Taking Space Seriously: Comparing Multilevel and Spatial Modeling in Addressing Spatial Associations in Public Administration Research

Ling Zhu
Department of Political Science
University of Houston
lzhu4@central.uh.edu

Hai (David) Guo
Department of Public Policy and Administration
Florida International University
haguo@fiu.edu

Zhirong (Jerry) Zhao
Humphrey School of Public Affairs
University of Minnesota
zrzhao@umn.edu

Shaoming Cheng
Department of Public Policy and Administration
Florida International University
scheng@fiu.edu

Abstract

Multilevel data that reflect spatial associations are ample across different substantive research areas in public administration, such as behavioral public administration, organizational studies, public management, and policy diffusion. In this paper, we discuss how insights from multilevel analysis and spatial regressions can help public administration scholars to account for spatial dependence between observations and to properly model spatially clustered phenomenon. We summarize how these two approaches conceptualize the role of space and the underlying data-generation process. We then offer detailed discussions on variants of multilevel and spatial model specifications and their statistical properties. The pros and cons of each method are illustrated with a multilevel dataset on the adoption of public-private partnerships (PPP) in Chinese cities. Showing various empirical applications of multilevel and spatial models, we offer practical guidance on various data contexts in which either the multilevel approach or the spatial econometric approach is more suitable.

1. Introduction

Public policy and administration scholars are increasingly interested in why and how administrative and policy phenomena interact across geographic areas. For example, public policy and administration scholars often study the extent to which a policy decision in one jurisdiction affects its neighbors (Berry and Berry 1990; Jun and Weare 2011; Mitchell 2017). Public management scholars have seen a growing interest in examining how macro-level contextual factors affect individual management decisions and organizational performance (Kelleher and Yackee 2009; Moulton and Bozeman 2011; O'Toole and Meier 2014; Whitford 2014). Public finance scholars often study fiscal decisions that are driven by inter-jurisdictional interactions (Hall and Ross 2010; Karuppusamy and Carr 2011). Despite different substantive questions, scholars who examine spatial associations of outcomes usually use multilevel datasets in which micro-level observations are nested with higher level administrative jurisdictions. Making sound cross-level inferences from such multilevel data requires both substantive considerations of the underlying spatial process and careful specification of the structure of spatial dependence.

In this paper, we offer a synopsis of two dominant approaches in studying spatial effects: the multilevel approach and the spatial econometric approach. First, we provide an overview of how these two approaches conceptualize the role of space and the underlying data-generation process and. The multilevel analytic approach recognizes how micro-level units (e.g. individual managers) vary across macro-level institutional or contextual areas by modeling higher-level spatial variations as random coefficients, or using spatial errors to account for between-area correlations. While most multilevel models implicitly assume geographic independence, spatial econometric models explicitly model and account for geographic interdependence through the inclusion of selective spatial weighting matrixes. As such, the spatial econometric approach allows for an explicit specification of spatial dependence among nested micro-level observations.

Second, we offer detailed discussions on variants of multilevel and spatial model specifications, their substantive considerations, and unique statistical properties. We start by discussing three commonly used multilevel models: random-intercept model, spatial fixed-effects model, and random-slope model. We then discuss spatial model specifications including spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). For each model specification, we will explain rationales pertaining to within-area variation and between-area interdependence, criteria for model selection, and relevant statistical tests.

The pros and cons of each method are then illustrated with a multilevel dataset on the adoption of public-private partnerships (PPP) in Chinese cities. Showing various empirical applications of the multilevel-model approach and the spatial-model approach, we illustrate the relative merit of each approach based on the pooled cross-sectional setting for a continuous dependent variable. We conclude this paper by offering practical guidance on the data contexts in which the multilevel approach or spatial econometric approach may be more suitable.

2. Modeling Spatial Dependence: Multilevel and Spatial Econometric Models

Public administration scholars have paid increasing attention to administrative behavior and outcomes that are geographically embedded. This trend is seen in various studies that explore spatial dependence referred to as "neighborhood effects". For example, public officials' managerial decisions can be attributed to the contextual characteristics of their administrative jurisdictions and decisions adopted by their peers, thus exhibit some "clustering" patterns across spatial units. Local fiscal decisions reflect spatial competition with or benefit spillover from neighboring localities. The performance of public organizations is attributed to crossjurisdictional learning and collaboration. In these empirical contexts, explaining such "neighborhood effects" requires proper statistical methods that can account for variations within and/or between different geographic units. Compared with the Ordinary Least Squares (OLS) approach, multilevel analysis is often deemed as an improved approach that allows for assessing how micro-level and higher-level factors generate variations within- and between- spatial areas. However, multilevel models do not concern the underlying processes that generate inter-jurisdictional correlations. On the contrary, spatial econometric models relax the assumption that micro-level observations are independent across each other and explicitly address the interdependence across geographic areas (Ward and Gleditsch 2008). Hence spatial econometric approach has become a particularly useful tool to model between-area correlations aa a function of geographic proximity (e.g. contagious diffusion, policy learning from neighbors, etc.). Below, we offer more detailed discussions on how the two approaches conceptualize spatial associations. We do so by focusing on the substantive considerations of each approach.

2.1 Addressing Spatial Dependence Using Multilevel Models

Multilevel regressions have gained popularity in recent public administration research that conceptualizes geographic space as a source of macro-level contexts, such as public organizations' external political and institutional constraints, inter-organizational competition, and local policy networks. The substantive focus on how administrative behavior and various policy outcomes might cluster across spatial units leads to increased applications of multilevel models. The standard multilevel approach treats space as the basis to group micro-level observations into different clusters (Luke 2004; Snijders and Bosker 2002). Information regarding spatial units is usually used to identify a hierarchical multilevel data structure, whereby micro-level cases are nested in higher-level spatial units. For simplicity, we discuss various multilevel models by using the general notation $\mathbf{Y}_{ij}$ to denote the outcome variable of interest. We use *i* and *j* to index the two-level hierarchical data structure. More specifically, *i* indexes cases measured at level-1 and *j* indexes level-2 geographic units (e.g. individual public managers nested in different bureaucratic agencies, counties nested in states, etc.).

A basic single-level OLS regression model ignores the hierarchical structure of the data and conceptualizes the outcome variable as Equation (1).

$$\mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{X_i} + \varepsilon_\mathrm{i} \tag{1}$$

where the outcome variable Y_i is defined as a linear combination of the explanatory variable X_i and the stochastic component ε_i. The OLS specification overlooks the possible associations among *i* observations due to shared spatial units *j*. In other words, observations nested in the same higher-level spatial unit might be dependent to each other. Without accounting for the cross-level spatial associations, relationships observed in groups are assumed to hold for micro-level observations (e.g. individuals) and hence produce ecological fallacy (King, Rosen and Tanner 2004; Luke 2002). Several multilevel models can be used to deal with the issue of cross-level inference. The choice of a specific multilevel model depends on how one would conceptualize the underlying data-generation process.

