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DOI
10.1111/pirs.12512

Publication date
2020

Document Version
Final published version

Published in
Papers in Regional Science

Received: 14 October 2019 | Revised: 24 January 2020 | Accepted: 25 January 2020
DOI: 10.1111/pirs.12512

FULL ARTICLE

Cross-city spillovers in Chinese housing markets: From a city network perspective

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Funding information
Fundamental Research Funds for the Central Universities, Grant/Award Number: 2018WB01

Abstract
Cross-city spillovers among housing markets are usually modelled by the classical spatial autoregressive models, which usually suffer from identification problems in practice. This paper investigates the cross-city house price spillovers arising from city network externalities wherein a city's connections with other cities in the urban network create the external house price premium through productivity and amenity gains. Using a cross-sectional data set for an urban system in eastern China, we present significant evidence for positive network spillovers by the application of spatial lag of X model and spatial Durbin error model. Besides, common shocks are also proved to be responsible for cross-city dependence of house prices.

KEYWORDS
China, city network externalities, house prices, spatial econometrics, spillovers

JEL CLASSIFICATION
R12; R23; R30

1 | INTRODUCTION

In the spatial equilibrium framework of Rosen (1979) and Roback (1982), house prices of cities are determined by local productivities and amenities (Glaeser et al., 2014). In this regard, the mainstream specification of empirical house price models usually includes local-specific indicators that reflect such two aspects (e.g., Malpezzi, 1996; Ozanne & Thibodeau, 1983; Potepan, 1996; Zheng et al., 2010). Nevertheless, the fact that house prices are geographically clustered, which is still prevalent after reasonably controlling for local-specific characteristics, suggests that cross-city spillovers might be also important in the formation process of house prices.

The cross-city dependence or spillovers of house prices has been documented in the vast literature. With the help of recently developed spatial econometric models, such as the spatial autoregressive model (SAR) and some of its variants, many empirical studies have provided significant evidence of cross-city spillovers in the housing markets of UK, US, Germany, China and so on (Brady, 2014; Fingleton, 2008; Guo & Qu, 2019; Otto & Schmid, 2018).[1] On the other hand, little is known about the theoretical foundation of the spillovers between housing markets. Previous studies attribute the house price spillovers either to displacement effects (e.g., Fingleton, 2008) or to yardstick competition (Brady, 2014),[2] which directly motivates the SAR-type specification of house price models. However, due to the inherent identification problems of SAR models, whether cross-city spillovers are truly caused by such mechanisms is difficult to judge even given the significant spatial autoregressive parameters (Gibbons & Overman, 2012).

The present paper, instead, investigates a particular type of house price spillovers that arises from city network externalities, which have attracted much attention in urban growth literature (Boix & Trullén, 2007; Camagni et al., 2016). In a city network where cities are linked with each other either hierarchically or horizontally, the close and frequent inter-city connections can create the external productivity benefits analogous to that of agglomeration economies (Johansson & Quigley, 2004). For example, small cities in the network can improve their productivity without increasing their own size through borrowing the technological externalities of major urban cores (Phelps et al., 2001). Similarly, 'borrowed size' effect also, to some extent, determines the amenity level of a city within the network (Meijers & Burger, 2017). With the support of other cities, a city can develop more functions than indicated by its own size; meanwhile the supporting cities can have access to these functions and thus perform better than they are isolated. Such network externalities on productivity and amenity will eventually be captitalized into the house prices, leading to the housing market spillovers between cities. In other words, the house price of a city depends not only on its own mass concentration, but also on the agglomeration economies of other cities.

The externalities of agglomeration economies are usually modelled by market potential measure, which represents the aggregated market demand weighted by inverse distance (Harris, 1954). This paper, being different from the traditional treatment, uses the toolbox of spatial econometrics to investigate the effect of network spillovers on house prices. As we will show below, the theoretical foundation of city network externalities in housing markets can motivate the so-called spatial lag of X model (SLX). This "reduced form" model is believed to be more credible in most application situations, given the identification problems of the SAR-type specifications (Gibbons & Overman, 2012). Further, Vega and Elhorst (2015) offer a comprehensive examination of the SLX model and prove it to be a much more powerful approach, owing to not only its strength in identification, but also its flexibility in specifying the spatial weight matrix and in modelling spatial spillovers. In this paper, we will follow the procedure suggested by Vega and Elhorst (2015) and mainly rely on the SLX model for the examination of network externalities in housing market. Some other spatial models, such as the spatial Durbin model (SDM) and spatial Durbin error model (SDEM), are then employed to investigate the other sources of cross-city house price spillovers.

Based on a cross-sectional data set of the Jiang-Zhe-Hu-Wan area in eastern China, which covers the territories of Jiangsu province (Jiang for abbreviation), Zhejiang province (Zhe), Anhui province (Wan) and Shanghai municipality (Hu), we find significant evidence for the presence of positive network spillovers. Furthermore, common shocks are the other sources that can generate house price spillovers, whereas pure price interaction process is not the driver. These results add to the literature on Chinese interurban housing markets by analysing its cross-city interaction process and the underlying mechanisms, which has been absent in most of the studies explaining house price variation across cities in China (e.g., Li & Chand, 2013; Zheng et al., 2010; Zheng et al., 2014). Besides, this paper also echoes the advocates of taking the spatial lag of X (SLX) model as point of departure in empirical studies.

[1]There are also numbers of studies that investigate the interdependence of house price dynamics of different housing markets, which sometimes is also referred to as "spillovers" though "diffusion" might be a more appropriate term. Most studies of this type are conducted based on the framework of vector autoregressive models (VAR); some examples are Holly et al. (2011), Cohen et al. (2016) and Yang et al. (2018).

[2]A detailed explanation can be found in the second (previous literature) section.

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature focusing on the spatial interaction of house prices. The theoretical foundation of city network externalities on house prices, as well as the empirical specifications, is presented in Section 3, followed by the data description in Section 4. Section 5 reports the empirical results, and Section 6 concludes.

2 | PREVIOUS LITERATURE

It is familiar to us that when predicting the price of a specific property the price information of nearby properties can be very helpful, which is known as adjacency effect or spillover effect. In this regard, the spatial econometric models, which can deal with various types of spatial effects, have proved to be superior to the traditional hedonic models and thus become the standard toolbox for hedonic house price analysis (Can, 1990, 1992).[3] Among the family of spatial econometric specifications, the spatial autoregressive model (SAR) including spatial lags of dependent variables (endogenous interaction) and the spatial error model (SEM) incorporating spatial lags of error terms (correlated effects) are the most popular approaches (Anselin et al., 2010; Kim et al., 2003). Besides, the spatial Durbin model (SDM) with spatial lags of both dependent and independent variables has also emerged in the hedonic analysis of housing markets (Osland, 2010).

The spillover of house prices is not unique to properties within an urban market, but also occurs between aggregate markets, such as between the city-level housing markets. Fingleton (2008) investigated the house price process among 353 unitary authority and local authority districts in England with a SAR model and the significant spatial autoregressive coefficients provided compelling evidence for house price spillovers among districts. The evidence of spillovers has not been overturned even after controlling for the spatial interaction structure or random nested structure in disturbances (Baltagi et al., 2014; Fingleton & Le Gallo, 2008). Other markets outside UK also witness the cross-market spillovers. Brady (2014), using a spatial impulse response function derived from a single equation spatial autoregressive panel model, revealed statistically significant and persistent spatial diffusion of house prices across continental US states for the, 1975–2011 period. Otto and Schmid (2018) examined the spatiotemporal nature of German real estate prices in 412 administrative districts with spatial dynamic panel data models and the results, with no doubt, turn out to support the existence of cross-district house price spillovers.

