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Time-varying inter-urban housing price spillovers in China: Causes and consequences

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ABSTRACT

The spatial spillovers of housing prices across regions are well documented by a large body of previous studies. This paper tries to investigate the dynamic (time-varying) evolution of spatial interactions and their underlying driving factors intensively. Using a recently developed Generalized Autoregressive Score (GAS) model, this paper examines the time-varying spatial spillovers of housing prices in 70 major and median cities of China from 2006 to 2019. We find that the GAS model can well capture the impact of time-varying critical events of Chinese real estate market on the whole. However, different regions display heterogeneous variation patterns over time. Further investigation shows that inter-regional labor mobility and trades are two major channels, accounting for 1.25% and 2.58% of the monthly standard deviations of spatial spillover effects from one city to another, respectively. We also characterize and distinguish between three time-varying patterns of spatial spillovers within different regions of China. Our results shed lights on the understanding of spatial spillovers across regional real estate markets across different city network structures within China.

1. Introduction

Started from Rosen (1974), economists fascinate to investigate the determinants of the housing prices from different angles, such as the value of air quality for individual (Chay & Greenstone, 2005), income shocks (Määttänen & Terviö, 2014), and fiscal climate (Gyourko & Tracy, 1991). Among them, the intensity of spatial spillovers across different regions has become a focal point of research interests recently. As is documented in the seminal work by Holly, Pesaran & Yamagata (2010) using the housing prices in the United States (US), the effect of spatial spillover remains strong even after conventional variables are controlled. As the housing prices rise and fall over time, we wonder *whether the spatial spillovers are also time-varying.* If so*, what are the driving factors underlying those time-varying variations?* Despite their apparent importance, and a large literature on housing prices, these important questions require further investigation given that the time-varying feature of spatial spillovers.

A more suitable framework to account for the time-varying concerns is needed. Conventional estimates of static spatial model fit our needs only when the underlying economic structure is stable. However, since the economy conditions have been changed enormously in the past decade, it seems inappropriate to assume that the spatial spillovers remain unchanged over time. Another motivation for time-varying spatial spillovers comes from policy evaluation. As is suggested by the recent studies(Gong, Hu, & Boelhouwer,

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2016; Teye & Ahelegbey, 2017; Yang, Yu, & Deng, 2018), economic units in a network exhibit strong interconnections, resulting in an amplification of policy impacts. Therefore, the spatial spillovers may serve as an important channel for related policies, which are usually subject to the discretion of local governors in China.[1]

In this paper, we investigate how and why the spatial spillovers would change over time using the data of China's real estate markets. This paper can be divided into two closely related part. The first part is aim to estimate the spatial spillover parameters with a time-varying panel spatial autoregressive model in line with the fast growing literature in spatial econometrics (Babii, Chen, & Ghysels, 2019; Blasques, Koopman, Lucas, & Schaumburg, 2016). With the help of this advanced model, we are able to characterize the monthly dynamics of city-level spatial spillovers in China. Following the mainstream literature (Helbich, Brunauer, Vaz, & Nijkamp, 2014; Jeanty, Partridge, & Irwin, 2010; Oikarinen, Bourassa, Hoesli, & Engblom, 2018), we use a city-level sample of housing prices in 70 major and median cities of China to estimate the spatial spillovers of housing prices among different cities. We show that the remarkable peaks of time-series figure of spatial spillover parameters coincide well with some national-wide governmental interventions. This feature, in general, makes the time-varying coefficient model more appealing.

The second part is to test the underlying channels of spatial spillovers. The dependent variable is constructed based on the novel idea of "Leave-One-Out (LOO)" method (Hué, Lucotte, & Tokpavi, 2019; Zedda & Cannas, 2020). We estimate 70×69 series of time-varying unilateral spatial spillovers from source city to destination city. By definition, it is the difference between the spatial spillovers estimated by a national model and that by a counter-factual model excluding the linkage of two cities. They are used as dependent variables in the subsequent regressions on determinants.

Using a fruitful hand-collected dataset, four bilateral proxies are constructed for possible channels as independent variables: *spatial arbitrage*, *transportation infrastructure*, *inter-regional migration*, and *inter-regional trades*. We first regress the parameters of spatial spillovers on each of the four channels as well as local economic and financial conditions. The regression analysis demonstrates that four aforementioned channels are both statistically and economically significant. For instance, one standard deviation increase in immigration increases the unilateral spillovers by 0.0147, which is around 18.45% of the standard deviation.

We further investigate the heterogeneities across three dominant coastal regions of China, namely, BTH, PRD, and YRD. We find that the long-term average spatial spillover parameters in these three regions are above the national level. In addition, we also compare the accumulated impulse responses before and after the announcement of the so-called "city-specific regulation" policy, which provides local government with greater authority to adjust to the shock. We show that the spatial spillover parameters after the policy are lower and the accumulated responses of shocks with the same initial size are also smaller after the announcement.

Our paper has threefold contributions to the existing literature. First, we add to the understanding of spatial spillovers of different city network structures using the monthly city-level data of China. The coastal regions of China have developed some more diversified network structures including core-periphery, neck-to-neck, and decentralized structures.[2] Furthermore, the interventions of municipal governments also contribute to the heterogeneity of city-level spillovers of housing prices (Han & Kung, 2015).

Second, under a unified framework, we depict and illustrate the dynamics of time-varying spatial paths of inter-city spillovers for both national and regional housing markets of China. In our benchmark analysis, we apply the generalized autoregressive score (GAS) model to estimate time-varying spatial spillovers of China's property markets. Therefore, we extend the pioneering work of housing prices by Holly et al. (2010); Holly, Pesaran, & Yamagata (2011) to a broader dynamic setting. Our model can provide a more intuitive and clear picture of spatial-temporal spillovers among regions.

Finally, we also conduct empirical tests concerning the determinants of spatial spillovers across different real estate markets in compliance with the theory of Meen (1999). While some previous papers mention the possible channels behind spatial interactions (Gong et al., 2016; Holly et al., 2011; Zhang & Fan, 2019), little evidence has been documented on the determinants of these spatial interactions. In recent contributions to this topic, Teye & Ahelegbey (2017) and Yang et al. (2018) have already explored the potential channels behind spatial spillovers at aggregate level. In contrast with their fixed-window rolling model, our research incorporates the spatial spillovers directly without loss in sample size, and further consider the underlying driving economic factors of *bilateral* spatial spillovers. We empirically show that the direction of inter-regional migration and capital flow are positive associated with the unilateral spatial spillovers of housing prices.

The remainder of this article is arranged as follows. Section 2 reviews the literature related to housing price and its spatial spillovers. Section 3 introduces the GAS methods and its corresponding impulse response functions. Section 4 concerns the data we use, while Section 5 presents our basic empirical results. Section 6 investigates the determinants of unilateral spatial spillovers. Section 7 concludes.

[1] In the middle of 2014, many municipal governments, such as Shenyang, Jinan and Hohhot in our sample, successively announced the removal of purchase restrictions on residential houses. This is a typical example of heterogeneity among different cities.

[2] In fact, many previous studies have already discussed the varied urban hierarchy in China. For example, Gong et al. (2016) and Gong, Boelhouwer, and de Haan (2015) have discussed the housing markets in pan-YRD and pan-PRD regions respectively. Gong et al. (2015) mention that some provincial capital cities (e.g., Nanjing, Hefei and Hanzhou) in the urban hierarchy of pan-YRD also provide urban products to lower tier cities just as Shanghai does, suggesting a decentralized urban hierarchy. Gong et al. (2016) argue that the housing price of Shenzhen, though not the provincial capital city like Guangzhou, may also have string effects on other underdeveloped cities. As a result, we argue that this decentralized urban hierarchy is becoming more and more common in China. In addition, Baum-Snow, Brandt, Henderson, Turner, and Zhang (2017) have discussed the trend of decentralization of Chinese cities in terms of population and industrial activities, which may be a direct consequence of China's fast-growing railway and highway systems. We complement their research by showing that housing-market network may be more poly-centric in YRD and PRD regions.

2. Literature review

A large number of studies have explored the determinants of the rise and fall of housing prices within a specific region, while the definition of “region” is subject to the degree of market segmentation. The initial rigorous paper to examine the determinants of housing prices can be dated back to Rosen (1974) and Roback (1982). However, their works basically concern with intra-regional housing prices.

The spatial spillovers are one typical important factor in explaining the regional housing prices. Meen (1999) and among others use the term “ripple effect” to describe spatial heterogeneity and co-movement across different regions, which is recently viewed as the nascent form of spatial diffusion of housing prices (Gong et al., 2016; Kuethe & Pede, 2011). Ripple effect says that a disturbance in housing prices of a given region will gradually propagate to other regions, regardless of whether they are adjacent or not. Therefore, given that the disturbance is fading away as time goes on, it eventually leads to a change of aggregate housing prices.

However, the dynamic evolution of spatial spillovers attracts more and more attentions recently. Some studies have already considered the level of spatial independence between two sub-periods. For instance, in an attempt to compare the magnitude and persistence of spatial diffusion in US, Brady (2014) has found that such diffusion is more pronounced in the sub-period from 1999 to 2011. Teye & Ahelegbey (2017), using Bayesian Graphical Vector Autoregression, also detect that the diffusion patterns from housing sub-markets in the Netherlands are different before and after the second quarter of 2005. Nevertheless, the split of sample period is more or less arbitrarily subject to the discretion of authors.

Recently, some scholars have estimated the dynamics of spillovers which are inherently in accordance with the variance decomposition from a series of rolling-estimated VAR models (Diebold & Yilmaz, 2009, 2014). For example, Tsai (2018) confirms that the ripple effect plays a key role in the regional housing markets of United States. Moreover, the monetary policy, overall economic performance and new housing markets are important determinants of the ripple effects. Antonakakis, Chatziantoniou, Floros, & Gabauer (2018) and Hwang & Suh (2021) and Hwang & Suh (2021) investigate the time-varying spatial spillovers of regional property returns. They find that the connectedness of regional housing markets exhibits diversified patterns in the sample period.

As for the housing markets in China, the most related work to ours is Chen & Chiang (2020), which also applies the rolling-window method to study the ripple effects among top-tier cities in China. They conclude that the time-varying spillover index is the best one to describe Chinese housing market. Likewise, Zhang & Fan (2019) document a trend of rising connectedness in China’s housing prices across cities by performing the rolling VAR models. However, both of them do not explicitly consider the determinants of connectedness. Yang et al. (2018) further demonstrate that education, population and GDP size are three determinants of net spillovers of housing prices. But they do not directly test the bilateral spillovers from one province to another.

Equipped with advanced spatial econometrics, another branch of literature tries to explicitly model the spatial interactions. Pesaran, Schuermann, & Weiner (2004), for example, propose a global error-correcting model to incorporate the spatial interdependency. Holly et al. (2010) decompose the error term of a hedonic price model into common factors and spatial lags of neighborhood regions, which uses state level data of US to show that even the real income per capita is controlled, spatial spillover effects still remain significant. Kuethe & Pede (2011) further run a spatial vector autoregressive model to illustrate how the shocks to one region’s macro-variables, such as real income and unemployment, will affect other regions’ housing prices. Holly et al. (2011) also provide spatial and temporal impulse response analysis of real estate market in UK. In doing so, they argue that the shocks to London will decay quicker in terms of time horizon than spatial horizon. Milcheva & Zhu (2016) use a spatial dynamic panel model to examine the effect of bank integration on co-movements across housing markets. Recently, Oikarinen et al. (2018) estimate a panel model for allowing spatial heterogeneity to investigate the short- and long-term price elasticity of housing supply. In a word, the spatial specification helps improve the estimation of housing prices.

