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Understanding real estate price dynamics: The case of housing prices in five major cities of China☆

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ABSTRACT

The developing technology of wavelet analysis offers a valuable tool in mitigating many of the limitations of earlier studies of housing price dynamics. This paper applies wavelet analysis to five first-tier cities in China to study housing price changes over time, to decompose housing prices into their trend and cycle components, and to explore co-movement and lead-lag relationships among these cities. We find the average cycle for all five cities to be 3.25 years, which is much shorter than the housing cycles observed in the United States. When we examine the cyclical lead-lag relationships among these cities, we find that during the 2008–2011 period, Shenzhen led Beijing, which led Guangzhou, which led Shanghai, and finally Tianjin followed. However, during the 2011–2014 period, the lead-lag relationships changed to Tianjin leading Shenzhen, then Shanghai, then Beijing, and finally Guangzhou. Although we generally observe a strong co-movement among the city pairs, the co-movement between Tianjin and each of the remaining four cities is weak. The weaker correlation between Tianjin and other cities indicates that real estate investors in these other four cities can improve their risk-return performance by adding Tianjin properties to their portfolios.

1. Introduction

The primary objective of this paper is to improve our understanding of residential price dynamics and our ability to measure co-movement of prices across markets over time and frequencies. To achieve this objective, we apply wavelet technology to analyze housing markets in five major cities in the People's Republic of China.

In modern economies, housing comprises a large segment of aggregate demand, as well as a large segment of personal investment. Therefore, housing values play a critical role in the stability of national economies and financial markets. At the same time, housing price level is one of the most dynamic and unpredictable variables in the economy (Mu et al., 2009). The interaction of housing, financial and economic activities, and political interventions all contribute to nonlinearity and cyclical changes in housing values. Typically, housing prices exhibit oscillatory behaviors, with cycle periods ranging from a few years to a few decades (Wheaton, 1990). Both trend and cycle are often accompanied by random shocks that cannot easily be observed, and their adjustments are often distorted by exogenous shocks such as changes in government policy, or by the inelasticity of land supply.

Although there have been previous attempts to understand price dynamics in real estate markets, the methods used in previous studies suffer from a critical limitation. The usual time-domain approach utilized by earlier studies omits frequency horizons, or simply assumes time-invariant frequency in examining the temporal properties of a financial or economic variable.[1] This approach does not convey any dynamic information regarding the frequency components of a variable. To overcome these problems, we utilize wavelet technology. Wavelet analysis captures both the frequency and the time variations of a time series. It thus captures the changing volatility of the price cycle by simultaneous treatment of the time-variant seasonal or frequency components along with the trend and cycle. It also facilitates a deeper understanding of co-movements in both short and long term horizons across asset types and markets.

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[1] For example, in Structural Time Series Models, the long-term trend is usually treated as polynomial of time variable and is estimated with a moving average method or exponential smoothing method. The cycle component is usually estimated with Fourier transform, requiring the cyclical pattern to be stable with a fixed period across time.

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In this study, we utilize wavelet technology to investigate both intra- and inter-regional dynamics of housing prices. We apply the analysis to examine price dynamics in the five first-tier cities in China: Beijing, Shanghai, Tianjin, Shenzhen and Guangzhou. Using wavelet transform, we decompose regional prices into their trend and cycle components, and compare different patterns among cities. We further use a wavelets coherence test to analyze the co-movement and lead-lag relationships of the five regional prices over frequency (or scale) and time.

This paper makes two contributions to previous research on dynamics of housing prices. Firstly, it applies wavelet tools to analyze the duration of the housing price cycle and how such duration evolves over time. As far as we know, this is one of the first papers to apply wavelet technology to the study of housing price dynamics. This method helps us detect break points in price cycles (Bowden and Zhu, 2008). In addition, decomposing time series into different frequencies can provide considerable improvement over traditional techniques (Funashima, 2016).[2] As a result, wavelet technology enables a deeper understanding of regional differences in the price formation process, including differences in cyclical activity, oscillatory amplitude, and variations in response to economic fundamental dynamics.

Secondly, we contribute to the literature on housing price dynamics by examining the degree of co-movement of housing prices in both time and frequency domains. Previous research on housing price dynamics assesses co-movement in the time domain by calculating the contemporaneous correlation coefficient or rolling window correlation coefficient, or, as a complementary, uses Fourier transform to measure the correlation between two series at each individual frequency (Rua, 2010). However, these methods consider the frequency and time components of the time series separately and require the data under investigation to be stationary or at least locally stationary. This is often not the case in real estate, since volatility in real estate markets is known to exhibit complicated patterns like jumps, clustering and long memory. The wavelet tools enable us to assess the evolution of co-movement strength and direction in housing prices and lead-lag relationships for different housing market pairs. Such analysis will clearly provide essential insights for policymakers and investors with differing investment horizons.

We find the average cycle for all five cities to be 3.25 years, which is much shorter than in the United States where long cycles are around 15–20 years and short cycles are around 5 years. The length of each cycle in the five Chinese cities, though similar, is slightly different, ranging from an average of 3.3 years in Shenzhen to 3.0 years in Tianjin. When we examine the cyclical lead-lag relationships among these cities, we find that during the 2008–2011 period, Shenzhen led Beijing, which led Guangzhou, which led Shanghai, and finally Tianjin followed. However, during the 2011–2014 period, the lead-lag relationships changed to Tianjin leading Shenzhen, then Shanghai, then Beijing, and finally Guangzhou. We observe a strong co-movement among the city pairs of Beijing–Shanghai, Beijing–Guangzhou, Beijing–Shenzhen, Shanghai–Guangzhou, Shanghai–Shenzhen and Guangzhou–Shenzhen, with the co–movement being stronger in the long term. In contrast, the co–movement between Tianjin and each of the remaining four cities is weak. Our finding that Tianjin exhibits weaker correlation with the other cities indicates that real estate investors in any of the other four cities may improve their risk-return performance by adding Tianjin properties to their portfolios.

The structure of this paper is as follows. In Section 2, we present a review of previous dynamic housing price studies and regional market price studies. In Section 3, we present an institutional background on the five cities studied. In Section 4, we present the technology of wavelet decomposition and coherency analysis. In Section 5, we discuss the data. In Section 6, we present the empirical findings. Section 7 concludes.

2. Literature review

2.1. Studies of temporal dynamics of housing prices

The temporal dynamics of home prices simply refers to the examination of changes in home prices over time. Because of the complexity of exogenous and endogenous determinants of the temporal dynamics of housing price, the most important step in this examination is to empirically disaggregate the permanent and transitory elements: namely, the trend and cycle components. Existing studies primarily use two approaches to examine the long-term trend and cycle of temporal dynamics. The first approach is to use parametric models to decompose the time series. Most of the studies in this line of literature derive fundamental values from an equilibrium model, and explain deviations from the equilibrium price as transitory shocks or bubbles (For example, see Abraham and Hendershott, 1994; Hort, 1998; Bourassa et al., 2001). Other studies adopt non-model-based statistical methods, including the Structural Time Series Model, VAR (or VECM) model, or common trend model, assuming that the given time series is the realization of an underlying stochastic process with a certain specification (Chen et al., 2004; Clark and Coggin, 2009; Yang et al., 2012).

There are two problems associated with existing temporal dynamic studies under this first approach. First, the results are heavily dependent on the parametric structure of the model, which to some extent compromises the findings by smoothing the time-variant dynamic nature of prices while neglecting to analyze the frequency and intensity of the fluctuations. Second, the effects of dynamic and nonlinear variables in the economy may not be sufficiently detected. This problem is especially troublesome in China, where the influences of government intervention are intense, and sharp spikes and jump points are frequently observed.

The second approach used to examine long-term trend and cycle is the nonparametric filtering methods, such as Kalman filtering, Hodrick–Prescott filtering, and Christiano–Fitzgerald filtering (Stock and Watson, 1993; Christiano and Fitzgerald, 2003). However, some studies have called the accuracy of these methods into question (Pham and Wong, 2001), because these decomposition methods impose strong restrictions on the stochastic properties underlying the dynamics of the series (e.g. stationarity, smoothness or non-correlated component assumption). In addition, since they lead to a pure frequency-domain representation of the data, time-varying characteristics of housing prices get lost.

Wavelet decomposition can make a special contribution to our analytical capacities because it is more effective at filtering out historical cycles and detecting break points. Wavelet analysis is essentially a transformation from time-space to the time-frequency domain. It allows us to break down the activity on the market into different frequency components and to study the dynamics of each of these components separately. As such, wavelet analysis transforms a time series into an image of time versus frequency and can be used to decompose the cycle and trend, analyze causal influences, and detect structural breaks.

2.2. Studies on the regional co-movement of housing prices

An understanding of co-movements of equity markets across regions is of crucial importance for maximizing portfolio diversification benefits and managing risk (Zhou, 2010). There are a number of established approaches to the estimation of regional price correlations: vector

[2] Wavelet tools can help avoid some estimation bias by capturing localized information in time at any specified frequency. In addition, in wavelet decomposition, removing certain frequency bands does not modify the dynamics that rely on the remaining bands. Thus, we can separate the amplitudes of the high and low frequency components orthogonally, which provides better reconstruction of the measured dynamics.

autoregression (VAR) (e.g., Clapp and Tirtiroglu, 1994; Dolde and Tirtiroglu, 1997; Forbes and Rigobon, 2002; Karolyi and Stulz, 2003), Impulse Response (IRs) analysis (e.g., Stevenson, 2004; and Oikarinen 2006), multivariate GARCH model (Michayluk et al., 2006; Liow et al., 2009), and rolling window model (Schindler, 2009; Yavas and Yildirim, 2011). It is a consistent finding of the existing studies that co-movements among regional markets are not constant over time, which has important practical implications for evaluating risk in spatial portfolios.

As a result, another important aspect of portfolio risk, and one that has been largely neglected in the literature, is the analysis of co-movement in the frequency domain (Zhou, 2010).[3] In the limited research on the frequency domain correlation, traditional Fourier transform is applied to the co-integrated systems (Croux et al., 2001; Breitung and Candelon, 2006). However, since these studies disregard the time dependence of co-movement, they provide only a snapshot of the co-movement at the frequency level, unable to capture time-varying features (Rua, 2010). Though subsequent methods, such as Short-Time Fourier Transform (STFT), are further developed to calculate evolving correlation by dividing the time signal into shorter segments of equal length (Richter, 2008), window function is imposed a priori and unchanged; thus, we cannot know what frequency exists at what time intervals and how the correlation at different frequencies evolves over time.

Wavelet analysis outperforms the traditional Fourier or STFT analysis based on its time-frequency localization process. Specifically, wavelet analysis ensures a tradeoff between frequency and time-resolution at different frequencies, as the high frequency components are studied with sharper time resolution than low frequency components. Thus, the scaling process in wavelet technology is selected adapting to the range of frequencies, which enables wavelet analysis to provide a more informative time-frequency transform. In addition, wavelet analysis can be applied when the data under investigation is non-stationary (with time-varying frequencies). This is often the case in real estate, since volatility in real estate markets is known to exhibit complicated patterns like jumps, clustering, and long memory.[4]

3. Institutional background: Chinese housing price dynamics

China has experienced a decade-long housing market boom. From 2004 to 2014, housing prices have grown persistently at an average annual rate of 10.7%, about 3.92 times higher than that from 1998 to 2003, according to the China Statistics Yearbook. Housing price increases have been particularly notable in larger cities such as Beijing, Shenzhen, and Shanghai. In Fig. 1, we plot housing prices from 2006 to 2014 for Beijing, Shanghai, Shenzhen, Guangzhou, and Tianjin. These cities are typically classified as ``first-tier" and have been examined in other Chinese housing studies (Wu et al., 2014). All five cities experienced significant increases in home prices during the period of our study. Beijing experienced the most rapid housing price growth, followed by Guangzhou. The annual price increase in Beijing during the study period is 22%, much higher than the national average of 8% for that time period. We observe the most stable prices in Tianjin, where the average growth rate was 11.8% annually. Notice that even though there is a similar trend in all five cities, we still notice large differences in the patterns of house price development during the period of study.

