In Search of Fiscal Interactions: A Spatial Analysis of Chinese Provincial Infrastructure Spending

Zheng, Xinye and Song, Feng and Yu, Yihua and Song, Shunfeng

Renmin University of China, Renmin University of China, Renmin University of China, University of Nevada; Tianjin Chengjian University

December 2014

In Search of Fiscal Interactions: A Spatial Analysis of Chinese Provincial Infrastructure Spending

Xinye Zheng
School of Economics
Renmin University of China
Beijing 100872, China
E-mail: zhengxinye@ruc.edu.cn

Feng Song
School of Economics
Renmin University of China
Beijing 100872, China
E-mail: songfeng@ruc.edu.cn

Yihua Yu (Corresponding author)
School of Economics
Renmin University of China
Beijing 100872, China
E-mail: yihua.yu@ruc.edu.cn

Shunfeng Song
Department of Economics
University of Nevada
Reno, NV 89557 USA
School of Economics and Management
Tianjin Chengjian University
Tianjin 300384, China
E-mail: song@unr.edu

Abstract

Using a dataset for 31 Chinese provinces from 1998 to 2006, this paper provides a spatial Durbin panel analysis to test for fiscal interactions among China's provinces in their public spending on infrastructure. We find significant positive interactions across Chinese provincial governments. Further analysis attempting to distinguish between the possible sources of such fiscal interactions reveals evidence of expenditure competition instead of yardstick competition.

JEL classification: H54, H7, C23
Key words: Infrastructure expenditure, Fiscal interactions, Spatial Durbin panel model, Two-stage least squares

1. Introduction

Public infrastructure (transportation, telecommunication, water and sanitation, etc.) investment has been widely used as a tool for economic development, although empirical work fails to find uniquely supportive evidence of the positive association between the two. Studies finding supportive evidence can be dated back to Aschauer (1989a, 1989b), who argues that infrastructure provides highly valuable services to the private sector and thus improves its marginal productivity. Numerous studies have attempted to examine the contribution of public infrastructure to productivity in China (Démurger, 2001; Fan and Zhang, 2004; Vijverberg et al., 2011). For instance, Fan and Zhang (2004) point out that governmental investment in roads, electricity, education, and other public investment in rural areas has contributed to the rapid growth in China's agricultural and rural non-agricultural production. Bom and Ligthart (2014) conduct a meta-analysis of numerous empirical studies (say, Pereira and Sagales (1999) in this journal) and find evidence that public spending on infrastructure contributes positively to economic growth.[1]

While there have been numerous studies on infrastructure during the past few decades, most of them focus on the perspective of the impact of public infrastructure on economic outcomes (economic growth, job opportunities, etc.) at the national or regional level, and they provide no deep understanding of the processes directing the level of infrastructure (Ghosh and Meagher 2004). In other words, what are the driving forces of public infrastructure investment? Studies from such a perspective are few.

Public infrastructure spending can be influenced by a range of factors. These include budget constraints (Vuchelen and Caekelbergh, 2010), political-economic factors such as fiscal stringency and frequent changes of government (De Haan et al. 1996), and some general economic and fiscal variables such as gross domestic product (GDP), output gap, long-term interest rates, public debt

(Bruce et al., 2007; Mehrotra and Välilä, 2006; Painter and Bae, 2001), and fiscal (revenue) decentralization (Kappeler et al., 2013). We argue that infrastructure investment can also be affected by politically motivated incumbents, as it can be used by local governors (at a provincial or city level) to achieve two goals. On the one hand, local governments have incentives to attract private investment by providing more infrastructure services/spending. On the other hand, they also have incentives to provide more infrastructure investment if local governments believe that their turnover (promotion or reappointment by the central government) is linked to their relative performance (prosperous economic growth, better job opportunities created, or better public services provided in their jurisdictions). In order to achieve these two goals, local governments have long been believed to engage in interjurisdictional interaction, as recognized in the fiscal federalism literature. Specifically, the former goal rests on the framework of expenditure competition, while the latter falls into the framework of yardstick competition across local jurisdictions. In brief, although some studies examine the determinants of public infrastructure spending, studies of the strategic interaction behavior of local governments in infrastructure spending are rare.

To our knowledge, the only paper (dealing with Chinese evidence) is Yu et al. (2011). However, their study only focuses on examining whether fiscal interactions in infrastructure spending exist across Chinese local governments using a cross-sectional dataset of 242 Chinese cities. Thus the possible sources of fiscal interactions with regard to local infrastructure spending remain untested. This study aims to fill that gap. Specifically, we examine the determinants of expenditure on public infrastructure in China using a panel dataset of 31 Chinese provinces during the 1998–2006 period. We propose a spatial Durbin panel model with spatial and time-period fixed effects to test whether China's provinces are engaged in strategic interaction behavior in spending on infrastructure. In addition, we proceed further to differentiate between different potential sources of fiscal interactions (expenditure competition, yardstick competition, etc.) across provincial governments. We mainly find that a provincial government tends to increase its own infrastructure spending in a response to a rise in the infrastructure spending of its neighboring provinces. Further analysis reveals that our results support for expenditure competition hypothesis instead of yardstick competition hypothesis.

The remainder of this paper is structured as follows. Section 2 specifies the spatial Durbin model with spatial fixed effects to test for possible sources of spatial interactions and provides the corresponding estimation techniques. Section 3 describes the data used in this analysis. Section 4 reports the empirical results with spatial interaction effects tested. The last section concludes with policy implications.

2. Spatial Model Formulation

Over the last two decades, a body of literature has arisen in an effort to empirically examine whether the level of public expenditure of a jurisdiction might be influenced by that of its neighbors,[2] and several different mechanisms were proposed by Manski (1993) through which one jurisdiction can be affected by the spending of its neighboring jurisdictions; namely, yardstick competition, expenditure competition, expenditure externalities, and 'common intellectual trend' that drives fiscal choices in the same direction.[3] In what follows, the presence of yardstick competition, fiscal competition, expenditure externality are likely to induce spatial dependence in public infrastructure expenditure in China. In what follows, we will test these hypotheses empirically using a spatial Durbin fixed effects model.