The SAR-type model, which indicates an endogenous interaction structure, has been the mainstream method for investigating cross-city house price spillovers. Such specification can be motivated by several mechanisms. One of them is the displaced demand and displaced supply effects whereby a high house price signal in one market will force demand to be displaced to and attract supply from nearby markets (Fingleton, 2008). As such, the spatial lag of house prices, which indicates the endogenous interaction, will be present in the reduced form house price equation. The other is the yardstick competition theory, which states that home buyers and developers take the actions of their counterparts in neighbouring markets into account when they make their buying and selling strategy (Brady, 2014). House prices are thus connected with each other. However, the endogenous interaction that derives from such mechanisms is often difficult to justify, and SAR-type models cannot clearly tell us whether there is truly an endogenous interaction in the house price formation process (Gibbons & Overman, 2012).

Besides endogenous interaction, cross-city spillovers can also arise from exogenous interaction, such as the agglomeration spillovers. In an urban hierarchy, many studies documented that house prices of hinterland urban areas are, to some extent, determined by the distance to higher-tier urban cores, which bears the agglomeration spillovers of higher-tier concentrations (De Bruyne & Van Hove, 2013; Gong et al., 2016; Partridge et al., 2009). As the

[3]Spatial econometric models are built based on three different interaction assumptions: endogenous interaction, exogenous interaction and correlated effects. *Endogenous* interaction assumes that the outcome of a spatial entity depends directly on the outcomes of other entities, while *exogenous* interaction assumes that the outcome of an entity depends on other entities' explanatory characteristics. The assumption of *correlated* effects is that the dependence of outcomes across spatial entities stems from omitted variables that are spatially correlated or from common shocks (Elhorst, 2010).

modern urban system is characterized by a network structure whereby the cities are connected both hierarchically and horizontally, a more general form of agglomeration spillovers, namely network spillovers, that stem from both the high-tier cities and the neighbouring cities arise. Several studies have presented evidence for network spillovers in housing markets. Using the measure of market potential, which aggregates the personal income of surrounding regions through an inverse distance weighting scheme (Harris, 1954), Partridge et al. (2009) provided strong evidence of spillovers on U.S. county house price. With a similar measure, Camagni et al. (2016) revealed that, among 136 European large urban zones, house prices are significantly affected by the density of external linkages and co-operation networks.

For a very long time, studies on Chinese regional house prices were largely absent in the literature because of the lack of housing transactions data. Only in recent years have we witnessed the emergence of studies on the role of fundamentals in explaining regional house prices (Li & Chand, 2013), especially the influence of urban environmental and climate conditions (Zheng et al., 2010, 2014, 2009). In contrast, the spatial dimension of regional house prices is less investigated. Hanink et al. (2012) considered the spatial dependence and spatial heterogeneity in Chinese county-level house prices using the spatial error model (SEM) and geographically weighted regression (GWR), respectively. However, cross-city spillovers cannot be properly investigated by the SEM specification. Guo and Qu (2019) revealed the presence of spatial interactive effects between Beijing and Shanghai through a multi-level spatial autoregressive hedonic pricing model, which allows for spatial interactive effects among housing units inside the same city and from other cities. However, as previously discussed, the model used in the paper is a SAR-type model and thus is silence about the underlying mechanisms of the spatial interactive effects.

Being different from the previous studies, the present paper links the network externalities hypothesis and the spatial econometric models based on the exogenous interaction assumption, and takes the SLX model as point of departure to investigate the underlying mechanisms of cross-city dependence of house prices.

3 | MODELLING CROSS-CITY SPILLOVER OF HOUSE PRICES

3.1 | Theoretical framework

Let us consider an economy that consists of J cities, which are linked by trade and migration. Workers are assumed to migrate freely between cities, but not to commute between cities for working purposes. In spatial equilibrium where the marginal worker is indifferent across cities, he must receive a constant utility $\underline{U}$ everywhere in the economy. Following Glaeser et al. (2006), utility in city j depends on the wage E_j that can be offered by firms, the level of amenity C_j that can be consumed by residents, as well as the housing cost P_j. In logarithmic form, the relationship can be written as:

$$\ln P_j = \delta_1 \ln E_j + \delta_2 \ln C_j - \delta_3 \ln \underline{U}, \tag{1}$$

where $\delta_1, \delta_2, \delta_3 > 0$ represent the responsiveness of house prices to the change in wage, amenity and utility level, respectively.

Suppose that the production of city j follows a linear production function $y_j = A_j l_j$, where y_j is the total numeraire product of city j, l_j the work force and A_j the productivity common to all firms in the city. Maximizing the firm's profit implies that the wage (E_j) equals the marginal product of labour, which is in turn equal to the common productivity level A_j. The common productivity level of city j is determined by city endowments and two types of external economies:

$$\ln E_j = \ln A_j = \lambda_w F_j + \gamma_w g_j + \mu_w h_j, \tag{2}$$

where F_j is the unique endowments of city j, such as climate, weather and so forth, g_j the local externalities that arise from agglomeration economies, and h_j the network externalities that arise from the connection with other cities.

The local externality g_j of city j is directly related to its agglomeration level of economic activities. There are several mechanisms that are responsible for that relationship (Duranton & Puga, 2004). First, the many firms and workers in large cities can improve the quality of each firm-worker match, which benefits the overall productivity of the city. Second, the close proximity and intense face-to-face contact between workers in large cities can facilitate the diffusion of knowledges and intellectual ideas, which positively contributes to the productivity of workers. Third, since there are certain indivisible goods and facilities that include enormous fixed costs, the great number of users in large cities can share such costs, which consequently improves the production efficiency.

If we switch the focus from a single point to a system of nodes which are closely linked by transportation and telecommunication, the latter connection can also generate the same external benefits that arise from agglomeration economies, which is known as network externalities[4] (Johansson & Quigley, 2004). One example is the so-called "borrowed size" effect, which claims that small cities that are readily accessible to large cities can borrow the technological externalities of those major urban cores and hence improve the productivity without increasing their own size (Phelps et al., 2001). The other example is the 'market access' effect embedded in the new economic geography (NEG) model—being access to large consumer and supplier markets contributes to the productivity of an area by saving on transportation costs (Fujita et al., 1999). Many studies have found that the wage level of an area is significantly related to its proximity to large markets (Brakman et al., 2004; Hanson, 2005).

It is assumed that consumption amenity in city j is generated in a similar way to the generation of urban productivity:

$$\ln C_j = \lambda_c F_j + \gamma_c g_j + \mu_c h_{j.} \tag{3}$$

The positive contribution of agglomeration economy (local externalities) to consumption amenity is already evident in literature. Glaeser et al. (2001) argues that, despite of sometimes unpleasant interaction, urban density can generally facilitate enjoyable social contacts, which attracts people to dense urban area. A typical example is that young single people disproportionately live in the densest cities, where the likelihood for them to find and meet like-minded peers is much higher. More likely, large urban markets increase the welfare of consumers because of the facilities which are subject to substantial scale economies. Higher-order amenities, such as opera, Michelin 3-star restaurants and Disney parks, all require very large audience to be sustained. Therefore, it is necessary for those who want to enjoy such amenities regularly to live in large cities.

