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Spatial Dependence in House Prices: Evidence from China's Interurban Housing Market

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Abstracts: "Spatial thinking" is increasingly popular in housing market studies and spatial dependence across properties has been widely investigated in the intra-city housing market. The contribution of this paper is to study the spatial dependence and spillover effect of house prices from an interurban perspective, referring to the spatial interaction across local housing markets. The extensive literature study concludes that following behavior, migration and equity transfer and spatial arbitrage of capital are the main behavioral reasons for interurban spatial interaction. Using a cross-sectional data set in eastern China, our empirical results from both parametric and nonparametric approaches provide strong evidence of spatial interaction in the interurban housing market. The parametric results suggest that the spatial lag model (SAR) is the best model specification to describe the interurban house price process, indicating an endogenous interaction pattern. Ignoring such interaction effect in the house price model will produce biased coefficients estimators and misleading interpretation. In SAR model, Spillover effects of explanatory variables caused by spatial interaction are calculated by partial derivative interpretation approach and are demonstrated to have the magnitude as much as half of their direct effects. Moreover, the comparison between different spatial weighted matrices reveals that the spatial interaction depends not only on distances, but also on the economic situation of each jurisdiction. Meanwhile, nonparametric approach draws a flexible relationship between spatial dependence and geographical distances. Using *spline correlogram*, we find monotonically declined spatial autocorrelation of house prices and explanatory variables within larger distances, whereas the significant spatial autocorrelation of OLS residuals can only be observed at short distance (60 Km). The spillover effect, being obtained from spatial covariance decomposition, is highly significant and declines within the radius of 250 Km. All the nonparametric results imply that though the house price determinants can satisfyingly account for the interurban house prices, the importance of spillover effect cannot be neglected within certain distances. That is the neighbor's housing market situation is quite useful in predicting the house price of a particular city. This study provides a good insight into explaining why the house prices in some cities always run above the level indicated by fundamentals, and highlights the importance of cooperation between local governments in making the housing policy.

Keywords: Spatial autocorrelation; spillover effect; interurban housing market; spatial econometrics; nonparametric estimation; China

JEL: R31; C21

Spatial Dependence in House Prices: Evidence from China's Interurban Housing Market

1. Introduction

"Spatial thinking" is increasingly popular in spatial science and spatial dependence, as one of the two typical features of spatial data, has especially been the major focus. From a theoretical perspective, spatial dependence reflects a general rule that dominates the behavior of geographical objects, namely the First Law of Geography (FLG): "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Many theoretical models that contain the spatial interaction have been advanced, such as the Brueckner's strategic interaction model (Brueckner, 2003). From an empirical view, ignoring the spatial dependence in empirical models by using the classic statistics and econometrics produces the biased estimates and thereby leads to the misleading and incorrect interpretation of empirical results, and that accelerates the development of spatial econometrics. This paper is attempting to apply the spatial thinking into investigating the house prices behavior in China's interurban housing market.

The data generation process (DGP) of house prices which is a typical spatial data is undoubtedly affected by spatial dependence. Numbers of studies have found strong evidence of spatial dependence across housing properties in an intra-urban housing market. Some studies model the spatial autocorrelation structure in house prices by using semivariogram method (Geostatistics) and advocate that the combination of the semivariogram and OLS results can significantly improve the performance of prediction (Basu and Thibodeau, 1998; Bourassa et al., 2007). Others explore the spatial dependence by employing the spatial regression models which introduce a spatial lagged dependent variable into the estimated model or directly account for the spatial dependence structure in the error term (Can, 1990; Osland, 2010; Yu et al., 2007). Furthermore, Gillen et al (2001) revealed the anisotropic features of autocorrelation of house prices, but also the direction.

Compared with the fruitful achievements in intra-urban housing market, spatial dependence across local housing markets, which we refer as interurban housing market, has not been widely

concerned, though it has been implicitly verified by those studies focusing on regional (interurban) housing market convergence or on ripple effect of house prices. Such studies appear in the regional (interurban) housing markets of UK, US and Australia (Canarella et al., 2012; Holmes and Grimes, 2008; Luo et al., 2007). However, the data sets they used, usually time series data based on few observations, cannot allow them to study the feature of spatial dependence which, by definition, is a special case of cross-sectional dependence (Anselin, 2006).

The main objective of this paper is to measure the strength and radius of spatial dependence (spillover effect) in the interurban housing market based on a cross-sectional data set that contains enough observations of jurisdictions' local housing markets. The modern spatial econometrics (parametric approach) is employed, especially the partial derivative interpretation approach developed by LeSage and Pace (2009) allows us to explain the spatial interaction more efficiently and measure the magnitude of spillover effect. Meanwhile, considering the drawback of parametric approach that *a priori* interaction structure is needed before analysis, a more flexible nonparametric approach is also utilized to intuitively exhibit the magnitude and radius of the spatial dependence with respect to distances. Besides, we briefly summarize the underlying behavioral reasons that lead to the spatial dependence across local housing markets.

The remainder of the paper is organized as follows. Section 2 briefly discusses the behavioral reasons for spatial dependence in the interurban housing market. Section 3 introduces the parametric and nonparametric models, while section 4 offers different strategies for constructing the spatial weights matrix. An introduction to the study area and data set is provided in section 5, followed by the empirical results in section 6. Finally, section 7 concludes our findings and draws some implications.

2. Behavioral reasons for spatial dependence

Spatial dependence across properties is mainly attributed to two reasons (Basu and Thibodeau, 1998; Can and Megbolugbe, 1997; Gillen et al., 2001). First, properties in close proximity tend to be developed at the same time and have similar structural characteristics, such as dwelling size, design features and architectural style, and hence these properties are related when determining the transaction prices; sometimes households pay the same prices for properties in a particular location just for "snob" purpose. Second, properties within same neighborhood share the

common neighborhood amenities, such as the public service provision and accessibility. These two reasons are considered to be *adjacent effects* (or *spatial spillover effects*) and *neighborhood effects*, respectively (Can, 1992; Can and Megbolugbe, 1997).