The Random-Intercept Model

Equation (2) presents a random-intercept model that recognizes the hierarchical nature of the data. Y_{ij} is the outcome variable measured at level-1 and nested in level-2 spatial units *j*. β_1 represents the association between *Y* and the explanatory variable *X*, measured at level-1. ε_{ij} is the residual term specific to level-1 units. u_j denotes the random effects component specific to level-2 units *j*. The random-intercept model conceptualizes that second-level spatial units will have varying group-baseline values, modeled random deviation from zero-mean. The model accounts for two types of variance: variance across micro-level observations that are within the second level spatial units, and variance across level-2 spatial units. In the random-intercept model, u_j is defined as spatially (group) dependent. In such a model, u_j is expressed in the second level model equation as the linear combination of γ, the average ntercept across level-2 spatial units, and U_j, spatial-dependent deviation from the common (population) mean (Anselin and Cho 2002; Gill 2003).

$$\mathrm{Y_{ij}} = \beta_0 + \beta_1 \mathrm{X_{ij}} + \mathrm{u_j} + \varepsilon_{\mathrm{ij}} \quad (2)$$
$$u_j = \gamma + U_j$$

Based on the above two-level random-intercept model, the variance between spatial units is assumed to have a normal distribution with zero mean: $U_j \sim N(0, \tau^2)$. Similarly, the level-1 within variance is also assumed to be normally distributed: $\varepsilon_{ij} \sim N(0, \sigma^2)$. Intra-class correlations then can be assessed by comparing the variance between spatial units to total variance, formally, $\frac{\tau^2}{\tau^2+\sigma^2}$.

The Spatial Fixed-Effects model

A variant of the multilevel random-intercept model is to model spatial dependence by assigning a unique baseline value to each higher-level spatial unit. This conceptualization results in spatial fixed-effects model expressed in Equation (3), in which z_j refers to the set of intercept values corresponding to *j-1* spatial units. Both random-intercept model and spatial fixed-effects model incorporate additional parameters to account for spatial dependence. The fixed-effects specification returns *j-1* set of group-level coefficients (in this case, intercepts), while the random-intercept model only returns the variance of the group-level coefficients (i.e. the random variance component tied to level-2 spatial units). Both models improve the estimation of population effects (level-1 effects). Gelman and Hill (2007) suggest that spatial fixed effects are preferred if one is interested in assessing group-level (level-2) coefficients, and the random-intercept model is proper if the substantive interests lie in the level-one observations. Statistically, the random-intercept model helps to improve estimation efficiency, because it adds fewer second-level parameters into the model than a spatial fixed-effects model does. Nevertheless, estimating a random-intercept model would require a large number of second-level units to ensure estimation consistency. Rabe-Hesketh and Skrondal (2008) recommend that there at least needs to 20 second-level units to apply the random-intercept model, whereas spatial fixed-effects model does not impose that statistical requirement. If one is dealing with a multilevel dataset that includes very few second-level spatial units, the spatial fixed effects specification will produce more consistent parameter estimation.

$$Y_{ij} = \beta_0 + \beta_1 X_{ij} + z_j + \varepsilon_{ij} \quad (3)$$

The Random-Slope Model

It is also possible that not only group average of *Y* is dependent to level-2 spatial units, but also the relationship between *X* and *Y* varies across level-2 spatial units. Equation (4) expresses a random-slope model to account for this different pattern of spatial dependent (Gelman and Hill 2007). In the statistical method literature, the random-slope model is also referred as random coefficient model (Rabe-Hesketh and Skrondal 2008). In the random-slope model, the regression coefficient β_j now becomes dependent to spatial units j. It also has a random component, defined as a linear combination of γ_1, the average coefficient across j spatial units, and U_{1j}, spatial-dependent deviation.

$$Y_{ij} = \beta_j X_{ij} + u_j + \varepsilon_{ij} \quad (4)$$
$$u_j = \gamma_0 + U_{0j}$$
$$\beta_j = \gamma_1 + U_{1j}$$

The random-intercept model and random-slope model focus on different types of spatial dependence, but they share a common set of statistical assumptions. First, both types of multilevel models assume that level-one residuals, ε_{ij}, are normally distributed with constant variance. Second, level-2 coefficients (i.e. random intercepts and random slopes) are normally distributed with zero means and a constant covariance matrix (Raudenbush and Bryk 2002).

2.2. Addressing Spatial Dependence Using the Spatial Econometric Approach

Spatial Durbin Model as A Generalized Spatial Econometric Approach

Spatial econometric methods have been increasingly and widely used in social science studies, when the unit of analysis is spatial units, such as states, counties, and municipalities. Spatial correlation arises when observation at one location, y_i, depends on neighboring observations, y_j, e.g., geographic clusters of newly created businesses. The existence of spatial correlation results in spatially correlated error terms (Anselin 1988; Getis 2007). The spatially correlated errors preclude OLS estimation (Anselin 1988) and require an alternative estimation procedure. Commonly used spatial models include the spatial autoregressive regression (SAR) and the spatial error model (SEM). Recently, a more general model, the spatial Durbin model (SDM) has been developed (LeSage and Pace 2009), which subsumes both SAR and SEM. Mathematically, SAR, SEM and SDM can be expressed as:

$$\begin{aligned}
&\text{SAR}: \ \mathbf{y} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\alpha\boldsymbol{\tau} + \mathbf{X}\boldsymbol{\beta}) + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \\
&\text{SEM}: \ \mathbf{y} = \alpha\boldsymbol{\tau} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\mu}, \quad \boldsymbol{\mu} = \rho\mathbf{W}\boldsymbol{\mu} + \boldsymbol{\varepsilon} \\
&\text{SDM}: \ \mathbf{y} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\alpha\boldsymbol{\tau} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\theta}) + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon}
\end{aligned} \tag{5}$$

where y is a [n×1] vector of the dependent variable, I is a conformable identity matrix, W is a [n×n] row-normalized spatial weight matrix defining relationships between spatial units, scalar parameter ρ is the spatial autoregressive coefficient reflecting the average or overall strength of spatial dependence between observations, α is a scalar parameter associated [n×1] vector τ of ones reflecting an intercept term, X is a [n×k] matrix of explanatory variables, β and θ

respectively is the [k×1] vector of parameters to be estimated, and ε is a [n×1] vector of i.i.d. error terms. Estimation of the SDM model can be achieved by either the Maximum Likelihood (ML) method (Anselin1988) or the Bayesian Markov Chain Monte Carlo (MCMC) method (LeSage and Pace 2009). The two estimation methods generate consistent estimators for relatively large samples, but the Bayesian approach avoids analytical solutions of the posterior distribution yet instead relies on conditional distributions for each parameter in the model (Gelfand and Smith 1990). Due to the relative computational ease of the Bayesian MCMC method, extensive toolkits for solving spatial econometric estimation problems have been developed, e.g., Professor James LeSage's Matlab spatial toolbox which can be downloaded free of charge at www.spatial-econometrics.com.