The rapid surge in house prices in most major Chinese cities has caused the issue of affordability to become a central social concern in China (Wang et al., 2010; Yang and Shen, 2008). It is feared that a slump in the housing market might occur, affecting the healthy growth of the economy and putting financial markets at risk. As a result, the central government of China has intervened in the housing market in recent years, launching a wide range of changes in fiscal policy, land use reforms, and direct market interventions in an attempt to exercise greater control over real estate prices. In fact, we have identified and listed no fewer than twenty major government interventions during our period of study. We do not include the list here, but it is available from the authors upon request. These interventions and regulations present challenges to analysts attempting to explain the price formation process in various regions of China. We believe that the wavelet technology discussed here can be helpful in evaluating the effects of government interventions such as these. Wavelet technology can be especially helpful in identifying varying responses at the regional level.

4. Method: wavelet decomposition and wavelet coherency

Our analysis includes two separate estimations. In the first, we apply wavelet filters to separate trend from cycle in the housing price time series for each of the five cities studied. We achieve that end using the process of wavelet decomposition. In the second one, we assess the co-movement of housing prices across these five cities based on wavelet coherency examination. Wavelet coherency means that, rather than testing co-movements using simple price correlations, we test the similarities of housing price dynamics in both time and frequency domains. In this section, we explain the development of each of these two estimations separately.

4.1. Wavelet decomposition

We begin with identifying the primary variable of interest, the time series of house prices, expressed as $f(x)$.[5] We observe a separate original function $f(x)$ for each of the five cities under study. We believe that this original time series will include long-term trends that will reflect the effects of economic fundamentals such as income and interest rates. We also know that the time series will be disturbed along the way by other intervening effects, such as cycles and temporary exogenous and endogenous shocks that will push the price line up above the trend line or down below it. The time line will also be disturbed by random noise. Specifically, we identify four fundamental movements: long-term trend

[3] Frequency domain analysis focuses not on the common trend over time, but rather on the nature of fluctuations above and below the trend line. These waves usually exhibit consistent patterns of activity across stretches of time. If the waves are close together, we consider them to be high frequency; if they are farther apart, we consider them to be low frequency. The difference can be important, especially to real estate investors with portfolios of different time horizons. For instance, co-movement of housing prices at higher frequencies is an evidence of short-term fluctuations, which are more important to a short-term investor, while co-movement at lower frequencies is more important to long-term investors. As an example, a 'flipper' would be a short-term investor while an investor in a rental property with a long holding horizon would be a long-term investor.

[4] By decomposing the original series into a time dependent sum of different frequency components, wavelet technology is also likely to improve the quality of forecasting. However, incorporating wavelet increases the model complexity due to more approximation steps, as well as more error sources. Schlüter and Deuschle (2010) discuss this trade-off by comparing the forecasting quality of wavelet-based method and other traditional methods (i.e., Census X-12, ARMA, ARIMA). They find that wavelet-based forecasting generally performs better than classical techniques, especially when strong long-term pattern dominates the short-term oscillation, or when prices consist of a mixture-term structure and an important oscillation. However, for time series with minor trend and a strong random component, wavelets generate only little improvements.

[5] To investigate the correlation between long-term trend of housing prices and economic fundamentals, we again use the wavelet decomposition method to extract the long-term trend component for each of the variables of economic fundamentals. Consistent with the existing literature (Mankiw and Weil, 1989; Capozza and Schwann, 1990; Hui and Shen, 2006; Case and Shiller, 1990; Quigley, 1999; Clapp and Giaccotto, 1994; Potepan, 1996; Malpezzi, 1999), we use the following variables that we believe to be largely determinative in the long trend of housing prices in each of the five cities: GDP, income, population, household consumption, fixed asset investment, interest rates, completed floor space, and the CPI.

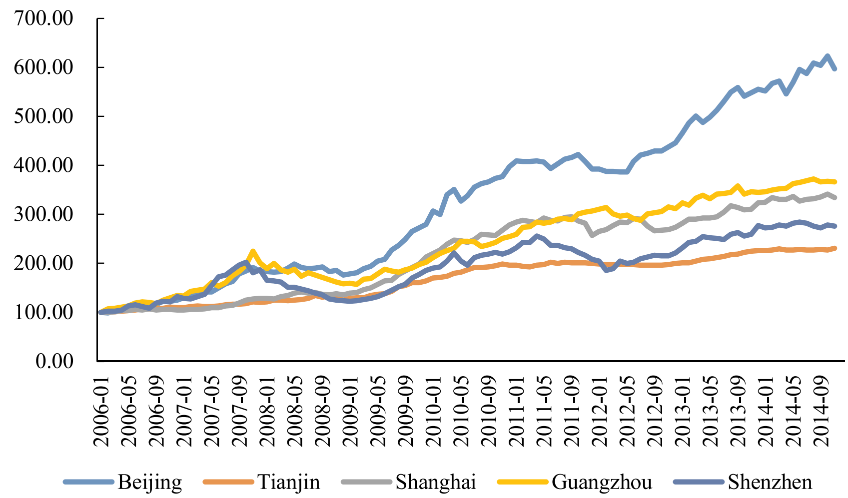

Fig. 1.. Housing prices in five first tier Chinese cities 2006–2014.
Data source: China Real Estate Index System.
The housing price index is developed using a quality consistent methodology.
The index on January of 2006 is set at 100.

(T), cyclical change (C), seasonal variation (SV) and random error (R).

$$S = T + C + SV + R \tag{3.1}$$

where S denotes the original time series to be decomposed. We then use wavelet decomposition to segregate these various effects (more technical details are provided in Appendix A). Through wavelet functions with different time-scale characteristics, we are able to decompose the original one-dimensional signal (S) into a two-dimensional plane (a, b) in the coordinate position b and scale a (the time and frequency domains, respectively). When all of the wavelet functions have been included in the reconstruction of the original signal S, we are ready to deconstruct S into its component parts using a multi-resolution process, through which we can separate the true trend in response to economic fundamentals from the noise of random error. However, where we observe high frequencies in the frequency domain as we move across the time line, we are more likely to be observing the influence of random errors.[6] We manage this trade off problem by smoothing the frequencies in a series of iterations called layers. In each iteration, we divide the signal over the full length of time into two parts: high-frequency (high-pass component, HPC), and low frequency (low-pass component, LPC). At the end of each iteration, we take the low-frequency part (LPC) to be the new expression of the frequency domain, and then we repeat the process, using a new designation for the threshold that will separate the two parts. At some point, we conclude that we have reached the optimal compromise between de-noising and loss of fidelity. We show an example of this process in Fig. 2. Empirical results for the five cities studied here are reported in Section 5.

4.2. Wavelet coherency

In our second estimation of this section, we introduce the wavelet coherence index to measure the co-movement of housing prices in response to changes in economic fundamentals across regions (Grinsted et al., 2004). The wavelet coherency test is employed to calculate the dynamic correlation of paired series at different time scales, while phase-difference (the corresponding phase-angle) is calculated to investigate the lead-lag relationships of two series. More detailed information is provided in Appendix A.

In the empirical section, we calculate the wavelet coherency of these five cities in pairs, investigating co-movement of price changes across time and across different frequencies.

5. Data

We study real estate prices in five major Chinese cities: Beijing, Tianjin, Shanghai, Guangzhou, and Shenzhen. We show the locations of these cities in Fig. 3. These five cities are characterized by large populations and prominent roles in the economy and culture of China. They are regions that are highly sensitive to the effects of government policies. In addition, because of their locational and political economic advantages, these five cities exert an important influence on the surrounding economy. Information sources for housing prices and economic fundamentals in these five cities are reliable and can be obtained both at the city and the provincial level.

Wavelet analysis requires a high frequency of data (Crowley, 2007). For this reason, we use monthly data.[7] The price index we use is the monthly City Housing Index (CHI), which is a constant quality index issued by the Ministry of Construction of China. Hedonic Model is applied to control for the physical, neighborhood, and location characteristics and to standardize the housing unit. We use this index from January 2006 to December 2014. The CHI covers more than 40 large and medium cities nationwide, and is produced using transaction records collected from regional real estate markets. CHI has been used for government macroeconomic regulation and management decision-making. It has also been used in regional real estate market analysis.

As the cultural and political center of China, Beijing shows the highest housing price level, and a strong growth trend. Under the constraint of limited land supply, the housing price index increased almost fivefold from 2006 to 2014.

Shanghai is the primary financial center and international metropolis of China. Although it ranks second among the five cities in population, the housing price index in Shanghai is much more stable than that of Beijing.

[6] The situation here can be likened to the experience of listening to a symphony on the radio, but hearing a lot of static in the transmission. The full fidelity of the music is there, but it is difficult to hear at times because of the static. The problem is that if we eliminate the static, we also eliminate some of the music underneath it. In wave analysis, then, there is a tradeoff of de-noising on the one hand, and fidelity on the other.

[7] The highest frequency of quality-controlled real estate transactions data we can access in China is on a monthly basis. As such, earlier wavelet analysis focusing on real estate returns and business cycles are also widely based on monthly data (e.g. Zhou, 2010; Crowley, 2007).

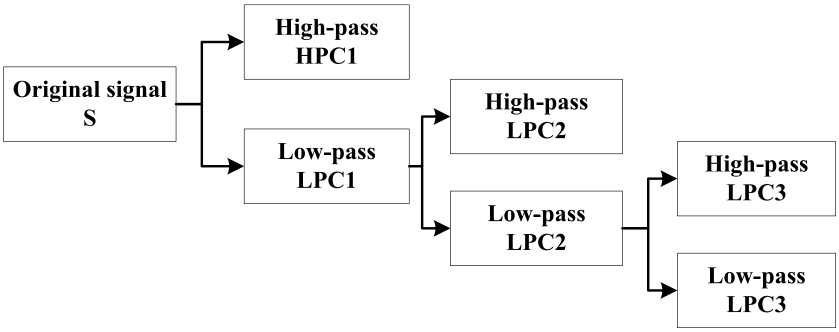

Fig. 2.. Fundamental principle of wavelet decomposition (three layers).

This figure exhibits the fundamental principle of 3-layer wavelet decomposition. Original signal (S) is the raw time-series to be decomposed. The high-pass component (HPC) denotes the signals with a frequency higher than a certain cutoff frequency, while the low-pass component (LPC) denotes the signals with frequencies lower than the cutoff frequency. Through the first layer filtering process, the original signal is decomposed into a high-pass component (HPC1) and a low-pass component (LPC1) respectively. The low-pass filtered signal (LPC1) is then used as the input for the next iteration step and is decomposed into a high-pass component (HPC2) and a low-pass component (LPC2), and so on.

Fig. 3.. Geographical distribution of five major cities included in analysis of house price movements in the People's Republic of China 2006–2014.

Tianjin, an important port city adjacent to Beijing, is regarded as the leading international shipping and logistics center of North China. It has been a center for rapid development. In response to the recession caused by the world financial crisis, Tianjin issued draconian policies in 2011 designed to regulate its housing market and to protect it from changing market conditions. As a result, housing prices in Tianjin are basically stable at a relatively lower level compared to the other five cities included in our study.

Guangzhou is the provincial capital of Guangdong and has been a historically important port city for foreign trade in China since the Qin Dynasty (221 BCE). It features a highly developed capability for foreign trade and has a large floating population. The pillar industries in Guangzhou include the automobile, manufacturing, and electronics industries.

Adjacent to Hong Kong, Shenzhen was the first established special economic zone in China,[8] and is also regarded as the pioneer city of China's reform policies. Shenzhen is China's largest city of immigrants. Moreover, it has an extremely young population, averaging just under thirty years of age. Shenzhen became adept in developing the capacities and competencies to design products instead of merely manufacturing them and is aiming at turning its financial sector into ``a strategic pillar industry'' of the city (Chen and de'Medici, 2009).

To compare the long run trends of housing prices for these five cities, we use eight monthly indicators as proxy variables for economic fundamentals. These fundamental indicators are drawn from the MacroChina Database and regional statistic bureaus, and measure economic fundamentals from both the supply side and the demand side.

