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Spatial-temporal analysis of residential housing, office property, and retail property price index correlations: Evidence from ten Chinese cities

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Abstract

Using correlation-based hierarchical analysis and synchronization analysis, this study focuses on monthly price indices for residential homes, office buildings, and retail properties in ten major Chinese cities for the years 2005 to 2021. Through these analyses, one can identify interactions and interdependence among the price indices, heterogeneous patterns in synchronizations of the price indices, and their evolving paths with time. Empirical findings suggest that the degree of real estate price comovements across all property types and cities is relatively low and stable from January 2017 to February 2020, followed by significant increases during the COVID-19 pandemic from March 2020 to January 2021 and significant decreases since February 2021 with the recovery of the economy. Several groups of property types and cities are determined in this study, each of which having its members reveal rather strong but volatile synchronizations of price indices. Rolling importance analysis does not suggest persistent increasing or decreasing trends for the real estate price associated with a specific property type and city. Policy studies on real estate price comovements may benefit from these findings here.

Keywords: Residential housing, Office property, Retail property, Price comovement, Network, Hierarchy

■1.0 INTRODUCTION

For more than ten years, China's real estate markets have experienced rapid growth. Almost everyone is now concerned about real estate prices for a variety of buying and investing goals (Xu and Zhang, 2021a), especially those involving residential, commercial, and retail properties. Thus, price trends and correlations are crucial because they have a direct impact on people's investing choices. A few studies have looked at this issue using the vector autoregression empirical paradigm to investigate contemporaneous or lead-lag causal links between real estate prices across various regional marketplaces. For instance, Yang, Liu, and Leatham (2013) examine residential housing price indices from four cities— Shenzhen, Beijing, Guangzhou, and Shanghai—for the time period of December 2000 to May 2010 in order to investigate their contemporaneous causality using the directed acyclic graph, and they discover that Shanghai's price index is the most significant source of price data. Gong, Hu and Boelhouwer (2016) consider residential housing price indices from Guangzhou, Xiamen, Fuzhou, Shenzhen, Nanchang, Chengdu, Changsha, Kunming, Nanning, and Guiyang for the period of June 2005 – May 2015 for examining their lead-lag causality and find diverged interurban housing markets in the Pan-Pearl River Delta region in China to which the ten cities belong and diffusions of housing price information taking longer to arrive at cities that are further away as compared to those that are nearby. Gong et al. (2016) and Yang et al. (2013)'s studies thus concentrate on a single property type.

According to Xu and Zhang (2023b), different degrees of price comovements across different property kinds and cities are useful indicators of systemic risks in real estate markets. When creating regulations to prevent possible market overheating, policymakers must take into account cross-regional and cross-property reliance as well as its transmission mechanism (Zhang and Fan, 2019). Investors may find it advantageous to optimize their portfolios and diversify their risk when they have a better awareness of the dynamic connections between real estate prices in various locations and property kinds (Antonakakis, Chatziantoniou, Floros and Gabauer, 2018; Xu and Zhang, 2022b).

Although time series models, such the vector autoregression, are effective econometric instruments for revealing spillover processes, the outcomes may be susceptible to model assumptions (Zhang, Ji, Zhao and Horsewood, 2021; Xu and Zhang, 2022a). For a big dataset, dimensionality may also place restrictions on estimations using vector autoregression (Zhang and Fan, 2019; Xu and Zhang, 2023a). Particular, it would be difficult to estimate a vector autoregression model based upon tens and hundreds of or even more variables. When constructing portfolios, investors frequently rely only on asset correlations (Zhang et al., 2021; Xu and Zhang, 2021b). Thus, estimations of parameters in vector autoregression types of models are generally not required in correlation based analysis. Other factors in a system may have an impact on correlations between two variables, and they may change over time. We choose the network analysis framework in light of probable difficulties with the vector autoregression and the practical requirements of the current investigation. When estimating a large number of parameters becomes challenging or impractical, this approach allows for the avoidance of common dimensionality constraints for many time series models and the incorporation of the practical concern that the investment diversification is primarily built on correlation understandings (Zhang et al., 2021).

The goal of the current study is to shed light on comovements and heterogeneities in monthly real estate prices of residential, commercial, and retail properties across ten major Chinese cities (Chengdu, Beijing, Wuhan, Shanghai, Nanjing, Tianjing, Hangzhou, Chongqing, Guangzhou, and Shenzhen) for the time period of July 2005 to April 2021. We use a correlation-based approach to gauge how closely prices are related, and we build a hierarchical network from correlations to characterize the topology and hierarchy and demonstrate how all prices in the network are interconnected[1]. According to the authors' understanding, this should be the first network analysis-based research of real estate pricing for the three main property kinds in China's ten largest cities. For these thirty price index time series, we create correlation and distance matrices. We create hierarchical structures of price interactions from these matrices, allowing us to identify groups of property kinds and cities with comparable price comovements and dynamics. Here, the entire dynamic connections in the pricing system are taken into account when measuring price comovements. The empirical methodology also makes it easier to pick groupings of cities and property kinds for better real estate pricing policy analysis. Particularly, we discover using minimal spanning tree analysis that prices of residential properties in Beijing and Wuhan, Shanghai and Hangzhou's residential properties, Chongqing and Chengdu's residential properties, Shenzhen's residential and office properties, and Beijing and Shenzhen's retail properties are connected directly. Through hierarchical tree analysis, we also discover that these five pairings of real estate pricing pairs define sectoral groupings. We go over possible explanations for these observations. Our findings demonstrate that real estate price comovements are generally low and stable across all property kinds and localities from January 2017 to February 2020, followed by significant increases during the COVID-19 pandemic from March 2020 to January 2021 and significant decreases since February 2021 with the recovery of the economy. Meanwhile, a number of groups of cities and property kinds are identified, each of which includes individuals exhibiting quite powerful but unstable price synchronizations. For instance, there are significant increases in synchronizations between Shanghai and Hangzhou's residential properties during the period of April 2009 – September 2010 and significant drops during the period of October 2010 – October 2011. Additionally, it has been shown that no group consistently exhibits high or low synchrony. Finally, the real estate price linked with a particular property type and city does not show a consistent upward or downward trend, according to rolling importance study of various property kinds and locations.

