglomeration did, thus, their housing prices were more connected with other cities'. The explanation might be the imbalanced spatial distribution of housing prices, poor coordination, and unobvious development effects in the real estate market in the BTHUA and the PRDUA.

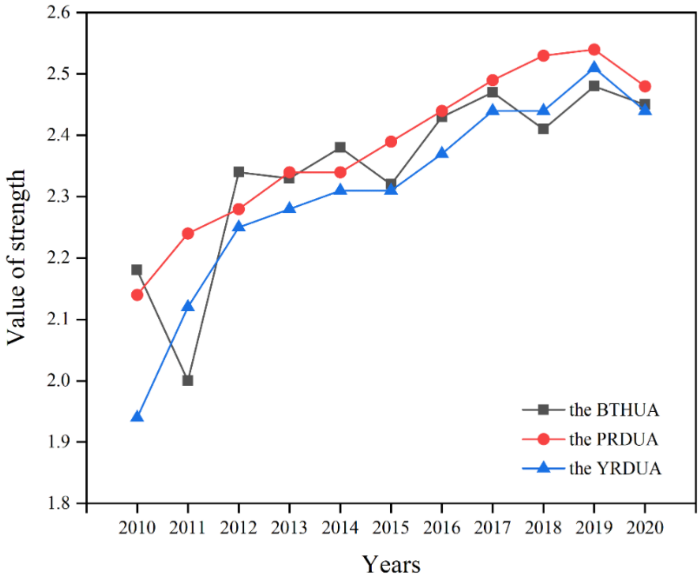

Figure 2. Arithmetic mean of housing prices' association strength in the BTHUA, the PRDUA, and the YRDUA from 2010 to 2020.

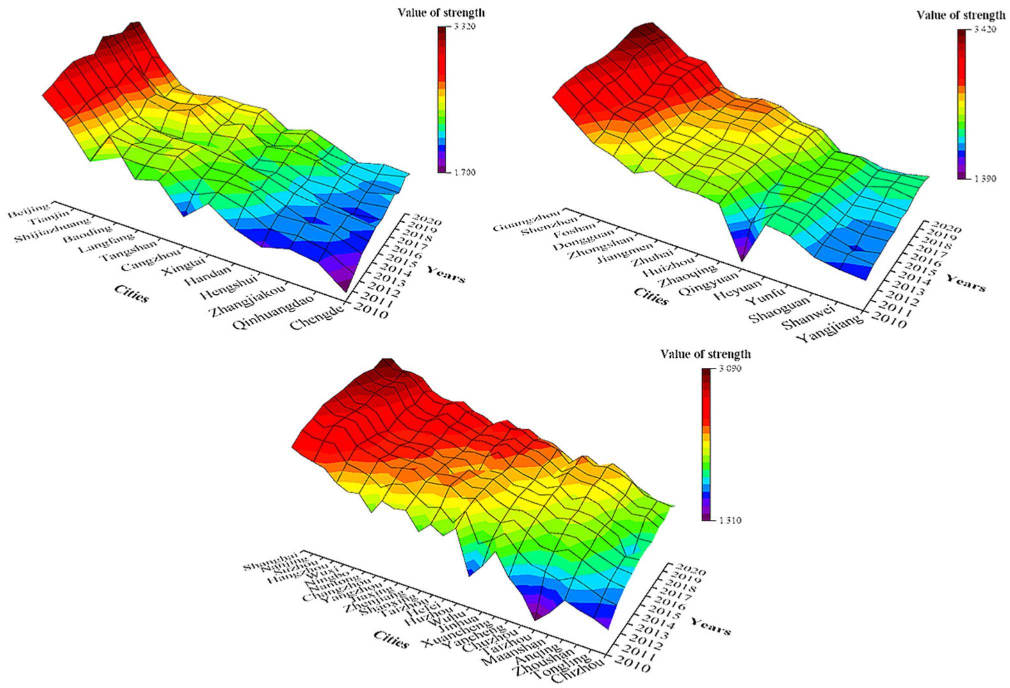

Figure 3. Arithmetic mean of housing prices' association strength in the BTHUA, the PRDUA, and the YRDUA from 2010 to 2020.

5.2. Overall Network Structure

5.2.1. Network Density

As can be seen in Figure 4, the network density for the study period ranged between 0.37 and 0.44, which means that the actual number of relationships between cities accounted for less than 44% of the maximum possible relationships, leaving ample room for more cities in their urban agglomerations to be connected. Particularly, the density value of the BTHUA fluctuated greatly. Furthermore, the density value of the YRDUA dropped from 0.44 to 0.427 from 2012 to 2019, meaning that the network was being gradually evacuated. The density value of the PRDUA dropped from 0.419 to 0.345 from 2015 to 2017 before flattening out, but generally was lower than that of the other two urban agglomerations.

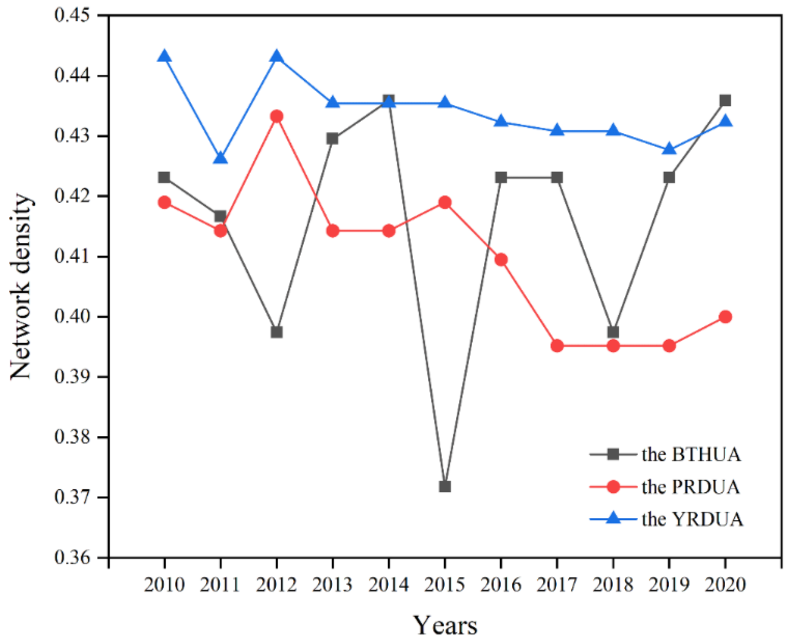

Figure 4. Network density of the housing prices' association network in the BTHUA, the PRDUA, and the YRDUA from 2010 to 2020.

5.2.2. Network Efficiency

As shown in Figure 5, overall, the YRDUA had a network efficiency value lower than that of the other two urban agglomerations, suggesting redundant connections and stability in the network. The reason behind this may be that the proportion of cities with strong connectivity in the YRDUA was higher than that in BTHUA and PRDUA, so as to provide a network with adequate connectivity and stability, such as Shanghai, Hangzhou, Ningbo, and Zhuhai, while fewer cities had strong housing price attraction abilities in the BTHUA and PRDUA.

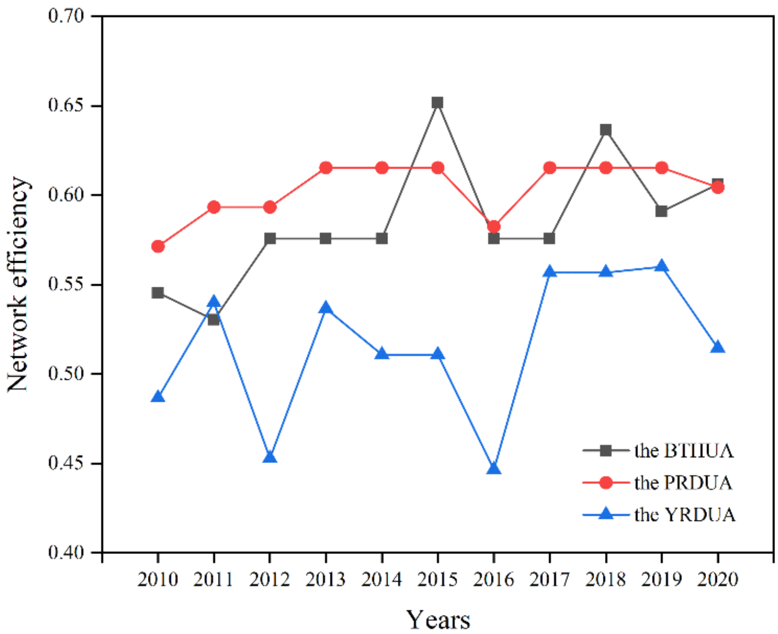

Figure 5. Network efficiency of housing prices' association network in the BTHUA, the PRDUA, and the YRDUA from 2010 to 2020.