In a system of cities, network externalities can also occur along the amenity dimension. It is highly related to the concept of "borrowed size" as claimed by Alonso (1973, p. 200): "a small city or a metropolitan area exhibits some of the characteristics of a larger one if it is near other population concentrations … people can use the shopping and entertainment facilities of other cities to complement their own." In its original meaning, "borrowed size" stressed the benefits to small cities thanks to its proximity to large cities. In contemporary city network paradigm where cities interact with others both hierarchically and horizontally (Boix & Trullén, 2007; Capello, 2000), Meijers and Burger (2017) has stretched this concept to incorporate both "borrowed performance" and "borrowed functions," which allows a mutual influence. A city needs other cities' support to maintain a higher level of functionality than indicated by its own size (borrowed function); meanwhile the supporting cities can have access to these functions and other agglomeration benefits, and thus perform better than they are isolated (borrowed performance). Empirical evidence for the effect of city network externality on presence of higher-order amenities has recently emerged. For instance, in an analysis of the distribution of metropolitan functions across Western European countries, Meijers et al. (2016) noted that network connectivity positively contributes to the presence of those higher functions.

[4]According to Camagni et al. (2016), network externalities include the benefits not only from the geographical proximity to other cities, but also from the horizontal and non-hierarchical links among cities of similar size, even ones located far from each other. In this paper, the network externality mainly refers to the former benefits.

Incorporating Equations (2) and (3) into (1), we obtain the house price model under spatial equilibrium:

$$\ln P_j = \alpha + \kappa F_j + \beta g_j + \theta h_{j,} \tag{4}$$

where $\kappa = \delta_1\lambda_w + \delta_2\lambda_c$ measures the effect of unique city endowments, $\beta = \delta_1\gamma_w + \delta_2\gamma_c$ the effect of local externalities (agglomeration economies), $\theta = \delta_1\mu_w + \delta_2\mu_c$ the effect of network externalities which generate the spillovers, and finally $\alpha = -\delta_3 \ln \underline{U}$ is a constant term.

3.2 | The specification of the model

In Equation (4), local externalities (g_j) can be measured by the widely used agglomeration indicators: urban size (s_j) and urban density (z_j), that is $g_j = [s_j, z_j]$. A common approach to model network externalities (h_j) is the market potential function, which produces an aggregation (or weighted by distance) of income or population within a certain radius of city j (Camagni et al., 2016; Hanson, 2005; Partridge et al., 2009). Recently, the development of spatial econometrics provides a more flexible way to model network externalities. It is assumed that agglomeration economies of a city that generate local externalities can spread out and yield network externalities on other cities:

$$\mathrm{h} = \mathrm{Wg}, \tag{5}$$

where **W** is the spatial weight matrix that represents the spatial links between cities. This treatment leads to the so-called spatial lag of X model (SLX) (Gibbons & Overman, 2012; LeSage & Pace, 2009; Vega & Elhorst, 2015):

$$\mathbf{P} = \boldsymbol{\alpha} + \mathbf{F}\boldsymbol{\kappa} + \mathbf{g}\boldsymbol{\beta} + \mathbf{W}\mathbf{g}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \tag{6}$$

where **P** is the vector of house prices (in logarithmic form), **F** the city-specific characteristics, **g** the agglomeration economies, and $\boldsymbol{\varepsilon}$ the independently and identically distributed disturbances. This specification, which has been largely overlooked in applied studies, is superior to SAR-type specifications because of its easiness of identification and its flexibility in measuring spillover effects (Gibbons & Overman, 2012; Vega & Elhorst, 2015).

It is very likely that the cross-city spillover of house prices is not only driven by network externalities, but also arises from other mechanisms, such as the yardstick competition whereby the house price formation process of a city takes into account the price signal of other cities. In this case, the spatial Durbin model (SDM), which has attracted increasing attention recently, can be estimated:

$$\mathbf{P} = \rho\mathbf{MP} + \boldsymbol{\alpha} + \mathbf{F}\boldsymbol{\kappa} + \mathbf{g}\boldsymbol{\beta} + \mathbf{W}\mathbf{g}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \tag{7}$$

where the term **MP** captures the pure spillovers of house prices. The matrix **M** could be the same as **W** or not. As a comparison, we also estimate the more restricted and well-known SAR model (Anselin, 1988):

$$\mathbf{P} = \rho\mathbf{MP} + \boldsymbol{\alpha} + \mathbf{F}\boldsymbol{\kappa} + \mathbf{g}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{8}$$

The interpretation of SAR model is difficult because, without prior knowledge on the true data generating process, this model is generally impossible to be told apart from the SLX model in practice (e.g.,Gibbons & Overman, 2012). The significant estimate of parameter ρ can either reflect pure spillovers of house prices, or pick up the information of omitted variables like the network externalities (Corrado & Fingleton, 2012). However, conditional on the restriction $\boldsymbol{\theta} = \mathbf{0}$ of model (7), model (8) will be more justified. Testing model (7) against (8) can indicate the role that network externalities play in the generation of house price spillovers and the extent to which the SAR model is misspecified.

Common shocks is another important source that can cause the spatial dependence of housing markets. In this case, model (6) can be extended to the spatial Durbin error model (SDEM), which takes the form (LeSage & Pace, 2009):

$$\begin{aligned} \mathbf{P} &= \boldsymbol{\alpha} + \mathbf{F}\boldsymbol{\kappa} + \mathbf{g}\boldsymbol{\beta} + \mathbf{W}\mathbf{g}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \\ \boldsymbol{\varepsilon} &= \lambda\mathbf{Q}\boldsymbol{\varepsilon} + \mathbf{u}, \end{aligned} \tag{9}$$

where the error terms $\boldsymbol{\varepsilon}$ follow a spatial autoregressive process and $\mathbf{u}$ denotes the independently and identically distributed disturbances. The matrix $\mathbf{Q}$, which captures the interaction of error terms, could be the same as $\mathbf{W}$ or not.

3.3 | Measuring cross-city spillovers

Due to the presence of spatial weight matrixes **M** (or **W, Q**) in spatial models, one cannot easily use the point estimates of spatial parameters ($\boldsymbol{\theta}$, ρ and λ) to draw conclusions about spillover effect. In this paper, we use the partial derivative approach proposed by LeSage and Pace (2009) to calculate the direct effect—the effect of changes of the *k*th variable in a city on its own house prices—and the indirect effect—the effect of changes of the *k*th variable in a city on the house prices of other cities. By definition, the indirect effects represent the cross-city spillovers that we are interested in.