In contrast, the underlying mechanism that results in the spatial dependence across local housing markets is more complicated. In the studies of strategic interaction among governments, Brueckner (2003) separated the theoretical models underlying empirical studies into two categories: spillover models and resource-flow models. The former one is based on the idea that the decision variable z_i in jurisdiction *i* is directly affected by the level of decision variables in other jurisdictions. The idea behind the latter one is that the decision variable z_i in jurisdiction *i* is affected by a particular "resource" within its border, the distribution of which is affected by the decision variables in all jurisdictions, that is jurisdiction *i* is indirectly affected. Despite their mechanism differences, both two models ultimately lead to the same reaction function that shows the interrelationship between jurisdictions. Correspondingly, we may apply the spillover framework and resource-flow framework to explore and categorize the underlying behaviors that cause the spatial dependence in the interurban housing markets.

Following behavior. The cities in close proximity tend to have the similar natural, cultural, historical and linguistic environment, as well as the common policy restriction. Hence, the households in these cities probably follow the same home-consuming behaviors, while the house developers are likely to provide house products with similar characteristics in adjacent cities. Such following behavior will be capitalized into the house prices and results in the spatial dependence. The second type of following behavior is to some extent analogous to the "snob" behavior proposed by Can and Megbolugbe (1997) in intra-urban housing market. This behavior is consistent with the positive-feedback hypothesis: Recent increase (or decrease) of house prices in one local housing market encourages positive (or negative) attitudes which will lead to a greater-than-expected effect on its neighbors' house prices (Pollakowski and Ray, 1997). The following behavior seems to be in accordance with the idea of spillover mechanism.

Migration and equity transfer. Jones and Leishman (2006) have proven the hypothesis that household migration across local housing markets creates a spatial arbitrage process in the form of equity transfer which leads to the spatial dependence. Migration across cities might be

triggered by two reasons. First, the migration is accompanied by the evolution of regional economic system. In a firstly segmented regional market, the initially booming city will increase the rate of real wages. According to Millington (1994), this increase of real wages will drive up the local house prices in that market, which in turn leads to migratory inflow of labor and the house prices adjust in an upward direction until the benefit from high real wages is offset by the higher cost of housing. The inflow movement will probably cause the negative spatial dependence. However, a unique form of migration in China, namely "migrant workers", may generate the positive spatial dependence pattern. Migrant workers are usually from the less developed cities (both the urban and rural area) and move to nearby developed cities for temporary jobs. They leave their family in their home-cities and most of their net income will be transferred to the families to pay for a home. In this way, a "trickle-down" effect of house prices is formed between local housing markets¹. Second, the fact that households take advantage of the house price differences among cities to maximize their utilities would drive the migration. The house purchasers moving from the city with higher house price level have a greater buying power and therefore force up the house prices in other cities, so that the different local housing markets are interlinked and the neighbor cities are more related (Meen, 1999). It seems that the physical household migration and its associated equity transfer result in the interurban housing market dependence by following the "resource-flow" framework.

Spatial arbitrage of capital. Although being similar to the arbitrage process of households, the spatial arbitrage of capital is mainly from the investment perspective. If the interurban housing market is an efficient market, arbitrage would take place over the space until reach a pattern of even return. However, The presence of search cost might imply that the arbitrage of capital follows a gradient transfer process, the capital being first transmitted to contiguous cities (Meen, 1999). In this case, local housing markets are linked through capital flow rather than physical movement, and the nearby local housing markets are connected more closely. This behavior seems also follow the "resource-flow" mechanism and thus spurs the indirect spillover effect.

3. Modelling the spatial dependence

¹ "Trickle-down" effect is a conception in development economics and means the accumulation of wealthy in the rich area can trickle down to the poor area. In the intercity housing market, it refers to the house price growth in developed cities can spread to the less developed cities.

3.1 Spatial econometrics – Parametric approach

An intuitive way to test the spatial dependence of interurban house prices is by Moran's I test and local indicators of spatial association (LISA) (Anselin, 1995). However, this is an informal way without controlling for the influence of house price determinants. For developing a formal approach, we first consider a linear regression model for house prices (OLS model)

$$P = \alpha \iota_{N} + X \beta + \varepsilon \tag{1}$$

where *P* denotes a $N \times 1$ vector of house prices, t_N is a $N \times 1$ vector of ones represented constant terms with estimated parameter α , *X* is a $N \times K$ matrix of house price determinants, β is a $K \times 1$ vector of regression coefficients, and ε denotes an $N \times 1$ vector of i.i.d. error terms. This model does not allow for spatial interaction since it implicitly assumes that the observations are independent of each other. The Moran's I test for residuals of OLS model can be conducted. If the Moran's I turns out to reject the null hypothesis that there is no spatial dependence, then we are convinced to employ the spatial models with spatial interaction effects.

There are mainly three types of spatial interaction effects (Elhorst, 2010; Manski, 1993). (1) Endogenous interaction effects, where the house price of a city behaves in a way that depends on the house prices of neighbor cities. (2) Exogenous interaction effects, where the house price of a city depends on the house price determinants in neighbor cities. (3) Correlated effects, where the spatial dependence of house prices is caused by correlated unobserved environmental characteristics.