5.3. Individual Network Structure

5.3.1. Degree Centrality and Network Diagram

Figure 6 shows the centrality degree of cities in sample urban agglomerations from 2010 to 2020. The distribution of degree centrality varies significantly among the cities. The YRDUA has a smoother distribution of the centrality degree among cities than the BTHUA and the PRDUA. Among the cities with a high centrality degree were Beijing, Tianjin (in the BTHUA), Guangzhou, and Shenzhen (in the PRDUA), and Shanghai, Nanjing, Suzhou, Hangzhou (in the YRDUA), proving that they were the core of the housing prices' network in the urban agglomeration. As well as being able to affect the housing prices of other cities, these cities were also able to accept their attractions. Apart from the above cities, most other cities had a relatively low centrality degree, showing weak influence on other cities, and they were easily influenced by the cities with high centrality degrees.

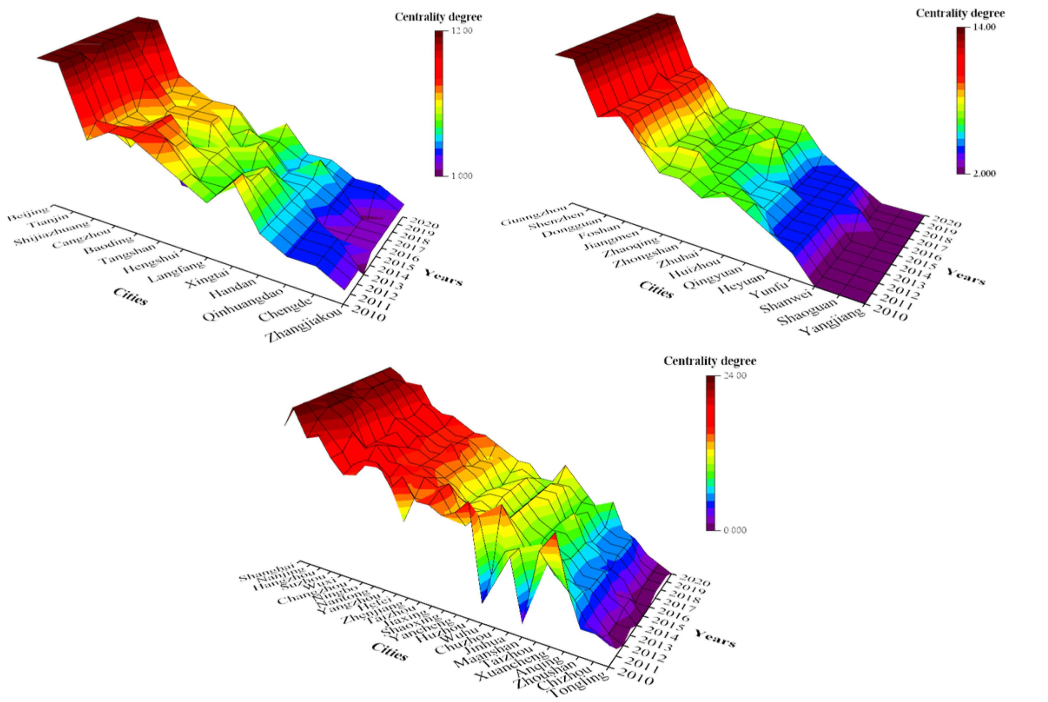

Figure 6. Cities' centrality degrees of the housing prices' association network in the BTHUR (**upper left**), the PRDUR (**upper right**), and the YRDUR (**bottom**) from 2010 to 2020.

On the basis of the centrality degree of each city, a network diagram of urban agglomerations from 2010 to 2020 was able to be created (Figure 7), providing a graphic representation of the dynamic network structure. This paper took a diagram of sample urban agglomerations in 2010, 2015, and 2020 as examples, which can be seen in Figure 6. The larger the node, the higher its degree centrality, and the arrow represents the association direction of housing prices between cities. In general, the BTHUA, the PRDUA, and the YRDUA all formed cluster distributions and were more aggregated within the entire network. Specifically, in the BTHUA and the PRDUA, the network structure was relatively evacuated, and the core cities such as Beijing, Tianjin, Guangzhou, and Shenzhen were prominent, while other cities produced a small number of housing price correlations, occupying marginal positions of the networks. Nonetheless, the network in the YRDUA was complex due its large number of cities, and most cities had a high degree centrality as previously analyzed, and few cities were marginal in the network, such as Wuhu, Maanshan, Zhoushan, and Tongling.

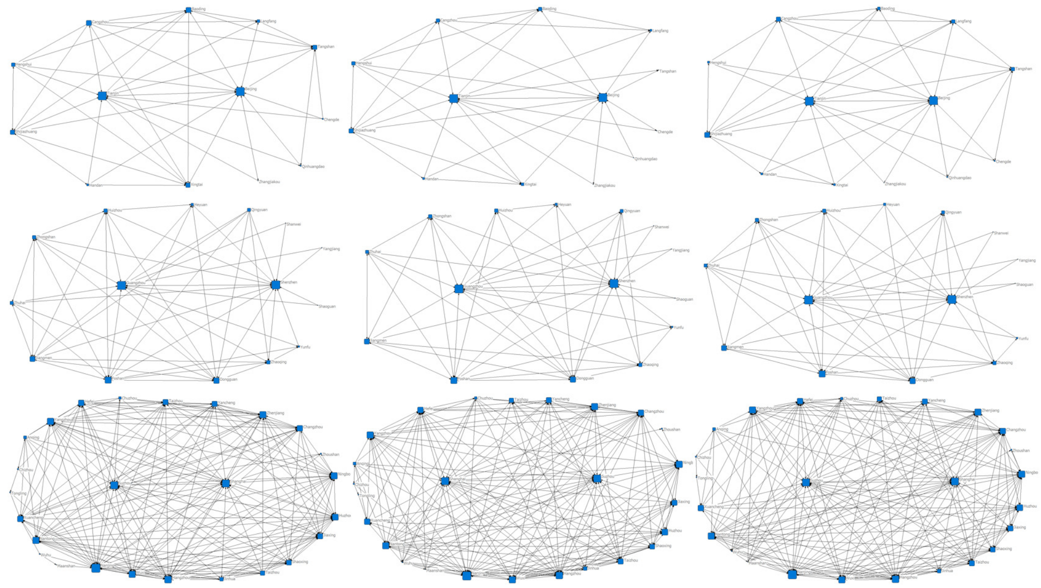

Figure 7. Network diagram of the housing prices' association network of the BTHUR (**top**), the PRDUR (**mid**), and the YRDUR (**bottom**) in 2010, 2015, and 2020 (from left to right).

5.3.2. Closeness Centrality

As it can be seen in Figure 8, even though the closeness degree varied among cities' urban agglomeration, most cities had a high closeness degree, proving that they were able to actively connect to other cities in the network. In particular, Beijing, Tianjin (in the BTHUA), Guangzhou, Shenzhen (in the PRDUA) Shanghai, Nanjing Hangzhou, and Suzhou (in the YRDUA) had a closeness degree higher than that of other cities in their urban agglomeration. This indicated that they had convenient access to other cities and were well-connected in the network.