In the SDM model, the partial derivatives of the expectations of **P** with respect to the *k*th agglomeration economy variable can be expressed as:

$$\left[\frac{\partial E(\mathbf{P})}{\partial x_{1k}} \cdot \frac{\partial E(\mathbf{P})}{\partial x_{nk}}\right] = (\mathbf{I}-\rho\mathbf{M})^{-1}[\mathbf{I}\beta_k + \mathbf{W}\theta_k] = \mathbf{S}_k(\mathbf{W}). \tag{10}$$

In the case of SLX and SDEM specification, the partial derivative matrix $\mathbf{S}_k(\mathbf{W})$ collapses to $(\mathbf{I}\beta_k+\mathbf{W}\theta_k)$, while $(\mathbf{I} - \rho\mathbf{M})^{-1}(\mathbf{I}\beta_k)$ is the representation of $\mathbf{S}_k(\mathbf{W})$ in the case of SAR specification. The diagonal and non-diagonal elements of the partial derivative matrix $\mathbf{S}_k(\mathbf{W})$ in (10) measure the direct effects and indirect effects, respectively. Since both direct and indirect effects differ across the cities in the sample, LeSage and Pace (2009) suggests to report the direct effect as the average of the diagonal elements and the spillovers as the average of the row (column) sums of the non-diagonal elements. Note that, in the SAR model, the ratio of spillover effect to direct effect is constant across variables whereas there are no such restrictions in the SLX, SDEM and SDM models (Elhorst, 2010).

4 | DATA

4.1 | Study area

The spatial context of our empirical analysis covers the territory of three provinces and one municipality directly under the central government, namely Jiangsu, Zhejiang, Anhui and Shanghai, respectively (Jiang-Zhe-Hu-Wan in abbreviation). The spatial units of observation are the urban housing markets of the municipality, the prefecture city, or the county (county-level city). In total, we have 196 spatial units, including 1 municipality, 40 prefecture cities and 155 counties (Figure 1).[5] For simplicity, we term each spatial unit as a 'city'.

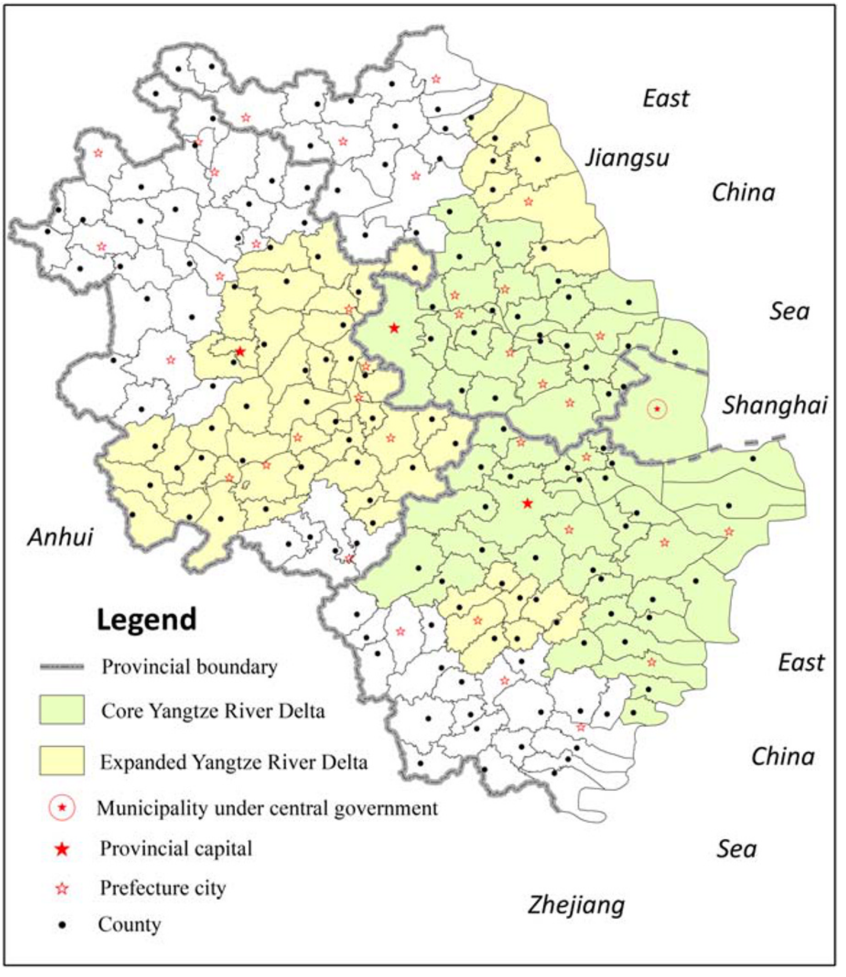

FIGURE 1 The sketch of study area

The Yangtze River runs through the study area from west to east and feeds up one of the most developed metropolitan region in China, the Yangtze River Delta, which is part of our study area. In the year 2016, the population size of our study area is about 222.05 million, accounting for 16% of China's total population, of which 145.11 million living in urban areas, making this area one of the most urbanized area in China. This area contributes 23% of the nation's total product, which is much higher than the population share. Cities within the area are connected by well-developed transportation and telecommunication infrastructure. Among the 196 cities, 186 (95%) cities are linked by motorways network; 138 (70%) cities have direct access to railways, and 77 (39%) cities to high-speed railways.

[5]China's spatial administrative system is structured in four levels: provinces (municipalities under the central government)—prefecture cities—counties (county-level cities) —townships. A prefecture city (or the municipality under the central government) is usually divided into counties and city districts, of which city districts make up the city proper ('*shiqu*') of the prefecture city (municipality). The urban housing markets of prefecture cities (municipalities) pertain to the corresponding city proper.

The current urban system of our study area is characterized by an urban hierarchy. The largest city Shanghai (SH), which has urban population over 20 million (2016 data), serves as the central city, followed by three cities with the population size greater than 5 million, namely Nanjing, Hangzhou and Suzhou. The remaining cities are almost evenly distributed among three population intervals: 1,000,000–5,000,000 (large cities), 500,000–1,000,000 (medium cities) and less than 500,000 (small cities). However, with the rapid development of transportation and telecommunication system, as well as the great endeavours made by the local governments to promote a regional cooperation economy, the horizontal interaction between cities is increasingly prominent within the urban system. In such an urban structure that is dominated by hierarchy and complemented by parallel connection, we expect the network externalities will play a role in the organization of housing markets, but might be limited to a relatively small area, which produces local spillovers.

4.2 | Data source

The data set is compiled from various sources. We have no access to property transaction data sets so that it is impossible for us to build a constant-quality house price measure across cities. Instead we rely on the market of listing properties in the year, 2016, which was obtained from *Xitai Real Estate Database* (www.creprice.cn). Every month the data provider collects the information of initially listed properties and cleans the data by deleting the cases that have unusual listing prices, apparent errors and so on. On average the markup for initial listing price relative to the selling price is 2.5%; there are very few cases wherein the selling price is higher than initial listing price. Finally, the data provider provides us with some general statistics of the local housing market, including the number of initially listed properties (n_m), the average listing value (v_m) and the average floor area (s_m). We then construct the yearly city-level averagehouse price by dividing the total listing floor area into the total value, that is $P = \sum_{m=1}^{12} v_m \times n_m / \sum_{m=1}^{12} s_m \times n_m$.[6]

The agglomeration economy of each city that generates local and network externalities is measured by the land area of a city and the urban population density. The land area is based on the year 2016 and extracted from the prefecture-level city statistical yearbooks. It is selected as a measure of urban size because we want to test if the physical expansion of a city can lift up its house prices. This can provide us with insights into the common belief in China that the economy can be considerably boosted by spatially merging two cities. The urban population density is calculated by dividing the land area of the city into urban population in the year 2010, which is derived from the Sixth National Population Census.[7] Since, in a spatial equilibrium framework, the housing price and population are simultaneously determined, it is a common practice to use lagged population for the purpose of avoiding endogeneity problem.