Incorporating the endogenous interaction effects into the OLS model forms the spatial lag model or spatial autoregressive regression (SAR)

$$P = \rho W P + \alpha \iota_N + X \beta + \varepsilon \tag{2}$$

where W is an $N \times N$ spatial weight matrix that specifies the spatial proximity between cities, WP denotes the spatially lagged dependent variable (endogenous interaction effect), ρ is defined as spatial autoregressive coefficient. The parameter ρ describes the intensity of spatial dependence of house prices. If $\rho = 0$, the spatial lag model reduces to the standard OLS model. The SAR model can be rewritten as:

$$P = (I - \rho W)^{-1} \alpha \iota_N + (I - \rho W)^{-1} X \beta + (I - \rho W)^{-1} \varepsilon$$
(3)

Because of the spatial multiplier matrix $(I - \rho W)^{-1}$, the house price in a particular city depends on not only its own error term, but also the error terms of neighbor cities. Therefore, the OLS estimate of SAR model is no longer consistent. Instead, maximum likelihood (ML) estimation can yield consistent and efficient parameter estimates (Anselin, 1988, 2006).

Unlike the OLS model, the interpretation of coefficients in SAR model becomes complicated and requires special approach (Kim et al., 2003)². In SAR model, a change in a house price determinant in a particular city not only exerts a "direct impact" on its own house price, but also potentially imposes an "indirect impact" on house prices of its neighbor cities. According to equation (3), the partial derivatives of *P* with respect to the *k*th independent variable can be obtained:

$$\begin{bmatrix} \frac{\partial P}{\partial x_{1k}} & \cdot & \frac{\partial P}{\partial x_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial p_1}{\partial x_{1k}} & \cdot & \frac{\partial p_1}{\partial x_{Nk}} \\ \cdot & \cdot & \cdot \\ \frac{\partial p_N}{\partial x_{1k}} & \cdot & \frac{\partial p_N}{\partial x_{Nk}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_k & 0 & \cdot & 0 \\ 0 & \beta_k & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \beta_k \end{bmatrix} = S_k(W).$$
(4)

In equation (4), the average of the diagonal elements of matrix $S_k(W)$ is defined as direct impact, while the average of the row sums of non-diagonal elements of matrix $S_k(W)$ is considered to be the indirect impact. The "indirect effect" means not only the impact of a change in explanatory variables in a particular city on the house price of other neighbor cities, but also the impact on house price of a particular city from changing the explanatory variables in all other neighbor cities. LeSage and Pace (2009) have demonstrated that these two measures yield the same results.

If the OLS model takes into account the correlated effects, the spatial error model (SEM) is formulated

$$P = \alpha \iota_N + X \beta + u \text{ and } u = \lambda W u + \varepsilon$$
(5)

² For a full discussion of the interpretation of parameter estimates in spatial model, please refer to LeSage and pace (2009).

where λ is called spatial autocorrelation coefficient. In this model, the correlated effect relates to the situation where the omitted house price determinants are spatially autocorrelated, or the situation where common shocks, which cover a scope of macroeconomic, technological, institutional, political and sociological shocks (Andrews, 2005), follow a spatial pattern. The estimates of parameters in SEM model will be unbiased, but not efficient, which can be solved by ML estimation. The interpretation of the parameter estimates in this model is the same as the explanation of OLS model.

Spatial Durbin Model (SDM) (LeSage and Pace, 2009) considers both the endogenous interaction effects and the exogenous interaction effects

$$P = \rho W P + \alpha \iota_{N} + X \beta + W X \theta + \varepsilon$$
(6)

where θ , just as β , denotes a vector of parameters. The SDM model is motivated by omitted variables. This model can produce unbiased coefficient estimates, even if the omitted or unobserved variables are correlated with the explanatory variables and follow the spatial autoregressive process. In general, the SDM model produces unbiased estimates, no matter the true data-generation process is spatial lag model or spatial error model. A likelihood ratio (LR) test can be conducted to test which model describes the true data-generation process best. The hypothesis H₀: $\theta = 0$ is used to test whether the SDM model can be simplified to SAR model, while the hypothesis H₀: $\theta + \rho\beta = 0$ is applied to test whether the SDM model is equal to the SEM model.

The parameter estimates of SDM model are obtained by ML estimation and can be interpreted in a similar way as SAR model. The only difference is the matrix of partial derivatives $S_k(W)$ will be

$$S_{k}(W) = (I - \rho W)^{-1} \begin{vmatrix} \beta_{k} & w_{12}\theta_{k} & \cdot & w_{1N}\theta_{k} \\ w_{21}\theta_{k} & \beta_{k} & \cdot & w_{2N}\theta_{k} \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\theta_{k} & w_{N2}\theta_{k} & \cdot & \beta_{k} \end{vmatrix} .$$

$$(7)$$

Besides, there are other model specifications containing at least one interaction effect, such as the Manski model that contains all three types of interaction effects (Elhorst, 2010), the SAC model

including the endogenous interaction effect and correlated effects (Kelejian and Prucha, 1998) and the SLX model only incorporating the exogenous interaction effects (Gibbons and Overman, 2012). However, we mainly focus on the three specifications SAR, SEM and SDM as they have been frequently used in applied research.

3.2 Nonparametric approach

As McMillen (2010) has pointed out, the spatial models have to impose a structure to the model *in prior* when the true model structure is not known. Alternatively, the nonparametric approaches are attractive because they admit the unknown true structure at first. Here, we will examine the spatial autocorrelation by a nonparametric function called *spline correlogram* (Bjørnstad and Falck, 2001), and measure the spillover effect by a spatial covariance decomposition approach advanced by Conley and Ligon (2002).

