National Institute Economic Review (2023), 264: 1, 110–128
doi:10.1017/nie.2021.34

ARTICLE

NETWORK ANALYSIS OF HOUSING PRICE COMOVEMENTS OF A HUNDRED CHINESE CITIES

Xiaojie Xu* and Yun Zhang

North Carolina State University, Raleigh, NC, USA
*Corresponding author. Email: xxu6@ncsu.edu

Housing price comovements are an important issue in economics. This study focuses on monthly housing prices of 99 major cities in China for the years 2010–2019 by using correlation-based hierarchical analysis and synchronisation analysis, through which one could determine interactions and interdependence among the prices, heterogeneous patterns in price synchronisations and their changing paths over time. Empirical results show that the degree of comovements is slightly lower after March 2017 but no persistent drop is found. Several groups of cities are identified, each of which has its members showing relatively strong but volatile price synchronisations. Certain cities show potential of serving as price leaders within a group. Results here could be useful to policy analysis regarding housing price comovements.

Keywords: housing price; comovement; network; hierarchy.

JEL codes: Q5; C31; C32; R31; R32.

Housing price comovements are an important issue in economics. This study focuses on monthly housing prices of 99 major cities in China for the years 2010–2019 by using correlation-based hierarchical analysis and synchronisation analysis, through which one could determine interactions and interdependence among the prices, heterogeneous patterns in price synchronisations and their changing paths over time. Empirical results show that the degree of comovements is slightly lower after March 2017 but no persistent drop is found. Several groups of cities are identified, each of which has its members showing relatively strong but volatile price synchronisations. Certain cities show potential of serving as price leaders within a group. Results here could be useful to policy analysis regarding housing price comovements.

1. Introduction

Housing markets have been growing fast in China for the past 10 years. Housing prices have become nearly everyone's concern. Regional price trends and inter-relationships are extremely important because they directly affect people's decisions on real estate investment and cities to reside and work. A few studies have approached this problem in a limited scope under the empirical framework of the vector autoregression. For example, Yang *et al.* (2013) focus on housing price dynamics from four cities, Beijing, Shanghai, Guangzhou and Chongqing, from December 2000 to May 2010. Gong *et al.* (2016) consider housing price relationships from 10 cities, Xiamen, Shenzhen, Chengdu, Kunming, Guiyang, Nanning, Changsha, Nanchang, Fuzhou and Guangzhou, from June 2005 to May 2015.

Different levels of housing price comovements across cities are helpful indicators of systemic risk in the housing market. It is important for policy makers to take cross-regional dependence, as well as its transmission mechanism, into consideration when designing policies (Zhang and Fan, 2019) to prevent potential market overheating. Meanwhile, understandings of dynamic connectedness among housing prices of different cities could benefit investors when optimising portfolios and diversifying risk (Antonakakis *et al.*, 2018).

While time series models, such as the vector autoregression, are powerful econometric tools to reveal spillover mechanisms, the results could be sensitive to model specifications (Zhang *et al.*, 2021). Vector autoregression-based estimations might be constrained by dimensionality as well for a large dataset (Zhang and Fan, 2019). In practice, investors often only need correlations across assets when building portfolios (Zhang *et al.*, 2021). Correlations between two variables could be influenced by other variables in a system and they might vary with time.

Motivated by potential challenges from the vector autoregression and practical needs of the current study, we employ the framework of network analysis. This approach allows for avoidance of typical dimensionality constraints for many time series models and incorporations of practical concerns that investment diversifications are essentially constructed on understandings of correlations (Zhang *et al.*, 2021).

The current study focuses on shedding light on comovements and heterogeneities in monthly housing prices of 99 major cities for the years 2010–2019. We adopt a correlation-based method that measures closeness of different prices and a derived hierarchical network from the correlation that allows for characterisations of the topology and hierarchy showing interactions and interdependence of all prices in the network.[1] To authors' knowledge, this is the first study on housing prices of all major cities in China by using network analysis. We build correlation and distance matrices for the 99 price series. From these matrices, we construct hierarchical structures of price interactions that allow for identifications of groups of cities with similar price comovements and dynamics. The measurement of price comovements here considers overall dynamic linkages in the price system. The empirical framework also facilitates selecting groups of cities for better policy analysis concerning housing prices. Specially, we find through minimum spanning tree (MST) analysis that housing prices of Nanjing and Kunshan, Tianjin and Wuhan, Changzhou and Changsha, Changchun and Zibo, and Shantou and Dongying are directly connected. We also find that these five pairs of cities form sectoral groups through hierarchical tree (HT) analysis. We discuss potential reasons behind these findings. Our results show that the degree of housing price comovements across all cities is slightly lower after March 2017 but no persistent drop is identified. Meanwhile, several groups of cities are determined, each of which has its members showing relatively strong but volatile price synchronisations. For example, there is a significant drop in the synchronisation between Tianjin and Wuhan, but a significant increase between Nanjing and Kunshan and between Shantou and Dongying after late 2018. It is also observed that there is no persistent high or low synchronisation within a specific group. Finally, rolling importance analysis of different cities reveals no persistent increasing or decreasing trend for a city's housing price.

2. Literature review

In economic analysis, much effort has been devoted to studying housing price relationships. Fundamental econometric models such as the autoregressive, vector autoregressive and vector error correction approaches, as well as their numerous variations, have been widely used to facilitate the analysis. For example, Zhu *et al.* (2013) use Case–Shiller housing price indices for 1995–2009 to examine spatial linkages in returns, idiosyncratic risks and volatilities across 19 U.S. regional housing markets under the framework of the dynamic space panel model including generalised autoregressive conditional heteroskedasticity terms and with the spatial weight matrix. They find that interconnections across markets could be wider than expected, as economic proximity, in addition to geographic closeness, is an important source of influence, and the interconnections could be stronger than expected due to the significant contagion effects during the 2007–2009 subprime and financial crises. Their results suggest that increased comovement and interdependence, particularly among geographically diverse regions

[1] Network analysis is a useful tool for economic problems (e.g., Hidalgo and Hausmann, 2009; Kristoufek *et al.*, 2012; Matesanz *et al.*, 2014; Minoiu and Reyes, 2013; Miśkiewicz and Ausloos, 2010; Reyes *et al.*, 2010; Xu and Zhang, 2021a,b,d).

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

with similar economic conditions, might help explain the failure of the geographic portfolio diversification strategy. Chiang (2016) uses data from six Chinese mega cities for 2003–2014 to create three submarket panels to investigate dynamic interactions among the residential, office and retail markets. Through panel cointegration tests, they do not find a long-run equilibrium among the three property submarkets. With panel causality tests, they find that changes in the residential market lead to those in the commercial market. Their results suggest that policy makers should specially emphasise on the residential market to restrain the rising real estate prices. Yang *et al.* (2018) explore housing price spillovers among 69 large- and medium-sized Chinese cities for July 2005–June 2015 under the high-dimensional generalised vector autoregressive framework. They find highly interactive housing prices. Their results suggest that important cities in price spillover networks appear to be consistent with core cities supported by regional development plans of the government and agglomerate in five relatively concentrated areas. They also identify significant determinants of the (net) positive spillover, including a higher administrative status, population, city gross domestic product and secondary education. Zhang and Fan (2019) utilise the vector autoregressive-based time series approach to study short-run dynamics of urban housing prices in 70 Chinese cities for April 2006–July 2016 and find that prices across cities have increasingly connected, which consequentially is associated with higher systemic risk.

Network analysis is a useful tool for economic analysis of comovements and heterogeneities among different variables. For example, Hidalgo and Hausmann (2009) use it to develop a view of economic growth and development which gives a central role to the complexity of a country's economy. Miśkiewicz and Ausloos (2010) utilise it to approach the question of whether the world economy has reached its globalisation limit. Reyes *et al.* (2010) employ it to facilitate analysis of the pattern of international integration followed by East Asian countries and Latin American countries. Kristoufek *et al.* (2012) adopt it to analyse relationships between prices of biodiesel, ethanol and related fuels and agricultural commodities. Minoiu and Reyes (2013) apply it to explore the global banking network with data on cross-border banking flows for 184 countries. Matesanz *et al.* (2014) exploit it to shed light on comovements in a wide group of commodity prices. Recently, it is used for housing price analysis. Zhang *et al.* (2021) propose a network approach based on partial correlations along with rolling-window analysis to analyse cross-regional dependency in the U.K. housing market, using regional house price indices. They find that regional housing market interactions are most strongly influenced by house prices in the outer South East region and the influence is stronger for highly interconnected markets. They also find that house prices in London would have the strongest influence when regional housing markets are less connected. Wu *et al.* (2021) use sale prices of stocking houses from 35 large- and medium-sized cities in China for 2010–2021 to investigate the spatial linkage through a modified gravity model and network analysis. They find that the integration degree of the housing price network is relatively low and housing price influences are polarised. They also identify several cities whose house prices have a relatively higher degree of centrality and several whose house prices are relatively isolated.

