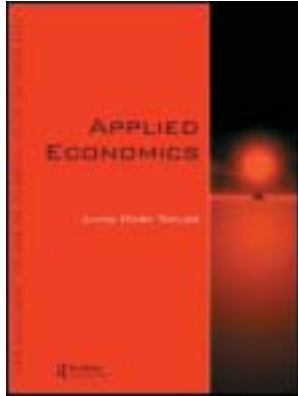


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The multi-market analysis of a housing price transmission model

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The multi-market analysis of a housing price transmission model

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In this article, we examine dynamic relationships among housing prices from four first-tier cities in China from December 2000 to May 2010 and present an equilibrium model of housing price in multi-markets. By explicitly incorporating and modelling endogenous price series in competing housing markets, our empirical model is able to capture the existence of long-run equilibrium relationships and important short-run dynamics and price structures such as price leadership, price transmission lag and asymmetric price responses. Such multi-market analysis has generalized implications and can easily be applied to analyse the pricing dynamics among other real estate markets in the world. Our major contribution lies in two aspects. First, we employ an Error-Correction Model (ECM) with Directed Acyclic Graphs (DAG) to study the price dynamics in the four largest and key housing markets in China. Second, we uncover a price transmission among these housing markets in China and provide an insightful understanding of price adjustment across markets. The revealed effective price transmission and high correlation among these different markets actually is not a good thing for a stable financial system and for the defence against price bubbles in the housing market.

Keywords: ECM; DAG; housing price dynamics

JEL Classification: P22; P25; R32

I. Introduction

Until 1999, most of the people in China's urban areas have lived under the welfare housing system in which the government provided virtually free housing for them. In March 1998, China started a series of housing reforms. Since then, the real estate market in China has been developing, which helped prompt the economic growth of China. Indeed, the real estate market accounts for the most important driving factor to spur the Chinese economy. The real estate capital as a percentage of Gross Domestic Product (GDP) increased from 36.7% in 1997 to 42.6% in 2005 (Fung *et al.*, 2010). However, the soaring house prices have initiated discussion on price instability and possible government intervention. Policy makers, investors and economists have periodically raised concerns over the housing market, in particular, the concern about the fast rising price of housing market in the first-tier cities.

Correspondingly, there have been numerous studies in this field, which include macro- and micro-level analysis. Generally, the macro analysis puts emphasis on the relationship between macro variables and the real estate variables. Wang and Wen (2011) show that rising housing prices and living cost *per se* cannot explain China's persistently high household saving rate. Guo and Huang (2010) investigated the extent of the impact of 'hot money' or speculative capital inflow on the fluctuations of China's real estate market and stock market. In particular, their results show that 'hot money' ranks as the second largest contributor in the fluctuations of China's real estate prices. Wei (2008) used a Structural Vector Autoregression (SVAR) model to investigate the role of different monetary policy variables such as interest rate and bank loans in influencing the real estate market. Nye and Liu (2005) apply the Granger and co-integration methods to analyse the relationship between monetary policy and the real

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estate variable. Their empirical result indicates that the effect of money supply on real estate investment and price is more significant than that of interest rates.

Micro analysis investigates the determinants of housing price, and explores reasons that cause the great disparity of housing price in different cities or regions. He *et al.* (2009) investigated the role of amenities in explaining the huge difference in housing prices among different regions, and showed that amenities such as altitude and excessive precipitation play a negative role in pricing the residence. Chen and Hao (2008) applied the hedonic method to the spatial-statistical analysis of housing prices in Shanghai, and focused on examining the effect of geographical distance to city centre on the selling price of residential housing in Shanghai. Cao and Keivani (2008) study the risks in commercial real estate market in four cities: Beijing, Shanghai, Guangzhou and Chongqing. They examined the impact of urban governance, government real estate administration, market practice and the current status of the property investment market on real estate market risks. Webb and Tse (2000) compare the office price and rentals in Shanghai, Guangzhou and Shenzhen and explore the relationship among the office prices in the three different cities. Some studies investigate whether China will have the next great housing bubble in major cities (Hui and Shen, 2006; Zhang and Sun, 2006a, b; Sun and Zhang, 2008). However, the study about the interconnections among the different markets and housing price transmission is rarely found in the literature, even for international housing markets. The most relevant study is by Brady (2011), where he explored how fast and how long (to what magnitude) a change in housing prices in one region affect its neighbours' housing price.

As the real estate market in China is growing faster and faster, the price transmissions across regions have become increasingly important for the conduct of appropriate regulations and policies to control the risk and prevent housing bubbles. This issue is also especially relevant because China is still in the process of urbanization. The relationship among housing prices of first-tier cities often signals the trend for the entire market. The comprehensive study of dynamic interactions and dependence of these markets may provide a better guidance for both investors and policy makers.

In this study, we focus on the housing market in four first-tier cities (Beijing, Shanghai, Guangzhou and Shenzhen). These four cities have the largest population, employment opportunities and GDP contributions in China and are a magnet for more efficient workers and businesses. Their housing markets are highly competitive in terms of both living and investment and thus we believe the housing prices in these markets won't stray far away from each other in the long run. Therefore, we will use Error-Correction Model (ECM) to investigate the housing prices across these different markets since the ECM assumes that there is a long-run cointegrating relationship in the time series. Such time series models have been commonly used in financial studies in both developed and developing markets (Jaebeom *et al.*, 2007; Wilcox and Geppert, 2007; Al-Shiab and Mohanmad, 2008; Wei, 2008).