The city-specific characteristics include variables on natural and environmental conditions, history and culture, and supply conditions. The natural condition of a city is approximated by average winter temperature and annual precipitation during the period spanning from 1981 to 2010, which are collected from National Meteorological Information Centre. The key indicator for environmental condition of a city used here is the percentage of urban built-up area covered by green space (green coverage). History and culture, which is expected to affect house prices because of its contribution to the living amenity of a city, is measured by the number of cultural heritage sites listed in “Key Cultural Relics Sites under State Protection”. On the supply side, the area of land that can be used for housing construction is strictly controlled by land use planning (2005–2020) through a quota system. With the aim of protecting against the massive loss of arable land, it is believed that the city with lower arable land *per capita* will face a stricter quota on the conversion of farmland into construction land, and thus reduce the supply of housing. Besides, we

[6]This price measure is identical to the average listing price weighted by the floor area of the property.

[7]The administrative border of some cities has changed from the year 2010 to 2016, we recalculate the census population in 2010 according to the 2016 boundary.

TABLE 1 Description and summary statistics of variables

Variables	Description	Mean	Std. deviation	Min	Max
House prices	Yearly average listing price by diving total listing floor area into listing value (Yuan/m^2); 2016	7065	4189	2971	43980
Urban population density	Urban population density by dividing land area into urban inhabitant (person per km^2); 2010	337	399	21	3242
Land area	The land area of a city (km^2); 2016	1820	973	97	6587
Winter temperature	Average temperature of December, January and February (centigrade); 1981–2010 average	4.87	1.86	1.67	9.87
Precipitation	Annual precipitation (mm); 1981–2010 average	1243	291	710	2048
Green coverage	The percentage of urban built-up area covered by green spaces (%); 2016	39.27	5.10	14.59	48.50
Cultural heritage sites	The number of cultural heritage sites listed in “key cultural relics sites under state protection”, 2016	3	6	0	49
Arable land per capita	Arable land per capita (m^2 per capita); 2005	716.24	368.10	19.16	1961.10
Administrative rank and location dummies					
Provincial capital	=1 if the city is the municipality under central government, or the capital of a province; =0 otherwise	0.02	0.14	0	1
Prefecture city	=1 if the city is a prefecture-level city; = 0 otherwise	0.19	0.39	0	1
Core Yangtze River Delta	=1 if belonging to the core area of Yangtze River Delta; = 0 otherwise	0.33	0.47	0	1
Expanded Yangtze River Delta	=1 if belonging to the expanded area of Yangtze River Delta; = 0 otherwise	0.30	0.46	0	1
Jiangsu	=1 if the city belongs to Jiangsu province; = 0 otherwise	0.28	0.45	0	1
Zhejiang	=1 if the city belongs to Zhejiang province; = 0 otherwise	0.33	0.47	0	1
Shanghai	=1 if the city belongs to Shanghai; = 0 otherwise	0.01	0.07	0	1

Notes: The basic unit for observation is the urban housing market of a municipality directly under central government, a prefecture city or a county. In total, there are 196 observations.

TABLE 2 Moran's I test of housing markets

	Autocorrelation of house prices	Cross-correlation with population density	Cross-correlation with land area
Neighbours within 60 km radius	0.6229*** (0.001)	0.2654*** (0.001)	0.2511*** (0.001)
Neighbours in 60–120 km radius	0.5086*** (0.001)	0.1708*** (0.001)	0.1427*** (0.001)
Neighbours in 120–180 radius	0.4159*** (0.001)	0.0849*** (0.001)	0.0518*** (0.004)
Neighbours in 180–240 radius	0.2663*** (0.001)	0.0150 (0.144)	−0.0179 (0.165)

Notes: the p-values drawn from the distribution of 999 simulations of spatially random distributed data are reported in the parentheses. ***, **, *indicate significance level at 1%, 5%, 10%, respectively.

include a bundle of dummy variables to indicate the location of a city and its political rank in the spatial administrative system. Table 1 provides a detailed description of the variables, as well as their summary statistics.

5 | RESULTS

5.1 | Spatial correlation of housing markets

If network spillovers indeed exist among housing markets, the house price of a city will be correlated with the agglomeration economies of neighbouring cities, and hence with their house prices as well. We simply test this hypothesis using Moran's *I* statistics. The spatial weight matrix that captures the linkage structure is defined as a binary matrix, with elements $w_{ij} = 1$ if two cities are located within a certain distance ranges, and 0 otherwise.[8] We design four matrixes, which connect the markets within 60 km, 60–120 km, 120–180 km and 180–240 km respectively, to test how the distance between housing markets influences the correlation nature.

The global Moran's *I* statistics in Table 2 clearly show a significantly positive autocorrelation of house prices and a cross-correlation between a city's house price and the neighbouring cities' urban population density and land area when the spatial structure is properly specified, providing preliminary evidence for network spillovers. However, a decreasing pattern of house price autocorrelation and cross-correlation is observed as the neighbouring cities move away from each other; the two indicators of cross-correlation are almost insignificant when the neighbouring city is defined in the 180–240 km radius. It is thus reasonable to infer that the network externalities produce local spillovers.

5.2 | Results of non-spatial models

The house price models without cross-city spillovers are first estimated and will serve as the benchmark. The first two columns of Table 3 report the results estimated by ordinary least squares (OLS), with the model of the second column controlling for location dummies.

The coefficient estimates of the two non-spatial models have expected signs and are statistically significant at 5% significance level except for the variable *arable land per capita* which turns insignificant after including location

[8]The distance measure used in this paper refers to the straightforward geographical distance between the city halls of two cities.

TABLE 3 Estimation results of nonspatial models and SLX models

	Dependent variable = Ln (house prices)				
	OLS (1) Without location	OLS (2) With location	SLX (3) OLS **W** = *binary*	SLX (4) nonl. OLS **W** = $1/d^r$	SLX (5) OLS $\mathbf{W}=1/d^{2.7531}$, $d \le 180\ km$
Constant	7.582163*** (42.75)	7.785471*** (50.76)	7.349289*** (17.94)	7.657871*** (48.55)	7.662255*** (48.95)
Winter temperature	0.192782*** (10.72)	0.120446*** (6.43)	0.129150*** (6.02)	0.100900*** (5.23)	0.099665*** (5.16)
Precipitation	−0.000535*** (−4.58)	−0.000331*** (−3.21)	−0.000316*** (−2.84)	−0.000217** (−2.06)	−0.000208** (−1.97)
Green coverage	0.017255*** (5.28)	0.007487** (2.48)	0.007848** (2.58)	0.006270** (2.16)	0.006330** (2.18)
Cultural heritage sites	0.011040*** (2.91)	0.007220** (2.18)	0.007154** (2.14)	0.004583 (1.42)	0.004528 (1.40)
Arable land per capita	−0.000124** (−2.13)	−0.000029 (−0.57)	−0.000027 (−0.51)	−0.000051 (−1.02)	−0.000049 (−0.99)
Urban population density	0.000324*** (4.75)	0.000305*** (4.42)	0.000299*** (4.31)	0.000239*** (3.53)	0.000239*** (3.52)
Land area	0.000105*** (4.72)	0.000091*** (4.46)	0.000091*** (4.46)	0.000100*** (5.08)	0.000100*** (5.08)
W*urban population density			0.000108 (0.56)	0.000288*** (4.34)	0.000282*** (4.38)
W*land area			0.000180 (1.14)	0.000034 (0.89)	0.000028 (0.79)
Distance decay parameter				2.7531*** (23.64)	
Rank dummies	Yes	Yes	Yes	Yes	Yes
Location dummies	No	Yes	Yes	Yes	Yes
Adj. R^2	0.750	0.826	0.825	0.841	0.841
Moran's I	0.1635*** (6.78)	0.0408*** (2.60)	0.0314** (2.36)	0.0290** (2.17)	0.0291** (2.17)