Previous studies on housing prices have linked them to different factors, including house-related characteristics (e.g., Peterson and Flanagan, 2009; Selim, 2009) such as the house age, type, number of units, lot size, number of stories, baths, exterior composition and location, macroeconomics (e.g., Kang *et al.*, 2020; Lam *et al.*, 2008; Rafiei and Adeli, 2016) such as the gross domestic product, gross national product, consumer price index, stock market index, interest rate, default rate and unemployment, and their own time series properties (e.g., Gong *et al.*, 2016; Gu *et al.*, 2011; Yang *et al.*, 2013). Our study here focuses on house prices themselves for analysis of price relationships.

3. Data

Data for analysis are sourced from the China Real Estate Index System (CREIS), which is an analytical platform designed to reflect market conditions and development trends of housing markets in major cities in China. Its origin dates back to 1994, initiated by the Development Research Center of the State Council, Real Estate Association and National Real Estate Development Group Corporation. In 1995 and

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

2005, CREIS was audited by academic experts from the Development Research Center of the State Council, Ministry of Construction, Ministry of Land and Resources, Banking Regulatory Commission, Real Estate Association and certain universities. Currently, it publishes periodically different housing price indices, including the 100 city index, city composite index, residential index, hedonic index, office building index, retail index, villa price index, second-hand housing sales index and rental price index, and becomes the system with the widest coverage in terms of housing markets. We make use of the 100 city index, which became available in CREIS in 2010.

For a specific city, the price index is calculated as: $P_j^t = \frac{\sum P_{ij}^t \times Q_{ij}}{\sum Q_{ij}}$, where P_j^t represents the average housing price in the jth city at time t, P_{ij}^t represents the housing price of the ith project in the jth city at time t and Q_{ij} represents the construction area of the ith project in the jth city.

The data span from June 2010 to May 2019.[2] Table 1 shows summary statistics of housing prices across the 99 cities plotted in figure 1, including the minimum, mean, median, standard deviation (SD), maximum, 1st percentile, 5th percentile, 95th percentile, 99th percentile and p-values of the Jarque–Bera test (Jarque and Bera, 1980), augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979) based on the raw series and first difference series, and Phillips–Perron test (Phillips and Perron, 1988) based on the raw series and first difference series. At the 5 per cent significance level, housing prices of 80 cities are found to be non-normally distributed based on the Jarque–Bera test, while those of the remaining 19 cities are not. Among the 19 cities, housing prices of Taizhou (Zhejiang), Fuzhou, Nantong, Zhangjiagang, Hohhot, Taizhou (Jiangsu), Baotou, Handan, Anshan and Yingkou appear to be closer to be normally distributed than other cities. However, we note that there is no single city showing housing prices nicely matching a normal distribution. The ADF and Phillips–Perron (PP) tests generally show that the raw series are not stationary but the first differences are.

4. Method

4.1. Hierarchical analysis

Consider two time series, TS_i and TS_j. The Pearson correlation coefficient between them is $\rho_{i,j}$ in equation (1), where N_{win} is the length of a temporal window and $\overline{TS}$ is the average of a time series over the window.

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

Following Gower (1966), the distance between the evolution of TS_i and TS_j is $D_{i,j}$ in equation (2), which is used to build the appropriate taxonomy. Intuitively, small distance is associated with two synchronised series and large distance with two independent series.

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

With $D_{i,j}$, the MST is built following the Kruskal (1956) algorithm, which starts with connecting the closest series revealed via their shortest distance. Through connecting the remaining series based on their closeness to previously linked series, one will arrive at the MST, which is a loop-free network showing the most important connections and communities.

The HT also is built following the single-linkage clustering algorithm (Johnson, 1967), which uses the hierarchical dendrogram to show clustering characteristics of the series. In complex networks, clustering

[2] It should be noted that there are actually 99, instead of 100, cities because data for a city called 'Yancheng' are no longer available from December 2016.

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

Table 1. Data summary statistics

City	Minimum	Mean	Median	SD	Maximum	1st per	5th per	95th per	99th per	Jarque–Bera	ADF (raw series)	ADF (first diff.)	PP (raw series)	PP (first diff.)
Sanya (City 1)	17,919	23,086	23,654	2933	28,293	17,961	18,053	26,965	27,750	0.0328	0.5157	0.0035	0.3958	0.0010
Shanghai (City 2)	24,268	35,475	32,364	8464	47,205	24,677	25,432	47,146	47,195	0.0095	0.9092	0.0010	0.9639	0.0010
Beijing (City 3)	22,545	32,901	32,719	7524	42,682	22,687	23,210	42,554	42,639	0.0159	0.8378	0.0100	0.9033	0.0010
Xiamen (City 4)	12,966	21,345	20,905	6253	29,976	12,972	13,649	29,621	29,944	0.0130	0.8458	0.0014	0.8637	0.0010
Shenzhen (City 5)	21,935	37,545	30,971	13,154	55,150	22,120	23,094	54,427	55,037	0.0073	0.8093	0.0103	0.9423	0.0042
Dongguan (City 6)	7544	11,006	9361	2822	16,151	7549	7826	15,875	16,135	0.0067	0.9724	0.0017	0.9960	0.0010
Nanjing (City 7)	11,485	15,475	13,916	3817	22,081	11,487	11,513	21,944	22,069	0.0084	0.9401	0.0256	0.9982	0.0034
Taizhou, Zhejiang (City 8)	9579	10,945	11,006	878	13,193	9614	9670	12,597	13,113	0.3643	0.9717	0.0010	0.9910	0.0010
Dalian (City 9)	10,029	11,135	11,071	703	13,194	10,079	10,100	12,515	13,033	0.0216	0.9774	0.0010	0.9990	0.0010
Tianjin (City 10)	9762	11,874	10,914	1788	15,003	9841	10,080	14,791	14,980	0.0053	0.8954	0.0077	0.9909	0.0010
Ningbo (City 11)	12,013	13,619	13,164	1344	16,641	12,124	12,146	16,385	16,618	0.0027	0.9896	0.0029	0.9971	0.0010
Guangzhou (City 12)	12,572	17,406	17,434	3002	22,049	12,636	13,095	21,709	21,850	0.0293	0.7303	0.0049	0.9122	0.0010
Kunshan (City 13)	8509	10,897	9121	2667	15,602	8538	8688	15,491	15,580	0.0045	0.9313	0.0099	0.9962	0.0020
Hangzhou (City 14)	15,830	18,388	17,202	2571	24,286	15,901	16,055	23,867	24,203	0.0035	0.9711	0.0046	0.9990	0.0010
Haikou (City 15)	9143	11,627	11,603	1850	14,833	9151	9210	14,579	14,707	0.0195	0.8639	0.0010	0.8911	0.0010
Wenzhou (City 16)	12,787	15,579	15,392	2012	21,083	12,804	12,855	19,761	20,959	0.0101	0.6771	0.0010	0.7621	0.0010
Zhuhai (City 17)	9892	15,346	13,171	3965	21,764	9928	10,709	21,660	21,755	0.0072	0.8757	0.0031	0.9542	0.0010
Fuzhou (City 18)	11,236	14,195	14,176	1339	16,700	11,247	12,035	16,187	16,532	0.1004	0.2111	0.0023	0.5836	0.0010
Suzhou (City 19)	10,800	13,347	12,568	1783	16,439	10,833	11,025	15,985	16,292	0.0086	0.8656	0.0013	0.9352	0.0010
Foshan (City 20)	8032	9770	8740	1886	13,197	8040	8077	13,045	13,162	0.0041	0.9768	0.0055	0.9961	0.0010

(Continued)