■2.0 LITERATURE REVIEW

The study of real estate price correlations has received a great deal of attention in economic research. The investigation has made extensive use of basic econometric models, including the autoregressive, vector autoregressive, and vector error correction techniques, as well as many of its variants. For instance, Zhu, Füss and Rottke (2013) utilize the Case & Shiller housing price indices during the period of 1995–2009 to investigate spatial linkages in idiosyncratic risks, returns, and volatilities across 19 regional housing markets in the United States. This was done within the framework of a dynamic space panel model that included generalized autoregressive conditional heteroskedasticity terms and a spatial weight matrix. They conclude that market interconnections may be more extensive than anticipated because economic proximity, in addition to geographic proximity, is a significant source of influence and because of the significant contagion effects during the subprime and financial crises of 2007–2009. According to their findings, the geographic portfolio diversification approach may have failed due to increased comovement and dependency, particularly within geographically different places with comparable economic conditions. Chiang (2016) creates three submarket panels using data from six Chinese megacities from 2003 to 2014 in order to examine the dynamic interconnections between the residential, office, and retail sectors. Chiang (2016) does not discover a long-run equilibrium between the three property submarkets using panel cointegration testing. Chiang (2016) discovers that changes in the residential market influence changes in the commercial sector using panel causality tests. Chiang (2016)'s findings imply that in order to stop the rise in real estate prices, policymakers should focus particularly on the residential sector. In 69 big and medium-sized Chinese cities between July 2005 and June 2015, Yang, Yu, and Deng (2018) investigate housing price spillovers using the high-dimensional generalized vector autoregressive approach. They discover incredibly dynamics among house prices. Their findings imply that significant cities in the price spillover networks are congruent with the core cities backed by the government's regional development goals and cluster in five fairly concentrated locations. They also point out important factors that influence the (net) positive spillover, such as a larger population, a greater city's GDP, and secondary education. Zhang and Fan (2019) study the short-run dynamics of urban housing prices in 70 Chinese cities from April 2006 to July 2016 using a vector autoregressive-based time-series approach. They discover that prices across cities have become more interconnected, which is consequently linked to higher systemic risk.

The economic examination of comovements and heterogeneities among several variables can be aided by network analysis. For instance, Hidalgo and Hausmann (2009) utilize it to create a theory of economic growth and development in which the complexity of a nation's economy plays a key role. It is used by Miśkiewicz and Ausloos (2010) to tackle the subject of whether the globalization of the economy has reached a limit. It is used by Reyes et al. (2010) to make it easier to analyze patterns of international integrations that Latin American and East Asian nations have adopted. It is used by Kristoufek et al. (2012) to examine the connections between the pricing of agricultural commodities and fuels like ethanol and biodiesel. It is used by Minoiu and Reyes (2013) to investigate the world's financial system using information on international banking transfers for 184 nations. It is used by Matesanz et al. (2014) to examine co-movements in a variety of commodities price movements. It is now utilized for price analysis of real estate. Using regional house price indices, Zhang

[1] Network analysis can be applied to solve various economic issues (e.g. Hidalgo and Hausmann, 2009; Miśkiewicz and Ausloos, 2010; Reyes, Schiavo and Fagiolo, 2010; Kristoufek, Janda and Zilberman, 2012; Minoiu and Reyes, 2013; Matesanz, Torgler, Dabat and Ortega, 2014).

et al. (2021) suggest a network strategy based on partial correlations and rolling-window analysis to examine cross-regional reliance in the UK housing market. They discover that home prices in the outer Southeast area have the strongest effect on regional housing market interactions, and the influence is higher for highly linked markets. Additionally, they discover that when regional property markets are less interconnected, London's home prices will be most affected. Through modified gravity models and network analysis, Wu, Li, Chong, and Niu (2021) look at the selling prices of stocked homes from 35 big and medium-sized Chinese cities during the period of 2010–2021 to study the geographical relationship. Stocked houses in China refer to residential properties built by commercial developers or individual owners, with certificates of titles issued by the government, and their sale prices in Wu et al. (2021) are sourced from Wind Information Co., Ltd. They discover that housing price networks have a very low degree of integration and that the impacts on house prices are polarized. Additionally, they provide a number of cities where housing costs are generally more centralized and a number where housing costs are substantially more dispersed.

Previous research on prices of real estate has connected them with a diverse variety of different factors, including property based characteristics (e.g. Peterson and Flanagan, 2009; Selim, 2009) such as property locations, types, ages, lot sizes, numbers of units, numbers of stories, and exterior composition, macroeconomic conditions (e.g. Rafiei and Adeli, 2016; Kang, Lee, Jeong, Lee and Oh, 2020; Lam, Yu and Lam, 2008) such as gross national products, consumer price indices, gross domestic products, interest rates, stock market indices, default rates, liquidities, and unemployment rates, and their own time-series properties (e.g. Gu, Zhu and Jiang, 2011; Yang et al., 2013; Gong et al., 2016). In particular, network analysis has been used to facilitate understandings of complex relations among real estate pricing, liquidity of financial institutions, and other macroeconomic factors for safety and robustness of financial systems (e.g. Neveu, 2018; Brunnermeier, 2009; Ardekani, Distinguin and Tarazi, 2020; Sheng, 2010; Alter, Dokko and Seneviratne, 2018; Feng, Wu and Guo, 2022; Deng, Zeng and Li, 2019; Markose, 2012; Battiston, Caldarelli and D'Errico, 2016; Allen and Babus, 2009). In order to analyze price correlations, our study here concentrates on prices of real estate themselves.

■3.0 DATA

The China Real Estate Index System (CREIS), an analytical tool created to represent market conditions and development patterns of real estate markets in key Chinese cities, is the data source for the analysis (Yang et al., 2013). The following provides some background information about the CREIS. It was first started in 1994 by the National Real Estate Development Group Corporation, Real Estate Association, and Development Research Center of the State Council. Academic specialists from the Development Research Center of the State Council, the Ministries of Construction and Land and Resources, the Banking Regulatory Commission, the Real Estate Association, and certain universities audited CREIS in 1995 and 2005. Currently, it releases a variety of real estate price indices on a regular basis, including the 100-city index, the city composite index, the residential property index, the hedonic index, the office property index, the retail property index, the villa price index, the second-hand housing sales index, and the rental price index. As a result, it has the broadest coverage of real estate markets. In the current work, we employ the residential, office, and retail property indices.

The following 10 major Chinese cities are included in the CREIS's residential, office, and retail property indices: Chengdu, Beijing, Wuhan, Shanghai, Nanjing, Tianjing, Hangzhou, Chongqing, Guangzhou, and Shenzhen. Some background information about data collection processes by the CREIS is as follows. Field surveys, telephone surveys, and online surveys are all used in the procedures. All residential, office, and retail properties in each city that are up for sale during a given month are included in the samples used to construct the index. On a monthly basis, new developments are included to the cities' computations of the indices. When a new construction project has many phases and phase p sells out before phase $p+1$ is open for sales, the phase p result is used in the index calculation. A multi-phase project would also be excluded from the index computation if the percentage of units that are offered for sale falls below 5% for the total number of units. The incentive, average listed price, property type, district, construction acreage, building category, number of units, land acreage, landscaping ratio, floor area ratio, average occupancy rate, main unit type square footage, furnishing standard, parking to unit ratio, clubhouse, property management fee, and outdoor playground are all included in each sample that was gathered. Before usage, the obtained data undergo a number of cross-checking steps. It is worth noting that these underlying data of property characteristics are not available to us and the only data available for analysis in the current work are the final price indices of residential, office, and retail properties across the ten major cities. The base period index for all 10 cities uses Beijing's index value from December 2000, which is set at 1,000.