Consider the measurement (like house price) Z_i in city *i* and suppose *Z* as stationary random field. That is, the expectation and covariance function of *Z* will be fixed through space. We further suppose the random field *Z* to be isotropic, implying that the covariance function only depends on distance, not direction. The spatial autocovariance of random field *Z* between city *i* and *j* is:

$$\operatorname{Cov}(Z_i, Z_j) = (Z_i - \overline{Z})(Z_j - \overline{Z}), \qquad (8)$$

where $\overline{Z} = 1/n \sum_{i=1}^{n} Z_i$ is the sample mean. According to Hall and Patil (1994), a nonparametric estimator of autocovariance at distance *d* can be given by:

$$\widehat{C}(d) = \left[\sum_{i}\sum_{j}K\left(\frac{d-d_{ij}}{h}\right)\left(Z_{i}-\overline{Z}\right)\left(Z_{j}-\overline{Z}\right)\right]\left[\sum_{i}\sum_{j}K\left(\frac{d-d_{ij}}{h}\right)\right]^{-1}$$
(9)

where $K(\cdot)$ is the kernel function, h(>0) is the bandwidth (a parameter to adjust the smoothness of the fitted value) and d_{ij} measures the geographic distance between city *i* and *j*. Bjørnstad and Falck (2001) used a cubic B-spline as an equivalent kernel smoother because it has

better performance than many regression kernels in simulating the irregularly spaced data. The asymptotic kernel function for the cubic B-spline is given by:

$$K(u) = \frac{1}{2} \exp\left(-\frac{|u|}{\sqrt{2}}\right) \sin\left(-\frac{|u|}{\sqrt{2}} + \frac{\pi}{4}\right),\tag{10}$$

where $u = (d - d_{ij})/h$ in our case. Note that if we substitute the term $n \cdot (Z_i - \overline{Z})(Z_j - \overline{Z})/\sum_{i=1}^n (Z_i - \overline{Z})^2$ for $(Z_i - \overline{Z})(Z_j - \overline{Z})$ in equation (9), then we obtain the nonparametric estimator of spatial autocorrelation which is defined as *spline correlogram*.

The measurement of spillover effect in the housing market is based on a decomposition of house prices into predicted values and residuals. Again, let p_i denotes the house price of city *i*, and $\hat{p}_i = f(X_i, \beta)$ denotes the prediction value of house price based on a vector of observable house price determinants X_i and unknown parameters β . The house price p_i can be written as

$$p_i = \hat{p}_i + u_i, \tag{11}$$

where u_i represents the residual. Then the spatial autocovariance of house prices can be decomposed into three terms

$$\operatorname{Cov}(p_i, p_j) = \operatorname{Cov}(\hat{p}_i, \hat{p}_j) + \operatorname{Cov}(u_i, u_j) + 2\operatorname{Cov}(u_i, \hat{p}_j).$$
(12)

The first and second term on the right hand of equation (12) is the spatial covariance of observables and unobservables (residuals), respectively. The third term, $2\text{Cov}(u_i, \hat{p}_j)$, measures the relationship between the observable features of city j and the part of house prices of city i that cannot be explained by the observable characteristics in city i. Accordingly, the quantity $2\text{Cov}(u_i, \hat{p}_j)$ can be regarded as the spatial spillover effect. Note that the definition of spillovers here should be regarded as a measure of covariance, not as something causal.

Before we use equation (9) to estimate the covariance functions in equation (12), we have to first solve the unknown parameters β for the prediction of house prices. Here, we assume a linear

function $p_i = X_i\beta + u_i$. Since one property of the spillover effect is that the spillover between a city and itself should be zero, that is

$$\operatorname{Cov}(u_i, X_i) = 0 \tag{13}$$

As long as observations on X_i satisfy a simple rank condition, Conley and Ligon (2002) suggest the sample analog of moment restriction (13) to obtain the estimators $\hat{\beta}$ which will correspond to the OLS estimators in this case.

4. Constructing spatial weights matrix

In spatial econometrics, the spatial matrix W is a core element to reflect the spatial interaction between spatial units and to represent the economic rationale (Corrado and Fingleton, 2012). Hence, modelling the spatial spillovers in the interurban housing market needs to correctly specify the spatial matrix at first. The traditional forms of spatial matrix are based on spatial contiguity measures, geographical distance and travel time. However, those measures will be less useful if the spatial interaction is caused by economic or social activities. Instead, the measure of economic distance (Conley and Ligon, 2002) or social distance (Conley and Topa, 2002) is advanced and employed. Since one aim of this paper is to choose the best spatial matrix that can correctly describe the spatial interaction pattern in the interurban housing market, we will design and employ four types of spatial matrices.

Spatial contiguity measure. This is a measure that can derive the relationships of polygons, and it has two forms: Rook and Queen. The former one defines the spatial polygons who share some length of common border as neighbors, while the latter one considers the units who share the common border or vertex to be neighbors. For this measure, the construction of spatial weight matrix (Rook contiguity) is simple and the spatial weights w_{ij} of unit *i* and *j* can be written as:

$$w_{ij} = \begin{cases} 1, & \text{Unites share common boundary} \\ 0, & \text{Otherwise.} \end{cases}$$
(14)

Geographical distance and travel time. These two measures are considered under the belief that geographical distance or travel time is highly related to the cost of interaction. The longer distance or time the two local housing markets hold, the more interaction cost will be. Besides,

the travel time measure reflects the influence of transport infrastructure on the interaction pattern. When constructing the spatial matrix, we treat all the spatial units as the neighbor of each other, but near neighbors have higher weights than distant neighbors. Here we use a popular Gaussian function form:

$$w_{ij} = \exp(-d_{ij}^2/b^2),$$
 (15)

where d_{ij} represents the geographical distance or travel time between object *i* and *j*, and *b* refers to the bandwidth.

Economic distance. Fingleton and Le Gallo (2008) have pointed out the big cities may be less remote than their geographic distance would imply, whereas very small cities are often separated from one another. If the house price in a large city is very high, some demand will displace to a similar large city (perhaps a remote city) rather than speared to a small neighbor city. In these cases, the relative economic distance will be more realistic. Therefore, we construct the economic distance matrix by incorporating the economic scales into distance measure. The spatial weights can be written as gravity forms:

$$w_{ii} = G_i G_i \times \exp(-d_{ii}^2 / b^2),$$
(16)

where G_i refers to the gross domestic products (GDP) of city i.