Specifically, we will use the Beijing, Shanghai, Guangzhou and Shenzhen housing market prices to find the dynamic price relationships among them. These relationships include the

long-run cointegration, price competitiveness, price leadership and the time lag for price transmission. Policy variables are not included in our model because we focus on checking the price dynamics and dependencies of these four markets, but not on the response of housing prices to policy. It remains an interesting question for future study to determine if macro policies play a more important role in linking these prices series together.

In addition, we use DAG with a PC algorithm to provide data-based evidence on causal ordering in contemporaneous time. ECM combined with DAG will allow us to identify the long-run, short-run and contemporaneous time structure of the series. In summary, we will study the complete time series properties of four selected major housing markets in China and discover a clear acting pattern of housing prices in these cities.

Our main results can be summarized as follows. First, all the four markets are linked together and cointegrated in the long run; second, Beijing market has stronger effects on other housing market prices in the long run, while the Shanghai market exhibits stronger influence on housing prices in contemporaneous time. Beijing appears to be the price leader in the long run and Shanghai exhibits strong price leadership in the short run. Third, the Shenzhen market seems to be the most dependent market in contemporaneous time while the most autonomous market in the long run. Fourth, the price transmission lag is quite small indicating that the price transmission among these four markets is quick and quite efficient. The price competition among these markets is significant. Fifth, there is an interesting negative response of the Shanghai market to positive shocks from Guangzhou market in the short and long run. Finally, the efficient price transmission and heavy dependency between these markets has important implication for policy maker; it may boost the possibility of a price bubble and is inefficient to diversify the system risk in the housing market.

The remainder of the article is organized as follows. Section II discusses the methodology, Section III describes the data, and Section IV presents empirical results. Finally, we offer some concluding remarks in Section V.

II. Methodology

Suppose a cointegration relationship exists among the variables, and let X_t denote a vector of nonstationary housing prices, then the data can be modelled in an ECM with k lags (which is equivalent to a VAR model with $k + 1$ lags):

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^k \Gamma_i \Delta X_{t-i} + \mu + e_t \quad (1)$$

where $\Pi = \alpha\beta'$ is a coefficient matrix, α can be viewed as the vector of adjusting speed, β is the matrix of cointegrating parameters. Γ_i is a matrix of short-run dynamics coefficients, μ represents the time trend (constant), e_t is a vector of innovations.

A weak-exogeneity test for each series is important to see if series respond to the deviation from the identified long-run relationship. That is to say, when observations from our series

are exogenous, the variable does not respond to perturbations. The hypothesis is framed as follows:

$$H_0: \alpha = 0 \quad (2)$$

The null hypothesis is that each series does not respond to disequilibrium among the variables and we test whether the i -th row of α has an element equal to zero. A formal discussion on weak exogeneity can be found in Johansen (1992).

Testing hypothesis on β to reveal the long-run structure refers to the test of exclusion from the cointegration vector. The hypothesis is expressed as

$$H_0: \beta' = 0 \quad (3)$$

The null hypothesis is that each series is not in the long-run equilibrium, which means we put zero restrictions on the each beta value in the vector.

Overall, though the ECM summarizes the dynamic interaction among all variables, the individual coefficients of the ECM (particularly those of short-run dynamics) are hard to interpret. The dynamic price relationships can be best captured through innovation accounting analysis as employed as the following three types: forecast error variance decomposition, historical decomposition and impulse response functions (Sims, 1980; Lutkepohl and Reimers, 1992; Swanson and Granger, 1997). Our study will conduct impulse response analysis since the graphs are more intuitive to understand.

As discussed in Hamilton (1994), a common interpretation of an impulse response function is the effect of a primitive impulse $\Sigma_{i,t}$ on variable $Y_{j,t+k}$. Sims (1980) and others have noted that, when there is contemporaneous correlation among variables, the choice of orderings in the Cholesky decomposition, which is the base of an impulse response derivation, may make a significant difference for interpretation of impulse responses.

In the Cholesky decomposition, we often assume that there exists a recursive contemporaneous causal structure. However, this assumption is restrictive and often hard to meet (Swanson and Granger, 1997). In practice, economic theory rarely provides guidance for contemporaneous causal orderings and many researchers rely on various stories to determine them arbitrarily. As Swanson and Granger (1997) advocated, the DAG could be used to uncover contemporaneous causal ordering in a data-determined and less *ad hoc* manner. Hence, we use DAG to determine the Cholesky ordering required in the impulse response.

The study is conducted by combining DAG and ECM. The directed graph with PC algorithm is a recently developed method to allow researchers to make causal inferences from observational data (Spirtes *et al.*, 1993; Pearl, 1995, 2000; Swanson and Granger, 1997). Heretofore, it has been common for researchers to apply this method to study many economic, financial and business problems (Bessler *et al.*, 2003, Haigh *et al.*, 2004; Yang *et al.*, 2006, Chong *et al.*, 2010). However, as recently noted by Spirtes *et al.* (2000), the ability of this approach to unveil causal relationships among variables is still in debate. Demiralp *et al.* (2008) advance a bootstrap method for assessing the confidence that can be placed on such results. It is not our purpose here to argue against those viewpoints, we

just use directed graphs with PC algorithm to investigate the contemporaneous causal relationships among different markets.