The Bayesian MCMC estimation method arises from Bayesian econometrics, which is briefly introduced below.[1] For two random variables A and B, their joint probability P(A, B) can be expressed as:

$$\begin{aligned} P(A,B) &= P(A \mid B)P(B), \text{or} \\ P(A,B) &= P(B \mid A)P(A) \end{aligned} \tag{6}$$

where P(A|B) and P(B|A) are conditional probabilities, and P(B) and P(A) are marginal probabilities. If setting the above two expressions equal, we have the Bayes' law as follows:

$$\begin{aligned} P(A \mid B)P(B) &= P(B \mid A)P(A) \\ P(A \mid B) &= \frac{P(B \mid A)P(A)}{P(B)} \end{aligned} \tag{7}$$

Let y=B represent model data and θ=A represent model parameters, so that:

$$P(\theta \mid y) = \frac{P(y \mid \theta)P(\theta)}{P(y)} \tag{8}$$

where P(θ) denotes the prior distribution of the parameters θ, reflecting previous knowledge or belief prior to examining the sample data. In contrast, P(θ | y) is the posterior distribution of the

[1] Please refer to Koop (2003) for a more detailed and complete introduction of Bayesian econometrics, and to LeSage and Pace (2009) for introduction of the Bayesian MCMC estimation method and its applications.

parameters θ, representing learning from sample data and model represented by the likelihood of P(y | θ) and from the prior distribution. The Bayesian MCMC method estimates parameters, θ, by drawing and examining a large number of random samples from the posterior distribution and approximating the form of its probability density (LeSage 1997; LeSage and Pace 2009).

The estimation of the SDM models requires a fully-specified spatial weight matrix W, which can be constructed in various ways, e.g., distances, a first-order continuity matrix, or a nearest-neighbor weight matrix based on m-nearest-neighboring regions. Since the spatial weight matrix can be specified in many different ways, the question of which one is appropriate for the model and sample data has been heatedly debated, and has been used as a major criticism to the "ad hoc" and "sensitive" estimation procedures of spatial econometrics in general (e.g., Arbia and Fingleton 2008). In a direct response to the criticism, LeSage and Pace (2010) suggested that spatial weight matrices from different specifications, such as first-order continuity and nearest neighbors, are highly correlated in part because the various spatial weight matrices almost always contain at least the contiguous or nearby neighbors. In addition to the different weight matrices that share common elements, in most cases, the contiguous neighbors, they all place higher weights on first-order neighbors and lower weights on higher-order neighbors. It is reasonable to expect that the exact form of W would become less important as many of the higher order neighboring relations play a limited and diminishing role in the spatial weight matrices and hence in the spatial regression models.

Model Selection in Spatial Econometric Analysis

Elhorst (2010) proposes a detailed procedure to test the spatial dependence and select the appropriate spatial econometric model. The procedure has two directions: specific-to-general and general-to-specific. The test procedure from specific to general starts with the OLS estimation. It is followed by two Lagrange multiplier (LM) tests-LM lag test and LM error test, to show whether there is spatial dependence in the dependent variable (SAR) or in the error term (SEM). The LM test results may direct to either SAR or SEM model, or both. If both LM tests are significant, rejecting OLS estimation. Florax, Folmer, and Rey (2003) suggested to compare the significance level of the LM lag test and LM error test and choose the one with higher significance. However, LeSage and Pace (2009) argue that the Spatial Durbin model (SDM) should be calibrated regardless of the true data generating process, because SDM is the generalized model that can produce unbiased estimates.

The general form of the spatial models is the following:

$$y = \alpha + \rho Wy + X\beta + WX\theta + \varepsilon \quad (9)$$
$$\varepsilon = \lambda W\varepsilon + v$$

If all the scalars equal to zero ($\rho = \theta = \lambda = 0$), the general form reduces to the OLS model. With different combination of restrictions on the scalars, the general form is reduced to different spatial models. if $\theta = \lambda = 0$, it is a SAR model the equation becomes:

$$y = \alpha + \rho Wy + X\beta + \varepsilon \quad (10)$$

where y is the $n\times1$ vector of the dependent variable; X is the $n\times k$ matrix of independent variables; ε is the $n\times1$ vector of errors. W is the $n\times n$ weight matrix $n\times n$ that defines the space and neighbor relations. $\rho \; and \; \lambda$ are coefficient of the spatially lagged dependent term and spatial error term respectively; θ is a $k\times1$ vector containing coefficients of the spatially lagged independent variables.

If $\rho = \theta = 0$, it is a SEM model with the equation of

$$y = \alpha + X\beta + \varepsilon \quad (11)$$
$$\varepsilon = \lambda W\varepsilon + v$$

if only $\lambda = 0$, it becomes SDM model.

$$y = \alpha + \rho Wy + X\beta + WX\theta + \varepsilon \quad (12)$$

The general-to-specific test starts with the estimation of SDM model. It is followed by the likelihood ratio (LR) tests or Wald tests to determine whether SDM model can be collapsed to either SAR or SEM. The LR tests and Wald tests are used to test two hypotheses: $H_0: \theta = 0 \; and \; H_0: \theta + \rho\beta = 0$, where θ, ρ, β are defined in the above equation (9). The rejection of both hypotheses indicates that SDM should be selected for model estimation. If the first hypothesis $H_0: \theta = 0$ cannot be rejected, it shows the model can be collapsed to SAR model, provided the LM test also clearly prefers SAR model. Similarly, if the second hypothesis $H_0: \theta + \rho\beta = 0$ cannot be rejected, then SEM will be employed as long as the LM test clearly points to SEM model. We need to satisfy both conditions to collapse the model to either SAR or SEM model. The specific-to-general LM test and the general-to-specific LR/Wald test needs to consistently point to SAR or SEM, otherwise, the SDM will be preferred.

3. Public-Private Partnership in China: Comparing Multilevel and Spatial Econometric Models

3.1 Chinese PPP as the Empirical Example

We illustrate the use of multilevel and spatial regression models with an empirical dataset that examines the adoption of public-private partnerships (PPP) in Chinese cities. The empirical dataset is a two-level multilevel dataset that nested observations at city level within provinces (the subnational administrative jurisdictions in China). The dataset includes the full sample of 282 Chinese cities from 2015 to 2017, resulting in a total sample size of 852 observations. There are in total of 31 provincial-level clusters in the dataset.

