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Housing Market Spillovers through the Lens of Transaction Volume: A New Spillover Index Approach

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Highlights (for review)

- A new spillover index approach based on data-determined structural VAR
- First evidence on housing market information spillovers via volume
- Substantial housing market information spillover via volume even within one day
- The informational transmission via volume is also fundamentals-based

Housing Market Spillovers through the Lens of Transaction Volume: A New Spillover Index Approach

Abstract

Through proposing and applying a new spillover index approach based on data-determined structural vector autoregression to measure connectedness, we examine the daily housing market information transmission via transaction volume among Chinese city-level housing markets from 2009 to 2018. We document substantial information transmission on Chinese housing markets even within one day and find that the role a city-level housing market may play in the information transmission network resembles a pattern observed on other financial markets, which can be generally classified into three distinctive groups: prime senders, exchange centers, and prime receivers. City hierarchy and some fundamental economic factors, such as city gross domestic product and average wage, appear to be significant determinants of such a pattern. The findings extend the existing voluminous literature solely based on housing prices or price volatility spillovers and shed new light on the recent government intervention strategy in China, which particularly focuses on the transaction volume in the housing markets.

Keywords: Transaction volume; Spillover index; Information transmission; DAG; Data-determined VAR

JEL Classification: G12; G15; C32, R31

1. Introduction

Price and quantity are the building blocks of all theories of market interactions, and yet trading volume behavior has received far less attention than the behavior of prices on asset markets (Lo and Wang, 2000; Halling et al., 2013; Roll et al., 2014; DeFusco et al., 2017). It has been shown (e.g., Wang, 1994; He and Wang, 1995; Lo and Wang, 2000) that because the asset markets under consideration may not be complete, and investors may be heterogeneous, which is assumed in early theoretical models (e.g., Lucas, 1978), both the price and trading volume theoretically can play a key informational role in asset markets. Furthermore, according to the observation that "[e]very asset price bubble… has coincided with a similar trading frenzy," Cochrane (2011) in his American Finance Association presidential address pointed out the serious inadequacy of existing theoretical models in not carefully exploring the informational role of trading volume. Specifically, he asks, "Is this a coincidence? Do prices rise and fall for other reasons, and large trading volume follows, with no effect on price? Or is the high price. . . explained at least in part by the huge volume? . . . To make this a deep theory, we must answer why people trade so much" (p. 1079).

Parallel to limitations in the theoretical works, trading volume as a variable of major interest (i.e., as a dependent variable) has not yet received much attention in the empirical finance literature (Lo and Wang, 2000; Halling et al., 2013; Roll et al., 2014). This might be partly due to the lack of clear evidence of the significant informational role of volume compared to prices on the stock market (e.g., Karpoff, 1987; Lee and Rui, 2002; Griffin et al., 2007; Gagnon and Karolyi, 2009; Chen, 2012; Wang et al., 2018), which is the asset market that receives the most attention. More relevant to this study, not surprisingly, voluminous literature on asset market spillovers and linkages including housing markets has exclusively focused on interactions based only on asset prices (or related price variables such as price volatility). To our knowledge, only two notable exceptions, Halling et al. (2013) and Roll et al. (2014), have focused on asset market spillovers and linkages across related markets based on trading volume.

Responding to Cochrane's (2011) remarks that "[p]erhaps the question of how information is incorporated in asset markets will come back to the center of inquiry", which, in his context, implies the potentially important informational role of trading volume, this study explores how housing market information is transmitted and incorporated into spatially segmented city-level housing markets through housing transaction volume, using the novel daily data of transaction volumes in China. The housing market is an interesting asset market in which to explore the informational role of volume for the following reasons. First, housing is the most important asset to average households in both the US and China. Second, housing market prices tend to have lower informational efficiency than the stock market (Case and Shiller, 1989), which could leave more room for the significant informational role of volume on the housing market than on the stock market. DeFusco et al. (2017) theoretically demonstrate and empirically confirm the leading informational role of volume over prices in US housing cycles, which is consistent with the earlier argument of Leamer (2007, 2015). Given this potentially leading informational role of volume, exploring housing market spillovers using volume rather than prices is both necessary and rewarding.

The study aims to contribute to the literature in the following ways. First, to the best of our knowledge, this study is the first to investigate housing information transmission across city-level housing markets using transaction volume and, equally important, at a daily frequency. As previously discussed, like numerous studies on financial market spillovers and linkages, the literature on housing market spillovers ignores the potentially important informational role of trading volume and commonly focuses on housing prices, which are typically measured at monthly or quarterly frequencies (e.g., Brady, 2011; Miao et al., 2011; Gong et al., 2016a; Yang et al., 2018). Recently, Bollerslev et al. (2016) promoted the advantages of using previously unavailable daily US housing prices, which include mitigating the potential aggregation bias problem plaguing the traditional coarser monthly and quarterly data and providing more accurate and timely information about the housing market and housing price diffusions. Hence, the use of daily housing transaction volume data in this study should enable us to provide a finer and more accurate picture of housing market spillovers.

Second, through applying graphical models (i.e., directed acyclic graph or DAG) (Pearl, 2000; Spirtes et al., 2000) to innovations of a vector autoregression (VAR) framework composed of housing transaction volume data from multiple markets (after filtering out seasonal factors and time trends), this study is the first to identify the contemporaneous information flow pattern on housing markets. Such an application is also in line with the econometric rationale for examining contemporaneous causal flow in the VAR framework in Swanson and Granger (1997) and Hoover (2005), which has received relatively little attention. In contrast, earlier studies, such as Yunus et al. (2012), focus on housing price information transmission patterns with time lags (i.e., Granger causal relationships). In this study, we document the new finding of substantial housing transaction information transmissions within one day, which supports the use of daily housing market data, as argued by Bollerslev et al. (2016). Different city-level housing markets also play varying roles in the information transmission network, with a pattern generally similar to the observed credit risk transmission network in Yang and Zhou (2013) and consistent with the theoretical model of Jarrow and Fan (2001).

These housing market information transmission roles can be classified into three distinct groups: prime senders, exchange centers, and prime receivers. The identification of prime senders and prime receivers of information in this empirical framework corresponds well to primary and secondary firms in the theoretical model of Jarrow and Yu (2001) on financial risk information transmission. As further collaborative evidence, the documented informational transmission pattern is shown to be fundamentals based, refuting the possibility that it is simply random or due to unique features (including frequent government intervention) in China. Specifically, the role a city-level housing market in China may play in the information transmission network is significantly correlated with its role in the city hierarchy and related basic economic factors (e.g., city gross domestic product [GDP], average wage, and GPD per capita).

Finally, extending Diebold and Yilmaz (2009, 2014), we propose a new spillover index approach, building on the data-determined structural VAR framework of Swanson and Granger (1997). This approach can also be easily applied in studying spillovers on other financial markets. Such a framework follows Swanson and Granger (1997), Bessler and Yang (2003), Demiralp and Hoover (2003), Hoover (2005), and Yang and Zhou (2013), among others.

The generalized VAR framework as the workhorse for the popular spillover index method of Diebold and Yilmaz (2014) is also a way to circumvent the problem of the arbitrary ordering of VAR innovations inherent in the Cholesky decomposition (see, e.g., Ballester et al., 2016,; Chevallier et al., 2018). However, it may have disadvantages compared with the DAG-based structural VAR framework, which translates into some serious limitations of the current spillover index approach of Diebold and Yilmaz (2014). First, unlike the data-determined structural VAR of Swanson and Granger (1997), the generalized VAR framework cannot shed light on the potential contemporaneous causality potentially hidden among significantly correlated VAR innovations. Second, the generalized VAR framework is not able to provide structural or economic interpretations of VAR innovations, unlike the DAG-based structural VAR framework (Swanson and Granger, 1997; Hoover, 2005). Thus, it can create some ambiguity in the interpretation of resulting forecast error variance decompositions and spillover indexes.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 illustrates the empirical methodology. Section 4 interprets the empirical results. Section 5 further investigates the determinants of both contemporaneous and dynamic spillover patterns. Section 6 concludes the paper.

2. Data

This study employs the daily housing transaction volume data (in units) of all eight major cities in the Chinese Yangtze River Delta area: Shanghai, Nanjing, Suzhou, Wuxi, Yangzhou, Xuzhou, Hangzhou, and Wenzhou. We focus on the Yangtze River Delta area because the volume data of other areas are unavailable and because of the leading role of this area in the Chinese economy. The Yangtze River Delta is perhaps the most economically developed area in China[1], where a housing market has

[1] Another economically well-developed area is the Pearl River Delta. However, the Pearl River Delta is located within just one province (Guangdong) or, more precisely, only part of Guangdong province, which might not be fully representative and offer enough variety. See Yang et al. (2018) for more details on the regional development strategies and city groups in China. The daily transaction volume data for some major cities in the Pearl River Delta are also not publicly available.

emerged and matured since the housing system reform was launched in 1998 (Gong et al., 2016b). It compromises one municipality (i.e., Shanghai) and two provinces (i.e., Jiangsu and Zhejiang), located at the lower reaches of the Yangtze River. A leading city group with Shanghai as the principal city and Nanjing and Hangzhou as the two vice-principal cities, this area is supported by the Chinese central government in leading the economic development of the whole country (see, e.g., The State Council of China, 2010, 2014). The Yangtze River Delta is also the only area that has various provincial-level jurisdictions sharing similar economic development levels and policies. Taking both data availability and two major sources of interconnectedness—economic similarity and geographic closeness—among different housing markets (Miao et al., 2011; Zhu et al., 2013) into consideration, our eight sample cities cover all of the city gradients in this area (Gong et al., 2016b) and, therefore, can provide a representative picture of housing market information flow through transaction volumes in China. Figure 1 portrays the geographic distribution of the sample cities. Table 1 provides further information about the cities' 2017 GDP, GDP per capita, population (household registration), population (usual residence), and employment data.[2]

[*Insert Figure 1 about here*]

[*Insert Table 1 about here*]

The original housing transaction volume data are reported by the Chinese local government (Bureau of Housing Management) and are collected from the CEIC database. The sample period spans from November 5, 2009, to February 8, 2018. The original transaction data are quite noisy because of irregular transaction records, potential time trends, and certain seasonal fluctuations (see Appendix, Figure A-1).

[2] The average 2017 exchange rate of one US dollar for Chinese RMB was about 6.75.

We, thus, follow the literature (Eichengreen et al., 2012; Yang and Zhou, 2013) to process the original data in the following steps. First, we compute a rolling average of 30 days to control for the time mismatch between the day the house was traded and the day it was registered in the local housing management system.[3] This process is also helpful in smoothing sharp daily movements and irregular trading. Second, we discard the first 29 observations and calculate the logarithm value of each series. Third, we regress the log-transformed transaction volumes on one weekend dummy variable, 11 monthly dummy variables, and nine yearly dummy variables to filter out the influence of seasonal changes and time trends.[4] The filtered value can ensure that what we find using the VAR framework is not merely driven by the common time trends or seasonal co-movements. The augmented Dickey-Fuller test (Dickey and Fuller, 1981) and the Phillips-Perron test (Phillips and Perron, 1988) both show that all of these eight processed housing transaction volume series are stationary (see Appendix, Table A-2).

3. Empirical Methodology

The empirical methodology used in this study is a combination of a directed acyclic graph (DAG) analysis (Pearl, 2000; Spirtes et al., 2000), data-determined structural VAR models (Swanson and Granger, 1997; Bessler and Yang, 2003; Demiralp and Hoover, 2003; Hoover, 2005; Yang and Zhou, 2013), and an extension of the

[3] According to the housing registration regulation of the Ministry of Construction, People's Republic of China, a newly purchased house must be registered in the local housing management system within 30 days (including weekends and public holidays, not only working days) after the transaction contracts are signed. The days open for registration vary in the same city during different time periods and in different cities during the same time period. The rolling average is able to alleviate the problems caused by these two situations.

[4] For convenience of illustration, we still refer to the filtered series as housing transaction volumes hereafter. See Appendix, Table A-1, for the detailed regression results.

spillover index approach of Diebold and Yilmaz (2009, 2014). The DAG, data-determined structural VAR and the network analysis built upon the DAG-based structural VAR are purely data-driven, which avoid many incredible assumptions (Sims, 1980; Swanson and Granger, 1997). We conduct the analyses in the following subsections to show that such a data-determined pattern is nonrandom and fundamentals-based.

3.1. VAR Models and Innovation Accounting

Let X denote a vector of transaction volumes in the eight housing markets, which can be introduced in a VAR model following Sims (1980):

$$X_t = A_0 + \sum_{i=1}^{p} A_i X_{t-i} + e_t \tag{1}$$

where A_0 denotes the deterministic components of the VAR model; A_i is the estimated coefficient matrix of the lag variables; e_t is the vector of regression residuals; t denotes the time; and p denotes the lags that are selected using the information criteria. The estimated coefficients of a VAR model are rarely interpreted because of overparameterization, and they complicatedly interact with each other. We, thus, use the innovation accounting method to illustrate the dynamic structure (Sims, 1980). Specifically, we rewrite X_t of equation (1) as a moving average process:

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

The error from the forecast of X_t at the n-step-ahead horizon, conditional on information available at t-1, Ω_{t-1}, is as follows:

$$\xi_{t,n} = \sum_{l=0}^{n} A_i \varepsilon_{t+n-l} \tag{3}$$

Therefore, the variance-covariance matrix of the total forecasting error is computed as:

$$Coc(\xi_{t,n}) = \sum_{l=0}^{n} A_l \Sigma A_l' \tag{4}$$

where Σ is the variance-covariance matrix of the error term in equation (1), e_t. The remaining basic problem is how to orthogonalize the VAR residuals. In accordance with Swanson and Granger (1997), Demiralp and Hoover (2003), Bessler and Yang (2003), and Yang and Zhou (2013), we use the DAG-based data-determined structural VAR approach to orthogonalize the residuals. Related to this study, Coulson and Kim (2000) are perhaps the first to illustrate the importance of avoiding arbitrary orthogonalized ordering in the context of real estate research, and they also use a preliminary version of DAG for the same purpose.