Many papers provide direct evidence of spatial spillover effects on housing prices in China’s markets. In China, the housing markets are nascent ones since late 1990s (Wang, 2011). Nevertheless, the Chinese property markets have witnessed a quick development. It is documented that from 1998 to 2012, the real rate of net return to capital hit 20% or more, which exceeds the GDP growth rates of the same period (Chen & Wen, 2017; Wu, Gyourko, & Deng, 2012). The reform of China’s economy accounts for a large part of that. Wang (2012) suggests that the reform of property rights reduced labor mobility costs and allowed residents to collateral their houses. Hence, the deregulation of labor mobility may provide information spillovers across regions, making the interconnections between regions tightened (Zhang & Fan, 2019).

Recently, many scholars have also tried to investigate the spatial independence among different regions of China. Gong et al. (2016), for example, consider the spatial interrelations of cities located in Pearl River Delta, southern China. They confirm that the spillovers from eastern-central China to western cities are dominating. Guo & Qu (2019) also establish the spatial independence relations between two top-tier cities in China. Chiang, Hui & Chen (2021) provide further time-varying evidence of investor sentiment among four top-tier cities in China. Notably, they point out that the negative outlook of investors is critical to the information transmission process. The studies above, both from developed countries (such as US and UK) and developing countries (such as China), have established the existence of spatial spillover effects in real estate markets.

The previous papers are good benchmarks and guidelines for our empirical settings, but we move one step ahead to seek more direct determinants of bilateral spatial and temporal spillover effects. Nevertheless, the rolling method of Diebold & Yilmaz (2014) does not fit in our research goal very well. The rolling method requires sufficient initial observations to start the estimation. Since the span of our data is short, we would miss some important events in the first several years of the sample period if we employed the rolling method. Another reason is that although rolling-window method is easy to be used, it requires expertize in choosing relevant parameters, such as the window size, which is experience-based and not quite objective. Hence, we resort to the GAS framework, which uses all available observations and relies on data-driven technique.

3. Methodologies

In this section, we will briefly introduce the methodologies used in the paper. The first part of our paper applies the GAS model[3] which provides a series of time varying of spatial spillover parameters (Subsection 1). We can also apply the conventional impulse response framework to the GAS model (Subsection 2). Based on the idea of leave-one-out (LOO) method, the second part of our paper estimates the bilateral spatial spillover parameters between two cities (Subsection 3), which, in turns, are treated as our dependent variables in the following regressions.

3.1. The static & time-varying models

From the very beginning, we consider a static Spatial Durbin Model for panel data

$$y_t = \alpha_n + \rho W y_t + \beta_1 \mathbf{1}_n + A_t \beta_2 + W A_t \beta_3 + e_t, \quad e_t \sim p_e(e_t; \Sigma, \lambda), \quad t = 1, \dots, T \tag{1}$$

where $y_t = (y_{1t}, \dots, y_{nt})'$ denotes a vector of n cross-sectional observations at time t. The meaning of coefficients is as follows. α_n is the city fixed effect, which is different from city to city, ρ is the spatial spillover parameter, W is an $n \times n$ matrix of exogenous spatial weights, β_1 is an unknown scalar intercept, $\mathbf{1}_n$ is an $n \times 1$-vector of ones, A_t is an $n \times k$ matrix of exogenous regressors, β_2 and β_3 are $k \times 1$ vectors of unknown coefficients, respectively, and e_t is an $n \times 1$ disturbance vector with multivariate density p_e (e_t; Σ, λ), mean zero, unknown $k \times k$ covariance (or scale) matrix Σ. Other parameters describing the shape of the distribution are collected in the parameter vector λ. Take Student's t-distribution for example, λ is known as the degree of freedom. As is suggested by Lee & Yu (2010) , we incorporate the city fixed effect using demeaned data, that is, we replace y_t by $\widetilde{y}_t = y_t - (\sum_{s=1}^{T} y_s)/T$. Under this circumstance, Eq. (1) is rewritten as

$$\widetilde{y}_t = \rho W \widetilde{y}_t + \widetilde{A}_t \beta_2 + W \widetilde{A}_t \beta_3 + \widetilde{e}_t, \tag{2}$$

where the tilde symbol ($\sim$) of other variables represents demeaned data using the same demean technique.

It is a standard practice to use a row-normalized weight matrix W such that $\sum_{j=1}^{n} w_{ij} = 1$ for $i = 1, \dots, n$, where w_{ij} is the (i, j)-entry of W. The impact of the spatially weighted contemporaneous dependent variable Wy_t on y_t is measured by the coefficient ρ. Blasques et al. (2016) argue that the Spatial Durbin Model nests many other widely used spatial model such as Spatial Auto-Regression Model and Spatial Error Model. If we further let $X_t := (A_t, WA_t)$ and $\beta := (\beta_2, \beta_3)$, it can be shown that the Eq.(2) is solved by

$$\widetilde{y}_t = Z X_t \beta + Z e_t, \tag{3}$$

where we assume that $I_n - \rho W$ is invertible and $Z = (I_n - \rho W)^{-1}$, with I_n representing the $n \times n$ identity matrix.

Note that in Eq. (2), Spatial Durbin Model says the spatial spillover parameter ρ is a cross-sectional measure of spillover effects. However, the spillover effects of housing prices in China may not be constant over the horizon. Therefore, we follow Blasques et al. (2016) and introduce time-varying spatial spillover parameters ρ_t in the model, that is,

$$y_t = \rho_t W y_t + X_t \beta + e_t, \quad e_t \sim p_e(e_t; \Sigma, \lambda), \quad t = 1, \dots, T. \tag{4}$$

In order to estimate Eq. (4), let ρ_t be a monotonic transformation h of a time-varying parameter f_t. The link function h is designed to be valued within the interval $(-1, 1)$, which is aligned with the economic implication of static parameter ρ. Now our main task is to find a dynamic description of f_t. We follow Creal, Koopman & Lucas (2011, 2013) , Blasques et al. (2016) and among others to use GAS model, which is popular in finance recently. In our specification, we also include the one-period lagged y_t in the regressors collection, that is,

$$y_t = \rho_t W y_t + X_t \beta + \gamma y_{t-1} + e_t \tag{5}$$

Details of estimation are provided in an Online Appendix.

3.2. The analysis of spatial spillover effects

To analyze the effect of price shocks from a given city, we rely on two well-accepted econometric tools, namely, the infinite power series expansion of and Generalized Impulse Response Function (GIRF). The power series expansion provides a clear picture about the spatial contagion of housing price shocks, while GIRF shows the diffusion along time dimension. Interested readers are also referred to the Online Appendix.

3.3. The leave-one-out method

The GAS model enables us to calculate the time-varying spatial spillovers ($Z_t = (I_n - \rho_t W)^{-1}$) for the actual case, but we are interested in the bilateral spillovers between two cities. To get a more suitable unilateral spatial spillover effects of city i on city j, we

[3] Interested readers can refer to the website www.gasmodel.com.

follow the idea of the “Leave-One-Out (LOO)” method which has become popular recently (Hué et al., 2019; Zedda & Cannas, 2020). The LOO method is originally proposed in the literature of financial systemic risk, which treats the whole financial system as an interconnected network. As is argued in Zhang & Fan (2019) and Chen & Chiang (2020), the level of spillovers may serve as a measure of systemic risk of housing market. Therefore, we apply the LOO method to the network of regional housing markets.

Fig. 1 clearly shows the idea behind the LOO method. Let us imagine a housing market network consisting of the 70 cities in China, whose edges (or the magnitude of links between two nodes) are described by the weight matrix W. The left panel of Fig. 1 illustrates this network setting with arrows indicating the directions of spillover effects. On the right panel, we manually set the (j, i)-entry of W to be zero, implying that there is no direct spillover effect from city i to j. The dashed line represents the removal of the direct spatial spillovers between city i and j. Note that we do not rule out the reverse link from city j to i. Therefore, this counter-factual network on the right panel resembles the actual one in terms of all the indirect spillover effects, except for the direct link from city i to j.

We denote the entire housing market spatial spillover effects of city i on city j with the (j, i)-entry of matrix Z_t, and the network without an edge from city i to j with the (j, i)-entry of matrix $Z_{t,-(ji)}$. Hence, the difference between the (j, i)-entry of Z_t and $Z_{t,-(ji)}$ can be viewed as a naïve estimation of the direct spillovers from city i to j. Readers should keep in mind that this difference may arise from two aspects. The first one is the spatial spillover parameters ρ_t, which would be different from that of the entire housing market network. The other one is the change of network structure since the only way city i affecting city j is through indirect links.

4. Data

In our empirical specification, we apply the methodology described above to urban housing price indices in 70 large and medium cities of China. These 70 major cities cover around 42.44% of China’s gross domestic product (GDP), 17% of its population and 49.60% of its real estate investment as of 2017. In other words, the sample we use is representative for the property sector in China. The data series cover monthly housing price changes over the period 2006m1 to 2019m12 for capital cities and others. Note that the housing price indices are expressed in percentage change, that is, an index of 101 this month stands for 1% increase in the housing price of the last month. The description of the dataset is available on Online Appendix A1.

5. Empirical findings

5.1. Benchmark results

Table 1 reports both static and time-varying models at the same time. In the first column of the static model, our estimation indicates that the static spatial parameter is around 0.1105 when we do not control any other variables. Given the fact that most of the cities in our sample are separated across China, it is a reasonable estimation in terms of the magnitude.[4]

We also report the augmented static model in column 2 of Table 1 with some monthly control variables. Due to data limitation, two observable determinants, the growth of industrial value added (IVA) and standing loan balance, are controlled at the provincial level. It is standard in empirical literature that using industrial production for economic activity (See, for example, Camacho & Perez-Quiros, 2010). We argue that the lion’s share of gross domestic product in China comes from manufacturing during the sample period. Therefore, the growth of IVA may reflect the monthly provincial economic conditions to a large extent.[5] Another control variable, standing loan balance, stems from the nature of financial development in China. As is suggested in Ayyagari, Demirgüç-Kunt & Maksimovic (2010), the bank sector is the dominating formal financing method in China, where the personal mortgage loan is also closely related to credit supply nationwide. Hence we believe that the standing loan balance could reflect the overall credit supply within each province.

The augmented static model helps improving the likelihood value marginally at the cost of adding four variables. The net effect makes the Akaike information criterion (AIC) larger in column 2. However, when it comes to the time-varying model in column 3, we see a sharp increase in likelihood value from −1992.23 to −1891.09, and also a significant decrease in AIC from 3994.46 to 3796.17. It suggests that the time-varying components are meaningful in explaining the growth of housing prices in China. Moreover, the factor loadings (i.e., ω, A, and B) are also statistical significant. Again, we do not see any evidence to suggest the need of adding control variables in column 4. Besides, the significances of control variables are not robust at all. Hence, the data may be better fitted without other covariates, which supports the view of parsimonious specifications when our interest is spillover effects (see Frankel & Romer, 1999 and Holly et al., 2011 for more details).

Fig. 2 displays the estimates of net spillover effects estimated from the augmented static model. The net spillover effects measure the difference between outgoing spillovers to other cities and incoming spillovers from other cities. Each net spillover effect is matched to its corresponding city on the map of China. We categorize the net spillover effects into six different ranges from less than −0.10 to

[4] In fact, our estimates are consistent with many other spatial models in the literature. Using intra-city housing transaction-level data, the (static) spatial spillover estimated in Jeanty et al. (2010) is about 0.28. In another research concerns real estate values in Austria, Helbich et al. (2014) find that this number is slightly higher than 0.20. Both of them take into account the level of housing prices, which may be different from our dependent variable in the static models. In the structural spatial VAR model based on US state-level data given by Kuethe and Pede (2011), the stand-alone coefficient estimates of spatial terms, though without much economic interpretation, range from −0.06–0.10.