Decisions pertaining to PPP adoption are affected by not only economic or fiscal conditionals inside cities but also spatial interactions among them. In this section, we introduce the empirical context about PPP in China, explain the spatial dynamics across various levels of government and geographic areas, and describe data and measures.

China's economic takeoff and rapid urbanization in recent decades have been accompanied by the dazzling growth of infrastructure system, which demands massive investment. A large proportion of infrastructure investment in China comes from untraditional sources of revenue or financial approaches (Zhao et al. 2018). A recent development that has attracted much attention is the sudden boom of PPP in China since 2014. Aiming to reduce local government fiscal pressure and to relieve the burden of local government debts, the central government has actively promoted "the collaboration between the government and social capital" across a wide range of public infrastructure and services, including utilities, transportation, irrigation, education, and health. By the end of 2017, Chinese cities have initiated more than 13,500 PPP projects, in different stages of formation, targeting a total investment of 16.5 trillion RMB (about 2.5 trillion US dollars) in the coming decades. Most of these projects started after 2014. To put the numbers in perspective: in UK, where Private Finance Initiatives (PFI, the UK-style PPP) has been widely used since early 1990s, the total project counts only reached 1,500 by the end of 2016. In the United States, within the highway sector where PPP is most active, there are only several dozen cases (Wang and Zhao 2014). With the unprecedented scale in global history, China's PPP boom has led to heated debates about its purpose, its causes and its potential effects.

In this study, we focus on PPP projects that have been successfully adopted in Chinese cities during 2015-2017, across 282 prefectural-level cities. The empirical context is suitable for multilevel and spatial approaches. On one hand, the adoption of PPP may be affected by with-city factors, such as infrastructure needs, economic conditions, fiscal pressure, or governmental capacity of Chinese cities. On the other hand, PPP adoption is likely to be affected by external factors, particularly, the spatial dynamics across levels of government and geographic areas.

Vertically, PPP activities at the local level are responding to the influence of higher-level governmental desires and goals. Following the central government, many provinces have issued PPP guidelines or set up specific agencies to promote or supervise PPP activities. Horizontally, PPP activities in Chinese cities are likely to correlate with those in their neighbors, for example, due to strategic interactions among cities as they compete with each other, or due to unobserved factors that are often spatially correlated for nearby cities. Multilevel and spatial approaches are both suitable for the contexts, and we are interested in their relative strengths in accounting for different spatial dynamics.

The data employed in this study come from multiple sources. The dependent variable measures total PPP investment amounts in RMB 10,000, collected by cities and by years. They are collected from the National PPP Database administered by China's Ministry of Finance.[2] Socio-economic variables include population, GDP, annual government revenue, and the annual changes of these measures. Population data come from Domestic Economic and Social Development Statistical Bulletin (2014-2017); economic and fiscal data come from China Statistic Yearbook (2014-2017). Data about multilevel relationship of Chinese cities are collected from governmental websites. Spatial variables – including distance to Beijing, distance to provincial capital city, and relative distance and neighboring relations across cities -- are derived from Geographic information system (GIS) files of Chinese governments.

3.2 Drivers of PPP in China: Empirical Applications of Multilevel Models

In Table 1, we present three empirical models that attribute city-level variations in PPP investment amounts to demographic and fiscal factors, as well as city-specific characteristics. The Model (1) is the baseline one-level OLS regression defined as Equation (1) in the earlier

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[2] See the Website of China Public Private Partnerships Center. Available at http://www.cpppc.org:8086/pppcentral/map/toPPPChooseList.do

section. This OLS model overlooks the underlying spatial associations across the two levels of geographic jurisdictions: cities (level-1) and provinces (level 2). Model (2) is estimated by adding random intercepts by province (level-2 units) to the OLS specification. Model (3) is the spatial fixed-effects model that adds a full set of province fixed effects. While all three models find that population size is positively associated with the total value of PPP projects adopted at the city level, the two multilevel models report smaller coefficients and greater standard errors than those produced by the OLS specification. The variable of "Administrated Directly" differentiates directly administrated municipalities from other prefectural-level cities in the sample. Table 1 shows that all three models report negative and statistically significant coefficients for this variable. The two multilevel models, however, produce smaller coefficient magnitudes and greater standard errors than those reported in the OLS model. Gelman and Hill (2007) summarize such a comparison as the shrinkage estimation incorporated by multilevel models (Morris and Lysy 2012). In other words, when data have a multilevel structure that higher-level spatial units are the source of variances, not accounting for spatial heterogeneity at the second level, one would obtain biased estimation of the impact of covariates X on Y at the first level. Such biases are more evident in comparing coefficients for variable "Revenue Growth". The adoption of PPP has been thought as a tool to reduce Chinese local governments' fiscal constraints resulting from budget shortfalls. Thus we expect that city governments' revenue growth might exhibit some "chilling effects" on the adoption of PPP. In Table 1, the OLS specification reports a statistically insignificant relationship on this variable, while the two multilevel models both find negative and statistically significant coefficients for this variable.

[Insert Table 1 Here]

Both multilevel models, though specifying provincial level spatial effects differently, allow us to account for systematic unexplained variation across the 31 provinces, thus producing different results from those based on the OLS specification. What factors would guide the choice between the spatial fixed-effects model and the multilevel random-intercept model? Researchers should consider both substantive and statistical considerations. Spatial fixed-effects model would be proper only if the target of inference are clusters in the dataset, while multilevel random intercept model is preferred if the target of inference is the first-level population (in our example, cities). To obtain consistent estimation, the spatial fixed-effects model requires a large number of first-level observations within each of second-level spatial units, while the random-intercept model requires a large number of second-level units. Because our data example satisfies both statistical conditions (i.e. a large number of observations within provinces and a large number of provinces), the two multilevel models produce comparable coefficients. In other data contexts, if one has a multilevel dataset that includes a large number of second-level units, but very limited number of observations within second level clusters, the random-intercept model would be more appropriate than the spatial fixed-effects model.