Table 1. *Continued*

City	Minimum	Mean	Median	SD	Maximum	1st per	5th per	95th per	99th per	Jarque–Bera	ADF (raw series)	ADF (first diff.)	PP (raw series)	PP (first diff.)
Nanning (City 21)	7054	8289	7940	1030	10,695	7122	7232	10,396	10,597	0.0032	0.9941	0.0010	0.9990	0.0010
Nanchang (City 22)	7643	9559	9129	1299	12,288	7671	8054	12,122	12,205	0.0110	0.9596	0.0010	0.9927	0.0010
Nantong (City 23)	8098	9594	9502	951	12,054	8104	8211	11,260	11,831	0.1263	0.9949	0.0010	0.9986	0.0010
Hefei (City 24)	6107	8453	7403	2175	12,832	6112	6273	12,503	12,591	0.0072	0.9990	0.0225	0.9990	0.0010
Jiaxing (City 25)	7227	8397	7828	1243	11,380	7232	7251	11,072	11,271	0.0023	0.9990	0.0010	0.9990	0.0010
Changzhou (City 26)	6889	8290	8141	1032	10,802	7010	7090	10,491	10,739	0.0083	0.9797	0.0010	0.9981	0.0010
Changshu (City 27)	7497	9767	9266	1768	14,429	7521	7812	13,740	14,297	0.0027	0.9990	0.0010	0.9990	0.0010
Langfang (City 28)	5832	8504	7216	2430	12,550	5933	6157	12,360	12,505	0.0054	0.9419	0.0268	0.9841	0.0010
Zhangjiagang (City 29)	8461	9404	9379	583	10,652	8469	8548	10,439	10,590	0.0666	0.7838	0.0010	0.8959	0.0010
Chengdu (City 30)	7177	8136	7950	700	10,055	7217	7336	9557	9958	0.0048	0.9904	0.0060	0.9990	0.0010
Yangzhou (City 31)	7924	9439	8993	1076	12,023	7950	8395	11,892	11,976	0.0010	0.9900	0.0010	0.9973	0.0010
Wuxi (City 32)	8086	9401	8808	1198	11,947	8163	8185	11,516	11,899	0.0067	0.9662	0.0010	0.9941	0.0010
Kunming (City 33)	7510	8560	8362	816	10,727	7557	7623	10,469	10,714	0.0010	0.9971	0.0010	0.9990	0.0010
Wuhan (City 34)	7026	9096	8273	1748	12,240	7071	7249	11,904	12,082	0.0070	0.9732	0.0247	0.9987	0.0010
Shantou (City 35)	6689	8462	8323	1181	10,938	6814	6959	10,876	10,917	0.0169	0.9523	0.0010	0.9894	0.0010
Jinan (City 36)	7674	9390	8726	1262	11,665	7755	8048	11,550	11,650	0.0050	0.9492	0.0010	0.9583	0.0010
Huzhou (City 37)	7448	8817	8645	694	10,554	7480	7868	10,174	10,365	0.0291	0.9511	0.0010	0.9612	0.0010
Shaoxing (City 38)	8174	9844	9896	1152	13,216	8220	8345	12,473	13,069	0.0036	0.9990	0.0123	0.9990	0.0010
Zhengzhou (City 39)	6524	9404	9252	1603	11,859	6597	7127	11,785	11,857	0.0320	0.6712	0.0010	0.7562	0.0010
Ordos (City 40)	7267	8412	8264	404	9410	7432	7913	9230	9296	0.0347	0.1261	0.0010	0.0436	0.0010
Jinhua (City 41)	8057	9253	9289	670	10,723	8093	8261	10,468	10,663	0.2787	0.9859	0.0010	0.9843	0.0010

(Continued)

Table 1. *Continued*

City	Minimum	Mean	Median	SD	Maximum	1st per	5th per	95th per	99th per	Jarque–Bera	ADF (raw series)	ADF (first diff.)	PP (raw series)	PP (first diff.)
Qingdao (City 42)	8410	9888	9274	1351	13,321	8422	8724	13,183	13,295	0.0010	0.9791	0.0367	0.9990	0.0011
Zhongshan (City 43)	5971	7373	6398	1649	10,655	5996	6010	10,540	10,615	0.0036	0.9860	0.0066	0.9990	0.0010
Urumchi (City 44)	4557	7090	7217	795	8120	4695	5296	8016	8071	0.0010	0.0016	0.0010	0.0010	0.0010
Lanzhou (City 45)	6277	7482	7254	724	8921	6302	6674	8784	8858	0.0123	0.9311	0.0010	0.9481	0.0010
Hohhot (City 46)	5853	6957	6995	458	8109	5867	6394	7924	8043	0.3787	0.6551	0.0010	0.8976	0.0010
Harbin (City 47)	6266	7456	7190	838	9506	6459	6662	9335	9467	0.0014	0.9990	0.0010	0.9990	0.0010
Taiyuan (City 48)	4964	7002	6957	1123	9714	5181	5561	9416	9657	0.0124	0.9990	0.0010	0.9990	0.0010
Weihai (City 49)	5354	6533	6293	878	8630	5377	5512	8438	8612	0.0032	0.9990	0.0010	0.9990	0.0010
Huizhou (City 50)	5556	7655	6691	1698	10,258	5573	5778	10,205	10,256	0.0059	0.8719	0.0028	0.9422	0.0010
Liuzhou (City 51)	5196	6978	7059	1043	9057	5202	5354	8809	9012	0.1086	0.9591	0.0010	0.9740	0.0010
Jiangyin (City 52)	6224	7199	7046	655	8866	6245	6306	8635	8861	0.0059	0.9953	0.0010	0.9990	0.0010
Shenyang (City 53)	5335	7360	7385	700	8792	5372	5872	8607	8755	0.0079	0.0907	0.0186	0.2261	0.0017
Quanzhou (City 54)	6102	7446	7626	732	8725	6233	6280	8645	8707	0.0797	0.8232	0.0010	0.7905	0.0010
Taizhou, Jiangsu (City 55)	5128	6649	6608	649	7813	5156	5712	7739	7773	0.2557	0.2940	0.0010	0.4303	0.0010
Zhanjiang (City 56)	4781	7433	7062	1405	10,483	4910	5459	10,414	10,464	0.0122	0.9392	0.0031	0.9599	0.0010
Yantai (City 57)	5699	6627	6399	687	8605	5765	5893	8363	8588	0.0010	0.9990	0.0020	0.9990	0.0010
Shijiazhuang (City 58)	5545	7355	7009	1606	10,574	5545	5594	10,288	10,479	0.0115	0.9990	0.0010	0.9990	0.0010
Qinhuangdao (City 59)	5781	7142	6892	805	9172	5854	6372	8826	9088	0.0028	0.9827	0.0010	0.9922	0.0010
Xi'an (City 60)	6403	7396	7144	884	9773	6407	6487	9366	9702	0.0011	0.9938	0.0047	0.9990	0.0010
Chongqing (City 61)	6691	7814	7339	1113	10,539	6719	6830	10,327	10,482	0.0013	0.9712	0.0165	0.9990	0.0040
Zhenjiang (City 62)	5446	6917	6567	971	9338	5471	5923	9060	9330	0.0020	0.9944	0.0010	0.9990	0.0010

(Continued)

Table 1. *Continued*

City	Minimum	Mean	Median	SD	Maximum	1st per	5th per	95th per	99th per	Jarque–Bera	ADF (raw series)	ADF (first diff.)	PP (raw series)	PP (first diff.)
Changchun (City 63)	5952	7064	6844	817	9058	5976	6124	8976	9034	0.0020	0.9990	0.0010	0.9990	0.0010
Changsha (City 64)	4929	6782	6549	813	8415	4929	5314	8218	8407	0.5000	0.4456	0.0010	0.7538	0.0010
Dongying (City 65)	5126	5534	5474	223	5971	5194	5240	5880	5920	0.0215	0.4387	0.0010	0.4891	0.0010
Baoding (City 66)	4143	6201	5606	1633	9062	4150	4422	8950	9030	0.0102	0.9962	0.0010	0.9990	0.0010
Baotou (City 67)	4964	5613	5549	273	6167	5024	5214	6114	6143	0.1929	0.4358	0.0010	0.8251	0.0010
Beihai (City 68)	5163	6002	5779	704	7958	5167	5417	7737	7907	0.0010	0.9987	0.0010	0.9990	0.0010
Jilin (City 69)	4915	5536	5519	400	6437	4958	4965	6262	6384	0.0645	0.6037	0.0043	0.7504	0.0010
Tangshan (City 70)	5749	6295	6100	542	7654	5757	5776	7468	7625	0.0017	0.9976	0.0010	0.9990	0.0010
Yichang (City 71)	4797	5761	5491	780	7676	4810	4992	7574	7671	0.0010	0.9958	0.0010	0.9978	0.0010
Xuzhou (City 72)	4704	6183	5885	894	8294	4705	5065	8026	8284	0.0059	0.9927	0.0010	0.9976	0.0010
Rizhao (City 73)	5547	6394	6354	521	7831	5601	5733	7525	7795	0.0042	0.9752	0.0010	0.9862	0.0010
Guilin (City 74)	4272	5507	5577	550	6495	4313	4590	6323	6402	0.0642	0.4247	0.0393	0.5903	0.0010
Jiangmen (City 75)	5470	6350	6086	671	7778	5548	5723	7696	7738	0.0038	0.9900	0.0010	0.9952	0.0010
Luoyang (City 76)	4451	5777	5335	976	8260	4478	4858	8082	8242	0.0010	0.9976	0.0010	0.9990	0.0010
Zibo (City 77)	5318	6134	5844	673	7869	5322	5507	7662	7863	0.0010	0.9990	0.0010	0.9990	0.0010
Huai'an (City 78)	4272	5025	4887	417	5986	4288	4492	5822	5939	0.0204	0.9475	0.0010	0.9720	0.0010
Mianyang (City 79)	4228	5044	4914	496	6400	4230	4424	6257	6390	0.0010	0.9990	0.0010	0.9990	0.0010
Liaocheng (City 80)	4035	5057	5124	463	6253	4048	4480	6013	6192	0.0560	0.7987	0.0010	0.9135	0.0010
Wuhu (City 81)	5483	6318	6144	608	7983	5508	5547	7567	7910	0.0049	0.9868	0.0010	0.9984	0.0010
Xining (City 82)	4668	5785	5871	489	6692	4734	4917	6627	6652	0.4109	0.6307	0.0010	0.7984	0.0010
Guiyang (City 83)	4472	5124	5005	547	6797	4487	4550	6415	6779	0.0010	0.9984	0.0010	0.9990	0.0010