3.2. Directed Acyclic Graph Analysis

The DAG technique (Pearl, 2000; Spirtes et al., 2000), which is also termed the Bayesian network, is a recent advance in causality analysis. The basic idea of DAG builds on the insight of a non-time sequence asymmetry in causal relations, which contrasts with the well-known Granger causality, exploiting the time sequence asymmetry that a cause precedes its associated effect (and, thus, an effect does not precede its cause). In this subsection, we briefly describe how we conduct the DAG analysis using the variance-covariance matrix of the VAR residuals in equation (1). The works of Bessler and Yang (2003), Hoover (2005), and Yang and Zhou (2013) offer related discussions.

A directed graph is essentially an assignment of the contemporaneous causal flow (or lack thereof) among a set of variables (or vertices) based on observed correlations and partial correlations. The "edge" relation characterizing each pair of variables represents the causal relation (or lack thereof) between these variables. The possible edge relationships in a DAG analysis are either (1) no edge (X Y), which indicates (conditional) independence between two variables or (2) a directed edge (Y $\rightarrow$ X), which suggests that a variation in Y, with all other variables held constant, produces a (linear) variation in X that is not mediated by any other variable in the system. Alternatively, as in this study, a DAG may represent the contemporaneous information causal flow and the data-determined conditions for further structural VAR forecast error variance decomposition (see, e.g., Swanson and Granger, 1997; Hoover, 2005).

Although correlation does not necessarily imply causation, under some circumstances, a DAG analysis can derive causality from correlation. As an illustration of the basic idea (Pearl, 2000), consider a causally sufficient set of three variables: X, Y, and Z. A causal fork that X causes Y and Z can be illustrated as Y $\leftarrow$ X $\rightarrow$ Z. Here, the unconditional correlation between Y and Z is nonzero (as both Y and Z have a common cause in X), but the conditional correlation between Y and Z, given the knowledge of the common cause X, is zero. In other words, common causes screen-off associations between their joint effects. Now, consider the inverted causal fork that X and Z cause Y, shown as X$\rightarrow$ Y $\leftarrow$ Z. Here, the unconditional correlation between X and Z is zero, but the conditional correlation between X and Z, given the common effect Y, is not zero. Thus, common effects do not screen-off associations between their joint causes. The studies of Pearl (2000) and Spirtes et al. (2000) offer more detailed discussions on DAG.

Spirtes et al. (2000) provide a quite powerful directed graph algorithm (i.e., PC algorithm, named for researchers Peter Spirtes and Clark Glymour) for removing edges and directing causal flows of information between variables. The PC algorithm is programmed in the Tetrad III software, which is also used for the DAG analysis. Yang and Zhou (2013) provide additional simulation evidence for the general effectiveness of the DAG.

3.3. Network Analysis Based on Data-Determined Structural VAR

In their studies, Diebold and Yilmaz (2009, 2014) point out that the forecast error variance decomposition (FEVD), indeed, is the network analysis (or spillover index). Nevertheless, they use the Cholesky (Diebold and Yilmaz, 2009) or generalized VAR FEVD (Diebold and Yilmaz, 2014) to build such a network. As previously discussed, compared with the DAG-based data-determined FEVD, such approaches are disadvantageous in several aspects. Our network analysis, therefore, is built upon the DAG-based data-determined structural VAR system.

Based on the DAG-based data-determined structural VAR FEVD, the population information spillover network can be fully shown in the connectedness table (Appendix, Table A-3), which provides a central understanding of the various connectedness measures and their relationships.[5] Its main upper-left $\mathrm{N} \times \mathrm{N}$ block contains the variance decompositions, with d_{ij}^{H} denoted as the ij-th H-step variance decomposition component. Hence, according to Diebold and Yilmaz (2014), we define the *pairwise directional connectedness* from j to i as:

$$C_{i\leftarrow j}^{H} = d_{ij}^{H} \qquad (5)$$

Note that $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$, so there are $N^2 - N$ separate pairwise directional connectedness measures. We can then define the *net pairwise directional connectedness* as:

$$C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H} \qquad (6)$$

The *total directional connectedness from others to* i is defined as:

$$C_{i\leftarrow \bullet}^{H} = \sum_{j=1, i\neq j}^{N} d_{ij}^{H} \qquad (7)$$

[5] See Appendix, Table A-3, or Table 1 in Diebold and Yilmaz (2014, p. 120) for more details.

The *total directional connectedness to others from i* is:

$$C^H_{\bullet\leftarrow i} = \sum_{i=1, i\neq j}^{N} d^H_{ij} \tag{8}$$

The *net total directional connectedness* is:

$$C^H_i = C^H_{\bullet\leftarrow i} - C^H_{i\leftarrow\bullet} \tag{9}$$

The *total connectedness* can be calculated as:

$$C^H = \frac{1}{N}\sum_{i,j=1, i\neq j}^{N} d^H_{ij} \tag{10}$$

The time-varying connectedness can be obtained using the fixed rolling window approach. In a further analysis to find the determinants of such housing market spillover networks, we also follow the regression analysis proposed by Yang and Zhou (2013), which is illustrated in detail later.

4. Empirical Results

4.1. DAG Analysis

As the first step of conducting the DAG analysis, we establish the two-lag VAR framework shown in equation (1) with the optimal lag selected by the Schwarz Bayesian criterion (SBC).[6] The Lagrangian multiplier test on the autocorrelation of the residuals cannot reject the null of white noise residuals at any conventional significance levels. We then estimate this eight-variable VAR system and extract its residuals (i.e., innovation). Equation (11) shows the innovation correlation matrix (lower triangular entries only are printed in the following order: Shanghai, Nanjing, Suzhou, Wuxi, Yangzhou, Xuzhou, Hangzhou, and Wenzhou), which provides the starting point for the analysis of the contemporaneous causal pattern. As discussed earlier, we remove edges by considering the unconditional (zero-order conditioning)

[6] The maximum lag allowed is set to 90 days (3 months).

and conditional correlations between variables.[7] The analysis is conducted using Tetrad III, and the resulting graph is reported in Figure 2.

$$V = \begin{bmatrix} 1 & & & & & & & \\ 0.63 & 1 & & & & & & \\ 0.64 & 0.55 & 1 & & & & & \\ 0.66 & 0.66 & 0.72 & 1 & & & & \\ 0.25 & 0.31 & 0.16 & 0.29 & 1 & & & \\ 0.28 & 0.36 & 0.29 & 0.36 & 0.32 & 1 & & \\ 0.75 & 0.71 & 0.73 & 0.78 & 0.25 & 0.46 & 1 & \\ 0.12 & 0.20 & -0.02 & 0.07 & 0.19 & 0.09 & 0.05 & 1 \end{bmatrix} \quad (11)$$

The contemporaneous pattern shown in Figure 2 reveals several interesting phenomena that are contrasted to our conventional impression of the housing market. First, most of the transactions in the eight housing markets are directly or indirectly linked to each other contemporaneously, which implies substantial information transmission within one day. Take the principal city (i.e., Shanghai) and two vice-principal cities (i.e., Nanjing and Hangzhou), for example: these three cities are contemporaneously connected with each other (i.e., Nanjing→Shanghai, Hangzhou→Shanghai, Hangzhou→Nanjing), as well as (directly or indirectly) with most of the other cities. Conventional wisdom states that housing market prices are, to a great extent, locally determined and segmented from other local housing markets. Miao et al. (2011) argue that the US housing market is distinguished by factors such as differences in spatial price dynamics, local income, demographics, and other localized characteristics that potentially impede intercity interaction. Piazzesi et al. (2015) demonstrate both theoretically and empirically that a typical home buyer in a housing market generally looks for a property in a search range that depends on the individual's geographic preference, budget, and family size. When that person settles

[7] Due to the somewhat low power of the PC algorithm and rather limited number of observations used in the DAG analysis, the conventional significance level of 10% seems to be the most appropriate for the sample size in this study (Spirtes et al., 2000; Bessler et al., 2003; Yang and Zhou, 2013).

down, the property is not likely to be traded in the market again. Thus, if local housing markets are mostly driven by home searchers' demand and are, therefore, largely segmented, as argued by Piazzesi et al. (2015), this should imply both the difference in the level of housing prices and the rather low level of interactions among various local housing markets. In this context, the segmentation of the Chinese housing markets can also be severe, particularly because inter-region migration is regulated by the Household Register System. The highly intensive contemporaneous connection shown in Figure 2, of course, does not necessarily reveal the interactions of actual housing transactions on these markets but rather intercity housing transaction information transmission. A plausible explanation is that housing is not only a consumer good but also an investment good (Piazzesi and Schneider, 2016; Liu and Xiong, 2018), which is particularly true in China with very limited investment choices for average households. Therefore, the housing market information transmission pattern in China might also exhibit the rapid information transmission pattern observed in other financial markets (see, e.g., Besseler and Yang, 2003; Yang and Zhou, 2013).

Second, the intercity information diffusion appears not to be bounded within provinces. Based on the results of the Granger causality tests using newly built monthly housing price indexes, Wu and Deng (2015) classify 35 Chinese major cities into three groups: national "Superstars," which have a nationwide influence, including Shanghai, Beijing, and Shenzhen; regional "Stars," which may have regional influence beyond their own province, consisting of 15 cities including Nanjing and Hangzhou; and "Normal" cities, whose influence is primarily constrained within the province. Our contemporaneous causal flow pattern, however, shows that the influence of "Normal" cities (Suzhou, Wuxi, Xuzhou, and Wenzhou) in Wu and Deng

(2015) appears to not be bounded within a province. For instance, Hangzhou (in Zhejiang province) is contemporaneously affected by Xuzhou (in Jiangsu Province), and Yangzhou (in Jiangsu province) is contemporaneously affected by Wenzhou (in Zhejiang province). Moreover, such contemporaneous transaction information diffusion cannot be fully attributed to geographical closeness or economic similarity (Ferreira and Gyourko, 2012; Zhu et al., 2013). For example, regarding the two contemporaneous causal flows from Xuzhou to Hangzhou and from Wenzhou to Nanjing, such connection obviously cannot be explained by being geographically close or economically similar (see Figure 1 and Table 1).

Third, more interestingly, similar to credit risk spillovers among financial institutions, as shown by Yang and Zhou (2013), cities in our contemporaneous transaction information transmission network can also be classified into three distinct groups: prime senders, exchange centers, and prime receivers. Shanghai, the principal city officially recognized by the government (see, e.g., The State Council of China, 2010, 2014) and the systematically important city in housing price spillovers detected in earlier work (Yang et al., 2018), is the only prime receiver—it is directly affected by Nanjing, Suzhou, Wuxi, and Hangzhou and indirectly affected by Yangzhou (e.g., Yangzhou→Nanjing→Shanghai), Xuzhou (e.g., Xuzhou→Hangzhou→ Shanghai), and Wenzhou (e.g., Wenzhou→Nanjing→Shanghai). Nanjing, Wuxi, Yangzhou, and Hangzhou are the information exchange centers: they contemporaneously absorb information from other cities and (indirectly) send it to the prime receiver Shanghai. Suzhou, Xuzhou, and Wenzhou are the three prime senders: they directly (Suzhou) or indirectly (Xuzhou and Wenzhou) affect the prime receiver Shanghai and the exchange center cities without being affected by others contemporaneously.

[*Insert Figure 2 about here*]

In summary, from the contemporaneous information causal flow using DAG, we find that daily housing transaction volumes in the eight cities exhibit a novel pattern of information transmission different from the ones shown in earlier literature focusing on housing prices. Such a contemporaneous information causal flow pattern, however, is primarily based on statistical significance. Thus, before further discussing the findings and their policy implications, we examine the economic significance of such a contemporaneous pattern using the DAG-determined structural VAR to conduct a forecast error variance decomposition and further construct spillover indexes to perform a network analysis.

4.2. Structural VAR Forecast Error Variance Decompositions

As vigorously argued by Swanson and Granger (1997), the contemporaneous causal pattern as identified through the DAG analysis of the correlation matrix provides a data-determined solution to the basic problem of the orthogonalization of VAR residuals and, thus, is critical to forecast the error variance decomposition of a VAR. There are two major advantages of employing the forecast error variance decomposition: (1) an allowance for time-lagged information transmission in addition to contemporaneous information transmission and (2) a description of the economic significance of dynamic causal linkages.

Based on the DAG result shown in Figure 2, Panel A of Table 2 reports the structural VAR forecast error variance decompositions. Panel A gives the percentages of forecast error variance (standard deviation in the table) at horizon *k*, which is attributable to earlier shocks (surprises) from each series (including itself). We list the horizons of 0 (contemporaneous time), 1, 2, 7, and 14 days (short horizon), and 30, 90, 180, and 365 days ahead (long horizon). These results confirm the previous conclusions based on the DAG analysis (Figure 2) and provide further information on daily intercity housing transaction information spillovers. First, the results shown in Panel A confirm that the contemporaneous causal flow is both statistically (see Figure 2) and economically significant. More than 50% of the variation of housing transaction volumes in Shanghai, Nanjing, Wuxi, and Hangzhou can be explained by the variation of housing transaction volumes from other cities within one day (contemporaneously). The housing transaction information transmission seems to be far quicker than the intercity housing price transmission pattern documented in earlier studies. For example, by detecting the structural breakpoint of the house price time series in different cities, Wu and Deng (2015) find that the average time lag of housing price transmission between the leading cities and the following cities in China is approximately three months, and Ferreira and Gyourko (2012) find a much longer time lag in the US.

Second, the results in Panel A confirm that intercity information diffusion is not bounded within a province. Taking Hangzhou as an example, its variation of housing transaction volumes can largely be explained by the two "Normal" cities from Jiangsu province (i.e., Suzhou and Xuzhou) rather than Wenzhou from the same province. Also, in the case of Hangzhou, the influence of Xuzhou cannot be fully attributed to geographical closeness or economic similarity (Ferreira and Gyourko, 2012; Zhu et al., 2013). However, these two factors do explain much of the detected information spillovers in many other cases, such as the influence of Suzhou on Shanghai, Wuxi, Nanjing, and Hangzhou and that of Hangzhou on Nanjing (see Table 1 and Figure 1).

Third, the three city groups (i.e., prime senders, exchange centers, and prime receivers) appear to have two distinctive styles of information transmission: prime senders are relatively less affected by other cities and exert a certain amount of influence in the exchange centers and prime receivers, whereas the exchange centers and prime receivers are heavily affected by other cities both contemporaneously and in the long run. Less than 5% variation of housing transaction volumes in the prime sender cities (i.e., Suzhou, Xuzhou, and Wenzhou) can be explained by others, whereas more than 50% of the prime receiver city (i.e., Shanghai) and the exchange center cities (except Yangzhou) can be explained by others. One plausible explanation for why Yangzhou is less heavily influenced by others is that it only has an indirect contemporaneous connection to the prime receiver Shanghai (see Figure 2) and is close to another major exchange center, Nanjing (see Figure 1).