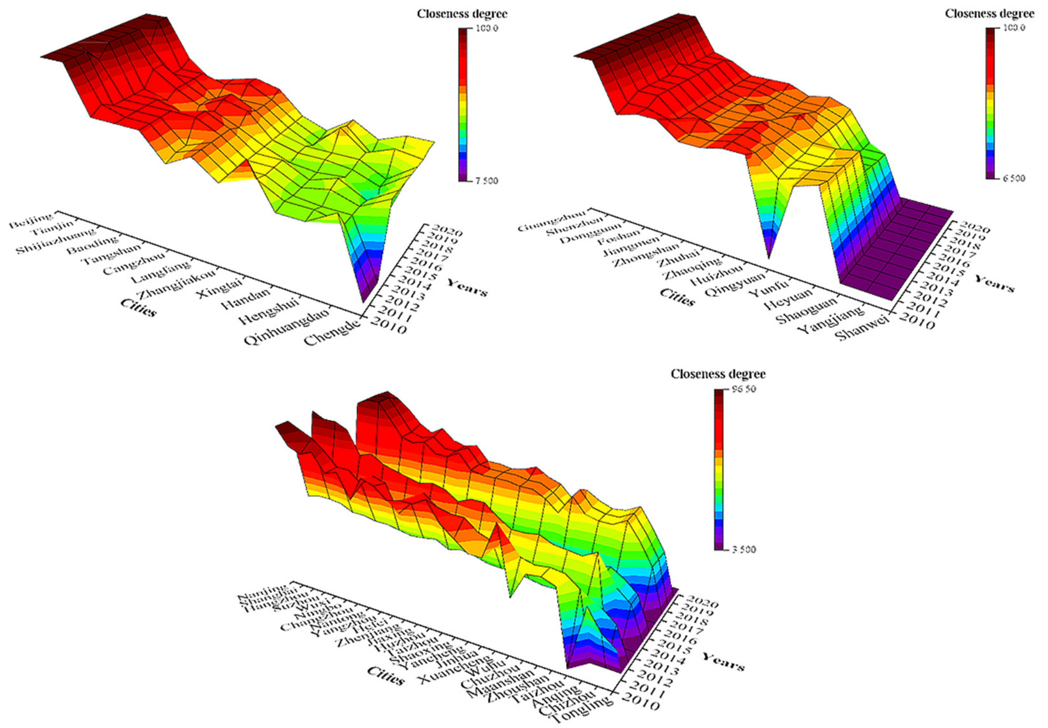

Figure 8. Cities' closeness degree of the housing prices' association network in the BTHUR (**upper left**), the PRDUR (**upper right**), and the YRDUR (**bottom**) from 2010 to 2020.

5.3.3. Betweenness Centrality

In Figure 9, there is a significant uneven distribution of betweenness degree of cities in sample urban agglomerations. Few cities had betweenness degrees higher than those of other cities in the urban agglomeration, such as Beijing (in the BTHUA), Guangzhou (in the PRDUA), and Nanjing (in the YRDUA). Further, these cities served as a bridge and were on the shortcut between other cities, connecting the core and marginal cities, so as to control the housing price associations in the network.

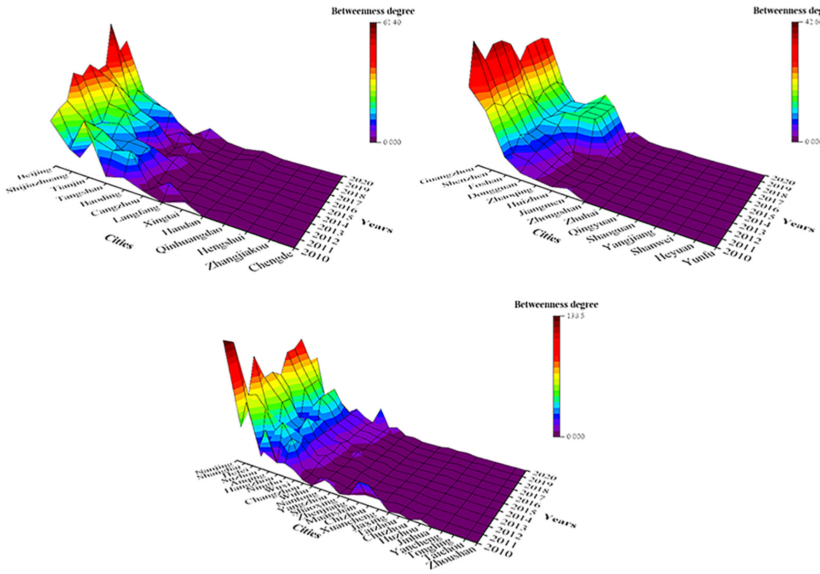

Figure 9. Cities' betweenness degree of the housing prices' association network in the BTHUR (**upper left**), the PRDUR (**upper right**), and the YRDUR (**bottom**) from 2010 to 2020.

5.4. Core-Marginal Analysis

The position of cities in the network can be measured by the core-marginal analysis. As the result show in Tables 3–5, the distribution of core and marginal cities in the three urban agglomerations remained relatively constant during the study period. Some cities were constantly at the core of the network in urban agglomerations, most of which were first-tier cities, with a high level of economic development, good comprehensive strength, and geographical advantages that could dramatically affect the entire housing markets. The rest were on the margin of the network, most of which were underdeveloped areas, with a low level of economic development and housing prices. Plus, the BTHUA had the lowest proportion of core cities of 46%, compared with 60% in the PRDUA and 61% in the YRDUA, meaning that more marginal cities in the BTHUA were affected by fewer core cities.

Table 3. Core-marginal analysis of the housing prices' association network in the BTHUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	√	√	√	√	√	√	√	√	√	√	√
Tianjin	√	√	√	√	√	√	√	√	√	√	√
Shijiazhuang	√	√	√	√	√	√	√	√	√	√	√
Baoding	√	√	√	√	√	√	√	√	√	√	√
Cangzhou				√	√	√	√	√		√	√
Tangshan	√	√	√	√	√		√	√	√	√	√
Langfang				√	√	√	√	√	√	√	√
Hengshui											
Xingtai											
Handan											
Qinhuangdao											
Chengde											
Zhangjiakou											

The √ indicates a core city of the network, otherwise, it is a marginal city.

Table 4. Core-marginal analysis of the housing prices' association network in the PRDUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Guangzhou	√	√	√	√	√	√	√	√	√	√	√
Shenzhen	√	√	√	√	√	√	√	√	√	√	√
Foshan	√	√	√	√	√	√	√	√	√	√	√
Dongguan	√	√	√	√	√	√	√	√	√	√	√
Jiangmen	√	√	√	√	√	√	√	√	√	√	√
Zhongshan	√	√	√	√	√	√	√	√	√	√	√
Zhaoqing	√	√	√	√	√	√	√	√	√	√	√
Zhuhai	√	√	√	√	√	√	√	√	√	√	√
Huizhou	√	√	√	√	√	√	√	√	√	√	√
Qingyuan											
Heyuan											
Yunfu											
Shanwei											
Shaoguan											
Yangjiang											

The √ indicates a core city of the network, otherwise, it is a marginal city.

Table 5. Core-marginal analysis of the housing prices' association network in the YRDUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Shanghai	√	√	√	√	√	√	√	√	√	√	√
Nanjing	√	√	√	√	√	√	√	√	√	√	√
Suzhou	√	√	√	√	√	√	√	√	√	√	√
Hangzhou	√	√	√	√	√	√	√	√	√	√	√
Wuxi	√	√	√	√	√	√	√	√	√	√	√
Changzhou	√	√	√	√	√	√	√	√	√	√	√
Ningbo	√	√	√	√	√	√	√	√	√	√	√
Nantong	√	√	√	√	√	√	√	√	√	√	√
Yangzhou	√	√	√	√	√	√	√	√	√	√	√
Hefei	√		√	√	√	√	√	√	√	√	√
Zhenjiang	√	√	√	√	√	√	√	√	√	√	√
Taizhou	√	√	√	√	√	√	√	√	√	√	√
Shaoxing	√	√	√	√	√	√	√	√	√	√	√
Jiaxing	√	√	√	√	√	√	√	√	√	√	√
Huzhou	√	√	√	√	√	√	√	√	√	√	√
Yancheng	√	√	√	√	√	√	√	√	√	√	√
Wuhu											
Chuzhou											
Jinhua		√									
Taizhou											
Maanshan											
Xuancheng											
Anqing											
Zhoushan											
Chizhou											
Tongling											

The √ indicates a core city of the network, otherwise, it is a marginal city.

5.5. Block Model Analysis

When a maximum split depth of 2 and a convergence standard of 0.2 were set, the block model categorized cities in the urban agglomerations into four blocks: spillover block, broker block, bidirectional spillover block, and beneficial block, from 2010 to 2020.

As shown in Table 6, in the BTHUA, Beijing and Tianjin were in the spillover block during the entire study period, showing an obvious and prolonged spillover effect of housing prices on other cities. Moreover, they were the most economically developed and had the highest housing prices in their urban agglomerations. Xingtai and Handan, which were in the beneficial block for most years, were steadily affected by other cities' housing prices.