Notes: The figures in the parentheses report the *t*-statistics for parameter estimates and *Z*-score for Moran's I statistic. An inverse distance matrix with elements $w = 1/d^2$ is employed for the calculation of Moran's I. ***, **, *indicate significance level at 1%, 5%, 10%, respectively.

dummies. However, the magnitudes of the coefficients of location model (2) are relatively smaller than that of the restricted model (1). In general, a city with a warmer winter, a higher proportion of green coverage and more cultural sites is likely to enjoy a higher house price premium. On the other hand, the abundant annual rainfall imposes a negative effect on house prices, *ceteris paribus*. As expected, the two variables measuring agglomeration economies have statistically and economically significant effects on house prices in both models. According to model (2), increasing the urban population density of a city by 100 persons per km^2 will drive up the house prices by 3.05%, while an increase of land area by 100 km^2 will result in a 0.91% inflation of house prices.

Overall, the explanatory variables we have chosen lead to a satisfying model specification as the model (2) with location dummies can explain 83% of the cross-city house price variation. Besides, the inclusion of location dummies also largely mitigates the spatial dependence in residuals. Using an inverse distance matrix with elements $w_{ij} = 1/d_{ij}^2$, we detect a significantly positive spatial dependence of residuals for model (1) where the global Moran's *I* stands at 0.164. For the model including location dummies, the Moran's I statistic noticeably drops to 0.041; however, it is still statistically significant according to the *Z* score, which suggests the existence of cross-city spillovers even after properly controlling for location factors.

5.3 | Results of spatial models

5.3.1 | The SLX model

The spatial weights matrix **W** is vital to estimating the SLX model of Equation (6) as **W** carries the underlying spatial interaction structure. The nature of spatial interaction can be captured by the inverse distance matrix with:

$$w_{ij} = 1/d_{ij}^r, \tag{11}$$

where *r* is the distance decay parameter. In Equation (11), a large value of *r* indicates some kind of local spillovers that are confined to very close neighbours. One advantage of the SLX model is that, instead of specifying the distance decay parameter in advance, it can be estimated by a nonlinear estimation technique.[9] When an inverse distance matrix is employed, the commonly used row-normalization will cause the spatial weights matrix to be asymmetric and thus lose the economic interpretation in terms of distance decay (Elhorst, 2001). In this regard, we normalize the spatial weights matrix by $\mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2}$, where **D** is a diagonal matrix with diagonal elements equal to the row sums of **W**. This operation is proposed by Ord (1975) and produces a symmetric matrix. Besides, the eigenvalues of this transformed matrix are identical to the eigenvalues of a row-normalized matrix.

Before estimating the SLX model with inverse distance matrixes, we first estimate the model using a binary matrix with w_{ij} = 1 if the distance between city *i* and city *j* is less than 180 km. Surprisingly, the coefficients of spatial lags of agglomeration economy indicators reported in the third column of Table 3 are all insignificant and hence fail to provide evidence for network spillovers, although the Moran's *I* tests in Table 2 suggest to some extent the existence of cross-correlation between the house price of a specific city and the agglomeration economies of neighbouring cities at the 120–180 km radius. We then immediately turn to the SLX model with parameterized distance decay factor and the results are reported in the fourth column of Table 3. In this model, the presence of network spillovers is supported by the large and statistically significant estimates of spatial lag of urban population density and the inclusion of such spillovers explains 1.5% more cross-city variation of house prices compared to the non-spatial model (2). However, it seems that the expansion of urban scale exerts no spillovers on other cities. In terms of the direct effect of agglomeration economies, the effect of urban population density on its own house prices

[9]We use the Matlab code developed by Vega and Elhorst (2015) to estimate the parameters. The procedure works as follows: given distance decay parameter *r*, the coefficient vectors $\boldsymbol{\alpha},\boldsymbol{\kappa},\boldsymbol{\beta},\boldsymbol{\theta}$ in Equation (6) can be estimated; given the coefficient vectors $\boldsymbol{\alpha},\boldsymbol{\kappa},\boldsymbol{\beta},\boldsymbol{\theta}$, the parameter *r* can be alternately estimated. The procedure stops until convergence occurs.

decreases slightly by about one fifth, compared to the non-spatial model (2), while the direct effect of land area remains relatively stable. For the variables of local-specific characteristics (excluding population density and land area), the parameter results are quite similar to that of the non-spatial model (2) except that the variable *cultural heritage sites* is no longer significant.

The estimated distance decay parameter is 2.7531 and statistically significant, which indicates an interaction pattern bounded within a small radius. If the effect of a particular city on one of its neighbours located 60 km away is supposed to 1, it falls to 0.15 at 120 km, and 0.05 at 180 km. Compared with the insignificant results of SLX model (3) which is based on an interaction structure that can reach neighbours very far away, it can be concluded that network externalities play an important role in the formation of house prices but the effect falls very sharply as distance increases, suggesting a nature of local spillovers. A further analysis of the parameterized spatial weight matrix shows that, for most of the cities, the neighbours within 180 km radius contribute at least 90% of the total spillovers imposed on a particular city. In this regard, we re-estimate the SLX model (4) using a cutoff distance matrix where the distance decay parameter and the distance cutoff are set to 2.7531 and 180 km, respectively. The results are shown in the fifth column of Table 3 and are almost identical to that of SLX model (4).

After the inclusion of network spillovers, the degree of spatial dependence of residuals of SLX models is further mitigated and almost approaches to zero, although it is still statistically significant at 5% significance level. Such weak spatial dependence might be caused by pure spillovers of house prices or common shocks. Thus it is necessary to proceed with the estimation of SDM or SDEM models.

5.3.2 | The SDM and SAR model

As previously discussed, if the spatial dependence of house prices after controlling for network spillovers is driven by pure house price spillovers, the SDM model of Equation (7), which produces both global spillovers and local network spillovers, will be a better specification.

The first column of Table 4 shows the ML estimates of SDM model (6), in which the element of spatial weight matrix **M** is specified as $m_{ij} = 1/d_{ij}^2$ and normalized by Ord-type transformation. Compared to SLX (5), the SDM model (6) that includes the variable **MY** does not improve the explanatory power of the house price equation; the insignificant coefficient estimate of the variable **MY** rejects the hypothesis of pure house price spillovers. Using the same spatial weight matrix **M** as employed by model (6), we then estimate the SAR model (7) which fails to consider the network externalities. Overall, the results reported in the second column of Table 4 show that the performance of SAR model (7) is inferior to the performance of SDM model (6). However, the coefficient estimate of the spatial lag of house prices turns out to be significant in model (7), which conflicts with the results of SDM model (6). Such disagreement indicates that it is the omission of network externalities but not the pure spillovers that leads to the significant coefficient of **MY** in the SAR model, which is consistent with the finding of Corrado and Fingleton (2012). Thus, when modeling house prices, one should interpret the results of SAR models with great caution.