(Continued)

Table 1. *Continued*

City	Minimum	Mean	Median	SD	Maximum	1st per	5th per	95th per	99th per	Jarque–Bera	ADF (raw series)	ADF (first diff.)	PP (raw series)	PP (first diff.)
Ganzhou (City 84)	4613	6014	5804	977	8340	4622	4900	7930	8328	0.0157	0.9990	0.0010	0.9990	0.0010
Lianyungang (City 85)	4604	5926	5814	754	7358	4644	4791	7313	7357	0.0475	0.9384	0.0010	0.9376	0.0010
Handan (City 86)	4100	5019	5030	471	6100	4139	4265	5854	6060	0.2789	0.9647	0.0010	0.9851	0.0010
Yinchuan (City 87)	4544	5059	5044	239	5771	4560	4740	5626	5743	0.0022	0.9627	0.0010	0.9771	0.0010
Anshan (City 88)	4655	5069	5093	141	5438	4698	4863	5288	5362	0.5000	0.0210	0.0010	0.0633	0.0010
Ma’anshan (City 89)	4909	5696	5631	568	7009	4915	4961	6822	6867	0.0147	0.9960	0.0010	0.9982	0.0010
Baoji (City 90)	3803	4300	4224	384	5290	3811	3854	5217	5249	0.0013	0.9851	0.0010	0.9937	0.0010
Suqian (City 91)	4002	4806	4688	357	5479	4004	4214	5421	5452	0.4605	0.5248	0.0010	0.6063	0.0010
Dezhou (City 92)	4186	4973	4824	577	6559	4219	4388	6157	6487	0.0019	0.9970	0.0010	0.9990	0.0010
Xinxiang (City 93)	2787	4244	4198	687	5617	2843	2949	5580	5613	0.5000	0.8489	0.0010	0.8249	0.0010
Zhuzhou (City 94)	3085	4860	4814	688	6235	3104	3559	6195	6232	0.3552	0.2684	0.0010	0.3298	0.0010
Xiangtan (City 95)	3228	4139	3978	533	5483	3253	3469	5344	5471	0.0015	0.9881	0.0010	0.9975	0.0010
Weifang (City 96)	3721	4755	4507	677	6401	3752	3891	6360	6399	0.0010	0.9844	0.0118	0.9990	0.0010
Heze (City 97)	2876	4457	4367	616	5350	2896	3140	5289	5332	0.0258	0.1644	0.0135	0.1576	0.0010
Yingkou (City 98)	4297	4620	4585	147	4942	4351	4442	4896	4928	0.0522	0.1555	0.0010	0.3129	0.0010
Hengshui (City 99)	3102	4744	4898	1043	6586	3133	3254	6362	6493	0.0451	0.9422	0.0031	0.9768	0.0010

Figure 1. (Colour online) Ninety-nine cities considered in this study

based on similarities of certain characteristics is one way to define communities (Wasserman and Faust, 1994).

Through the MST and HT, one could arrive at clusters based on correlations showing similar patterns in terms of price dynamics. When conducting hierarchical analysis, time series in the first differences representation are employed and N_{win}=107.

4.2. Synchronisation

For N_{win}=12, 1 year, two rolling-window-based synchronisation measurements are considered to show the evolution of interdependence among series. The first one is the global correlation (GC), which is the sum of all correlation pairs among series normalised by the number of pairs. The second one is the MST cost (MSTC), which is the sum of all distance pairs among series normalised by the number of pairs. The normalisation enables comparisons of results when different numbers of series are studied. Intuitively, the tighter the series are linked, the higher the GC or the low the MSTC. Due to this reason, we will focus on presenting GC-based results.

Also for N_{win}=12, another rolling-window-based measurement considered is the synchronisation intensity (SI), which is the number of connections for each series inside the MST weighed by the distance of the connections. The SI helps characterise how each series moves within the network over time and whether it turns to be more or less synchronised.

5. Result

One main advantage of network analysis is that it allows one to go beyond first-order relationships and capture the whole structure of relationships (Reyes *et al.*, 2010) that form the housing price system.

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

For example, one could study housing price interactions between any two or more cities that relate to a given one and evaluate the closeness of housing price relationships among a set of cities. This could help us understand specific properties of housing price linkages characterising different (groups of) cities. In network analysis, relatively important housing prices might not necessarily be those whose corresponding cities have the most advanced economy but rather those involved in a large number of linkages.

Figure 2 shows the MST, which provides a rough representation of the topological organisation in the sense that price series are directly linked if they tend to be more synchronised. In other words, one could see from the MST those cities that tend to be more connected with others and those that tend to have more specific or idiosyncratic price paths. For example, Cities 7 (Nanjing) and 13 (Kunshan), 10 (Tianjin) and 34 (Wuhan), 26 (Changzhou) and 64 (Changsha), 63 (Changchun) and 77 (Zibo), and 35 (Shantou) and 65 (Dongying) are directly connected. The connection between Nanjing and Kunshan is not surprising as they both locate in Jiangsu province and share certain regional economic development commonalities. The connection between Tianjin and Wuhan could be partly due to their logistics linkage (van de Bovenkamp and Fei, 2016) that contributes to the economic integration. The connection

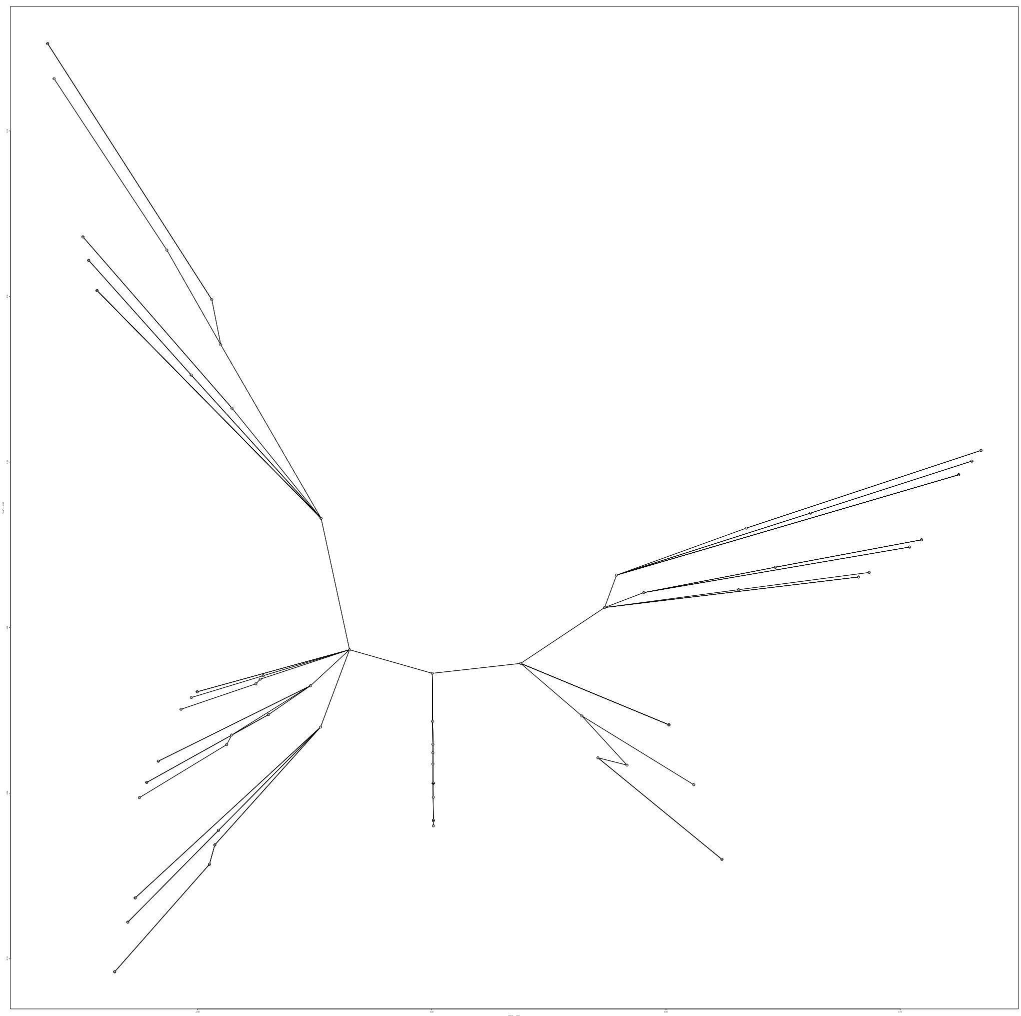

Figure 2. Minimum spanning tree. The numbers represent the 99 cities whose indices are shown in table 1. Please zoom in for a better view of the numbers in this plot

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

between Changzhou and Changsha should be related to their synergistic development along the Yangtze River economic belt (Ma *et al.*, 2017; Xu *et al.*, 2017; Zeng *et al.*, 2018, 2020; Zhong *et al.*, 2016) and similarities in some key economic sectors (Wang and Chen, 2011; Xu *et al.*, 2017; Zhou, 2014). The connection between Changchun and Zibo is probably related to the national initiative aiming at promoting economic development and industrial transformation and upgrading in these cities. The connection between Shantou and Dongying is likely due to their similar coastal economies (Chen, 2007) and characteristics of urban land use (Cao *et al.*, 2009; Lu *et al.*, 2020).