Beyond the consideration that city-level PPP adoption might be driven by spatial correlations within provinces, one might also posit that the relationship between certain explanatory variable (e.g. population, fiscal factors, and city characteristics) and PPP adoption might vary across provinces. If such spatial (province-specific) heterogeneity exists, the multilevel random-slope model can be useful. Table 2 presents a two-level random-slope model, in which we allow the relationship between variable "Directly Administrated" and total value of PPP projects to vary by provinces. As Table 2 illustrates, the coefficient magnitude for the variable of "Directly Administrated" becomes smaller in the random-slope model than those produced by the spatial fixed-effects model and the random-intercept model in Table 1. The first-level slope coefficient, -6,477, now refers to the average differences between directly administrated municipalities and other prefectural-level cities across the 31 provinces. The second-level random-effect parameters show that the estimated random-slope standard deviation (for variable "Directly Administrated") is 4.031, indicating sizable heterogeneity in the first-level slope coefficient, and this heterogeneity is tied to second level spatial units, provinces. What does this random-slope parameter mean substantively? It suggests that the comparison between directly administrated municipalities and other prefectural-level cities in PPP adoption varies based on which province these other cities belong to.

[Insert Table 2 Here]

3.3 Empirical Applications of Spatial Econometric Models

The three multilevel models discussed in section 3.2 focus on modeling spatial heterogeneity that are specifically tied to higher-level spatial units. Though with different substantive foci, these multilevel models assume that city-level observations within one provincial cluster is independent from those in another provincial cluster. One might doubt about this statistical assumption, if the underlying data-generation process reflects spatial dependence across cities. Spatial econometric models then become particularly useful to model such underlying spatial associations. As aforementioned, we consider SDM as a general spatial econometric approach.

To perform the specification test of spatial dependence, we need to fully specify a spatial weight matrix **W** to capture the spatial neighboring relations. In this study, we construct the weight matrix based on the "k-nearest-neighbors" criterion. The observation of the study is the prefecture-level cities in China. The administrative region governed by each prefecture-level city exhausts the geographical space, which are contiguous. On average, the prefectural regions have five contiguous neighboring regions. Therefore, we choose k as five and define the neighbors for a prefecture-level city as five prefecture-level cities that are closest to its geographic center.

If W is specified above, we conduct the Elhors's (2010) spatial dependence test and select the appropriate spatial econometric model. First, we estimate the OLS model and conduct the LM tests. Table 3 presents the results of these LM tests for our dependent variable—log transformed PPP values. Both LM tests reject the null hypothesis that no spatial lag dependence or no spatial error dependence is present. The LM tests suggest the spatial dependence may exist in both the dependent variable and the error terms. The next step is to estimate the SDM model and conduct Wald test to determine whether the model can be collapsed to either SAR or SEM model. Table 3 reports the Wald test results for both pooled cross-sectional OLS and the panel random effect model. Given our data is a panel of 284 prefecture-level cities from 2015 to 2017, it is possible to incorporate the feature of panel data structure. Our explanatory variables include ones that are time-invariant, therefore we only estimate the panel random effect SDM model. With respect to the pooled cross-sectional OLS model, the Wald tests reject the hypothesis of $\theta = 0$, but cannot reject the hypothesis of $H_0: \theta + \rho\beta = 0$, which may suggest the collapse to SEM model, however the LM tests direct to both SAR and SEM, not SEM alone. Thus, we decide to proceed with the SDM model. With respect to the panel random effect SDM model, the Wald tests afterward reject both hypotheses, which also leads us to the SDM model. Furthermore, we test the null hypothesis of $\rho = 0$, to see whether SLX should suffice. In both the pooled cross-sectional SDM and the panel random effect SDM model, the null hypotheses have been rejected. These specification tests allow us to decide the SDM model.

[Insert Table 3 Here]

Tables 4 and 5 present the estimation results of both non-spatial OLS/panel random-effect and the cross-sectional SDM and panel random-effect SDM for comparison. Although both tables contain the coefficients and standard errors for the independent spatially lagged variables, we cannot interpret these coefficients as marginal effects as in the case of the non-spatial OLS and panel random effect models, because the SDM contain spatially lagged dependent variables ($\rho \neq 0$). LeSage and Pace (2009, P. 74) shows that the marginal effect is calculated by multiplying the point estimates with the spatial multiplier matrix ($(I - \rho W)^{-1}$. Furthermore, the marginal effects contain both the direct effects and indirect effects. The direct effects indicate how the explanatory variables affect the dependent variable in their own unit, whereas the indirect effects indicate how the explanatory variables in a unit affect the dependent variables affect its neighbors, or how the explanatory variables in neighboring units affect the dependent variable in the unit. They provide a decomposing procedure, which involves the weight matrix-W to divide the total marginal effects to direct and indirect effects. The calculation of the direct and indirect effects of a SDM model also involves the coefficients of spatially lagged independent variables, which has no prior restriction. Thus, each independent variable has a different ratio between direct and indirect effect, which makes SDM model more appealing in an empirical study.

[Insert Tables 4 and 5 Here]

Table 6 and 7 present the direct effects, indirect effects, and the total effects of both the pooled SDM model and the panel random effect SDM model, with random intercepts by cities. The interpretation of the spatial model estimates is based on the results in these two tables. Two variables exhibit a significant association with the PPP value, namely population and directly administered city. As population increase by one percent, holding other variables at the same level, the PPP value on average increases by more than two percent. The magnitude of the association is roughly the same between the non-spatial pooled OLS model and the pooled SDM model. Comparing the non-spatial panel random effect and the panel random effect SDM model, the direct effect of population on the PPP value is 2.091, which is 0.33 less than the coefficient in the non-spatial panel random effect model, suggesting that the non-spatial panel random effect model may overestimate the association without considering the spatial dependence. The coefficient of directly administered city is -7.947 and -7.717 in the pooled SDM model and panel random effect SDM model respectively and is statistically significant at 1 percent level. It means that the average PPP value in a directly administrated city is about one eighth of that in other cities. Spatial models—pooled SDM and panel effect SDM show less degree of association to their non-spatial counterpart models, which again suggest that the models overlook the spatial dependence may overestimate the association. GDP growth shows statistically significant positive association with the PPP value in both SDM models, but not the non-spatial models. The different statistical findings suggest that as the GDP growth increase by one percent, on average, the PPP value increases by six to eight percent.

Besides the direct effects (i.e., the association between variables belonging to the same city), the SDM model also captures the indirect effects, which show the association between the PPP value in one prefecture city and the independent variables in its neighboring cities. The distance to Beijing and the distance to the capital city exhibit significantly indirect effects in both the pooled SDM model and panel random effect SDM model. It shows that if the neighboring cities' average distance to the capital city in a province is one percent higher, the average PPP value in the city is about one percent higher. The distance to Beijing exhibits an opposite effect. The higher average neighboring cities' distance to Beijing is associated with lower PPP value in the city itself. Population exhibits a negative indirect effect in the panel random effect model and the population change shows a positive indirect effect in the pooled SDM model.