Here we just present a brief introduction about this newly developed method. A directed graph is a picture communicating the causal flows among a set of vertices (variables). Lines with arrowheads are used to represent such flows; the graph $A \rightarrow B$ indicates that variable A causes variable B . A line connecting two variables, say $C - D$ indicates that C and D are connected by information flow but we cannot tell if C causes D or vice versa. Here we consider DAG, which means that we do not consider inference on systems such that information created in one variable (say variable A) passes on to other variables (B and C), but ultimately returns to its source (A); we do not study cyclical systems such as $A \rightarrow B \rightarrow C \rightarrow A$.

Mathematically, DAG is designed to represent conditional independence as implied by the recursive product decomposition

$$pr(v_1, v_2, \dots, v_n) = \prod_{i=1}^n pr(v_i/\pi_i) \quad (4)$$

In Equation 4, pr is the probability of variables v_1, v_2, \dots, v_n . The symbol, π_i , refers to the realization of a subset of variables that precede (come before in a causal sense) v_i in order ($i=1, 2, \dots, n$). The symbol Π , refers to the multiplication operator.

Here we present one algorithm (PC algorithm), which can be used to build DAG. The algorithm starts from a complete undirected graph and removes edges from vertices based on correlation or partial correlation between vertices.

Spirtes *et al.* (2000) have proposed to incorporate the notion of d-separation into PC algorithm for building DAG. The fundamental notion which allows us to assign the direction of causal flow to a set of variables is formally named d-separation (Pearl, 1995, 2000), which is a graphical characterization of the independent relations given by Equation 4.

The basic idea of DAG builds on the insight of a nontime sequence asymmetry in causal relations, whereas the well-known Granger causality exploits the time sequence asymmetry that a cause precedes its associated effect (and thus an effect does not precede its cause). The Granger causality compared to DAG has obvious drawbacks. For example, variable A Granger causes variable B if knowledge of variable A and its past history help to predict variable B . In essence, variable A Granger causes variable B is a test that variable A precedes variable B in a predictive sense at different lag levels. Nevertheless, the DAG performs better to specify the contemporaneous causality without any lag. Hence, we will utilize the DAG results to build our analysis of the four housing markets in China.

III. Data

The data for this study comes from China Real Estate Index System (CREIS), which is the first housing index system in China. It is the most authoritative databank with the most comprehensive and detailed information on the Chinese property market covering most major cities, complete histories

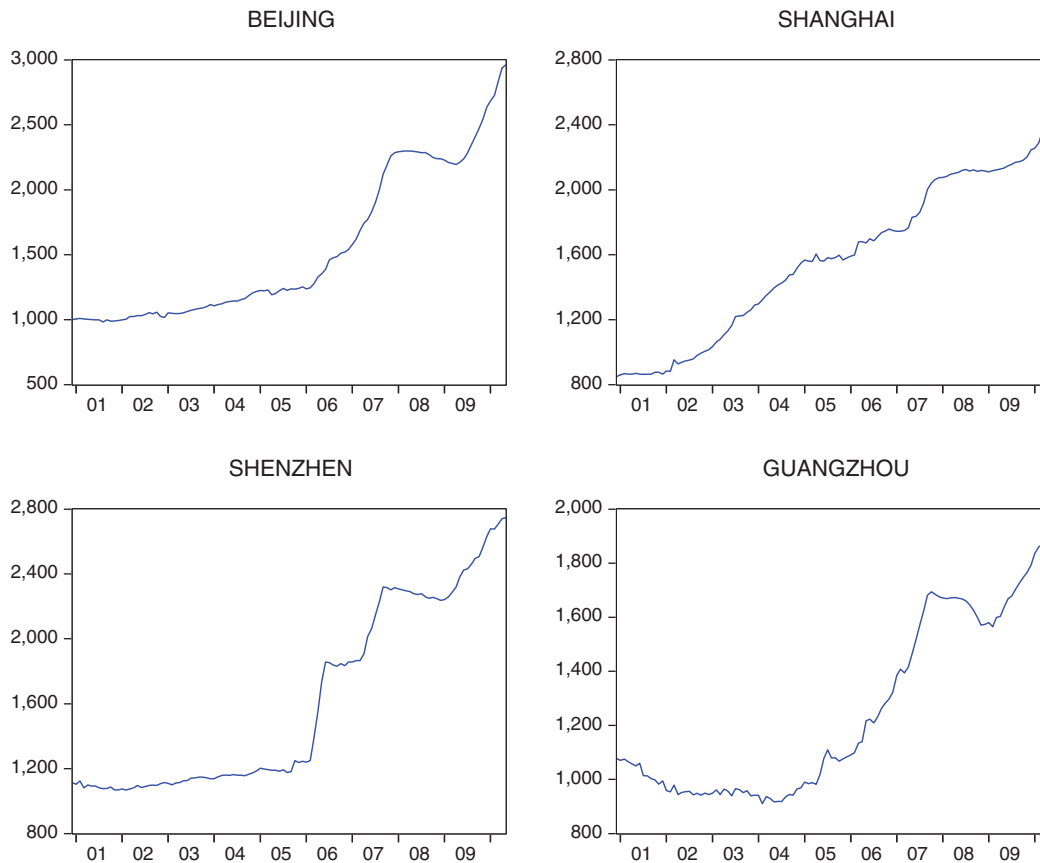


Fig. 1. Plots of housing price index (monthly) on four markets: Beijing, Shanghai, Shenzhen and Guangzhou, December 2000 to May 2010