Figure 3 shows the HT, which shows the hierarchical structure based on proximity of price dynamics. In other words, one could discover groups of cities with similar price dynamics and cities with more idiosyncratic price paths. As compared to the MST, the HT also reveals comovements of price clusters that are created endogenously (Matesanz *et al.*, 2014). While we could see different degrees of heterogeneities in price dynamics from the HT, several sectoral groups are formed, including Group 1—Cities 7 (Nanjing) and 13 (Kunshan), Group 2—Cities 10 (Tianjin) and 34 (Wuhan), Group 3—Cities 26 (Changzhou) and 64 (Changsha), Group 4—Cities 63 (Changchun) and 77 (Zibo), and Group 5—Cities 35 (Shantou) and 65 (Dongying). For Group 1, housing prices of Kunshan might be influenced by those of Nanjing. Kunshan is surrounded by three of the largest cities in China that include Shanghai, Nanjing and Hangzhou of Zhejiang province (Long *et al.*, 2007). Kunshan is unique due to its high population density and agricultural intensity. The growth of Shanghai, prosperity of Nanjing and Hangzhou and policies established by the Kunshan local government for developing townships and village enterprises have pushed the economic development of Kunshan (Long *et al.*, 2007). Our result of the sectoral group between housing prices of Nanjing and Kunshan is likely to be related to their regional economic relationships. For Group 2, housing prices of Tianjin might be influenced by those of Wuhan. Being the central location in China, Hubei province has obvious advantages in terms of regional transportation. Wuhan, the capital city of Hubei province, is being promoted by the provincial government to become a major industrial and commercial city. One of the goals is to construct Wuhan

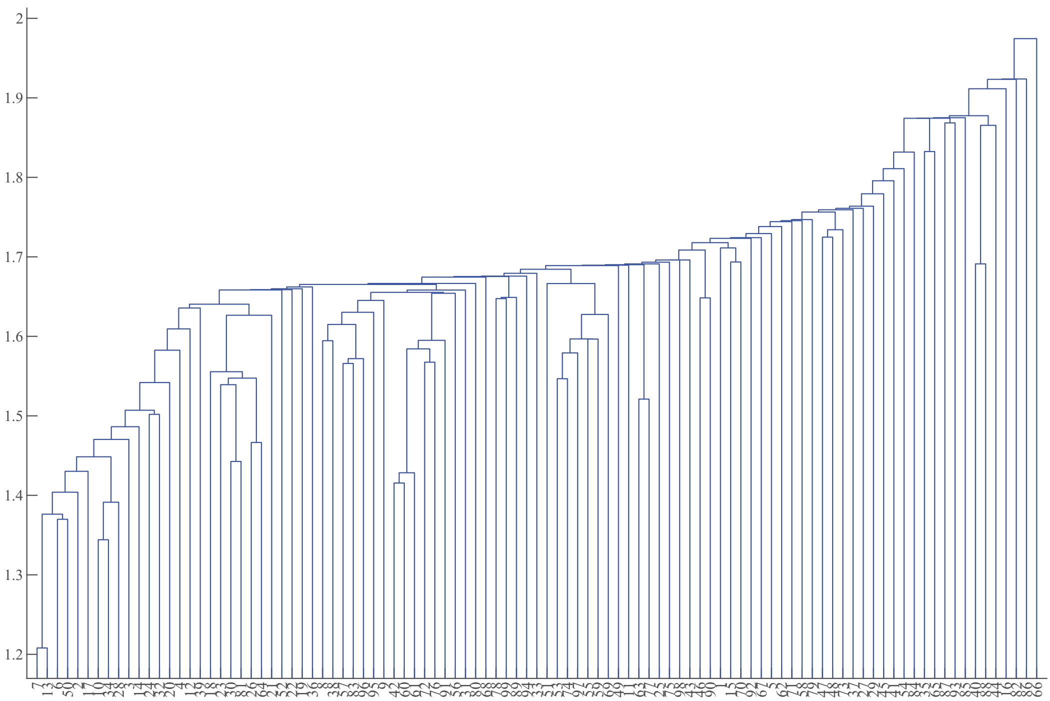

Figure 3. (Colour online) Hierarchical tree. The numbers on the horizontal axis represent the 99 cities whose indices are shown in table 1

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

as a national logistics hub with good layouts of modern logistic parks, logistic centres and distribution centres that fulfil domestic and global (e.g., the 'one belt one road' initiative) needs (van de Bovenkamp and Fei, 2016). Wuhan also serves as the shipping centre of the Yangtze River's middle section. Over the past few years, the 'four horizontal and four vertical' passenger line initiative's speed transport networks have been significantly expanded in China, which lead to an 8-hour provincial capital traffic circles. Wuhan serves as the intersection of the high-speed transport networks and is within a 4-hour traffic circle from important cities in China, which include Beijing, Shanghai, Chongqing, Guangzhou and Tianjin. Our result of the sectoral group between housing prices of Wuhan and Tianjin is likely driven by their economic integration facilitated by the logistics linkage. For Group 3, housing prices of Changzhou and Changsha might affect each other. Zeng *et al.* (2018) rank both cities of regional importance along the Yangtze River economic belt, considering their economic development, technological innovation, transportation infrastructure and ecological environment. Zhong *et al.* (2016) point out that Changzhou was one of six central cities along the Yangtze River economic belt in 1988 and 2001, considering their economic connections with other cities, and the six central cities are changing over time. For example, Zhong *et al.* (2016) find that Changsha was one of six central cities in 2012 while Changzhou was not on the list for that year. Ma *et al.*'s (2017) study suggests that Changsha is becoming more important along the Yangtze River economic belt in 2015, while Changzhou needs to improve its population size and economic scale to rejoin the list of central cities along the belt. More recently, Zeng *et al.* (2020) rank both Changzhou and Changsha as regional significant central cities along the belt in 2019, with Changsha leading Changzhou. These two cities also have similarities in some key economic sectors, such as the tourism (Wang and Chen, 2011), construction machinery (Zhou, 2014) and innovative output (Xu *et al.*, 2017). Our result of the sectoral group between housing prices of Changzhou and Changsha might be partly explained by the synergistic development along the belt, evolving economic scales, similarities of economic sectors, and thus migrating labour force. For Group 4, housing prices of Zibo might be influenced by those of Changchun. These two cities' economies both used to heavily rely on energy and resources. The national initiative aiming at industrial transformation and upgrading for green and innovative economic growth covers Zibo and Changchun, with the latter showing more promising outcomes in recent years and the former facing the slow population growth challenge. Nevertheless, both cities are ranked as achieving satisfying industrial transformation and upgrading results in 2020 by pushing the establishment of green and innovative industrial enterprises with local governments' efforts. These new enterprises in the two cities have similarities in terms of the economic sectors covered, such as the agriculture, education, service and technology, for balanced development and compete for labour force. While industrial transformation and upgrading could be a way to help local governments avoid relying on the real estate sector and land fiscal revenue in the long run, such reliance might be hard to avoid during the transition period (Liu, 2010) that could be discovered from these two cities' land policies and housing prices in the past decade. Our result of the sectoral group between housing prices of Changchun and Zibo should be tied to the common national initiative. For Group 5, housing prices of Shantou and Dongying might affect each other. These two cities have similar coastal economies and Shantou's economy has developed significantly so that it has similar economic scales as Dongying (Chen, 2007). Chen (2007) also finds that these two cities have the same regional industrial structure. Cao *et al.* (2009) and Lu *et al.* (2020) study the urban land use issue for 2005–2006 and 2003–2017, respectively, and find that these two cities show close results in terms of the land use efficiency. Our result of the sectoral group between housing prices of Shantou and Dongying could stem from their similar economic structures and land use characteristics.