[Insert Tables 6 and 7 Here]

4. Concluding Discussions: Substantive and Statistical Considerations in Modeling Spatial Effects

In the previous section, we illustrate various multilevel regression models and spatial econometric models with a two-level dataset about the adoption of PPP projects in Chinese cities. We show that both approaches can be used to model spatial effects, but they make different conceptualizations about how observations at the micro-level (in our example, at the city level) are spatially associated cross two geographic levels. These different substantive and statistical considerations merit further discussions.

The Focus of Inference and the Nature of Spatial Effects

Multilevel models and spatial econometric models can both be useful statistical approaches to model spatially clustered effects. However, the two approaches have different focuses of inference. Standard multilevel models focus on capturing correlations among observations due to shared spatial boundaries. Variants of multilevel models provide flexible ways to account for cross-level variances specifically tied to spatial clusters. Yet most multilevel models "assume" away correlations between spatial units at the same level. As such, multilevel models emphasize the inference on spatial heterogeneity, that is, how traits, events, and relationships may vary along spatial units, particularly, along higher-level spatial clusters.

Spatial econometric models relax the assumption of no spatial correlations cross lower-level units, and explicitly use model parameters to account for specific types of spatial dependence. For spatial econometric models, the focus of the inference is not about how coefficients vary along spatial units; it is rather about how dependence across spatial units can be considered as part of the underlying data-generation process. While in some empirical contexts (e.g. our data example), the two approaches might produce similar coefficients for some covariates (e.g. the effect of population size on PPP adoption), one should always be explicitly about the substantive focus when choosing between these two approaches.

Furthermore, when spatial variations of outcomes are of central research interests, one needs to carefully consider the sources of spatial variation when choosing between the multilevel and spatial econometric approach. In a nutshell, the multilevel approach focuses on *spatial hierarchy* and conceptualizes shared spatial areas as the primary source of spatial associations. Spatial econometric models, however, focuses on *spatial proximity* and conceptualizes spatial dependence as "neighboring effects". As we show in our empirical illustration, the two approaches rely on distinct estimation strategies. Multilevel models incorporate spatial effects by adding variance parameters at the higher level. The statistical focus is to distinguish different sources of variance along the spatial hierarchy. One advantage of the multilevel approach is that model specification is often parsimonious, and it imposes minimum data requirement regarding the number of spatial units and minimum cluster size in the dataset. For example, the spatial fixed-effects model can be estimated as long as the number of spatial clusters equals to or greater than 2. The random-intercept model is parsimonious as it only includes one second-level variance parameter for all higher-level spatial units (Rabe-Hesketh and Skrondal 2008). Multilevel models, nevertheless, are built upon the strong assumption that there is no spatial dependence across units at the same level. As we show in our empirical example, when spatial dependence reflects the underlying data-generation process, ignoring it would lead to biased estimation of the direct effects of space and an overlook of substantively interesting indirect effects of space.

Conversely, spatial econometric models rely on geographically informed correlations among spatial units. To estimate spatial econometric models, a key substantive consideration is to properly define "neighboring units", so that one can and then parameterize a priori specification of spatial weights matrix. A major advantage of the spatial econometric approach is in its ability to reflect nuances about how spatial dependence (such spillover effects) can be different for each key explanatory variable in the equation. Spatial econometric models also allow researchers to explicitly account for the direct and indirect effects of spatial relations, offering extra spatial information pertaining to the structure and magnitude of spatial dependence.

Thinking "Space" More Broadly: Some Extensions

Thus far, we have discussed and illustrated the empirical applications of the multilevel approach and spatial econometric approach regarding how the concept of space can be incorporated in empirical public administration research. Despite the availability of numerous statistical tools, the concept of "space" remains to be under-appreciated in our field. In the existing public administration literature, applications of both multilevel models and spatial econometric models often rely on defining "space" as discrete geographic areas. Though substantively different, both approaches use discrete spatial units to impose and identify spatial structure to data. While one approach focuses on spatial hierarchy and the other focuses on spatial proximity, these two approaches are not necessarily to be mutually exclusive. A natural extension to both standard multilevel models and spatial econometric models is the spatial multilevel modeling approach that allows scholars to account for spatial dependence with geographically nested data (for example, see Arcaya et al. 2012). The spatial multilevel framework may also allow a more flexible way to define data patterns and the incorporation of temporally lagged spatial weights matrix in the panel data setting (Elborst 2009, Cheng et al. 2014).

Furthermore, we illustrate the multilevel approach and spatial econometric approach with an empirical dataset using geographic areas to define key spatial units. It does not mean that the notion of space should just be narrowly understood based on geographic areas. Policy outcomes and administrative decisions often are results of various types of social interactions — interactive relationships among individual managers, public organizations, different levels of governments, and so on. Thinking about "spatial clustering" more broadly by moving beyond the notion of geographic area can allow researchers to apply multilevel regression models and spatial econometric models to study interdependent administrative phenomenon. For example, in the context of multilevel modeling, group-membership and common exposure to shared political contexts can be used to identity "spatial clusters", ones that are not necessarily align by geographic areas. Similarly, public administration scholars might consider broader conceptualization of "neighboring effects" (e.g. spillover or learning across similar "neighbors") based on shared traits. For example, spatial econometric models can easily be adapted to explore inter-dependence among peer service organizations that do not share geographic proximity.

Last but not least, in this paper, we illustrate and compare various multilevel models and spatial econometric models with an empirical example of a continuous dependent variable. Recent methodological develop pertaining to both multilevel models and spatial econometric models make it possible to apply both approaches to categorical variables such as dichotomous choice variables (Gelman and Hill 2008) and count data (Wakefield 2007).

References

Anselin, Luc and Wendy K. Tam Cho. 2002. "Spatial Effects and Ecological Inference." Political Analysis, 10(3): 276-297.

Arcaya, Mariana, Mark Brewster, Corwin M. Zigler and S.V. Subramania. 2012. "Area Variations in Health." Health Place, 18(4): 824-831.

Arbia, G., & Fingleton, B. (2008). New spatial econometric techniques and applications in regional science. *Papers in Regional Science*, *87*(3), 311-317.

Berry, Frances Stockes and William D. Berry. 1990. "State Lottery Adoptions and Policy Innovations: An Event History Analysis." *The American Political Science Review*, 84(2): 395-415.

Cheng, Tao, Jaiqiu Wang, James Haworth, Benjamin Heydecker, and Andy Chow. 2014. "A Dynamic Spatial Weight Matrix and Localized Space-Time Autoregressive Integrated Moving Average for Network Modeling." *Geographical Analysis,* 46: 75-97.

Elborst, J. Paul. 2009. "Spatial Panel Data Models." In Manfred M. Fischer and Authur Getis ed. *Handbook of Applied Spatial Analysis: Software Tools, Methods, and Applications.* Springer, 377-407.

