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Administrative Cost of US Counties and Local Context Dependence*

Yong Chen[a], Lan Xue[b], Jaeho Jung[a], and Myungjin Kim[c]

[a]*Department of Applied Economics, Oregon State University, USA*

[b]*Department of Statistics, Oregon State University, USA*

[c]*Department of Statistics, Kyungpook National University, South Korea.*

Abstract: In this paper, we investigate the spatial variations in the operational expenditures of US county governments using a novel method: the bivariate penalized spline estimation over triangulation (BPST) method. We find that the costs of providing population- and health-related services are spatially non-stationary and are affected by local characteristics, like governance structure, natural amenities, and rural-urban status. In general, county operational expenditures are higher in rural counties with more governance autonomy. The marginal administrative cost for providing population-related services is lower for counties with more elected officials. In amenity-rich counties, the administrative costs are less responsive to wage and population increases but more responsive to health-related services.

Keywords: local government performance, urban and regional finance, efficiency, governance structure, public expenditure, autonomy

JEL Codes: R00, R50, C14

1. INTRODUCTION

In the US, total government expenditure as a share of gross domestic product (GDP) increased from 6.86% in 1902 to 49.02% in 2021(See Figure 1)[1]. Because government expenditure now accounts for almost half of the US GDP, government efficiency has become a

*We wish to thank two anonymous referees and participants of SRSA 2022, WRSA 2023 for helpful comments and suggestions. All remaining errors are our own. Yong Chen is an Associate Professor of Applied Economics at Oregon State University, Corvallis, OR 97333. Lan Xue is a Professor of Statistics at Oregon State University, Corvallis, OR 97333. Jaeho Jung was a graduate student of Applied Economics at Oregon State University, when this manuscript was written. Myungjin Kim is Assistant Professor of Statistics, Kyungpook National University, Daegu, 41566, South Korea. *Corresponding Author:* Yong Chen, E-mail: yong.chen@oregonstate.edu

[1]Even though the expenditure data for federal, state, and local governments are available for years 1900 and 1901, the inter-government transfer data are not available until 1902. The data are obtained from Johnston and Williamson (2022).

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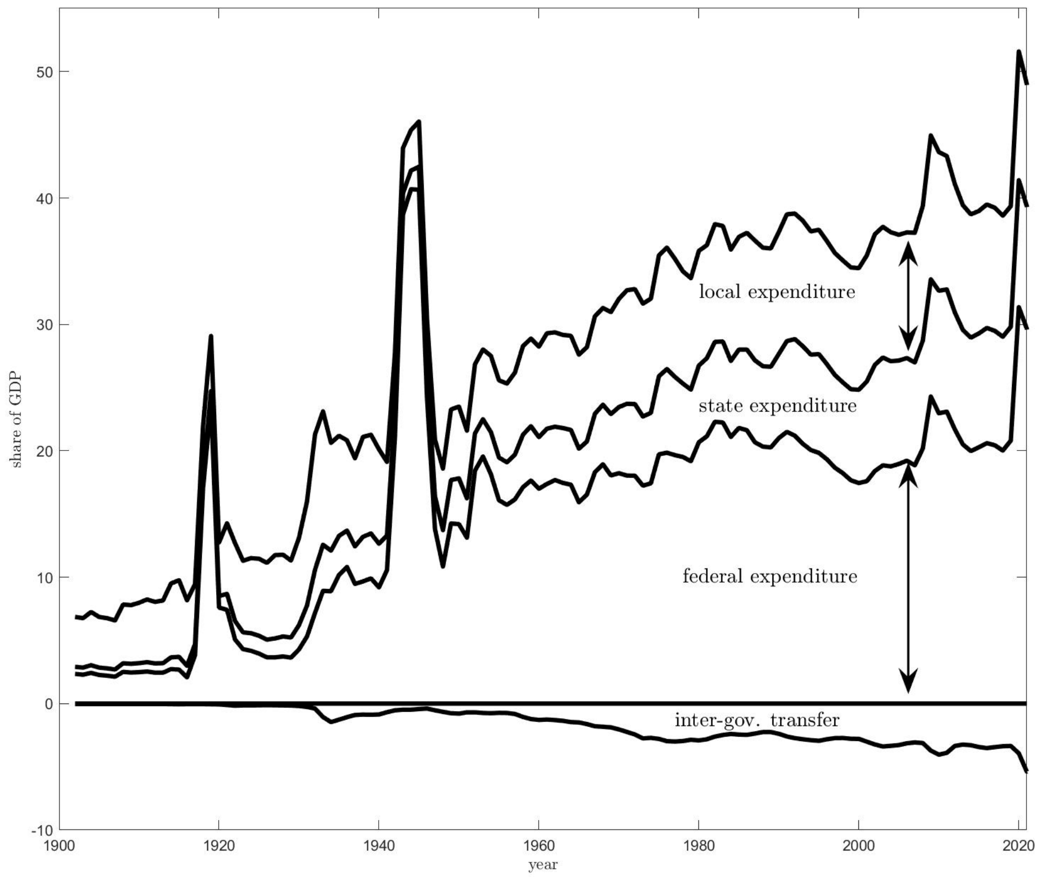

Figure 1: Share of Government Expenditure in GDP

critically important question. So far, there are abundant empirical studies on the causal impacts of specific government programs. However, it is difficult to correctly evaluate the overall government efficiency without identifying the opportunity cost of government expenditures and establishing the counterfactual without government expenditures. As a result, existing literature on government efficiency has focused on the local government expenditures and the relative efficiency performance of local governments.

These existing studies agree on the existence of an efficiency frontier and construct the efficiency frontier by creating some lower envelope of the government cost correspondences. However, they differ in how such lower envelopes are constructed (see Section 2 for a summary). The relative distance to the constructed frontier measures a local government's relative efficiency. A shorter distance indicates higher efficiency. These efficiency measures are then correlated with various explanatory factors like geographical/natural (like climate, topography, and geology), social/demographic (like population density, retired population, and immigrants), economic (like unemployment and income), political and financial factors (like tax revenues, intergovernmental transfer, and government debt).