5. Study area and data

This paper uses the data from Jiang-Zhe-Hu area (JZH area) which contains Shanghai municipality, Zhejiang and Jiangsu province in eastern China. The JZH area is one of the most developed area in China, as well as one of the largest urban agglomerations in the world. According to the sixth national population census, about 156.10 million people lived in the JZH area as of 2010, of which 101.77 million are in urban area. Specifically, the JZH area is comprised by 1 municipality under the central government, 24 prefecture cities and 109 counties or county-level cities³. The transportation infrastructure in this area is highly developed, and characterized by railways and highways (including motorways, national highways, provincial

³ For a detailed description of Chinese administrative division system, see Gong et al (2014).

highways and prefectural highways). The longest travel time by car between two separate urban areas is about 13 hours. In this study, we define the housing market associated with the urban area of each jurisdiction (municipality, prefecture city or county) as local housing market.

Insert figure 1 about here

We utilize a cross-sectional dataset containing 134 observations in 2010. The data on house prices and house price determinants are mainly extracted from the statistical yearbook. There are by far no direct house price indices that can cover all the jurisdictions in our study area. So the average house price (*HPrice*), calculated by dividing total sales of newly-sold residential buildings by the total floor spaces, is taken as an alternative measure.

Gong et al (2014) have developed a theoretical approach to explore the house price determinants on aggregate city level. Since the empirical results reveal the highly significant influences of income and mortgage and marginal significant effect of population, we only consider the former two determinants in this study. The first explanatory variable is the disposable income (*Income*) directly extracted from the statistical yearbook. It is expected that the jurisdictions with higher income level tend to be the more expensive house prices. The second variable is related to the mortgage which can promote the households' access for housing market and stimulate the housing demand, which consequently drive up the house prices. Though the data of mortgage for housing purchase is not available, we believe the loan balance per capita (Loan) to be an appropriate alternative measure⁴. Besides, taking into account the fact that prefecture cities or municipality can provide better living infrastructures and public services in terms of amount and quality and thereby have more expensive house prices because of the capitalization of such amenities, a dummy variable (*Rank*) indicating the rank of administrative level of jurisdictions is chosen as the third explanatory variable. If the jurisdiction is a county or county-level city, then the variable *Rank* will be 0; otherwise, 1. At last, a dummy variable *Coastal city* is also included in the model, as many empirical studies have demonstrated its marked influence on house prices. The value of 1 will be designated to *Coastal city* if the urban area of the jurisdiction shares the coastline.

⁴ Due to the huge difference of development between urban and rural area, the majority of the loans is believed to flow into the urban area. Therefore, the loan balance per capita is calculated by dividing the total loan balance of financial institutions by non-agriculture population.

To construct the four types of spatial matrices W mentioned above, the geographical distance, travel time and data for GDP are needed. The GDP data is published directly in the statistical yearbook, while the two distance measures are calculated by the following procedure. First, the coordinates of the city (county) hall are defined as the representative of each jurisdiction. Then the geographical distance (straightforward distance) is calculated from the latitude/longitude coordinates, and the travel time corresponds to the shortest driving time extracted from Google Map⁵. The descriptive statistics of variables and various distances are reported in table 1. Note that the Moran's I tests provide strong evidence for positive spatial autocorrelation of variables HPrice, Income and $Loan^6$.

6. Results

We start with testing and measuring the spatial dependence and spillover of interurban house prices under a given interaction structure by using the parametric approach, and then turn to investigate the flexible feature of such dependence and spillover by using nonparametric approach.

6.1 Results of parametric approach

The estimation results of different model specifications are reported in table 2^7 . The OLS estimation is shown in the second column and serviced as a benchmark. The OLS regression model performs quite well as about 71% of the interurban house price differences can be explained. However, the Moran's I test for OLS residuals based on economic distance matrix is 0.322 and significantly rejects the null hypothesis of no spatial autocorrelation⁸, indicating a strong evidence of spatial interaction in the interurban housing market. And hence, we are motivated to employ the spatial models.

The classic Lagrange Multiplier tests (LM-tests) and robust LM-tests, LM_{ρ}^{r} and LM_{λ}^{r} , are then utilized to find out whether spatial lag model (SAR) or spatial error model (SEM) is the better choice for describing the data generation process of interurban house prices. As indicated by

⁵ The travel time in Google Map is calculated according to the real time traffic situation. In order to reduce the bias, the data is collected in non-peaking period from 10:00 PM to 3:00 AM.

⁶The Moran's I tests and inference here are calculated based on spatial contiguity matrix and normality assumption.

⁷ All the spatial models and diagnostic tests are operated in the R package 'spdep'.

⁸ The geographical distance is employed to build the economic distance matrix, because it performs better than the matrix based on travel time. A bandwidth of 30 kilometers is chosen here on which the AIC of the SAR model is minimum.

classic LM tests, the OLS model is rejected to be in favour of either the SAR model or the SEM model at 1% significant level. Further, the robust LM tests reveal that the SAR model is still in fovour whereas the null hypothesis of no spatially autocorrelated error term is no longer rejected. As a result, it is believed that the SAR model is the more appropriate specification. In order to avoid the biased and inconsistent estimators caused by omitted variables which relate to the explanatory variables, the Spatial Durbin Model (SDM) is also estimated and the results are reported in the last two columns in table 1. Our model specification turns not to be suffered from omitted variables as all the coefficients of spatially lagged independent variables (WX) appear not to be significant. Further, a formal test is conducted. The likelihood ratio (LR) test, $H_0: \theta = 0$, is performed and the result cannot reject the null hypothesis, indicating that there is no reason to reject the SAR model and accept the SDM model. Another LR test, $H_0: \theta + \rho\beta = 0$, shows that the SEM model is rejected to be in support of SDM model. Therefore, both the LM and LR tests convince us to choose the SAR model as the best candidate for our model specifications. In conclusion, our choice of explanatory variables is surprisingly satisfactory and the spatial interaction pattern in the interurban housing market is characterized by an endogenous interaction effects.