Elhorst, J. Paul. 2010. "Applied Spatial Econometrics: Raising the Bar." *Spatial Economic Analysis*, *5*(1): 9-28.

Florax, Raymond J., Hendrick Folmer and Sergio J. Rey. 2003. "Specification Searches in Spatial Econometrics: The Relevance of Hendry's Methodology." *Regional Science and Urban Economics*, *33*(5): 557-579.

Gelman, Andrew and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models.* New York, NY: Cambridge University Press.

Hall, Joshua C. and Justin M. Ross. 2010 "Tiebout Competition, Yardstick Competition, and Tax Instrument Choice: Evidence from Ohio School Districts." *Public Finance Review*, 38 (6): 710-737.

Jun, Kyu-Nahm and Christopher Weare. 2011. "Institutional Motivations in the Adoption of Innovations: The Case of E-Government." *Journal of Public Administration Research and Theory*, 21(3): 495-519.

King, Gary, Ori Rosen, and Martin A. Tanner. 2004. *Ecological Inference: New Methodological Strategie*s. New York, NY: Cambridge University Press.

Karuppusamy, Shanthi and Jered B. Carr. 2011. "Interjurisdictional Competition and Local Public Finance: Assessing the Modifying Effects of Institutional Incentives and Fiscal Constraints." *Urban Studies*, 49(7):1549-1569.

LeSage, James P. and Pace, Robert Kelly. 2009. *Introduction to Spatial Econometrics*. CRC Press, Boca Raton, FL.

Luke, Douglas A. 2002. *Multilevel Modeling.* Thousand Oaks, CA: Sage Publication.

Mitchell, Joshua. 2017. "Does Policy Diffusion Need Space? Spatializing the Dynamics of Policy Diffusion." *Policy Studies Journal*, forthcoming.

Morris, Carl N. and Martin Lysy. 2012. "Shrinkage Estimation in Multilevel Normal Models." *Statistical Science*, 27(1): 115-134.

Moulton, Stephanie and Barry Bozeman. 2009. "The Publicness of Policy Environment: An Evaluation of Subprime Mortgage Lending." Journal of Public Administration Research and Theory

O'Toole, Laurence J., Jr. and Kenneth J. Meier. 2014. "Public Management, Context, and Performance: In Quest of a More General Theory." *Journal of Public Administration Research and Theory*, 25(1): 237-256.

Rabe-Heskeh, Sophia and Anders Skrondal. 2008. *Multilevel and Longitudinal Modeling Using Stata. Second Edition.* College Station, TX: Stata Press.

Raudenbush, Stephen W. and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods.* Second Edition. Thousand Oaks, CA: Sage Publication.

Wakefield, Jon. 2007. "Disease Mapping and Spatial Regression with Count Data." *Biostatistics*, 8(2): 158-183.

Wang, Yin and Zhirong Zhao. 2014. "Motivations, Obstacles, and Resources: Determinants of Public-Private Partnership in State Toll Road Financing." *Public Performance & Management Review*, (31): 679-704.

Ward, Michael and Krisgtian Skrede Gleditsch. 2008. *Spatial Regression Models*. Thousand Oaks, CA: Sage Publication.

Whitford, Andrew. 2014. "Information and Uncertainty in Policy Implementation: Evidence from the Implementation of EPA Waivers." *Journal of Public Administration Research and Theory*, 24(2): 267-288.

Zhao, Zhirong, Guocan Su, and Dan Li. 2018. "The Rise of Public-Private Partnerships in China." *Journal of Chinese Governance*. (DOI information will be available within recent weeks.)

Table 1. Determinants of PPP in China: Comparing Results based on OLS and Multilevel Models

Variable	(1) OLS		(2) Random-intercept Regression		(3) Spatial Fixed -Effects	
	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
Population	**2.254****	**(0.371)**	**2.114****	**(0.389)**	**2.121****	**(0.430)**
Per Capita Revenue	0.242	(0.729)	-0.068	(0.852)	-0.405	(0.952)
Per Capita GDP	1.307	(1.133)	1.295	(1.280)	1.564	(1.414)
Revenue as % GDP	-0.014	(0.033)	0.011	(0.034)	0.027	(0.037)
Population Change	0.023	(0.080)	0.045	(0.077)	0.055	(0.077)
Revenue Growth	0.007	(0.014)	**-0.024†**	**(0.014)**	**-0.026†**	**(0.013)**
GDP Growth	0.014	(0.031)	-0.033	(0.036)	-0.058	(0.039)
Distance to Capital	0.073	(0.136)	-0.033	(0.141)	-0.040	(0.170)
Distance to Beijng	**-0.609****	**(0.234)**	-0.176	(0.307)	0.778	(1.013)
Directly Administered	**-8.914**	**(2.089)**	**-6.537****	**(2.528)**	**-7.387†**	**(3.844)**
Capital City	1.079	(1.753)	0.238	(1.787)	0.261	(2.101)
Intercept	**-19.856†**	**(10.239)**	**-20.724†**	**(11.184)**	**-38.1284***	**(17.526)**
Random Effects						
sd(_cons)	--	--	2.177	(0.407)	--	--
sd(Residual)	--	--	5.390	(0.133)	--	--
N	852		852		852	
Number of Provinces	--	--	31		31	
R^2	0.114		--	--	0.248	

Notes:

1. The dependent variable is measured as total PPP investment amount in 10,000 Chinese Yuan.
2. For simplicity, spatial fixed effects (by provinces) are not reported in Table 1.
3. Model (2) is the multilevel random-intercept model, using the maximum likelihood estimation method. Hence we do not report R^2 for model 2.
4. Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 2. Alternative Multilevel Specification: Two-Level Random-slope Regression

Variable	Coeff.	(SE)
Population	**2.119****	**(0.388)**
Per Capita Revenue	-0.027	(0.847)
Per Capita GDP	1.326	(1.274)
Revenue as % GDP	0.011	(0.034)
Population Change	0.044	(0.077)
Revenue Growth	-0.022	(0.014)
GDP Growth	-0.033	(0.036)
Distance to Capital	-0.026	(0.140)
Distance to Beijng	-0.141	(0.380)
Directly Administered	**-6.477***	**(3.329)**
Capital City	0.272	(1.782)
Intercept	**-22.039†**	**(11.623)**
Random-slope Parameters		
sd(Directly Administrated)	4.031	(2.690)
sd(_cons)	2.077	(0.385)
sd(Residual)	5.383	(0.133)
N	852	
Number of Provinces	31	

Notes:

1. The dependent variable is measured as total PPP investment amount in Chinese Yuan.
2. Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 3. Specification Test