Spatial econometricians generally are of two minds on whether to apply the specific-to-general or the general-to-specific approach (Elhorst, 2010; Mur and Angulo, 2009). In this study, we use the general-to-specific approach; in other words, we specify an unconstrained spatial Durbin model that includes a spatially lagged dependent variable in addition to spatial lags of all independent variables. Specifically, the model is written in stacked form as:

$$Y = (\iota_T \otimes \alpha) + \rho(I_T \otimes W_N)Y + X\beta + (I_T \otimes W_N)X\theta + \varepsilon,\ N = 1,\ldots 31;\ T = 1998,\ \ldots 2006 \qquad (1)$$

where Y is a $NT \times 1$ vector, X is a $NT \times K$ vector, β and θ are respectively a $K \times 1$ vector of slope parameters to be estimated, ρ is a spatial autoregressive parameter that measures the magnitude of interdependence across provinces. ι_T is a column vector of ones of dimension T, α is a $N \times 1$ vector of provincial fixed effects, $\otimes$ is the Kronecker product and $\varepsilon \sim N(0, \sigma^2 I_{NT})$. W_n is the predetermined $N \times N$ spatial weights matrix in which the element is usually interpreted as the strength of spatial interaction between two units (provinces in this study). This is being posited as being the inverse function of the distance between two provinces i and j $(i \neq j)$.[4] W is commonly row standardized such that the elements of each row sum to one. By convention, the diagonal elements of the weights matrix are set to be zero, since each province is not a neighbor of itself. Eq. (1) can be estimated using the maximum likelihood estimation (MLE) techniques (see Elhorst and Fréret (2009) for the mathematical details).[5]

LeSage and Pace (2009) provide two reasons why the spatial Durbin model can be the best point of departure for testing spatial interaction effects. If unobserved or unknown but relevant variables following a first-order spatial autoregressive process are omitted from the model, and if these variables are correlated with independent variables not omitted from the model, the spatial Durbin model will produce unbiased coefficient estimates in contrast to a spatial lag model. In addition, the spatial Durbin model will produce unbiased coefficient estimates even if the true data generation process is the spatial error model.

Several empirical tests are implemented in this study to select the preferable model. First, the likelihood ratio (LR) tests are used to examine whether the spatial Durbin model can be simplified into a spatial lag model, a spatial error model, or an ordinary least squares (OLS) model. Failing to reject the null hypothesis H_0: $\theta = 0$ implies that the spatial Durbin model can be reduced to a spatial lag model, while failing to reject the hypothesis H_0: $\theta = -\rho\beta$ leaves us with a spatial error model. In addition, if $\rho = 0$, an OLS model with a spatial lag on the regressors can be used. Second, the LR tests can also be used to examine the null hypothesis that the spatial or time-period fixed effects are jointly significant. Lastly, the Hausman's specification test (Lee and Yu, 2010) is performed to test the fixed effects versus the random effects model.

3. Data Source

The dataset for this study consists of a panel of 31 provinces in mainland China (including four municipalities – Beijing, Tianjin, Shanghai, and Chongqing – and four autonomous regions – Guangxi, Inner Mongolia, Ningxia, and Tibet) during 1998–2006. The dependent variable examined is the per capita infrastructure investment made by the provincial government (*PROV*), which is calculated as the difference between the total infrastructure investment made by all governments in that province (taken from the *China Statistical Yearbook*) and infrastructure investment made by city and lower-tier governments in the same province (taken from *Statistical Materials of City and County Public Finances*, *Quanguo dishixian caizheng tongji ziliao* in Chinese). As the public finance dataset does not provide anymore the information on the city-level public infrastructure expenditure since 2007, our dataset covers until 2006.

With respect to the explanatory variables, unless otherwise noted all variables are taken from the *China Statistical Yearbook*. In particular, *REV* indicates the own-source revenue from the provincial government, which measures the availability of resources that can be devoted to public spending on infrastructure. We expect the coefficient on the revenue variable to be positive if the public good (i.e., infrastructure) is normal and Wagner's law is satisfied. All expenditure and revenue data are converted into real value per capita using the provincial consumer price index and total provincial population as the divisors (2006 = 100).

The next two sets of fiscal variables are public infrastructure spending by city governments (*CITY*) and by the central government (*CENTRAL*), respectively. The *CITY* variable is calculated as the sum of each city government's real public expenditure (2006 = 100) in a particular province divided by the total population of all cities in that province. As mentioned earlier, accounting for these two vertical fiscal variables is necessary to identify the true horizontal spatial effects of public infrastructure spending across provinces. The omission of these two variables could result in biased estimates for the horizontal effects.

Theoretically, the effect of the variable *CITY* on provincial public infrastructure spending is ambiguous. On the one hand, if two city governments within the same province increase their own spending on infrastructure (i.e., building a new road), the provincial government may also have incentives to increase its own infrastructure spending for the purpose of connecting these two roads, or connecting them with the main road within the province. On the other hand, if a city government invests in a project that the provincial government also wants to invest in, the provincial government may reduce its own efforts in response. Therefore the sign of this variable can be positive or negative.

The variable *CENTRAL* is defined as the central government's spending on infrastructure. The sign for this vertical fiscal variable can also be positive or negative. Infrastructure spending by the central government increases the marginal productivity of the province's investment and thus the provincial government may have incentives to increase its own infrastructure spending.

Alternatively, the provincial government may tend to reduce its infrastructure spending if the central government finances the project in which the province would otherwise invest.

EDU is defined as the percentage of total fiscal spending on education. Under the budgetary constraints of local governments, more public spending on education can imply that the provincial government should reduce spending on infrastructure. However, the provincial government might increase both infrastructure and education spending while cutting other types of expenditure if public spending on infrastructure and education are two priorities for the provincial government in making its budgetary decisions. Hence the sign of the *EDU* variable is indeterminate.

URBAN measures the percentage of the population living in urban areas, which is expected to have two inverse effects. On the one hand, if economies of scale in infrastructure provision dominate, then *ceteris paribus* cities with a higher percentage of the population living in urban areas are expected to spend less on infrastructure per capita. On the other hand, higher urbanization rates may demand more infrastructure service provision if agglomeration economies increase the return to infrastructure expenditure in urban areas, or if there is an urban bias in service provisions (Randolph et al., 1996). Hence the influence of urbanization on infrastructure spending is ambiguous and this is left for empirical investigation.