Table 6. Results of the block model of a housing prices' association network in the BTHUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	○	○	○	○	○	○	○	○	○	○	○
Tianjin	○	○	○	○	○	○	○	○	○	○	○
Shijiazhuang	○	○	○	○	□	□	□	□	○	○	△
Baoding	□	□	○	○	□	□	□	□	△	○	△
Cangzhou	□	○	□	○	□	△	□	□	□	□	□
Tangshan	□	□	□	○	□	□	□	□	□	□	△
Langfang	□	□	□	□	□	△	△	×	□	□	□
Hengshui	□	□	□	□	×	△	△	×	□	□	□
Xingtai	□	□	□	□	□	△	△	×	□	×	□
Handan	△	△	△	△	△	×	□	△	△	△	△
Qinhuangdao	×	×	×	△	△	×	×	□	△	△	△
Chengde	△	△	△	×	△	×	×	△	×	×	×
Zhangjiakou	×	×	×	×	△	×	×	△	×	×	×

The ○, □, △, × indicate that the city is categorized into the spillover block, broker block, bidirectional spillover block, or beneficial block, respectively.

As shown in Table 7, in the PRDUA, Guangzhou and Shenzhen were constantly in the spillover block during the study period. However, the number of cities in the spillover block decreased from five to two, and the number of cities in the benefit block increased relatively, proving that housing price spillover effects were increasingly centralized by Guangzhou and Shenzhen, and there were fewer cities taking the lead and more cities following the headers in the network.

Table 7. Results of the block model of a housing prices' association network in the PRDUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Guangzhou	○	○	○	○	○	○	○	○	○	○	○
Shenzhen	○	○	○	○	○	○	○	○	○	○	○
Foshan	○	□	○	○	○	□	○	○	○	○	□
Dongguan	○	□	□	□	□	□	○	○	○	○	□
Jiangmen	○	□	□	□	□	□	□	□	□	□	□
Zhongshan	□	□	□	□	□	□	□	□	□	□	□
Zhaoqing	△	□	□	□	□	△	△	△	△	△	△
Zhuhai	□	□	□	□	□	□	□	□	□	□	□
Huizhou	□	□	□	△	△	△	□	△	△	△	□
Qingyuan	×	×	×	△	△	△	△	△	△	△	△
Heyuan	□	△	△	△	△	×	×	×	×	×	×
Yunfu	×	△	△	×	×	×	×	×	×	×	×
Shanwei	×	△	△	×	×	×	×	×	×	×	×
Shaoguan	×	△	△	×	×	×	×	×	×	×	×
Yangjiang	△	×	×	×	×	△	△	×	×	×	×

The ○, □, △, × indicate that the city is categorized into the spillover block, broker block, bidirectional spillover block, or beneficial block, respectively.

Results in Table 8 show that compared to the above urban agglomerations, more cities were in the spillover block in the YRDUA, suggesting that more cities could generate a spillover effect of housing prices on other cities. Among them, Shanghai and Suzhou were always in the spillover block during the research period, showing a dominant position of the network.

Table 8. Results of the block model of a housing prices' association network in the YRDUA from 2010 to 2020.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Shanghai	○	○	○	○	○	○	○	○	○	○	○
Nanjing	○	○	○	○	○	○	○	○	○	○	○
Suzhou	□	○	○	○	○	○	○	○	○	○	○
Hangzhou	○	○	○	○	△	○	○	○	△	○	○
Wuxi	○	○	○	○	△	○	○	△	△	○	○
Changzhou	○	○	○	△	△	△	△	△	△	○	○
Ningbo	○	○	○	○	△	○	○	○	○	○	○
Nantong	□	□	□	□	□	□	□	□	□	□	□
Yangzhou	□	□	□	□	□	□	□	□	□	□	□
Hefei	○	○	○	□	△	□	□	□	□	□	□
Zhenjiang	□	□	□	□	□	□	□	□	□	□	□
Taizhou	□	○	□	□	□	□	□	□	□	□	□
Shaoxing	□	○	□	□	□	□	□	□	□	□	□
Jiaxing	○	○	○	△	△	△	△	△	△	○	○
Huzhou	□	□	□	□	□	□	□	□	□	□	□
Yancheng	□	□	□	△	□	△	△	△	△	△	△
Wuhu	○	○	○	△	△	△	△	△	△	△	△
Chuzhou	○	△	△	△	△	△	△	△	△	△	△
Jinhua	○	○	○	△	△	△	△	△	△	△	△
Taizhou	△	△	△	×	×	△	△	△	△	△	△
Maanshan	×	△	△	△	×	△	△	△	△	△	△
Xuancheng	△	△	△	×	×	△	△	△	△	△	△
Anqing	○	□	△	×	×	△	△	×	×	×	△
Zhoushan	×	×	△	×	×	×	△	×	×	×	×
Chizhou	×	×	×	×	×	×	×	×	×	×	×
Tongling	△	×	×	×	○	×	×	×	×	×	×

The ○, □, △, × indicate that the city is categorized into the spillover block, broker block, bidirectional spillover block, or beneficial block, respectively.

By applying block model analysis, multiple cities were found in the spillover block during the entire study period in each urban agglomeration, which were Beijing, Tianjin (in the BTHUA), Guangzhou, Shenzhen (in the PRDUA), Shanghai, and Suzhou (in the YRDUA). These cities had compelling and prolonged impacts on the housing prices of other cities in their urban agglomerations. Accordingly, these cities were identified as the central cities of their urban agglomerations, proving the polycentricity of the housing prices' association networks.

5.6. Spillover Effect Analysis

The above analysis studied the spatial characteristic of the housing prices' association network of the BTHUA, the PRDUA, and the YRDUA. The following will use the GIRF method to temporally analyze the spillover effect and study the linkage of housing price fluctuation of cities in sample urban agglomerations. Based on the results of the block model analysis, the central cities were considered as the impulse cities, and the remainder as responding cities in the urban agglomeration in this analysis.

Date were processed by STATA software, and data smoothness and the existence of a long-term equilibrium relationship of the time series data were tested by an ADF unit root and cointegration test, respectively. The results showed that the time series data were first-order single integer series, and the housing prices in the sample cities may have had a long-term equilibrium relationship, so the generalized impulse response function could be applied based on its differential series. Considering the choice of the number of lag periods in the long-term equilibrium relationship, in Chien's study on examining the long-term equilibrium relationship between housing prices' volatility and global liquidity shocks, the lag periods of the GIRF model were set to be eight [59]. Wang et al. adopted 12 lag periods in the GIRF model in exploring the long-term relationship between housing prices and economic fundamentals [60]. Additionally, Jeong used a 10-lag period GIRF method to measure the long-term equilibrium relationship and shock response effects of housing prices with economic variables in the stock market [63].

Therefore, under the GIRF method with short-term observations, the number of lags was set from 1 to 11 in this paper to examine the spillover effects and guarantee the reliability of the statistical results.

The results of impulse responses of impulse cities for responding cities of the BTHUA, the PRDUA, and the YRDUA are given below, and the results of the ADF unit root test, the cointegration test, and the error correction model are not repeated. In the following figures, the horizontal axis indicates the number of lags of the spillover effect from impulse cities, and the vertical axis indicates the responding cities.

From Figure 10, the unit impact on Beijing and Tianjin's housing prices could have had a positive impact on most of the responding cities' housing prices, specifically Shijiazhuang, Baoding, and Langfang, which were in the bidirectional spillover block or beneficial block in the long run. Moreover, the impulse response persisted during the lag period from 1 to 11, and the results of Tianjin were less volatile than those of Beijing, but were not as intense.