Fig. 4 compares these variables for the five cities. We observe that they share increasing trends in response to economic fundamentals in the long term, but we also observe obvious differences in the shapes of the price formation processes over time.

6. Empirical results

6.1. Intra-regional dynamics: long run trend and cycle

Using the technology discussed above, we estimate the wavelet decomposition for housing prices in each of the five cities, as well as for each of the macroeconomic variables that impact housing prices. The details regarding the parameter selection process and the output of multilayer one-dimensional discrete wavelet decomposition are shown in Appendix B.

6.1.1. Long-term regional housing price trends

The long-term trends of housing price in the five cities are shown in Fig. 5. Although the long trend in house prices is upward sloped for all five cities over the period of study, we can observe differences in the growth rate and the patterns of growth.

To further understand the potential differences or similarities in trends among the five regions, we need to test the correlations between the long run trend of housing prices and the economic fundamentals for each city. Using a similar process, we decompose the long-term trend of each variable. Therefore, we are able to use linear regression to measure the relationship between housing prices and fundamental economic variables. The results are presented in Table 1.

We include the commonly used demand and supply side economic variables: regional real domestic production per capita (*rgdp*),[9] regional population (*pop*), household real disposable income (*inc*), regional real fixed asset investment per capita (*rinv*),[10] the 5-year benchmark interest rate (*int*), the consumer price index (*cpi*),[11] and floor space completed (*comp*). In deciding the specific form of long run regression models, we use ADF (Augmented Dickey–Fuller) test and Johansen test to examine the stable and co-integration status of involved variables (results are not shown here). We find that both the housing price variable and economic fundamental variables in the five cities can be regarded as stable with second-difference; meanwhile, there is a co-integration relationship between the housing price variable and economic fundamental variables, which eliminates the pseudo-causality problem. Therefore, we can directly run the long run models of housing price for the five cities. We then use the AIC (Akaike Information Criterion) to

[8] On August 26, 1980, the 15th meeting of the fifth session of the standing committee of the National People's Congress passed the regulation on special economic zones in Guangdong province, which approved the establishment of Shenzhen as a special economic zone.

[9] To limit the impact of multicollinearity of fundamental variables, we use *rgdp* rather than *gdp*.

[10] Similar to the calculation of *rgdp*, we use *rinv* rather than *inv* to limit the impact of multicollinearity of fundamental variables.

[11] *cpi** is regarded as a proxy variable of inflation, which is calculated as the following equation: $\mathrm{cpi}_t^* = \frac{cpi_t}{cpi_{t-6}} - 1$

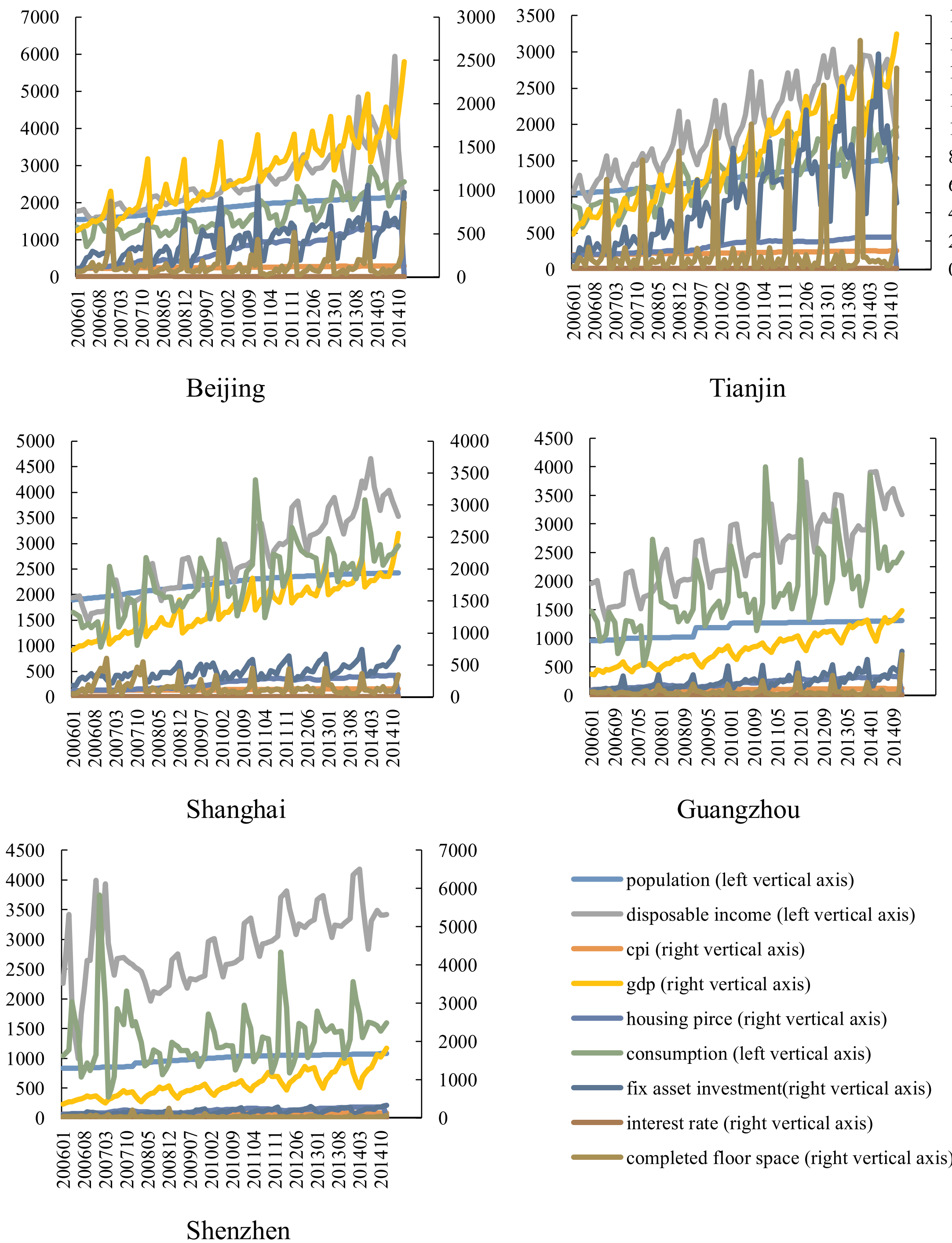

Fig. 4.. Housing prices and fundamental economic variables in five cities.

Housing prices are taken from the China Real Estate Index System. Interest rates are the price of 1–3 year loans from the People's Bank of China. Data for other fundamental economic variables are collected from the MacroChina Database for Beijing, Tianjin, and Shanghai; from the Guangzhou City Bureau of Statistics for Guangzhou; and from the Shenzhen City Bureau of Statistics for Shenzhen. "Population" is the population of the respective region at the end of the corresponding year. "Disposable income" is household disposable income. "Consumption" is household consumption. The unit of population is 10 thousand. The unit of disposable income is RMB. Regional GDP is in 10 million RMB. CPI is the regional CPI. The unit of completed floor space is 10 thousand squared meters.

determine the optimal lag intervals of different economic fundamental proxies and use one-month lagged variables in the regression.

As anticipated, we find significant long run correlations between fundamental economic variables and regional housing prices in all five cities. Thus, the trends of housing prices in these five cities can be explained by fundamental economic variables.

Comparing the results for different cities, we find that the explanatory power of the model in Tianjin is the weakest. In Tianjin, long run housing prices can be explained by a subset of the fundamental variables, and the proxy variables from the household side are not significant. One possible factor contributing to this result may be that household disposable income in Tianjin is the lowest among the five cities, suggesting that there may be a smaller demand elasticity there. As a port city that depends mainly on the manufacturing industry, Tianjin's economic structure is also much less diversified than that of the other four cities.

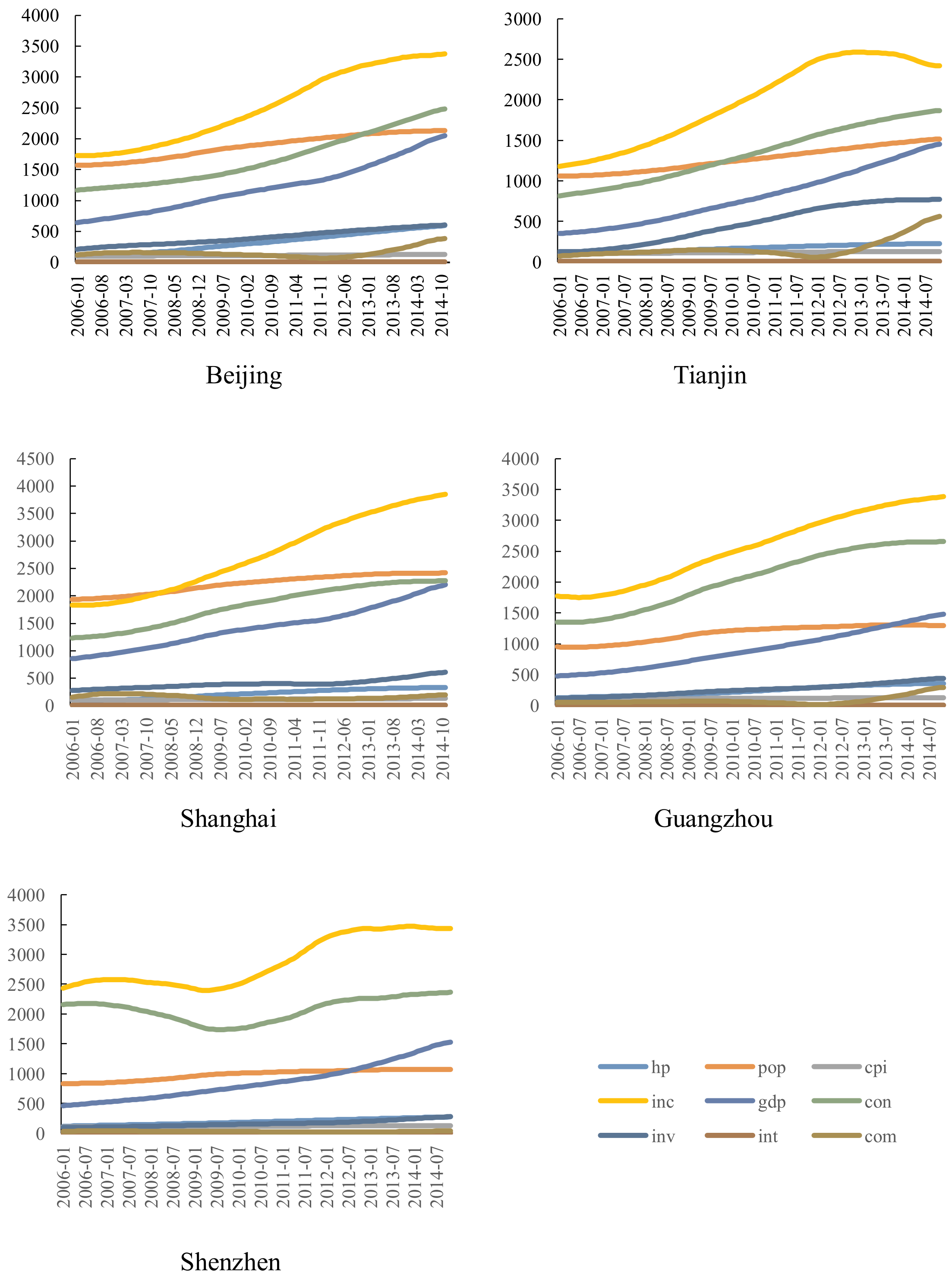

Fig. 5.. Long-term trend of housing prices and fundamental economic variables in five Chinese cities based on wavelet decomposition (2006–2014).
hp is the index value of the China Real Estate Index System, 2006 = 100. Pop is the local population in 10,000s. cpi is the value of the regional Consumer Price Index. inc is the household annual disposable income in RMB. gdp is the regional Gross Domestic Product in ten millios RMB. con is the household expenditure on consumption in RMB. inv is the regional fixed asset investment in RMB. Int is the benchmark interest rate (1–3 years). All data represent the long run trend computed using Wavelet Decomposition Technology.

