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Time-varying causality between stock and housing markets in China

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ABSTRACT

Based on the rolling-window bootstrap Granger causality test, this paper investigates the relationship between stock and housing markets from the perspective of China's first-, second- and third-tier cities. The result indicates that the relations between stock and housing prices change across time and city tiers. The causality mainly exists in bull market periods and financial crises. During a bull market, the effect of stock prices on housing prices is positive in cities of all tiers, and the strongest effect is found in first-tier cities; during a financial crisis, housing prices have a negative effect on stock prices, and the effect diminishes gradually from first-tier cities to third-tier cities. Therefore, economic policy makers could take these differences into account to improve policy efficiency.

1. Introduction

Research on the relationship between stock and housing markets falls into three main branches. First, researchers investigate whether the two markets are segmented or integrated using linear and nonlinear co-integration tests (Lin and Fuerst, 2014). Second, the dynamic correlation between the two markets is discussed using the DCC-IGARCH model (Heaney and Sriananthakumar, 2012). Third, the Granger causality between the two markets has been widely studied and the findings are still inconclusive (Li et al., 2015). Okunev et al. (2000) found evidence of strong unidirectional causality from the stock market to the real estate market in the United States, whereas Sim and Chang (2006) showed that housing prices Granger cause stock prices and that no reverse causation exists in South Korea. Furthermore, Ding et al. (2014) found no causality between the two markets in China using a linear Granger-causality test, but a bidirectional causal relationship was found using a quantile causality test.

This paper investigates the relation between the stock and housing markets in China. On one hand, as an emerging economy, China often uses economic reform and macro policies to regulate markets, which might generate a non-linear dependence between the stock and housing markets. On the other hand, the real estate market in China's first-, second- and third-tier cities are quite different. According to housing sale price data for 70 cities published by the National Bureau of Statistics of China, housing prices in first-tier cities increased more quickly than those in second- and third-tier cities before July 2015. After August 2015, housing prices in some second-tier cities, such as Hefei, Nanjing and Zhengzhou, increased more quickly than first-tier cities, while housing prices still increased slowly or even decreased in most third-tier cities.

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Table 1
Typical cities selection.

	Selected cities
The first-tier cities	Beijing; Shanghai; Shenzhen; Guangzhou
The second-tier cities	Tianjin; Chongqing; Hangzhou; Nanjing; Wuhan; Shenyang; Chengdu; Xian; Dalian; Qingdao; Ningbo; Changsha; Jinan; Xiamen; Fuzhou; Changchun; Haerbin; Taiyuan; Zhengzhou; Hefei; Nanchang
The third-tier cities	Shijiazhuang; Huhehaote; Nanning; Haikou; Guiyang; Kunming; Lanzhou; Yinchuan; Xining; Wulumuqi; Tangshan; Qinhuangdao; Baotou; Dandong; Jinzhou; Jilin; Mudanjiang; Wuxi; Yangzhou; Xuzhou; Wenzhou; Jinhua; Bengbu; Anqing; Quanzhou; Jiujiang; Ganzhou; Yantai; Jining; Luoyang; Pingdingshan; Yichang; Xiangyang; Yueyang; Changde; Huizhou; Zhanjiang; Shaoguan; Guilin; Beihai; Sanya; Luzhou; Nanchong; Zunyi; Dali

Therefore, we discuss the relations between stock and housing prices separately for first-, second- and third-tier cities, using the time-varying causality test.

We bring forward several contributions to the literature. First, we analyze the relation between stock and housing prices from the perspective of comparisons between different tiers of cities. Second, a rolling-window bootstrap Granger causality test is employed to examine stock-housing price nexuses and the parameter stability tests is used to support the nonlinear causality method. Third, we provide not only the causal relationship but also the magnitude of impact between stock and housing prices in the different tiers of cities. Fourth, we focus on special economic events such as the bull market and the financial crisis to discuss their impact on the linkage between stock and housing prices. The rest of the paper is structured as follows. Section 2 describes the data and methodology employed. Section 3 provides the empirical results, while Section 4 concludes.

2. Data and methodology

2.1. Data

In order to study the interaction between stock and housing prices in different tiers of Chinese cities, we select the following first-, second- and third-tier cities for our analysis, as shown in Table 1. They cover all 70 key cities. We chose the new housing prices index of the 70 cities to represent housing prices for each city. The average housing price index of the first-tier cities is calculated by equally averaging the housing prices of all first-tier cities and is adjusted based on the X-13 season adjustment. Similarly, we obtain the average housing price indexes of the second- and third-tier cities. We use the Shanghai Stock Exchange Composite Index to indicate stock prices. The data cover the period from July 2005 to March 2017 and are from the Wind database. All data are transformed into natural logarithms.

2.2. Rolling-window bootstrap Granger causality test

We began with the bivariate VAR(p) process:

$$\begin{bmatrix} y_{sp,t} \\ y_{hp,t} \end{bmatrix} = \begin{bmatrix} \phi_{hp} \\ \phi_{hp} \end{bmatrix} + \begin{bmatrix} \phi_{sp,sp}(L) & \phi_{sp,hp}(L) \\ \phi_{hp,sp}(L) & \phi_{hp,hp}(L) \end{bmatrix} \begin{bmatrix} y_{sp,t} \\ y_{hp,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{sp,t} \\ \varepsilon_{hp,t} \end{bmatrix} \tag{1}$$

where sp means stock prices, hp means housing prices, $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k} L^k$, $i, j = sp, hp$, p is the optimal lag order, L is the lag operator defined as $L^k x_{i,t} = x_{i,t-k}$, and $\varepsilon_t = (\varepsilon_{sp,t}, \varepsilon_{hp,t})$ is a white noise process with zero mean. From Eq. (1), the null hypothesis that stock prices do not Granger cause housing prices can be tested by $\phi_{hp,sp,\ i} = 0$, for $i = 1, 2, \ldots, p$. Similarly, the null hypothesis that housing prices do not Granger cause stock prices can be tested by $\phi_{sp,hp,\ i} = 0$, for $i = 1, 2, \ldots, p$.

The modified-LR statistic for testing the null hypothesis can be written as

$$LR = (T-k)\ln\left(\frac{\det \eta'_r \eta_r}{\det \eta'_u \eta_u}\right) \tag{2}$$

where $k = 2(2p+1)+p$ and η_u and η_r are the estimated residuals matrixes for (1) using the least square method with and without the restriction of the null hypothesis, respectively. Then, we use the adjusted OLS residuals $\eta_r - \overline{\eta_r}$ for $i = 1, \ldots, T$ to draw i.i.d. $\eta_1^*, \eta_2^*, \ldots, \eta_T^*$ and obtain the bootstrap sample$Y^* = \hat{B} Z^* + \eta^*$, where$\hat{B}$ is the last square estimator. Based on Y^*, we obtain the corresponding residual-based bootstrap statistic LR^*. By repeating this process N_b times, the bootstrap p value, which is denoted by $P^*(LR^* \geq LR)$, can be obtained.

Following Nyakabawo et al. (2015), we use the L_c, *Sup-LR, Mean-LR* and *Exp-LR*tests to examine the stability of the parameters. If the parameters are found to be unstable, they may cause the pattern of causality to change over time. Then, in addition to a full sample with length T, we apply the bootstrap causality test to rolling subsamples for $t = \tau - l + 1, \ \tau - l, \ \ldots, \ l, \ \tau = l, \ l+1, \ \ldots, \ T$, where l is the size of the rolling window.