[5] It is worth to note that the IVA is an analog to “industrial production (IP)” in U.S. This monthly indicator has been commonly used as a proxy for real economic conditions in the literature. See Giglio, Kelly, and Pruitt (2016), for example.

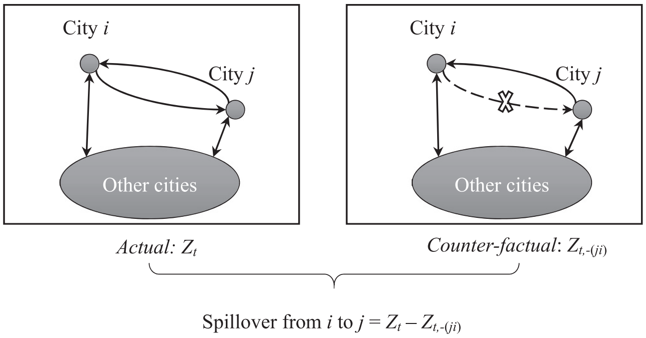

Fig. 1. The Illustration of LOO Method.

Table 1
Spatial durbin models of housing prices. This table reports the estimation results from static and time-varying spatial Durbin models. The static model is given by $\widetilde{y}_t = \rho W \widetilde{y}_t + \widetilde{X}_t \beta + \widetilde{e}_t, e_t \sim p_e(e_t; \Sigma, \lambda)$. And the time-varying model is given by $\widetilde{y}_t = \rho_t W \widetilde{y}_t + \widetilde{X}_t \beta + \widetilde{e}_t, e_t \sim p_e(e_t; \Sigma, \lambda)$, where $\rho_t = \tanh(f_t)$, and the evolution of f_t is governed by $f_{t+1} = \omega + As_t + Bf_t$. The dependent variables are the percentage changes in housing price indices of 70 major and median cities in China. The monthly control variables in column (2) and (4) are the year-on-year growth rate of industrial value added (*IVA*) and standing bank loans (*Loan*) of the province where the given city locates, as well as their spatial lags (*WIVA* and *WLoan*). All control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The *t*-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

	(1) Static	(2) Static	(3) Time-varying	(4) Time-varying
ρ	0.1105**	0.1074**		
	(2.52)	(1.99)		
ω			0.0471***	0.0452***
			(3.64)	(5.57)
A			0.1645***	0.1664***
			(4.40)	(4.22)
B			0.5189***	0.5245***
			(7.01)	(8.28)
Lag	0.5948***	0.5870***	0.5725***	0.5644***
	(10.31)	(6.34)	(5.88)	(4.54)
IVA		0.0132*		0.0126
		(1.67)		(0.65)
WIVA		0.0302**		0.0265*
		(2.18)		(1.96)
LOAN		0.0518		0.0684
		(0.46)		(0.45)
WLOAN		0.0652		0.0814
		(0.79)		(0.12)
λ	3.0020***	3.0039***	3.0018*	3.0020***
	(4.61)	(5.15)	(1.67)	(4.48)
AIC	3994.46	4001.44	3796.17	3803.26
Log Likelihood	-1992.23	-1991.72	-1891.09	-1890.63
Obs.	11,690	11,690	11,690	11,690

more than 0.10. The darker an area is, the higher is its corresponding net spillovers to other areas. It clearly shows the net spillovers are becoming stronger as we move from the hinterland to the coastal regions of China. This cross-sectional distinction in net spillover effects may serve as evidence of universal spatial spillovers among cities, and also a guide for us to investigate some regional-level heterogeneity in the following sections.

Given the fact of China's institution background, the national real estate market is under the control of central government. Hence, the related policies such as monetary policy, fiscal policy and land-supplying policy may play an important role in affecting the overall real estate market. To enhance our comprehension of the underlying mechanism, we first analyze in the next subsection whether our time-varying model can capture China's real estate market condition and the effects of government interventions on the spatial spillovers.

5.2. Analysis of time-varying behaviors

In Fig. 3, we report the estimation results for the time-varying spatial score model for Student's *t*-distributed error terms. The dashed line is the long-term average of spatial spillover parameters ρ_t, which is around 0.0980. It is close to the static spatial parameter (0.1105) with one-period lagged y_t. Hence the static coefficient can be viewed as the unconditional mean of dynamic spatial spillover

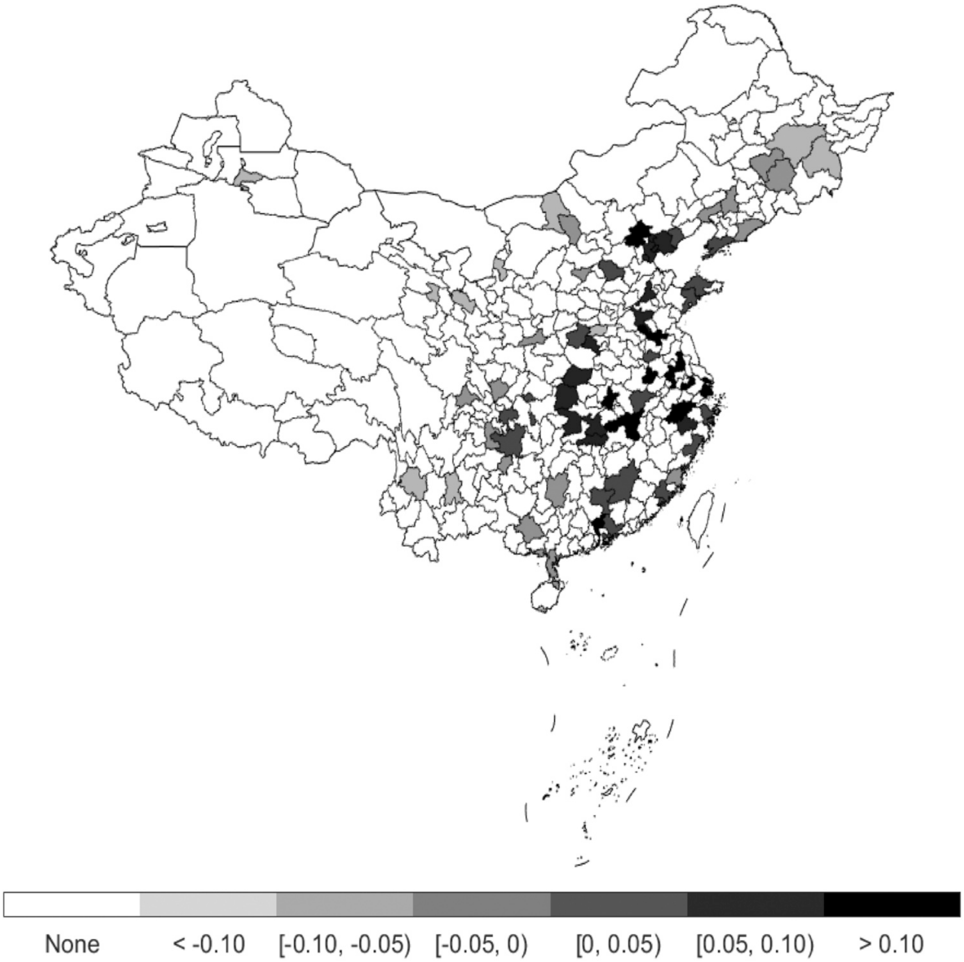

Fig. 2. Net Spillover Effects of 70 Large and Medium Cities of China. The net spillover effects are estimated by the difference of spillovers to all other cities and spillovers from all other cities. The spillovers from all other cities to city i are given by the row sum of matrix $Z_t = (I_n - \rho_t W)^{-1}$ excluding city i itself, while the spillovers of city i to all other cities are given by the column sum of $Z_t = (I_n - \rho_t W)^{-1}$.

parameters under the transformation defined by link function h.

Fig. 3 illustrates the evolution of the spatial spillover parameters over the sample period. In addition to the evolution of spatial spillover parameters, we can identify some important events and policies in China's real estate markets. Note that the peaks can be related to a number of important policy events that aim to regulate the housing price market in China. For example, the "Eight Regulations" that came into effect in 2005 mainly prohibited land sales. Accompanied with this policy, the interest rates went up and credit supplies decreased from 2006. However, people agree that these policies did not cool down the real estate markets but shore up the cost of national-wide residential houses. Fig. 3 captures this event by a rapid growth from 2006 to 2007 until it hits a peak higher than 0.31, indicating a systemic contagion of house prices.

In November 2008, the central government of China initiated a large fiscal stimulation to fight against global financial crisis. The down payment on the first personal residential house loan was reduced to 20% at the end of 2008. Combined with tax cutting, the real estate market just played a vital role in giving the economy a major boost. This property boom lasts for another two years as is shown in Fig. 3. People's Bank of China increased both the lending rates three times and reserve requirement rates five times in 2011, showing its strong determination to curtail the housing prices. In addition, the State Council stressed that regulations over real estate market would not be weakened. This sharply lowers the spatial spillover parameter back to the normal level.

It remained stable, bounding up and down around the long-term average, until 2014. The restrictions on purchasing made the number of unsold residential buildings continued to climb, putting the whole market at risk. As a result, many municipal governments, such as Shenyang, Jinan and Hohhot in our sample, successively announced removal of purchase restrictions on residential houses in the mid of 2014. Hence, the spatial spillover parameter hit the top number of the whole sample period and stayed higher than long-term average from 2014 to 2015.

At the end of 2015, the leaders of Chinese government commenced "destocking" the inventory of residential houses, which aims to make the real estate market liquid again. As of 2016, the housing prices of top-tier cities surged at first, then second-tier cities followed,

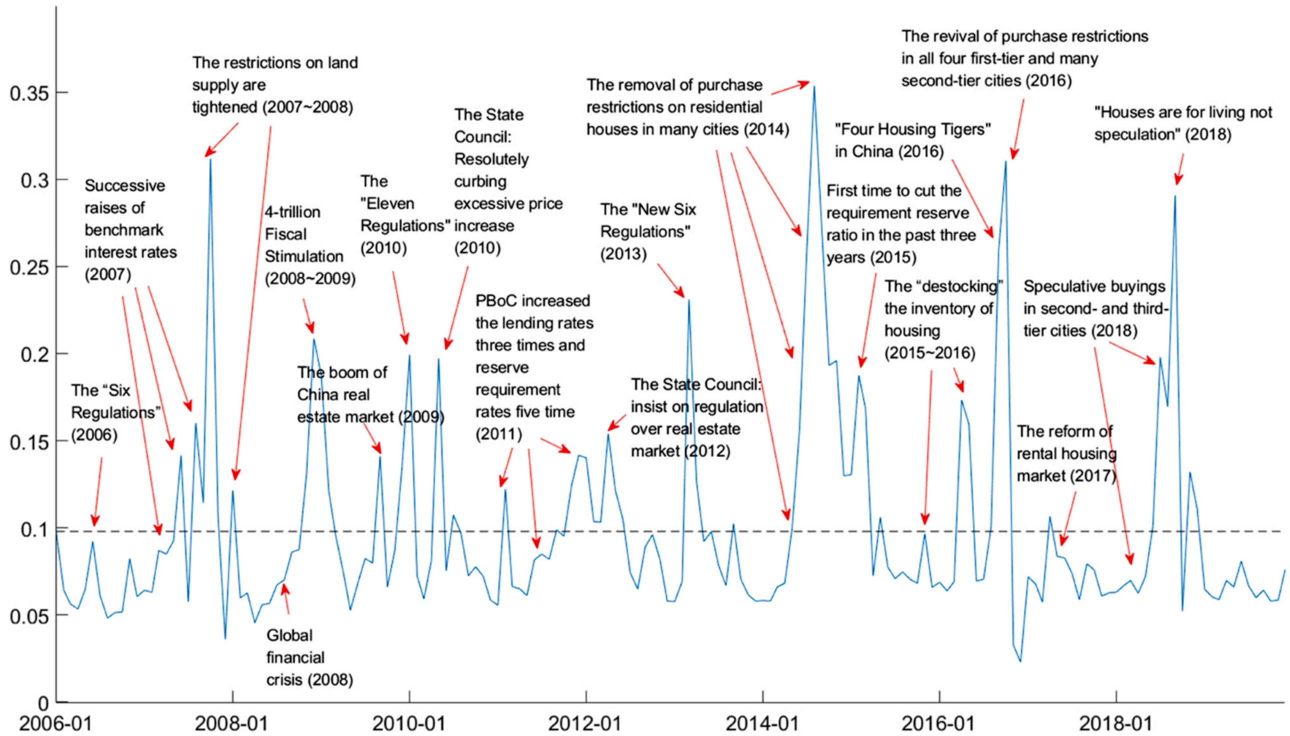

Fig. 3. Spatial Spillover Parameters (ρ_t) Estimated from Eq. (5) under the Assumption of Student's t distribution. The solid line is the estimated monthly value of ρ_t. The dashed line is the long-term average of ρ_t over the sample horizon.

such as Nanjing, Hefei, Xiamen and Suzhou, or known as "Four Housing Tigers". During that time, anecdote evidence shows that many buyers traveled from the east coasts to inlands so as to speculate in the housing markets for extra gains.[6] This is clearly captured in the peaks standing in 2016, one of which reaches the second highest value of all spatial spillover coefficients.