The estimation results of OLS model and SAR model are then comprehensively compared. The estimated coefficients of independent variables in both models are generally as expected with respect to signs and significant at 1% level, except for the significance of *Coastal city* in SAR model at 5% level. Those cities with higher income or mortgage level generally tend to drive up their house prices, while the house prices in prefecture cities (municipalities) and coastal cities are demonstrated to be more expensive than in counties and inland cities, respectively. The spatial autoregressive coefficient ρ is 0.350 and significantly different from 0 at 1% level, which is strong indicative of endogenous interaction. Since the estimated coefficients in the OLS model are biased because of the spatial autocorrelation process in error term, a simple comparison between OLS model and SAR model indeed reveals obvious differences between estimated coefficients of these two models, especially for the variables *Income* and *Loan*.

Insert Table 2 about here

To precisely compare the differences, we first calculate the "direct effect", "indirect effect" and "total effect" of SAR model using approaches introduced in section 3.1. Note that the direct effect in the SAR model is slightly different from the response estimators due to the feedback effects, through which the impacts pass through neighbor cities and back to itself. However, the magnitudes of feedback effects are quite small. Compared the response estimators of OLS model with the direct effects of SAR model, the extent to which the OLS estimators are biased becomes clear. The marginal effect of *Income* in OLS model is highly overestimated by 60.6%, then of *Loan* by 44.3%, of *Coastal city* by 29.8%, whereas the effect of *Rank* is underestimated by 36.6%.

In the SAR model, the house price in a particular city depends not only on its own determinants but also on neighbors' house prices through endogenous interaction, indicating an indirect interdependence between the particular city's house price and neighbors' house price determinants. This indirect interdependence is defined as 'spillover effect' and corresponds to the 'indirect effect' in the SAR model. The responsible indirect effects show that a 1% change in *income* and *mortgage* in a particular city will increase the house prices in other neighbor cities by totally 0.19% and 0.08%, respectively. The magnitude of spillover of a prefecture city or municipality on neighbor cities' house prices will be 14.61%, while that of a coastal city is about 5.34%. Compared indirect effect to direct effect, it can be seen that the strength of the spillover effect of each explanatory variable is nearly half of the direct effect.

Insert Table 3 about here

As is known to us, the parameter estimates of SAR model, especially for estimating the amount of indirect effect, directly depend on the spatial weights matrix. Therefore, the choice of an appropriate spatial matrix will be crucial in explaining the spatial process of house prices. For the sake of comparison, another three alternative specifications of spatial matrices are also considered, namely spatial contiguity matrix, geographical distance matrix and travel time matrix⁹. The widely used approach to determine the best spatial matrix is to compare the log-likelihood function values. However, we employ the Bayesian posterior model probability approach offered by LeSage and Pace (2009) to select the best specified W, as the posterior model probabilities can still differ largely even if the estimation results are quite robust to

⁹ The bandwidths for constructing the geographical matrix and travel time matrix are 40 kilometers and 60 minutes, respectively, according to the criteria of minimizing the AIC of SAR model.

different specifications of spatial matrices (Elhorst, 2010). In this study, the posterior probabilities of SAR models based on four different spatial matrices are computed and the one with highest probability is selected¹⁰. As shown in table 3, the posterior probability of the SAR model based on "economic distance matrix" is far larger than the models based on other spatial matrices. This finding indicates that the spatial interaction pattern in the interurban housing market is complicated, depending not only on the distances between cities, but also on the economic features of the cities, such as the city size. An anti-intuitive finding in table 3 is that the travel time measure which is designed to represent the influence of transportation infrastructures does not perform better than geographical distance. That may be a response to the fact the usage of motorways in China is rather costly, but not free. As a result, the cities connected by motorways may have a short travel time, but not communicate frequently because of the high cost. That is, the travel time may be a biased measure to reflect the true interaction pattern.

6.2 Results of nonparametric approach

Given the specification for house price prediction in section 6.1 and the OLS estimates of unknown parameters β , we can then use the nonparametric approach in section 3.2 to estimate the spatial autocorrelation of each variable and measure the spillover effect¹¹.

6.2.1 Spatial autocorrelation

Using the nonparametric technique *spline correlogram*, the spatial autocorrelation functions of dependent variable, independent variables (except for dummy variables) and unobservables (residual) are estimated and shown in Figure 2. The solid lines in this figure are estimated spatial autocorrelations, while the regions enveloped by dashed lines are 95% confidence region simulated by bootstrap algorithm. For all panels of Figure 2, the confidence envelope at distances greater than 600 km becomes much wider because the lack of enough observations for inference. Therefore, we mainly concern the spatial correlation for cities less than 600 km. In contrast to Moran's I tests which need to base on certain spatial structures, *spline correlogram* flexibly describes the autocorrelation patterns with respect to distances.

¹⁰ We used the matlab routine *sar_g* at the "spatial econometrics" toolbox posted by LeSage to perform the estimation of Bayesian posterior model probabilities.

¹¹ The nonparametric estimation of spatial autocorrelation and spillover effect was operated in R package 'ncf', and we only utilized the geographical distance in this section.