As a comparison, we also decompose long-term trend and cyclical change using traditional filtering methods such as Hodrick–Prescott Filter and Christiano–Fidgerald Filter built on Kalman Filter.[12] There is a significant difference in the results of wavelet technology and these traditional methods: the long-term trend extracted using either Hodrick–Prescott Filter or Christiano–Fidgerald Filter still contains cyclical fluctuation that is not totally filtered out. The non-smoothness of the long-term trend using these traditional methods could be due to (1) their assumption that the trend component is non-correlated with fluctuation component, or (2) their assumption that the state equation follows a random walk process. As confirmed by Pham and Wong (2001), wavelet analysis does not have the non-correlated

[12] To save space, results are not shown here, but are available from the authors upon request.

Table 1.
Regressions of housing prices on selected macroeconomic variables in five major cities of China 2006–2014.

Variables	Beijing *lnhp*	Tianjin *lnhp*	Shanghai *lnhp*	Guangzhou *lnhp*	Shenzhen *lnhp*
L.lnrgdp	3.901***	−0.731	3.813***	4.259***	1.694***
	(0.0925)	(0.561)	(0.425)	(0.127)	(0.0824)
L.lnpop	1.283***	−0.392	−0.587	−2.214***	−0.305***
	(0.203)	(0.438)	(0.694)	(0.0663)	(0.0130)
L.lninc	−1.951***	4.182***	2.098**	1.243***	1.211***
	(0.523)	(0.539)	(1.025)	(0.263)	(0.0490)
L.lncon	−4.525***	1.619	0.388	6.146***	0.147***
	(0.285)	(1.046)	(0.614)	(0.573)	(0.0260)
L.lnrinv	−1.309***	0.293**	−2.477***	−1.833***	−1.470***
	(0.0713)	(0.123)	(0.239)	(0.0383)	(0.0759)
L.int	0.261***	−0.0767***	−0.240***	−0.164***	0.0601***
	(0.0101)	(0.00522)	(0.0262)	(0.0276)	(0.00496)
L.cpi*	−2.50e−08	−3.73e−08	−2.73e−08***	−3.93e−10	5.11e−08**
	(3.75e−08)	(4.30e−08)	(7.14e−08)	(2.60e−09)	(2.06e−08)
L.lncom	−0.0399***	0.00637*	0.314***	0.00230***	0.0474***
	(0.00459)	(0.00340)	(0.0322)	(0.000839)	(0.00465)
Constant	6.883**	−3.132	−6.384**	14.64***	−3.402***
	(2.977)	(4.282)	(2.983)	(2.035)	(0.382)
Obs	100	100	100	100	100
AIC	−1037.58	−1092	−943.439	−1123.13	−1299.05
BIC	−1011.53	−1063.34	−917.388	−1097.08	−1273

Notes: Fundamental variables include: regional real domestic production per capita (rgdp), regional population (pop), household real disposable income (inc), household consumption level (con), regional real fix asset investment per capita (rinv), the benchmark interest rate (int), the consumer price index (cpi), and completed floor space (comp). L identifies the use of a one-month lag of the variable. ln identifies the natural logarithm of the variable. Standard deviation statistics are in parentheses.

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

component or specific motion assumption, and hence can capture the interaction between trend and fluctuation as well as the time-varying characteristics.

6.1.2. Cycles of regional housing price

Based on the decomposition results, we further identify the Kitchin cycles from housing prices for all five cities.[13] Results are shown in Fig. 6.

Fig. 6 shows that the price cycles for each of the five cities. The average duration of a cycle was 3.25 years for all five cities. The characteristics of the short cycles are not all the same; four of the five cities complete two full cycles during the study period, but Shanghai does not. The length of the cycles, though similar, is also slightly different, ranging from an average of 3.3 years in Shenzhen to 3.0 years in Tianjin. Because of the non-linear and heterogeneous interactions of the variables in the economy, it is usually difficult to explain the differences in cycle behavior across markets, but the results reported here can still be very valuable in evaluating regional co-movements, which is critical in constructing efficient real estate portfolios. The results suggest that even though these five regions tend to have similar trends in the long run, they present different cyclical performances. Thus, regional housing markets are responding differently to any government interventions or exogenous shocks, which suggests that correlation between regional prices should be captured over time as well as over frequencies, which we will investigate below.

Comparing our results on housing price cycles in China to those in the United States, we observe that price cycles in China are markedly shorter than in the United States where long cycles are around 15–20 years and short cycles are around 5 years (Shiller, 2007; Case, 1978). This difference could be explained by several factors.

One explanation is that the tax system in China leaves local governments with a limited source of fiscal revenues, and land sales is a key source of fiscal income. This motivates Chinese local governments to be more enthusiastic about new construction, which leads to a lower supply elasticity. In addition, property taxes in the US create a sizable cost to holding real estate. In contrast, Chinese real estate taxes are imposed only on transactions, creating an incentive to buy-and-hold (Glaeser et al., 2017). The resulting ‘inventory’ could contribute to oscillations in housing price dynamics.

Another potential explanation is that there is much less historical data available for price discovery in Chinese real estate markets. In addition, the frequent policy intervention in China makes it more difficult to forecast prices and the impact of unanticipated shocks.

A third potential explanation is the larger role the Chinese government plays in real estate finance. State-owned financial institutions have historically dominated China's banking system, which help implement the government's favorable credit policies toward developers, resulting in higher leverage for Chinese developers. Banks are also under government influence to adjust mortgage rates to discourage or occasionally subsidize home purchases due to market stability concerns (Glaeser et al., 2017). As a consequence, the strong demand for housing in China is mostly supported by households who flood the real estate market with their savings and purchase houses as investments, which could further increase the oscillation around the fundamental values.

As an alternate measure, we also calculate the wavelet power spectrum of each particular market to compare the amplitude of housing cyclical fluctuations.[14] The wavelet power in each city is normalized to white noise. Based on the results in Fig. 7, we can see that, in the cyclical perspective, i.e., within the scale band of 16 to 32,[15] the red

[13] Kitchin cycle is a short business cycle of about three to four years.

[14] Since the original time series is not normal distribution, Monte Carlo method is used here to establish significance levels and confidence intervals for the wavelet power spectrum.

[15] We have specified the average duration of a short cycle and long cycle by observing the low-pass component remaining after the third and fourth layers of decomposition, respectively. In our discrete wavelet decomposition, the fourth and fifth layers correspond to the scale of 16 and 32, respectively. That is why they the scale band of 16 to 32 corresponds to cyclical perspective.

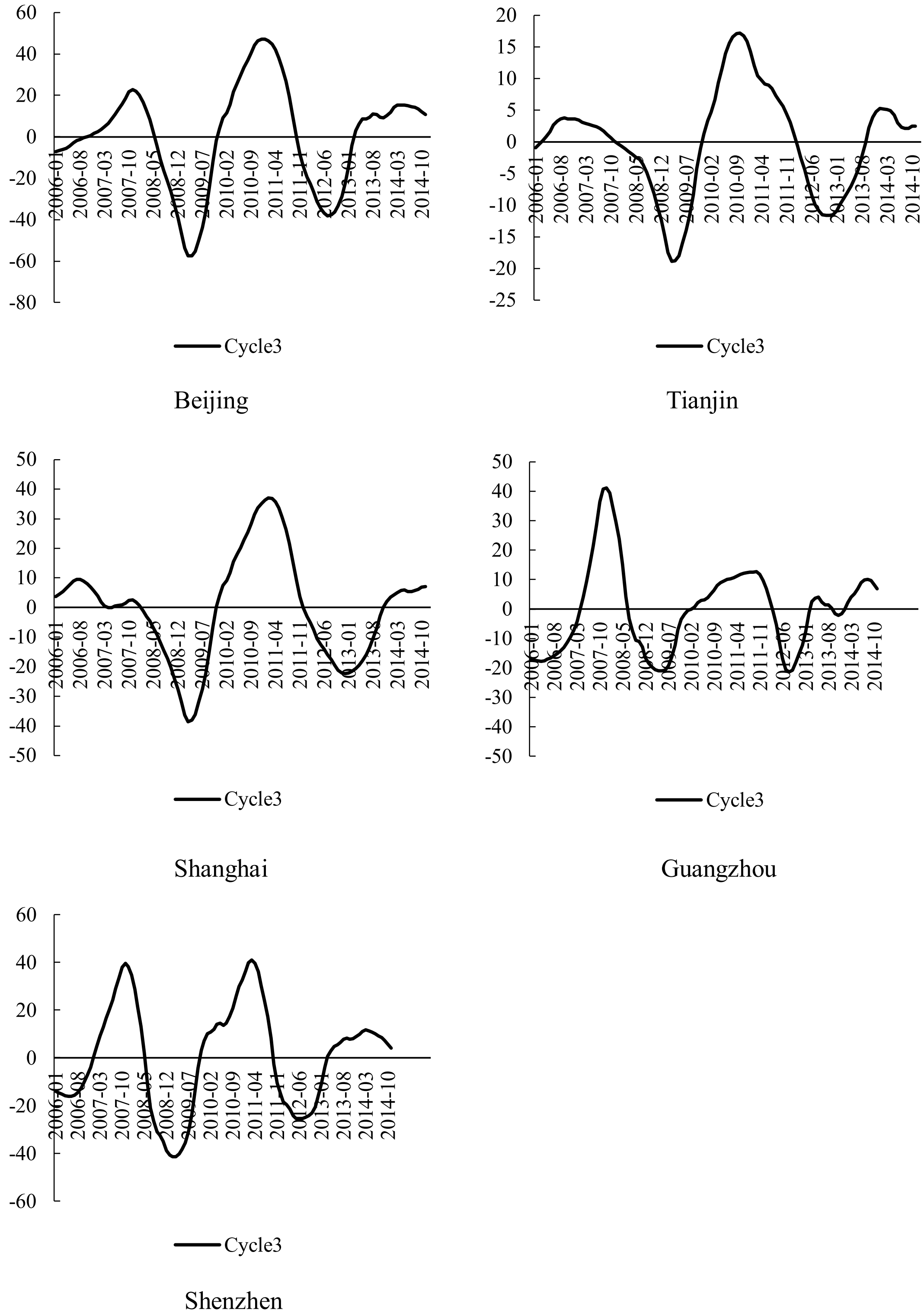

Fig. 6.. Housing price cycles in five Chinese cities as estimated using wavelet decomposition analysis 2006–2014.
Cycle 3 is the result of the third layer of iteration (de-trended) filtering out high frequency events in the price waves over time to some extent, thus reducing the effects of transitory shocks and random noise on price performance. The y-axis records price movements around a long-term trend line that is normalized to equal zero.

area dominates across the entire horizontal axis, which implies housing prices in each city are varying considerably over time, especially after the financial crisis of 2008. Comparing the cities, we find that Tianjin has the lowest amplitude magnitude in cyclical fluctuation, which implies the housing market in Tianjin is relatively stable. In contrast, the amplitude of cyclical changes in Beijing and Shanghai is significantly higher. This difference could be due to two main reasons. First, as the political and economic center of China, Beijing and Shanghai experience much higher frequent policy intervention in their housing markets. In particular, following the global recession and financial crisis of late 2008, a series of tightening measures were imposed with the aim of "controlling" continuously climbing prices in these two cities. For instance, beginning in February 2011, the Beijing and Shanghai governments imposed restrictions on home purchases in an attempt to minimize the speculative demand and stabilize home prices. In addition, the Beijing government requires developers to submit their