One may argue that the process of pure house price spillovers may not be properly modelled by geographical relationship, as pointed out by Pollakowski and Ray (1997). Fingleton and Le Gallo (2008) also stated that big cities may be less remote than their distance indicates, while very small cities may in fact be more isolated. This argument is quite true because, when making a decision, households who come from a large city are more likely to refer to the price signal of a large, distant city rather than a nearby, small city. Therefore, the pure house price spillovers might be better captured by spatial weight matrixes defined on the dimension of economic distances. In this paper, an economic distance measure that combines geographical distance and economic similarities is constructed. The "economic similarity" (*es*) of two cities, say city *i* and *j*, is measured by the difference in their disposable income, $es_{ij} = |income_i - income_j|$. For the sake of avoiding potential endogeneity of this distance measure, income of the year 2010 is used. The economic distance (ed_{ij}) between city *i* and *j* is then calculated by:

TABLE 4 Estimation results of SDM, SAR and SDEM models

	Dependent variable = Ln (house prices)				
	SDM (6) ML $\mathbf{M} = 1/d^2$ $\mathbf{W} = 1/d^{2.7531}$, $d \le 180\ km$	SAR (7) ML $\mathbf{M} = 1/d^2$	SDM (8) ML $\mathbf{M} = 1/ed^2$ $\mathbf{W} = 1/d^{2.7531}$, $d \le 180\ km$	SDEM (9) ML $\mathbf{Q} = 1/d^2$ $\mathbf{W} = 1/d^{2.7531}$, $d \le 180\ km$	SDEM (10) ML $\mathbf{Q} = 1/ed^2$ $\mathbf{W} = 1/d^{2.7531}$, $d \le 180\ km$
Constant	7.669542*** (44.39)	7.556863*** (42.72)	7.629441*** (46.08)	7.650673*** (48.74)	7.681272*** (47.38)
Winter temperature	0.099502*** (5.35)	0.122578*** (6.88)	0.099910*** (5.41)	0.094710*** (4.86)	0.085199*** (4.23)
Precipitation	−0.000206** (−2.00)	−0.000353*** (−3.60)	−0.000214** (−2.10)	−0.000178* (−1.70)	−0.000133 (−1.23)
Green coverage	0.006340** (2.28)	0.006799** (2.36)	0.006268** (2.26)	0.006976** (2.53)	0.006454** (2.36)
Cultural heritage sites	0.004558 (1.46)	0.006041* (1.89)	0.004274 (1.36)	0.005048* (1.62)	0.005050* (1.63)
Arable land per capita	−0.000049 (−1.02)	−0.000044 (−0.89)	−0.000054 (−1.11)	−0.000048 (−0.99)	−0.000044 (−0.89)
Urban population density	0.000240*** (3.67)	0.000270*** (4.01)	0.000239*** (3.69)	0.000250*** (3.89)	0.000222*** (3.36)
Land area	0.000099*** (5.05)	0.000106*** (5.17)	0.000101*** (5.32)	0.000097*** (5.07)	0.000091*** (4.74)
W*urban population density	0.000285*** (3.98)		0.000276*** (4.40)	0.000273*** (4.44)	0.000252*** (4.13)
W*land area	0.000029 (0.77)		0.000024 (0.67)	0.000014 (0.41)	0.000009 (0.26)
M*Ln (house prices)	−0.001459 (−0.08)	0.032460** (2.26)	0.006129 (0.46)		
M*error				0.235000 (1.41)	0.493000*** (2.81)
Rank dummies	Yes	Yes	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.841	0.830	0.841	0.843	0.846
Log-likelihood	142.58	134.97	142.69	143.26	144.11

Notes: The spatial weight matrixes of **M**, **Q** and **W** are normalized by Ord-type transformation $\mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2}$. ***, **, *indicate significance level at 1%, 5%, 10%, respectively.

$$ed_{ij} = \sqrt{\left(\frac{es_{ij}}{\mathrm{std}(es)}\right)^2 + \left(\frac{d_{ij}}{\mathrm{std}(d)}\right)^2}, \tag{12}$$

where std(es) and std(d) denote the standard deviation of economic similarities and geographical distance, respectively.

We first reproduce the results of Table 2 using the economic distance measure, which are reported in Appendix Table A1. On the space of economic distance, we detect a stronger degree of spatial autocorrelation of house prices and cross-correlation between a city's house price and the neighbouring cities' agglomeration economies, suggesting the superiority of economic distance in measuring the connectivity between cities. The detected decreasing pattern of house price autocorrelation and cross-correlation, on the other hand, is quite similar to the pattern based on geographical distance. Using the economic distance measure to specify the spatial weight matrix **M,** we re-estimate the SDM model and the results are shown in the third column of Table 4. No matter the point coefficient estimates nor the model performance, the SDM model (8) are almost identical to the model SDM (6), which indicates that there is no pure house price spillover even on the economic-distance space.

5.3.3 | The SDEM model

The rejection of the pure house price spillovers leads us to consider the role that common shocks play in the formation of house prices. We thus estimate the SDEM model specified in Equation (9) by ML techniques. In SDEM model (9) which defines the spatial weight matrix **Q** on the space of geographical distance, no evidence of common shocks is revealed given the insignificant coefficient estimates of spatial lag of residuals. However, when we specify the spatial weight matrix **Q** using economic distance in SDEM model (10), the point estimate of spatial error term becomes statistically and economically significant, while the coefficient estimates of other variables are almost in line with that of SLX (5) except that the effect of *precipitation* is no longer significant. Furthermore, according to log-likelihood, the SDEM model (10) performs slightly better than SDEM model (9). It seems that common shocks influence the cities that are economically connected more than the geographically close cities.

Combining the evidence of SLX, SDM and SDEM models, it can be concluded that the cross-city spillovers of Chinese house prices are mostly driven by network externalities and common shocks, but not the pure house price spillovers. However, the spatial interaction structure underlying the network externalities is different from that of common shocks.

5.4 | Network spillovers

As previously discussed, the point estimates of spatial regressors in spatial models, namely SLX, SAR, SDM and SDEM, are not exactly equal to the spillovers. The partial derivative approach represented by Equation (10) is hence employed to calculate the spillover effects, as well as the direct effects of SAR and SDM models.[10] Table 5 summarizes the direct and spillovers effects of different models.

The direct effect of urban population density estimated by OLS (2) model is much more pronounced than that estimated by spatial models, while the direct effect of land area is almost the same among the non-spatial and spatial models. Given the significant spillovers of population density and the statistically and economically insignificant spillovers of land area, it can be concluded that the upward bias of OLS (2) model is very likely caused by the omission of

[10]Theoretically, the direct effects of SAR and SDM models are greater than the point estimates because of the presence of feedback effects, which are those impacts passing through the neighbours and back to the unit itself. In this paper, however, the statistically insignificant and economically small parameter estimate ρ results in a very weak feedback effect and thus the direct effects are consistent with the point estimates.