GAP is defined as the difference between the private fixed assets investments of a given province and the spatially weighted average of the private fixed assets investment of the rest provinces. The current performance evaluation system of Chinese local governments consists of several indexes, some of which are used to evaluate regional economy and social development, such as regional GDP growth, the growth rate of fixed asset investment, or the growth rate of foreign investment in real use. We argue that in an unevenly developed nation, benchmarking is one of the evaluation strategies that Chinese central government will be used to determine the extent to which one specific local government is better than others or "wise enough to try and learn how to match and even surpass them at it" (IBC 1996). In this study, we use local government's private fixed assets investments to reflect the central government's benchmarking strategy to evaluate the local government's performance. We hypothesize that if the private investment in fixed assets in a particular province is high compared to the national average, or the private investment is relatively high in that province, the given province 'outperforms' others from the eyes of their upper government (i.e., the central government). Hence, if the region already has a higher level of private investment, the regional government will be not be motivated to spend more on infrastructure. In empirical implementation, the sign for *GAP* therefore is expected to be negative. Table 1 presents the summary statistics for these data.

Table 1. Summary statistics of 31 Chinese provinces during 1998–2006

	Unit	*Obs.*	*Mean*	*Std. dev.*	*Min.*	*Max.*
Dependent Variable						
PROV	RMB Yuan (2006 = 100)	279	159.02	318.44	8.85	2,521.97
Independent Variable						
CENTRAL	RMB Yuan (2006 = 100)	279	727.78	708.79	90.44	3,810.48
CITY	RMB Yuan (2006 = 100)	279	147.12	301.65	6.77	2,307.52
REV	RMB Yuan (2006 = 100)	279	951.47	1,190.45	155.55	8,683.60
EDU	%	279	15.15	2.41	8.56	21.14
URBAN	%	279	25.40	8.46	15.00	46.00
GAP	1 billion RMB Yuan (2006 = 100)	279	181.50	177.01	4.44	1,111.14

4. Empirical Results

In this section, we report the empirical regression results using a panel of 31 provinces over the period 1998–2006. The analysis of the spatial panel model in this empirical study is performed using Paul Elhorst's MATLAB routines from his website (http://www.regroningen.nl/elhorst). This section first identifies and examines the major determinants of provincial public infrastructure spending, while focusing on the spatial interaction effects. Then, this section proceeds further to test for the yardstick competition and expenditure competition hypotheses, respectively.

Spatial Regression Results

Table 2 reports the results of the spatial Durbin model with spatial fixed effects. Column 1 presents the results using the basic weighting matrix specification−the distance-based weighting scheme. To investigate whether the spatial Durbin model can be reduced to the spatial lag or error model, we performed an LR test. The LR test results ($p < 0.01$ for the null hypothesis $\theta = 0$, and for the null hypothesis $\theta = -\rho\beta$) indicate that the spatial Durbin model may be properly applied to describe the public infrastructure expenditure relationship among provinces in China. Furthermore, we test the random effects model against the fixed effects model using Hausman's specification test. The results ($\chi 2 = 22.18$, $df = 12$, $p < 0.05$) nullify the usage of the random effects model and favor the fixed effects specification. Lastly, we control for both spatial fixed effects and time-period fixed. In summary, these test results justify the adoption of the spatial Durbin model with spatial fixed effects. The coefficient of the spatially lagged dependent variable in the spatial Durbin model is 0.443 and is statistically significant at 1%. The result shows that a provincial government tends to increase its own spending in response to the rise in the public infrastructure spending of its neighbors, showing evidence that Chinese provincial governments are engaging in strategic interactions in infrastructure spending.

With respect to the other explanatory variables, it should be noted that in the spatial model, the interpretation of the parameter is different from conventional least square interpretation (LeSage and Pace, 2009). In the traditional OLS model the coefficients represent marginal effects, while in the spatial models (SAR or SDM model) one could distinguish between (average) direct effects, indirect effects, and total effects that take into account also the feedback effects arising from the spatial dependence. For the case of the SAR model, the sign of each X variable can be proved to the same as the calculated direct effect, the indirect effect, or the total effect (LeSage and Pace, 2009), while the sign of each X variable in the SDM model can be different from the direct effect, the indirect effect, or the total effect. In other words, the coefficient on each individual X variable is not directly interpretable with regard to how explanatory variables in the model affect the dependent variable. The detailed derivations of the direct effects, indirect (spatial spillover) effects, and total effects of each X variable on the dependent variable can be found at LeSage and Pace (2009) in a cross-sectional setting and Elhorst (2014) in a spatial panel data setting. The inferential statistics (say, t-values for the direct/indirect/total effect) can be obtained via the Delta method.

Table 2 shows that the direct effect of revenue is significant and positive with a coefficient equal to 0.060, which implies that the provincial government's own-source of a specific province has a positive impact on its public infrastructure spending. The indirect effect of revenue is negative but insignificant with a coefficient equal to −0.033. This means that neighboring provinces' revenue has no effect on the infrastructure expenditure of the particular province, implying there are no spatial spillovers of government's own-source revenue. Overall, the positive direct impact of revenue is partially offset by the negative indirect impact, which generates a positive total effect that is significantly different from zero. Turing to other covariates, we find that, in general, the direct effect dominates the indirect effects which enables the total effect to have the same sign and statistical significance like the direct effect estimates. Focusing on the total effects estimates, the central government's provision of infrastructure is found to complement the provincial government's provision. Likely, the city government's provision of infrastructure is a complement as the positive spillovers effect dominates the negative direct effects of city government's infrastructure spending. Education expenditure competes with infrastructure expenditure under constant budgetary constraints. A higher degree of urbanization has neither positive nor negative effect on infrastructure spending. One possible explanation could be due to the interplay of the negative spillover effect of urbanization and the dual effects of urbanization as mentioned in the data source section. Finally, the total effect of the GAP variable on public infrastructure is statistically insignificant, which seems to be inconsistent with our early conjecture that if the region already has a higher level of private investment, the regional government will be not be motivated to spend more on infrastructure. From Table 2, we can see that the negative direct impact of the GAP variable is offset to a large extent by the positive indirect (spillovers) impact, which generates a total effect that is statistically insignificant. This does not mean that the private investment variable has no effect on public infrastructure spending in China. Indeed, such variable does have effects on public infrastructure spending in China but its effects are opposite and cancel each other out.