[*Insert Table 2 about here*]

4.3. Static and Dynamic Network Analysis

Based on the forecast error variance decomposition, the recently developed network analysis (Diebold and Yilmaz, 2009, 2014) provides a complementary and intuitive approach to investigating the static and dynamic housing market spillovers. We use the two-week-ahead DAG-based structural VAR forecast error variance decomposition for further analysis on Chinese housing market spillovers, as we have found that each market absorbs a large portion of transaction information from other markets within two weeks (see Panel A of Table 2).[8] Panel B of Table 2 reports the full-sample connectedness results, generally consistent with the previous result based on the DAG. The prime senders (i.e., Suzhou, Xuzhou, and Wenzhou) generally show low values of *total directional connectedness from others* (*from* for short) and high values of *total directional connectedness to others* (*to* for short); therefore, they indicate positive values of *net total directional connectedness* (*net* for short). Conversely, the exchange centers (i.e., Nanjing, Wuxi, Yangzhou, and Hangzhou) and,

[8] The connectedness using other steps, in fact, also show a similar pattern. Results are available on request.

particularly, the prime receiver (i.e., Shanghai) show high values of *from* and low values of *to*; therefore, they indicate negative values of *net*. The average of *total connectedness* is 28.3, implying that approximately 28.3% of the transaction volume variation in each of the housing markets is affected by others during the sample period. Obviously, such value is non-negligible and does not offer full support for the conventional wisdom of generally segmented housing markets.

To further investigate the dynamic housing market spillovers, we use a one-year-fixed rolling window to extract the dynamic connectedness among the sample cities. To be concise, we only report the extracted dynamic total connectedness here (Figure 3); the detailed dynamic connectedness of *from*, *to*, *net*, and the *net pairwise directional connectedness* appears in the Appendix (see Figures A-2 and A-3). Chinese housing market spillovers through transaction volumes change over time, similar to what has been documented on Chinese housing price spillovers (e.g., Yang et al., 2018). The dynamic estimation results also further confirm our previous findings based on the full sample. The prime senders show low values of *from* and high values of *to*, and, thus, on average, positive values of *net* (e.g., Suzhou), whereas the exchange centers and prime receiver show the opposite (Appendix, Figure A-2). Such results are more evident in the *net pairwise directional connectedness* (Appendix, Figure A-3). During most of the sample period, the *net pairwise directional connectedness* shows positive values from the prime senders and exchange centers to the prime receivers or from the prime senders to the exchange centers. These values are, of course, not constant but time-varying, sometimes even reversed, indicating a much more complicated spillover pattern over time.

[*Insert Figure 3 about here*]

5. Further Analysis

To further investigate the specific driving forces behind the intercity housing market spillovers through volume over time, we follow the literature (Yang and Zhou, 2013; Yang et al., 2018) and use the Newey-West robust standard error regression:

$$Y_{it} = \alpha_0 + \beta X_{it} + \varepsilon_{it} \tag{12}$$

where Y_{it} is the assigned value for a city in the connectedness network (e.g., whether a city can be classified into the exchange center group) or the extracted dynamic connectedness (e.g., *from*, *to*, or *net*) of city i at time t; X_{it} is the certain factor(s) that may affect Y, including the rank of a city in the city hierarchy, demographic and economic factors, education and health amenities, amenities for consumption, and amenities for communication; α_0 is the constant term; and ε_{it} is the error term. In accordance with Yang and Zhou (2013), we first run a simple regression to examine whether a specific factor significantly affects Y and then conduct a multiple regression to further allow for the possibility that many significant factors may highly correlate with each other (see Appendix, Table A-5). As we only have yearly city-level observations for most of the explanatory variables, we treat the extracted dynamic connectedness at the end of a year as its proxy of that year. All other data are collected from the CEIC database, with a detailed description given in Table A-4 and their correlation matrix shown in Table A-5, both in the Appendix.

5.1. Determinants of Contemporaneous Spillover Pattern

The contemporaneous housing market spillover pattern revealed by the DAG analysis shows that cities can be broadly classified into three distinctive groups like that of the financial network (see Yang and Zhou, 2013): prime senders, exchange centers, and prime receivers (see Figure 2). A first impression of such a pattern is that it might highly correlate with the city hierarchy: the prime receiver Shanghai is the principal city and the main exchange centers Nanjing and Hangzhou are the vice-principal cities in the city clusters of the Yangtze River Delta area (The State Council of China, 2010, 2014; Gong et al., 2016b; Yang et al., 2018). Similar to Yang and Zhou (2013), we assign value 3 for the prime receiver (i.e., Shanghai), 2 for the exchange centers (i.e., Nanjing, Wuxi, Yangzhou, and Hangzhou), and 1 for the prime senders (i.e., Suzhou, Xuzhou, and Wenzhou). For the rank of a city,[9] we assign value 3 for the principal city Shanghai, 2 for the vice-principal cities Nanjing and Hangzhou, and 1 for the rest. A simple Newey-West robust standard error regression further confirms the first impression (see Appendix, Table A-6). Nevertheless, city hierarchy is relatively constant, whereas the housing market spillovers are dynamic. Therefore, we need to further explore other determinants beyond the city hierarchy.

Following Yang et al. (2018), we examine the roles played by fundamental factors from four categories in determining the contemporaneous housing market spillover pattern: demographic and economic factors, education and healthcare amenities, amenities of consumption, and amenities of communication. Specifically, for the demographic and economic factors addressed in the literature (Miao et al., 2011; Bardhan et al., 2014; Garriga et al., 2014; Cotter et al., 2015), we examine the effects on the housing market spillovers of city GDP size, GDP growth, number of city employees, population of household registration and its growth, population of usual residence and its growth, average wage, GDP per capita, and unemployment rate. For the education and healthcare amenities (Glaeser, 2005; Eichholtz and Lindenthal, 2014), we examine the influence of the number of schools (primary, secondary, and higher educational institutions) and the corresponding numbers of teachers and enrolled students, as well as the effects of the number and sizes

[9] See Gong et al. (2016b) and Yang et al. (2018) for more details about city hierarchy in the Chinese Yangtze River Delta area.

(measured by number of beds) of hospitals and health centers. For the amenities of consumption (Glaeser et al., 2001), we examine the influence of the number of firms in the wholesale, retail, and catering sectors and the number of star hotels. Finally, for the amenities of communication (Glaeser et al., 2001; Baum-Snow, 2007; Coulson and Tang, 2013), we examine the influence of the number of public vehicles, buses, and trolleybuses, number of taxies, number of private vehicles, and the area of paved roads. To show more clearly the impact of each of these potential determinants, we start with the univariate regression and then proceed further with the multiple regression. For concision, we only report the multiple regression using the variables that were detected as significant at 10% in the univariate regressions.[10]

Table 3 reports the results of the multiple regression for the determinants of the contemporaneous causal flow pattern. As the significant factors detected from the univariate regressions may highly correlate with each other (see Appendix, Table A-5), the multiple regression can shed light on their relative importance. The results show that the significance of the city rank in the city hierarchy and GDP per capita are improved, whereas the significance of other variables are decreased (i.e., area of road paved), lost (i.e., growth of the population of usual residence, unemployment rate, and number of higher education institutes and the corresponding students enrolled), or even reversed (i.e., city GDP, average wage, number of teachers in higher education institutes, number of star hotels, number of public vehicles, buses, and trolleybuses, and number of taxies). The results are robust when we further control for the time-fixed effects (column 2 of Table 3). This finding reveals that although other factors (like GDP per capita) might have an effect, the city hierarchy is the key factor in determining the contemporaneous housing market spillover pattern.

[10] See Appendix, Table A-6, for the detailed results of the simple regressions.

[*Insert Table 3 about here*]

5.2. Determinants of Dynamic Connectedness

In this section, we examine the impact of the same fundamental factors (see Appendix, Table A-4) on the dynamic connectedness of a specific city or city pair. The dynamic connectedness is the extracted *total directional connectedness from others* (*from* for short), *to others* (*to* for short), *net total directional connectedness* (*net* for short), or *net pairwise directional connectedness* (see Appendix, Figures A-2 and A-3).

Table 4 reports the multiple regression results for the impact on *from*, *to*, and *net*, whereas Table A-7 in the Appendix reports the simple regression results. The results show that the rank of a city in the city hierarchy, GDP per capita, and area of paved roads are the three most important factors in determining *from*; GDP per capita is the only factor of slight significance (at 10% significance level) affecting *to*; and rank in the city hierarchy and the number of taxies are the two significant factors affecting *net*. These results are robust when we further control for the time-fixed effects. Recall that *net* is the difference of *to* and *from* (i.e., $net = to - from$). Such results imply that city hierarchy along with some demographic and communication amenities determine the dynamic spillovers (particularly on *from*).

[*Insert Table 4 about here*]

As the *net pairwise directional connectedness* is the spillover between two cities (see equation (6) or Appendix, Figure A-3), we examine the differences in fundamental factors on it. For instance, we examine the impact of the difference in GDP between city j and i on the *net pairwise directional connectedness* from city j to i, resembling the other factors. The fundamental factors under consideration remain the same. Table 5 reports the results of the multiple regression. It shows that all of the determinants detected as significant from the simple univariate regressions (see

Appendix, Table A-8) disappear (column 1). The results remain the same when controlling for the time-fixed effects (column 2). However, when we further control for both the time-fixed and city-fixed effects, the differences of the city rank, unemployment rates, and private-owned vehicles become the three significant determinants (column 3). Such results again show that the city hierarchy, certain economic factors, and amenities of communication might be among the important factors in determining the *net pairwise directional connectedness*.

[*Insert Table 5 about here*]

6. Conclusions

Housing markets are conventionally regarded as generally segmented with thin transaction volumes and, thus, largely affected by local factors. Related literature on information transmission among different housing markets is, therefore, commonly focused on prices rather than volumes. We propose and apply a new spillover index approach based on the data-determined structural VAR and use it to examine the daily housing market information transmission via transaction volume among eight Chinese city-level housing markets in the most economically developed area in China from 2009 to 2018. We find substantial information transmission even within one day on the housing markets, and the role that a city-level housing market may play in the information transmission network resembles a network pattern observed in some other financial markets, which can be classified into three distinct groups: prime senders, exchange centers, and prime receivers. City hierarchy appears to be a major determinant of such a pattern, although other demographic and economic factors and amenities of communication may also play a role.

Our findings cast doubt on the effectiveness of the intervention policy for housing markets advocated by the Chinese central government. In the past few years, soaring housing prices in major Chinese cities have attracted global attention because of the growing importance of China's economy and its extensive linkage with the world economy (Bardhan et al, 2014; Liu and Xiong, 2018; Song and Xiong, 2018). The Chinese government also has made great efforts to stabilize its housing market with particular attention on housing transaction volumes (see Koss and Shi, 2018). A major policy instrument advocated by the Chinese central government is to reduce real estate inventory through "One City One Policy" (*"Yicheng Yice"* in Chinese).[11] The intervention policies have been particularly targeted at large cities like Shanghai, Nanjing, and Hangzhou. Our results show that such large cities act like the exchange centers or prime receivers of information in the housing market spillover network, which are highly influenced by other cities. Hence, the policy instrument might not be sufficiently effective.

On the other hand, our findings also shed new light on related research. From the perspective of information transmission, we show that housing transaction volumes also play an important informational role, which has not yet received much attention. Thus, in line with the limited and yet growing literature (e.g., Lo and Wang, 2000; Leamer, 2007; Cochrane, 2011; Halling et al., 2013; Roll et al., 2014; DeFusco, Nathanson, and Zwick, 2017), the informational role of volume in a wide range of asset markets deserves more attention in empirical financial research.

[11] See, for example, the *2016 Annual Government Work Report* by the Premier Li Keqiang (Li, 2017).

References

Ballester, L., Casu, B., González-Urteaga, A., 2016. Bank Fragility and Contagion: Evidence from the Bank CDS Market. *Journal of Empirical Finance,* 394-416.

Bardhan, Ashok; Robert H. Edelstein and Cynthia Kroll. 2014. "Housing Market Stability in China and the Potential for Global Contagion." Working Paper, UC Berkeley.

Bessler, David A. and Jian Yang. 2003. "The Structure of Interdependence in International Stock Markets." *Journal of International Money and Finance*, 22(2), 261-87.

Bernanke, Ben. 1986. "Alternative Explanations of the Money-Income Correlation." *Carnegie-Rochester Conference Series on Public Policy*, 25, 49–99.

Bollerslev, Tim; Andrew J. Patton and Wenjing Wang. 2016. "Daily House Price Index: Construction Modelling and Longer-run Predictions." *Journal of Applied Econometrics*, 31, 1005-1025.

Brady, Ryan R. 2011. "Measuring the Diffusion of Housing Prices across Space and over Time." *Journal of Applied Econometrics*, 26(2), 213-31.

Case, Karl E. and Robert J. Shiller. 1989. "The Efficiency of the Market for Single-Family Homes." *American Economic Review*, 79(1), 125-38.

Chen, Shiu-Sheng. 2012. "Revisiting the Empirical Linkages between Stock Returns and Trading Volume." *Journal of Banking & Finance*, 36(6), 1781-88.

Chevallier, J.; Nguyen, D.K.; Siverskog, J.; Uddin, G.S. 2018 "Market integration and financial linkages among stock markets in Pacific Basin countries." *Journal of Empirical Finance*, 46, 77–92.

Cochrane, John H. 2011. "Presidential Address: Discount Rates." *Journal of Finance*, 66(4), 1047-108.

Cotter, John; Stuart Gabriel and Richard Roll. 2015. "Can Housing Risk Be Diversified? A Cautionary Tale from the Housing Boom and Bust." *Review of Financial Studies*, 28(3), 913-36.

Coulson, N. E. and Kim, M. S., 2000. "Residential Investment, Non-residential Investment and GDP." *Real Estate Economics*, 28(2), 233-247.