China's leaders warned that houses are for living in but not for speculation in March 2017. Hence the regulators clamped down on speculation in the top-tier cities with tight measures. However, many speculative purchase happened in the second- and third-tier cities, driving up the housing prices again in early 2018. In July 2018, the Political Bureau of the Central Committee of Communist Party of China claimed that "the increase of housing prices must be resolutely curbed". After that, the spatial spillover parameter in Fig. 3 dives deep below the long-term average till the end of 2019.

We may obtain two interesting observations from Fig. 3. First, we categorize these interventions into two types. We find that the *indirect intervention* (such as monetary policy) cannot effectively reduce or increase the spatial spillovers. For example, the benchmark interest rates are increased many times in 2007, but the spatial spillovers are still moving up. Also in 2011, the increase of lending rates and reserve requirement ratio still imposes insignificant effects on the dynamics of spatial spillover parameters. Instead, the *direct intervention* (mainly administrative regulations) are more influential in changing the spatial spillovers. One example is the removal of purchase restrictions in 2014, where we can see a steep upward trend of spatial spillovers thereafter. Another interesting example is the revival of purchase restrictions two years later, which generates the lowest level of spatial spillover parameters.

Second, different from those peaks before 2014, we can identify that the driver of spatial spillovers turns into city-level factors. This is intuitive since roughly after 2014, the regulations on real estate markets are made city-specific. For example, the removals of purchase restrictions are announced by municipal governments one by one, and the soaring prices in some second-tier cities have triggered the revival of purchase restrictions in these cities. Quantitatively, we find that the China's property market experienced a higher spatial spillover, say 0.1068 in the latter period, which is 0.0923 in the first period. We argue that this decentralized phenomenon may be an evidence of growing spillovers between cities and is gradually taking places in shaping the connection of regional real estate markets. Hence we shall investigate what contributes to the connection in the following section.

6. Determinants of spatial spillover effects

The dynamics of spatial spillover parameters so far suggest that the differences in the evolution of regional real estate markets depend on the region-specific inherent heterogeneity. While the spatial spillovers of regional housing prices are well understood, little evidence exists on the determinants of these spatial interactions. In this section, we attempt to examine the possible channels explicitly by running a regression of spatial spillover ($Z_t = (I_n - \rho_t W)^{-1}$) on some proxies for possible channels.

6.1. The basic regression model

To examine the determinants of spatial spillover effects in details, we turn to the possible channels suggested by the literature. Generally speaking, the housing price diffusion ought to be related to spatial speculation, transportation infrastructure, migration, domestic inter-broader trades as well as economic conditions and credit supply in both regions. Since the high frequency macro-data at city level is scarce in China, we merge some yearly variables with monthly housing price data.

To establish a level playing field, we would like to see to what extent the economic activities and financial development could explain the bilateral spillover effects at first. To be more specific, the regression is given by

$$z_{ijmt} = \alpha + \beta X_{im} + \gamma X_{jm} + \lambda_i + \eta_j + \tau_t + \varepsilon_{ijt} \tag{6}$$

where z_{ijmt} is the spillover from Province j to Province i in month m of year t. It is the (i, j)-entry of matrix Z_t since we can view z_{ijmt} as the ith entry of the product of Z_{mt} and an exogenous shock vector e_t, which are all zeros except for the jth element. As a result, z_{ijmt} is the unilateral effect from Province i to j. For any province with more than one city included in our sample, we aggregate the shocks in proportion to cities' GDP at the beginning of year t. We label Province j as "source province" and Province i as "destination province" for the sake of clarity. X_{im} and X_{jm} are control variables in Province i and j, respectively, including the growth of IVA and loan balance. As for regression models at a yearly frequency, we replace IVA by the real growth of provincial gross domestic products. We also include the fixed effects in both spatial and time dimensions to alleviate the concern of any possible unobserved factors.

Table 2 reports the results for the regression of Eq. (6). The dependent variables in columns 1–3 are the unilateral spatial spillover effects from city i (*SRC*) to city j (*DST*) at a monthly frequency, and, in columns 4–6, are aggregated unilateral spatial spillover effects at province-year level. All these six models give similar results that economic condition and financial development have little power in explaining the direct spillover effects. The only significant coefficients are in columns 2 and 3, which suggests that the source province's credit supply will detain the spillovers to destination province. This result is not that robust since the significance disappears in columns 5 and 6 at yearly frequency. Table 2 provides somewhat surprising results to us since the housing prices are closely related to disposal income (measured by GDP) and access to personal mortgage according to conventional hedonic models. Hence, Table 2 calls for further examination of spatial spillover effects of housing prices.

We come up with four possible channels following the framework in Meen (1999). The variables standing for these channels will be added into Eq. (6), the basic regression model.

[6] Seehttps://www.reuters.com/article/us-china-property/fever-spreads-chinas-property-speculators-descend-on-inland-cities-idUSKCN12008K.

Table 2
Regressions of Spillover Effects on Control Variables. This table reports the ordinary least square regression of estimated spatial spillover effects on city-and province-specific variables with fixed effects. The dependent variables in column (1) to (3) are the unilateral spatial spillover effects from city *i* (*SRC*) to city *j* (*DST*), and, in column (4) to (6), aggregated unilateral spatial spillover effects using gross domestic products of cities within a province as weights, which are averaged over the months in the same year. To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq.(5). After that, we set the weight between city *i* and *j* to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,-(ji)}$. The difference between Z_t and $Z_{t,-(ji)}$ is the unilateral spatial spillover effects from city *i* to city *j*. The monthly control variables in column (1) to (3) are the year-on-year growth rate of industrial value added (*IVA*) and standing bank loans (*Loan*) of the given province, while the yearly control variables in column (4) to (6) are the growth of gross domestic products (GDP) and standing bank loans (*Loan*) of the given province. All control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The *t*-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

Dep. Var. Model	(1) Spillovers monthly	(2) Spillovers monthly	(3) Spillovers monthly	(4) Spillovers yearly	(5) Spillovers yearly	(6) Spillovers yearly
IVA SRC	-0.0548		-0.0539			
	(−1.40)		(−1.40)			
IVA DST	-0.0069		-0.0093			
	(−0.28)		(−0.37)			
GDP SRC				0.0099		0.0654
				(0.06)		(0.38)
GDP DST				0.1222		0.1453
				(0.76)		(0.85)
Loan SRC		-0.2513***	-0.2506***		-0.0754	-0.0882
		(−4.06)	(−4.08)		(−0.84)	(−0.92)
Loan DST		-0.0811	-0.0825		-0.0082	-0.0368
		(−1.61)	(−1.62)		(−0.09)	(−0.38)
Constant	-0.0341***	0.0030	0.0107	0.0438*	0.0007***	0.0005**
	(−8.28)	(0.33)	(1.00)	(1.79)	(4.50)	(1.96)
SRC FE	Yes	Yes	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	811,440	811,440	811,440	11,310	11,310	11,310
Adj. R^2	0.016	0.016	0.016	0.113	0.113	0.113

Table 3
Regressions of Spillover Effects on Secondary Housing Market. This table reports the ordinary least square regression of estimated spatial spillover effects on city-specific variables with fixed effects. The dependent variables are the unilateral spatial spillover effects from city *i* (*SRC*) to city *j* (*DST*). To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq. (5). After that, we set the weight between city *i* and *j* to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,-(ji)}$. The difference between Z_t and $Z_{t,-(ji)}$ is the unilateral spatial spillover effects from city *i* to city *j*. The main explanatory variable is the growth of secondary housing price indices of a given city. The definitions of control variables are referred to the note of Table 2. All explanatory and control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The *t*-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

Dep. Var. Model	(1) Spillovers monthly	(2) Spillovers monthly	(3) Spillovers monthly	(4) Spillovers monthly
SHM SRC	0.0031	0.0046	-0.0075	-0.0059
	(0.11)	(0.17)	(−0.28)	(−0.22)
SHM DST	0.0904***	0.0903***	0.0950***	0.0949***
	(3.38)	(3.37)	(3.53)	(3.53)
IVA SRC		-0.0245		-0.0238
		(−1.02)		(−0.99)
IVA DST		0.0086		0.0066
		(0.36)		(0.28)
Loan SRC			-0.1432***	-0.1430***
			(−3.62)	(−3.61)
Loan DST			0.0534	0.0525
			(1.35)	(1.33)
Constant	-0.0328***	-0.0310***	-0.0204***	-0.0184**
	(−29.28)	(−8.64)	(−2.95)	(−2.36)
SRC FE	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	753,480	753,480	753,480	753,480
Adj. R^2	0.018	0.018	0.018	0.018

6.2. Channel 1: spatial speculation

The first channel is spatial speculation. As is argued in Meen (1999), if housing markets were efficient, the returns would be indifferent between two regions. However, the real estate market is known to be less liquid than stock market (Rosenthal, 1999), which makes spatial speculation profitable (Case & Shiller, 1990). Kou, Peng & Zhong (2018) find that the spatial spillovers act as a significant factor in explaining the returns in real estate markets of United States. Hence, speculators may try to chase for the arbitrage opportunities. The second-hand housing markets is also where speculators could sell the house in exchange for cash. Recently, Deng, Li, Yu & Zhang (2021) find that the house purchase restrictions will decrease the volumes of city's housing market, which is a sudden reduction of the housing market liquidity. In response to this reduction, speculators would move to the unregulated cities to trade houses. Intuitively, speculators will favor the high returns of properties in the second-hand housing markets, which predicts a positive relationship between spatial spillovers and the changes in price of second-hand housing market in destination city.

The regression analysis is reported in Table 3. The monthly series of second-hand housing prices of the 70 cities in our sample are also collected from NBSC. We only include second-hand housing prices (SHM) in column 1. It shows that the spillover effects are significantly correlated with the growth of second-hand housing prices in destination city, but not with that in source city. To gauge the economic significance, one standard deviation (0.049) increase in the second-hand housing prices of destination will pull up the monthly unilateral spatial spillover effects by 0.0044, which is around 4.57% of the standard deviation. This result coincides with our intuition that the development of secondary housing market would attract speculators from other cities. Besides, the adjusted R-squares are marginally increased to 1.8%. We also augment the basic regression models by the growth of second-hand housing prices in column 2–4. The magnitudes and significance of the coefficients are qualitatively the same. Altogether these results suggest the existence of speculation channel, that is, the higher growth of second-hand markets the destination city experiences, the stronger spillover effects from the source city are.