The CREIS calculates a city's residential, office, or retail property price index as follows: $I_t' = (\sum P_i^t A_i^{t-1}) / (\sum P_i^{t-1} A_i^{t-1}) \cdot I_{t-1}'$, where I_t' and I_{t-1}' signify the price indices associated with time t and time $t-1$, A_i^{t-1} signifies the area of total construction associated with project i at time $t-1$, and P_i^t and P_i^{t-1} signify average prices of properties (Unit: RMB per Square Meter) of project i at time t and time $t-1$.

Figure 1 shows the data for the period from July 2005 to April 2021. Table 1 displays summary data for the 10 cities' residential, office, and retail property price indices, including the minimum value, mean value, median value, standard deviation (std) value, maximum value, 1st percentile value, 5th percentile value, 95th percentile value, 99th percentile value, and p-values associated with Jarque-Bera tests (Jarque and Bera, 1980) and augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1979) based upon the raw price timeseries and the corresponding first-difference time series. The Jarque-Bera test reveals that the thirty price indices are not normally distributed at the 5% level of significance, which may not be unexpected for economic time series. The ADF test reveals that while the first differences are stationary, the raw series are not.

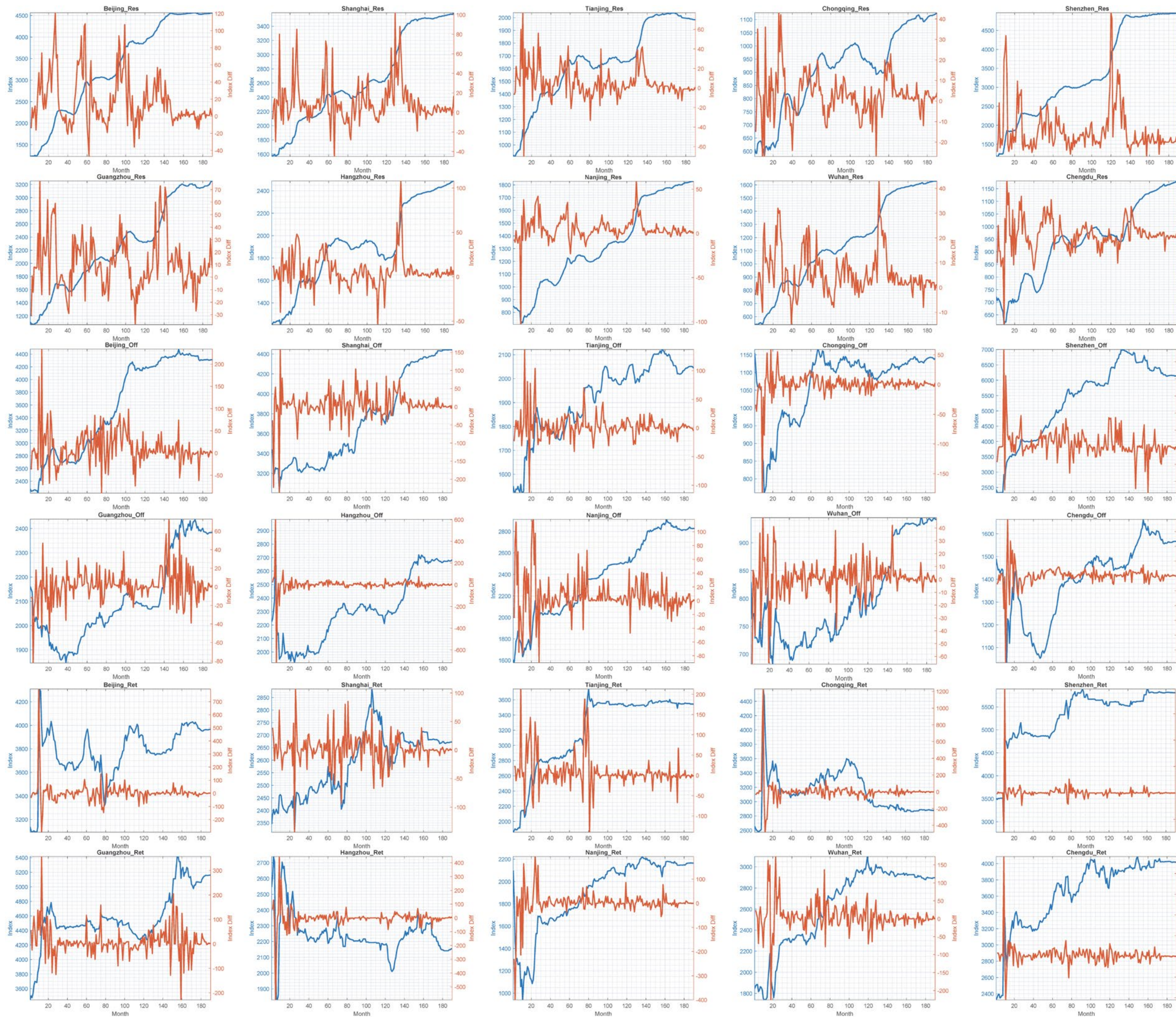

Figure 1 Residential (Res), office (Off), and retail (Ret) property price indices and their first differences of Chengdu, Beijing, Wuhan, Shanghai, Nanjing, Tianjing, Hangzhou, Chongqing, Guangzhou, and Shenzhen for July 2005 – April 2021