This paper continues this line of research but proposes an alternative perspective, along with a novel method. We argue that a universal (or spatially non-varying) efficiency frontier may not exist if local contexts vary significantly. For instance, the provision of the same government service can be more costly in a large and mountainous county (like Elko County, Nevada) than in a small county on a plain (like Jackson County, Florida). Even though these two counties had similar population sizes in 2020, the former has a land area ten times larger than the latter, and its terrain is much more rugged. The consequent cost difference between these two counties does not necessarily imply that one is more efficient than the other. In this case, even if we could technically construct an efficiency frontier that constitutes the lower envelope of the government cost correspondence, the distance to such a frontier may have no efficiency implications because it reflects variations in local contexts. In general, these local contextual variables can also include institutional characteristics because different institutional constraints create different incentives and induce different government behavior. This may further challenge the assumed existence of a universal efficiency frontier, a spatially non-varying efficiency frontier that applies to all locations.

As an alternative to constructing a universal efficiency frontier, this paper directly investigates local government expenditure on operational expenses and their determinants. We adopt a spatially varying coefficient model (SVCM) to allow for the dependence on local contexts. Such dependence on local contexts could give rise to spatially varying relations between government outputs and local government expenditures. Because the SVCMs encompass spatially non-variant coefficients as a particular case, this nested feature makes it possible to test the spatial stationarity (or the existence of universal structures) implicit in the data generation processes. Our results show that there are significant spatial variations and local contextual dependence. These results challenge the existence of a universal efficiency frontier. At the least, constructing an efficiency frontier in future research needs to consider local contextual variables. However, multiple local contextual variables and complex interactions between them could over-complicate the efficiency analysis. Moreover, the constructed efficiency frontiers may become manifolds with complex structures, which will severely diminish the practical applicability of the efficiency frontier analysis.

Another contribution of this paper is its focus on the US county governments, also referred to as the "forgotten governments" (Marando and Thomas, 1977; Schneider and Park, 1989). Even though the existing literature predominantly focuses on municipal governments, county governments are better suited for the current study because county governments are less heterogeneous than municipal governments in the US. First, county government behavior is less heterogeneous than municipal government behavior. County governments only have authority when the state constitution or law gives it to them. According to an 1845 Supreme Court case: "counties are nothing more than certain portions of the territory into which the state is divided for the more convenient exercise of powers of government" (State of Maryland v. Baltimore Ohio Railroad Co., 44 US 534, 1845).[2] While municipal boundaries often

[2]The incorporation process of municipalities in the US is much more complicated. It is typically a bottom-up process that needs state approval. Different states specify different incorporation processes and impose different requirements. For instance, Iowa, Minnesota, and Connecticut have no requirement on population size. Many other states have minimum population requirements for cities/towns ranging between 20 (Arkansas) to 12,000 (Massachusetts) residents (Census Bureau, 1994). Some states also have requirements

change due to annexations, county boundaries are static and change only rarely (Census Bureau, 1994). Second, services provided by county governments are less heterogeneous than those by municipal governments. The core function of a county government is housekeeping, which includes "assessing and collecting property taxes, registering voters and administering elections, providing law enforcement, prosecuting criminals, administering a jail, recording deeds and other legal records, maintaining roads, keeping vital statistics, and controlling communicable diseases" (Sherman, 2016).[3] Because county governments are less heterogeneous if spatial stationarity is rejected for county governments, it is likely to be rejected for municipal governments. This paper also introduces variables on county governance structure as potential contributors to the observed differences in local government expenditures.

2. LITERATURE REVIEW

In the existing literature on local government efficiency, researchers construct the efficiency frontier using three main approaches: one parametric frontier approach (De Borger and Kerstens, 1996) and two non-parametric approaches: data envelopment analysis (DEA) and free disposal hull (FDH) methods (Charnes et al., 1978; Färe and Grosskopf, 1985; Seiford and Thrall, 1990; Liu et al., 2016). The parametric frontier method postulates a functional form for the cost function $C(y, w; \beta)$, which defines a lower bound to all the observed local government expenditures C_i necessary to produce a vector of outputs y_i at given input prices w_i. β is a parameter vector to be estimated. Because the cost frontier is supposed to be the lower envelope of all observed costs, a one-sided distribution of the error term is imposed $C_i = C(y_i, w_i; \beta)exp(u_i)$ with $u_i \geq 0$. The relative distance between the observed costs C_i to the estimated cost frontier, $E_i = C_i/\hat{C}$, is used to measure cost (in)efficiency. A smaller distance E_i indicates a more cost-efficient local government.

The non-parametric approaches construct the efficiency frontier without imposing functional forms about the cost frontier as in the parametric approach. The DEA approach constructs a convex hull to envelop the observed data on cost (C_i) and outputs (y_i) (Charnes et al., 1978; Färe and Grosskopf, 1985; Seiford and Thrall, 1990; Liu et al., 2016), under weak economic assumptions like disposibility in both inputs and outputs. The FDH approach drops the convexity requirement in the DEA method (Deprins et al., 1984; Lovell et al., 1994; Simar and Zelenyuk, 2011). The government efficiency is then measured as the distance to the constructed frontier. A smaller relative distance to the constructed frontier indicates more government efficiency.

on population density and distance to nearby cities/towns.

[3]In comparison, municipal services are defined by the municipal citizens in exchange for the municipal taxes they pay. As a result, there is more heterogeneity in the service provided by municipal governments. For instance, the services provided by the municipal government of Monowi, Nebraska (a municipality with only one resident) are vastly different from those provided by the municipal government of New York City (a municipality with 8.8 million people). Despite these differences, the basic municipal services typically include the provision of utilities (like water and sewage), the maintenance of city facilities (like parks and streetlights), the provision of public services (like law enforcement and fire protection), the enforcement of zoning and building regulations, and the promotion of economic development. Even though law enforcement is common in municipalities and counties, the county sheriff's department differs from a municipal policy in the jurisdiction and legal requirements.