Figure 4 shows the GC for all of the 99 cities (Group 0) and cities in Groups 1–5, which sheds light on price interactions between all city pairs of a group and thus price comovement information in the group. The distribution of the GC is also plotted in figure 5. For Group 0, the synchronisation is relatively low and stable over time, which slightly decreases on average after March 2017, indicating that the housing market might become more regionalised recently. For Groups 1–5, the synchronisation is much more volatile but also at significantly higher levels on average as compared to Group 0, suggesting obvious heterogeneous price dynamics within specific groups of cities. For example, there is a significant drop in

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

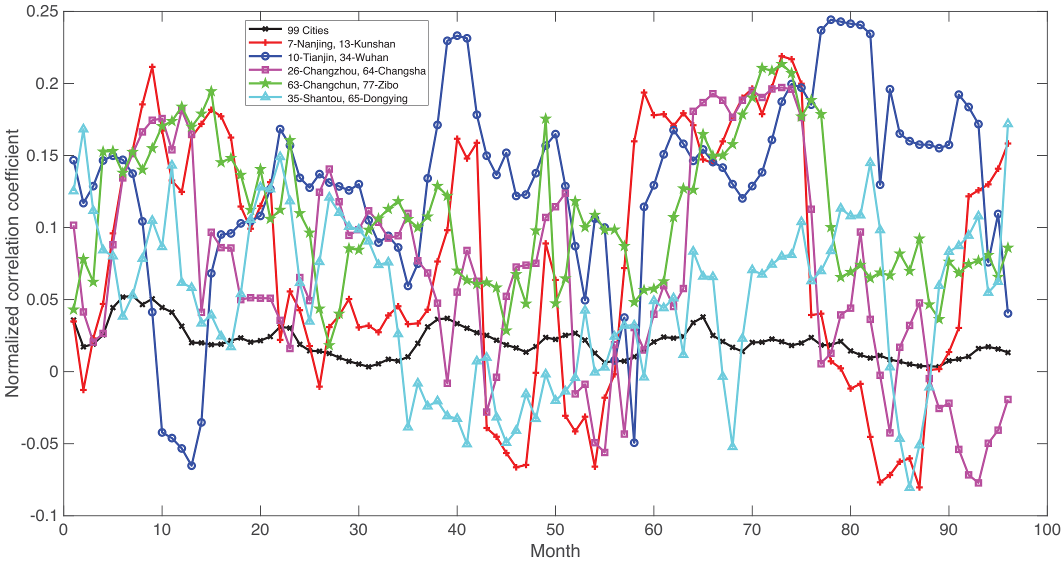

Figure 4. (Colour online) Global correlation

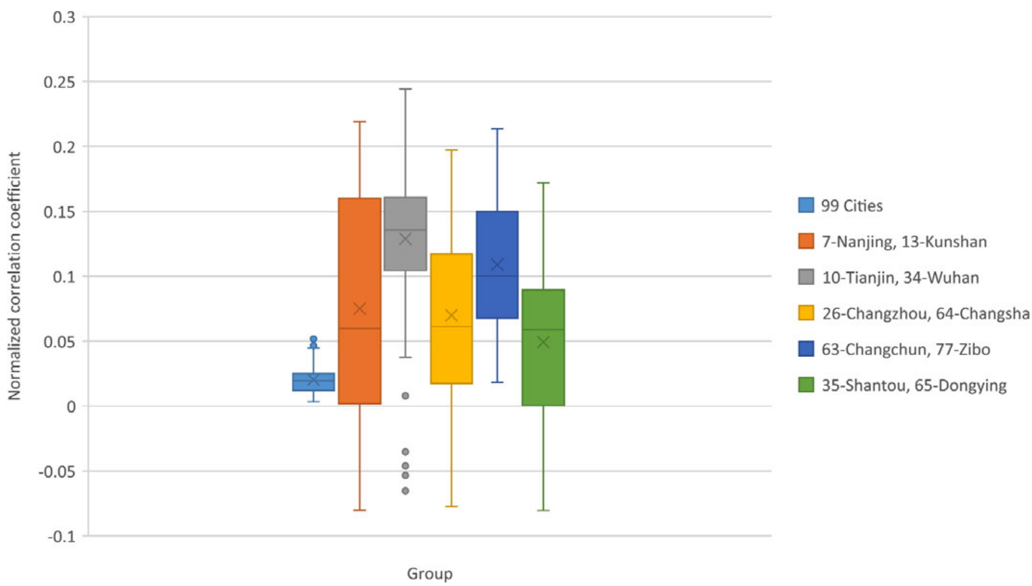

Figure 5. (Colour online) The box and whisker plot of the global correlation in figure 4. The box and whisker plot contains the mean, median, first quartile, third quartile, interquartile range (IQR) and outliers, where a point is considered an outlier if it exceeds a distance of 1.5 times the IQR below the first quartile or above the third quartile

the synchronisation between Tianjin and Wuhan, but a significant increase between Nanjing and Kunshan and between Shantou and Dongying after late 2018. For Groups 1–5, it is also observed that there is no persistent high or low synchronisation within a specific group, revealing that economic development within a specific group could be related but there exist obvious idiosyncratic paths contributing to the ever-fluctuating synchronisation. These results indicate that certain policy analysis, for example, market microstructure and forecasting (Xu and Zhang, 2021c), related to housing prices of

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

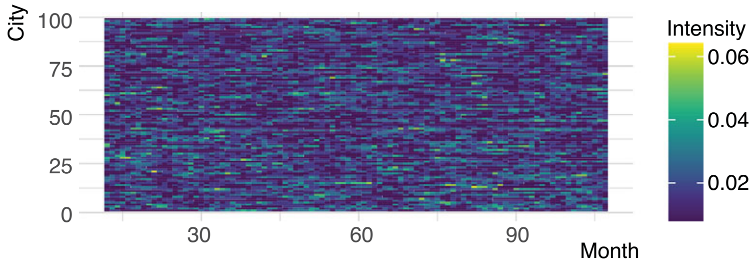

Figure 6. (Colour online) Synchronisation intensity. City indices are shown in table 1

individual cities might be better conducted by taking into consideration the synchronisation and heterogeneity.

Figure 6 shows the SI, which helps determine the rolling importance of different cities in the network. One could see that over time, the SI is fluctuating, with no persistent increasing or decreasing trend for a city. There are cities [e.g., City 63 (Changchun)] whose prices appear to be more connected to other prices in the network. These cities could be price leaders in their respective groups (Matesanz *et al.*, 2014), which might be tested by lead-lag (e.g., Li *et al.*, 2005; Xu, 2014b,c, 2015b, 2017b,c, 2018a,b,c,d,e, 2019a,c, 2020; Xu and Thurman, 2015a,b; Yang *et al.*, 2001, 2003, 2006, 2012, 2020; Yang and Leatham, 1999) and contemporaneous (e.g., Awokuse and Bessler, 2003; Bessler *et al.*, 2003; Bessler and Akleman, 1998; Bessler and Yang, 2003; Bizimana *et al.*, 2015; Chopra and Bessler, 2005; Haigh and Bessler, 2004; Lai and Bessler, 2015; Xu, 2014a, 2015a, 2017a, 2019a,b; Yang and Bessler, 2004) causality. Here, it is worth noting that the fact that the MST and HT methodologies are very straightforward is not only their advantage but also potentially their limitation depending on specific research purposes. Particularly, one could not directly comment on causality-related questions based on the results (Kristoufek *et al.*, 2012).

6. Conclusion

This study analyses comovements of monthly housing prices of 99 major cities in China for the years 2010–2019 by shedding light on interdependence and synchronisation through network analysis and topological and hierarchical characterisations of price dynamics. The empirical framework facilitates endogenous identifications of city groups with similar price synchronisation patterns, which can benefit policy analysis concerning housing prices of individual cities. The framework also enables us to figure out price interactions, allowing for complexities and heterogeneities in the price system.

We find that housing prices of Nanjing and Kunshan, Tianjin and Wuhan, Changzhou and Changsha, Changchun and Zibo, and Shantou and Dongying are directly connected. We also find that these five pairs of cities form sectoral groups. Potential reasons for these findings include factors such as economic integration, synergistic development and policy initiatives. The degree of comovements is generally slightly lower after March 2017 but no persistent drop is discovered. This suggests that there could be supply and demand pattern changes after March 2017 that decrease regional housing price synchronisation. We identify several groups of cities, each of which has its members generally showing relatively strong but volatile price dynamics across the sample period. Price synchronisation, on average, within a certain group also is higher than that across all of the 99 cities. Housing prices of cities in an identified group might be driven by group specific factors in addition to common factors across the nation. Further, we show that certain cities have potential of being price leaders within an identified group due to their increasing connectivities over time with other cities. These heterogeneities in price dynamics should be useful to policy analysis aiming at housing market stabilisation.

As one could not directly comment on causality-related questions based on results here (Kristoufek *et al.*, 2012), it could be a worthwhile avenue to pursue this topic for future research. Results here might be of use when selecting certain cities for analysis, which could help alleviate the dimensionality issue of

https://doi.org/10.1017/nie.2021.34 Published online by Cambridge University Press

time series models (Zhang and Fan, 2019). Our analysis focuses on the 100 major cities. As there are more than 700 cities in China, it would be interesting to extend the analysis to this magnitude if data become available in the future. Analysis of housing price comovements can be helpful in monitoring nationwide and regional overheating in the real estate market and thus risks and bubbles. Excessive comovements identified could serve as warning indicators to policy makers when designing policies to cool down the market from the perspective of multiple locations. The evolving pattern of housing price comovements over time can also help shed light on different cities' economic development processes. It might be valuable to policy makers to sort out if it is the speculative capital inflow or fundamental economic development that makes a city's housing prices more important and connected to other cities over time.