Coulson, N. Edward and Mingzhe Tang. 2013. "Institutional and Demographic Influences on the Presence, Scale and Geographic Scope of Individual Chinese Real Estate Investment." *Regional Science and Urban Economics*, 43(2), 187-196.

DeFusco, Anthony; Charles Nathanson and Eric Zwick. 2017. "Speculative Dynamics of Prices and Volume." NBER Working Paper, No. 23449.

Demiralp, Selva and Kevin D. Hoover. 2003. "Searching for the Causal Structure of a

Vector Autoregression." *Oxford Bulletin of Economics and Statistics*, 65(s1), 745-67.

Diebold, Francis X. and Kamil Yilmaz. 2009. "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets." *The Economic Journal*, 119(534), 158-171.

Diebold, Francis X. and Kamil Yılmaz**.** 2014. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics*, 182(1), 119-34.

Dickey, David A. and Wayne A. Fuller. 1981. "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica*, 49(4), 1057-72.

Eichengreen, Barry; Ashoka Mody; Milan Nedeljkovic and Lucio Sarno. 2012. "How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads." *Journal of International Money and Finance*, 31(5), 1299-318.

Eichholtz, Piet and Thies Lindenthal. 2014. "Demographics, Human Capital, and the Demand for Housing." *Journal of Housing Economics*, 26, 19-32.

Ferreira, Fernando and Joseph Gyourko. 2012. "Heterogeneity in Neighborhood-Level Price Growth in the United States, 1993-2009." *American Economic Review*, 102(3), 134-40.

Gagnon, Louis and G. Andrew Karolyi. 2009. "Information, Trading Volume, and International Stock Return Comovements: Evidence from Cross-Listed Stocks." *Journal of Financial and Quantitative Analysis*, 44(4), 953-86.

Garriga, Carlos; Yang Tang and Ping Wang. 2014. "Rural-Urban Migration, Structural Transformation, and Housing Markets in China." Federal Reserve Bank of St. Louis Working Paper Series, 2014-028A.

Glaeser, Edward L. 2005. "Reinventing Boston: 1630–2003." *Journal of Economic Geography*, 5(2), 119-153.

Glaeser, Edward L.; Jed Kolko and Albert Saiz. 2001. "Consumer City." *Journal of Economic Geography*, 1(1), 27-50.

Griffin, John M.; Federico Nardari and René M. Stulz. 2007. "Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries." *Review of Financial Studies*, 20(3), 905-51.

Gong, Yunlong; Jinxing Hu and Peter J. Boelhouwer. 2016a. "Spatial Interrelations of Chinese Housing Markets: Spatial Causality, Convergence and Diffusion." *Regional Science and Urban Economics*, 59, 103-17.

Gong, Yunlong; Peter Boelhouwer and Jan de Haan. 2016b. "Interurban House Price Gradient: Effect of Urban Hierarchy Distance on House Prices." *Urban Studies*, 53(15), 3317-35.

Halling, M., P. Moulton, and M. Panayides. 2013. "Volume Dynamics and

Multimarket Trading.” *Journal of Financial and Quantitative Analysis*, 48, 489–518.

He, Hua and Jiang Wang. 1995. "Differential Information and Dynamic Behavior of Stock Trading Volume." *Review of Financial Studies,* 8(4), 919-72.

Hoover, R. 2005. “Automatic Inference of the Contemporaneous Causal Order of a System of Equations.” *Econometric Theory*, 21, 69-77.

Jarrow, R., Yu, F. 2001 “Counterparty Risk and the Pricing of Defaultable Securities.” *Journal of Finance*, 56, 1765-1799.

Karpoff, Jonathan M. 1987. "The Relation between Price Changes and Trading Volume: A Survey." *Journal of Financial and Quantitative Analysis,* 22(1), 109-26.

Koss, Richard and Xinrui Shi. 2018. "Stabilizing China’s Housing Market." IMF Working Papers, No. WP1889.

Leamer, Edward E. 2007. "Housing Is the Business Cycle," NBER Working Paper, No. 13428.

Leamer, Edward E. 2015. "Housing Really Is the Business Cycle: What Survives the Lessons of 2008–09?" *Journal of Money, Credit and Banking*, 47(S1), 43-50.

Lee, Bong-Soo and Oliver M. Rui. 2002. "The Dynamic Relationship between Stock Returns and Trading Volume: Domestic and Cross-Country Evidence." *Journal of Banking & Finance*, 26(1), 51-78.

Lo, Andrew and Jiang Wang. 2000. "Trading Volume: Definitions, Data Analysis, and Implications for Portfolio Theory." *Review of Financial Studies*, 13, 257–300.

Li, Keqiang. 2017. *The 2016 Annual Chinese Government Report*.

Liu, Chang and Wei Xiong. 2018. "China's Real Estate Market." NBER Working Paper, No. 25297.

Lucas, R. E. 1978. "Asset Prices in an Exchange Economy." *Econometrica*, 1429-45.

Miao, Hong; Sanjay Ramchander and Marc W. Simpson. 2011. "Return and Volatility Transmission in U.S. Housing Markets." *Real Estate Economics*, 39(4), 701-41.

Pearl, Judea. 2000. *Causality: Models, Reasoning and Inference*. Cambridge University Press.

Phillips, Peter C. B. and Pierre Perron. 1988. "Testing for a Unit Root in Time Series Regression." *Biometrika*, 75(2), 335-46.

Piazzesi, Monika; Martin Schneider and Johannes Stroebel. 2015. "Segmented Housing Search." NBER Working Paper, No. 20823.

Piazzesi, Monika, and Martin Schneider. 2016. "Housing and Macroeconomics," J. B. Taylor and H. Uhlig, *Handbook of Macroeconomics.* Elsevier, 1547-640.

Roll, R.; E. Schwartz and A. Subrahmanyam. 2014. "Trading Activity in the Equity Market and Its Contingent Claims: An Empirical Investigation." *Journal of Empirical Finance*, 28, 13-35.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica*, 48(1), 1-48.

Sims, Christopher A. 1986. Forecasting models for policy analysis. Quarterly Review of Federal Reserve Bank of Minneapolis 10, 2–16.

Song, Zheng Michael and Wei Xiong. 2018. "Risks in China's Financial System." NBER Working Paper, No. 24230.

Spirtes, Peter; Clark Glymour and Richard Scheines. 2000. *Causation, Prediction, and Search*. The MIT Press.

Swanson, N.R. and C.W. Granger. 1997. "Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions." *Journal of the American Statistical Association*, 92(437), 357-67.

The State Council of China, 2010. *Notice of the State Council on Issuing the National Main Functional Area Plan*, letter no. 46 [2010].

The State Council of China, 2014. *National New-type Urbanization Plan*.

Wang, Jiang. 1994. "A Model of Competitive Stock Trading Volume." *Journal of Political Economy*, 102, 127-168.

Wang, Yi-Chiuan; Jyh-Lin Wu and Yi-Hao Lai. 2018. "New Evidence on Asymmetric Return–Volume Dependence and Extreme Movements." *Journal of Empirical Finance*, 45, 212–227.

Wu, Jing and Yongheng Deng. 2015. "Intercity Information Diffusion and Price Discovery in Housing Markets: Evidence from Google Searches." *Journal of Real Estate Finance and Economics*, 50(3), 289-306.

Yang, Jian and Yinggang Zhou. 2013. "Credit Risk Spillovers among Financial Institutions around the Global Credit Crisis: Firm-Level Evidence." *Management Science*, 59(10), 2343-59.

Yang, Jian; Ziliang Yu and Yongheng Deng. 2018. "Housing Price Spillovers in China: A High-Dimensional Generalized VAR Approach." *Regional Science and Urban Economics*, 68, 98-114.

Yunus, Nafeesa; J. Andrew Hansz and Paul J. Kennedy. 2012. "Dynamic Interactions between Private and Public Real Estate Markets: Some International Evidence." *Journal of Real Estate Finance and Economics*, 45(4), 1021-40.

Zhu, Bing; Roland Füss and Nico B. Rottke. 2013. "Spatial Linkages in Returns and Volatilities among U.S. Regional Housing Markets." *Real Estate Economics*, 41(1), 29-64.

Table 1: Some demographic and economic factors of the sample cities during 2017

	Shanghai	Nanjing	Suzhou	Wuxi	Yangzhou	Xuzhou	Hangzhou	Wenzhou
GDP (unit: billion RMB)	3267.99	1282.04	1143.86	675.52	1859.75	546.62	1350.92	600.62
GDP per capita (unit: RMB)	126634	141103	160706	75611	162388	112559	135113	58854
Population: household registration (unit: thousand people)	14551.3	6806.7	4930.5	10394.2	6910.7	4599.8	7538.77	8245.47
Population: usual residence (unit: thousand people)	24151.5	8335	6553	8763.5	10683.6	4508.2	9468	9215
Employee (unit: thousand people)	13726.5	4576	3883	4827	6916.00	2650	6810.6	5752.6

Notes: All of the statistics are based on the year 2017 and are collected from the National Bureau of Statistics of China. The average 2017 exchange rate was 6.75 RMB per US dollar.

Table 2: Forecast error variance decomposition and full-sample connectedness

Panel A: Forecast error variance decomposition results (percentage)								
day	Shanghai	Nanjing	Suzhou	Wuxi	Yangzhou	Xuzhou	Hangzhou	Wenzhou
	Variance of Shanghai explained by transaction shocks to the eight cities							
0	43.11	1.17	37.27	0.54	0.08	3.15	14.61	0.08
1	45.52	1.46	34.32	0.39	0.21	3.25	14.72	0.13
2	46.86	1.60	32.79	0.33	0.32	3.30	14.65	0.15
7	49.91	1.64	30.10	0.30	0.64	3.35	13.92	0.15
14	52.42	1.43	28.37	0.38	0.99	3.35	12.93	0.13
30	56.32	1.05	25.46	0.65	1.61	3.35	11.45	0.11
90	59.61	1.46	21.44	1.17	1.99	3.74	10.51	0.09
180	58.19	2.01	21.39	1.18	1.94	4.19	11.00	0.11
365	57.92	2.02	21.30	1.22	1.96	4.30	11.13	0.16
	Variance of Nanjing explained by transaction shocks to the eight cities							
0	0.00	46.91	25.82	2.21	1.35	4.61	16.11	2.99
1	0.13	49.62	24.39	1.94	1.38	4.16	15.08	3.31
2	0.21	50.73	24.04	1.83	1.42	3.86	14.45	3.47
7	0.16	51.21	25.13	1.87	1.86	3.16	13.00	3.60
14	0.19	49.88	27.16	2.25	2.68	2.65	11.79	3.41
30	1.41	45.94	30.26	3.35	4.51	1.88	9.70	2.95
90	8.01	36.91	30.47	7.15	6.86	1.54	6.85	2.21
180	9.49	35.21	29.26	8.58	6.69	2.10	6.57	2.10
365	9.46	35.12	29.24	8.58	6.70	2.19	6.62	2.10
	Variance of Suzhou explained by transaction shocks to the eight cities							
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.21	0.00	99.33	0.14	0.01	0.11	0.04	0.17
2	0.37	0.01	98.68	0.27	0.01	0.24	0.08	0.35
7	0.41	0.05	97.33	0.37	0.09	0.63	0.33	0.79
14	0.26	0.20	96.17	0.24	0.30	0.97	0.91	0.95
30	0.68	0.68	92.10	0.32	0.80	1.64	2.75	1.04
90	3.88	1.62	78.14	3.25	0.97	3.39	7.88	0.87
180	4.34	1.65	73.50	5.26	1.47	4.04	8.70	1.05
365	4.32	1.64	73.08	5.32	1.62	4.17	8.66	1.19
	Variance of Wuxi explained by transaction shocks to the eight cities							
0	0.00	0.00	48.51	36.45	1.20	3.21	10.60	0.04
1	0.02	0.01	45.92	39.14	1.20	3.47	10.20	0.04
2	0.03	0.01	44.55	40.71	1.21	3.56	9.90	0.04
7	0.03	0.01	42.09	43.92	1.31	3.30	9.31	0.03
14	0.23	0.01	40.44	46.04	1.51	2.70	9.04	0.03
30	1.25	0.02	37.13	49.23	1.79	1.78	8.79	0.02
90	4.48	0.43	28.82	53.36	1.66	2.12	9.12	0.02
180	4.74	1.21	26.69	52.21	1.63	3.45	10.06	0.02
365	4.70	1.33	26.51	51.79	1.64	3.70	10.27	0.06
	Variance of Yangzhou explained by transaction shocks to the eight cities							
0	0.00	0.00	0.00	0.00	87.95	9.32	0.00	2.73
1	0.02	0.00	0.01	0.13	87.95	9.98	0.01	1.90
2	0.03	0.01	0.01	0.25	87.87	10.27	0.03	1.54
7	0.02	0.05	0.04	0.48	87.43	10.64	0.14	1.20
14	0.03	0.15	0.10	0.58	86.63	10.77	0.31	1.42
30	0.22	0.48	0.28	0.72	84.22	10.93	0.81	2.34
90	0.83	1.37	0.66	0.91	75.72	11.65	3.01	5.85
180	0.90	1.45	0.83	0.91	71.13	12.36	4.78	7.65
365	0.92	1.43	0.91	0.90	70.19	12.53	5.23	7.90

(to be continued)