The existing empirical evidence suggests that government efficiency is affected by population density (de Duren and Compean, 2016; Ladd, 1992), population size (Fukushige and Shi, 2016; Hortas-Rico and Rios, 2020), terrain ruggedness (Hortas-Rico and Rios, 2020), expenditure spillovers and strategic interactions between local governments (Case et al., 1993; Besley and Case, 1995; Sole-Olle, 2006). In recent decades, local governments have been under social, economic, and political pressure to improve the cost-efficiency in the provision of quality government services. Researchers have empirically examined the impact of amalgamation (Blom-Hansen et al., 2014), privatization (or outsourcing) (Bel and Miralles, 2003), and inter-government cooperation (Bel and Warner, 2015; Blaka, 2017; Dijkgraaf and Gradus, 2013) on government cost-efficiency. Researchers have also examined the impact of many political factors, which include political ideology, political competition, political participation (Buch-Gomez and Cabaleiro-Casal, 2020; Narbon-Perpina et al., 2020), political accountability (Bruns and Himmler, 2011), political transparency (Guillamón and Cuadrado-Ballesteros, 2021), the form of municipal government (the mayor-council form, the mayor-manager form, and whether the mayor is elected) (Grossman et al., 1999), and the electoral system (Baraldi, 2008; Santolini, 2017).[4] Among the limited number of studies examining county government expenditures, Morgan and Kickham (1999) find that the change of government forms has no effect on the fiscal behavior of the US county governments, which contradicts the strong association documented by Benton (2003) and McDonald (2015). De Benedictis-Kessner and Warshaw (2020) find that the partisan composition of county legislatures significantly affects county fiscal policies. In this paper, we introduce county governance structures into the analysis.

While Morgan and Kickham (1999) noted evidence suggesting that the change of government forms could induce spatially varying impacts on county government fiscal behavior, Mulamba and Tregenna (2020) was the first to adopt a spatially varying coefficient model (SVCM). Mulamba and Tregenna (2020) use the geographically weighted regression (GWR) method to explore the spatial non-stationarity in the operational expenditure of Italian municipal governments. Technically, this paper follows Mulamba and Tregenna (2020) by adopting an SVCM. It complements Mulamba and Tregenna (2020)'s study by showing that spatial non-stationarity may naturally occur even without spatial interactions as assumed in the GWR method. We also propose an alternative estimation method called Bi-variate Penalized Spline Estimation with Triangulation (BPST), which is more efficient than GWR (Mu et al., 2018). This method also avoids imposing the spatial weight matrices, as seen in the traditional spatial econometric models and the recent GWR development.

3. LOCAL CONTEXTS AND GOVERNMENT ADMINISTRATIVE COSTS

According to economic theory, cost ($y \in \mathbb{R}$) is a function of the factor price ($w \in \mathbb{R}^+$) and outputs ($x \in \mathbb{R}^J$). In this paper, we use the county government's direct expenditure on current operations (y) to measure the administrative cost (in current dollars) for local government services. As of 2020, the expenditure on current operations constitutes 79.5% of the local government's direct expenditure and 78.8% of the local government's total expen-

[4]For a detailed list of these factors, please refer to the reviews by Da Cruz and Marques (2014) and Narbon-Perpina and De Witte (2018)

diture, respectively.[5] This expenditure on current operations includes "Direct expenditure for compensation of own officers and employees and for supplies, materials, and contractual services except for any amounts for capital outlay" (United States Census Bureau, 2006, p.5-5). Because of this, we include the county average wage rate (w) as an input price in the cost function because wage compensation for county government officers and employees is a substantial component of current operations expenditure.

The core function of a county government includes housekeeping functions such as "assessing and collecting property taxes, registering voters and administering elections, providing law enforcement, prosecuting criminals, administering a jail, recording deeds and other legal records, maintaining roads, keeping vital statistics and controlling communicable diseases" (Sherman, 2016). These housekeeping functions are used to quantify the vital public services provided by county governments. In particular, county population, county health index, and crime rates are selected to quantitatively measure these core output services (x) provided by county governments. County population directly affects the workload for "registering voters and administering elections". Both population and crime rate can help measure the amount of county government service related to "law enforcement, prosecuting criminals, administering a jail, recording deeds and other legal records". We include population and health index in the equation and hope they capture the county services related to "keeping vital statistics and controlling communicable diseases". The county service related to "assessing and collecting property taxes" is not explicitly included because housing value is driven by housing demand via local population and because housing cost is an essential element of living cost reflected in the local wage rate.

Because of the spatial heterogeneity in the county characteristics (s), like climate, topographical, and institutional conditions, the provision of county government services may face different constraints and result in different cost-efficiency. Because these local characteristics are location specific and vary over space, we explicitly represent these location dependencies in function $s(u, v)$, where (u, v) are the latitude and longitude of a location. The cost functions then take their general form:

$$y = C(w, x \mid s(u, v)). \tag{1}$$

While these local characteristics may directly affect the administrative costs, we are more interested in how they affect the administrative cost indirectly. For instance, faced with re-election pressure, a county with more elected officials may have a stronger incentive to provide services more cost-effectively. This institutional characteristic would indirectly reduce operation expenditure through a more cost-effective county service provision. The spatially differentiated institutional characteristics ($s(u, v)$) would imply a spatially varying relationship between the service provided (x) and the administrative cost (y) and justifies a spatially varying coefficient model. To illustrate this point, we apply Taylor series expansion

[5] According to US Census Bureau, *2020 Annual Surveys of State and Local Government Finances*, government expenditures can be classified by character and object or by function. The former classifies total government expenditure into inter-government expenditure, current operations, capital outlay, assistance and subsidies, interest on debt, and insurance benefits and repayments. Because the category of direct expenditure on current operations is the best measure available for government administrative cost, this is the classification scheme used in the paper.

of Equation (1) around a point $(\bar{y}, \bar{w}, \bar{x})$ to generates a first-order approximation of the form:

$$y - \bar{y} = \beta_0(u,v) + \beta_w(u,v)(w - \bar{w}) + \sum_{j=1}^{J} \beta_{x,j}(u,v)(x - \bar{x}), \tag{2}$$

where $\beta_0 = C(\bar{w}, \bar{x} \,|\, s(u,v)) - \bar{C}$, $\beta_w = C_w(\bar{w}, \bar{x} \,|\, s(u,v))$ and $\beta_x = C_x(\bar{w}, \bar{x} \,|\, s(u,v))$. The location-specific characteristics $s(u,v)$ may directly affect administrative cost through the county-specific intercept term $\beta_0(u,v)$. However, we are more interested in their indirect effects through $\beta_w(u,v)$ and $\beta_{x,j}(u,v)$, which respectively capture the marginal impacts of factor price and outputs on the government's administrative cost.

This specification allows us to examine whether counties with more elected officials can provide government services $\beta_{x,j}(u,v)$ at a lower marginal cost because the elected officials tend to face more election pressure. This question can be addressed in two steps. In the first step, we estimate the SVCM model as specified in Equation(2) and test whether the estimated coefficients are spatially varying (i.e.,$H_0 : \beta_{x,j}(u,v) = \overline{\beta}_{x,j}$). If there is spatial variation, then we can test the correlation between the estimated coefficients $\beta_{x,j}(u,v)$ (i.e., the marginal cost of service provision) and the number of elected officials. If there is no spatial variation, then the correlation analysis between the estimated coefficients $\beta_{x,j}(u,v)$ and the number of elected officials is unnecessary.