References

Antonakakis, N., Chatziantoniou, I., Floros, C. and Gabauer, D. (2018), 'The dynamic connectedness of UK regional property returns', *Urban Studies*, **55**, pp. 3110–134. doi:10.1177/0042098017739569.

Awokuse, T.O. and Bessler, D.A. (2003), 'Vector autoregressions, policy analysis, and directed acyclic graphs: An application to the US economy', *Journal of Applied Economics*, **6**, pp. 1–24. doi:10.1080/15140326.2003.12040583.

Bessler, D.A. and Akleman, D.G. (1998), 'Farm prices, retail prices, and directed graphs: Results for pork and beef', *American Journal of Agricultural Economics*, **80**, pp. 1144–149. doi:10.2307/1244220.

Bessler, D.A. and Yang, J. (2003), 'The structure of interdependence in international stock markets', *Journal of International Money and Finance*, **22**, pp. 261–87. doi:10.1016/S0261-5606(02)00076-1.

Bessler, D.A., Yang, J. and Wongcharupan, M. (2003), 'Price dynamics in the international wheat market: Modeling with error correction and directed acyclic graphs', *Journal of Regional Science*, **43**, pp. 1–33. doi:10.1111/1467-9787.00287.

Bizimana, J.C., Angerer, J.P., Bessler, D.A. and Keita, F. (2015), 'Cattle markets integration and price discovery: The case of Mali', *The Journal of Development Studies*, **51**, pp. 319–34. doi:10.1080/00220388.2014.963564.

van de Bovenkamp, J. and Fei, Y. (2016), 'Economic overview of Hubei province', Series of Economic Overviews of Important Regions in China, Netherlands Business Support Office Wuhan.

Cao, Y.g., Yuan, C., Zhou, W. and Qian, M.J. (2009), 'Evaluation of intensive use of city land based on urban classification', *Soils*, **41**, 288–94.

Chen, Y.Y. (2007), 'Characteristic of regional economic differentiation of littoral belt of China in 1984–2003', *Scientia Geographica Sinica*, **27**, pp. 642–47. doi:10.13249/j.cnki.sgs.2007.05.642.

Chiang, S.h. (2016), 'Interaction among real estate properties in china using three submarket panels', *Habitat International*, **53**, pp. 243–53. doi:10.1016/j.habitatint.2015.11.038.

Chopra, A. and Bessler, D.A. (2005), 'Price discovery in the black pepper market in Kerala, India', *Indian Economic Review*, **40**, pp. 1–21.

Dickey, D.A. and Fuller, W.A. (1979), 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association*, **74**, pp. 427–31. doi:10.1080/01621459.1979.10482531.

Gong, Y., Hu, J. and Boelhouwer, P.J. (2016), 'Spatial interrelations of Chinese housing markets: Spatial causality, convergence and diffusion', *Regional Science and Urban Economics*, **59**, pp. 103–17. doi:10.1016/j.regsciurbeco.2016.06.003.

Gower, J.C. (1966), 'Some distance properties of latent root and vector methods used in multivariate analysis', *Biometrika*, **53**, pp. 325–38. doi:10.1093/biomet/53.3-4.325.

Gu, J., Zhu, M. and Jiang, L. (2011), 'Housing price forecasting based on genetic algorithm and support vector machine', *Expert Systems with Applications*, **38**, pp. 3383–86. doi:10.1016/j.eswa.2010.08.123.

Haigh, M.S. and Bessler, D.A. (2004), 'Causality and price discovery: An application of directed acyclic graphs', *The Journal of Business*, **77**, pp. 1099–121. doi:10.1086/422632.

Hidalgo, C.A. and Hausmann, R. (2009), 'The building blocks of economic complexity', *Proceedings of the National Academy of Sciences*, **106**, pp. 10570–75. doi:10.1073/pnas.0900943106.

Jarque, C.M. and Bera, A.K. (1980), 'Efficient tests for normality, homoscedasticity and serial independence of regression residuals', *Economics Letters*, **6**, pp. 255–59. doi:10.1016/0165-1765(80)90024-5.

Johnson, S.C. (1967), 'Hierarchical clustering schemes', *Psychometrika*, **32**, pp. 241–54. doi:10.1007/BF02289588.

Kang, J., Lee, H.J., Jeong, S.H., Lee, H.S. and Oh, K.J. (2020), 'Developing a forecasting model for real estate auction prices using artificial intelligence', *Sustainability*, **12**, p. 2899. doi:10.3390/su12072899.

Kristoufek, L., Janda, K. and Zilberman, D. (2012), 'Correlations between biofuels and related commodities before and during the food crisis: A taxonomy perspective', *Energy Economics*, **34**, pp. 1380–91. doi:10.1016/j.eneco.2012.06.016.

Kruskal, J.B. (1956), 'On the shortest spanning subtree of a graph and the traveling salesman problem', *Proceedings of the American Mathematical Society*, **7**, pp. 48–50. doi:10.2307/2033241.

Lai, P.C. and Bessler, D.A. (2015), 'Price discovery between carbonated soft drink manufacturers and retailers: A disaggregate analysis with PC and LiNGAM algorithms', *Journal of Applied Economics*, **18**, pp. 173–97. doi:10.1016/S1514-0326(15)30008-8.

Lam, K.C., Yu, C. and Lam, K. (2008), 'An artificial neural network and entropy model for residential property price forecasting in Hong Kong', *Journal of Property Research*, **25**, pp. 321–42. doi:10.1080/09599910902837051.

Li, Q., Yang, J., Hsiao, C. and Chang, Y.J. (2005), 'The relationship between stock returns and volatility in international stock markets', *Journal of Empirical Finance*, **12**, pp. 650–65. doi:10.1016/j.jempfin.2005.03.001.

Liu, Z. (2010), 'Promoting industrial transformation and upgrading with urbanization—also on the historical role of "land finance" in the transitional period', *Academic Monthly*, **10**, pp. 65–70.

Long, H., Tang, G., Li, X. and Heilig, G.K. (2007), 'Socio-economic driving forces of land-use change in Kunshan, the Yangtze River delta economic area of China', *Journal of Environmental Management*, **83**, pp. 351–64. doi:10.1016/j.jenvman.2006.04.003.

Lu, X.-h., Yang, X. and Chen, Z.-x. (2020), 'Measurement and temporal spatial evolution characteristics of urban land green use efficiency in China', *China Population, Resources and Environment*, **30**, pp. 83–91.

Ma, J., Deng, H. and Zhang, H. (2017), 'Analysis of regional economic disparities and spatial patterns in the Yangtze River economic zone', *Statistics & Decision*, **484**, pp. 86–9. doi:10.13546/j.cnki.tjyjc.2017.16.021.

Matesanz, D., Torgler, B., Dabat, G. and Ortega, G.J. (2014), 'Co-movements in commodity prices: A note based on network analysis', *Agricultural Economics*, **45**, pp. 13–21. doi:10.1111/agec.12126.

Minoiu, C. and Reyes, J.A. (2013), 'A network analysis of global banking: 1978–2010', *Journal of Financial Stability*, **9**, 168–84. doi:10.1016/j.jfs.2013.03.001.

Miśkiewicz, J. and Ausloos, M. (2010), 'Has the world economy reached its globalization limit?', *Physica A: Statistical Mechanics and Its Applications*, **389**, pp. 797–806. doi:10.1016/j.physa.2009.10.029.

Peterson, S. and Flanagan, A. (2009), 'Neural network hedonic pricing models in mass real estate appraisal', *Journal of Real Estate Research*, **31**, pp. 147–64. doi:10.1080/10835547.2009.12091245.

Phillips, P.C. and Perron, P. (1988), 'Testing for a unit root in time series regression', *Biometrika*, **75**, pp. 335–46. doi:10.1093/biomet/75.2.335.

Rafiei, M.H. and Adeli, H. (2016), 'A novel machine learning model for estimation of sale prices of real estate units', *Journal of Construction Engineering and Management*, **142**, p. 04015066. doi:10.1061/(ASCE)CO.1943-7862.0001047.

Reyes, J., Schiavo, S. and Fagiolo, G. (2010), 'Using complex networks analysis to assess the evolution of international economic integration: The cases of East Asia and Latin America', *The Journal of International Trade & Economic Development*, **19**, pp. 215–39. doi:10.1080/09638190802521278.

Selim, H. (2009), 'Determinants of house prices in turkey: Hedonic regression versus artificial neural network', *Expert Systems with Applications*, **36**, pp. 2843–52. doi:10.1016/j.eswa.2008.01.044.

Wang, D.G. and Chen, T. (2011), 'Spatial analysis for regional difference of tourism economy in China', *Scientia Geographica Sinica*, **31**, pp. 528–36. doi:10.13249/j.cnki.sgs.2011.05.528.

Wasserman, S. and Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Volume 8, Cambridge: Cambridge University Press.