6.3. Channel 2: transportation infrastructure

The second channel is transportation infrastructure, which is captured by a city's access to the national high-speed railway (HSR) system of China. As is suggested by Baum-Snow (2007) and Baum-Snow et al. (2017), the access to transportation networks would displace central city population to suburbs. Recent studies have established the role of HSR in carrying passengers with lower costs and facilitating job-seeking for commuters in other cities (Lin, 2017). If there were no barrier to factor mobility, the housing prices would be gradually converged between central and peripheral cities as the commuting time and cost drop (Banerjee, Duflo, & Qian, 2020).

We complement and extend Lin (2017)'s HSR lines dataset by hand-collecting related information from Internet.[7] For each month within our sample period, a dummy variable is used to indicate whether a city have access to the HSR network of China in that month. Table 4 reports the corresponding regression results when we include this variable. To make the coefficients of HSR openness more readable, we multiply them by a factor of 100. It is observed from column 1 of Table 4 that connecting to the HSR network in the source city or destination city only decreases the spillover effects. We believe that this observation is meaningful since its sign can be hardly explained by other alternative theories such as some unobserved local economic conditions. Suppose that the source city has already connected to the HSR network, but the destination city does not, then the only plausible reason for this negative marginal effect is that the spillover effects of housing price in the source city are re-directed to other destination cities. This is reinforced by the positive sign of the interaction term of source and destination city (*HSR both* in Table 4). Once both cities have opened a HSR station, the spillover effects will be stronger than the case where they are isolated from HSR network. Roughly speaking, both cities connected to the HSR network will increase the direct spillover effects by 0.0214% (=0.0454–0.0240%) in the source city, and by 0.0248% in the destination city.[8] Adding other control variables in column 2–4 does not change our main results. This evidence is consistent with the hypothesis that housing prices in different submarkets also interact with decisions to commute.

6.4. Channel 3: inter-provincial trades

The third and fourth channels are also related to interactions between different regions. However, since the available data is at yearly frequency, we have to merge the city-month panel of direct spillover effectswith some provincial and yearly proxy variables accordingly. In Table 5 we consider the inter-provincial trades between the source and destination province. Aizenman & Jinjarak (2009) find that the appreciation of real estate prices are predicted in a large proportion by the rise of lagged current account deficits (basically the net exports). Given the fact that current account deficits are correlated with capital inflows, one of the possible explanations is that inter-boarder trades may attract a large chunk of capital inflows. Badarinza & Ramadorai (2018) further point out that the injection of foreign capital into city like London will long-lastingly drive up the local real estate prices. Hence the economic links between two regions are supposed to be associated with spatial spillover effects too. As is suggested by Tombe & Zhu (2019), the secret of China's success in economic development can be accrued to the reforms of reducing the cost of internal trade and migration. In particular, this reduction accounts for aggregate labor productivity more than 3 times than that in the external trade costs, which

[7] We download the map of HSR lines from a famous social media user on *Weibo*, named *ChinaRailwayFan* (see weibo.com/tielumi). Then we search for the opening dates of each HSR line via multiple sources, such as Wikipedia, some official (local government news) and nonofficial (news.gaotie.cn) websites of China's HSR.

[8] This is around 2.20% of the standard deviation of dependent variables.

Table 4

Regressions of Spillover Effects on the Openings of High-Speed Railway. This table reports the ordinary least square regression of estimated spatial spillover effects on city-specific variables with fixed effects. The dependent variables are the unilateral spatial spillover effects from city *i* (*SRC*) to city *j* (*DST*). To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq. (5). After that, we set the weight between city *i* and *j* to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,\,-(ji)}$. The difference between Z_t and $Z_{t,\,-(ji)}$ is the unilateral spatial spillover effects from city *i* to city *j*. The main explanatory variable is a dummy variable indicating the opening of a high-speed railway (HSR) station in a given city. To make the coefficients of HSR openness more readable, we multiply them by a factor of 100. We also include an interaction term of source and destination city. The definitions of control variables are referred to the note of Table 2. All explanatory and control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The *t*-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

Dep. Var. Model	(1) Spillovers monthly	(2) Spillovers monthly	(3) Spillovers monthly	(4) Spillovers monthly
HSR SRC (%)	-0.0240***	-0.0239*	-0.0254***	-0.0253**
	(−5.06)	(−1.94)	(−5.35)	(−2.11)
HSR DST (%)	-0.0206***	-0.0206**	-0.0206***	-0.0205**
	(−4.36)	(−2.16)	(−4.34)	(−2.16)
HSR Both (%)	0.0454***	0.0452***	0.0445***	0.0443**
	(8.68)	(2.66)	(8.51)	(2.62)
IVA SRC		-0.0245		-0.0238
		(−1.02)		(−0.99)
IVA DST		0.0086		0.0066
		(0.36)		(0.28)
Loan SRC			-0.1432***	-0.1430***
			(−3.62)	(−3.61)
Loan DST			0.0534	0.0525
			(1.35)	(1.33)
Constant	-0.0328***	-0.0310***	-0.0204***	-0.0184**
	(−29.28)	(−8.64)	(−2.95)	(−2.36)
SRC FE	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	811,440	811,440	811,440	811,440
Adj. R^2	0.019	0.019	0.019	0.019

Table 5

Regressions of Spillover Effects on the Inter-Provincial Trades. This table reports the ordinary least square regression of estimated spatial spillover effects on city-specific variables with fixed effects. The dependent variables are the unilateral spatial spillover effects from city *i* (*SRC*) to city *j* (*DST*). To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq.(5). After that, we set the weight between city *i* and *j* to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,\,-(ji)}$. The difference between Z_t and $Z_{t,\,-(ji)}$ is the unilateral spatial spillover effects from city *i* to city *j*. The main explanatory variable is the proportion of the amount of cargos (in *yuan*) shipped by trains from province *l* to *k* over the total imported cargos of province *k*. The definitions of control variables are referred to the note of Table 2. All explanatory and control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The *t*-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

Dep. Var. Model	(1) Spillovers monthly	(2) Spillovers monthly	(3) Spillovers monthly	(4) Spillovers monthly
Trade	0.0147***	0.0147***	0.0147***	0.0147***
	(25.35)	(3.57)	(25.32)	(3.56)
IVA SRC		-0.0553		-0.0548
		(−1.42)		(−1.43)
IVA DST		-0.0038		-0.006
		(−0.15)		(−0.23)
Loan SRC			-0.2582***	-0.2574***
			(−7.17)	(−4.10)
Loan DST			-0.1150***	-0.1165**
			(−3.19)	(−2.36)
Constant	-0.0650***	-0.0579***	-0.0150**	-0.0076
	(−53.36)	(−10.18)	(−2.37)	(−0.65)
SRC FE	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	788,928	788,928	788,928	788,928
Adj. R^2	0.019	0.019	0.019	0.019

shows the power of intensive internal trades in reallocating resource, including real estate assets.

To test whether this is true, we use the proportion of the amount of cargos (in *yuan*) shipped by trains from "destination" to "source" province. This seemingly weird notation is designed to capture the capital inflows, the main driver of local real estate prices in source province in the reverse direction of cargo shipping, from source to destination province. The data is retrieved from China Transportation and Communications Yearbook, covering the inter-provincial cargo shipping from 2005 to 2016.

Table 5 shows the regression results for including the inter-provincial trades. It is clearly shown that the trade between two cities will enhance the strength of direct spillover effects of housing prices. In general, one standard deviation increase of bilateral trades (1.9305) results in a 0.0284 increase in unilateral spatial spillovers, which is 2.92% of its standard deviation. The estimates for this marginal effect remain stable across different specifications in column 2–4 of Table 5. As a result, the overall results suggest that the capital inflows also have an impact on housing prices diffusion.

6.5. Channel 4: inter-provincial migration

The last but not the least channel is the migration between two regions. In the famous Rosen-Roback hedonic framework, the relative difference of housing prices across regions would gradually converge to the spatial equilibrium induced by migration across cities (Roback, 1982; Rosen, 1974). Based on this theory, many economic studies reach a consensus that migration is accompanied by new demand for housing markets, but they may disagree concerning the effect of housing prices. On one hand, studies in labor economics advocate a negative link between immigration and housing prices. For example, Saiz (2003) argues that immigration in Miami is associated with the increase in local rents, but the relative housing prices collapse because the immigrants are mainly unskilled workers from abroad. Sá (2014) attributes this negative effects to the mobility response of the native population. On the other hand, housing market literature documents that housing prices are driven up by immigration. Ley & Tutchener (2001) find that the globalization of Canadian cities attract more immigrations and experience higher housing prices. Mussa, Nwaogu & Pozo (2017) recognize that the immigration inflows will increase the rents and housing prices in US, along with huge spillover effects to neighboring areas. In sum, the immigration would be related to the spatial spillover of housing prices.

The restriction of inter-provincial migration in China (the "*Hukou*" system) is weakened since 1980s, which makes the connection among regional submarkets tighter (Gong et al., 2016). We use the data retrieved from China Migrants Dynamic Survey[9] to construct the inter-provincial migration measure from 2010 to 2015. The migration ratio is defined by the proportion of migration from source to destination province over all immigrations into the destination. We include the immigration ratio in the basic regression model, whose results are shown in Table 6.

Consistent with the previous literature, the migration between source city and destination city will significantly amplify the direct spillover effects of housing prices. Note that our dependent variable indicates the unilateral spillovers from one city to another. Therefore, we use immigration ratio instead of net migration ratio as the proxy variable. The migration channel turns out to be an important carrier of spatial spillovers since one standard deviation increase in immigration ratio (2.2013) causes an increase in around 1.68% of the standard deviation of direct spillover effects based on the estimates of column 1. This result is not undermined by including control variables into column 2–4. Therefore, we believe that the migration would be an underlying channel for spatial spillover effects of regional real estate markets.

6.6. Relative strength of determinants

Although we have examined four possible channels above, they are not mutually exclusive at all. For example, the development of the HSR system will facilitate the inter-provincial migration. We cannot rule out the possibility that the effects of one or more channels would be absorbed by the remaining channels. Hence, we run a horse race of these four determinants. We include all four proxies into the basic regression model simultaneously.

Two results are observed from column 1 of Table 7. One is the coefficients of inter-provincial migration and trade become smaller, as well as the significant decrease in the coefficient of the returns in secondary housing markets. Compared with the stand-alone regressions, the effects of spatial speculation are weakened a lot. The other is the inter-provincial trade is the strongest determinant among others, followed by migration. Similarly, the economic significance is also considerable. The migration would account for 1.25% of the *monthly* standard deviation of spillover effects, while trade is doubled, i.e., 2.58%. Both are stronger than any other remaining explanatory variables, which may extend the results of Tombe & Zhu (2019) that internal trades and migration would not only affect labor productivity but also the spread of shocks to real estate markets.

7. Dynamic analysis in three coastal regions

The flexibility of the time-varying model provides us a tool to monitor the changes in regional housing markets. To show this, we choose three coastal regions in China, namely, Beijing-Tianjin-Hebei (BTH), Pearl-River-Delta (PRD), and Yangtzi-River-Delta (YRD).[10] As is mentioned in the introduction, these regions contain all top-tier cities in China, attracting many people to work

[9] See http://www.chinaldrk.org.cn/wjw/#/home.