This example also explains the two-stage estimation strategy employed in this paper, similar to the two-stage estimation commonly seen in the existing literature on local government efficiency. However, it differs in the first-stage estimation. Instead of estimating the efficiency frontier, we directly estimate the spatially varying coefficient model for the cost function (Equation 2). If the estimated coefficients exhibit significant spatial variation, we reject the existence of a common cost function across space. As cost functions vary over space, the efficiency frontier of the cost functions would also change over space. We then proceed to the second stage. In the second stage, we regress the estimated marginal impacts of factor price $\beta_{w,j}(u,v)$ and marginal output $\beta_{x,j}(u,v)$ on the local characteristics and test the dependence on local contexts. It reveals the potential correlation between local characteristics and cost efficiency. Note that spatial interactions are not considered in the specification of Equation (2) because counties exist only as agents of the states, perform mainly housekeeping functions, and strategic competitions are less of a concern.

4. ESTIMATION METHOD AND HYPOTHESIS TESTING

As proposed by Mu et al. (2018), the BPST estimation does not involve the specification of a presumed spatial weight matrix to allow spatial variation in the relationship. Instead, it starts with a partition of the domain Ω using triangulation, which is a collection of triangles $\Delta = \{\delta_1, \cdots, \delta_K\}$ such that $\Omega = \bigcup_{k=1}^{K} \delta_k$ and the intersection of any two triangles must be either a common vertex or edge. This paper generates triangulation using "DistMesh" available at http://persson.berkeley.edu/distmesh/. Other triangulation packages include the "Delaunay" algorithm in MATLAB and "DelaunayTriangulation" in MATHEMATICA.

Given the triangulation Δ, splines approximate the spatially varying relations $\beta_j(u,v)$ using low order polynomials on each triangle δ_k and spliced together along the common edges and vertices. One appealing feature of the spline method is that it yields a fitted model with a parsimonious explicit expression. In particular, using Bernstein basis (Lai and Schumaker, 2007), spatially varying relation $\beta_j(u,v)$ on triangle δ_k can be approximated by $\beta_j(u,v) \approx \mathcal{B}_k^T(u,v)\gamma_{jk}$, for $(u,v) \in \delta_k$, where $\mathcal{B}_k(u,v)$ is the Bernstein basis on triangle δ_k. Therefore, on the entire domain Ω, $\beta_j(u,v)$ can be approximated by $\mathcal{B}^T(u,v)\gamma_j$ where $\mathcal{B}(u,v) = \{\mathcal{B}_k(u,v)\}_{k=1}^K$ and $\gamma_j = \{\gamma_{jk}\}_{k=1}^K$, that is, $\beta_j(u,v) \approx \mathcal{B}^T(u,v)\gamma_j$ for $(u,v) \in \Omega$. In this way, the spatially explicit functional relation $\beta_j(u,v)$ can be expressed as a linear combination of the Bernstein basis functions with the combination coefficients γ_j.

Given the spatial data $\{u_i, v_i, \mathbf{X}_i, Y_i\}_{i=1}^n$, where $\mathbf{X}_i = (X_{i1}, \cdots, X_{iJ})$, to estimate the spline coefficients, we follow Mu et al. (2018) and consider a regularized minimization problem

$$\min_{\{\gamma_k\}_{k=1}^K} \sum_{i=1}^n \left\{Y_i - \sum_{j=0}^J \mathbf{X}_{ij}\mathcal{B}^T(u_i,v_i)\gamma_j\right\}^2 + \sum_{j=0}^J \lambda_j \gamma_j^T P_j \gamma_j, \tag{3}$$

where P_j is the diagonal block penalty matrix satisfying

$$\gamma_j^T P_j \gamma_j = \int_\Omega \left[\left(D_u^2\mathcal{B}^T(u,v)\gamma_j\right)^2 + 2\left(D_u D_v \mathcal{B}^T(u,v)\gamma_j\right)^2 + \left(D_v^2\mathcal{B}^T(u,v)\gamma_j\right)^2\right] dudv.$$

The second term in the objective function (Equation 3) is a roughness penalty based on the second-order derivatives of spline functions. Tuning parameters λ_j control the balance between the goodness of fit and the roughness of the function estimates. In particular, a larger value of λ_j entails a more parsimonious fit but a larger residual sum of squares.

In addition, to ensure the smoothness of splines along the shared edges of triangles, a set of linear constraints $H_j\gamma_j = 0$ for $j = 1, \cdots, J$ is imposed on the spline coefficients, where H_j is the linear constrain matrix for the j-th covariate. The form of H_j depends on the triangulation and the order of smoothness r.

Mu et al. (2018) proposed an efficient algorithm to solve (3) subject to the linear constraints and developed R codes that are available in the R package (BPST). Mu et al. (2018) also established a large sample theory for the spline estimators. They showed that the BPST estimators are asymptotically consistent and converge at an optimal convergence rate.

We consider two types of hypotheses to test whether the observed spatial variation in regression coefficients is statistically significant. For the global stationarity test, consider the null hypothesis that assumes all regression coefficients are spatially stationary with

$$H_0 : \beta_j(u,v) = \beta_{0j}, \text{ for all } j = 1, \ldots, J, \tag{4}$$

where $\{\beta_{0j}\}_{j=1}^J$ are unknown constant effects. For global stationarity, the null hypothesis is rejected if at least one β_j is spatially non-stationary.

We construct test statistics by comparing the model fitting under null and alternative hypotheses. Denote RSS_0 and RSS_1 as the residual sum of squares (RSS) under the global null hypothesis, as assumed in Equation (4), and under the alternative hypothesis, as assumed in Equation (2), respectively. Consider test statistics

$$T_0 = \frac{RSS_0 - RSS_1}{RSS_1}. \tag{5}$$

It calculates the percentage of improvement in RSS if the regression coefficients are allowed to be spatially varying under alternatives rather than fixed as constants in the null hypothesis. The null hypothesis is rejected when the improvement is large, or T_0 is large. In order to obtain the p-value or critical value for the test, bootstrapping method is used to approximate the distribution of test statistics under the null hypothesis. The details of the bootstrapping procedure can be found in Mu et al. (2018).