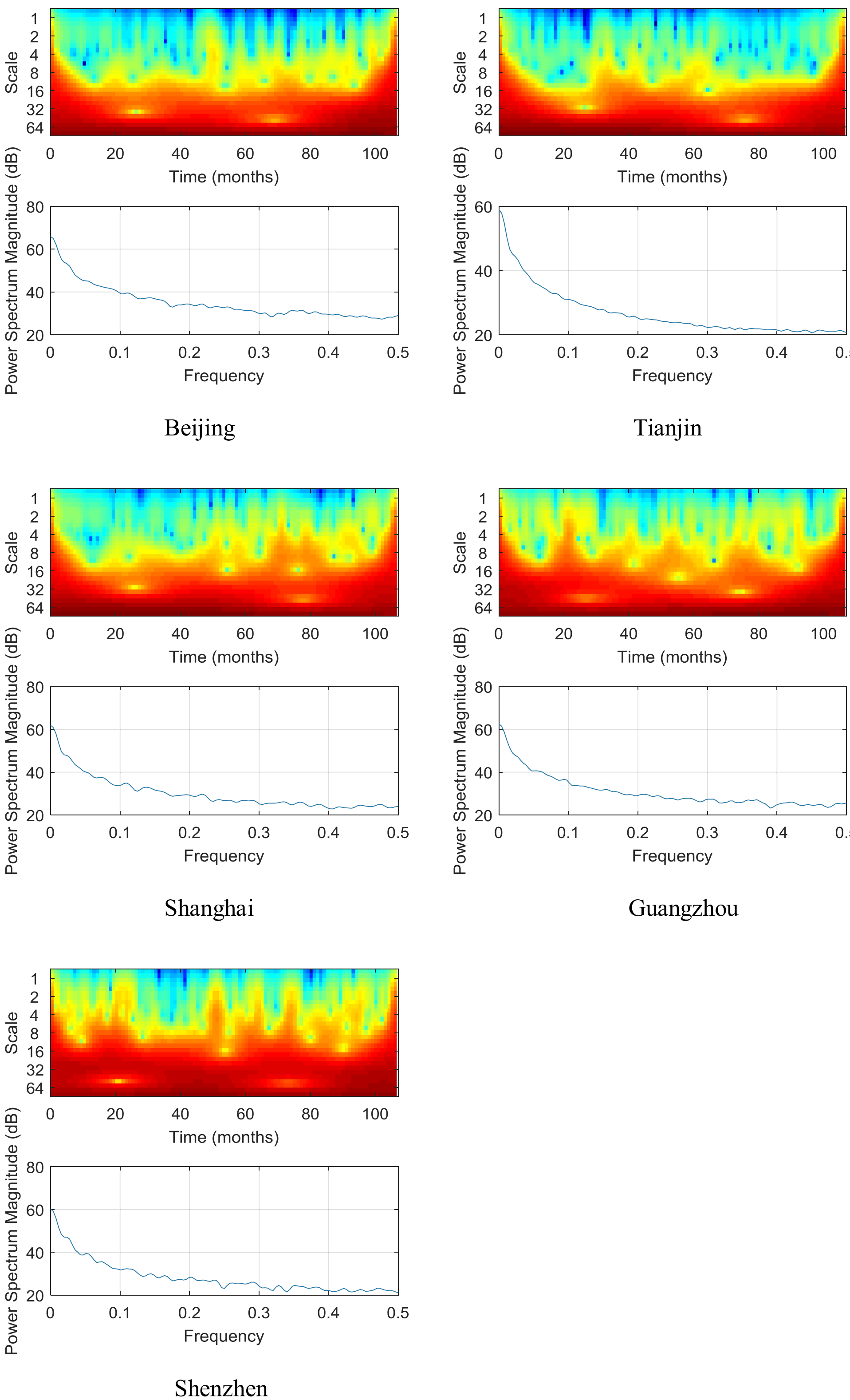

Fig. 7.. Wavelet power spectrum of house prices over time in major Chinese cities 2006–2014.
In the upper subplot, the color code ranges from blue, corresponding to low power (low variance), to red, corresponding to high power (high variance); axis x represents distance from January 2006 in months; axis y represents the scale of the housing price fluctuation. Note that higher scale corresponds to lower frequency. The lower subplot denotes the normalized global wavelet power spectrum across different frequencies. Taking the average of wavelet power spectrum across time, prices in Tianjin market have a lower amplitude in both low frequency intervals (long term) and high frequency intervals (short term) compared to other markets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

target selling prices of units in their proposed projects when applying for pre-sale licenses.[16] Meanwhile, the Shanghai government has experimented with implementing a property tax system. All of these policy shocks have greatly shaped the development of the housing markets in these cities. This also implies that policy changes may not only add residuals to housing price dynamics but also change the cyclical patterns in terms of amplitude. Second, the land supply elasticity is relatively higher in Tianjin. According to statistics, the land supply elasticity during 2009–2012 reached 0.712 in Tianjin, which is much higher than Beijing (0.537), Shanghai (0.411), Guangzhou (0.467) and Shenzhen (0.268).

[16] Once approved, the proposed prices become binding and developers cannot raise prices above their proposed selling prices during the pre-sale process.

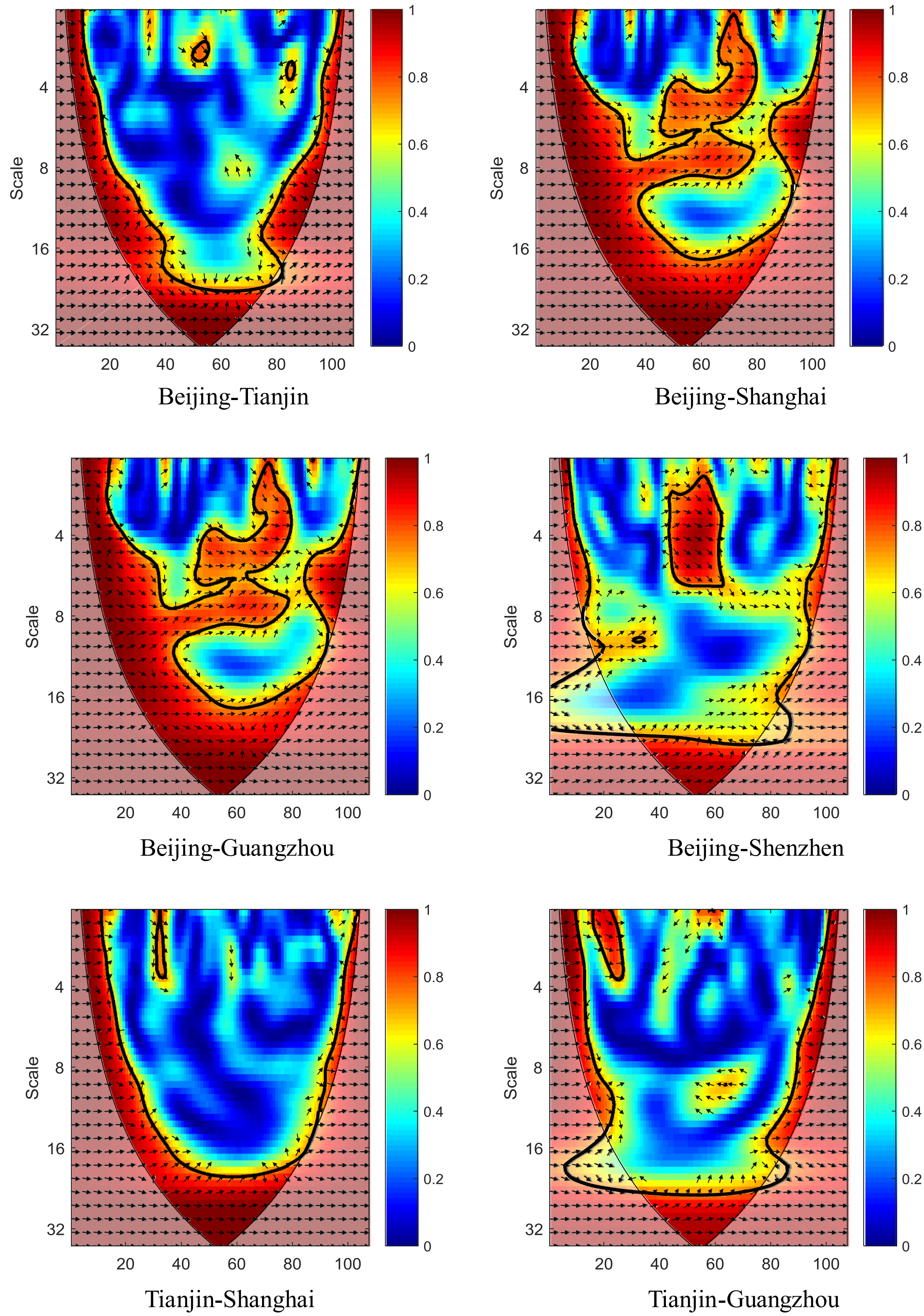

Fig. 8.. Wavelet coherence of house prices over time in pairings of major Chinese cities 2006–2014.
The color code on the right of each graph ranges from blue, corresponding to low coherency, to red, corresponding to high coherency. The thick black lines of frontier designate the 5% significance level for wavelet coherencies. Axis x represents distance from January 2006 in months. Axis y represents the scale of the housing price fluctuation. The arrows indicate the lead-lag relationship between the two series. In an index pair of city A–city B, the relative phase relationship is shown as pointing arrows: pointing right is in-phase, and pointing left is anti-phase. If arrows point down, it means that city A leads city B. Otherwise, city B leads city A. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6.2. Inter-regional dynamics: the wavelet coherency test

We use Eq. (3.5) to calculate the wavelet coherence in the five cities in pairs to evaluate the degree of co-movement between the two cities in each pair. The results are presented in Figs. 8 and 9.

In Fig. 8, the horizontal axis represents the number of months from January 2006, and the vertical axis represents the frequency component (scale) of the housing price fluctuation, with the shorter frequency range closest to the origin. The co-movement of housing prices for the specific pair of cities is exhibited in the scale plot to the right of each

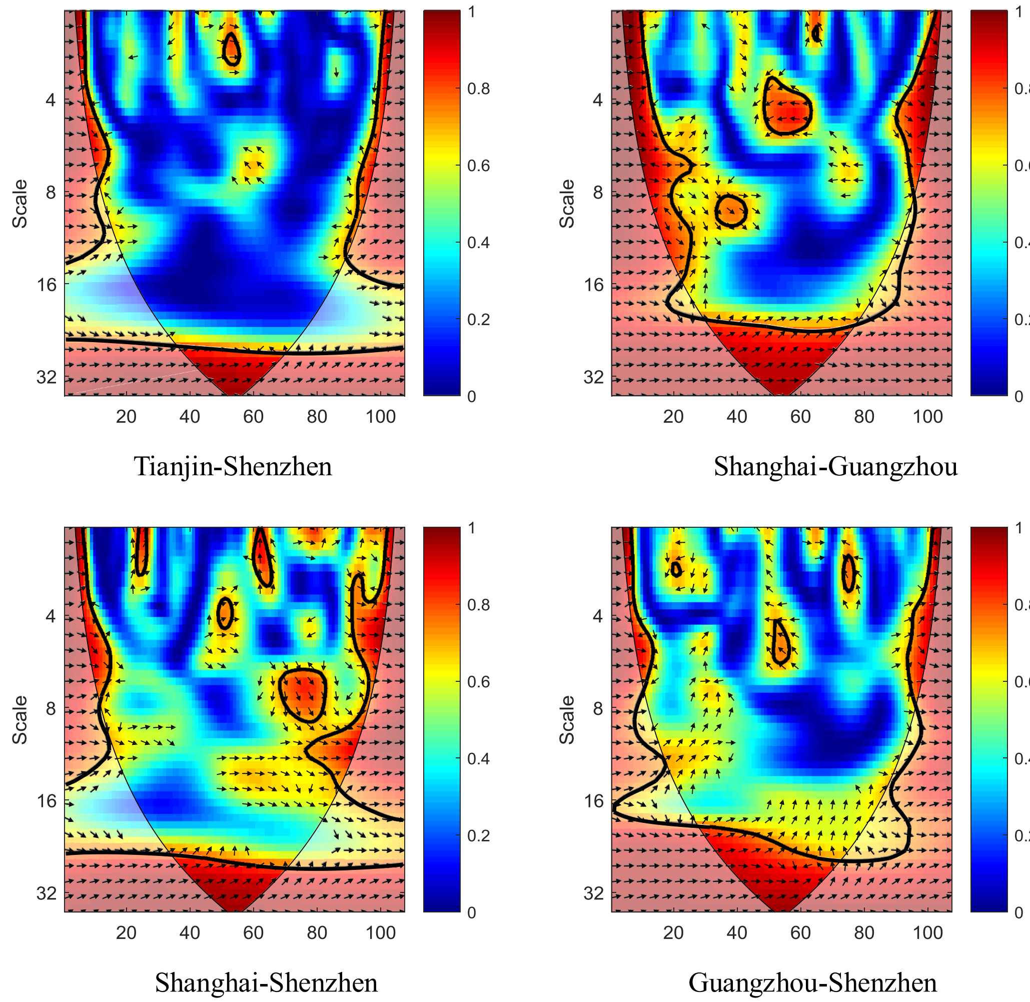

Fig. 8.. (*continued*)

figure. Red areas indicate a higher coherency of housing prices between the two cities, while blue areas correspond to a lower co-movement between the two cities. The black solid contours denote that the co-movement is statistically significant at the 5% level for a particular time and frequency area. For instance, in the coherency figure of Beijing–Tianjin, the blue area covers a large proportion of the cone, which indicates that the time-domain co-movement is generally relatively weak. However, the blue area is more significant in the low-scale area (i.e. the blue area is more prevalent in the higher end of axis y), which indicates that the co-movement is more pronounced in the long term than it is in the short term. We also observe that the proportion of blue area declines throughout the observation time, which reflects an increasing trend of co-movement between regional housing markets.