[10] Beijing, Tianjin, Shijiazhuang, Tangshan and Qinhuangdao are located in BTH, while Guangzhou, Shenzhen and Huizhou in PRD. The YRD contains 12 cities, including Shanghai, Nanjing, Wuxi, Yangzhou, Xuzhou, Hefei, Bengbu, Anqing, Hangzhou, Ningbo, Wenzhou and Jinhua.

Table 6
Regressions of Spillover Effects on the Inter-Provincial Immigrations. This table reports the ordinary least square regression of estimated spatial spillover effects on city-and province-specific variables with fixed effects. The dependent variables are the unilateral spatial spillover effects from city i (*SRC*) to city j (*DST*). To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq.(5). After that, we set the weight between city i and j to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,-(ji)}$. The difference between Z_t and $Z_{t,-(ji)}$ is the unilateral spatial spillover effects from city i of province k (*SRC*) to city j of province l (*DST*). The main explanatory variable is the proportion of immigration from province k to l over immigration into province l. The definitions of control variables are referred to the note of Table 2. All explanatory and control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The t-statistics are reported in parenthesis. The symbol *, **, and *** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	Spillovers	Spillovers	Spillovers	Spillovers
Model	monthly	monthly	monthly	monthly
Migration	0.0074***	0.0074***	0.0073***	0.0073***
	(16.56)	(16.56)	(16.55)	(16.55)
IVA SRC		-0.0346		-0.0355
		(−1.32)		(−1.35)
IVA DST		-0.0363		-0.0391
		(−1.38)		(−1.49)
Loan SRC			-0.2557***	-0.2566***
			(−6.21)	(−6.23)
Loan DST			-0.1833***	-0.1840***
			(−4.45)	(−4.46)
Constant	-0.0652***	-0.0555***	-0.0039	0.0065
	(−43.78)	(−11.65)	(−0.52)	(0.74)
SRC FE	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	619,596	619,596	619,596	619,596
Adj. R^2	0.011	0.011	0.011	0.011

Table 7
Regressions of Spillover Effects on the Determinants. This table reports the ordinary least square regression of estimated spatial spillover effects on city-and province-specific variables with fixed effects. The dependent variables are the unilateral spatial spillover effects from city i (*SRC*) to city j (*DST*). To estimate the unilateral spillover effects, we first retrieve the time series of $Z_t = (I_n - \rho_t W)^{-1}$ from Eq.(5). After that, we set the weight between city i and j to zero and re-estimate the model without other changes, which leads to the "Leave-One-Out" spatial spillover effects $Z_{t,-(ji)}$. The difference between Z_t and $Z_{t,-(ji)}$ is the unilateral spatial spillover effects from city i of province k (*SRC*) to city j of province l (*DST*). The main explanatory variables include migration proportion, inter-provincial trades, access to the high-speed railway network, and the annual growth of second-hand housing prices (see Table 3 to Table 6). The definitions of other control variables are referred to the note of Table 2. All explanatory and control variables are deflated by CPI, season-adjusted, and winsorised at 1% and 99%. The t-statistics are reported in parenthesis. The symbol * , * *, and * ** stands for the point estimates are significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	Spillovers	Spillovers	Spillovers	Spillovers
Model	monthly	monthly	monthly	monthly
Migration	0.0055***	0.0052***	0.0052***	0.0052***
	(6.92)	(6.90)	(6.90)	(6.91)
Trade	0.0130***	0.0130***	0.0130***	0.0130***
	(16.95)	(16.95)	(16.94)	(16.94)
HSR both (%)	0.0105***	0.0105***	0.0104***	0.0104***
	(7.44)	(7.43)	(7.40)	(7.38)
SHM SRC	-0.0002	-0.0002	-0.0002	-0.0002
	(−0.49)	(−0.50)	(−0.73)	(−0.74)
SHM DST	0.0017***	0.0018***	0.0017***	0.0017***
	(5.61)	(5.64)	(5.46)	(5.50)
Economics	No	Yes	No	Yes
Finance	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes
SRC FE	Yes	Yes	Yes	Yes
DST FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	563,244	563,244	563,244	563,244
Adj. R^2	0.010	0.010	0.010	0.010

there. In addition, their regional real estate markets are relatively more integrated than other regions.

7.1. The spatial spillover effects

The most outstanding feature of these three coastal regions is that they have different economic connection types: BTH has a structure of core-periphery connection, PRD is affected by two neck-to-neck top-tier cities, and YRD is more decentralized than other regions. We would wonder if our model may capture these inherent heterogeneous structures. To do so, the weight matrix is re-normalized in these subsample, respectively.

As what we have done in Fig. 3, the broken lines of Fig. 4 are long-term averages of regional spatial spillover parameters, which are 0.1828, 0.1567 and 0.1500 from the top figure to the bottom. We also plot the national dynamics of spatial spillover parameters on the same figure for comparison. Basically speaking, the long-term averages are above the national level, implying that these coastal regions are more spatially interdependent than other regions.

From Fig. 4, we may clearly see how regional spatial spillovers differentiate with each other. First, we can observe that the troughs and peaks in these curves do not coincide with each other in most of the time window except the year of 2016. Consistent with our benchmark results, the spatial spillover parameters rally rapidly in 2016. Then they all decrease at the same time and remain stable around long-term average from then on. This may be a strong evidence suggesting that China's housing prices are largely affected by central governmental interventions such as the steps to "curb excessive bubbles" in the property sector. However, the responses may show different patterns from region to region, at least, in terms of the dynamics of spatial spillovers.

Second, we observe that not all regions are assembling the movements of national spatial spillover parameters over time. Not surprisingly, the BTH region, where the capital city of China is located, exhibits strong correlation with the national spatial spillover parameters. Since the nation-wide policy is made from the central government in Beijing, the spillover effects of BTH region may be largely overlapped with the national one. The correlation between the dynamics of BTH region and that of the whole nation is around 0.8, which is larger than the other two regions. We would attribute this to the core-periphery structure of regional real estate markets in BTH region.

In contrast, we can see that the dynamics in PRD is the least volatile, ranging from 0.1056 to 0.2404. This could be attributed to the presence of two top-tier cities (Guangzhou and Shenzhen). Note that in February 2019, the central government issued a guideline for developing the "Guangdong-Hong Kong-Macau Greater Bay Area". This guideline spurred the regional spillovers of housing prices around the Pearl-River Delta, which leads to a peak at the beginning of 2019. This is a regional-specific event, which has insignificant effects on the other two regions.

As for YRD, it has an obviously different pattern from that of national real estate market. At the end of 2012, the decrease in housing prices of Hangzhou gradually spreads to Nanjing first, then Shanghai. Some buyers of the houses under construction in those cities were not satisfied with the drop of housing prices and waged a petition for refunds. This event to some extent implies the integration of regional property markets within YRD. Another remarkable point is that three of the aforementioned "Four Housing Tigers" are located in YRD region. The revival of purchase restrictions made the speculators fail to sell what they are holding. Hence, the housing prices of those cities dropped a lot compared with other cities, leading to negative spatial spillover effects. However, we may not witness the same results in other regions during the same period.

7.2. Spatial and temporal impulse responses

The qualitative analysis based on the estimated spatial spillover parameters sheds lights on the role that regulations play in China's property markets. However, we are more interested in how the market would respond to an exogenous shock (such as tightened policy in a certain city) given the presence of spatial connectedness. In other words, we investigate how the network of regional real estate markets would spread a shock in one city to another.

First, we consider the cross-sectional diffusion to other cities given one unit of positive exogenous shock. Theoretically speaking, the total effect is given by $Z_t = (I_n - \rho_t W)^{-1}$, which could be decomposed into two components. One is the direct impact of exogenous shock, and the other is also known as "echo effect" or "ripple effect" from other cities. That is why we may expect a non-linear response of exogenous shock. Generally speaking, the direct effect is the trace of matrix Z_t while the ripple effect is the sum of non-diagonal elements of matrix Z_t.

Fig. 5 reveals how the spatial spillovers evolve with respect to the increasing spatial lags. Beijing, as the capital city of China, is selected to be an illustrative example to exhibit such an effect. We also choose the particular spatial spillover parameter (ρ_t) in August 2014 when it reaches the maximum.

As is expected, the spatial spillovers converge quickly to their steady states, showing that the spillover effects decay to almost zero within 3 spatial lags. Another observation is that Beijing may exert greater impact on its surrounding cities than its remote cities. Fig. 5 also shows that spatial spillover effects on the cities within BTH are around 0.019% (Qinhuangdao) to 0.024% (Tianjin). The spatial spillover effects account for 10% of their own average housing price growth according to Table 1, which means that shocks affecting Beijing's housing prices would also affect those of the cities nearby. The spillovers are not that significant in the cities outside BTH. In order to evaluate the importance of ripple effect, we find that the average direct effect is 0.0144 and the average ripple effect is around 0.0078. Therefore, the average ripple effect takes up to 35.07% of the average total effect, or about one half of the average direct effect.

In the remaining of this subsection, we consider the time profile of shocks both over time and across regions. As is discussed in the subsection of the benchmark results, the regulations on real estate markets have been city-specific since the August of 2014, which is also the peak of our estimated spatial spillover parameters. Besides, there were two similar events that happened just before and after

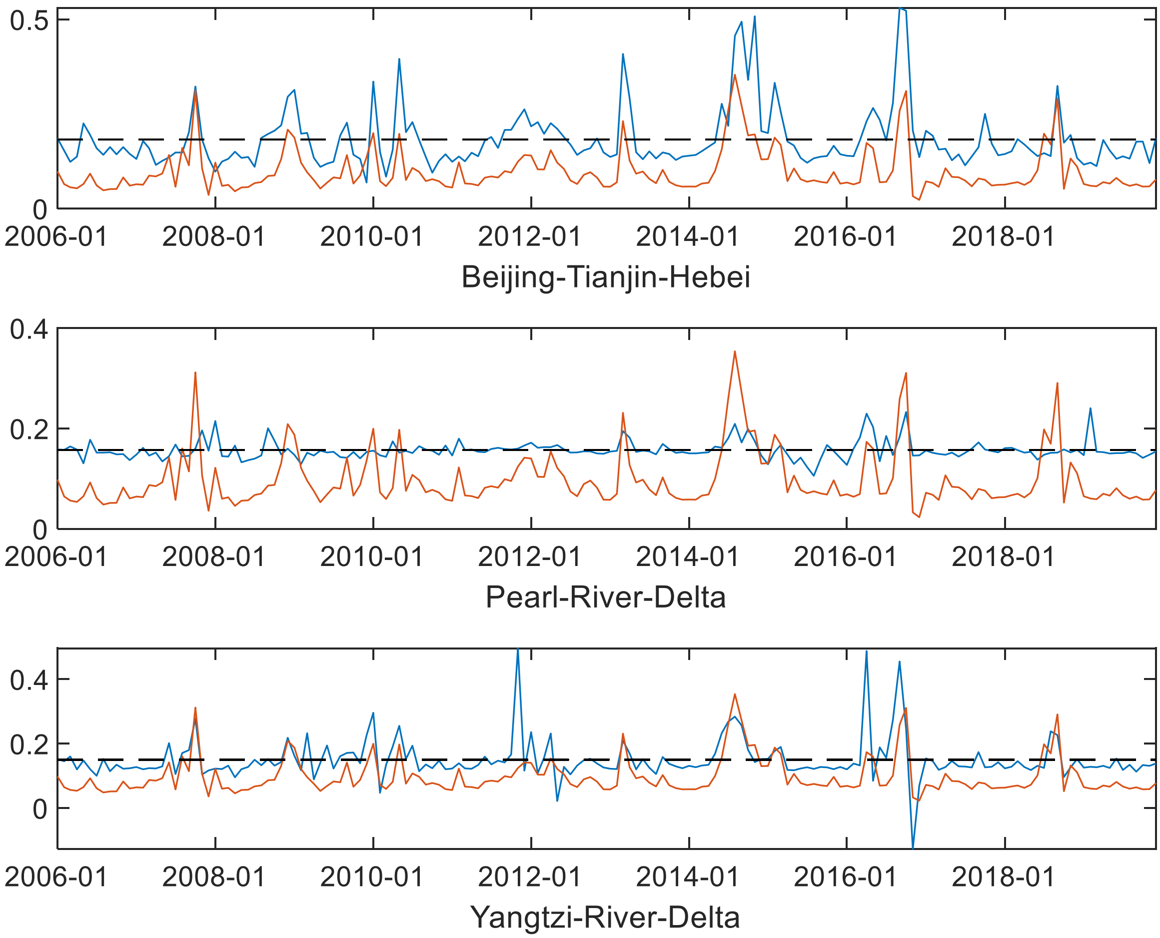

Fig. 4. Spatial Spillover Parameters (ρ_t) Estimated from Eq.(5) under the Assumption of Student's t distribution, for Different Regions. The blue solid line is the estimated monthly value of ρ_t. The orange solid line is the national spatial spillover parameters retrieved from Fig. 2. The dashed line is the long-term average of ρ_t over the sample horizon.