To test whether an individual coefficient $\beta_j(u,v)$ is spatially stationary, consider an individual stationarity test, where the null hypothesis is given as

$$H_0 : \beta_j(u,v) = \beta_{0j}, \text{ for some } j \in \{1, \cdots, J\}. \tag{6}$$

Under this null hypothesis, there is no spatial variation in the jth coefficient $\beta_j(u,v)$. Mu et al. (2018) considered a test statistics as

$$V_{nj} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\hat{\beta}_j(u,v) - \hat{\beta}_{0j} \right)^2, \tag{7}$$

which compares estimates of β_j under null and alternative hypotheses respectively. The null hypothesis is rejected for large values of V_{nj}. Because $\beta_j(u,v)$ is spatially unchanged under the null hypothesis, the random shuffling of the location should not affect the estimate. Using the shuffled data, we can randomly shuffle the location and estimate Equation (2). Repeating this B times to generate $\left\{V^*_{nk,b}\right\}_{b=1}^{B}$, which is used to approximate the null distribution of the test statistic. The null hypothesis is rejected if the p value $p = \sum_{b=1}^{B} I(V^*_{nk,b} \geq V_{nk})/B$ is less than the significance level α.

The spatial stationarity only tests whether the estimates vary over space. To test whether an estimated coefficient is significantly different from zero, we need the individual significance test with the null hypothesis as

$$H_0 : \beta_j(u,v) = 0, \text{ for some } j \in \{1, \cdots, J\} \text{ and } (u,v) \in \Omega \tag{8}$$

This tests whether coefficient estimate $\beta_j(u,v)$ for location (u,v) is statistically different from zero. Using the bootstrap method, we estimate Equation (2) 100 times and obtain the distribution of $\{\beta_{j,b}(u,v)\}_{b=1}^{B}$. If less than α percent of the $\{\beta_{j,b}(u,v)\}_{b=1}^{B}$ is above zero, we reject the null hypothesis $\beta_j(u,v) \geq 0$. If less than α percent of the $\{\beta_{j,b}(u,v)\}_{b=1}^{B}$ is below zero, we reject the null hypothesis $\beta_j(u,v) \leq 0$.

5. DATA AND ESTIMATED SPATIALLY VARYING COEFFICIENTS

Following the specification of the cost function in Equation (1), the explanatory variables $\mathbf{X}$ include the average county wage rate (as a proxy for factor price), population, the health index and crime rate (as measures for the core services provided by county governments). The annual average weekly wage data is from the US Bureau of Labor Statistics. Population data is the 5-year estimate of the 2013-2017 American Community Survey data from the US Census Bureau. The county-level health measure is obtained from the County Health Rankings and Roadmaps maintained by the University of Wisconsin Population Health Institute

(Remington et al., 2015). The higher the health measure, the better the health conditions in a county.[6] Crime is the number of "actual all crimes" per capita in 2017 from the Uniform Crime Reporting Program (Federal Bureau of Investigation, 2013). Table 1 reports the summary statistics of this data.[7] These variables are standardized so that they have a mean of zero and a standard deviation of one.

Table 1: Summary statistics of data

	Mean	Sd	Min	Max	N
ln(oper_exp)	10.06	1.80	1.10	16.80	2,960
wage	761.81	162.72	438.00	2,437.00	2,960
population	94,599.92	319,983.47	112	10,170,292	2,960
health	6.50	2.47	0.48	23.71	2,960
crime	0.03	0.02	0.00	0.43	2,960

Figure 2 plots the estimated BPST coefficients β_w and β_x for Equation (2). Table 2 reports the summary statistics for these estimated coefficients. It also includes OLS estimates in the last column. The results exhibit obvious spatial variation in the estimates. Neither the mean nor median of the BPST estimates are statistically close to the OLS estimates. In addition, all the standard errors from the OLS regression are much smaller than those from SVCM.

As shown in Table 3, the null hypothesis of global spatial stationarity is rejected from 100 bootstrap simulations, which confirms significant spatial variations in at least one of the estimated coefficients of wage, population, health, and crime. The individual tests of spatial stationarity reject the spatial stationarity for wage, population, and health. However, we cannot reject the spatial stationarity for the coefficient of crime. So crime is not included in the subsequent analyses.

Table 2: Summary statistics of estimated coefficients

	Mean (Std.)	Min	Median	Max	OLS (std.)
Constant	9.75 (0.31)	8.82	9.76	10.52	10.06 (0.03)
Wage	0.31 (0.23)	-0.55	0.31	0.86	0.54 (0.06)
Population	4.64 (0.92)	2.31	4.70	6.59	0.56 (0.16)
Health	0.19 (0.23)	-0.45	0.17	0.93	-0.10 (0.03)
Crime	-0.03 (0.82)	-3.16	-0.02	1.98	0.18 (0.06)

A detailed read of these results reveals more interesting details that might be counter-intuitive at first sight. For instance, the impact of wage on operational expenditure exhibits strong spatial variations in Figure 2 and 3, a pattern that is concealed by the spatially non-varying models like OLS Some regions (in green) exhibit positive correlations, others

[6]The health measure in this paper includes health outcome measures (like the length of life and quality of life) and health factors (like health behavior measures and clinical care measures) as proposed by Remington et al. (2015). However, it excludes the "social and economic factors" because they include measures like median household income and homicide that are redundant. The relative weights used to construct the health measure are the same as proposed by Remington et al. (2015).

[7]There are 31 counties with zero operational expenditure, and those observations do not qualitatively change the paper's key conclusions.