TABLE 5 The direct and spillover effects of agglomeration economy on house prices

	OLS(2)	SLX(5)	SAR(7)	SDM(8)	SDEM(10)
Direct effects					
Urban population density	0.000305*** (4.42)	0.000239*** (3.54)	0.000270*** (3.82)	0.000239*** (3.69)	0.000222*** (3.28)
Land area	0.000091*** (4.46)	0.000100*** (5.14)	0.000106*** (5.16)	0.000101*** (5.49)	0.000091*** (4.63)
Spillover effects					
Urban population density		0.000267*** (4.08)	0.000009** (1.97)	0.000265*** (4.53)	0.000239*** (4.03)
Land area		0.000026 (0.78)	0.000003* (1.84)	0.000023 (0.69)	0.000009 (0.27)

Notes: *t* values, which are calculated based on 1000 simulated parameter combinations drawn from the variance–covariance matrix following the procedure introduced in Elhorst (2014), are reported in the parentheses. ***, **, *indicate significance level at 1%, 5%, 10%, respectively.

spatial interaction effect. Among the four spatial models which consider the spatial interaction, the SAR (7) model estimates much lower magnitude of spillovers than the SLX, SDM and SDEM models do. Such underestimation of spillovers is the result of the fact that a pure interaction process is not the source of cross-city spillovers of Chinese housing markets; the significant spatial parameter in SAR (7) just picks up the effect of network externalities when the model is not properly specified. The results of SLX, SDM and SDEM models confirm the importance of network spillovers in the formation of house prices. Since the SDEM (10) model is shown to be the best specification, our following interpretation will be mainly based on the results of this model.

The agglomeration of a city's population is the most important factor that generates the network externalities in the housing markets; the magnitude of spillover effect is even more noticeable than the direct effect on its own market. According to the results of SDEM (10) model, if a city's population grows by 100 persons per km^2, the total house price increases of neighbouring cities are about 2.39%, whereas its own house price only rises by 2.22%. Nevertheless, considering that each city on average has 42 neighbours within the radius of 180 km, the network spillover on each neighbouring city is by average around 0.06%, which is much lower than the magnitude of the direct effect.

6 | CONCLUDING REMARKS

Conventional wisdom suggests that local housing markets are segmented from each other and hence house prices are locally determined. However, the spatial clustering pattern of house prices cannot be fully explained by local-specific characteristics, pointing to the importance of spillovers. Spatial econometrics, especially the spatial model with spatial lag of house prices (known as SAR-type models), has been the standard toolbox for investigating spillover effect. Nevertheless, SAR-type models have been heavily criticized because the endogenous interaction is difficult to justify.

This paper differs from traditional spatial analysis of interurban house prices in that we investigate spillovers caused by city network externalities. In a city network system, the house price of a city is, to some extent, influenced by the agglomeration economies of accessible neighbouring cities, because the amenity and productivity advantages of the specific city, which are the two fundamental components of house prices, can be somewhat “borrowed” from its neighbours. The network spillovers justify the assumption of exogenous interactions in spatial econometrics which has been overlooked in applied studies. Hence, we argue that, when analysing house price spillovers, the SLX and SDEM models are attractive alternatives to SAR-type models.

The empirical results based on a cross-sectional data set of Jiang-Zhe-Hu-Wan area in eastern China strongly support our assertion. The SLX model, which incorporates exogenous interaction, proves the presence of network spillovers among geographically adjacent housing markets; the magnitude of spillover effect generated by urban population density is comparable to that of the direct effect on its own house prices. Besides, another important mechanism that causes the interdependence of house price is related to common shocks, which play the role on the economic space considering both geographical distance and economic similarity. On the other hand, the pure house price interaction process, which directly motivates SAR-type models and produce global spillovers, is not a source for cross-city spillovers, as demonstrated by the results of SAR and SDM models. Thus, one should be highly cautious about applying the SAR-type models to the housing markets.

In conclusion, network spillovers of agglomeration economies are noticeable in the formation of house prices, which is in line with findings based on the measure of market potential, such as Partridge et al. (2009). This deepens our understanding about the cross-city variation of house prices: the prosperity of a city's house price should be attributed not only to its local characteristics, but also to its proximity to prosperous markets. Furthermore, This paper is also relevant to the increasing studies that focus on “borrowed size,” which is currently used to explain the faster growth of small and medium-sized cities in Europe (Meijers et al., 2016). We provide new evidence of “borrowing size” effect from the perspective of housing markets in a fast growing country, China. The results also have broad implications for the making of regional policies in China. To narrow spatial inequality, the policy for the rise of laggard, peripheral cities should not only focus on their collaboration and integration with central cities. It is also important to cultivate a few vibrant, thriving growth poles in the neighbouring peripheral area to enhance the network externalities.

ACKNOWLEDGEMENT

The authors would like to thank the editor, John Winters, two anonymous referees, and Evert J Meijers for their constructive comments on the earlier version of the article. Thanks are also given to the participants at the Urban Agglomeration and Urban Network Workshop, November 2018, Wuhan, for their helpful discussion.

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How to cite this article: Gong Y, de Haan J, Boelhouwer P. Cross-city spillovers in Chinese housing markets: From a city network perspective. *Pap Reg Sci*. 2020;99:1065–1085. https://doi.org/10.1111/pirs.12512

APPENDIX A.

TABLE A1 Moran's I test of housing markets based on economic distance

	Autocorrelation of house prices	Cross-correlation with population density	Cross-correlation with land area
Neighbours within 0.8 radius	0.6338*** (0.001)	0.3310*** (0.001)	0.3081*** (0.001)
Neighbours in 0.8–1.6 radius	0.5454*** (0.001)	0.2246*** (0.001)	0.1992*** (0.001)
Neighbours in 1.6–2.4 radius	0.3434*** (0.001)	0.1408*** (0.001)	0.1287*** (0.004)
Neighbours in 2.4–3.2 radius	−0.0238* (0.082)	−0.0086 (0.297)	−0.0249** (0.023)

Notes: the p-values drawn from the distribution of 999 simulations of spatially random distributed data are reported in the parentheses. ***, **, *indicate significance level at 1%, 5%, 10%, respectively.

DOI: 10.1111/pirs.12512

Resumen. Los *spillovers* entre ciudades para los mercados de la vivienda se suelen modelizar mediante los modelos clásicos de autorregresión espacial, que en la práctica suelen sufrir problemas de identificación. Este artículo investiga los *spillovers* del precio de la vivienda entre las ciudades que se derivan de las externalidades de la red de ciudades, en las que las conexiones de una ciudad con otras ciudades de la red urbana crean la prima externa del precio de la vivienda mediante el aumento de la productividad y servicios. Utilizando un conjunto de datos transversales para un sistema urbano en el este de China, se presentan pruebas significativas de los *spillovers* positivos de la red mediante la aplicación del desfase espacial del modelo X y el modelo espacial de error de Durbin. Además, se demuestra que las perturbaciones comunes son también responsables de la dependencia entre ciudades de los precios de la vivienda.

抄録: 住宅市場間の都市間のスピルオーバーは、通例、古典的な空間的自己回帰モデルでモデル化されるが、大抵は実用すると同定問題が発生する。都市ネットワークにおける都市と都市のつながりは生産性とアメニティの利益を介して外部住宅価格プレミアム生み出すが、本稿では、その都市ネットワークの外部性から生じる都市間の住宅価格スピルオーバーを検討する。中国東部の都市システムから得られた横断的データセットを使用し、Xモデルの空間ラグモデルおよび空間ダービン誤差モデルを用いてネットワークの正のスピルオーバー有意に示すエビデンスを提示する。さらに、都市間の住宅価格依存性がショックの原因であることが判明した。