Wu, G., Li, J., Chong, D. and Niu, X. (2021), 'Analysis on the housing price relationship network of large and medium-sized cities in China based on gravity model', *Sustainability*, **13**, p. 4071. doi:10.3390/su13074071.

Xu, W., Yang, L., Liu, C., Zhang, L. and Li, L. (2017), 'Temporal-spatial evolution characteristics and its causes of innovation output in the Yangtze River economic belt', *Scientia Geographica Sinica*, **37**, pp. 502–11. doi:10.13249/j.cnki.sgs.2017.04.003.

Xu, X. (2014a), 'Causality and price discovery in US corn markets: An application of error correction modeling and directed acyclic graphs'. Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, Minnesota, July 27–29. doi:10.22004/ag.econ.169806.

Xu, X. (2014b), 'Cointegration and price discovery in US corn markets'. Agricultural and Resource Economics Seminar Series, North Carolina State University, Raleigh, North Carolina, September 30.

Xu, X. (2014c), 'Price discovery in US corn cash and futures markets: The role of cash market selection'. Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, Minnesota, July 27–29. doi:10.22004/ag.econ.169809.

Xu, X. (2015a), 'Causality, price discovery, and price forecasts: Evidence from US corn cash and futures markets'.

Xu, X. (2015b), 'Cointegration among regional corn cash prices', *Economics Bulletin*, **35**, pp. 2581–94.

Xu, X. (2017a), 'Contemporaneous causal orderings of US corn cash prices through directed acyclic graphs', *Empirical Economics*, **52**, pp. 731–58. doi:10.1007/s00181-016-1094-4.

Xu, X. (2017b), 'The rolling causal structure between the Chinese stock index and futures', *Financial Markets and Portfolio Management*, **31**, pp. 491–509. doi:10.1007/s11408-017-0299-7.

Xu, X. (2017c), 'Short-run price forecast performance of individual and composite models for 496 corn cash markets', *Journal of Applied Statistics*, **44**, pp. 2593–620. doi:10.1080/02664763.2016.1259399.

Xu, X. (2018a), 'Causal structure among US corn futures and regional cash prices in the time and frequency domain', *Journal of Applied Statistics*, **45**, pp. 2455–80. doi:10.1080/02664763.2017.1423044.

Xu, X. (2018b), 'Cointegration and price discovery in US corn cash and futures markets', *Empirical Economics*, **55**, pp. 1889–923. doi:10.1007/s00181-017-1322-6.

Xu, X. (2018c), 'Intraday price information flows between the CSI300 and futures market: An application of wavelet analysis', *Empirical Economics*, **54**, pp. 1267–95. doi:10.1007/s00181-017-1245-2.

Xu, X. (2018d), 'Linear and nonlinear causality between corn cash and futures prices', *Journal of Agricultural & Food Industrial Organization*, **16**, p. 20160006. doi:10.1515/jafio-2016-0006.

Xu, X. (2018e), 'Using local information to improve short-run corn price forecasts', *Journal of Agricultural & Food Industrial Organization*, **16**, p. 20170018. doi:10.1515/jafio-2017-0018.

Xu, X. (2019a), 'Contemporaneous and granger causality among US corn cash and futures prices', *European Review of Agricultural Economics*, **46**, pp. 663–95. doi:10.1093/erae/jby036.

Xu, X. (2019b), 'Contemporaneous causal orderings of CSI300 and futures prices through directed acyclic graphs', *Economics Bulletin*, **39**, pp. 2052–77.

Xu, X. (2019c), 'Price dynamics in corn cash and futures markets: Cointegration, causality, and forecasting through a rolling window approach', *Financial Markets and Portfolio Management*, **33**, pp. 155–81. doi:10.1007/s11408-019-00330-7.

Xu, X. (2020), 'Corn cash price forecasting', *American Journal of Agricultural Economics*, **102**, pp. 1297–320. doi:10.1002/ajae.12041.

Xu, X. and Thurman, W. (2015a), 'Forecasting local grain prices: An evaluation of composite models in 500 corn cash markets'. Selected Poster prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Joint Annual Meeting, San Francisco, California, July 26–28. doi:10.22004/ag.econ.205332.

Xu, X. and Thurman, W.N. (2015b), 'Using local information to improve short-run corn cash price forecasts'. Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri. doi:10.22004/ag.econ.285845.

Xu, X. and Zhang, Y. (2021a) 'Corn cash price forecasting with neural networks', *Computers and Electronics in Agriculture*, **184**, p. 106120. doi:10.1016/j.compag.2021.106120.

Xu, X. and Zhang, Y. (2021b), 'House price forecasting with neural networks', *Intelligent Systems with Applications*, **12**, p. 200052. doi:10.1016/j.iswa.2021.200052.

Xu, X. and Zhang, Y. (2021c), 'Individual time series and composite forecasting of the Chinese stock index', *Machine Learning with Applications*, **5**, p. 100035. doi:10.1016/j.mlwa.2021.100035.

Xu, X. and Zhang, Y. (2021d), 'Network analysis of corn cash price comovements', *Machine Learning with Applications*, **6**, p. 100140. doi:10.1016/j.mlwa.2021.100140.

Yang, J. and Bessler, D.A. (2004), 'The international price transmission in stock index futures markets', *Economic Inquiry*, **42**, pp. 370–86. doi:10.1093/ei/cbh067.

Yang, J., Bessler, D.A. and Leatham, D.J. (2001), 'Asset storability and price discovery in commodity futures markets: A new look', *Journal of Futures Markets*, **21**, pp. 279–300. doi:10.1002/1096-9934(200103)21:3<279::AID-FUT5>3.0.CO;2-L.

Yang, J., Hsiao, C., Li, Q. and Wang, Z. (2006), 'The emerging market crisis and stock market linkages: Further evidence', *Journal of Applied Econometrics*, **21**, pp. 727–44. doi:10.1002/jae.889.

Yang, J., Kolari, J.W. and Min, I. (2003), 'Stock market integration and financial crises: The case of Asia', *Applied Financial Economics*, **13**, pp. 477–86. doi:10.1080/09603100210161965.

Yang, J. and Leatham, D.J. (1999), 'Price discovery in wheat futures markets', *Journal of Agricultural and Applied Economics*, **31**, pp. 359–70. doi:10.22004/ag.econ.15375.

Yang, J., Li, Z. and Wang, T. (2020), 'Price discovery in Chinese agricultural futures markets: A comprehensive look', *Journal of Futures Markets*, **41**, pp. 536–55. doi:10.1002/fut.22179.

Yang, J., Liu, H. and Leatham, D.J. (2013), 'The multi-market analysis of a housing price transmission model', *Applied Economics*, **45**, pp. 3810–19. doi:10.1080/00036846.2012.734595.

Yang, J., Yang, Z. and Zhou, Y. (2012), 'Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China', *Journal of Futures Markets*, **32**, pp. 99–121. doi:10.1002/fut.20514.

Yang, J., Yu, Z. and Deng, Y. (2018), 'Housing price spillovers in China: A high-dimensional generalized VAR approach', *Regional Science and Urban Economics*, **68**, pp. 98–114. doi:10.1016/j.regsciurbeco.2017.10.016.

Zeng, G., Cao, X. and Wang, F. (2020), 'Preliminary research on coordinated development pattern and optimization strategy of cities in the Yangtze River economic belt', *Bulletin of the Chinese Academy of Sciences*, **35**, pp. 951–59. doi:10.16418/j.issn.1000-3045.20200430004.

Zeng, G., Yang, S. and Wang, F.l. (2018), 'Study of the urban coordinated development capability index in the Yangtze River economic belt', *Resources and Environment in the Yangtze Basin*, **27**, pp. 2641–50. doi:10.11870 /cjlyzyyhj201812001.

Zhang, D. and Fan, G.Z. (2019), 'Regional spillover and rising connectedness in China's urban housing prices', *Regional Studies*, **53**, pp. 861–73. doi:10.1080/00343404.2018.1490011.

Zhang, D., Ji, Q., Zhao, W.L. and Horsewood, N.J. (2021), 'Regional housing price dependency in the UK: A dynamic network approach', *Urban Studies*, **58**, pp. 1014–31. doi:10.1177/0042098020943489.

Zhong, Y., Feng, X. and Wen, Y. (2016), 'The evolvement and driving mechanism of economic network structure in the Changjiang river economic zone', *Scientia Geographica Sinica*, **36**, pp. 10–19. doi:10.13249/j.cnki.sgs.2016.01.002.

Zhou, W. (2014), 'Research about international competitiveness of China's construction machinery industry', Jilin University, Ph.D. Dissertation.

Zhu, B., Füss, R. and Rottke, N.B. (2013), 'Spatial linkages in returns and volatilities among U.S. regional housing markets', *Real Estate Economics*, **41**, pp. 29–64. doi:10.1111/j.1540-6229.2012.00337.x.

Cite this article: Xu, X. and Zhang, Y. (2023), 'Network analysis of housing price comovements of a hundred Chinese cities', *National Institute Economic Review*, **264**, pp. 110–128. https://doi.org/10.1017/nie.2021.34