2014. In May of 2010, the State Council first showed its determination to curb the nation-wide uprising housing prices. In October of 2018, the Political Bureau of the Central Committee of Communist Party of China claimed that "the increase of housing prices must be resolutely curbed". Both of these two events conveyed similar signals to the real estate market, but would they be different given the occurrence of city-specific regulations? Given the time-varying property of spatial spillover parameters, we may evaluate such effects with impulse response analysis. In view of the observation that the spatial effect outside the region is weak, we restrict our attention on the three coastal regions (BTH, YRD, and PRD) defined above. In Fig. 6 to Fig. 8, we select three different months mentioned above to illustrate its influences, namely, May 2010, August 2014, and October 2018.

In Fig. 6, we illustrate the cumulative effect of one positive unit shock to Beijing on cities within BTH region. There are three impulse responses for each city, where the dashed, solid, and star-dashed lines represent the spatial spillover parameters of August 2014, May 2010, and October 2018, respectively. We observe some interesting results in both spatial and temporal dimensions.

As for the spatial one, housing prices within the same region exhibit different patterns across cities. The evidence of how positive shocks to Beijing's housing price growth gradually spill over to other cities is both economically and statistically significant, roughly ranging from 0.14 to 0.68 unit of standard deviation. This is consistent with the fact that Beijing is the dominant city within BTH region. In addition, we find the effects of the shocks on surrounding cities are diminishing along with the geographic distance, which is consistent with Fig. 5. For example, the response of Tianjin, a city 162 kilometers away from Beijing, is twice stronger than that of Shijiazhuang, which is 239 kilometers away. These results suggest that spatial spillover effects eventually converge across all surrounding cities. However, not all cities will react positively to the shocks. We observe that the growth of housing prices in Tangshan, unlike the other three cities, adjusts negatively at the first place to the shocks to Beijing and it takes longer time to bounce back. It probably suggests that the uprising housing prices may drive residents in Beijing to other surrounding cities, except Tangshan. In the long run, the ripple effect may gradually contribute to the recovery of housing prices in Tangshan.

The pattern in the temporal dimension is much more similar across cities. We place the different responses together to see how a shock will affect the growths of housing prices at different time. At first glance, we observe that the impulse responses basically mimic

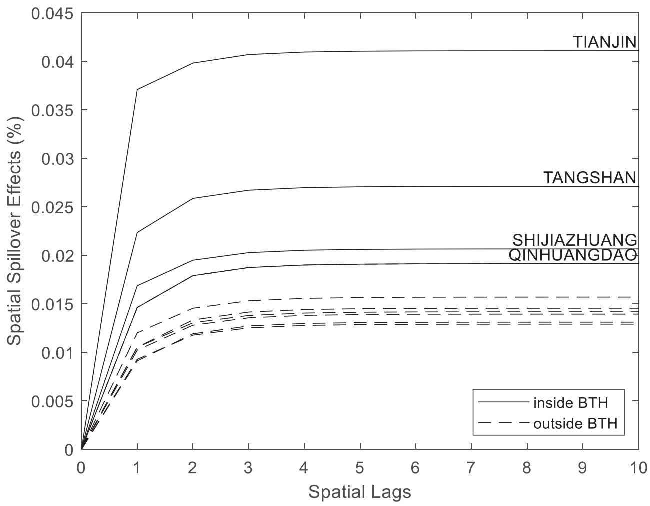

Fig. 5. The Spatial Spillover Effects of One Unit Positive Shock on Beijing's House Price on Other Cities. The evolution of spatial spillover effects is based on the spatial spillover parameter in August 2014 ($\rho_t = 0.3536$). We select the 10 cities based on spillover effects ranking from top to bottom. The solid line represents cities inside the Beijing-Tianjin-Hebei (BTH) region with their names labeled above corresponding lines, while the dashed one represents cities outside the region.

one another within the same subplot. It is true since all other factors are kept constant except the spatial spillover parameters. Hence, the relative position of impulse responses may reflect the accumulative effects of shocks with the same size. The dashed lines in all subplots show that the removal of purchase restrictions in August 2014 imposed remarkably strong effects on spatial spillovers. This is consistent with the dynamics in Figs. 2 and 4 where the spatial spillovers reached the peak in August 2014. Hence, the dashed lines eventually reach higher steady states in terms of magnitude.

On the other hand, similar policies before and after the announcement of city-specific regulation result in different outcomes. As is mentioned above, this announcement entitles local government to set city-specific regulations. Hence, the local government is more capable of adjusting to the shock. In both May of 2010 and October of 2018, the central government released a relatively strong signal to curb the uprising of housing prices. However, we find that the final effects on returns are quite different. Generally speaking, one unit (standard deviation) of positive shock to Beijing's housing prices after the announcement would increase the growth less than before. This result may suggest that city-specific regulations help adjust to the shocks from surrounding cities and hence level down the corresponding systemic risk.

We also replicate the similar analyzes for PRD and YRD region. The dynamics of GIRFs are shown in Figs. 7 and 8. For the purpose of comparability, we consider one positive unit of shocks to housing prices of these top-tier cities (i.e., Shenzhen, Guangzhou and Shanghai), respectively. Just as what we have observed in Fig. 6, the accumulated responses to the shock is the strongest in August 2014, while the city-specific regulations may result in a lower level of accumulated responses. Nevertheless, we still find some different spatial pattern from that of BTH region.

The top three subplots in Fig. 7 relate to Guangzhou city, while the bottom three concern Shenzhen city. Though the dynamics are qualitatively similar to Fig. 6, we notice some interesting results specific to the PRD region. The effect of shocks to Guangzhou on Shenzhen is almost the same as that of the shocks to Shenzhen on Guangzhou. Put it in another word, Guangzhou (or Shenzhen) yields similar influence on the other city's housing prices. This may suggest that the neck-and-neck pattern between Guangzhou and Shenzhen. In addition, shocks to both cities will not immediately change the housing prices of Huizhou, a less-developed city to the northeast of Shenzhen, in a significant way. Instead, it takes considerably longer time for Huizhou to adjust to the shocks.

Fig. 8 reinforces our understanding on the time profile of shocks across cities scattered in a wider range. A positive price shock to Shanghai, as one of the financial center located in the southern riverbank of Yangtze River, would impact little on the second-tier cities in the far north of the river, say, Bengbu, Anqing, and Xuzhou. However, the responses of capital cities (Hefei, Nanjing and Hangzhou) of given provinces will rise to a general higher level than others, even though they share the same distance from Shanghai. For example, Hefei is around 394 kilometers away from Shanghai, while this number is 419 for Anqing city and 417 for Bengbu city. It is clear that the immediate effects on Anqing and Bengbu are negligible, but those on Hefei are significant. What is more, its response is still as one and a half large as that on Wuxi city (108 kilometers). This observation is consistent with the diversified pattern of YRD region.

8. Conclusions

In this paper, we consider the spatial and temporal diffusion of housing prices in China from 2006 to 2019. We extend the static spatial model to a time-varying one, where the conventional static spatial spillover parameter could be viewed as the long term average. With the help of GAS model, we first estimate the dynamics of the time-varying spatial spillover parameters. We find that the

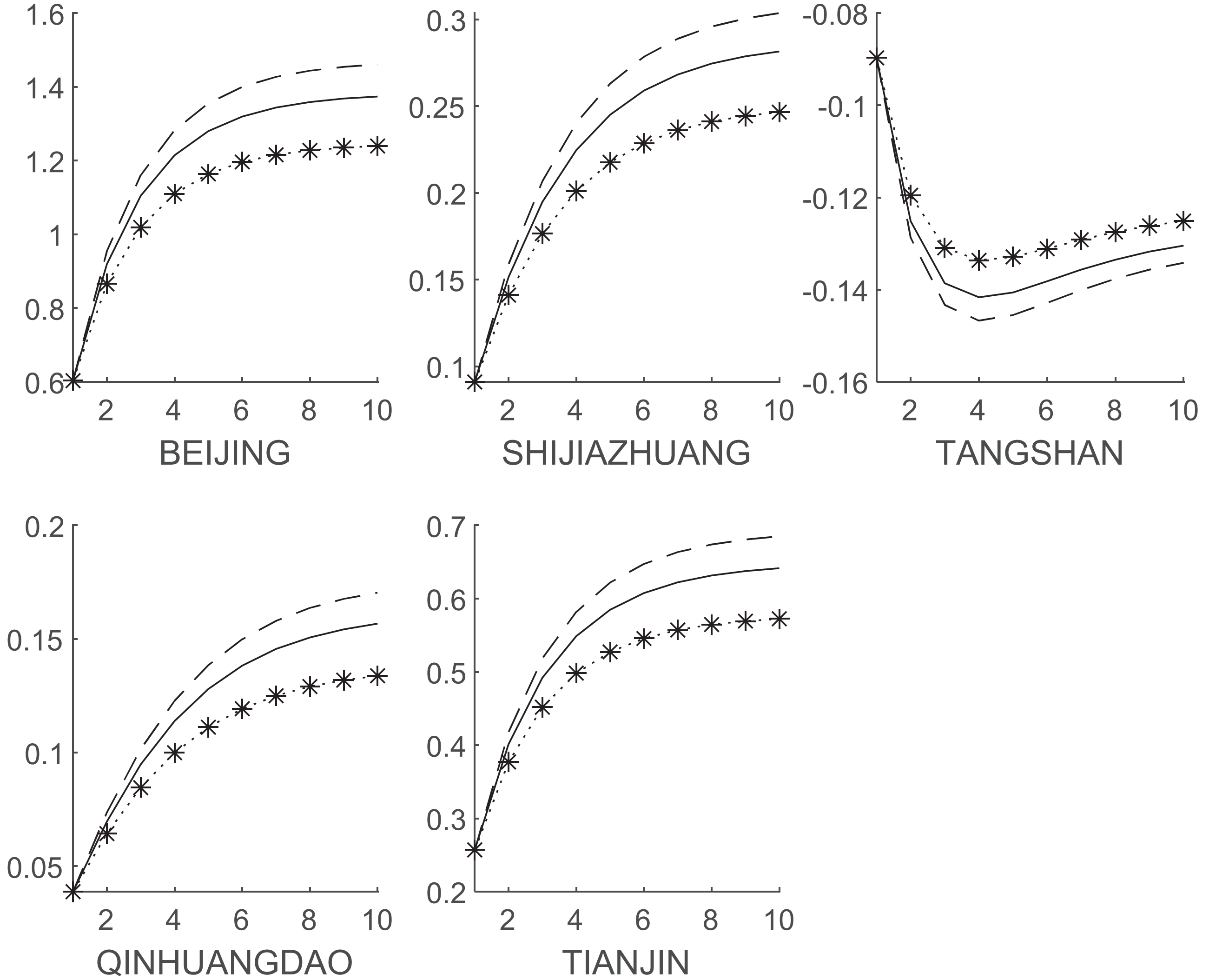

Fig. 6. Generalized Impulse Response Functions for Cities in BTH Region of One Standard Error Shock to Beijing House Prices. The evolution of accumulated GIRF is based on the spatial spillover parameter evaluated in May 2010 (solid), August 2014 (dashed), and October 2018 (starred dashed). We select four cities, Qinhuangdao, Shijiazhuang, Tangshan and Tianjin within BTH region.