Table 1 Summary statistics associated with different price indices

City	Price Index	Minimum	Mean	Median	Std	Maximum	1st Per	5th Per	95th Per	99th Per	Jarque-Bera p value	ADF (raw series) p value	ADF (1st diff) p value
Beijing	Residential	1227	3329	3479	1075	4565	1237	1339	4554	4560	0.006	0.999	0.001
	Office	2216	3590	3808	740	4479	2249	2399	4395	4418	0.002	0.999	0.001
	Retail	3092	3779	3788	220	4309	3095	3332	4018	4061	0.001	0.839	0.001
Shanghai	Residential	1567	2660	2510	631	3590	1579	1679	3550	3571	0.011	0.999	0.001
	Office	3006	3734	3710	455	4446	3162	3225	4440	4443	0.003	0.987	0.001
	Retail	2313	2587	2613	125	2884	2380	2401	2785	2825	0.020	0.878	0.001
Tianjing	Residential	909	1653	1660	303	2039	919	1045	2031	2036	0.011	0.999	0.001
	Office	1523	1917	1976	156	2122	1526	1549	2103	2116	0.001	0.959	0.001
	Retail	1858	3199	3528	496	3743	1888	2105	3586	3617	0.001	0.995	0.001
Chongqing	Residential	580	912	939	155	1126	593	615	1115	1120	0.007	0.999	0.001
	Office	761	1070	1113	92	1165	779	855	1145	1161	0.001	0.584	0.001
	Retail	2574	3144	3120	292	4572	2593	2862	3546	4048	0.001	0.596	0.001
Shenzhen	Residential	1176	3405	3097	1186	4966	1192	1633	4944	4957	0.008	0.999	0.001
	Office	2329	5356	5824	1252	7004	2334	2995	6888	6982	0.003	0.995	0.001
	Retail	2771	5326	5561	568	5891	3503	4638	5819	5878	0.001	0.862	0.001
Guangzhou	Residential	1068	2261	2301	654	3254	1079	1171	3198	3233	0.019	0.999	0.001
	Office	1846	2110	2070	177	2439	1862	1882	2409	2432	0.004	0.903	0.001
	Retail	3445	4588	4509	374	5416	3498	3939	5198	5354	0.020	0.985	0.001
Hangzhou	Residential	1206	1913	1913	374	2488	1216	1244	2446	2480	0.034	0.999	0.001
	Office	1921	2318	2303	249	2983	1946	1969	2687	2718	0.021	0.743	0.001
	Retail	1830	2244	2221	131	2739	1860	2080	2534	2704	0.001	0.417	0.001
Nanjing	Residential	706	1336	1289	338	1828	725	790	1814	1826	0.013	0.999	0.001
	Office	1579	2384	2439	367	2912	1631	1749	2857	2884	0.013	0.998	0.001
	Retail	940	1895	2038	319	2223	1083	1172	2189	2207	0.001	0.619	0.001
Wuhan	Residential	539	1165	1154	336	1630	540	572	1617	1629	0.017	0.999	0.001
	Office	682	800	773	83	945	690	708	941	944	0.002	0.822	0.001
	Retail	1738	2621	2818	383	3098	1744	1834	2988	3027	0.001	0.972	0.001
Chengdu	Residential	611	942	959	152	1181	623	699	1168	1179	0.030	0.999	0.001
	Office	1034	1402	1446	163	1663	1051	1082	1611	1639	0.004	0.655	0.001
	Retail	2325	3650	3837	416	4086	2354	2874	4034	4061	0.001	0.915	0.001

4.0 METHODOLOGY

4.1 Hierarchical Analysis

Think about two different time series, TS_i and TS_j . The Pearson correlation coefficient between TS_i and TS_j is denoted as $\rho_{i,j}$, as shown in Equation (1), where N_{win} signifies the temporal window's length and $\overline{TS}$ signifies a time series' average value over the window.

$$\rho_{i,j} = \frac{\sum_{k=1}^{N_{win}}\left(TS_i(k)-\overline{TS_i}\right)\left(TS_j(k)-\overline{TS_j}\right)}{\sqrt{\sum_{k=1}^{N_{win}}\left(TS_i(k)-\overline{TS_i}\right)^2 \sum_{k=1}^{N_{win}}\left(TS_j(k)-\overline{TS_j}\right)^2}}$$

(1)

According to Gower (1966), the distance between the evolution of TS_i and the evolution of TS_j is denoted as $D_{i,j}$, as shown in Equation (2), which is employed to create the proper taxonomy. Small distance is intuitively linked to two synchronized series, whereas high distance is linked to two independent series.

$$D_{i,j} = \sqrt{2\left(1-\left|\rho_{i,j}\right|\right)}$$

(2)

The minimal spanning tree (MST) is constructed using $D_{i,j}$ in accordance with the Kruskal (1956) method, a bottom-up procedure that begins by linking the nearest series as determined by their shortest distance. One can reach the MST, a loop-free network that displays the key connections and communities, by joining the remaining series according on how closely they are related to previously linked series. More specifically, the Kruskal (1956) algorithm is utilized to generate the MST for a given graph. A MST is essentially a subset of a graph, whose number of vertices is the same as that of the graph and whose number of edges is the number of vertices minus one. The "minimum (M)" part of the name "minimum spanning tree (MST)" stems from the fact that the MST has the minimal cost for the sum of all edge weights in a spanning tree[2]. When using the Kruskal (1956) algorithm, nodes are only kept from being added to the tree if the selected edge does not form a cycle. The algorithm ranks all edges in ascending order of their edge weights. The algorithm chooses the edge with the lowest cost first, and the edge with the highest cost last. The following steps are involved when implementing the algorithm for arriving at the MST.

Step 1: Sort all edges in the increasing order of their edge weights.

Step 2: Pick the smallest edge.

Step 3: Check whether the new edge creates a cycle or loop in a spanning tree.

Step 4: If it does not form the cycle, include that edge in the MST; Otherwise, discard it.

Step 5: Repeat from Step 2 until it includes $V-1$ edges in the MST, where V is the number of vertices.

The hierarchical tree (HT) is also constructed using the single-linkage clustering technique (Johnson, 1967), which displays the series' clustering features via a hierarchical dendrogram. Communities can be identified in complicated networks by grouping nodes based on

[2] A spanning tree is a subset of a graph that, in order to have no cycles, has all of the vertices and some of the edges of the original graph. For a given graph, there could be more than one spanning tree. But there will always be at least one spanning tree in a given graph. The edges that are part of a spanning tree are known as "branch edges," whereas the edges that are not part of the spanning tree are known as "cycle edges." And this kind of graph aids in determining the smallest number of edges necessary to link each graph's vertices. Additionally, it is adopted to create minimally secured networks with redundant paths. A subset of edges known as an MST connects all vertices of a linked, edge-weighted graph with no cycles and with the least amount of total edge weight. It is a technique for determining the most economical way to join a group of vertices.

shared traits (Wasserman and Faust, 1994). Given O observations to be grouped and an $O \times O$ distance matrix, Johnson (1967)'s method defines the overall process of hierarchical clustering. The following steps are involved when implementing the algorithm for hierarchical clustering.

Step 1: Start with the disjoint clustering with level $L(m)$ = 0 and m = 0.

Step 2: For the case of the single linkages, determine the pair that has the minimum distance, with the pairs denoted by r and s, based on: $d[(r), (s)] = min(d[(i), (j)])$, where d signifies the Euclidean distance.