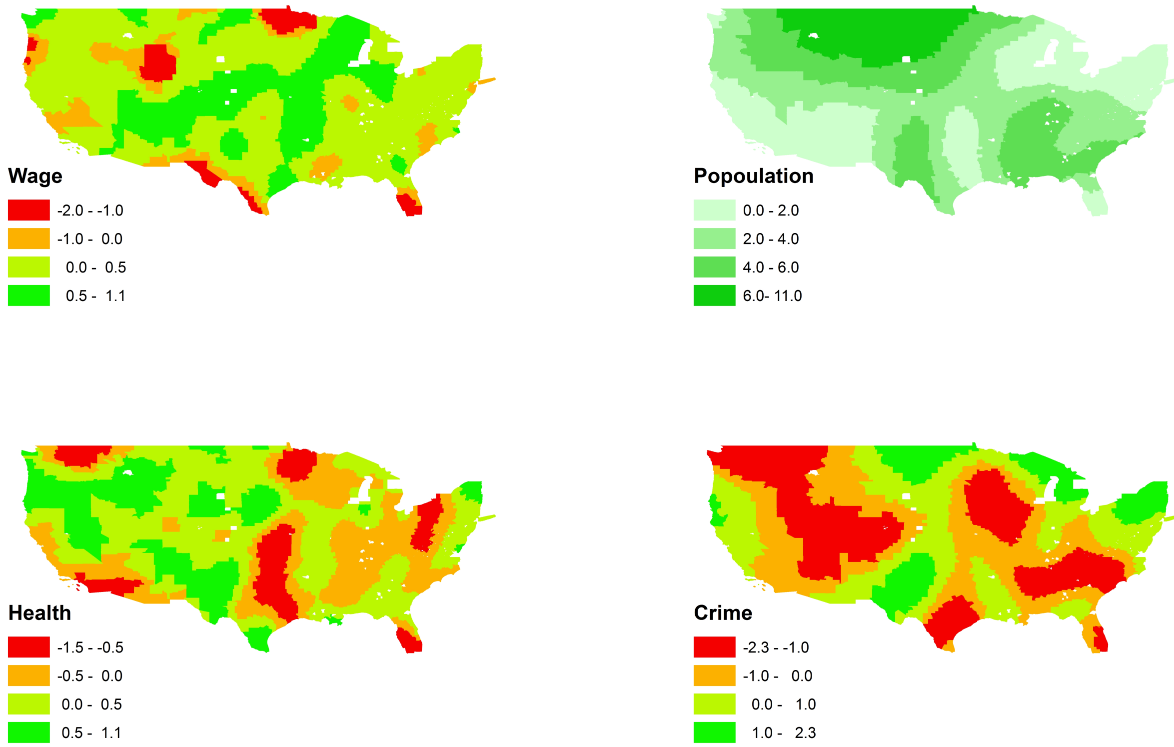

Figure 2: Estimates of spatially varying coefficients for wage, population, health, and crime.

(in yellow) show no significant correlations, while a few (in red) demonstrate negative correlations. These spatial variations could reflect context-dependent complexity in reality. Consider a local economy that comprises two labor markets: one for the government sector and one for the non-government sectors. The average wage rate in a county can be interpreted as the wage rate in the non-government sectors or the opportunity cost given up by government employees. Other things equal, a higher county wage rate implies a higher cost per government employee (cost effect). It also implies a higher opportunity cost for potential government employees and a lower labor supply (supply effect) in the government sector. Therefore, a higher county wage rate could imply a higher cost per government employee but a lower number of government employees. In the green regions, the cost effect dominates the labor supply effect and generates a positive correlation between the wage rate and the operational expenditure of local governments. When the supply effect is strong enough, the correlation becomes statistically insignificant. The fringe benefits provided to government employees could further weaken the relationship between wage rate and labor supply, leading to statistical insignificance. Finally, 13 counties show a statistically significant negative association. Almost all 13 counties have tiny population sizes and a significant presence in the government sector. It is possible that the supply effect dominates the cost effect in these

Table 3: Global and individual test on spatial stationarity

	p-value
Global test	0.00
Individual tests	
Wage	0.06
Population	0.00
Health	0.00
Crime	0.44

counties and creates a negative association.[8]

There are significant variations in the impact of health on operational costs. On the one hand, counties with poor health may focus heavily on those outcomes and incur more operational costs. On the other hand, counties may have to spend more to achieve a good health index. As for the impact of crime rate on local operational costs, the hypothesis of no significant spatial variation cannot be rejected (see Table 3).

The spatial stationarity only tests whether the estimates vary over space. To test the statistical significance of estimates, we need the individual significance test using the bootstrapping method, as discussed in the previous section. Based on these tests of statistical significance, we create a dummy variable called significance (ψ), which takes value 1 (or -1) if the estimate is significantly greater (or less) than zero and takes value 0 otherwise. Figure 3 plots the spatial distribution of this significance variable (ψ). The apparent spatial variation in the significant estimates further challenges the spatial stationarity assumed in the existence of the universal efficiency frontier. For local policymaking, these spatially varying estimates are far more critical than an estimated national average because they provide local estimates about how local government operational costs would be affected by local changes in wage, population, health index, and crime. However, factors contributing to these spatial variations still need to be explored.

6. CONTRIBUTING FACTORS TO THE SPATIALLY VARYING COEFFICIENTS

With the rejection of spatial stationarity in the estimated coefficients of wage, population, and health, it is interesting to investigate factors contributing to the observed spatial nonstationarity. As an exploratory exercise, we regress the estimated coefficients (see Figure 2) on a set of local characteristics. We are particularly interested in the impact of county governance structures like home rule and the number of elected officials. The home rule measures local government authority. States that adopt Dillon's rule give local governments a narrowly defined authority. According to court decisions by Judge John F. Dillon of Iowa in 1868, a sub-state government can only exercise powers explicitly granted to them by the state government. States that adopt home rule give local governments more autonomy. According to court decisions by Judge Thomas Cooley in 1871, local governments have some inherent rights. Under home rule, local governments can exercise some authority without

[8] It is also possible that these 13 counties are just some outliers.