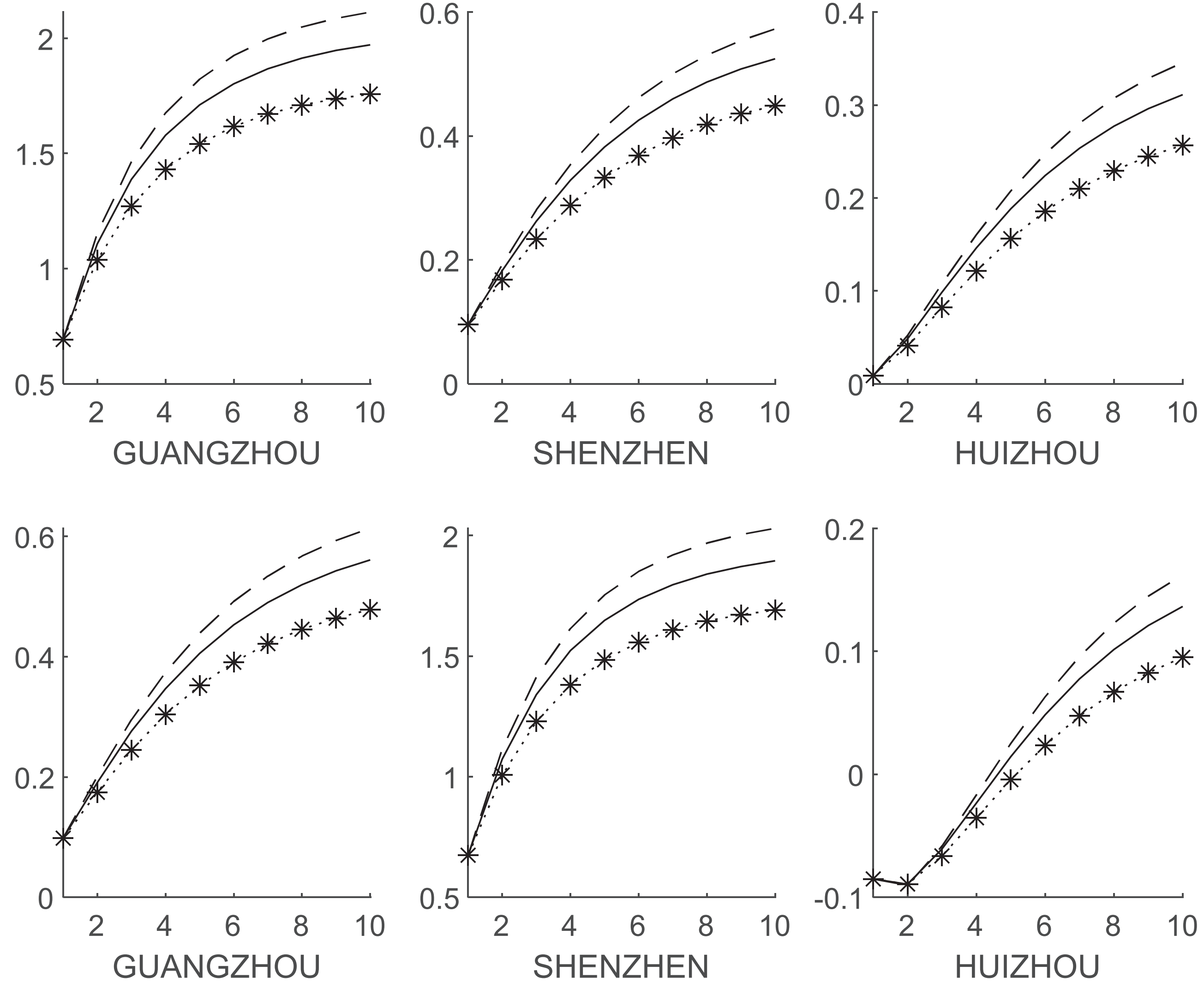

Fig. 7. Generalized Impulse Response Functions for Cities in PRD Region of One Standard Error Shock to Guangzhou (Top) and Shenzhen (Bottom) House Prices. The evolution of accumulated GIRF is based on the spatial spillover parameter evaluated in May 2010 (solid), August 2014 (dashed), and October 2018 (starred dashed). We select Huizhou within PRD region.

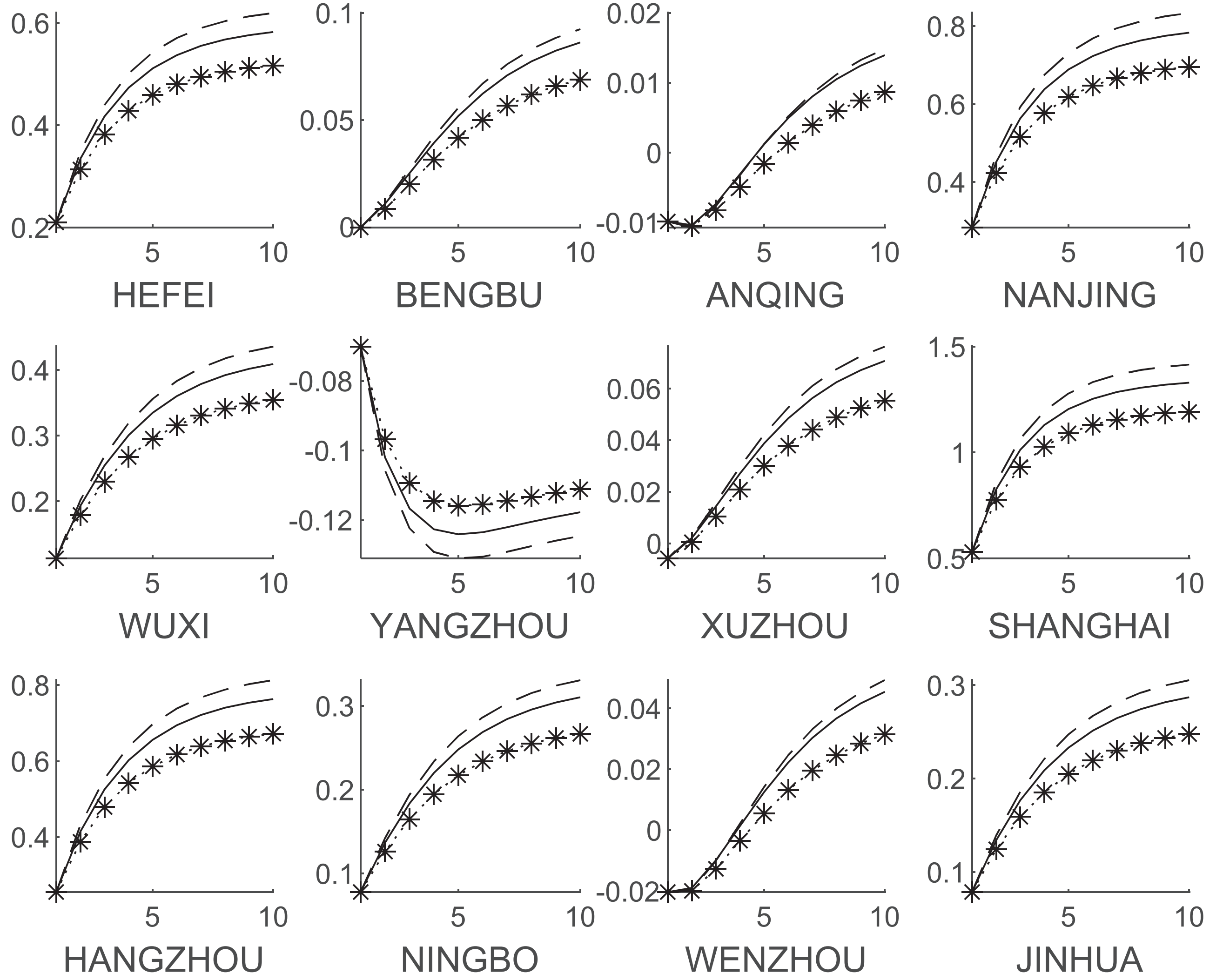

Fig. 8. Generalized Impulse Response Functions for Cities in YRD Region of One Standard Error Shock to Shanghai House Prices. The evolution of accumulated GIRF is based on the spatial spillover parameter evaluated in May 2010 (solid), August 2014 (dashed), and October 2018 (starred dashed). We select Hefei, Bengbu, Anqing, Nanjing, Wuxi, Yangzhou, Xuzhou, Hangzhou, Ningbo, Wenzhou, and Jinhua within YRD region.

troughs and peaks of its evolution well capture the underlying changes in national property markets, and the network structure remains stable over the whole sample period except when some interventions are announced by the government. An investigation of three coastal regions documents the evidence of spatial diffusion from the top-tier cities to the surrounding cities.

In addition, we also document substantial heterogeneity in temporal diffusion patterns of housing prices across regions. For instance, when we shock Beijing, the immediate effects on cities in BTH region are significantly large and gradually die away. However, when we shock Guangzhou or Shenzhen, the effects on the other cities are quite symmetric in terms of magnitude. In order to consider the determinants of the spatial spillover effects, we first run a regression on two proxies for economic condition and credit supply. We find that the real growth of GDP and credit supply have little power in explaining the spatial spillover dynamics across regions. Besides, we also formally test four possible channels affecting the bilateral spillover effects, including spatial speculation, transportation infrastructure, inter-provincial trade and migration, the last two of which are the strongest determinants.

The findings of our time-varying model contribute to the current literature and have important policy implication. First, this paper offers a framework to explore the dynamics of systemic risks inherited in real estate markets. As is indicated by the dynamics of spatial spillover parameters, we find that the regulations on housing prices change not only the growth of housing prices in individual cities, but also the spatial spillovers among them. In addition, we also find that the spatial spillovers across different regions do not mimic each other.

These results may also highlight the importance of preventing irrational speculation. The dynamic evolution of spatial spillover effects clearly shows that the speculation will amplify the effects of regulations on the housing price levels in surrounding cities. Though our results seem to justify the principle of interventions at the city's discretion recently, the presence of spatial spillovers may deteriorate the surrounding cities' real estate markets. To cool down the overheated real estate markets, we need to ask for a higher-level and effective coordination across borders.

Finally, we attempt to identify the possible determinants of the spatial spillover effects from housing price increase in other regions. The economic condition and financial development cannot explain the bilateral spatial spillover. This result should be interpreted cautiously. It does not challenge the traditional hedonic housing prices model, which concerns the price level within a region. Instead, our results formally confirm that the inter-provincial trade and migration may serve as two important carriers for ripple effects. We complement the ripple effects by showing the inter-regional migration and capital flow have positive effects on the spatial spillovers of housing prices.

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