Step 3: Add one to m, $m = m + 1$. Merge cluster r and cluster s into 1 cluster to create the next clustering at m. $L(m)$ then turns to be $L(m) = d[(r), (s)]$.

Step 4: By deleting the rows and columns that correspond to cluster r and cluster s and introducing a row and column for the newly created cluster, the distance matrix is updated. The distance between the newly created cluster (r, s) and the old cluster k is computed again based on the minimum distance (for the case of the single linkages): $d[(k), (r, s)] = min(d[(k), (r)], d[(k), (s)])$.

Step 5: If all O observations are included in a single cluster, stop; otherwise, repeat from Step 2.

One might reach clusters based on correlations demonstrating comparable price dynamics patterns using the MST and HT. Time series using the first differences representation are used for hierarchical analysis and N_{win} = 189. For this reason, one could interpret results here as stemming from price growth.

4.2 Synchronization

Two rolling window-based synchronization measurements are taken over the course of one year for N_{win} = 12 in order to demonstrate how series dependencies change over time. The total of all correlation pairings between series, normalized by the number of pairs, is the global correlation (GC), which comes first. T The second is called the MST cost (MSTC), which is the total of all distance pairs between series normalized by the quantity of pairings. When examining various numbers of series, the normalization makes it possible to compare the findings. Intuitively, the GC (or MSTC) will be higher (or lower) depending on how closely the series are related. We will concentrate on presenting GC-based results for this reason.

The synchronization intensity (SI), which is the number of connections for each time series within the MST that is weighted by the distance of the connections, is another rolling window-based statistic taken into account for N_{win} = 12. Each series' movement within a network over time and whether it becomes more or less synchronized are both defined by the SI.

■5.0 RESULT

One key benefit of network analysis is that it enables one to capture the entire relationship structure by going beyond the first-order relations (bilateral relations) (Reyes et al., 2010; Xu and Zhang, 2023b) that form the real estate price system. For instance, one may research the interactions between real estate prices between any two or more cities and property categories that are related to one another and assess how closely the prices of various cities and property types are related. This could make it easier for us to comprehend certain characteristics of real estate price correlations that distinguish various (groups of) property kinds and localities. When conducting network analysis, it's possible that the most significant real estate values are not always those whose corresponding cities have the most developed economies, but rather those with a lot of connections.

According to the MST, which is depicted in Figure 2, price series are directly connected if they have a tendency to be more synchronized, which serves as a rough depiction of the topological organization. In other words, one may determine from the MST which cities and property kinds tend to be more related to one another and which have more distinct or irregular pricing pathways. For example, prices of Beijing and Wuhan's residential properties, Shanghai and Hangzhou's residential properties, Chongqing and Chengdu's residential properties, Shenzhen's residential and office properties, and Beijing and Shenzhen's retail properties are directly connected. The residential properties thus are the most connected property type in terms of price indices. This result might be expected as investment in residential properties are much more active and easier to enter than office or retail properties (Chin and Chow, 2012; Chiang, 2016). Importance of the residential property is consistent with Chiang (2016), where it was determined that price information of commercial properties is led by that of residential properties in China. The connection between residential property price indices of Shanghai and Hangzhou as well as between those of Chongqing and Chengdu is not hard to understand and probably not surprising, given their geographical closeness and tight economic relationships. Previous studies have also well documented active population flows between Shanghai and Hangzhou (Qian, 2015; Wen and Tao, 2015) and between Chongqing and Chengdu (Feng and Han, 2021; Nong, 2022), which could contribute as well to the connections between these two pairs of cities. The connection between residential property price indices of Beijing and Wuhan is somewhat interesting as these two cities are rather far from each other and there does not seem to be obvious tight economic relationships. Ai, Ding and He (2008) offer a potential explanation that both cities' residential property prices are driven by their respective land prices under same time lags. Han and Wu (2004)'s work offers another potential explanation that Wuhan, as the largest city in central China, strategically links with Beijing from the transportation perspective. The connection between price indices of Shenzhen's residential and office properties should be related to the unique fast development of the real estate market in this city, for which building of clustered office properties generally contributes to that of residential properties. The connection between retail property price indices of Beijing and Shenzhen could be due to these two cities being people's top choices when considering retail business (Chin and Chow, 2012; Chiang, 2016) and Shenzhen getting closer and possibly even becoming more important than Beijing in terms of commercial real estate markets during the past decade (Lee, Chiang and Wen, 2023).

The HT, which depicts the hierarchical structure based on the closeness of price dynamics, is shown in Figure 3. In other words, groups of property kinds and cities might be identified, along with those with more atypical pricing patterns. The HT also displays comovements of different price clusters that are generated endogenously, in contrast to the MST (Matesanz et al., 2014). Several sectoral groupings are created, despite the fact that we could see varying degrees of heterogeneities in the price movements from the HT, including prices of Beijing and Wuhan’s residential properties (Group 1), Shanghai and Hangzhou’s residential properties (Group 2), Chongqing and Chengdu’s residential properties (Group 3), Shenzhen’s residential and office properties (Group 4), and Beijing and Shenzhen’s retail properties (Group 5). These sectoral groups are in line with direct connectedness found through the MST. The HT also shows that price indices of residential properties are more likely to share similar price dynamics across cities while those of office and retail properties are more likely to have idiosyncratic price paths (e.g., office properties of Wuhan, Beijing, Nanjing, Hangzhou, and Guangzhou and retail properties of Tianjing, Shanghai, and Wuhan). This should be understandable as switching residential properties is usually easier than office or retail properties. Chiang (2016) pointed out that price indices of residential, office, and retail properties in different cities in China are generally not driven by common fundamentals. In other words, price indices of the same property type across regional markets are more likely to be connected, which is confirmed by our results here to a large extent. The HT reveals that connections among price indices of residential properties are generally tighter than those among price indices of commercial (i.e. office and retail) properties. This result should not be surprising and great urbanization during the past decade at the national level in China (Cooper and Cowling, 2015) could have contributed to tightened price connections among regional residential real estate markets.