Table 2. Results of the spatial Durbin fixed effects model (dependent variable: real per capita provincial infrastructure expenditure, 2006 = 100)

	Spatial Durbin Panel Model with Distance-based W
Main	
CENTRAL	0.320^{***}(16.70)
CITY	-0.277^{**}(2.17)
REV	0.052^{**}(2.37)
EDU	-36.654^{***}(5.28)
URBAN	5.218(1.39)
GAP	-0.212^{*}(2.21)
Wx	
W*CENTRAL	-0.209^{***}(2.57)
W*CITY	1.776^{***}(3.84)
W*REV	-0.290^{***}(3.06)
W*EDU	−27.413(0.76)
W*URBAN	2.384(0.11)
W*GAP	−0.220(0.30)
Spatial	

θ	0.443^{***}(3.99)		
Partial effects	Direct	Indirect	Total
CENTRAL	0.357^{***}(18.42)	0.169^{**}(2.31)	0.526^{**}(2.62)
CITY	-0.100^{*}(2.01)	3.803^{**}(2.25)	2.803^{**}(2.40)
REV	0.060^{**}(2.48)	−0.033(1.20)	0.027^{*}(1.95)
EDU	-40.534^{***}(5.24)	-50.224^{*}(1.84)	-90.758^{**}(2.76)
URBAN	6.291(1.33)	-2.952^{*}(1.91)	3.339(1.37)
GAP	-0.445^{*}(2.44)	0.217^{*}(2.00)	−0.228(0.69)
Log-likelihood	−1,488.875		
N	279		
Number of cross-sections	31		
Number of time periods	9		
Spatial fixed effects	Yes		
Time-period fixed effects	Yes		
LR test of $\theta = 0$	[0.0000]		
LR test of $\theta = -\rho\beta$	[0.0000]		
Hausman test of fixed vs. random effects	[0.0355]		

Notes: (i) ***,**, and *, respectively, denote significance at the 1% level, 5% level, and 10% level; (ii) Absolute *t* statistics are reported in parentheses; (iii) *p* values are reported in brackets.

The obvious question in previous analysis is that of endogeneity of the regressors due to *WY* (i.e., the spatially lagged dependent variable) and other explanatory variables like government revenues and expenditures on education, if infrastructure spending in one province depends on the amount of infrastructure spending in other provinces, then spending in other provinces depends on spending in the province of interest. Similarly, the explanatory variables like government revenues and expenditures on education, together with the dependent variable can be simultaneous outcomes of the overall provincial budgeting process. If so, instruments are required. However, our attempt to deal with the possible endogeneity problem using instruments suggested by Kelejian and Prucha (1998) and Arraiz et al. (2010) seems not to be successful as the instruments fail to pass either the under-identification test (Anderson canonical correlation LR test) or over-identification test (Sargan test. The instrumental variable regression results are not reported.

Test for the Yardstick Competition Hypotheses

The above empirical evidence supports the spatial Durbin fixed effects model. Mainly, we find that the spatial autoregressive parameter is positive, indicating that a provincial government seems to increase its own infrastructure spending in response to a rise in the infrastructure spending of its neighboring provinces. So far it is not clear whether such positive spatial interdependence stems from yardstick competition, from expenditure competition, or from both. In what follows, we first propose two alternative ways to test for possible yardstick competition, then test for expenditure competition in the next section.

We hypothesize that the effect of yardstick competition is more manifest right before election or appointment, which happens when the National People's Congress (NPC) is held. This implies that we may observe two phenomena if the yardstick competition exists. First, before attending the NPC local officials are more prone to providing better public services (by spending more on public goods such as infrastructure) in order to 'show off' their economic performance or accomplishments. Second, the competition among provinces would become more intensive before NPC. Our sample covers the period 1996–2008, during which the NPC was held twice (in 1998 and 2003). We propose two ways to test the yardstick competition hypothesis. The first testing procedure rests on the idea that, if the yardstick competition theory holds, the parameters for the two-year dummy variables *year1997* and *year2002* should be expected to be positive, statistically significant, and bigger than their 'neighboring' dummy variables by using the spatial Durbin model (Eq. 1 or Table 2). It turned out that the two dummy variables (*year1997*, *year2002)* are positive but statistically insignificant (results not shown). In a further step, we ran a simple *t*-test respectively on *year1997* and *year2002* and their 'neighboring' time dummy variables under the null hypothesis H_0: *year1997* = *year1996* or *year1997* = *year1998,* and H_0: *year2002* = *year2003* or *year2002* = *year2001*. The null hypotheses are not rejected for any case. Thus we conclude that yardstick competition hypothesis is not supported via this empirical implementation. The second testing procedure is to test whether the spatial autoregressive parameters of the interaction terms (*WY*1997, WY*2002*) are significantly different from (and also bigger than) those of the interacted term of *WY* with other year dummies. If so, they may imply that the provincial competition is more fierce before the election year and we may conclude that the yardstick competition hypothesis is verified. The coefficient estimates of these spatial autoregressive parameters (i.e., the ρ terms) are plotted in Figure 1 based on estimating a SAR model where the parameters are estimated based on cross-sectional data for each year. Clearly we can see that there is no evidence showing that these two values (0.51 and −0.25) are larger than their neighboring values. This result implies that the yardstick competition hypothesis cannot be verified empirically in such a model specification. In sum, neither of the proposed procedures finds empirical evidence in favor of yardstick competition.

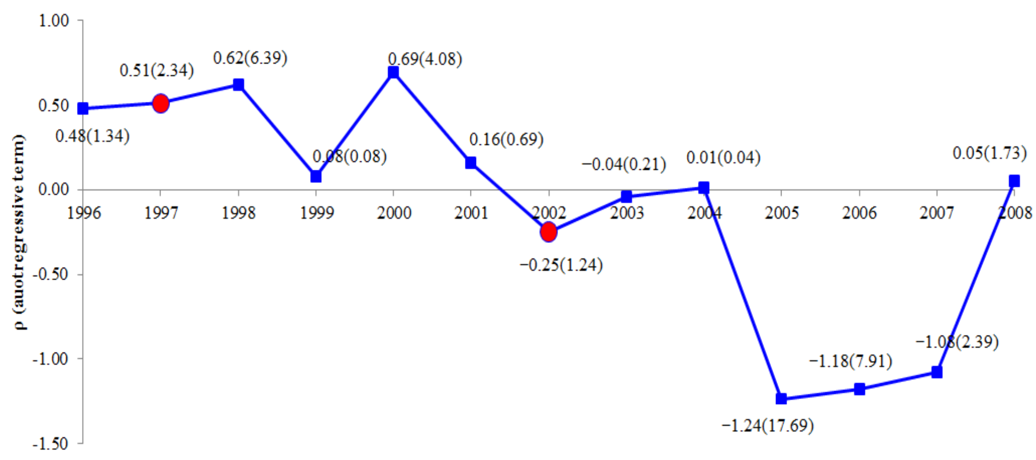

Figure 1. Spatial autoregressive parameters (yearly spatial regression)
Note: absolute *t* values are reported in parenthesis

Test for the Expenditure Competition Hypothesis

Next, we test whether the positive spatial interdependence stems from expenditure competition. The literature on the expenditure competition hypothesis suggests that local governors are expected to compete with their neighbors in order to attract households or firms. Our strategy to empirically examine the existence of this type of competition is to test whether local governors have strong incentives to improve their infrastructure in order to attract more capital in the form of foreign direct investment (FDI). In other words, we consider whether governmental infrastructure expenditure is an important determinant in the location choice of FDI.