Wavelet phase-difference captures the dynamics of price linkages by observing the lead-lag relationship between the paired housing markets. The arrows in Fig. 8 indicate the lead-lag relationship between the series. If the phase arrows point to the right, they indicate that housing prices in city A and city B are in phase (positive co-movement); but if the phase arrows point left, then the housing prices in city A and city B are out of phase (negative co-movement). If arrows point down, it means that city A leads city B. If arrows point up, then city B leads city A.

For clearer exhibition of the lead-lag relationship, we also calculate the average phase-difference across cities with different scale intervals, including residual horizon (2–4; 4–8), seasonal horizon (8–16), cyclical horizon (16–32) and long-term trend horizon (above 32). The comparisons are shown in Fig. 9. If phase-difference equals to 0, then housing prices in city A and city B are in-phase (move together at the specified time-frequency interval). If phase-difference is located in the (0, 90) interval, then housing prices in city A are leading housing prices in city B. If phase-difference is located in the (−90, 0) interval, then city B leads city A.

An analysis of color-scale distribution in Fig. 8 suggests that the pairings among the five cities may be divided into two groups. The first group includes Beijing–Shanghai, Beijing–Guangzhou, Beijing–-Shenzhen, Shanghai–Guangzhou, Shanghai–Shenzhen and Guangzhou–Shenzhen. In these pairings, we observe a strong co-movement that is stronger in the long term. Further, we find a “red hole” in the 4 to 8 scale (corresponding to roughly 7 to 13 months) during the 2009–2011 period, indicating that the middle term synchronization of housing price fluctuations is higher in the beginning of the Post Financial Crisis Era. However, since the Twelfth Five-year Plan,[17] the short-term co-movement is disappearing over time.

The second group includes pairings of Tianjin with other cities: Beijing–Tianjin, Tianjin–Shanghai, Tianjin–Shenzhen and Tianjin–Guangzhou. Though long-term co-movement does exist, the results indicate a weaker co-movement between Tianjin and the other four cities than those four cities experience with each other in the short

[17] In mid-March 2011, the National People's Congress (NPC), China's top legislature, approved the new Five-Year Plan (FYP). China's FYPs are blueprints that outline key economic and development targets for the country in the next five-year period. The Plan emphasizes improving the housing supply system, increasing the supply of low-income housing, as well as improving real estate market regulation.

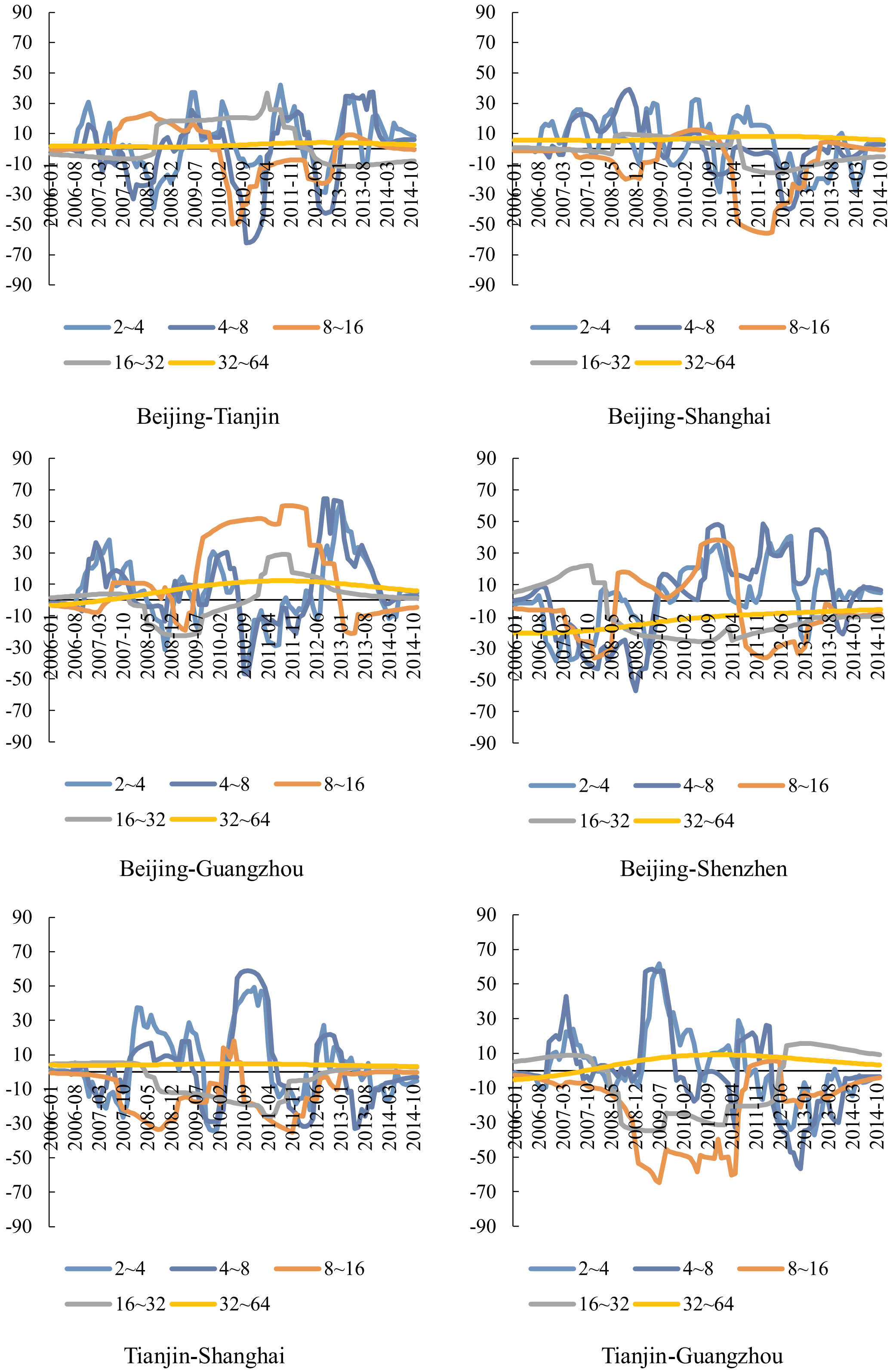

Fig. 9.. Lead-lag relationship of house prices over time in pairings of major Chinese cities 2006–2014.
This figure shows average phase difference across cities with different scale intervals, including residual horizon (2–4; 4–8), seasonal horizon (8–16), cyclical horizon (16–32) and long-term trend horizon (above 32). Axis x represents time. Axis y represents phase-difference between city A and city B. If phase-difference equals to 0, then housing prices in city A and city B are in-phase (move together at the specified time-frequency interval). If phase-difference is located in (0, 90), then housing price in city A is leading housing price in city B. Otherwise, city B leads city A.

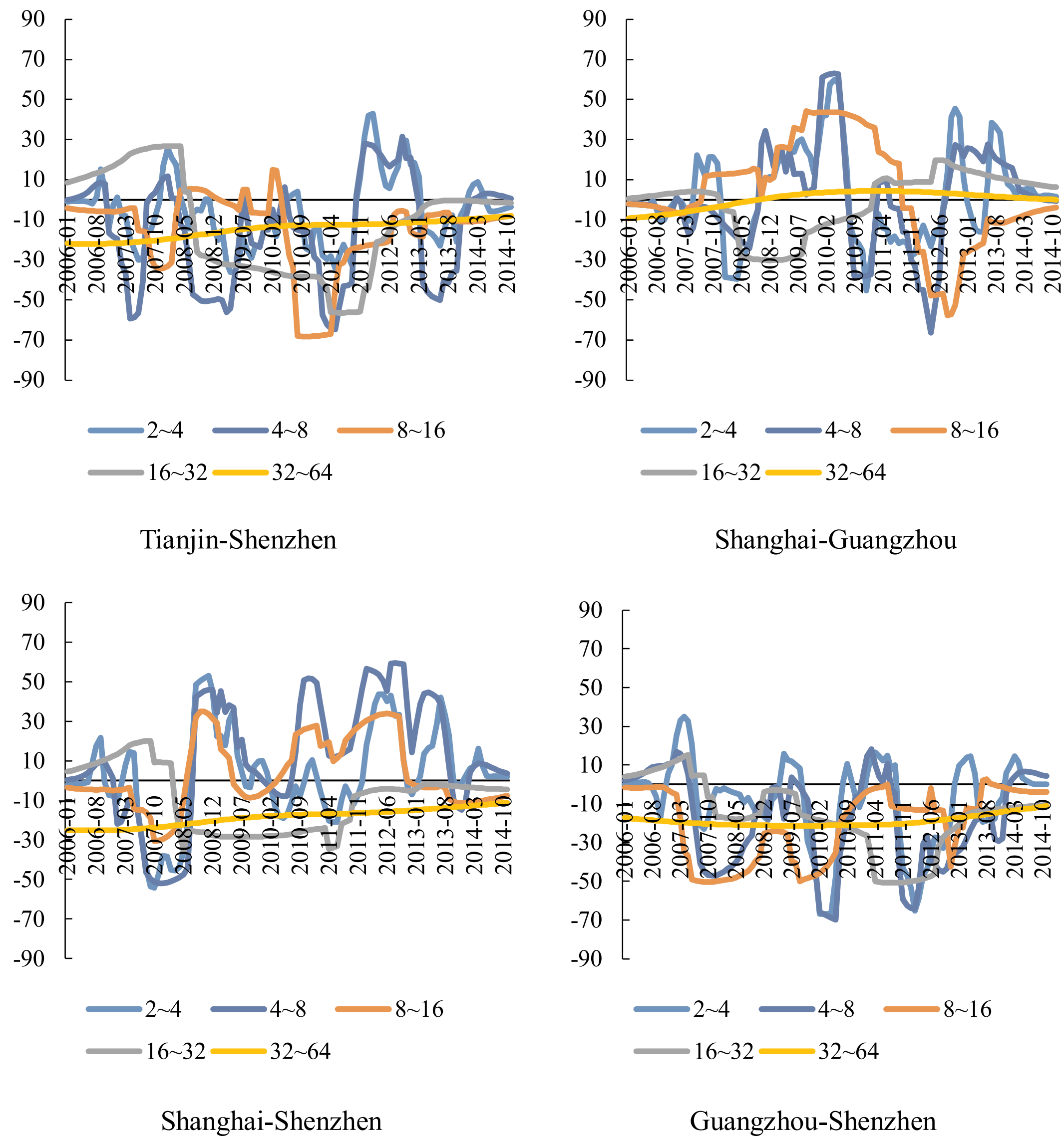

Fig. 9.. (*continued*)

and medium term. We also discover that, since the beginning of 2014, the co-movement between Beijing and Tianjin has increased in the short term. One possible explanation is the enactment of integration in Jing-Jin-Ji Area.[18] According to the plan, Beijing will reorganize its industry structure and divert some of its population to neighboring cities (i.e. Hebei and Tianjin) to ease population pressure in the capital.