Table 1. ADF test on Beijing, Shanghai, Shenzhen and Guangzhou

Variable	<i>t</i> -statistics	<i>p</i> -value*	<i>D</i> -variable	<i>t</i> -statistics	<i>p</i> -value
Beijing	-1.2596	0.8924	ΔBeijing	-4.6659	0.0013
Shanghai	-1.9893	0.6006	ΔShanghai	-8.8048	0.0000
Shenzhen	-2.1824	0.4943	ΔShenzhen	-5.0148	0.0004
Guangzhou	-2.0071	0.5909	ΔGuangzhou	-8.0425	0.0000

Notes: *p*-value* represents MacKinnon (1996) one-sided *p*-values. Variable represents time series for each housing price, *D*-variable is the one-order difference of each variable.

for hundreds of listed developers, and tens of thousands of building and industrial companies. The CREIS housing price index reflects price movements on a monthly basis of repeating sales on housing market. This article uses the housing price index from December 2000 to May 2010¹ for each city for a total of 456 observations.

Plots of data are given in Fig. 1. Notice that for all the four markets, prices continued to rise until the year of 2008 and reach a trough in 2009, which was affected by great financial crisis and macro control at that time.

IV. Empirical Results

Formal tests on unit root are applied. We fail to reject the null hypothesis of a unit root (using the Augmented Dickey–Fuller (ADF) test²) in each market. The test statistics are found in Table 1. Since all these four series have unit root, it is possible that they are cointegrated and can be modelled by ECM.

The common procedure to establish an ECM is to use either a trace test or information criterion to determine the lag order

¹ The data starts from December 2000 because CREIS uses December 2000 as base period, set the price level of Beijing housing market in December 2000 as 1000 base point, the average prices of other markets in other periods are compared to this base point and reported in CREIS.

² The ADF test model can be represented by $y_t = c + a^*t + b^*y_{t-1} + \sum_1^i d_i^* \Delta y_{t-i} + \varepsilon_t$.

Table 2. One step Schwarz loss criteria by lags on the number of co-integrating vectors (r) and model specifications fit over the period December 2000–May 2010

Lag	Rank	Models				
		No intercept no trend ^a	Intercept no trend I ^b	Intercept no trend II ^c	Intercept trend I ^d	Intercept trend II ^e
1	0	36.8099				
1	1	36.2641	36.2013	36.2426	36.2141	36.3169
1	2	36.4717	36.4431	36.4487	36.4479	36.5233
1	3	36.7284	36.7418	36.7061	36.7079	36.7493
2	0	36.3685				
2	1	36.6919	36.6581	36.7218	36.6156	36.7182
2	2	36.9070	36.9096	36.9310	36.8652	36.9255
2	3	37.1611	37.1874	37.1686	37.1446	37.1798
3	0	36.8273				
3	1	37.0117	37.0299	37.0704	37.0746	37.1855
3	2	37.2633	37.2274	37.2468	37.2527	37.3287
3	3	37.5299	37.5307	37.5156	37.5035	37.5368
4	0	37.1736				
4	1	37.5682	37.6040	37.6273	37.6342	37.7347
4	2	37.8100	37.8201	37.8433	37.8421	37.9160
4	3	38.0850	38.1214	38.1134	38.1076	38.1388
5	0	37.7678				
5	1	38.0878	38.1308	38.1357	38.1630	38.2784
5	2	38.2920	38.3731	38.3403	38.3949	38.4691
5	3	38.5534	38.6227	38.6035	38.6502	38.6814

Notes: The optimal lag and rank combination is marked in bold in the table, for rank 0, it means no cointegration and we use unrestricted VAR for estimation.

^aTest assumes no deterministic trend in data, and no intercept or trend in Cointegrating Equation (CE) or test VAR.

^bTest assumes no deterministic trend in data, have intercept (no trend) in CE, but no intercept in VAR.

^cTest allows for linear deterministic trend in data, and assume intercept (no trend) in CE and test VAR.

^dTest allows for linear deterministic trend in data, and assume intercept and trend in CE, but no trend in VAR.

^eTest allows for quadratic deterministic trend in data, and assume intercept and trend in CE and linear trend in VAR.

of the unrestricted VAR in the first step, and then use the same criterion to determine the cointegration rank and appropriate specification for ECM in the second step. However, we will use a one-step Schwarz Loss Criterion (SLC) to determine the lag order and the cointegration vectors in the ECM simultaneously, which has been proven to work at least as well as or even better than the traditional trace test or the two-step approach in both efficiency and consistency (Wang and Bessler, 2005).

Step by step, we check the SLC value for rank = 1, 2, ... and lag = 1, 2, ... (with a maximum lag 12) for each model specification, and choose the one that yields the lowest SLC value. Part of the results is shown in Table 2. With this method, we identify the optimal specification is the model with one lag and deterministic trend in data, having intercept (no trend) in CE, but no intercept in VAR (Table 2).