Table 2: (continued)

day	Shanghai	Nanjing	Suzhou	Wuxi	Yangzhou	Xuzhou	Hangzhou	Wenzhou
	Variance of Xuzhou explained by transaction shocks to the eight cities							
0	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
1	0.01	0.01	0.01	0.00	0.01	99.90	0.07	0.01
2	0.02	0.01	0.01	0.01	0.02	99.82	0.12	0.01
7	0.05	0.00	0.02	0.02	0.03	99.70	0.14	0.03
14	0.11	0.01	0.05	0.03	0.02	99.62	0.09	0.06
30	0.26	0.04	0.12	0.07	0.02	99.24	0.12	0.14
90	0.46	0.12	0.15	0.13	0.39	97.36	1.03	0.38
180	0.43	0.12	0.14	0.13	1.07	95.99	1.71	0.42
365	0.43	0.15	0.14	0.13	1.21	95.64	1.87	0.43
	Variance of Hangzhou explained by transaction shocks to the eight cities							
0	0.00	0.00	47.90	0.00	0.00	8.47	43.62	0.00
1	0.09	0.02	44.87	0.07	0.02	8.09	46.80	0.05
2	0.13	0.04	43.53	0.12	0.06	7.77	48.24	0.11
7	0.10	0.07	43.23	0.19	0.42	6.87	48.87	0.26
14	0.13	0.07	45.17	0.17	1.30	6.09	46.69	0.38
30	1.01	0.06	48.33	0.11	3.96	4.77	41.09	0.67
90	5.79	0.19	48.08	0.42	8.83	3.31	31.67	1.71
180	6.91	0.40	46.75	0.76	8.90	3.26	30.75	2.28
365	6.89	0.42	46.61	0.77	8.88	3.25	30.84	2.36
	Variance of Wenzhou explained by transaction shocks to the eight cities							
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.13	0.01	0.11	0.10	0.10	0.04	0.04	99.48
2	0.29	0.01	0.22	0.20	0.21	0.08	0.06	98.94
7	0.77	0.01	0.50	0.33	0.66	0.06	0.04	97.63
14	1.08	0.15	0.71	0.27	1.22	0.11	0.22	96.23
30	1.46	0.97	1.22	0.17	2.29	0.93	1.49	91.49
90	1.29	4.42	3.67	0.90	2.67	5.07	6.87	75.11
180	1.51	5.13	4.89	2.14	2.41	6.29	9.11	68.51
365	1.65	5.08	4.88	2.36	2.41	6.28	9.56	67.77

Panel B: Full-sample connectedness table

	Shanghai	Nanjing	Suzhou	Wuxi	Yangzhou	Xuzhou	Hangzhou	Wenzhou	**FROM**
Shanghai	52.42	1.43	28.37	0.38	0.99	3.34	12.93	0.13	47.6
Nanjing	0.19	49.88	27.16	2.25	2.68	2.65	11.79	3.41	50.1
Suzhou	0.25	0.2	96.17	0.24	0.3	0.97	0.91	0.95	3.8
Wuxi	0.23	0.01	40.44	46.04	1.5	2.7	9.04	0.03	54
Yangzhou	0.03	0.15	0.1	0.58	86.63	10.77	0.31	1.42	13.4
Xuzhou	0.11	0.01	0.05	0.03	0.02	99.62	0.09	0.06	0.4
Hangzhou	0.13	0.07	45.17	0.17	1.3	6.09	46.69	0.38	53.3
Wenzhou	1.08	0.15	0.71	0.27	1.22	0.11	0.22	96.23	3.8
TO	2	2	142	3.9	8	26.6	35.3	6.4	TC=28.3
NET	-45.6	-48.1	138.2	-50.1	-5.4	26.2	-18	2.6	

Notes: In Panel A, the data-determined structural VAR variance decomposition is based on the directed acyclic graph (DAG) on innovations shown in Figure 2. In Panel B, TC denotes the total directional connectedness. The underlying decomposition is based upon the DAG-determined structural VAR. The (*i*, *j*)-th value is the estimated contribution to the variance of the 14-day-ahead forecast error of city *i* coming from innovation in the city *j*.

Table 3: The determinants of contemporaneous causal flow pattern—multiple regression

	(1)	(2)
city_rank	**2.176*****	**2.121*****
	(14.65)	(12.76)
gdp	**-0.639*****	**-0.724*****
	(-5.21)	(-6.49)
pop_URg	0.0333	0.0207
	(1.23)	(0.76)
awage	**-0.507*****	**-0.907*****
	(-3.32)	(-3.52)
GDPper	**1.301*****	**1.336*****
	(14.50)	(14.54)
unemplrate	-0.00959	0.0512
	(-0.11)	(0.56)
teacher_hi	**-1.030*****	**-0.849*****
	(-3.55)	(-2.97)
no_hi	0.101	**0.311***
	(0.93)	(1.97)
enroll_hi	0.261	-0.0610
	(0.86)	(-0.20)
StarHotel	**-0.288*****	**-0.310*****
	(-3.45)	(-3.92)
vehicle_public_no	**-0.151***	-0.0614
	(-1.91)	(-0.70)
vehicle_taxi	**-0.197***	**-0.200***
	(-2.04)	(-1.88)
road_paved	**0.293****	**0.278****
	(2.72)	(2.77)
constant	-4.792**	0.411
	(-2.44)	(0.15)
Time-fixed effect	No	Yes
Observations	44	44
Adj-R^2	0.994	0.994

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it}$, in which y_{it} is the index of city information status (assigned 1 for information senders, 2 for information exchangers, and 3 for information receivers), and X_{it} denotes the fundamental variables that are estimated as significant at the 10% level in the simple regressions in Appendix, Table A-6. Specifically, *city_rank* is the rank of a city in the city cluster; *gdp* is the city GDP; *pop_URg* is the population growth measured by yearly change of usually residence; *awage* denotes average wage; *GDPper* is the GDP per capita; *unemplrate* is unemployment rate; *teacher_hi* is the number of full-time teachers in higher institutions; *no_hi* is the number of higher institutions; *enroll_hi* is the number of enrolled students of higher institutions; *StarHotel* is the number of star hotels; *vehicle_public_no* is the number of public vehicles, buses, and trolley buses; *vehicle_taxi* is the number of taxies; *road_paved* is the area of paved road. The *t*-statistics are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics that are significant at conventional significance levels.

Table 4: Determinants of the total directional connectedness *FROM* others, *TO* others, and the *NET* total directional connectedness—multiple regression

	(1) FROM	(2) FROM	(3) TO	(4) TO	(5) NET	(6) NET
city_rank	**112.1*** **	**121.9*** **			**-139.0** **	**-155.1** **
	(5.32)	(5.32)			(-2.46)	(-2.40)
gdp	**-65.74*** **	**-62.15** **				
	(-4.00)	(-2.66)				
awage	**-75.12*** **	**-99.17** **				
	(-3.83)	(-2.24)				
GDPper	**91.16*** **	**94.46*** **	**32.26* **	**41.42* **		
	(6.27)	(5.63)	(1.89)	(2.01)		
unemplrate	**-36.18*** **	**-37.45*** **			-18.02	-20.73
	(-3.16)	(-3.25)			(-0.92)	(-1.07)
teacher_hi	-10.35	-10.39			38.45	28.91
	(-0.41)	(-0.29)			(0.45)	(0.27)
no_hi	-6.869	-14.49				
	(-0.51)	(-0.43)				
enroll_hi	-18.62	-17.10			-17.34	-7.509
	(-0.91)	(-0.42)			(-0.22)	(-0.08)
StarHotel	**-16.13* **	-16.05				
	(-1.80)	(-1.41)				
WRC	**13.05* **	12.52	5.669	-18.64		
	(1.75)	(1.51)	(0.30)	(-0.87)		
vehicle_public_no	5.271	9.894				
	(0.43)	(0.59)				
vehicle_taxi	**-26.96* **	-32.12			**75.44** **	**88.72** **
	(-1.73)	(-1.46)			(2.45)	(2.43)
road_paved	**46.88*** **	**50.53*** **				
	(3.25)	(3.10)				
vehicle_private			0.732	33.66		
			(0.04)	(1.25)		
Constant	111.1	310.3	-371.3*	-550.5**	79.79	68.18
	(0.97)	(0.54)	(-1.92)	(-2.12)	(0.35)	(0.24)
Time-fixed effect	No	Yes	No	Yes	No	Yes
Observations	52	52	59	59	57	57
Adj-R^2	0.734	0.727	0.107	0.109	0.302	0.238

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it}$, in which y_{it} is the total directional connectedness *FROM* others, *TO* others, or the *NET* total directional connectedness, and X_{it} denotes the fundamental variables that are estimated as significant at the 10% level in simple regressions (see Appendix, Table A-7). Specifically, *city_rank* is the rank of a city in the city cluster; *gdp* is the city GDP; *awage* denotes average wage; *GDPper* is the GDP per capita; *unemplrate* is unemployment rate; *teacher_hi* is the number of full-time teachers in higher institutions; *no_hi* is the number of higher institutions; *enroll_hi* is the number of enrolled students of higher institutions; *StarHotel* is the number of star hotels; *WRC* is the number of enterprises in wholesale and retail sector; *vehicle_public_no* is the number of public vehicles, buses, and trolley buses; *vehicle_taxi* is the number of taxies; *road_paved* is the area of paved road; *vehicle_private* is the number of private-owned vehicles. The *t*-statistics are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics that are significant at conventional significance levels.

Table 5: Determinants of net pairwise spillovers—multiple regression

Difference of :	(1)	(2)	(3)
city-rank	-6.084	-6.348	**-24.53*****
	(-0.82)	(-0.80)	(-2.71)
awage	15.29	16.00	-19.99
	(0.84)	(0.88)	(-0.94)
unemplrate	-4.229	-4.129	**-9.932****
	(-1.14)	(-0.96)	(-1.99)
teacher_hi	4.656	5.452	8.603
	(0.58)	(0.60)	(0.84)
enroll_hi	-2.084	-2.712	8.498
	(-0.29)	(-0.34)	(0.90)
enroll_ps	6.336	6.463	-8.261
	(1.47)	(1.48)	(-1.38)
vehicle_taxi	-4.610	-4.752	-7.064
	(-0.75)	(-0.72)	(-1.19)
vehicle_private	2.206	2.108	**8.181***
	(0.47)	(0.43)	(1.75)
Constant	3.421	3.748	4.397
	(1.30)	(0.93)	(0.97)
Time-Fixed effect	No	Yes	Yes
City-fixed effect	No	No	Yes
Observations	196	196	196
Adj-R^2	0.239	0.216	0.292

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it}$, in which y_{it} represents the net pairwise spillovers from city *i* to city *j*, and X_{it} denotes the difference of fundamental variables (factor in city *i* minus that in city *j*) that are estimated as significant at the 10% level in simple regressions (see Appendix, Table A-8). Specifically, *city_rank* is the rank of a city in the city cluster; *awage* denotes average wage; *unemplrate* is unemployment rate; *teacher_hi* is the number of full-time teachers in higher institutions; *enroll_hi* is the number of enrolled students of higher institutions; *enroll_ps* is the number of enrolled students of primary schools; *vehicle_taxi* is the number of taxies; *vehicle_private* is the number of private-owned vehicles. The *t*-statistics are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics that are significant at conventional significance levels.

Figure 1: Geographical distribution of sample cities

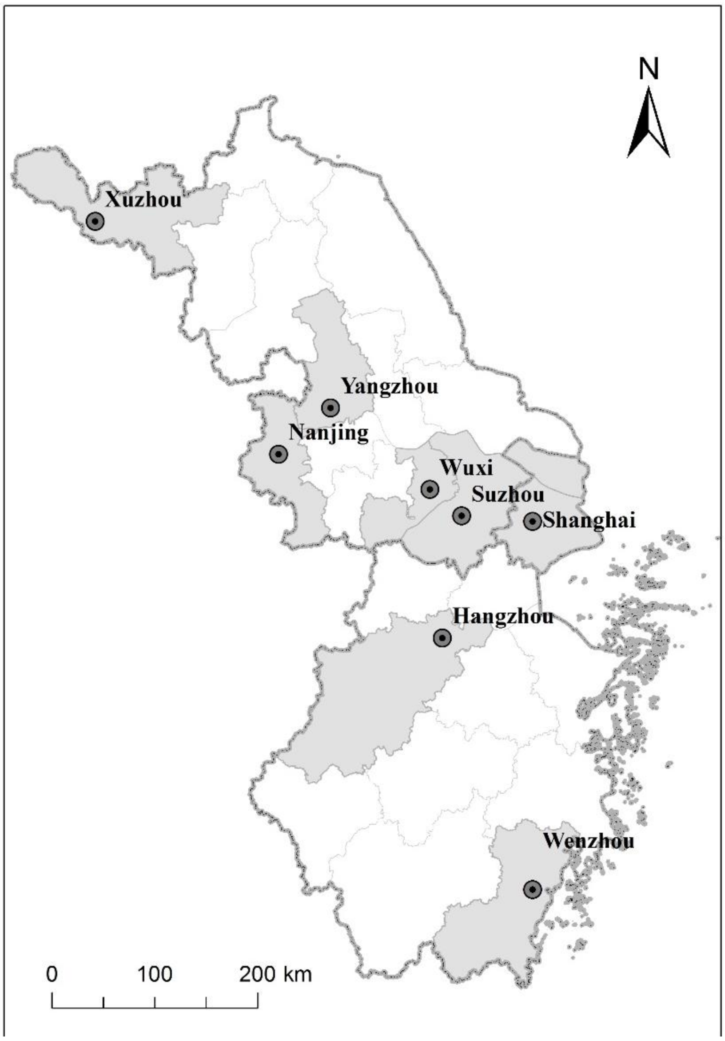


Figure 2: Contemporaneous causal flow patterns among the eight city-level housing markets