Causes of regional FDI distribution have been extensively explored in the literature (Branstetter and Feenstra, 2002; Buckley et al., 2007; Chou et al., 2011; He, 2002; Poelhekke and Van der Ploeg, 2009). However, most existing studies, except for Chou et al. (2011), fail to take into account the spatial dependence effect of regional FDI (or outward FDI). In other words, these studies do not consider that the FDI locational decision behavior of a region can be affected by its 'neighboring' regions.

Built on several studies by Coughlin and Segev (2000), Garretsen and Peeters (2009), and Chou et al. (2011), and also considering the dynamic nature of FDI distribution, we specify the following spatial dynamic panel model (Lee and Yu, 2014) on regional FDI in China to empirically test the expenditure hypothesis:

$$FDI_{it} = \alpha + \theta LFDI_{i,t\text{-}1} + \rho\sum_{j=k}W_{ij}FDI_{jt} + \psi\sum_{j=k}W_{ij}FDI_{jt\text{-}1} + \gamma INFRA_{it} + \sum_{k}Z_{it}^{(k)}\beta_k + \mu_i + \varepsilon_{it},$$

$$i = 1,\ldots,27;\ t = 1998,\ldots,2006 \qquad (2)$$

where FDI_{it} ($LFDI_{i,t\text{-}1}$) indicates the FDI of province i at time t ($t-1$). $\sum_{j=k}W_{ij}FDI_{jt\text{-}1}$ is neighboring provinces' FDI at the $t-1$ period. Detailed definitions of the dependent variable and independent variables, data sources, and descriptive statistics are reported in Table 3. $INFRA_{it}$ denotes the infrastructure investment made by the provincial government, and *Zs* are vectors of control variables which are identified as determinants to affect regional FDI distribution. They include *GDP*, which measures the market demand and size effect, *MARKET* which is defined as *W·GDP* and is a proxy variable for market potential. *WAGE* which is the provincial average wage of staff and workers and measures production/labor cost, $HUMAN_{it}$ which is defined as the number of students enrolled in higher education in province i at time t, which is used to capture the average level of provincial human capital. The model also includes provincial dummies to control for provincial variation from changes in economic environment common across time. All variables (except *Human*) variable are taken in logarithmic form.

Table 3 Variable definitions and descriptive statistics (FDI model, 1998–2006)

Variable	Description	Source	Mean	Std Dev	Min	Max
Dependent variable						
FDI	Per capita real foreign direct investment (FDI), which is defined as FDI (US $) that is first converted to Chinese RMB using yearly averaged dollar/RMB exchange rate, converted again to 1995 constant RMB using the provincial CPI deflator, and divided by population (RMB Yuan/person, 1995 = 100)	NBS (2010)	1,396.87	1,926.28	3.52	9,651.95
Independent variable (provincial/time dummies omitted)						
GDP	Per capita real provincial GDP (RMB Yuan/person, 1995 = 100)	NBS (2010)	10,299.37	7,500.39	2,191.27	41,075.82
WAGE	Real provincial average wage of staff and workers (RMB Yuan, 1995 = 100)	NBS (2010)	11,083.79	4,561.13	5,027.59	31,611.59
HUMAN	Number of students enrolled in higher education per 10,000 persons (%)	NBS (2010)	0.99	1.05	0.11	6.90
MARKET	Defined as $W{\cdot}GDP$, where the W is the distanced-based spatial weighting matrix, and is a proxy variable for market potential. Longitude and latitude data for each province are taken from Google Earth (Yuan/person, 1995 = 100)	NBS (2010)	323.10	143.64	69.83	780.10
INFRA	Per capita infrastructure investment made by the provincial government, which is calculated as the difference between the total infrastructure investment made by all governments in that province (taken from the *China Statistical Yearbook*) and infrastructure investment made by city and lower-tier governments in the same province (*Statistical Materials of City and County Public Finances*, *Quanguo dishixian caizheng tongji ziliao* in Chinese) (RMB Yuan/person, 1995 = 100)	NBS (various years)	171.00	224.90	15.53	1,567.46

Note: All variables described here are expressed in logarithmic form in the regression model.

In terms of model estimation, it is recognized that econometric analysis of dynamic panel models is now fairly standard (Blundell and Bond, 1998) and spatial econometric literature is well documented (LeSage and Pace, 2009); econometric analysis combining both spatial and dynamic panel models remains at an early stage of development. Following Kukenova and Monteiro (2009), we extend the system-GMM estimator of Blundell and Bond (1998) to account for spatial effects.[6] Table 4 reports the results of the spatial dynamic panel model of FDI.[7]

Recalling that our main goal is to test the expenditure hypothesis, under which we should expect the coefficient of the variable *INFRA* to be positive, we find that public spending on infrastructure is statistically significant at the 5% level, and it is positively associated with provincial FDI. This result confirms the general expectation that better infrastructure reduces production and trade cost and FDI tends toward regions with better infrastructure facilities. Clearly this result lends some support for the expenditure competition hypothesis.[8]