These four markets are cointegrated with one identified relationship.³ The existence of this cointegration relationship among these four nonstationary series implies they must be linked in some way and each market will not move far away from the others. The optimal lag for our model is one meaning that the price in one market is transmitted to other market

within a month. The transmission lag is quite small and the price transmission among these four markets is quick and quite efficient, which implies the price competition among these markets is quite significant.

We also investigate whether imperfect competition in housing markets results in such cointegration relationship through practice of price leadership and strategic interactions among government agents who regulate price in some markets. Our expectation is that the market price in some markets will not move too far from the market price of the others before a government intervention on long-run relations among the market prices.

The cointegration vector and adjustment coefficients are estimated as follows (t -statistics are in parentheses):

$$\begin{bmatrix} \Delta \text{Beijing} \\ \Delta \text{Shanghai} \\ \Delta \text{Shenzhen} \\ \Delta \text{Guangzhou} \end{bmatrix} = \alpha \beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i}$$

³The fact that co-integrated variables share common stochastic trends provides a very useful way to understand cointegration relationships (Stock and Watson, 1988).

$$\begin{aligned}
 &= \begin{bmatrix} -0.0094 \\ (-0.6816) \\ 0.0633 \\ (4.8247) \\ 0.0099 \\ (0.5044) \\ 0.0143 \\ (1.0193) \end{bmatrix} \\
 &\times \begin{bmatrix} 1 & -0.2849 & 0.0993 & -1.8046 & 1084.074 \\ & (-2.1464) & (0.3284) & (-3.9332) & (5.6106) \end{bmatrix} \\
 &\times \begin{bmatrix} \text{Beijing}(-1) \\ \text{Shanghai}(-1) \\ \text{Shenzhen}(-1) \\ \text{Guangzhou}(-1) \\ 1 \end{bmatrix} \\
 &+ \begin{bmatrix} 0.6104 & 0.1122 & 0.1033 & 0.2476 \\ (8.2371) & (1.0709) & (1.6352) & (2.3841) \\ 0.3926 & -0.0500 & -0.0551 & 0.2191 \\ (5.5672) & (-0.5017) & (-0.9178) & (2.2173) \\ 0.1503 & -0.0900 & 0.6254 & 0.2550 \\ (1.4188) & (-0.6005) & (6.9300) & (3.3750) \\ 0.2550 & -0.2182 & 0.1640 & 0.1535 \\ (3.3750) & (-2.0420) & (2.5467) & (1.4494) \end{bmatrix} \\
 &\times \begin{bmatrix} \Delta\text{Beijing}(-1) \\ \Delta\text{Shanghai}(-1) \\ \Delta\text{Shenzhen}(-1) \\ \Delta\text{Guangzhou}(-1) \end{bmatrix}
 \end{aligned}$$

Given one cointegrating vector, it is interesting to examine whether each market enters the cointegrating vector, or put another way, whether the market i could be omitted from the cointegrating space. The test of exclusion from the cointegrating vector is conducted based on Equation 3. Under the null hypothesis, market i is not in the cointegrating vector, and the test statistic is distributed chi-squared with one degree of freedom. We fail to reject the hypothesis for Shenzhen at the 10% significant level, and could reject the hypothesis for the others (see the test statistics in Table 3). This provides evidence that the Shenzhen housing market is more autonomous in the long run, which may be due to the fact that the demand in Shenzhen housing market is special because of its proximity to Hong Kong. This is unique because some Hong Kong residents live in Shenzhen but work in Hong Kong. This causes its prices to constantly deviate from the housing market equilibrium in the long run. The other three markets, Beijing, Shanghai and Guangzhou are in the long-run cointegrating relationship.

The weak exogeneity of each market relative to the long-run equilibrium based on Equation 2 is also investigated, and the test statistics are reported in Table 3. We test if each market

Table 3. Test of hypotheses on the cointegration space

Hypothesis	Degree of freedom	Test statistics	Decision
$\beta_1 = 0$	1	3.7560	Reject
$\beta_2 = 0$	1	-2.1464	Reject
$\beta_3 = 0$	1	0.3284	Fail to reject
$\beta_4 = 0$	1	-3.9322	Reject
$\alpha_1 = 0$	1	-0.6816	Fail to reject
$\alpha_2 = 0$	1	4.8247	Reject
$\alpha_3 = 0$	1	0.5044	Fail to reject
$\alpha_4 = 0$	1	1.0193	Fail to reject

Notes: Subscripts indicate markets as follows: Market 1 is the Beijing market, Market 2 is Shanghai market, Market 3 is Shenzhen and Market 4 is Guangzhou. If there is a single cointegrating vector, it is common to rely on the estimated ECM to test restrictions on α and β , the usual t -statistic is asymptotically equivalent to χ^2 statistic.

Table 4. Correlation matrix of innovations (errors)

	Beijing	Shanghai	Shenzhen	Guangzhou
Beijing	1.000000			
Shanghai	0.329293	1.000000		
Shenzhen	0.196640	0.402857	1.000000	
Guangzhou	0.192712	0.154689	0.352353	1.000000

Notes: Time series of errors come from ECM. Higher correlation (>0.2) of errors are treated as significant and the identification problem may be especially important (Walter Enders, Applied Econometric Time Series).

responds to perturbations in the long-run relationship and find that only Shanghai market responds to deviations from the cointegrating vector, while Beijing, Shenzhen and Guangzhou markets do not respond at the 10% significant level.