As for the lead-lag relationship, we find that in the long term, housing prices in Shenzhen lead the other four cities, followed by Beijing, then Tianjin, then Shanghai and finally Guangzhou. This finding is consistent with the historical background that Shenzhen was the first trial zone of "commodity housing" in China,[19] and the first city to implement the bidding process for government land sales. Hence, the real estate market started earlier and is relatively more mature in Shenzhen compared to other cities. When we focus on cyclical lead-lag relationship, we find that during the first post-crisis interval (2008–2011), Shenzhen leads all of the other four cities, followed by Beijing, then Guangzhou, then Shanghai, and finally Tianjin. However, during the second post-crisis interval (2011–2014), the lead-lag relationships change with Tianjin leading, followed by Shenzhen, then Shanghai, then Beijing, and finally Guangzhou. This structural change could be explained by the announcement of the Twelfth Five-Year Plan in 2011 after which Tianjin has emerged as the only city occupying a strategic position in "One Belt, One Road",[20] "Free Trade Zones",[21] "National Innovation Demonstration Zones,"[22] and "Jing-Jin-Ji

[18] The General Administration of Customs (GAC) released an announcement on integrating the customs procedures of Beijing, Tianjin, and Hebei (GAC Announcement [2014] No. 45), marking an important milestone in the integration of the three jurisdictions into a single "megaregion" in China's northeast.

[19] This term is coined to describe housing supplied by private developers as opposed to the old-style public housing provided by the government in a centrally planned economy.

[20] President Xi Jinping launched China's "One Belt, One Road" (OBOR) initiative in 2013 with the stated aim of connecting major Eurasian economies through infrastructure, trade and investment. The "Belt" is a network of overland road and rail routes, oil and natural gas pipelines, and other infrastructure projects. The "Road" is its maritime equivalent: a network of planned ports and other coastal infrastructure projects.

[21] Free trade zones in China are a specific class of special economic zones—areas where goods may be landed, handled, manufactured and re-exported without intervention of the customs authority.

[22] The National Innovation Demonstration Zone (NIDZ) was approved by the Chinese government to promote independent innovation and the development of high-tech industry in a pioneering trial.

integration" policies. All four initiatives created a significant influx of population and capital into Tianjin. We also find that Beijing leads both Shanghai and Shenzhen in the short term. This could be explained by the political center role of Beijing. Beijing housing market experiences frequent policy interventions from both the central and local government. Beijing, for instance, was the first city to implement the policy of home purchase restrictions (HPR). Beijing government has also initiated a series of pre-sale restrictions as price control instruments. All these high frequent policy interventions add noise to housing price fluctuations and also send signals to other markets.

Our finding that Tianjin exhibits weaker correlation with the other cities indicates that real estate investors in any of these four cities can improve their risk-return performance by adding Tianjin properties to their portfolios. For example, an investor who owns residential property in Beijing would expect to achieve greater portfolio diversification from investing in Tianjin than from investing in Shanghai.

As a further comparison, we also calculate the cross correlations of housing prices in five cities using the traditional method.[23] We still find a significant low co-movement degree between Tianjin–Shanghai (less than 0.42), Tianjin–Guangzhou (less than 0.45), and Tianjin–Shenzhen (less than 0.36), which confirms our result about the uniqueness of Tianjin.

7. Conclusion

In this paper, we analyze the intra- and inter-regional variability of housing prices in five major cities of China using wavelet decomposition and coherency testing. We examine correlations between housing prices and economic fundamentals in the long term, and investigate housing price cycles in the short term. We find that macroeconomic variables, as suggested by the literatures, have strong explanatory power in determining long-term price trends in all five cities, but that this explanatory power is weakest in Tianjin. Using wavelet deconstruction technology, we estimate that the average cycle of the trend in response to economic fundamentals is 3.25 years, ranging from an average of 3.3 years in Shenzhen to 3.0 years in Tianjin.

We use the Wavelet Coherency Test to examine coherency in price structure and lead-lag relationship among the five cities. We observe a strong co-movement among the city pairs of Beijing–Shanghai, Beijing–Guangzhou, Beijing–Shenzhen, Shanghai–Guangzhou, Shanghai–Shenzhen, and Guangzhou–Shenzhen. In contrast, the co-movement between Tianjin and each of the other four cities is weak. Our finding that Tianjin exhibits weaker correlation with the other cities indicates that real estate investors in any of these four cities may improve their risk-return performance by adding Tianjin properties to their portfolios. When we examine the cyclical lead-lag relationships among these cities, we find that during the 2008–2011 period, Shenzhen led Beijing, which led Guangzhou, which led Shanghai, and finally Tianjin followed. However, during the 2011–2014 period, the lead-lag relationships changed to Tianjin leading Shenzhen, then Shanghai, then Beijing, and finally Guangzhou.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jhe.2018.09.003.

Appendix A. Description of wavelet technology

The wavelets are generated from a single basic wavelet: $\psi(x)$, the so-called mother wavelet. For each region, we define the wavelet basis, $\psi(x)$, which is a square integrable function whose Fourier transform $\psi(\omega)$ must satisfy the following admissible condition to insure the wavelet transform to be invertible (Daubechies, 1992)[24]:

$$\int_R \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty \tag{A.1}$$

Wavelets are then generated from the mother wavelet by scaling and translation: $\psi(x)$ function is dilated or compressed to a time interval (scale) a and translated (shifted) along the time line by b, thus defining a new wavelet function (van der Burgt, 2009):

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) \tag{A.2}$$

The time interval a is defined as a scale factor denoting the cycle length of the wavelet (which is similar to the concept of period of cosine function in Fourier transform). Scale is the opposite of frequency. Higher scale, a, means stretching wavelet basis $\psi(x)$ to a longer period, and thus to a lower frequency. Going from a large scale to small scale is akin to zooming in; while large scales show the big picture, small scales show the details. b is defined as shift factor, which represents a transition in the time domain. The multiplier $\frac{1}{\sqrt{a}}$ is to normalize the power of $\psi(x)$, making sure that wavelet transforms are comparable across scales (frequency bands).

The modified wavelet function can now be drawn up into the envelope of the original function using a Continuous Wavelet Transform (CWT) that defines the overlap between $f(x)$ and $\psi_{a,\,b}(x)$ as follows:

$$W_x(a, b) = \int_{-\infty}^{\infty} f(x) \cdot \psi_{a,b}{}^*(x)\, dx = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x) \cdot \psi^*\left(\frac{x-b}{a}\right) dx \tag{A.3}$$

where $W_x^0(a, b)$ is the wavelet coefficient. $\psi^*(\cdot)$ is the complex conjugate of $\psi(\cdot)$ in (A.2). There will be a different CWT for each wavelet in each of the five cities studied. $|W_x(a, b)|$ could be regarded as an indicator of amplitude. Accordingly, the wavelet power spectrum is defined as $W_{xy}(a, b)$,

[23] To save space, results are not shown here, but are available from the authors upon request.

[24] According to Daubechies (1992), this condition ensures that wavelet basis will have good attenuation properties, which allows the efficient reconstruction of a function from its continuous wavelet transforms without loss of information. Specifically, the Fourier transform of $\psi(x)$ is $\psi(\omega) = \int_R \psi(x) e^{-ix\omega} dx$. The admissibility condition implies that $\psi(\omega) \to 0$ both as $\omega \to 0$ and $\to \infty$, so $\psi(\omega)$ must be band-limited (with sharp declining, or attenuation). This condition creates a bandpass impulse response that looks like a wavelet (more graphic details in Appendix A). If the band is narrow or attenuating faster, the time domain localization of the wavelet will be better.

It also implies that the Fourier transform of $\psi(x)$ vanishes at the zero frequency. A zero at the zero frequency also means that the average value of the wavelet basis in the time domain must be zero, i.e., $= \psi(0) = \int \psi(x) dx$, and therefore it must be oscillatory. In other words, $\psi(x)$ must be a wave.

which can be interpreted as the local variance of specific time series at each time and frequency.

Since housing price signal is a discrete series, we need to further discretize CWT through sampling specific wavelet coefficients. We define $a = 2^j$ and $b = k2^j$, where integers j and k denote the set of discrete translation and discrete dilations, and produce an orthogonal basis with a dyadic dilation.[25] This method is also called multi-resolution analysis (MRA), which is an approach of fast wavelet transformation (Mallat, 2008). In Mallat's algorithm, the decomposition of a signal is accomplished by repeating a linear transformation involving a scaling function H (a low pass filter) and a wavelet function G (a high pass filter). Thus, in the jth scale decomposition, we obtain $c^{j+1} = Hc^j$ and $d^{j+1} = Gc^j$, where c and d are the approximation (low-frequency) and detail (high-frequency) coefficients, respectively, whose lengths decrease dyadically at higher scales or coarser resolutions.

With the individual wavelet transform determined, we can assume a pair of time series representing a pairing of two cities included in the study, $x(t)$ and $y(t)$. The wavelet coherence $R_{x,\,y}(a, b)$ of two time series x and y is defined as

$$R_{x,y}(a, b) = \frac{S(W_{xy}(a, b))}{\sqrt{S(|W_x(a, b)|^2)}\sqrt{S(|W_y(a, b)|^2)}} \tag{A.4}$$

where $W_x(a, b)$ and $W_y(a, b)$ denote continuous wavelet transforms of x and y at scales a and positions b respectively. $|W_{xy}(a, b)| = |W_x(a, b)\cdot W_y^*(a, b)|$ is the cross-wavelet power, and the superscript * is the complex conjugate of the

CWT for the time series $y(t)$. S($\cdot$) is a smoothing operator in time and scale.[26] $R_{x,\,y}(a, b)$, as module identification, must lie between 0 and 1. A high value indicates a strong co-movement in the time series.

Since coherency is module, which cannot distinguish positive or negative co-movement, we then introduce phase-difference (the angle) to investigate the lead-lag relationships of two series. The phase-difference is defined as

$$\theta_{x,y}(a, b) = tan^{-1}\left(\frac{I\{S(S^{-1}(W_{xy}(a, b)))\}}{R\{S(S^{-1}(W_{xy}(a, b)))\}}\right) \tag{A.5}$$

where $I\{\cdot\}$ and $R\{\cdot\}$ represent imaginary and real parts of the cross-wavelet power spectrum $W_{xy}(a, b)$. Intuitively, if $\theta_{x,y} = 0$, then time series $x(t)$ and $y(t)$ move together at the specified time-frequency. $\theta_{x,y}(a, b)\epsilon(0,\ 90)$ means $x(t)$ leading $y(t)$ while $\theta_{x,y}(a, b)\epsilon(-90,\ 0)$ means $y(t)$ leading $x(t)$.

Appendix B. Decomposition process of trend and cycle

In wavelet empirical applications, optimal choice must be made at three crucial steps: the selection of wavelet function (the so called Mother Wavelet), decomposition layers, and threshold (Gençay et al., 2002). Firstly, the selection process of wavelet basis is done according to the fundamental properties of the multi-scaling functions, such as regularity, symmetry, finite support, and orthogonality. In existing literatures, the Daubechies wavelet family (dbN Wavelet) is used widely by researchers. Referencing the empirical work of Yousefi et al. (2005), we choose 3 types of wavelet (db1 wavelet, db4 wavelet and db10 wavelet) for comparison. Due to the law of minimum mean square error, db4 wavelet is finally chosen to be the wavelet function in our empirical test, which is shown in Fig. A1.

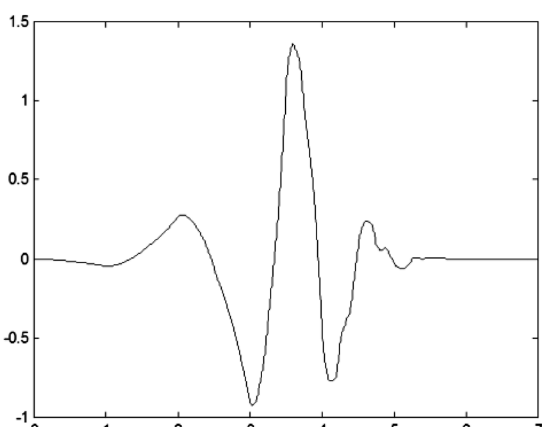

Fig. A1.. db4 wavelet function.