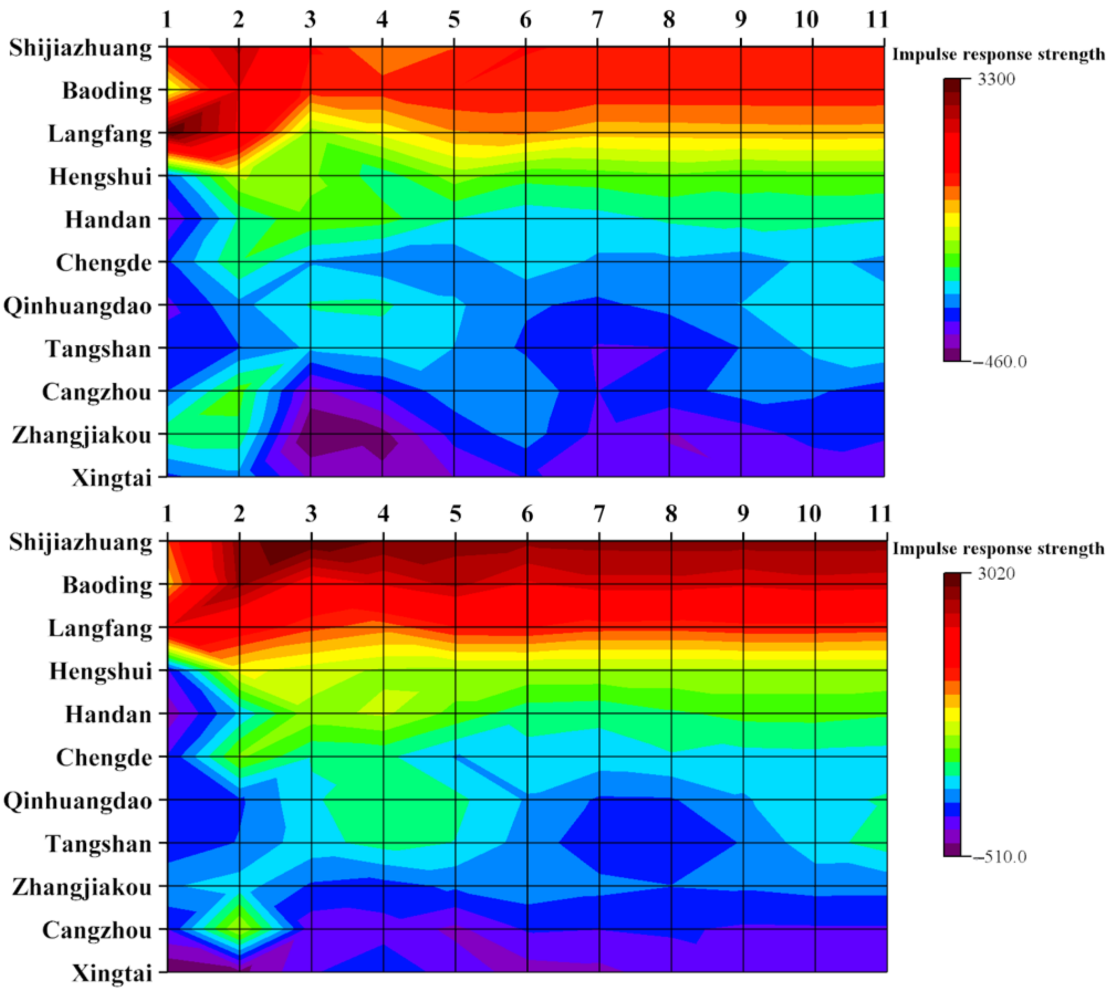

Figure 10. Impulse response results of responding cities caused by a unit impact on Beijing (**top**) and Tianjin (**bottom**) housing prices in the BTHUA.

It can be seen from Figure 11 that the overall intensity and breadth of the impact on responding cities caused by Shenzhen were significantly higher than that of Guangzhou and, except for Heyuan, the unit impact on Shenzhen' housing prices could have had a positive impact on most responding cities from lag period 1 to 11. This indicates that Shenzhen was the dominant city of the housing prices' association network in the PRDUA, while Guangzhou did not assume this role. This may be due to the scarcity of land in Shenzhen over the past ten years, along with higher housing prices and close proximity to neighboring cities, resulting in its significant housing prices' spillover effect, that is, the more scarce the land, the more significant the housing prices' spillover effect [64,65].

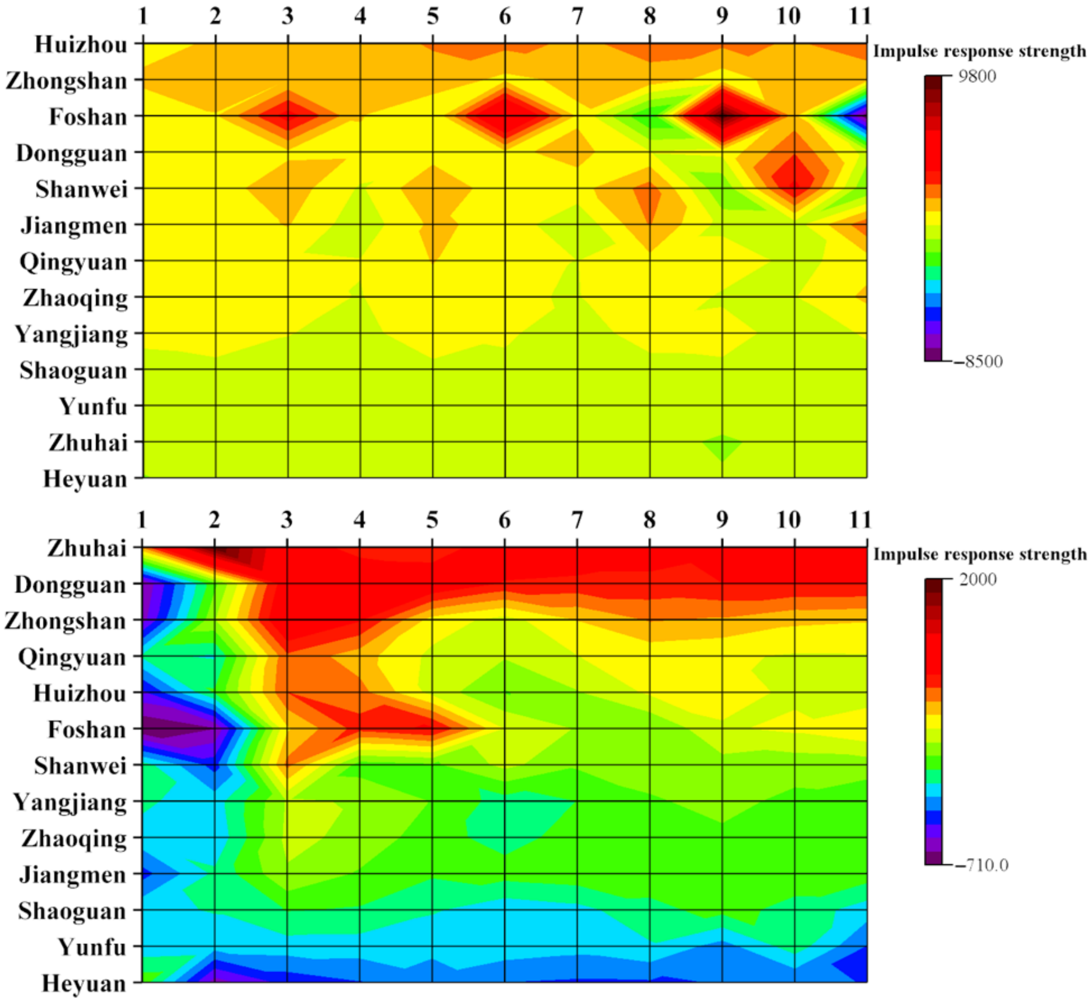

Figure 11. Impulse response results of responding cities caused by a unit impact on Guangzhou (**top**) and Shenzhen (**bottom**) housing prices in the PRDUA.

As shown in Figure 12, the impulse response strength of Shanghai was generally more significant than that of Suzhou, but both were more uniformly distributed among the responding cities compared with the above impulse cities and persisted during the lag period from 1 to 11. Hangzhou reacted remarkably from the spillover effect caused by Shanghai and Suzhou, but other cities did not. Nevertheless, for cities in the beneficial block such as Tongling, Anqing and Chizhou, the strength was low. This may be a result of a high proportion of cities in the YRDUA that had strong spillover effects of housing prices' fluctuations, which is consistent with the results of the block model possibly weakening the overall impulse effects of Shanghai and Suzhou.