In terms of other independent variables, the coefficient on the time-lagged FDI (*LFDI*) is 0.779 and is statistically significant at 1% level. This result justifies the usage of the dynamic model and, more importantly, it is consistent with Kinoshita and Campos (2004) that past FDI can exert a positive feedback effect on current FDI; that is, FDI is found to be persistent over time. The spatially lagged FDI (*W·FDI*) is found to be 0.032 and statistically significant, confirming the presence of spatial interdependence of FDI across Chinese provinces. Specifically, increased FDI in neighboring provinces has positive effects on FDI of one province. However, the previous FDI in neighboring provinces does not affect the current FDI of that province. There is some evidence that larger economies (*GDP*) attracts more investment, which is consistent with the finding of numerous studies of FDI location that foreign investors are attracted to a large domestic market. Market potential (*MARKET*) is negative and bears an insignificant sign. In other words, the multinational companies' decision to enter a particular region in China is not affected by that the market size/demand of its 'neighboring' regions. This result may imply that multinational companies may serve China's whole market irrespective of the region they are located in, or that transportation costs are not important within China. The coefficient on labor cost (*WAGE*) is significant and positive. This result confirms the common belief that labor cost should be one main determinant of FDI, as one goal of multinational companies is to invest in developing countries (like China) which have lower labor costs and huge growth potential. This result hence is consistent with Coughlin and Segev (2000), but contrary to studies by Defever (2006), Guimaraes et al. (2000), and Lucas (1993). Finally, as expected, the labor quality variable (*HUMAN*) is positive and an important determinant of FDI, which is a result consistent with Coughlin and Segev (2000) and Noorbakhsh and Paloni (2001). This result implies that regional capacity to attract foreign firms relies on high labor quality (productivity) instead of low costs of labor.

In summary, it seems clear that the positive spatial interdependence in the main regression model in Section 4.1 stems from expenditure competition instead of yardstick competition, as the former hypothesis is supported by the empirical test we just implemented in this section.

Table 4. A simple test for the expenditure competition hypothesis: Spatial dynamic panel model of FDI (dependent variable: FDI)

	Spatial system GMM model
θ (FDI(t−1))	0.779^{***}
	(24.62)
ρ (W*FDI)	0.032^{***}
	(3.74)
ψ (W*FDI(t−1))	−0.010
	(1.49)
INFRA	0.142^{**}
	(2.18)
GDP	0.481^{*}
	(1.92)
WAGE	0.614^{***}
	(3.86)
HUMAN	1.671^{*}
	(1.68)
MARKET	−1.703

	(0.58)
Constant	0.848
	(0.11)
Province dummy	Y
Observations	216
No. of provinces	27
(Buse 1973) R^2 adj.	0.45
Spatial Panel Autocorrelation Tests	
LM Error (Burridge) test	[0.6089]
LM Error (Robust) test	[0.6160]
LM Lag (Anselin) test	[0.0488]
LM Lag (Robust) test	[0.0894]

Notes: 1) Absolute robust *t* statistics are reported in parentheses; 2) *p* values are reported in square brackets; 3) *, **, ***, respectively, indicate significance at the 90%, 95%, and 99% level; 4) The Lagrange Multiplier (LM) diagnostics test statistics in a panel data setting can be found in Anselin et al. (2006), while the detailed derivations of these tests for a spatial panel data model with spatial fixed effects can be found in Debarsy and Ertur (2010). Under the null hypothesis, these tests follow a chi-squared distribution with one degree of freedom.

5. Conclusions

The expenditure behaviors of local governments (municipalities, regions, or provinces) were traditionally explored through three channels: yardstick competition, fiscal competition (tax competition or expenditure competition), and expenditure externality (Manski, 1993). Using a panel of 31 Chinese provinces during 1998–2006 we identified the determinants of expenditure on public infrastructure in China. In particular, we examined whether China's provincial governments are engaged in strategic interaction behavior in infrastructure. Specifying a spatial Durbin model with fixed effects, which was identified to be the preferable model using the LR tests and Hausman's specification test, we found that the spatial autoregressive parameter is positive, indicating that a provincial government tends to increase its own infrastructure spending in response to a rise in the infrastructure spending of its neighboring provinces.

This empirical finding has three implications. First, it rules out the expenditure externality (spillover) hypothesis, which implies that the spatial autoregressive parameter is negative in its empirical implementation. In this study, as we used provinces instead of smaller administrative regions (counties or cities) as our analytical units, it is less likely that the benefits of the public infrastructure expenditure of one province would spread to its neighboring provinces. Hence such an empirical finding is not unexpected. Second, the positive spatial autoregressive parameter indicates the possible validity of both yardstick competition hypothesis and expenditure competition hypothesis. Further analysis is implemented to distinguish between these two possible hypotheses by estimating two additional empirical models. The regression results eventually lead us to a conclusion that provincial competition on infrastructure spending takes the form of expenditure competition rather than yardstick competition. This result implies that, in order to promote local economic growth, local governors have incentives to engage in expenditure competition with their (geographic or economic) neighbors to attract mobile sources, agreeing with Chen et al. (2005), Tao et al. (2009), and Xu (2011), together with others who argue that local governments are engaged in fiscal competition for economic development and growth and will take investing in infrastructure as the prior tool to reach their goals, which may result in a 'race to the top' of government expenditures. Last, an interesting phenomenon can be revealed if this study is contrasted to a closely related empirical study by Yu et al. (2011) that uses cities (smaller administrative regions than provinces) as the analytical units. Using China's city-level cross-sectional data in 2005 to examine the city governments' infrastructure expenditure behavior, they find that a city government tends to reduce its own infrastructure spending as a response to the rise in infrastructure expenditure of its neighboring cities, which is reasonable as it is more likely that the benefits of the public infrastructure expenditure of one city would spread to its neighboring cities. In contrast, this study uses provinces as the analytical units; intuitively, it should be expected that provincial governments' infrastructure spending will be less likely to have spillovers to its neighboring provinces. The empirical analysis of this study confirmed such intuition. In brief, the implication is that, on the particular public spending category infrastructure, the lower-tier governments will tend to free ride, while the upper-tier governments tend to engage in expenditure competition (for mobile resources).

The findings from this study also show that, with greater financial capacity and efforts by the central government to invest in local infrastructure, local governments can play a more active role in financing local infrastructure, thereby acting as better agents of social-economic and physical transformation. Furthermore, education spending is found to crowd out infrastructure spending. Public expenditures on infrastructure and education are considered to be the two most important spending categories by local governments as their contributions to local economic growth and development have long been recognized. Under budgetary constraints, if China's local governments are unwilling to sacrifice either spending category, they may choose to cut back other less important spending, such as expenditure on government administration, which has been observed to be much higher than some developed nations such as the United States, the United Kingdom, Canada, Korea, and Japan.[9]

References

Albala-Bertrand, Jose and Emmanuel Mamatzakis, "The Impact of Public Infrastructure on the Productivity of the Chilean Economy," *Review of Development Economics* 8(2004): 266–278.