Figure 2(A) provides strong evidence of spatial autocorrelation of house prices. The positive dependence between cities less than 350 kilometers monotonically decreases with geographical distances, which is in accordance with Geographical First Law. For cities that separated more than 350 km, there is no significant evidence for their dependence of house prices. However, the cities apart farther than 450 km seem to show a negative dependence, indicating that the farther the cities are separated, the larger differences of house prices they have. One explanation for the negative dependence may be related to the fact that the southern part (Southern Zhejiang province) of our study area is generally more developed than the northern part (Northern Jiangsu province). However, it is still a bit difficult to imagine a behavior which would generate such negative dependence and we will leave this for the future work.

Insert Figure 2 about here

The estimated spatial autocorrelation functions of disposable income (*Income*) and loan balance per capita (*Loan*) are displayed in Figure 2(B) and 2(C), and they exhibit a similar decline pattern with house prices. One difference is that the range of positive dependence of *Income* is about 220 km and much smaller than that of house price (350 km) and *Loan* (300 km). The negative autocorrelations of these two independent variables are, of course, detected at a moderate distance ranges, except that the negative dependence of *Income* no longer monotonically changes with distances, which again differs from other variables.

We next turn to formally consider the spatial interaction of housing market by estimating the spatial autocorrelation of OLS residuals. If the house price determinants that appear in the OLS specification can efficiently predictive the house prices, then the spatially uncorrelated residuals ought to be observed; otherwise, there is evidence for spatial interaction. Figure 4(D) shows the nonparametric estimation of spatial autocorrelation of OLS residuals. There is significant evidence of positive dependence at short distances less than 60 km, but we cannot reject the hypothesis of independence at other distances. Considering that almost all the cities in our study area have at least one neighbor within the radius of 60 km, we are convinced that spatial interaction indeed play an important role in determining the interurban house prices. This finding is strictly in line with the LM and LR tests in spatial parametric models which indicate an endogenous effect in the interurban housing market.

6.2.2 Spillover effect

Having explored the spatial autocorrelation functions of house prices, observables and residuals, our focus shifts to decompose the spatial covariance of house prices represented in equation (12) and discuss the final component $\text{Cov}(u_i, \hat{p}_j)$, which we have called spillovers. Figure 3(A) draws nonparametric estimation of spatial covariance of each component. And again, we only consider the spatial covariance functions at distances less than 600 km.

Our conclusion for spatial dependence in housing market are enhanced by Figure 3(A), as the spatial covariance functions of house price and residuals are the same in form to the spatial autocorrelation functions. Further, the importance of observables in predicting the house prices is also underpinned by the fact that the spatial covariance for observables declines quite similar to the function for house prices and accounts for the greatest part of covariance of house prices at distances less than 600 km. Nevertheless, the role of both the covariance in spillovers and unobservables in explaining the house price covariance cannot be ignored, especially at short distances.

As mentioned in our earlier discussion and displayed in Figure 3(A), the amount and scope of spatial covariance of unobservables are both quite small. So the spillover effect ought to be largely responsible for explaining the house price differences at where the observables fail to perfectly account for house prices. This is convinced by Figure 3(B) which contains the nonparametric estimation of spillovers and 95% confidence envelope. Figure 3(B) demonstrates that the spillover effect is not only appreciable in magnitude, but also significant at distances less than 250 km. The spatial distribution of cities in our study area can provide us with a deeper understanding of the range of spillovers. The distance between central city (Shanghai) and one subcentral city (Hangzhou), which is the capital of Zhejiang province, is within this range, while another subcentral city Nanjing (capital of Jiangsu province) locates at the marginal of this range (270 km). For Zhejiang and Jiangsu province, about 79% and 73% of its cities are apart within the radius of 250 km, respectively. It can be concluded that spillover effect is quite important in explaining the house prices of interurban housing market, especially for the cities under the same provincial government.

Just as discussed in parametric models, a further question related to spillover effect is that which house price determinants are primarily responsible for generating the total spillovers. The answer is found by simply decomposing the total spillover function $\text{Cov}(u_i, X_j^{\dagger}\hat{\beta})$ into a sum of covariance functions between each determinant and residuals, $\sum_{k=1}^{l} \hat{\beta}_k \text{Cov}(u_i, X_{kj})$, where X_{kj} denotes the *k*th determinant (except for dummies). We define the covariance functions $\{\text{Cov}(u_i, X_{kj})\}$ as the estimated *components* of the spillovers. Figure 3(C) and 3(D) show the estimates of each spillover component created by *Income* and *Loan* and their 95% confidence envelope, and the results are quite revealing. The spillover functions of both *Income* and *Loan* have similar declining patterns with the total spillover, as well as almost the same significant ranges. All these findings are consistent with our earlier parametric results. An increase in the *Income* and *Loan* in a particular city will exert a positive spillover effect in its neighbor cities' house prices within 250 km.

7 Conclusion and implication

While the spatial dependence in the intracity housing market has been extensively studied, this paper contributes to the understanding of spatial interaction of house prices from an interurban perspective. Based on a cross-jurisdictional data set, our empirical results of both parametric and nonparametric approach provide convincible evidence of spatial dependence and spillover effect in the interurban housing market.

Through extensive literature study, we conclude that *following behavior*, *migration and equity transfer* and *spatial arbitrage of capital* are the most important behavioral reasons for spatial interaction (spatial dependence) in the interurban housing market. Due to such spatial interaction, the OLS specification cannot perfectly explain the house price differences and will produce biased coefficients estimation. In the parametric approach, the Moran's I test of OLS residuals indicates that spatial models will be the better specification. Further, the LM and LR tests suggest the spatial lag model (SAR) as the best one, indicating that the house price process follows an endogenous interaction pattern. It should be noted that the spatial interaction depends not only on distances between jurisdictions, but also on jurisdictions' economic situation. The results of SAR model are interpreted by partial derivative approach. They reveal that the coefficients estimators

are seriously biased, especially for *Income* and *Loan*, of which the coefficients are overestimated by 61% and 44% respectively. Spillover effects, referring to the interdependence between one jurisdiction's house prices and its neighbors' determinants, are proved to be significant in explaining the house prices, and their strength reaches nearly half of the direct effects.