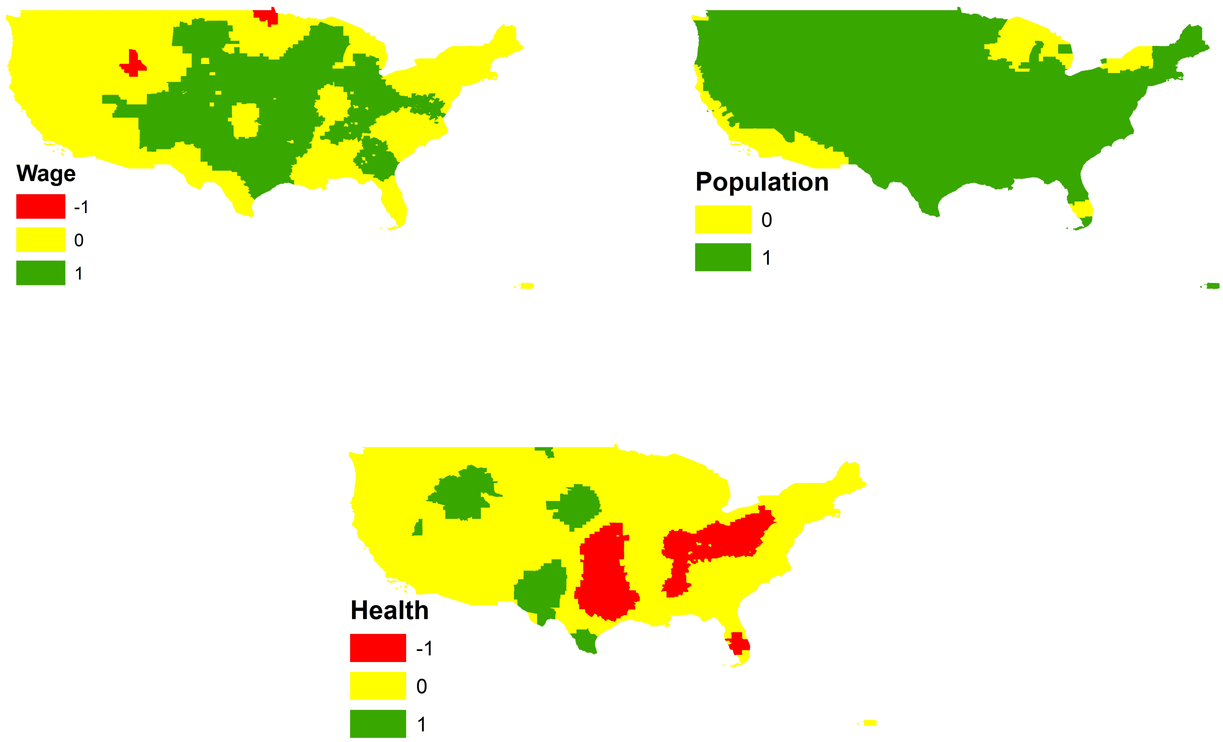

Figure 3: Significance of spatially varying coefficients for wage, population, and health.

state interference (Russell and Bostrom, 2016). The number of elected officials measures the number of officials facing election pressure, which might affect the administration cost. These county governance data are openly available in the National Association of Counties.

We also include the natural amenity scale (amenity) and rural-urban continuum code (rucc) from the Economic Research Service (ERS) because the former captures some local natural conditions, and the latter depicts the rural-urban context. As a robustness check, we include a set of demographic, social, economic, and other local characteristics. The demographic variables include county population, the share of the population with ages between 19 and 64, and the share of the population with bachelor's degrees. The economic variables include the share of employment in agriculture, manufacturing, and proprietor employment. We include a Bartik index to capture the growth potential given the employment structure. Some other control variables, like a social capital measure and distance to the nearest metropolitan statistical area, are also included. The social capital data are from Northeast Regional Center for Rural Development, Penn State University. In particular, we use the number of non-profit organizations (nccs). Table 4 reports the summary statistics.

Table 5 summarizes the ordinary least square (OLS) estimates of the correlation between the BPST estimates and the local characteristics. The top panel of the table explains the

Table 4: Summary Statistics of Location Characteristics

	Mean	Sd	Min	Max	N
home_rule	0.31	0.46	0.00	1.00	2,942
num_elected	12.70	6.25	3.00	62.00	2,942
amenity	0.03	2.31	−6.40	11.17	2,942
rucc	5.07	2.68	1.00	9.00	2,942
nccs	0.41	1.29	0.00	37.55	2,942
population	93,897.86	319,778.66	112.00	10,170,292.00	2,942
bachelor	0.19	0.08	0.04	0.70	2,942
age19_64	0.59	0.03	0.47	0.75	2,941
bartik	0.90	0.14	0.00	1.27	2,942
agri_rate	0.09	0.08	0.00	0.58	2,940
manu_rate	0.08	0.07	0.00	0.60	2,940
prop_rate	0.29	0.10	0.06	0.69	2,940
msa_dist	79,665.67	58,020.60	1,089.49	381,947.65	2,942

model specifications. Model A includes only the key explanatory variables like county governance structure (home rule and the number of elected officials), the natural amenity scale, and the rural-urban continuum code. Model B includes the aforementioned demographic variables. Model C adds the economic variables. Model D introduces other control variables like the distance to the nearest metropolitan statistical area and the number of non-profit organizations. The second panel of the table reports the regression results using the estimated spatially varying coefficients for wage (β_w) as the dependent variable. The third panel uses β_p as the dependent variable, and the final panel use β_h. Note that the dependent variables, the estimates reported in Figure 2, capture the marginal impact of the corresponding factor (wage, population and health services) on the administrative cost of local government (see Equation 2). So Table 5 essentially reports how the location-specific characteristics affect these marginal impacts.

Table 5: Factors contributing to the spatially varying coefficients

	A	B	C	D
Demographic		Yes	Yes	Yes
Economic			Yes	Yes
Other				Yes
Observations	2942	2941	2939	2939
		β_w		
Home_Rule	0.046***	0.047***	0.052***	0.051***
	(0.011)	(0.011)	(0.011)	(0.011)
Num_Elect	0.008***	0.008***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Amenity	−0.014***	−0.013***	−0.011***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Rucc	0.013***	0.012***	0.006**	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Adjusted R^2	0.059	0.060	0.085	0.090
		β_p		
Home_Rule	0.172***	0.180***	0.260***	0.248***
	(0.062)	(0.062)	(0.062)	(0.060)
Num_Elect	−0.028***	−0.025***	−0.018***	−0.015***
	(0.003)	(0.004)	(0.003)	(0.003)
Amenity	−0.032***	−0.026**	−0.032**	−0.047***
	(0.012)	(0.012)	(0.013)	(0.013)
Rucc	0.173***	0.163***	0.102***	0.035***
	(0.010)	(0.012)	(0.012)	(0.013)
Adjusted R^2	0.130	0.141	0.189	0.221
		β_h		
Home_Rule	0.038***	0.039***	0.043***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)
Num_Elect	0.001	0.002**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Amenity	0.017***	0.019***	0.020***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)
Rucc	0.020***	0.018***	0.011***	−0.000
	(0.002)	(0.002)	(0.003)	(0.003)
Adjusted R^2	0.044	0.073	0.099	0.120

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The second panel of Table 5 reports how the marginal impact of wage on the administrative cost (β_w) is correlated with county governance variables. The estimated impacts of county governance variables are consistent across different model specifications. For a wage increase, the operational expenditure in counties with the home rule is higher than in counties with Dillon's rule. Applying Shephard's Lemma, the marginal impact of wages on administrative costs can be interpreted as conditional labor demand of local governments. This result suggests that other things equal, local county governments with home rule are likely to expand faster than counties with Dillon's Rule. This is consistent with the data that counties with home rule have an average of 5561 employees as compared to an average of 3229 employees in counties with Dillon's rule. For a wage increase, the counties with more elected officials tend to have more operational expenditure, which is also consistent with the positive correlation between the number of local government employees and the number of elected officials in the data. Other things equal, a wage increase has a smaller impact on operational expenditure in urban (low rucc value) counties with high natural amenities. The insignificance of the rural-urban continuum code in model (D) is due to the inclusion of distance to the metropolitan area. These differences in conditional labor demand may also be affected by differences in other local characteristics, as specified in Equation (2). For instance, rural counties need to hire more employees to provide the same government services due to the scattered population distribution.