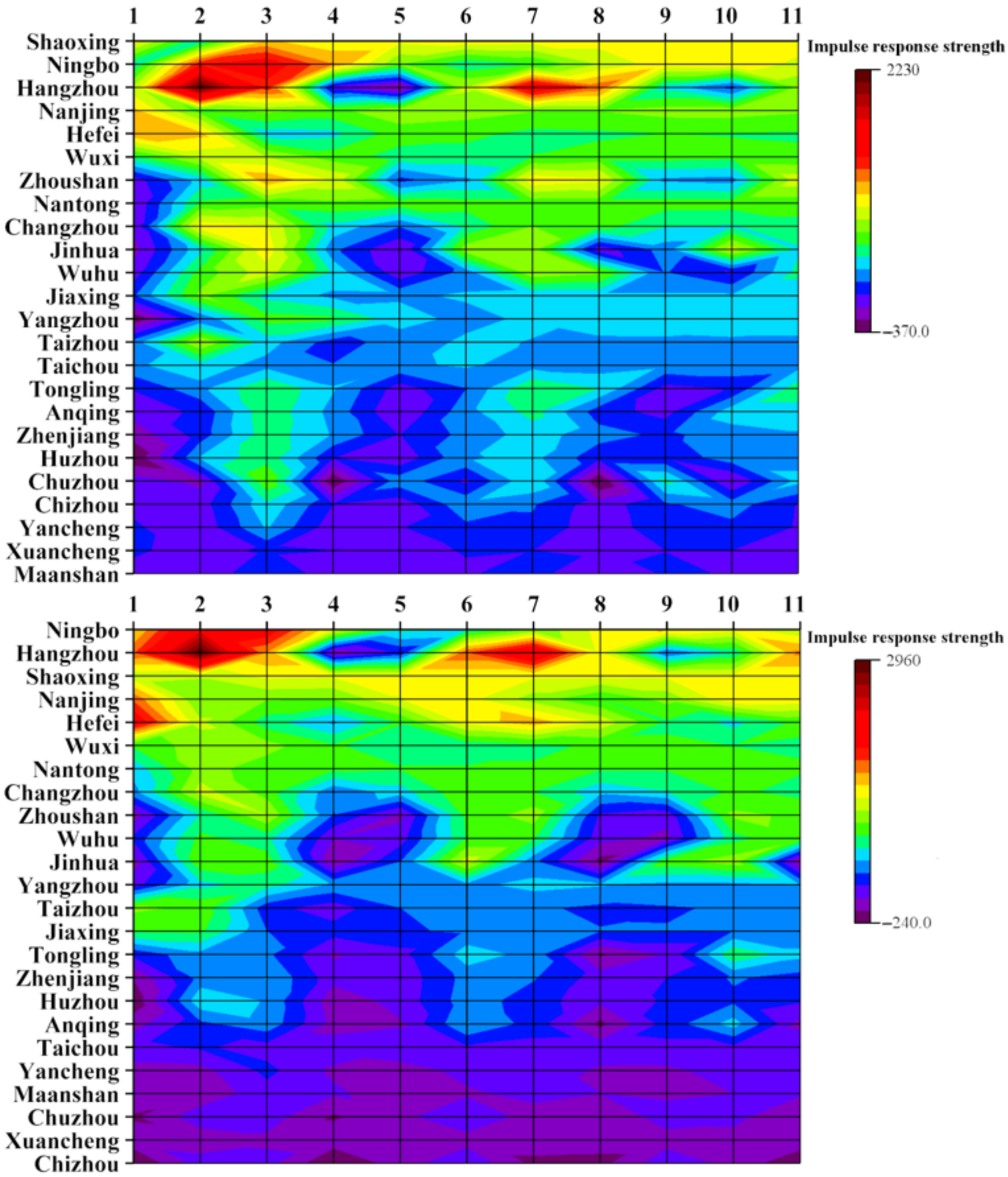

Figure 12. Impulse response results of responding cities caused by a unit impact on Shanghai (**top**) and Suzhou (**bottom**) housing prices in the YRDUA.

The impulse responses caused by central cities in three urban agglomerations did not dissipate quickly, but persisted during the lag period, which is inconsistent with Zhu and Zhang's analysis [20]. This may be because they focused on cities in the national area, without considering the aggregated phenomenon of regional housing prices that stretches and reinforces the association of housing prices in an urban agglomeration. This provides evidence for the aggregated housing prices' associations in the urban agglomerations.

6. Discussion and Conclusions

This paper examines the spatial-temporal heterogeneity of regional housing prices' variation and distribution in three well-developed urban agglomerations in China: the BTHUA, the PRDUA, and the YRDUA from 2010 to 2020.

Compared with previous studies on urban housing prices' associations [6,66], this paper theoretically and empirically investigated the housing price association networks under consideration of the economic distance and spillover effects on the entire network, and measured the characteristics of the overall and individual network in urban agglomerations, aiming to provide the intrinsic laws of the inter-regional spatial-temporal differential distribution and spillover mechanism of housing prices under the background of urban agglomerations. The main findings of this research are as follows.

First, compared with the research on the national geography area [13,33,34], regional housing prices were gradually aggregating in the urban agglomerations. This may be due to the fact that the intensity and speed of information, capital and population flows within urban agglomerations have exceeded that of cross-urban agglomeration units, causing a concentration of regional housing prices. However, the association relationships of housing prices were not sufficient with a relatively low network density, indicating that the connections need to be strengthened further. Owing to the unevenness of capital wealth owned, real estate values and information connectivity between cities, there was heterogeneity in overall and individual network structure of different urban agglomerations. The networks of the BTHUA and the PRDUA were relatively polarized and sparse, of which housing price associations mainly relied on a few core cities and more peripheral cities existing in the network. Nonetheless, the network of the YRDUA was closely connected and complex with obvious trickle-down effects, and most cities had the ability to generate significant associations with other cities.

Second, differently from the previous studies that demonstrated monocentricity for spillover effects of regional housing prices [67,68], a polycentric structure of the network was observed, and central cities in each urban agglomeration were identified by the block model analysis. Plus, the impulse responses on other cities' housing prices caused by central cities showed different characteristics in terms of intensity and breadth, but all persisted in the lag period. In the BTHUA, a unit impact on Beijing and Tianjin's housing prices had a similar positive spillover effect on responding cities, especially cities in the beneficial block. In the PRDUA, the spillover effects caused by Shenzhen's housing prices were more intensive than those of Guangzhou, demonstrating the dominant position of Shenzhen in the PRDUA. The spillover effect of Shanghai and Guangzhou in the YRDUA was not significant, due to the high proportion of cities that had a strong spillover effect of housing prices in the YRDUA. This is attributed to the fact that housing market fluctuations are amplified by the divergent distribution of regional socioeconomic factors [69], which will lead to uneven housing prices' spillover effects among cities.

Among China's three largest urban agglomerations, housing prices are aggregating and the spatiotemporal heterogeneity of the housing prices' association is apparent and more evident than in previous studies of small urban regionals' interactions [15,22,27]. By examining the associations between and within mega-regions, the results could reflect differences in housing prices' fluctuations, economic development and population flow between cities in China's urban agglomerations. The divergent development pattern of housing prices in urban agglomerations will further intensify alongside the rapid urbanization process caused by national economic growth [68] and population migration [70]. Based on the above conclusion, the following policy recommendations are proposed:

First, "one-size-fits-all" real estate regulation policy cannot meet the development needs of China's real estate market. The aggregated phenomena and heterogeneous characteristics of regional housing prices should be taken into account by the state, as well as the "city-specific policy" and the "one-city one-policy" regulation strategy.

Second, governments at all levels should pay adequate attention to the central cities in urban agglomerations. In the event of a rapid and soaring rise in housing prices in central cities, it may lead to synergy in other cities, resulting in an overall excessive rise in housing prices in the entire region, and once confronted with unexpected external shocks, this could trigger a global housing prices' decline. It is therefore crucial to closely monitor the trend and bubbles of housing prices in central cities such as Beijing, Shanghai, and Shenzhen. In the face of unreasonable price increases in central cities, prompt measures should be taken to prevent and reduce the price contagion phenomenon.

Third, local governments should also make greater efforts to establish a reasonable housing prices' system that suits the local supply and demand situation accordingly to the socioeconomic capacities of various cities, especially for marginal cities, and strengthen their connection to the growth of the real estate market in their urban agglomeration to increase the overall stability in the market. To coordinate the local housing market with economic development, the central government is urged to formulate regulations, set policy directions, and prevent excessive fluctuations in the network.