Parametric approach offers quite revealing conclusions based on a certain structure, while the nonparametric approach draws a flexible relationship between spatial dependence and distances. We find monotonically declined spatial autocorrelation of house prices and explanatory variables at moderate distances, such as distances less than 220 km. In contrast, though the OLS residuals also exhibit significant autocorrelation, its scope is really small (60 km). Spillover effect is again investigated by decomposing the spatial covariance function. The results show that the importance of total spillover effect in explaining the house prices should be paid attention to within the radius of 250 km. Moreover, the spillover effects created by *Income* and *Loan* follow a similar decreasing pattern with the total spillover effect.

Although we chose only few interurban house price determinants in the model specification, the model performs quite well when taking the spatial interaction into account and we can draw a few useful implications. First, the spatial dependence and spillover effect offers us a deeper understanding of the interurban house price behavior. It provides a good insight into accounting for why the house prices in some cities run above the level indicated by fundamentals. So it should be much careful to judge if there are 'bubbles' in those cities' housing markets. Second, policy makers have to consider the spillover effect and enhance the cooperation with neighbors when making policies or regulations to govern the local housing market, especially for countries whose policy-making procedure is not centralized. Though we did not fully consider the policy variables in our study, the spillover effect of variable *Loan* indeed reveals that a looser monetary environment in one jurisdiction can generate a positive shock to its neighbors' housing market, which may imply the spillovers of other policies. However, a lot of work about the spillover effect of policy in the housing market needs to be done in the future.

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	Description	Min	Max	Mean	S.D.	Moran's I
HPrice	Average house prices (Yuan/m ²)	1950.56	23969.18	6057.26	3410.18	0.3643** (6.71)
Income	Disposable income (Yuan per capita)	11783.00	35220.00	22555.37	5724.19	0.3813**(7.02)
Loan	Loan balance per capita (10 million Yuan)	1.25	58.82	16.25	12.84	0.3903**(7.18)
Rank	The administrative level of jurisdictions $(0,1)$	0.00	1.00	0.19	0.39	/
Coastal city	Cities share coastline (0,1)	0.00	1.00	0.29	0.46	/
Geographic distance	Straightforward distance (km)	6.96	877.09	303.91	178.98	/
Travel time	Shortest driving time (minutes)	19.00	803.00	275.43	143.12	/
GDP	Gross domestic products (100 million Yuan)	26.70	16971.55	651.83	1618.53	/

Table 1. Description of variables and distances

Note: Moran's I tests are calculated based on spatial contiguity matrix; standard deviations of Moran's I are computed under normality assumption and reported in parentheses; ** indicates significance at 1% level.



Figure 1. Study Area

	OLS	SAR		SEM	SDM			
	-	Coefficient	Direct	Indirect	Total		X	WX
Ln (Income)	0.6408**	0.3971**	0.3990**	0.1939**	0.5929**	0.6390**	0.4922**	-0.2776
	(4.270)	(2.853)	(2.887)	(2.624)	(2.972)	(4.151)	(2.969)	(-1.178)
Ln (Loan)	0.2209**	0.1474**	0.1531**	0.0753**	0.2284**	0.1539**	0.1190**	0.0627
	(5.202)	(3.826)	(3.830)	(3.025)	(3.897)	(3.594)	(2.722)	(1.030)
Rank	0.1840**	0.2770**	0.2902**	0.1461**	0.4362**	0.2112**	0.2562**	-0.0815
	(3.140)	(5.246)	(5.541)	(2.902)	(4.639)	(4.695)	(4.584)	(-1.052)
Coastal city	0.1404**	0.0999*	0.1082*	0.0534*	0.1616*	0.1304*	0.1192**	-0.0385
	(2.783)	(2.246)	(2.513)	(2.165)	(2.493)	(2.342)	(2.015)	(-0.512)
Constant	1.5779	1.1340				1.7371	2.46	4
	(1.116)	(0.924)				(1.186)	(1.37	0)
ρ		0.350**					0.403	**
		(28.464)					(18.72	23)
λ						0.460**		
						(21.478)		
\mathbf{R}^2	0.711							
Log likelihood	-6.626	7.606				4.113	9.23	9
AIC	25.252	-1.212				5.774	3.52	3
Obs.	134	134				134	134	
Moran's I	0.322**							
(OLS Residual)	(5.122)							
LM test between SAR and OLS						LR te	st between SAR	and SDM
LM_{ρ}	31.805**						$LR_{\theta=0}$	3.265
$LM^{r}_{ ho}$	10.806**							
LM test between SEM and OLS						LR test between SEM and SDM		
LM_{λ}	21.825**						$LR_{\theta+ hoeta=0}$	10.251*
LM^{r}_{λ}	0.826							

Table 2. Estimation results of different model specifications (Dependent variable= $\ln(HPrice)$)

Note: Results reported in this table are based on the *economic distance* matrix. t-values are reported in parentheses. ** and * indicate significant at 1% and 5%, respectively. For spatial parameters, LR tests are employed. Moran's I and LM tests are based on OLS residuals. LR tests are based on log-likelihood values.

Table2. Bayesian posterior model probabilities of different matrix specifications

Matrix	Spatial contiguity	Geographical distance	Travel time	Economic distance
Posterior probability	0.0003	0.0624	0.0416	0.8957
37	11.6 6.1166			

Note: the parameter estimates and inferences of different spatial weights matrices are available upon request.



B. Spatial correlation of income



Figure 2. Nonparametric spatial autocorrelation functions

A. Covariance decomposition

B. Covariance decomposition: Spillover effect





C. Covariance decomposition: Spillover effect of income



D. Covariance decomposition: Spillover effect of Loan



Figure 3. Spatial covariance decomposition