Anselin, Luc, Julie Le Gallo, and Jayet Jayet, "Spatial Panel Econometrics," in Laszlo Matyas and Patrick Sevestre (eds), *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice*. Dordrecht: Kluwer (2006).

Arraiz, Irani, David Drukker, Harry Kelejian, and Ingmar Prucha, "A Spatial Cliff-Ord-type Model with Heteroskedastic Innovations: Small and Large Sample Results," *Journal of Regional Science* 50 (2010): 592–614.

Aschauer, David, "Is Public Expenditure Productive?" *Journal of Monetary Economics* 23 (1989a): 177–200.

______, "Does Public Capital Crowd out Private Capital?" *Journal of Monetary Economics* 24 (1989b): 171–188.

Baicker, Ketz, "The Spillover Effects of State Spending," *Journal of Public Economics* 89 (2005): 529–544.

Blundell, Richard, and Stephen Bond, "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* 87 (1998): 115–143.

Bom, Pedro, and Jenny Ligthart, “What Have We Learned from the Three Decades of Research on The Productivity of Public Capital?” *Journal of Economic Surveys*. 28 (2014): 889–916.
Branstetter, Lee, and Robert Feenstra, “Trade and Foreign Direct Investment in China: A Political Economy Approach,” *Journal of International Economics* 22 (2002): 335–358.
Bruce, Donald, Deborah Carroll, John Deskins, and Jonathan Rork, “Road or Ruin? A Spatial Analysis of State Highway Spending,” *Public Budget and Finance* 27 (2007): 65–85.
Brueckner, Jan, “Strategic Interaction among Governments: An Overview of Empirical Studies,” *International Regional Science Review* 26 (2003): 175–188.
Buckley, Peter, Jeremy Clegg, Adam Cross, Xin Liu, Hinrich Voss, and Ping Zheng, “The Determinants of Chinese Outward Foreign Direct Investment,” *Journal of International Business Studies* 38 (2007): 499–518.
Case, Anne, James Hines, and Harvey Rosen, “Budget Spillovers and Fiscal Policy Interdependence,” *Journal of Public Economics* 52 (1993): 285–307.
Chen, Ye, Hongbin Li, and Li-An Zhou, “Relative Performance Evaluation and the Turnover of Provincial Leaders in China,” *Economics Letters* 88 (2005): 421–425.
Chou, Kuang-hann, Chien-Hsun Chen, and Chao-Cheng Mai, “The Impact of Third-country Effects and Economic Integration on China’s Outward FDI,” *Economic Modelling* 28 (2011): 2154–2163.
Coughlin, Cletus, and Eran Segev, “Foreign Direct Investment in China: A Spatial Econometric Study,” *World Economy* 23 (2000): 1–23.
Debarsy, Nicolas, and Cem Ertur, “Testing for Spatial Autocorrelation in a Fixed Effects Panel Data Model,” *Regional Science and Urban Economics* 40 (2010): 453–470.
Defever, Fabrice, “Functional Fragmentation and the Location of Multinational Firms in the Enlarged Europe,” *Regional Science and Urban Economics* 36 (2006): 658–677.
De Haan, Jakob, Jan Sturm, and Bernd Sikken, “Government Capital Formation: Explaining the Decline,” *Weltwirtschaftliches Archive* 132 (1996): 55–74.
Démurger, Sylvie, “Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China?” *Journal of Comparative Economics* 29 (2001): 95–117.
Elhorst, Paul, “Applied Spatial Econometrics: Raising the Bar,” *Spatial Economic Analysis* 5 (2010): 9–28.
_____, “Matlab Software for Spatial Panels,” *International Regional Science Review* 37 (2014): 389–405.
Elhorst, Paul, Eelco Zandberg, and Jakob De Haan, “The Impact of Interaction Effects among Neighbouring Countries on Financial Liberalization and Reform: A Dynamic Spatial Panel Data Approach,” *Spatial Economic Analysis* 8 (2013): 293–313.
Fan, Shenggen, and Xiaobo Zhang, “Infrastructure and Regional Economic Development in Rural China,” *China Economic Review* 15 (2004): 203–214.
Garretsen, Harry, and Jolanda Peeters, “FDI and the Relevance of Spatial Linkages: Do Third-country Effects Matter for Dutch FDI?” *Review of World Economics* 145 (2009): 319–338.
Ghosh, Arghya, and Kieron Meagher, “Political Economy of Infrastructure Investment: A Spatial Approach,” North American Econometric Society Summer Meetings, Brown University (2004).
Guimaraes, Paulo, Octavio Figueiredo, and Douglas Woodward, “Agglomeration and the Location of Foreign Direct Investment in Portugal,” *Journal of Urban Economics* 47 (2000): 115–135.
Han, Chirok, and Peter Phillips, “GMM Estimation for Dynamic Panels with Fixed Effects and Strong Instruments Are Unity,” *Econometric Theory* 26 (2010):119–151.

He, Canfei, "Information Costs, Agglomeration Economies and the Location of Foreign Direct Investment in China," *Regional Studies* 36 (2002): 1029–1036.

IBC (International Benchmarking Clearinghouse), "Benchmarking". Presentation overheads from the International Benchmarking Clearinghouse, 1996, p. 20.

Kappeler, Andreas, Albert Solé-Ollé, Andreas Stephan, and Timo Välilä, "Does Fiscal Decentralization Foster Regional Investment in Productive Infrastructure?" *European Journal of Political Economy* 31 (2013): 15–25.

Kelejian, Harry, and Ingmar Prucha, "A Generalized Spatial Two-stage Least Squares Procedure Estimating a Spatial Autoregressive Model with Autoregressive Disturbances," *Journal of Real Estate Finance and Economics* 17 (1998): 99–121.

Kukenova, Madina, and Jose-Antonio Monteiro, "Spatial Dynamic Panel Model and System GMM: A Monte Carlo Investigation," MPRA Paper 11569, University Library of Munich, Germany (2009).

Lee, Lung-fei, and Jihai Yu, "Some Recent Developments in Spatial Panel Data Models," *Regional Science and Urban Economics* 40 (2010): 255–271.

______, "Efficient GMM Estimation of Spatial Dynamic Panel Data Models with Fixed Effects," *Journal of Econometrics* 180(2014): 174–197.

LeSage, James, and Kelley Pace, *Introduction to Spatial Econometrics*. London: CRC Press/Taylor & Francis Group (2009).