	Lagrange Multiplier Tests		Wald Tests		SDM vs SLX	Suggested Model
	LM lag	LM error	SDM vs SAR	SDM vs SEM	Rho $H_0: \rho = 0$	
Pooled Cross sectional	52.2051**	62.2782**	24.104**	3.3371	0.302***	SDM
Random Effect Panel			22.765**	20.4703	0.129***	SDM

Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 4 Determinants of PPP in China: OLS and SDM

Variable	(1) Non-Spatial Pooled OLS		(2) Spatial Durbin Model (Pooled)			
	Coeff.	(SE)	Coeff.	(SE)	Coeff * W	(SE)
Population	**2.254****	**(0.371)**	**2.314****	**(0.401)**	**-1.579***	**(0.692)**
Per Capita Revenue	0.023	(0.729)	-0.201	(0.829)	0.382	(1.303)
Per Capita GDP	0.242	(1.133)	1.715	(1.205)	-0.774	(1.967)
Revenue as % of GDP	-0.007	(0.033)	-0.031	(0.036)	0.025	(0.060)
Population Change	-0.014	(0.081)	-0.009	(0.077)	**0.373***	**(0.168)**
Revenue Growth	1.307	(0.014)	0.002	(0.018)	0.002	(0.023)
GDP Growth	0.042	(0.031)	0.064	(0.041)	-0.017	(0.051)
Distance to Capital	**-0.609****	**(0.136)**	0.022	(0.144)	**0.764***	**(0.341)**
Distance to Beijing	0.073	(0.234)	-0.220	(0.303)	**-0.719†**	**(0.420)**
Directly Administered	**-8.915****	**(2.098)**	**-7.755***	**(2.106)**	-0.197	(4.718)
Capital City	1.079	(1.753)	0.626	(1.922)	**8.536†**	**(4.912)**
W*PPP Value					**0.302****	**(0.047)**
Intercept	**-19.856†**	**(10.240)**	-9.352	(16.189)		
N	852		852			
R^2	0.114		R2: 0.1901 corr-squared: 0.136 log likelihood:-2664.4351			

Notes:

1. The dependent variable is measured as total PPP investment amount in 10,000 Chinese Yuan.
2. Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 5. Determinants of PPP in China: Non-Spatial Random Effect and Random Effect SDM

Variable	(1) Non-Spatial Random		(2) Spatial Durbin Model (Random Effect)			
	Coeff.	(SE)	Coeff.	(SE)	Coeff * W	(SE)
Population	**2.421****	**(0.416)**	**2.134****	**(0.451)**	**-2.136****	**(0.794)**
Per Capita Revenue	0.123	(0.815)	-0.195	(0.914)	1.156	(1.449)
Per Capita GDP	1.683	(1.258)	1.544	(1.328)	-2.340	(2.246)
Revenue as % of GDP	0.005	(0.036)	**-0.036***	**(0.04)**	-0.063	(0.071)
Population Change	0.032	(0.08)	-0.035	(0.074)	0.252	(0.164)
Revenue Growth	-0.013	(0.014)	0.005	(0.018)	0.028	(0.023)
GDP Growth	0.019	(0.033)	0.079	(0.041)	0.062	(0.053)
Distance to Capital	0.066	(0.155)	0.059	(0.162)	**0.811***	**(0.382)**
Distance to Beijing	**-0.578***	**(0.266)**	-0.313	(0.34)	**-0.974***	**(0.47)**
Directly Administered	**-9.164****	**(2.375)**	**-7.695****	**(2.357)**	-0.548	(5.303)
Capital City	0.934	(1.99)	1.145	(2.151)	**9.474†**	**(5.493)**
W*PPP Value					**0.129****	**(0.054)**
Intercept	**-24.803***	**(11.346)**				
N	852		852			
R^2	0.114		R2: 0.304 corr-squared: 0.1598 log likelihood:-4620.7841			

Notes:

1. The dependent variable is measured as total PPP investment amount in Chinese Yuan.
2. Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 6. Pooled SDM Direct and Indirect Effect

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	(SE)	Coefficient	(SE)	Coefficient	(SE)
Population	**2.265****	**(0.409)**	-1.266	(0.919)	0.999	(0.97)
Per Capita Revenue	-0.186	(0.817)	0.418	(1.64)	0.233	(1.605)
Per Capita GDP	1.687	(1.187)	-0.314	(2.522)	1.373	(2.566)
Revenue as % of GDP	-0.032	(0.037)	0.02	(0.078)	-0.012	(0.079)
Population Change	0.013	(0.078)	**0.505***	**(0.235)**	**0.517***	**(0.268)**
Revenue Growth	0.002	(0.018)	0.004	(0.03)	0.005	(0.027)
GDP Growth	**0.066†**	**(0.04)**	0.001	(0.063)	0.067	(0.060)
Distance to Capital	0.063	(0.154)	**1.062***	**(0.510)**	**1.125**	**(0.600)**
Distance to Beijing	-0.266	(0.295)	**-1.066***	**(0.524)**	**-1.332***	**(0.517)**
Directly Administered	**-7.947****	**(2.108)**	-3.021	(6.501)	-10.967	(7.152)
Capital City	1.083	(2.084)	12.017	(7.484)	13.099	(8.974)

Notes:

1. The dependent variable is measured as total PPP investment amount in 10,000 Chinese Yuan.
2. Significance levels: **p<0.01; * p<0.05;† p<.01.

Table 7 Panel Random Effect SDM Direct and Indirect Effect

	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	(SE)	Coefficient	(SE)	Coefficient	(SE)
Population	**2.091****	**(0.473)**	**-2.116***	**(0.878)**	-0.026	(0.902)
Per Capita Revenue	-0.102	(0.891)	1.221	(1.531)	1.12	(1.404)
Per Capita GDP	1.42	(1.311)	-2.288	(2.447)	-0.869	(2.337)
Revenue as % of GDP	-0.038	(0.04)	-0.072	(0.078)	-0.11	(0.075)
Population Change	-0.03	(0.074)	0.29	(0.184)	0.26	(0.207)
Revenue Growth	0.005	(0.017)	0.032	(0.024)	**0.037**	**(0.021)**
GDP Growth	**0.081***	**(0.041)**	0.08	(0.058)	**0.161****	**(0.054)**
Distance to Capital	0.071	(0.162)	**0.903***	**(0.437)**	**0.974***	**(0.503)**
Distance to Beijing	-0.329	(0.353)	**-1.135***	**(0.504)**	**-1.463****	**(0.450)**
Directly Administered	**-7.717****	**(2.378)**	-1.784	(5.915)	-9.500	(6.482)
Capital City	1.212	(2.126)	**10.485**	**(6.192)**	11.697	(7.335)

Notes:

1. The dependent variable is measured as total PPP investment amount in Chinese Yuan.
2. Significance levels: **p<0.01; * p<0.05;† p<.01.