Combining results of exclusion test of cointegrating vector and weak-exogeneity, we can infer that both Beijing and Guangzhou markets are in the long-run equilibrium but exhibit weak response to deviations of the equilibrium, providing evidence of the price leadership in the long run for these two markets. Accordingly, we report the lower triangular elements of the estimated correlation matrix on innovations (errors) from the ECM (see correlation matrix Table 4).

This matrix provides the starting point for our analysis of contemporaneous causation using DAG. Using the PC algorithm and the assumption of causal sufficiency⁴ as programmed in Tetrad IV, we derive the DAGs which are shown in Fig. 2. Based on the sample size and simulation evidence in Spirtes *et al.* (2000), the 10% significance level is chosen. We also obtain similar results using the 5% significance level. The edge revealed in the Fig. 2 represents the contemporaneous causality relationship existing among

⁴The assumption of causal sufficiency means that we use a sufficiently rich set of theoretically relevant variables. By using the CREIS housing price index, the major national policy effects have been recorded in each index, and housing price could be explained mostly by its own and cross lags. More importantly, the main focus of this article is to examine the dynamic interactions of prices movement across major markets, and these four cities are commonly recognized as first-tier cities in China and their prices are expected to be closely related. There are no clear evidences showing other cities could join this group yet.

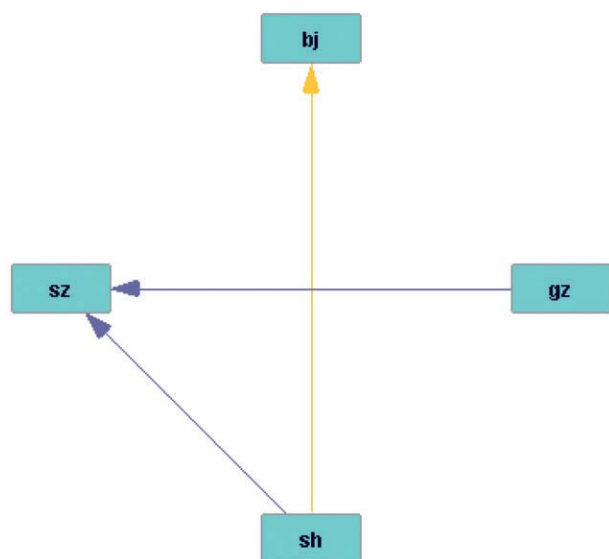


Fig. 2. DAGs on innovations

Notes: bj: Beijing, sz: Shenzhen, sh: Shanghai, gz: Guangzhou. The line between bj and sh in DAG represents the relative weak (ambiguous) contemporaneous causality identified by the available data. The edge between Shanghai and Beijing remains undirected with the PC algorithm alone. Using the information criterion proposed by Harwood and Scheines (2002), we can direct the edge as Shanghai → Beijing.

these markets. Moreover, the power for the PC algorithm to find correct edges increases with the data sample size. Wang (2010) found that the probabilities of PC search procedure making Type I edge errors (missing edges), Type II edge errors (extra edges) and both type errors are reduced greatly when the sample size is greater than 200.

In Fig. 2, there are two edges, one of which is from Guangzhou to Shenzhen, the other from Shanghai to Shenzhen, indicating that the innovations in Guangzhou and Shanghai market drive the innovations in Shenzhen market. The Guangzhou and Shanghai markets lead the Shenzhen market contemporaneously. Interestingly and perhaps somewhat surprisingly, Shenzhen market is among the most influenced by other markets in contemporaneous time. This may be due to the quick government policy adjustment, or the fast response of local real estate developers to shocks from other markets. From the DAG results, the other edge running from Shanghai to Beijing indicates that the innovations in Shanghai market causes innovations in Beijing market in contemporaneous time. Overall, the results indicate the contemporaneous interactions among four markets and Shanghai market might exhibit strong contemporaneous effect on the other markets.

Once we have identified the order of contemporaneous innovations, the next step is to check the impulse response associated with this ECM in 114 periods (9.5 years) to cover both short-run and long-run horizon, as shown in Fig. 3. The advantage of this approach is to allow for the properties exhibited in the data and is less arbitrary than the recursive causal structure embedded in the commonly used Cholesky decomposition. This difference is found to be important in this

study because if we change the Cholesky ordering, we get a different result.

The impulse responses obtained in Fig. 3 illustrate how price in each market reacts to price shocks from other markets. In Fig. 3, we can see that Beijing market responds to price shocks from its own, Guangzhou, Shanghai and Shenzhen market. The greatest movement is from its own price shock and the movement is less from shocks in the other markets. On the other hand, all the other markets also respond positively and significantly to shocks from the Beijing market. Compared to the other market, Beijing market exhibits strongest and consistent influence on the other market in the long run.

Other markets (Shanghai, Shenzhen and Guangzhou) share the similar response pattern as Beijing does, and they all respond significantly to shocks from each other in the short and long run though most influences show up in the first 3 years. Put another way, the price is transmitted among different markets with significant positive effect except in that channel between Shanghai and Guangzhou. This helps explain why there can be a 'bubble' in the housing market as prices are pushed up recursively among the different markets. It also helps to justify the necessity for governments to cooperate together to stabilize the housing market.