The GC for each of the thirty price indices (Group 0), as well as the property types and cities in Groups 1–5, is displayed in Figure 4. This provides insight into the price interactions between all property and city pairings within a group and, consequently, data on price comovement within the group. In Figure 5, the GC distribution is also displayed. Group 0’s synchronization is comparatively low and stable across time, particularly from January 2017 to February 2020. This result is consistent with Chiang (2016), where it was determined that price indices of different property types in different regional markets in China tend to be fragmented. The synchronization significantly increases during the COVID-19 pandemic from March 2020 to January 2021 and significantly decreases since February 2021 with the recovery of the economy. This result is due to systematic impacts of the pandemic on the real estate market, as pointed out by many recent studies (e.g. Tian, Peng and Zhang, 2021; Huang, Lan, Xu, Zhang and Zeng, 2022; Yang and Zhou, 2022). In comparison to Group 0, the synchronization for Groups 1 through 5 is significantly more variable but also typically at higher levels, indicating clear diverse pricing dynamics within certain categories of property kinds and localities. Yu (2015) proposed investigations into influences of changing patterns of income levels, interest rates, and regional policy factors over time on these heterogeneous price dynamics in the real estate market. Taking Group 2 as an example, we could observe that there are significant increases in the synchronization between Shanghai and Hangzhou’s residential properties during the period of April 2009 – September 2010 and significant drops during the period of October 2010 – October 2011. This is mainly due to significant amounts of investments flowing into the residential real estate sector shortly after the global financial crisis, which pushed property price upwards in a significant manner and cities such as Shanghai and Hangzhou were major targets of money inflows in China (Huang, Li and Li, 2010). However, with asset prices going up too significantly within a short time period, national and regional level market and policy interference were strongly implemented for controlling market overheating, which contributed to drops in the synchronization. Figure 4 also shows that there are no persistent high or low synchronization within a particular group, indicating that while economic development and investment within a particular group may be related, there are clear idiosyncratic paths that contribute to the synchronization’s ever-fluctuating nature. These findings suggest that taking into account the synchronization and heterogeneity may improve certain policy studies, such as market microstructure and forecasting, connected to real estate prices of certain property kinds and localities.

The results of the SI, which are available upon request, are used to calculate the relative value of various types of properties and cities throughout the network. The SI is erratic over time, showing neither a consistent upward nor downward tendency for the cost of real estate in a given city and property type. The prices of some types of real estate and some places (like Beijing's residential properties) appear to be more linked to other values in the network at particular points in time. These corresponding property types and cities are possible to be the price leaders in their associated groups (Matesanz et al., 2014), which can be examined by lead-lag (e.g., Yang and Leatham, 1999; Yang, Bessler and Leatham, 2001; Yang, Kolari and Min, 2003; Li, Yang, Hsiao and Chang, 2005; Yang, Hsiao, Li and Wang, 2006; Yang, Yang and Zhou, 2012; Yang, Li and Wang, 2021) and contemporaneous (e.g. Bessler and Akleman, 1998; Awokuse and Bessler, 2003; Bessler, Yang and Wongcharupan, 2003; Bessler and Yang, 2003; Haigh and Bessler, 2004; Yang and Bessler, 2004; Lai and Bessler, 2015; Bizimana, Angerer, Bessler and Keita, 2015; Chopra and Bessler, 2005) causality. Our analysis here thus could help identify potential important sources of price discovery in the real estate market across different regions and different property types. This could also benefit policy analysis in a more targeted and more precise manner. It is important to note that depending on the exact study objectives, the MST and HT methodology's virtue of being relatively simple may also be its drawback. In particular, based on the findings, one could not conclusively address issues about causation (Kristoufek et al., 2012). The directed acyclic graph and the spillover index of Diebold and Yılmaz (2014) are two networks that Yang, Tong and Yu (2021) have recently combined into a single framework. It could be useful to investigate how dynamic price connections based on high-dimensional innovation accounting have changed over time. Such further research may be beneficial to take into account for future studies.

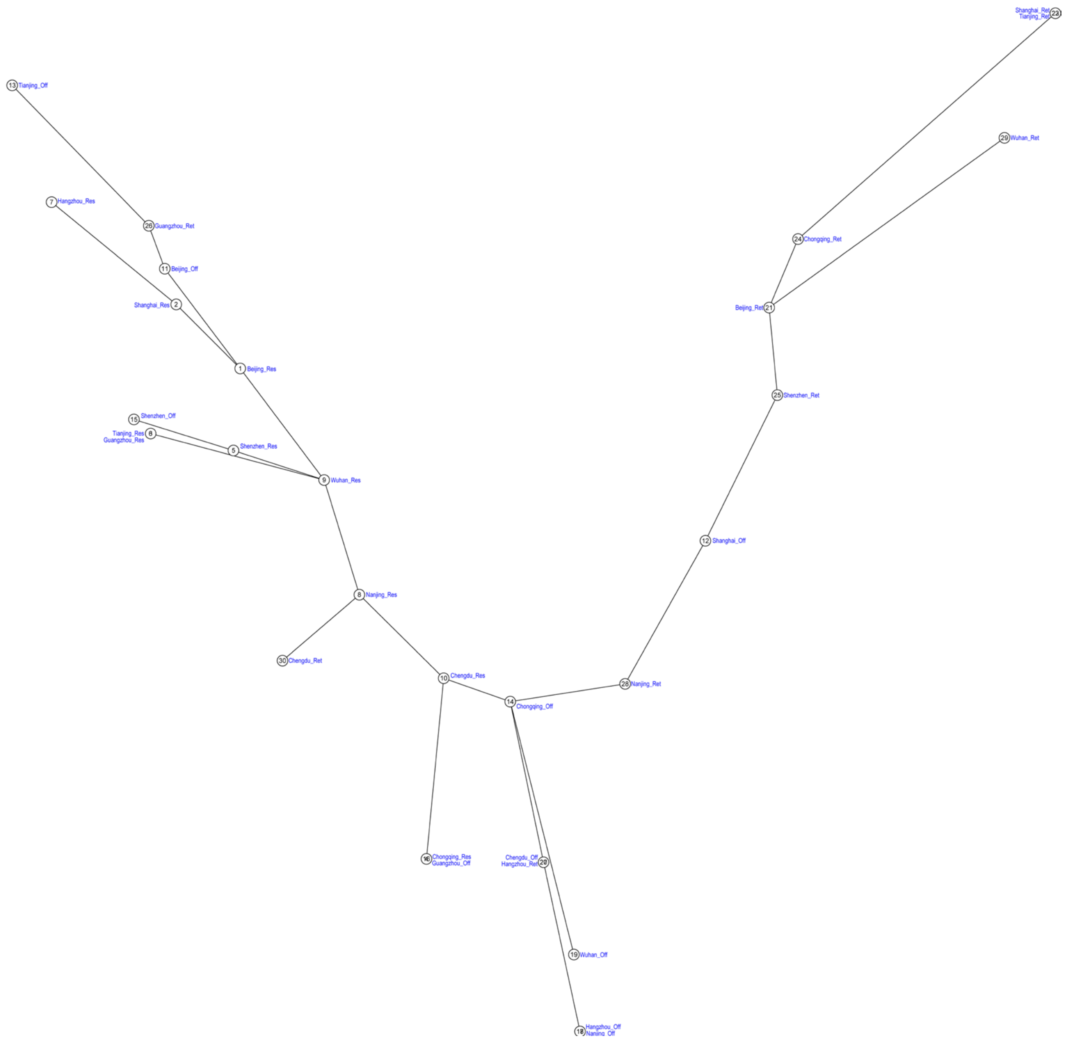

Figure 2 The minimum spanning tree (MST). The numbers (1, 2, ..., 30) in the circles represent price indices of different cities and property types. For example, the number 14 represents the office (Off) property price index of Chongqing, the number 10 represents the residential (Res) property price index of Chengdu, and the number 30 represents the retail (Ret) property price index of Chengdu. The lines connecting the circles provide a representation of the topological organization in the sense that price indices of different cities and property types are linked directly if they tend to be more synchronized.