Note: db4 denotes one specific type (with two vanishing moments) of wavelet in the Daubechies wavelet family. The Daubechies wavelets (dbN) are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support.

The tradeoff between de-noising efficiency and fidelity is the standard of judgment in the selection of decomposition layers, due to the regulation that with rising decomposition level, both the de-noising effect and distortion degree will increase accordingly. In this consideration, the existing empirical studies imply that the optimal layers are usually less than 5. Borrowing the practice from current literatures, we compared the calculated minimum mean square error when $N = 3$, $N = 4$ and $N = 5$, and finally determine the decomposition layer to be 5.

Finally, the selection of threshold is also an exercise in balancing de-noising efficiency and fidelity. In order to strengthen the de-noising effect and maximize the low-pass (trend) information, we use the ddencmp function in MATLAB to automatically select the superior threshold in the

[25] In orthogonal wavelet analysis, the number of convolutions at each scale is proportional to the width of the wavelet basis at that scale. It is gives the most compact representation of the signal as it produces a wavelet spectrum that contains discrete "blocks" of wavelet power.

[26] Smoothing is needed because without it coherency would be identically one at all times and scales. Smoothing can be achieved by a convolution (see Cazelles et al., 2007).

process of de-noising and compression.

Based on this fundamental work, we use MATLAB to estimate the wavelet decomposition result. The output of multilayer and one-dimensional discrete wavelet decomposition is exhibited in Fig. A2, where LFA5 denotes the low-pass component remaining after the last decomposition process, while LFD1 to LFD5 denote the high-pass component in layer 1 to layer 5 respectively.

Similarly, we also use wavelet decomposition to extract the long-term trend of economic fundamentals of each municipality. The detailed results are not shown here to save space.

According to the decomposition result in Fig. A2, the component LFA5 is directly regarded as the long-term trend of both housing price index and economic fundamentals. Meanwhile, we use the "proof by contradiction" method to diagnose the cycle component combining Eq. (A.3) and the

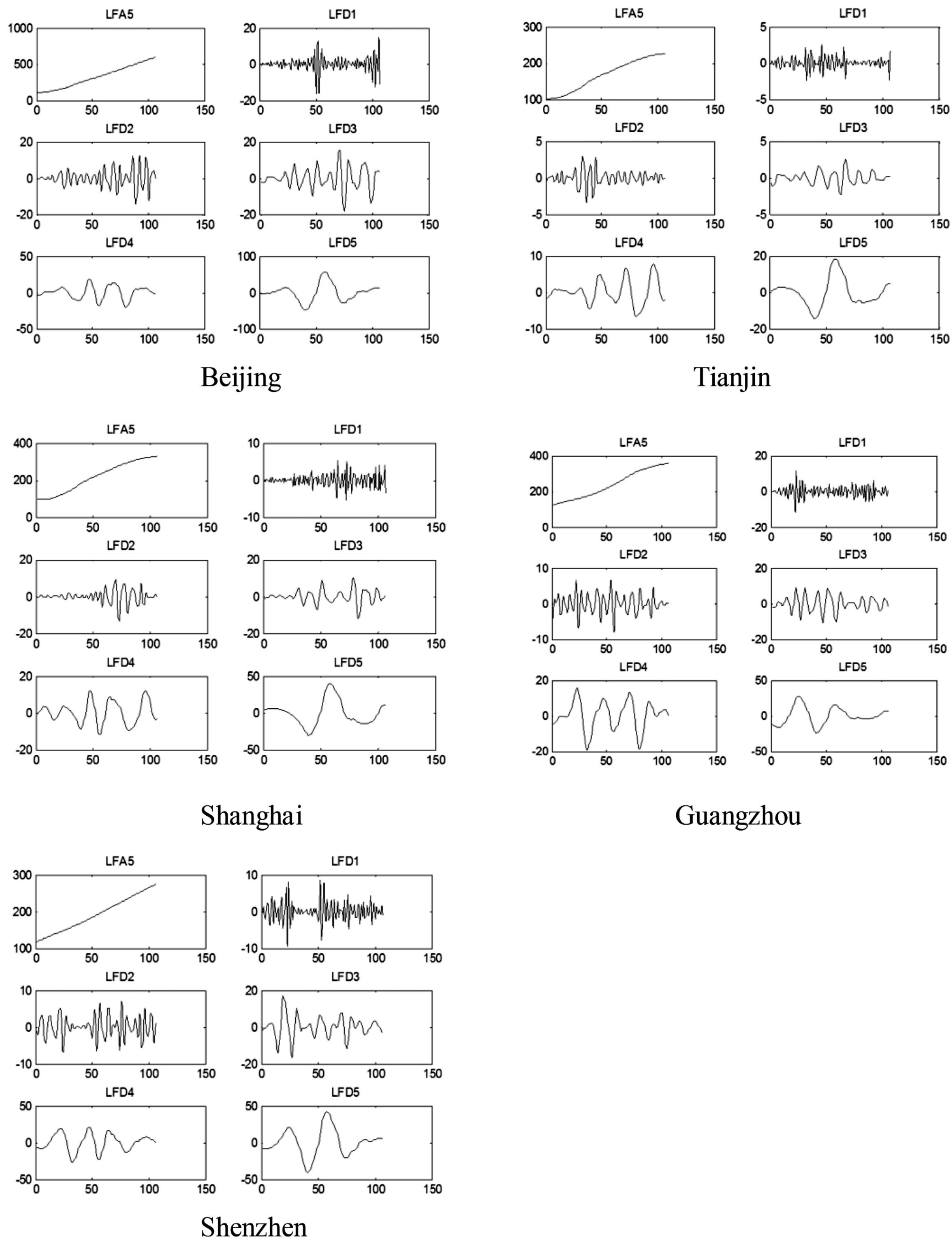

Fig. A2.. Output of multilayer and one-dimensional wavelet decomposition.
According to the principle exhibited in Fig. 1, LFA5 denotes the low-pass component remaining after the last decomposition process, while LFD1 to LFD5 denote the high-pass component in layer 1 to layer 5 respectively.

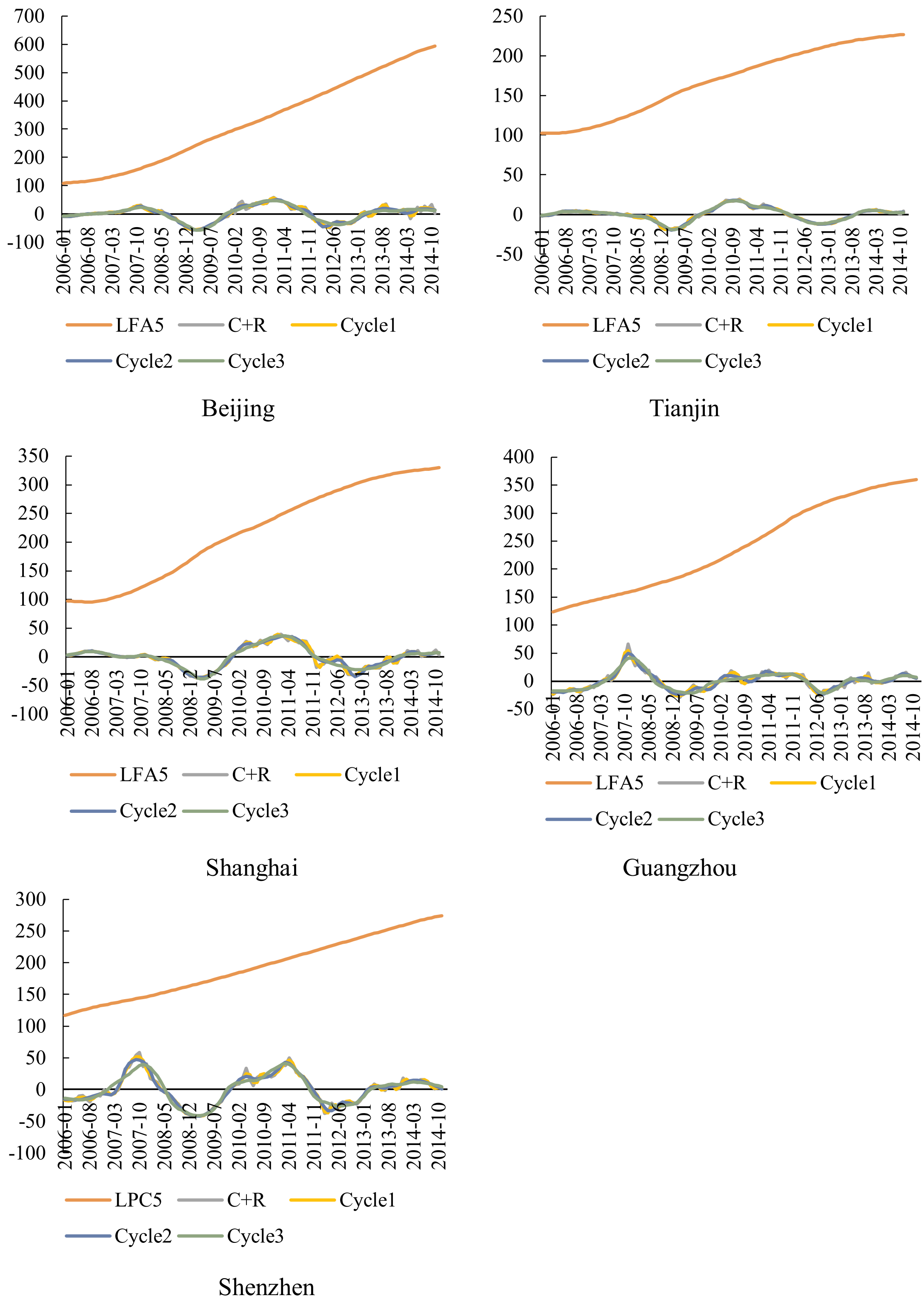

Fig. A3.. Long-term trend and cycle of housing index (CHI) in four Chinese cities from wavelet decomposition (2006–2014).
Note: LFA5 denotes long-term trend. C + R denotes the reconstruction signal excluding component LFA5. Cycle 1 exhibits the reconstructed signal excluding LFA5 and LFD1. Cycle 2 exhibits the reconstructed signal excluding LFA5, LFD1 and LFD2. Cycle 3 exhibits the reconstructed signal excluding LFA5, LFD1, LFD2 and LFD3.

wavelet decomposition output in Fig. A2. More details can be found below.

Based on the process of elimination principle, we then gradually diagnose the corresponding component combining equation (3.4) and the wavelet decomposition output in Fig. A2. Obviously, LFA5 component can be regarded as the long-term trend of housing price. After the ADF (Augmented Dickey-Fuller) test, we find the time series of high-pass component LFD1 and LFD2 to be stable, which implies that these two high frequency fluctuations can be regarded as random parts. However, components LFD3, LFD4 and LFD5 do not represent either trend characteristics or white noise characteristics, which are tentatively included into the cycle component. Comparing the results of different components of Cycle 1, Cycle 2 and Cycle 3,[27] we find that only Cycle 3 demonstrates a relatively smooth fluctuation with a cycle exceeding one year. Thus, we choose Cycle 3 to denote cyclical fluctuation in empirical studies.

Long-term trend and cycle of housing index (CHI) in four Chinese cities extracted by wavelet decomposition are shown in Fig. A3.

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[27] Cycle 1 exhibits the reconstructed signal excluding low-pass component (LFA5) and high-pass component in layer 1 (LFD1). Cycle 2 exhibits the reconstructed signal excluding low-pass component (LFA5), high-pass component in layer 1 (LFD1) and high-pass component in layer 2 (LFD2). Cycle 3 exhibits the reconstructed signal excluding low-pass component (LFA5), high-pass component in layer 1 (LFD1), high-pass component in layer 2 (LFD2) and high-pass component in layer 3 (LFD3).