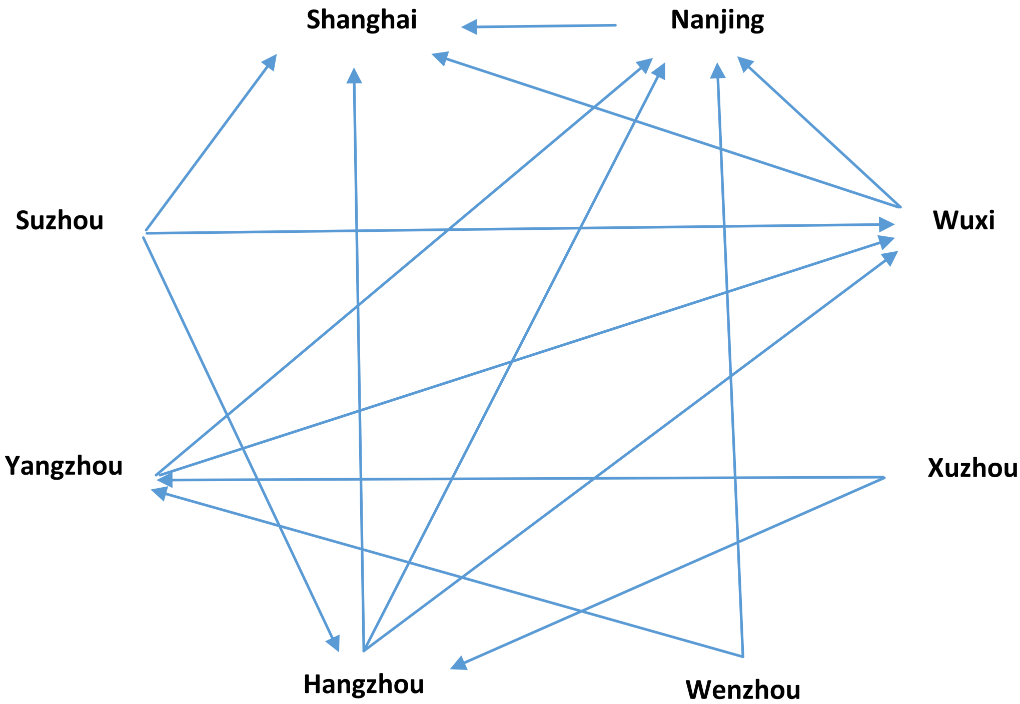
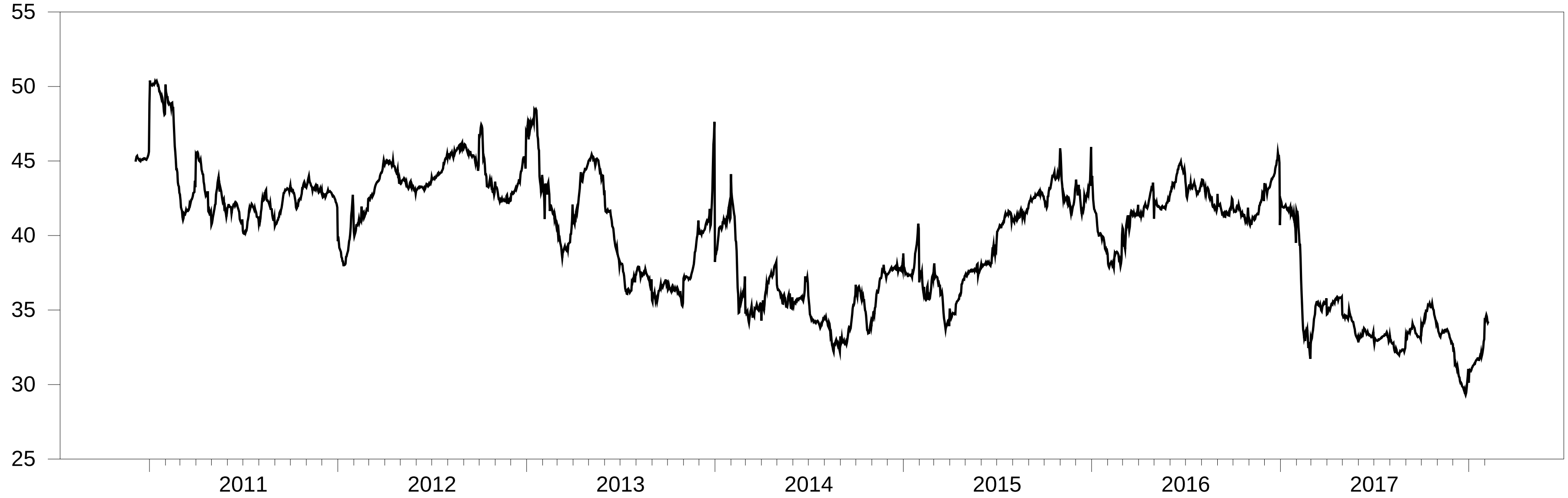


Figure 3: Total directional connectedness, 14-day-ahead, one-year-fixed rolling window



Appendix:

Table A-1: Results of Newey-West Regression on seasonal dummy variables

	Shanghai	Nanjing	Suzhou	Wuxi	Yangzhou	Xuzhou	Hangzhou	Wenzhou
Weekend	-0.007***	-0.019***	-0.004	0.001	-0.012***	-0.020***	-0.013**	0.003
	(-2.64)	(-4.47)	(-1.01)	(0.36)	(-4.40)	(-5.01)	(-2.47)	(0.65)
FEB	-0.350***	-0.389***	-0.455***	-0.401***	-0.041	-0.262*	0.071	-0.590***
	(-5.64)	(-2.70)	(-4.60)	(-3.71)	(-0.39)	(-1.67)	(0.39)	(-3.80)
MAR	-0.277***	-0.414***	-0.209*	-0.166	0.038	-0.190	-0.080	-0.446***
	(-3.27)	(-2.92)	(-1.68)	(-1.35)	(0.37)	(-1.21)	(-0.41)	(-2.86)
APR	-0.057	-0.184	0.060	0.067	-0.033	-0.024	-0.049	-0.027
	(-0.90)	(-1.25)	(0.48)	(0.56)	(-0.33)	(-0.16)	(-0.26)	(-0.18)
MAY	-0.254***	-0.201	-0.104	-0.035	-0.067	0.108	-0.110	-0.014
	(-3.66)	(-1.42)	(-1.00)	(-0.33)	(-0.62)	(0.78)	(-0.70)	(-0.11)
JUN	-0.231***	-0.291**	-0.060	-0.037	-0.130	0.041	0.014	-0.016
	(-3.45)	(-2.04)	(-0.47)	(-0.32)	(-1.26)	(0.32)	(0.10)	(-0.10)
JUL	-0.132**	-0.221	-0.032	-0.064	-0.202*	0.038	-0.146	0.102
	(-1.97)	(-1.31)	(-0.24)	(-0.55)	(-1.92)	(0.29)	(-0.80)	(0.71)
AUG	-0.125**	-0.273*	-0.018	-0.048	-0.185*	-0.054	-0.027	0.017
	(-2.16)	(-1.85)	(-0.17)	(-0.53)	(-1.83)	(-0.40)	(-0.15)	(0.14)
SEP	-0.123**	-0.190	0.197*	0.095	-0.104	-0.018	-0.002	0.092
	(-2.05)	(-1.41)	(1.86)	(0.97)	(-1.02)	(-0.12)	(-0.01)	(0.72)
OCT	-0.077*	-0.081)	0.169	0.261	0.076	0.082	-0.057	0.149
	(-1.07)	(-0.60	(1.36)	(2.40)	(0.62)	(0.52)	(-0.28)	(1.11)
NOV	-0.070*	-0.058)	0.081	0.076	0.112	0.220*	0.023	0.102
	(-0.83)	(-0.38)	(0.61)	(0.62)	(1.09)	(1.68)	(0.15)	(0.72)
DEC	-0.060*	0.026	0.016	0.073	-0.010	0.204	0.287*	0.097
	(-0.74)	(0.15)	(0.12)	(0.48)	(-0.08)	(1.52)	(1.89)	(0.71)
YR_{2010}	-0.402***	-0.770***	-0.632***	-0.534***	-0.444***	-0.141	-0.511**	-0.590***
	(-4.83)	(-4.84)	(-4.44)	(-3.83)	(-4.15)	(-1.29)	(-2.49)	(-4.68)
YR_{2011}	-0.519***	-0.992***	-0.499***	-0.984***	-0.788***	-0.199	-0.526***	-0.805***
	(-6.34)	(-7.01)	(-3.85)	(-7.23)	(-5.50)	(-1.49)	(-3.99)	(-6.18)
YR_{2012}	-0.528***	-0.425***	0.169	-0.567***	-0.819***	-0.101	-0.195	-0.266**
	(-5.98)	(-2.90)	(1.08)	(-4.10)	(-6.32)	(-0.81)	(-0.98)	(-2.12)
YR_{2013}	-0.256***	-0.144	-0.206**	-0.554***	-0.191***	0.307*	0.687***	-0.017
	(-3.85)	(-1.17)	(-1.95)	(-4.52)	(-2.13)	(1.91)	(5.49)	(-0.20)
YR_{2014}	-0.300***	-0.385***	-0.202*	-0.599***	-0.396***	0.279**	0.763***	0.012
	(-4.11)	(-2.92)	(-1.79)	(-4.58)	(-4.08)	(2.24)	(7.75)	(0.11)
YR_{2015}	0.048	-0.024	0.098	-0.449***	-0.206**	-0.077	0.913***	0.365***
	(0.69)	(-0.17)	(0.77)	(-3.48)	(-2.31)	(-0.60)	(9.39)	(4.07)
YR_{2016}	0.002	0.213	-0.092	-0.113	0.203**	0.505***	1.325***	0.824***
	(0.02)	(1.09)	(-0.52)	(-0.50)	(2.12)	(3.25)	(13.71)	(7.16)
YR_{2017}	-0.368***	-0.426***	-0.180	-0.810***	0.395***	0.889***	1.358***	0.647***
	(-5.08)	(-3.01)	(-1.49)	(-5.85)	(4.34)	(7.09)	(11.44)	(6.35)
YR_{2018}	-0.461***	0.158	-0.152	-0.552***	0.455***	1.000***	1.459***	0.903***
	(-5.18)	(0.90)	(-1.05)	(-3.51)	(3.50)	(7.19)	(8.80)	(5.70)
Constant	6.532***	5.857***	5.463***	5.382***	4.467***	5.280***	3.521***	5.625***
	(76.96)	(31.98)	(39.76)	(35.28)	(35.67)	(36.46)	(23.24)	(39.84)
Adjusted-R^2	0.610	0.588	0.470	0.470	0.773	0.569	0.731	0.762
Observation	2989	2989	2989	2989	2989	2989	2989	2989

Notes: This table reports the Newey-West estimation results of$\log(DailyTransactions_i) = \alpha_0 + \alpha_1 Weekend + \sum_{j=2}^{12} \beta_j month_j + \sum_{k=2010}^{2018} \beta_k YR_k + \varepsilon_i$. Where the dependent variable $\log(DailyTransactions_i)$ means log-transformed daily transactions of housing units in city *i*, while *i* named Shanghai, Nanjing, Suzhou, Wuxi, Yangzhou, Xuzhou, Hangzhou, Wenzhou respectively. α_0 means the constant term; $Weekend$ means dummy variable of weekends (equals 1 when the day is Saturday or Sunday); $month_j$ means dummy variable of the j-th month of the year, namely FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, and DEC; YR_k means the yearly dummy variable of year k. *, **, and *** indicate significance level of 10%, 5%, and 1%, respectively.

Appendix:

Table A-2: Unit root tests

	Without Trend		With Trend	
Markets	ADF	PP	ADF	PP
Shanghai	-5.855***	-5.444***	-5.854***	-5.444***
Nanjing	-5.479***	-4.718***	-5.478***	-4.718***
Suzhou	-6.010***	-4.874***	-6.008***	-4.873***
Wuxi	-5.167***	-4.620***	-5.166***	-4.620***
Yangzhou	-5.077***	-6.105***	-5.076***	-6.105***
Xuzhou	-4.188***	-3.775***	-4.187***	-3.775**
Hangzhou	-5.469***	-4.898***	-5.468***	-4.897***
Wenzhou	-3.662***	-5.033***	-3.663**	-5.033***

Notes: This table reports the results of ADF (Dickey and Fuller, 1981) and PP (Phillips and Perron, 1988) unit root tests. Lags used for the tests are selected by the Bayesian Information Criterion (BIC). *, **, and *** denote the test rejects the hypothesis of the variable has a unit root at 10%, 5%, and 1% significance level, respectively.

Appendix:

	x_1	x_2	$\cdots$	x_N	From others
x_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H$, j ≠1
x_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H$, j ≠2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	$\cdots$	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H$, j ≠N
To others	$\sum_{i=1}^N d_{i1}^H$, i ≠1	$\sum_{i=1}^N d_{i2}^H$, i ≠2	$\cdots$	$\sum_{i=1}^N d_{iN}^H$, i ≠N	$\frac{1}{N}\sum_{i,j=1}^N d_{ij}^H$, i ≠j

Table A-3: Connectedness table schematic

Source: Diebold and Yilmaz (2014)

Appendix:

Table A-4: Summary statistics of (processed) fundamental variables, 2010-2017

Variable	Description (unit)	process	Observations	Mean	Standard deviation
gdp	GDP (RMB bn)	log transformed	64	6.638	0.639
gdpg	GDP growth	percentile of log growth	56	10.018	3.578
employee	No. of city employees (person th)	log transformed	64	8.596	0.435
pop_HR	No. of population, household registration (person th)	log transformed	64	8.892	0.355
pop_HRg	Population growth, household registration	percentile of log growth	56	0.792	0.642
pop_UR	No. of population, usual residence (person th)	log transformed	64	9.103	0.449
pop_URg	Population growth, usual residence	percentile of log growth	56	0.464	0.619
awage	Average wage (RMB)	log transformed	56	11.012	0.278
GDPper	GDP per capita(RMB)	log transformed	64	11.363	0.397
unemplrate	Unemployment rate	$100 \times \frac{unempoyed}{employmed + unemployed}$	58	1.011	0.524
teacher_hi	No. of full-time teachers in higher institution (person th)	log transformed	62	2.540	0.907
teacher_ss	No. of full-time teachers in secondary school (person th)	log transformed	62	3.312	0.350
teacher_ps	No. of full-time teachers in primary school (person th)	log transformed	62	3.299	0.406
no_hi	No. of higher institution (unit)	log transformed	64	2.907	0.845
no_ss	No. of secondary school (unit)	log transformed	64	5.711	0.480
no_ps	No. of primary school (unit)	log transformed	64	6.025	0.526
enroll_hi	No. of enrolled student of higher institution (person th)	log transformed	64	5.341	0.845
enroll_ss	No. of enrolled student of secondary school (person th)	log transformed	64	5.729	0.359
enroll_ps	No. of enrolled student of primary school (person th)	log transformed	64	6.143	0.427
health_no	No. of hospital and health centre (unit)	log transformed	63	5.592	0.452
health_bed	No. of bed in hospital and health centre (unit)	log transformed	61	10.561	0.536
StarHotel	No. of star hotels (unit)	log transformed	60	4.686	0.566
WRC	No. of enterprises in Wholesale & Retail sector (unit)	log transformed	59	7.730	0.711
vehicle_public_no	No. of public vehicle, bus and trolley bus (unit th)	log transformed	62	1.477	0.777
vehicle_taxi	No. of Taxi (unit th)	log transformed	62	1.911	0.935
vehicle_private	No. of private-owned vehicles (unit th)	log transformed	64	6.994	0.659
road_paved	Area of paved road (sq m mn)	log transformed	60	4.149	0.812

Appendix:

Table A-5: Correlation matrix of the variables used in further investigation

	gdp	*gdpg*	*employee*	*pop_HR*	*pop_HRg*	*pop_UR*	*pop_URg*	*awage*	*GDPper*	*unemplrate*	*teacher_hi*	*teacher_ss*	*teacher_ps*
gdp	1.00												
gdpg	-0.45	1.00											
employee	0.81	-0.25	1.00										
pop_HR	0.50	-0.12	0.83	1.00									
pop_HRg	0.11	-0.14	0.17	0.18	1.00								
pop_UR	0.81	-0.24	0.98	0.88	0.12	1.00							
pop_URg	0.32	0.04	0.33	0.28	-0.10	0.36	1.00						
awage	0.84	-0.58	0.56	0.33	0.03	0.57	0.19	1.00					
GDPper	0.67	-0.48	0.15	-0.28	0.05	0.11	0.09	0.71	1.00				
unemplrate	0.49	-0.04	0.33	0.36	-0.40	0.48	0.42	0.54	0.21	1.00			
teacher_hi	0.67	-0.04	0.61	0.49	0.08	0.63	0.45	0.63	0.33	0.56	1.00		
teacher_ss	0.56	-0.14	0.89	0.98	0.19	0.92	0.26	0.35	-0.22	0.33	0.46	1.00	
teacher_ps	0.58	-0.26	0.88	0.94	0.37	0.88	0.23	0.36	-0.14	0.15	0.43	0.96	1.00
no_hi	0.83	-0.15	0.74	0.51	0.09	0.74	0.48	0.71	0.47	0.56	0.95	0.52	0.50
no_ss	0.55	-0.17	0.90	0.94	0.10	0.92	0.29	0.38	-0.22	0.35	0.45	0.96	0.91
no_ps	0.23	-0.01	0.65	0.93	0.31	0.69	0.17	0.06	-0.50	0.09	0.33	0.90	0.90
enroll_hi	0.65	-0.03	0.56	0.42	0.13	0.57	0.43	0.60	0.37	0.50	0.99	0.39	0.38
enroll_ss	0.47	-0.09	0.86	0.96	0.17	0.87	0.27	0.25	-0.31	0.27	0.39	0.98	0.94
enroll_ps	0.49	-0.29	0.80	0.88	0.44	0.80	0.18	0.26	-0.17	0.01	0.29	0.90	0.98
health_no	0.63	-0.23	0.94	0.93	0.16	0.94	0.31	0.46	-0.11	0.33	0.53	0.96	0.93
health_bed	0.89	-0.38	0.93	0.81	0.23	0.94	0.37	0.72	0.32	0.45	0.70	0.84	0.86
StarHotel	0.67	-0.10	0.88	0.71	0.13	0.83	0.46	0.42	0.09	0.30	0.72	0.73	0.71
WRC	0.85	-0.36	0.91	0.69	0.31	0.88	0.42	0.60	0.34	0.27	0.67	0.74	0.80
vehicle_public_no	0.89	-0.26	0.80	0.57	0.10	0.80	0.47	0.79	0.49	0.57	0.90	0.59	0.58
vehicle_taxi	0.80	-0.19	0.82	0.72	-0.03	0.85	0.48	0.73	0.26	0.71	0.87	0.72	0.64
vehicle_private	0.90	-0.50	0.80	0.48	0.33	0.76	0.30	0.78	0.58	0.23	0.68	0.54	0.63
road_paved	0.92	-0.30	0.74	0.55	0.05	0.80	0.41	0.82	0.55	0.71	0.82	0.56	0.53

Appendix:

Table A-5: (continued)

	no_hi	*no_ss*	*no_ps*	*enroll_hi*	*enroll_ss*	*enroll_ps*	*health_no*	*health_bed*	*StarHotel*	*WRC*	*vehicle_public*	*vehicle_taxi*	*vehicle_private*
no_hi	1.00												
no_ss	0.52	1.00											
no_ps	0.29	0.83	1.00										
enroll_hi	0.94	0.37	0.28	1.00									
enroll_ss	0.45	0.96	0.89	0.32	1.00								
enroll_ps	0.37	0.84	0.89	0.25	0.89	1.00							
health_no	0.61	0.98	0.81	0.46	0.95	0.86	1.00						
health_bed	0.81	0.80	0.62	0.66	0.77	0.78	0.87	1.00					
StarHotel	0.80	0.78	0.57	0.68	0.72	0.62	0.82	0.80	1.00				
WRC	0.81	0.72	0.53	0.66	0.69	0.74	0.79	0.92	0.84	1.00			
vehicle_public_no	0.97	0.60	0.33	0.88	0.53	0.46	0.69	0.87	0.78	0.85	1.00		
vehicle_taxi	0.91	0.74	0.48	0.82	0.67	0.50	0.78	0.86	0.79	0.79	0.94	1.00	
vehicle_private	0.80	0.56	0.30	0.67	0.47	0.58	0.66	0.84	0.69	0.89	0.87	0.73	1.00
road_paved	0.90	0.53	0.28	0.80	0.45	0.42	0.61	0.85	0.64	0.78	0.92	0.89	0.80

Appendix:

Table A-6: The determinants of contemporaneous causal flow pattern—simple regression

	Estimated	*Adj*-R^2	Obs.
	Panel A: City hierarchy		
city_rank	**0.750***** (7.75)	0.637	64
	Panel B: Demographic and economic factors		
gdp	**0.526**** (2.18)	0.242	64
gdpg	-0.0125 (-0.41)	-0.014	56
employee	0.442 (1.13)	0.069	64
pop_HR	0.347 (0.66)	0.019	64
pop_HRg	-0.232 (-1.45)	0.032	56
pop_UR	0.527 (1.47)	0.112	64
pop_URg	**0.297*** (1.74)	0.059	56
awage	**1.335***** (3.16)	0.296	56
GDPper	**0.649**** (2.20)	0.136	64
unemplrate	**1.116***** (7.77)	0.729	58
	Panel C: Amenities of education and healthcare		
teacher_hi	**0.418***** (3.01)	0.309	62
teacher_ss	0.340 (0.63)	0.015	62
teacher_ps	0.00991 (0.02)	-0.017	62
no_hi	**0.468***** (3.10)	0.342	64
no_ss	0.290 (0.75)	0.028	64
no_ps	-0.161 (-0.53)	0	64

(To be continued)

Appendix:

Table 6-A: (Continued)

enroll_hi	**0.415*****	0.266	64
	(2.95)		
enroll_ss	0.231	0	64
	(0.44)		
enroll_ps	-0.235	0.007	64
	(-0.64)		
health_no	0.324	0.032	63
	(0.81)		
health_bed	0.447	0.119	61
	(1.45)		
Panel D: Amenities of Consumption			
StarHotel	**0.429***	0.121	60
	(1.67)		
WRC	0.296	0.081	59
	(1.22)		
Panel E: Amenities of communication			
vehicle_public_no	**0.536*****	0.376	62
	(3.04)		
vehicle_taxi	**0.508*****	0.495	64
	(4.71)		
vehicle_private	0.221	0.032	64
	(0.92)		
road_paved	**0.505*****	0.36	60
	(3.20)		

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 x_{it} + \varepsilon_{it}$, in which y_{it} is the index of city information status (assigned 1 for information senders, 2 for information exchangers, and 3 for information receivers), while x_{it} denotes the fundamental variables including the rank of a city in the city hierarchy (assigned value of 3 for the principle city Shanghai, 2 for vice-principle city Nanjing and Hangzhou, and 1 for others). Detail information for all fundamental variables is reported in Appendix Table A-4 except the city hierarchy variable *city_Rank*. The t-statistics are reported in parentheses. "Obs." is the number of observations used in each regression. To save space, the results for the constants in the regressions are not reported. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics significant at conventional significance levels.

Appendix:

Table A-7: Determinants of the total directional connectedness *FROM* others, *TO* others, and the *NET* total directional connectedness—simple regression

	From			**TO**			**NET**		
	Estimated	adj-R^2	Obs.	Estimated	adj-R^2	Obs.	Estimated	adj-R^2	Obs.
Panel A: City hierarchy									
City_rank	**18.51*****	0.308	64	-8.014	0.007	64	**-26.52*****	0.137	64
	(4.43)			(-1.00)			(-2.76)		
Panel B: Demographic and economic factors									
gdp	**12.53****	0.103	64	18.90	0.087	64	6.375	-0.009	64
	(2.25)			(1.67)			(0.42)		
gdpg	-0.085	-0.016	64	-0.309	-0.015	64	-0.224	-0.016	64
	(-0.09)			(-0.18)			(-0.10)		
employee	7.781	0.005	64	21.07	0.043	64	13.29	-0.002	64
	(0.99)			(1.45)			(0.64)		
pop_HR	-5.083	-0.01	64	-9.309	-0.008	64	-4.226	-0.015	64
	(-0.38)			(-0.81)			(-0.22)		
pop_HRg	-2.620	-0.011	64	4.266	-0.011	64	6.886	-0.007	64
	(-0.55)			(0.67)			(0.83)		
pop_UR	6.851	0.001	64	12.89	0.008	64	6.036	-0.013	64
	(0.94)			(1.05)			(0.32)		
pop_URg	0.922	-0.008	64	2.089	0	64	1.167	-0.013	64
	(0.64)			(0.65)			(0.30)		
awage	**34.50*****	0.156	56	8.881	-0.015	56	-25.62	0.002	56
	(3.16)			(0.45)			(-1.02)		
GDPper	**22.48****	0.132	64	**31.62***	0.096	64	9.139	-0.01	64
	(2.57)			(1.95)			(0.40)		
unemplrate	**23.47*****	0.274	58	-19.13	0.049	58	**-42.60*****	0.188	58
	(3.59)			(-1.41)			(-2.69)		
Panel C: Amenities of education and healthcare									
teacher_hi	**12.92*****	0.235	62	1.341	-0.016	62	**-11.58***	0.029	62
	(3.50)			(0.29)			(-1.91)		
teacher_ss	-3.667	-0.014	62	-2.983	-0.016	62	0.685	-0.017	62
	(-0.28)			(-0.27)			(0.04)		
teacher_ps	-7.930	0.002	62	5.496	-0.013	62	13.43	-0.004	62
	(-0.71)			(0.50)			(0.79)		
no_hi	**14.64*****	0.269	64	7.430	0.012	64	-7.212	0	64
	(4.04)			(1.45)			(-1.07)		
no_ss	-1.560	-0.015	64	-5.078	-0.012	64	-3.518	-0.015	64
	(-0.17)			(-0.62)			(-0.25)		
no_ps	-12.35	0.062	64	-9.380	0.001	64	2.971	-0.015	64
	(-1.57)			(-1.04)			(0.25)		

(to be continued)

Appendix:

Table A-7: (Continued)

enroll_hi	**13.99***** (3.68)	0.244	64	3.058 (0.64)	-0.011	64	**-10.93*** (-1.84)	0.021	64
enroll_ss	-4.817 (-0.37)	-0.011	64	-6.812 (-0.57)	-0.012	64	-1.995 (-0.11)	-0.016	64
enroll_ps	-12.66 (-1.25)	0.038	64	7.265 (0.63)	-0.009	64	19.93 (1.31)	0.015	64
health_no	0.876 (0.09)	-0.016	63	-1.237 (-0.14)	-0.016	63	-2.113 (-0.14)	-0.016	63
health_bed	10.69 (1.63)	0.042	61	13.43 (1.24)	0.018	61	2.748 (0.17)	-0.016	61
				Panel D: Amenities of consumption					
StarHotel	**13.31**** (2.03)	0.088	60	16.10 (1.60)	0.039	60	2.792 (0.20)	-0.016	60
WRC	**9.082*** (1.72)	0.064	59	**14.44*** (1.71)	0.054	59	5.355 (0.45)	-0.011	59
				Panel E: Amenities of communication					
vehicle_public_no	**15.19***** (3.43)	0.239	62	5.491 (0.96)	-0.004	62	-9.698 (-1.22)	0.007	62
vehicle_taxi	**11.72***** (3.69)	0.204	62	-3.410 (-0.66)	-0.01	62	**-15.13**** (-2.21)	0.067	62
vehicle_private	5.805 (0.97)	0.011	64	**15.40*** (1.77)	0.057	64	9.597 (0.75)	0.001	64
road_paved	**12.35***** (3.56)	0.17	60	6.643 (1.03)	0.002	60	-5.702 (-0.73)	-0.008	60

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 x_{it} + \varepsilon_{it}$, in which y_{it} denotes the total directional connectedness *FROM* others, *TO* others, or the *NET* total directional connectedness, while x_{it} denotes the fundamental variables including the city hierarchy (assigned value of 3 for the principle city Shanghai, 2 for vice-principle cities of Nanjing and Hangzhou, and 1 for others). Detail information for all fundamental variables is reported in Appendix Table A2 except the city hierarchy variable *city_Rank*. The t-statistics are reported in parentheses. "Obs." is the number of observations used in each simple regression. To save space, the results for the constant in the regressions are not reported. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics significant at conventional significance levels.