Surprisingly, we find that Shanghai market reacts negatively to innovations in Guangzhou after a small initial increase. To some extent, this can explain why shanghai market rose while Guangzhou market dropped during the periods 2000–2003 and 2007–2008. After around 2 years, Shanghai market exhibits significant negative response to innovations in Guangzhou market. It seems that the Shanghai market can neutralize the rising price pressure from the Guangzhou market, and such a negative relationship is good for the central government, because it provides the government more policy options to balance the different markets and reduce the pressure to control all the markets. However, the Guangzhou market always reacts positively to Shanghai market.

We also want to check what drives this interesting result. The cross correlogram of Guangzhou and Shanghai market is listed in Table 5. We find that with a lead (suggesting the impact of Guangzhou on Shanghai), Guangzhou price starts negatively correlated to Shanghai price since a lead of 32 months, while with a lag (suggesting effect of Shanghai on Guangzhou), Guangzhou price is always positively correlated to Shanghai price. The possible reason for such asymmetric negative and positive response between Guangzhou and Shanghai market is the different market characteristics. Among the four markets, the Shanghai market exhibits the strongest and the most stable upward trending throughout the study. At the same time, only Guangzhou market has the most significant price bust and boom (price cycle), and thus the time series model reveals the negative response of Shanghai market to Guangzhou market. As Shanghai market always leads to the price rise in the contemporaneous and short run, the positive response of Guangzhou market to Shanghai market is reasonable. Such market difference might be due to the divergence in local government policies and specific location effect. In the past decade, Shanghai has experienced a huge development as the national centre in finance and economics.

In the fact the negative correlation as well as negative impulse response is not a bad thing for the economy and helps

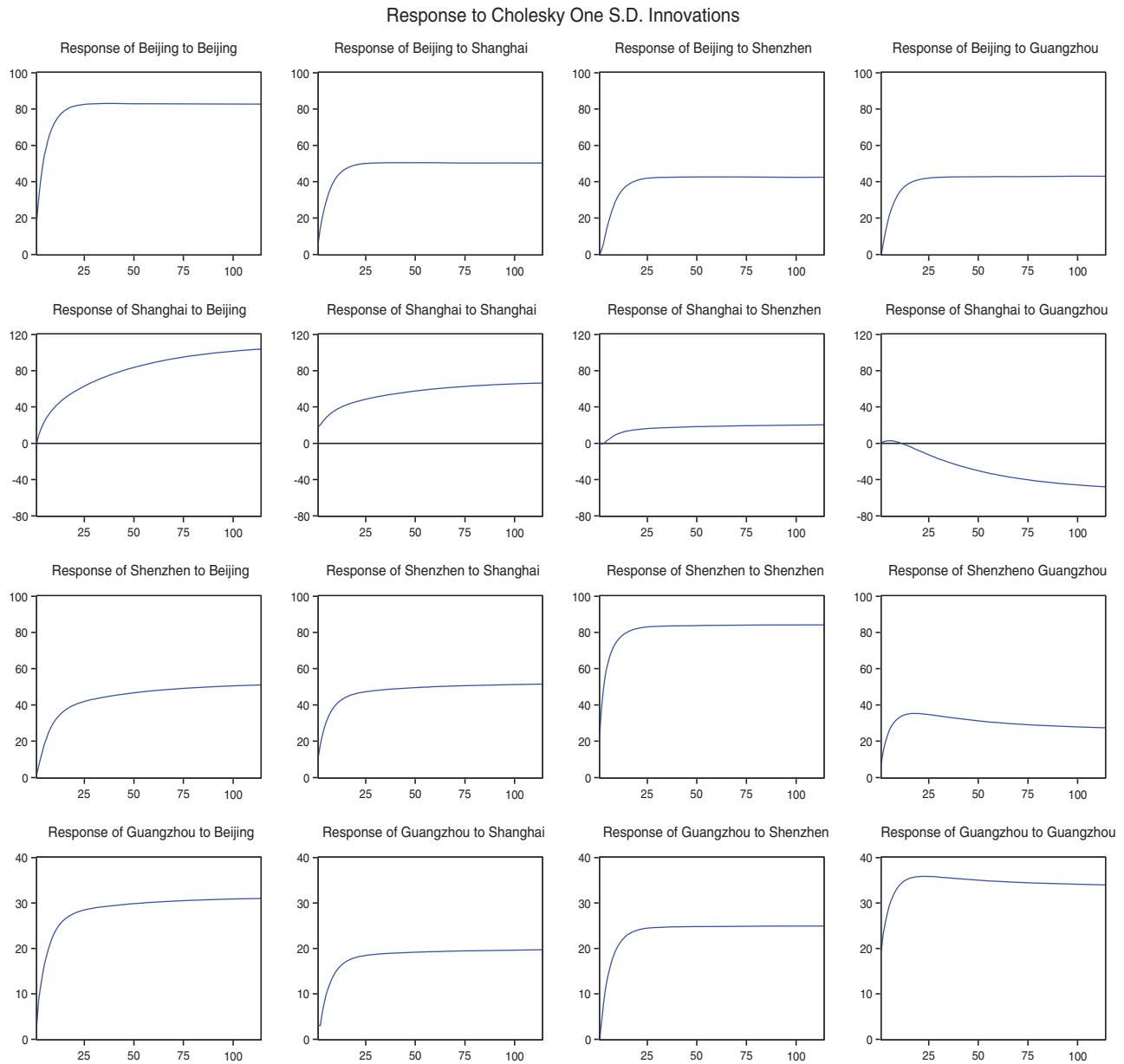


Fig. 3. Impulse response of each housing market price to a one-time-only shock in innovations in each market price

to diversify the risk and dampen the price bubble, however, we do not know if such response pattern is persistent over time.