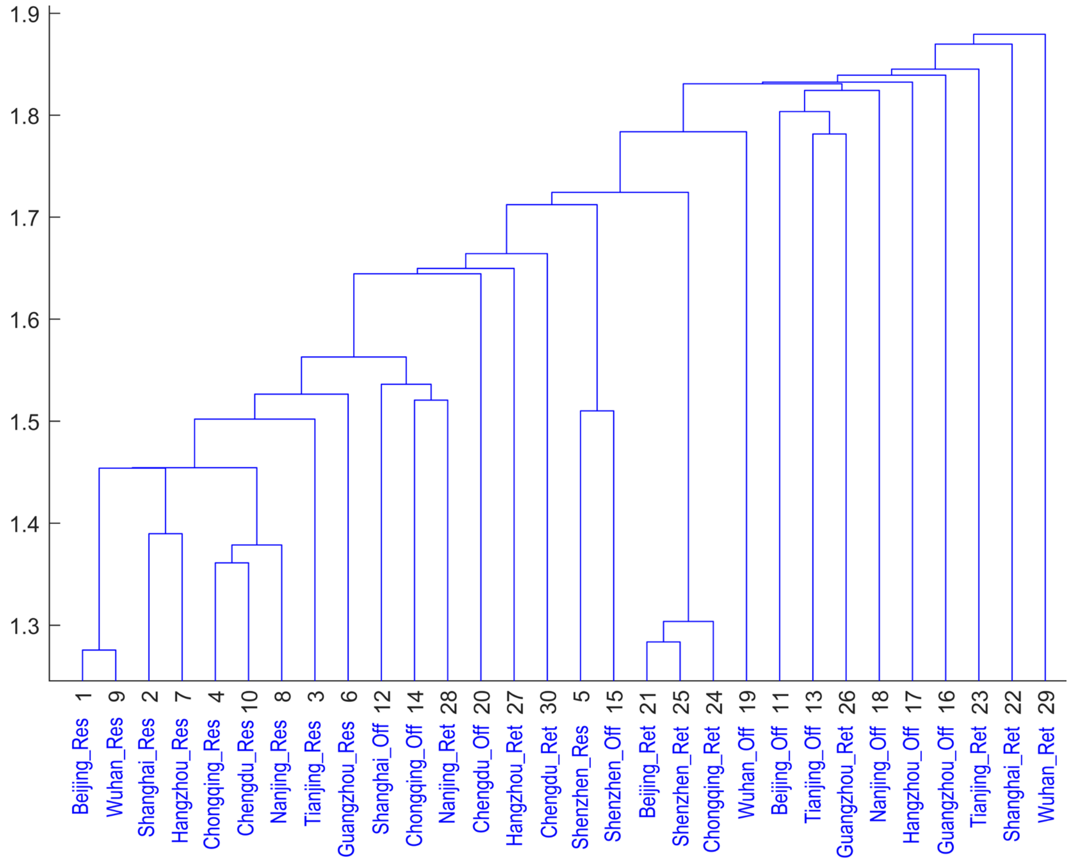

Figure 3 The hierarchical tree (HT). The numbers (1, 2, ..., 30) on the horizontal axis represent price indices of different cities and property types. For example, the number 14 represents the office (Off) property price index of Chongqing, the number 10 represents the residential (Res) property price index of Chengdu, and the number 30 represents the retail (Ret) property price index of Chengdu. The vertical axis shows the hierarchical dendrogram. A dendrogram is constituted of many U-shaped lines (i.e. blue lines in this figure) connecting data points (i.e. property price indices) in a hierarchical tree. The height of each U represents the distance between the two data points being connected.

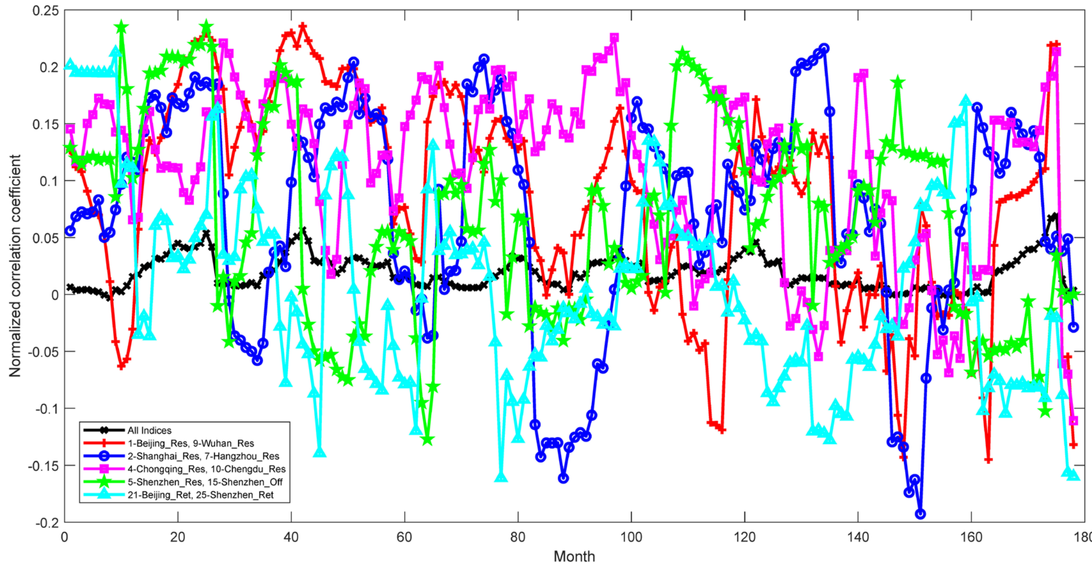

Figure 4 The global correlation (GC). The dark line represents the GC for price indices of all cities and property types. The red line represents the GC for the price index of the residential (Res) property of Beijing and that of the residential (Res) property of Wuhan. The blue line represents the GC for the price index of the residential (Res) property of Shanghai and that of the residential (Res) property of Hangzhou. The magenta line represents the GC for the price index of the residential (Res) property of Chongqing and that of the residential (Res) property of Chengdu. The green line represents the GC for the price index of the residential (Res) property of Shenzhen and that of the office (Off) property of Shenzhen. The cyan line represents the GC for the price index of the retail (Ret) property of Beijing and that of the retail (Ret) property of Shenzhen.