Lucas, Robert, "On the Determinants of Direct Investment: Evidence from East and South Asia," *World Development* 21 (1993): 391–406.

Manski, Charles, "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies* 60 (1993): 531–542.

Mehrotra, Aron, and Timo Välilä, "Public Investment in Europe: Evolution and Determinants in Perspective," *Fiscal Studies* 27 (2006): 443–471.

Mur, Jesus, and Ana Angulo, "Model Selection Strategies in A Spatial Setting: Some Additional Results," *Regional Science and Urban Economics* 39 (2009): 200–213.

NBS (National Bureau of Statistics), *China Statistical Yearbook*. Beijing: China Statistics Press (various years).

NBS (National Bureau of Statistics), *Comprehensive Statistical Data and Materials on 60 Years of New China*. Beijing: China Statistics Press (2010).

Noorbakhsh, Farhad, and Alberto Paloni, "Human Capital and FDI Inflows to Developing Countries," *World Development* 29 (2001): 1593–1610.

Painter, Gary, and Kwi-Hee Bae, "The Changing Determinants of State Expenditure in the United States: 1965–1992," *Public Finance and Management* 1 (2001): 370–392.

Pereira, Alfredo, and Jorge Andraz, "Public Investment in Transportation Infrastructure and Economic Performance in Portugal," *Review of Development Economics* 9(2005): 177–196.

Pereira, Alfredo, and Oriol Roca Sagales, "Public Capital Formation and Regional Development in Spain," *Review of Development Economics* 3 (1999): 281–294.

Poelhekke, Steven, and Frederick Van der Ploeg, "Foreign Direct Investment and Urban Concentrations: Unbundling Spatial Lags," *Journal of Regional Science* 49 (2009): 749–775.

Randolph, Susan, Zeljko Bogetic, and Dennis Hefley, "Determinants of Public Expenditure on Infrastructure: Transportation and Communication," Policy Research Working Paper Series, 1661. World Bank, Washington DC (1996).

Revelli, Federico, "On Spatial Public Finance Empirics," *International Tax and Public Economics* 12 (2005): 475–492.

_____, “Performance Rating and Yardstick Competition in Social Service Provision,” *Journal of Pubic Economics* 90 (2006): 459–475.

Rioja, Felix, “The Penalties of Inefficient Infrastructure,” *Review of Development Economics* 7(2003): 127–131.

Tao, Ran, Xi Lu, Fubin Su, and Hui Wang, “China’s Transition and Development Model under Evolving Regional Competition Patterns,” *Economic Research Journal* 7 (2009): 21–33 (in Chinese).

Vijverberg, Wim, Feng-cheng Fu, and Chu-ping Vijverberg, “Public Infrastructure as a Determinant of Productive Performance in China,” *Journal of Productivity Analysis* 36 (2011): 91–111.

Vuchelen, Jef, and Stijn Caekelbergh, “Explaining Public Investment in Western Europe,” *Applied Economics* 42 (2010): 1783–1796.

Xu, Cheng-Gang, “The Fundamental Institutions of China’s Reforms and Development,” Journal of Economic Literature 49 (2011): 1076–1151.

Yu, Yihua, Li Zhang, Fanghua Li, and Xinye Zheng, “On the Determinants of Public Infrastructure Spending in Chinese Cities: A Spatial Econometric Perspective,” *Social Science Journal* 48 (2011): 458–467.

____, “Strategic Interaction and the Determinants of Public Health Expenditures in China: A Spatial Panel Perspective,” *Annals of Regional Science* 50(2013): 203–271.

Zheng, Xinye, Yihua Yu, Jing Wang, and Huihui Deng, “Identifying the Determinants and Spatial Nexus of Provincial Carbon Intensity in China: a Dynamic Spatial Panel Approach,” *Regional Environmental Change* 14 (2014): 1651–1661.

Notes

1. Other related studies published in this journal yet not cited in the meta-analysis include: Albala-Bertrand and Mamatzakis (2004), Pereira and Andraz (2005), Rioja (2003).
2. See Brueckner (2003) and Revelli (2005) for overviews of the empirical research on strategic interactions among local governments.
3. See Manski (1993) and Yu et al. (2013) for details on explaining these sources.
4. Other commonly used weights matrix specifications include: the contiguity-based binary matrix, the spatial weight matrix constructed based on the k^{th} nearest neigbours, and the social-economic spatial weights matrix.
5. If the distribution of idiosyncratic error is misspecified, the estimator can be viewed as Quasi-MLE. In this case, the information matrix inequality does not hold anymore. To make statistical inference, we can estimate the information matrix and expected Hessian matrix, respectively, to obtain a consistent estimate for asymptotic variance-covariance matrix. This shall be the direction that future research might usefully take. We would like to thank one of the reviewers for raising this issue.
6. The spatial system-GMM estimator is known as having the advantage over traditional spatial MLE in that the SYS-GMM estimators can also be used to instrument endogenous explanatory variables (other than Y_{t-1} and WY_t). More importantly, both studies find that the SYS-GMM estimator substantially reduces the bias for the spatially lagged parameter (an issue appeared from estimating spatial difference-GMM estimator. An alternative line of research could be to account for spatial effects in the DDLS (double-difference least squares) estimator (for linear dynamic panel model) that is developed by Han-Phillips (2010) under the premise that the dynamic panel autoregressive coefficient approaches a unity and contains a deterministic time

trend (i.e., there is a unit root). We did not follow such an approach here.

7. Details on the spatial dynamic panel (system GMM) model can be found at Kukenova and Monteiro (2009), Lee and Yu (2014), and Zheng et al. (2014). Thanks to one anonymous reviewer, it is worth mentioning that the system GMM that uses internal instruments "within the data" (due to difficulties on finding the external instruments) could suffer from the potential weak instrument problem in the level model when the series are persistent, or when the dynamic panel autoregressive coefficient (ρ) approaches unity, which causes the IV estimator to perform poorly (inconsistency, inaccurate inference, etc.).
8. Elhorst (2012) summarized the mathematical formulas of the direct and indirect effects estimates of several types of spatial dynamic panel models. However, to the best of our knowledge, the partial effects have not been derived so far for the spatial system GMM model. So this part of empirical analysis, we have to use point estimates of the spatial system GMM model for interpretation, recognizing that, though, this may lead to misleading conclusions.
9. China Youth Daily, accessed on August 6, 2014 from http://zqb.cyol.com/content/2006-03/06/content_1328768.htm.