7. Limitations

There are certainly some limitations to this research. Urban housing prices are aggregating regionally, as demonstrated in China's represented urban agglomerations by this paper. However, whether the national urban housing prices' associations share the same characteristics in other urban agglomerations needs further analysis based on larger samples and a longer study period. Additionally, this paper examined the heterogeneity of housing prices' associations in urban agglomerations, but the reasons for the diverse housing markets remain unclear. Further research is suggested to focus on the empirical evidence for the formation of aggregated urban housing prices and the polycentric structure of the network derived from that in order to deeply understand the mechanism of regional divergence of China's real estate market and improve the policy effectiveness accordingly.

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Abbreviations

BTHUA: Beijing-Tianjin-Hebei Urban Agglomeration; YRDUA: Yangtze River Delta Urban Agglomeration; PRDUA: Pearl River Delta Urban Agglomeration; GDP: gross domestic product; SNA: social network analysis; IRF: impulse response function; GIRF: generalized impulse response function.

References

1. Lan, F.; Jiao, C.; Deng, G.; Da, H. Urban Agglomeration, Housing Price, and Space-Time Spillover Effect-Empirical Evidences Based on Data from Hundreds of Cities in China. *Manag. Decis. Econ.* **2021**, *42*, 898–919. [CrossRef]
2. Short, J.R. Black Holes and Loose Connections in a Global Urban Network. *Prof. Geogr.* **2004**, *56*, 295–302.
3. Zhao, Y.; Wei, R.; Zhong, C. Research on Spatial Spillover Effects and Regional Differences of Urban Housing Price in China. *Econ. Comput. Econ. Cybern. Stud. Res.* **2021**, *55*, 211–228. [CrossRef]
4. Lin, X.; Wang, P. Relationship between Rising Housing Prices and Reduction in Urban Agglomeration. *J. Urban Plan. Dev.* **2020**, *146*, 04020031. [CrossRef]
5. Wang, Y.; Hu, F.Z.Y. Housing Market Booms in Chinese Cities: Boon or Bane for Urban Entrepreneurship? *J. Asian Public Policy* **2021**. [CrossRef]
6. Guo, J.; Qu, X. Spatial Interactive Effects on Housing Prices in Shanghai and Beijing. *Reg. Sci. Urban Econ.* **2019**, *76*, 147–160. [CrossRef]
7. Hwang, M.; Quigley, J.M. Housing Price Dynamics in Time and Space: Predictability, Liquidity and Investor Returns. *J. Real Estate Financ. Econ.* **2010**, *41*, 3–23. [CrossRef]

8. Feng, L.; Ying, T. *Study on Commodity Residential House Price Volatility of The Guanzhong Urban Agglomeration Using Spatial Econometric Analysis*; Liang, J., Wu, X., Yang, W., Chen, W., Eds.; Trans Tech Publications Ltd.: Stafa, Zurich, Switzerland, 2014; Volume 638–640, pp. 2436–2441.
9. Kim, L.; Seo, W. Micro-Analysis of Price Spillover Effect among Regional Housing Submarkets in Korea: Evidence from the Seoul Metropolitan Area. *Land* **2021**, *10*, 879. [CrossRef]
10. Weng, Y.; Gong, P. On Price Co-Movement and Volatility Spillover Effects in China's Housing Markets. *Int. J. Strateg. Prop. Manag.* **2017**, *21*, 240–255. [CrossRef]
11. Tsai, I.-C. Spillover Effect between the Regional and the National Housing Markets in the UK. *Reg. Stud.* **2015**, *49*, 1957–1976. [CrossRef]
12. Chen, M.H.; Liu, H.J.; Sun, Y.N.; He, L.W. Empirical Study on the Characteristics of Network Structure and Its Influence Factors of Urban Housing Price Linkage: Based on Monthly Data of 69 Large and Medium Cities in China. *S. China J. Econ.* **2016**, *34*, 71–88. [CrossRef]
13. Wu, G.; Li, J.; Chong, D.; Niu, X. Analysis on the Housing Price Relationship Network of Large and Medium-Sized Cities in China Based on Gravity Model. *Sustainability* **2021**, *13*, 4071. [CrossRef]
14. Zhang, D.; Zhang, X.; Zheng, Y.; Ye, X.; Li, S.; Dai, Q. Detecting Intra-Urban Housing Market Spillover through a Spatial Markov Chain Model. *Isprs Int. J. Geo-Inf.* **2020**, *9*, 56. [CrossRef]
15. Baltagi, B.H.; Bresson, G.; Etienne, J.-M. Hedonic Housing Prices in Paris: An Unbalanced Spatial Lag Pseudo-Panel Model with Nested Random Effects. *J. Appl. Econom.* **2015**, *30*, 509–528. [CrossRef]
16. Grigoryeva, I.; Ley, D. The Price Ripple Effect in the Vancouver Housing Market. *Urban Geogr.* **2019**, *40*, 1168–1190. [CrossRef]
17. Chica-Olmo, J.; Cano-Guervos, R.; Chica-Olmo, M. A Coregionalized Model to Predict Housing Prices. *Urban Geogr.* **2013**, *34*, 395–412. [CrossRef]
18. Barreca, A.; Curto, R.; Rolando, D. Urban Vibrancy: An Emerging Factor That Spatially Influences the Real Estate Market. *Sustainability* **2020**, *12*, 346. [CrossRef]
19. Wang, Y.; Wang, S.; Li, G.; Zhang, H.; Jin, L.; Su, Y.; Wu, K. Identifying the Determinants of Housing Prices in China Using Spatial Regression and the Geographical Detector Technique. *Appl. Geogr.* **2017**, *79*, 26–36. [CrossRef]
20. Zhu, L.; Zhang, H. Analysis of the Diffusion Effect of Urban Housing Prices in China Based on the Spatial-Temporal Model. *Cities* **2021**, *109*, 103015. [CrossRef]
21. Brady, R.R. The Spatial Diffusion of Regional Housing Prices across U.S. States. *Reg. Sci. Urban Econ.* **2014**, *46*, 150–166. [CrossRef]
22. Deutsch, E.; Quettier, A.; Simon, A. District influence in Parisian housing prices formation: Spillover or location? *Rev. Econ. Reg. Urbaine* **2017**, 673–708. [CrossRef]
23. Wang, W.-C.; Chang, Y.-J.; Wang, H.-C. An Application of the Spatial Autocorrelation Method on the Change of Real Estate Prices in Taitung City. *Isprs Int. J. Geo-Inf.* **2019**, *8*, 249. [CrossRef]
24. Drake, L. Testing for Convergence Between UK Regional House Prices. *Reg. Stud.* **1995**, *29*, 357–366. [CrossRef]
25. Clapp, J.; Tirtiroglu, D. Positive Feedback Trading and Diffusion of Asset Price Changes-Evidence from Housing Transactions. *J. Econ. Behav. Organ.* **1994**, *24*, 337–355. [CrossRef]
26. de la Paz, P.T.; Lopez, E.; Juarez, F. Ripple Effect on Housing Prices. Evidence from Tourist Markets in Alicante, Spain. *Int. J. Strateg. Prop. Manag.* **2017**, *21*, 1–14. [CrossRef]
27. Holly, S.; Pesaran, M.H.; Yamagata, T. The Spatial and Temporal Diffusion of House Prices in the UK. *J. Urban Econ.* **2011**, *69*, 2–23. [CrossRef]
28. Yang, X.; Zhang, Y.; Li, Q. The Role of Price Spillovers: What Is Different in China. *Empir. Econ.* **2021**, *60*, 459–485. [CrossRef]
29. Fang, C.; Yu, D. Urban Agglomeration: An Evolving Concept of an Emerging Phenomenon. *Landsc. Urban Plan.* **2017**, *162*, 126–136. [CrossRef]
30. Li, G. Study on the Spatial Effect of Economic Growth on the Price of Real Estate—Re-examination from the Perspective of Urban Agglomeration. *Mod. Manag.* **2022**, *42*, 29–33. [CrossRef]
31. Yan, J.; Haffner, M.; Elsinga, M. Embracing Market and Civic Actor Participation in Public Rental Housing Governance: New Insights about Power Distribution. *Hous. Stud.* **2021**, *37*, 435–458. [CrossRef]
32. Wang, Q.H.; Cheng, L.F.; Zhang, F.Q. Research on the Network Structure of Housing Price Interaction in Beijing-Tianjin-Hebei Region. *Areal Res. Dev.* **2019**, *38*, 51–56. [CrossRef]
33. Fang, D.C.; Pei, M.D. The Empirical Analysis of the Spatial Correlation Network Structure of Housing Price. *Shanghai J. Econ.* **2018**, 63–73. [CrossRef]
34. Quan, S.F.; Fan, S.T.; Ma, J.; Zhang, X.Q. Spatial Correlation and Explanation of Housing Prices in 35 Large and Medium-sized Chinese Cities. *Stat. Decis.* **2020**, *36*, 104–108. [CrossRef]
35. Knoke, D.; Yang, S. Social Network Analysis. *Encycl. Soc. Netw. Anal. Min.* **2008**, *22*, 109–127. [CrossRef]
36. Matsumoto, H.; Domae, K.; O'Connor, K. Business Connectivity, Air Transport and the Urban Hierarchy: A Case Study in East Asia. *J. Transp. Geogr.* **2016**, *54*, 132–139. [CrossRef]
37. Liu, H.J.; Liu, C.M.; Sun, Y.N. Spatial Correlation Network Structure of Energy Consumption and Its Effect in China. *China Ind. Econ.* **2015**, *5*, 83–95. [CrossRef]
38. Yang, G.Y.; Wu, Q.; Xu, Y. Researches of China's Regional Carbon Emission Spatial Correlation and Its Determinants: Based on the Method of Social Network Analysis. *J. Bus. Econ.* **2016**, *4*, 56–68. [CrossRef]