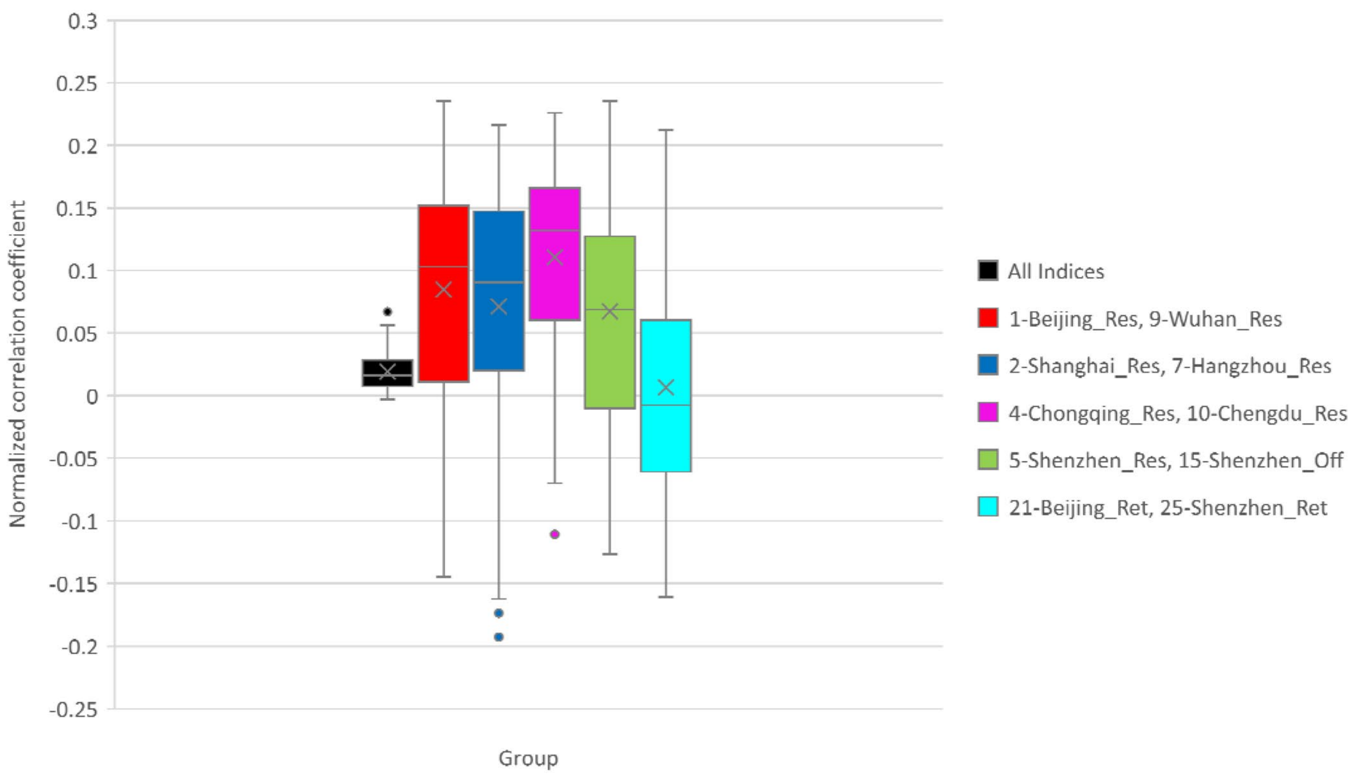

Figure 5 Box and whisker plots of the global correlation (GC) shown in Figure 4. Box and whisker plots contain the mean value, median value, 1^{st} quartile value, 3^{rd} quartile value, interquartile range (IQR) values, and outliers, where a point is considered to be an outlier if the point exceeds a distance of 1.5 times the IQR below the 1^{st} quartile value or above the 3^{rd} quartile value.

6.0 CONCLUSION

Through network analysis, topological and hierarchical characterizations of price dynamics, and analyses of monthly price indices for residential, office, and retail properties in ten major Chinese cities (Chengdu, Beijing, Wuhan, Shanghai, Nanjing, Tianjing, Hangzhou, Chongqing, Guangzhou, and Shenzhen), this study examines the comovements of these indices for the years 2005 to 2021. The empirical approach makes it easier to identify groupings of cities and property kinds with comparable price synchronization patterns, which is useful for policy analysis on the real estate costs in various cities and property types. We may also determine price interactions using the framework, which takes into account the pricing system's complexity and heterogeneity.

We find that the price indices of Beijing and Wuhan's residential properties, Shanghai and Hangzhou's residential properties, Chongqing and Chengdu's residential properties, Shenzhen's residential and office properties, and Beijing and Shenzhen's retail properties are directly connected. Our findings here indicate that degrees of real estate price index comovements across all property types and cities are relatively low and stable from January 2017 to February 2020, followed by significant increases during the COVID-19 pandemic from March 2020 to January 2021 and significant decreases since February 2021 with the recovery of the economy. Meanwhile, a number of groups of cities and property kinds are identified, each of which includes individuals exhibiting quite powerful but unstable price synchronizations. Additionally, it has been shown that no group consistently exhibits high or low synchrony. Finally, the real estate price linked with a particular property type and city does not show a consistent upward or downward trend, according to rolling importance study of various property kinds and locations. These differences in price dynamics could be helpful for policy analyses aimed at stabilizing the real estate market.

Future study on this subject may be beneficial because, based on the findings presented, one cannot conclusively address problems about causation (Kristoufek et al., 2012). These findings may be helpful in deciding which cities and types of properties to analyze, which might assist time series models overcome their dimensionality problem (Zhang and Fan, 2019). The 10 largest cities are the subject of our investigation. If data were to become accessible in the future, it would be fascinating to expand the research to include all of China's more than 700 cities. Monitoring national and regional overheating in the real estate market, and consequent dangers and bubbles, may be done with the use of analysis of price comovements. When creating policies to calm down the market from the standpoint of various regions, the excessive comovements that were observed might act as warning indications for policy makers. Real estate price comovements' changing patterns throughout time might provide insight into how various cities are developing economically. Policymakers could find it useful to determine if speculative capital inflow or basic economic growth is ultimately responsible for a city's real estate values becoming more significant and interconnected to other cities.

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