Consistent with the previously presented weakly exogeneity test, in Beijing, Shenzhen and Guangzhou market, their own innovations account for dominant influence on future movements. Only the Shanghai market is an exception. The innovations of Beijing account for the dominant fluctuations of future movement of the Shanghai market indicating that Shanghai market is more responsive to perturbations from equilibrium.

It is also interesting to note that although Shenzhen is the most affected by other markets in contemporaneous time, it is much less affected over a longer horizon. In the long run, its own price change has the largest influence on its future price (change in the index of 80 points) compared to Beijing

(index change of 75), Shanghai (index change of 75) and Guangzhou (index change of 40). This result is also consistent with the cointegrating vector test conducted according to Equation 2 and weak exogeneity test based on Equation 3, which indicates that Shenzhen market is exempted from long-run cointegrating space and also shows weak response to deviations from long-run equilibrium. All these results suggest Shenzhen market might be the most autonomous market in the long run.

In sum, we find that the Beijing market has stronger effects on other housing markets in the long run, while Shanghai market exhibits stronger influence in contemporaneous time on housing prices. Shenzhen market seems to be the most autonomous market in the long run, while is influenced most in contemporaneous time. The interesting negative response of

Table 5. Cross correlogram of Guangzhou and Shanghai market

<i>i</i>	Lag	Lead
0	0.8862	0.8862
1	0.8739	0.8582
2	0.8611	0.8305
3	0.8496	0.8008
4	0.8396	0.7699
5	0.8302	0.7391
6	0.8203	0.7097
7	0.8121	0.681
8	0.8023	0.6524
9	0.7923	0.6239
10	0.7817	0.5953
11	0.7708	0.5677
12	0.7591	0.5399
13	0.7487	0.513
14	0.7364	0.4876
15	0.7239	0.4623
16	0.7123	0.4392
17	0.6987	0.4144
18	0.6846	0.39
19	0.6696	0.3659
20	0.6541	0.3403
21	0.6372	0.3136
22	0.62	0.2859
23	0.6012	0.2575
24	0.5822	0.2287
25	0.5621	0.1996
26	0.5415	0.1706
27	0.5206	0.1415
28	0.4986	0.1121
29	0.4767	0.0826
30	0.4534	0.0525
31	0.4288	0.0215
32	0.4053	-0.0101
33	0.3821	-0.0418
34	0.3603	-0.0712
35	0.3395	-0.0985
36	0.3182	-0.1236

Note: The '*i*' represents the periods that Guangzhou market lead or lag the Shanghai market.

Shanghai market to Guangzhou market may provide more options for the government to implement some macro controls.

V. Conclusion

This article examines dynamic price relationships in the housing markets of first-tier cities in China for the period from December 2000 to May 2010 using an ECM framework combined with DAGs.

We uncover a broad linkage of housing price dynamics among these four cities after the national housing reform launched in China in 1998. The housing price is transmitted among these markets significantly and positively except for the price response from Shanghai to Guangzhou. The transmission lag is short indicating that these four markets are actually closely related and price transmission is efficient. The prices could be easily pushed up recursively with such a transmission mechanism and it helps to explain the coexistence of bubble.

The existence of such price transmission and tight correlation between different markets has important implication for a policy maker. Since all markets are cointegrated and moving together in the long run, the tight correlation may not be good to defend the possible price bubble and diversify the system risk. During prosperous times, such price transmission and interactive dependency may strengthen the economy in a good way. However in bad times, such a relationship will make the crisis more severe and cause more instability to the housing market.

Our results also indicate that it is difficult for the government to act alone to combat the rising housing prices because these markets are linked together in a cointegrated system and move in a close pattern. Therefore, a collective effort of local governments is needed to induce stable house prices and avoid a bubble.

It is important to note that the Beijing market has stronger effect on the housing market prices in the long run, while the Shanghai market exhibits stronger influence in contemporaneous time on housing prices. In the long run, the Beijing market plays an important role as a price leader and should be watched for policy control if housing inflation is a concern. The Shenzhen market seems to be the most autonomous market in the long run, while the most influenced market in contemporaneous time. More research is needed to study the uniqueness of the Shenzhen market in its price determination. In summary, our result suggests that in order to monitor the national housing market, the Shanghai market should be watched more in the contemporaneous time and in the short run, and the Beijing market is worth more attention in the long run. Also, there exists an interesting negative response of the Shanghai market to the Guangzhou market, which may provide more choices for government to implement macro controls in the future.

The empirical advantage of our model is its ability to capture the existence of long-run equilibrium relationships and important short-run dynamics and price structures such as price leadership, price transmission lag and asymmetric price response. Given the general assumptions about real estate market such that there exists high competition and that there are price interdependencies, this type of multi-market analysis has generalized implication and could be easily applied to analyse the pricing dynamics among other real estate markets in the world.

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