Appendix:

Table A-8: Determinants of net pairwise spillovers—simple regression

Difference of	**Estimated**	***Adj.-R^2***	**Obs.**
	Panel A: City hierarchy		
city_rank	**-4.286*****	0.093	224
	(-2.79)		
	Panel B: Demographic and economic factors		
gdp	1.397	0.001	224
	(1.17)		
gdpg	-0.0885	-0.004	224
	(-0.28)		
employee	1.771	0.003	224
	(1.19)		
pop_HR	-0.565	-0.004	224
	(-0.31)		
pop_HRg	0.990	0	224
	(1.42)		
pop_UR	0.834	-0.003	224
	(0.59)		
pop_URg	0.255	-0.002	224
	(0.76)		
awage	**-9.772***	0.025	196
	(-1.74)		
GDPper	2.097	0	224
	(0.85)		
unemplrate	**-10.31*****	0.185	197
	(-3.41)		
	Panel C: Amenities of education and healthcare		
teacher_hi	**-1.992***	0.027	211
	(-1.78)		
teacher_ss	0.00804	-0.005	211
	(0.00)		
teacher_ps	1.705	0.001	211
	(1.06)		
no_hi	-1.303	0.007	224
	(-1.34)		
no_ss	-0.449	-0.004	224
	(-0.33)		
no_ps	0.386	-0.004	224
	(0.30)		

(To be continued)

Appendix:

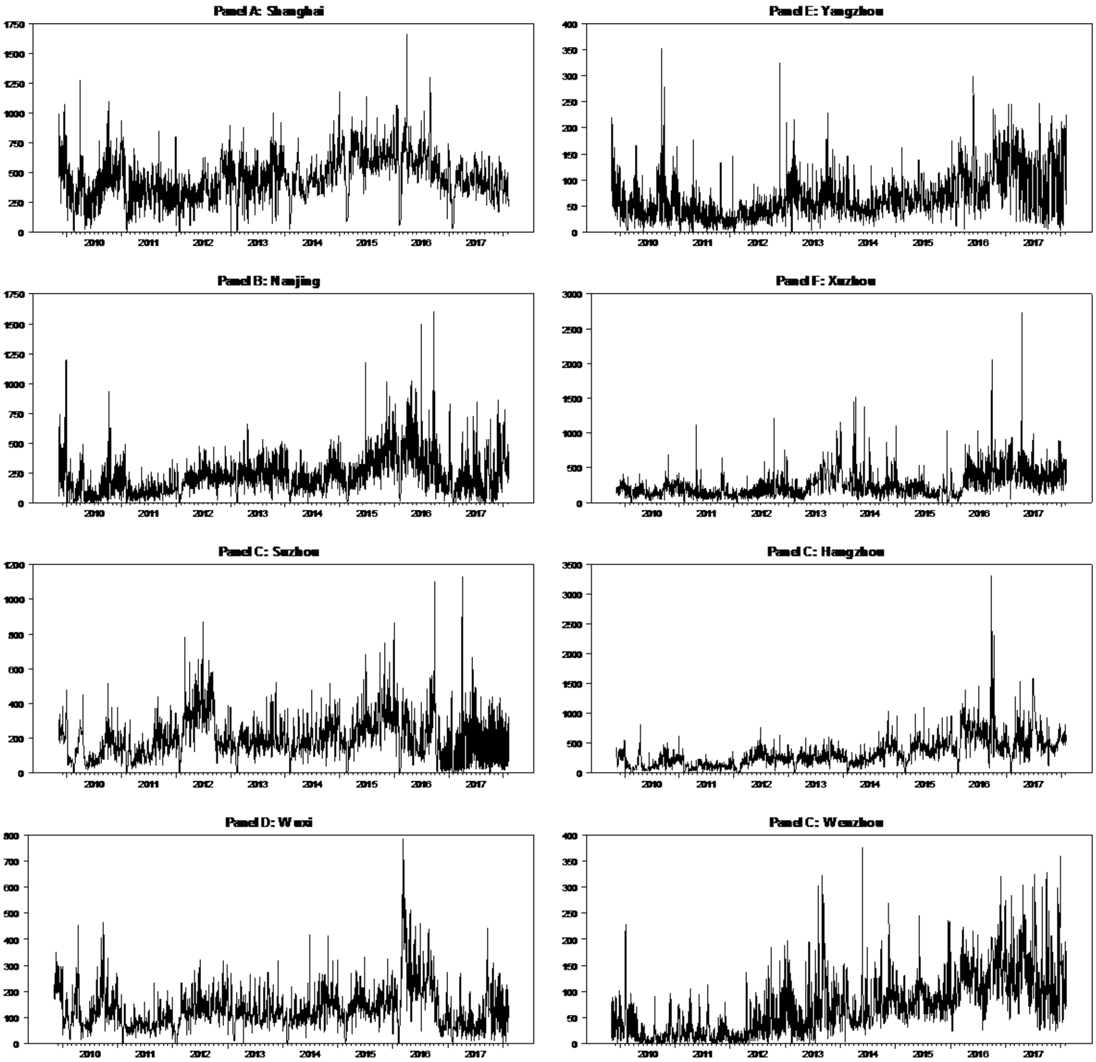
Table A-8: (continued)

enroll_hi	**-1.832***	0.02	224
	(-1.69)		
enroll_ss	-0.255	-0.004	224
	(-0.14)		
enroll_ps	**2.616***	0.011	224
	(1.67)		
health_no	-0.189	-0.005	217
	(-0.13)		
health_bed	0.404	-0.004	206
	(0.30)		
Panel D: Amenities of consumption			
StarHotel	-0.0210	-0.005	196
	(-0.01)		
WRC	0.970	-0.000	199
	(1.17)		
Panel E: Amenities of communication			
vehicle_public_no	-1.755	0.012	211
	(-1.37)		
vehicle_taxi	**-2.585****	0.052	211
	(-2.19)		
vehicle_private	**1.714***	0.007	224
	(1.96)		
road_paved	-1.478	0.003	198
	(-1.04)		

Notes: This table reports the Newey-West robust standard error estimations for $y_{it} = \alpha_0 + \beta_1 x_{it} + \varepsilon_{it}$, in which y_{it} denotes net pairwise spillovers from city i to city j, while x_{it} denotes the difference of fundamental variables (factor in the city *i* minus that in city *j*) including the city hierarchy (assigned value of 3 for the principle city Shanghai, 2 for vice-principle cities of Nanjing and Hangzhou, and 1 for others). Detail information for all fundamental variables is reported in Appendix Table A2 except the city hierarchy variable *city_rank*. The t-statistics are reported in parentheses. "Obs." is the numbers of observations used in each simple regression. To save space, the results for the constant in the regressions are not reported. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Numbers in bold are coefficient estimates and related statistics significant at conventional significance levels.

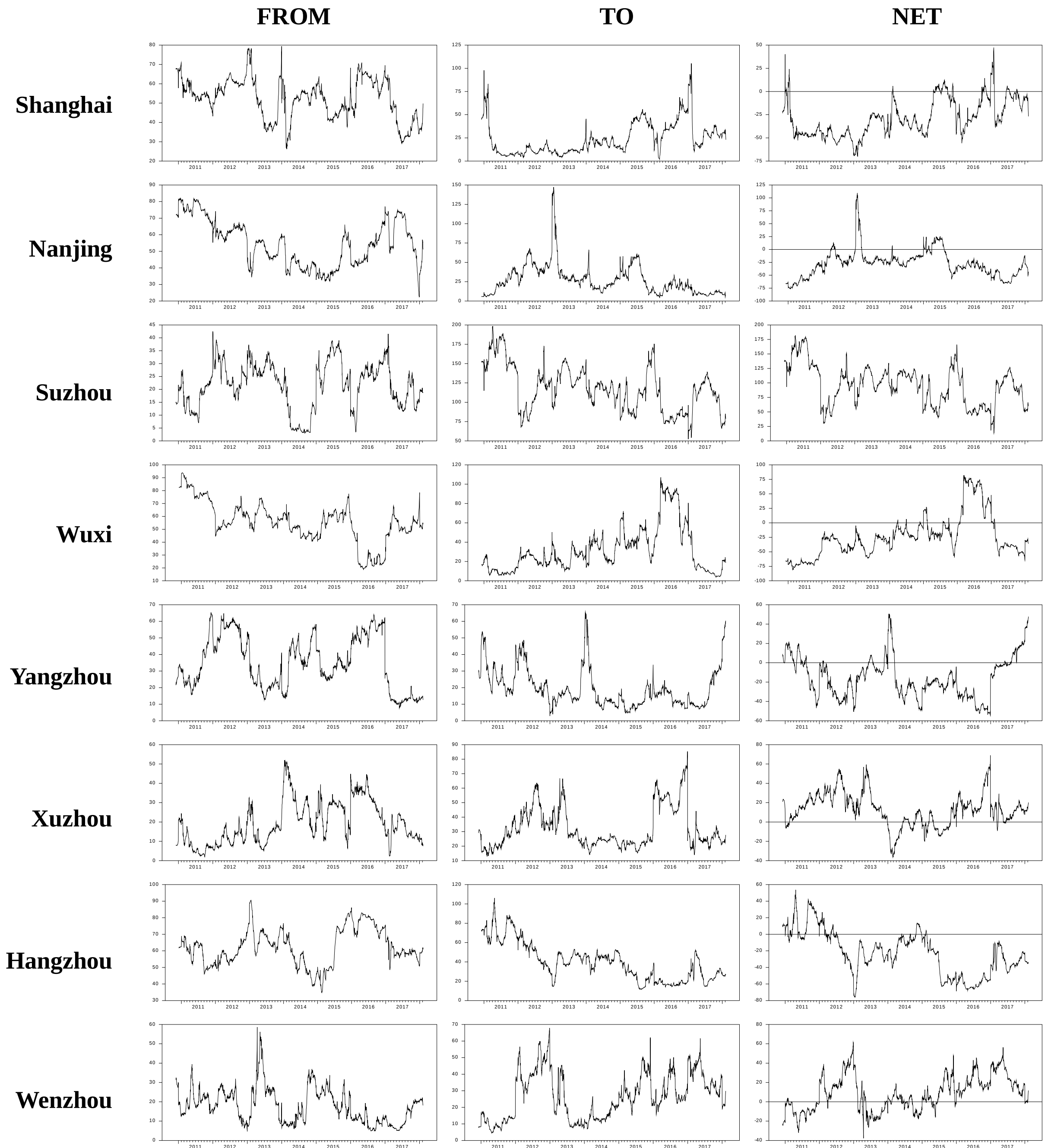
Appendix:

Figure A-1: Daily housing transaction units, 2009.11.5~2018.2.8



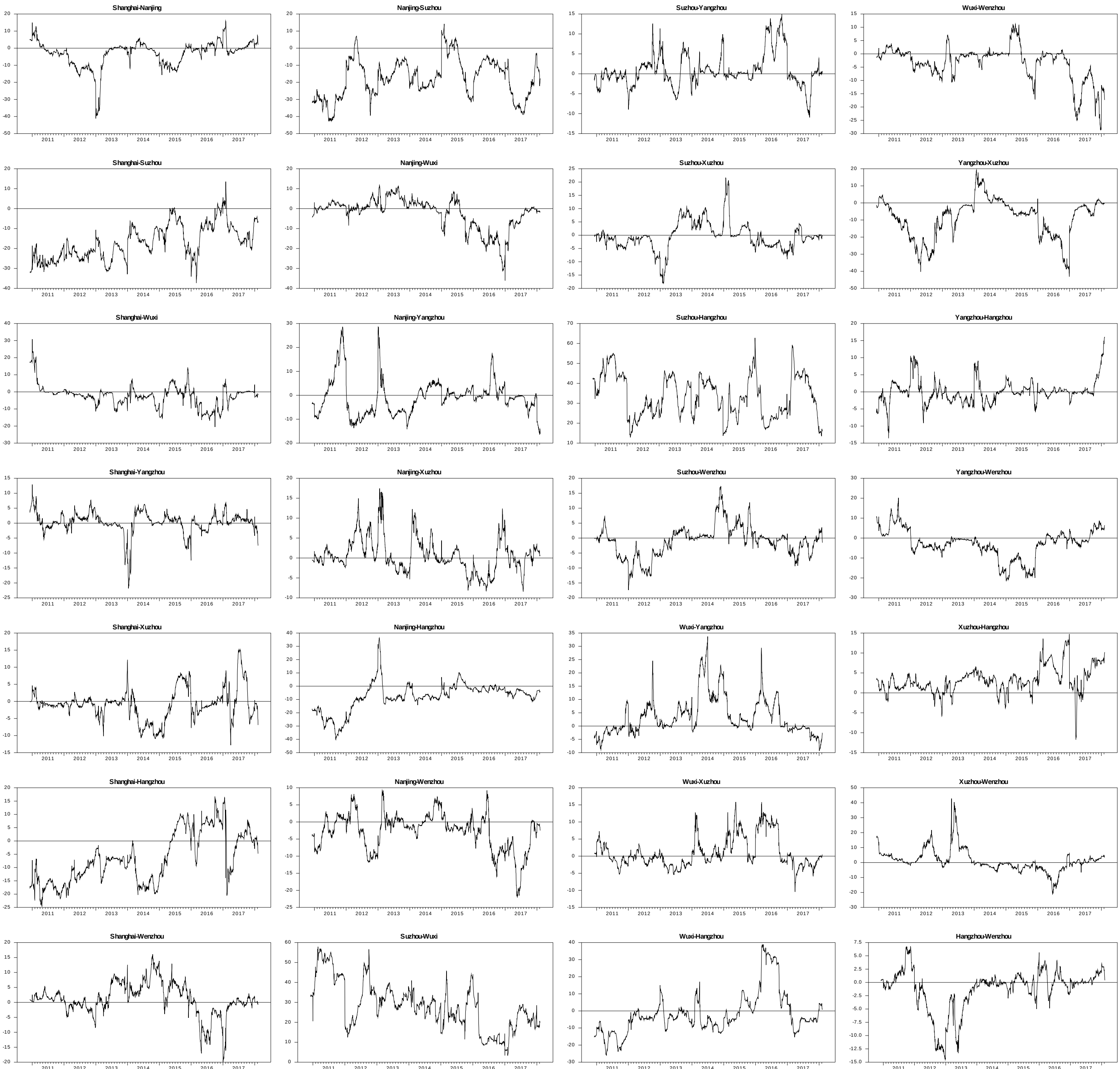
Appendix:

Figure A-2: Dynamic total directional connectedness of FROM others, TO others, and NET total directional connectedness, 14-day-ahead, one-year-fixed rolling window



Appendix:

Figure A-3. Net pairwise directional connectedness, 14-day-ahead, one-year-fixed rolling window



Housing Market Spillovers through the Lens of Transaction Volume: A New Spillover Index Approach

Abstract

Through proposing and applying a new spillover index approach based on data-determined structural vector autoregression to measure connectedness, we examine the daily housing market information transmission via transaction volume among Chinese city-level housing markets from 2009 to 2018. We document substantial information transmission on Chinese housing markets even within one day and find that the role a city-level housing market may play in the information transmission network resembles a pattern observed on other financial markets, which can be generally classified into three distinctive groups: prime senders, exchange centers, and prime receivers. City hierarchy and some fundamental economic factors, such as city gross domestic product and average wage, appear to be significant determinants of such a pattern. The findings extend the existing voluminous literature solely based on housing prices or price volatility spillovers and shed new light on the recent government intervention strategy in China, which particularly focuses on the transaction volume in the housing markets.

Keywords: Transaction volume; Spillover index; Information transmission; DAG; Data-determined VAR

JEL Classification: G12; G15; C32, R31