39. Carey, H.C. Principle of Social Science. In *The History of Economic Thought Books*; Kessinger Publishing, LLC: Whitefish, MT, USA 2004.
40. Zipf, G.K. The P(1)p(2)/D Hypothesis: The Case of Railway Express. *J. Psychol.* **1946**, *22*, 3–8. [CrossRef]
41. Zipf, G.K. The P1 P2/D Hypothesis: On the Intercity Movement of Persons. *Am. Sociol. Rev.* **1946**, *11*, 677–686. [CrossRef]
42. De, T.; Tao, L.; Guicai, L.; Lei, Y. Empirical Analysis of City Contact in Zhujiang (Pearl) River Delta, China. *Chin. Geogr. Sci.* **2014**, *24*, 384–392. [CrossRef]
43. Zhao, J.; Peng, Z.; Liu, L.; Yu, Y.; Shang, Z. Public Space Layout Optimization in Affordable Housing Based on Social Network Analysis. *Land* **2021**, *10*, 955. [CrossRef]
44. Matsumoto, H. International Urban Systems and Air Passenger and Cargo Flows: Some Calculations. *J. Air Transp. Manag.* **2004**, *10*, 239–247. [CrossRef]
45. Wanghe, K.; Guo, X.; Wang, M.; Zhuang, H.; Ahmad, S.; Khan, T.U.; Xiao, Y.; Luan, X.; Li, K. Gravity Model Toolbox: An Automated and Open-Source ArcGIS Tool to Build and Prioritize Ecological Corridors in Urban Landscapes. *Glob. Ecol. Conserv.* **2020**, *22*, e01012. [CrossRef]
46. Lukermann, F.; Porter, P. Gravity and Potential Models in Economic-Geography. *Ann. Assoc. Am. Geogr.* **1960**, *50*, 493–504. [CrossRef]
47. Meen, G. Regional House Prices and the Ripple Effect: A New Interpretation. *Hous. Stud.* **1999**, *14*, 733–753. [CrossRef]
48. Conley, T.G. GMM Estimation with Cross Sectional Dependence. *J. Econom.* **1999**, *92*, 1–45. [CrossRef]
49. Pesaran, M.H.; Schuermann, T.; Weiner, S.M. Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model. *J. Bus. Econ. Stat.* **2004**, *22*, 129–162. [CrossRef]
50. Conley, T.G.; Topa, G. Socio-Economic Distance and Spatial Patterns in Unemployment. *J. Appl. Econom.* **2002**, *17*, 303–327. [CrossRef]
51. Wang, X.W.; Liu, Z.Y.; Luan, C.J.; Liang, Y.X. Analysis of SSCI Human Geography Journals. *Acta Geogr. Sin.* **2009**, *64*, 243–252. [CrossRef]
52. Liu, C.Q.; Ren, L. Urbanization, Housing Price and Urban-Rural Income Gap. *Rev. Econ. Manag.* **2021**, *37*, 58–69. [CrossRef]
53. He, X.; Cai, X.-J.; Hamori, S. Bank Credit and Housing Prices in China: Evidence from a TVP-VAR Model with Stochastic Volatility. *J. Risk Financ. Manag.* **2018**, *11*, 90. [CrossRef]
54. Duan, J.; Tian, G.; Yang, L.; Zhou, T. Addressing the Macroeconomic and Hedonic Determinants of Housing Prices in Beijing Metropolitan Area, China. *Habitat Int.* **2021**, *113*, 102374. [CrossRef]
55. Sims, C. Macroeconomics and Reality. *Econometrica* **1980**, *48*, 1–48. [CrossRef]
56. Pesaran, H.H.; Shin, Y. Generalized Impulse Response Analysis in Linear Multivariate Models. *Econ. Lett.* **1998**, *58*, 17–29. [CrossRef]
57. Wang, S.T.; Yang, Z.; Liu, H.Y. An empirical study of the interaction between urban house prices in China's regional markets. *Res. Financ. Econ. Issues* **2008**, 122–129. [CrossRef]
58. Zheng, T.G.; Gong, J.J.; Song, T. The Measurement of Urban Housing Price Bubbles in China and Its Time-Varying Contagion Effects. *J. World Econ.* **2021**, *44*, 151–177.
59. Chien, M.-S.; Liu, S.-B. The Impacts of Global Liquidity on International Housing Prices. *IJHMA* **2022**. [CrossRef]
60. Wang, J.; Xia, B.; Qiao, H. Time-Varying Impact of Housing Price Fluctuations on Banking Financial Risk. *Manag. Decis. Econ.* **2022**, *43*, 457–467. [CrossRef]
61. Han, G.-S. The Dynamic Relationship between Household Loans of Depository Institutions and Housing Prices after the Financial Crisis. *Inst. Manag. Econ Res.* **2020**, *11*, 189–203. [CrossRef]
62. Zhang, H.L.; He, Y.Y. Research on the Impact of Retail Consumer Finance Development on China's Economic Internal Circulation. *Econ. Rev. J.* **2021**, 121–128. [CrossRef]
63. Jeong, D.-B. A Dynamic Study on Housing and Stock Market in Europe: Focused on Greece. *East Asian J. Bus. Econ.* **2020**, *8*, 57–69. [CrossRef]
64. Vansteenkiste, I. Regional Housing Market Spillovers in the US: Lessons from Regional Divergences in a Common Monetary Policy Setting. *Soc. Sci. Electron. Publ.* **2021**. [CrossRef]
65. Vansteenkiste, I.; Hiebert, P. Do House Price Developments Spillover across Euro Area Countries? Evidence from a Global VAR. *J. Hous. Econ.* **2011**, *20*, 299–314. [CrossRef]
66. Zhang, D.; Fan, G.-Z. Regional Spillover and Rising Connectedness in China's Urban Housing Prices. *Reg. Stud.* **2019**, *53*, 861–873. [CrossRef]
67. Hu, J.; Xiong, X.; Cai, Y.; Yuan, F. The Ripple Effect and Spatiotemporal Dynamics of Intra-Urban Housing Prices at the Submarket Level in Shanghai, China. *Sustainability* **2020**, *12*, 5073. [CrossRef]
68. Gross, J.; Ouyang, Y. Types of Urbanization and Economic Growth. *Int. J. Urban Sci.* **2021**, *25*, 71–85. [CrossRef]
69. Li, X.; Kao, C. Spatial Analysis and Modeling of the Housing Value Changes in the U.S. during the COVID-19 Pandemic. *J. Risk Financ. Manag.* **2022**, *15*, 139. [CrossRef]
70. Guo, Y.; Qiao, W. Rural Migration and Urbanization in China: Historical Evolution and Coupling Pattern. *Sustainability* **2020**, *12*, 7307. [CrossRef]

71. National Bureau of Statistics of China. Available online: http://www.stats.gov.cn/tjsj/ndsj/ (accessed on 10 January 2021).
72. National Historical House Prices. Available online: https://www.anjuke.com/fangjia/ (accessed on 10 January 2021).
73. Gaode Map. Available online: https://www.amap.com/ (accessed on 10 January 2021).