The third panel of Table 5 reports how the marginal impact of population on the administrative cost (β_p) is correlated with county governance variables. The estimated impact of county governance variables is again consistent across the different model specifications. For an increase in population, the consequent increase in the operational expenditures in counties with home rules is significantly higher than in those without home rule. Other things equal, β_p can be interpreted as the marginal cost of providing population-related services (see Equation 2). The higher β_p, the marginal cost of population-related services, in counties with home rule could be due to the fewer institutional constraints against government expansion under home rule. Moreover, β_p is negatively associated with the number of elected officials. This negative association suggests that, for a population increase, the consequent increase in the marginal cost of population-related services is smaller in counties with more elected officials, probably due to the election pressure. The marginal cost of population-related services (β_p) is also negatively associated with natural amenities. This negative association could arise from the compensating effect of amenity (Roback, 1982), as workers are willing to locate in amenity-rich locations for lower wages. The positive correlation with the rural-urban continuum code is probably due to the decreasing population density along the urban-rural gradient.

The last panel of Table 5 reports how the marginal impact of health measures on the administrative cost (β_h) is correlated with the county governance variables. To improve health conditions in a county, the consequent increase in the operational expenditure on health-related services is higher in rural counties with more governance autonomy (home rule), more elected officials, and better natural amenities. Other things equal, (β_h) can be interpreted as the marginal cost of providing health-related services. In this context, the results suggest that the marginal cost of health-related services is, on average, higher in rural counties with more governance autonomy, more elected officials, and a better natural amenity scale.

In order to investigate potential urban-rural differences, we split the data into metropolitan and non-metropolitan subsets according to the official categorization of the Office of Management and Budget. As reported in Table 6, the regression results are consistent with those in Table 5 with a noticeable urban-rural difference in some contributing factors. For instance, the estimated impacts of the number of elected officials in metropolitan and non-metropolitan counties are similar to those in Table 5. At the same time, the estimated impact of home rule and amenities on current expenditures exhibit interesting differences between metro and non-metro counties. For instance, in non-metropolitan counties with more autonomy (i.e., home rule), the current operational expenditures are much more sensitive to the changes in county wage rates than those with Dillon's rule. The estimated marginal impact of wage on operational cost in non-metropolitan counties are 60% higher than the corresponding estimate in Table 5. However, in metropolitan counties, there is no significant difference between counties with home rule and Dillon's rule. The impact of health services on current operational expenditure is more significant in metropolitan counties but less so in non-metropolitan counties. These results reiterate the importance of context dependence observed in county expenditures.

Table 6: Contributing factors in metro and non-metro counties

	b_w		b_p		b_h	
	Non-Metro	Metro	Non-Metro	Metro	Non-Metro	Metro
Home_Rule	0.088***	−0.008	0.197**	0.208***	0.016	0.071***
	(0.015)	(0.016)	(0.088)	(0.071)	(0.013)	(0.017)
Num_Elect	0.009***	0.008***	−0.013***	−0.012***	0.005***	0.002**
	(0.001)	(0.001)	(0.005)	(0.004)	(0.001)	(0.001)
Amenity	−0.003	−0.024***	−0.070***	0.002	0.024***	0.006
	(0.004)	(0.004)	(0.018)	(0.017)	(0.003)	(0.005)
Demographic	Yes	Yes	Yes	Yes	Yes	Yes
Economic	Yes	Yes	Yes	Yes	Yes	Yes
Other	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1883	1056	1883	1056	1883	1056
Adjusted R^2	0.074	0.149	0.230	0.106	0.169	0.034

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a robustness check, we regress the significance variable (Figure 3) on the local characteristics, and the results are similar to the baseline. It is important to acknowledge that the factors included in this section are far from exhaustive. The simple correlation analyses only offer a preliminary glance at the localized estimates from the spatially varying coefficient model. Despite its simplicity, these simple correlation analyses after spatially varying coefficient (SVCM) estimations provide an alternative approach to investigating the heterogeneous efficiency performances among local governments. A better understanding of spatial non-stationarity, as shown in the localized estimates, requires in-depth knowledge of the local context and can help to improve the overall understanding of the issue. Despite the statistical significance, the overall explanatory power of these factors is still limited, as illustrated by the low adjusted R^2. This suggests that there is still a lot more to be explored for the contributors of spatial non-stationarity.

7. CONCLUSION

This paper investigates county government efficiency as measured by operational expenditure. Applying the BPST method, we find that county government expenditure exhibits significant spatial variations affected by the local natural and institutional context. Significant spatial non-stationarity exists in the impact of wage, population, and health index. We further explore the determinants of this spatial non-stationarity. The counties with more autonomy, as stipulated by the home rule, tend to have higher operational expenditures. This is because those counties with more autonomy tend to have more government employees and a higher marginal cost of providing population- and health-related services. Other things equal, more remote non-metropolitan counties tend to have higher operational expenditures. Compared to metropolitan counties, the operational expenditures of non-metropolitan counties are more responsive to wage increases and less responsive to changes in health-related services. While some previous literature finds that whether the municipal mayors are elected by popular election has no impact on local government expenditure, our results suggest the opposite. That is, the number of elected officials in a county significantly affects the county's administrative costs. This could be because the nationwide average estimate covers the significant local variations. One probable reason is that the effect of election pressure depends on other local contexts. With many variations in the local contexts, the increased variation of the estimate makes the global average estimate insignificant. We also find that, in amenity-rich counties, the administrative costs are less responsive to wage and population increases but more responsive to health-related services.

One limitation of this proposed research is that it can only identify correlation but not causal relationships. However, as a first attempt to explore the spatial non-stationarity in the administrative costs of county governments, it reveals some exciting correlation patterns between county administrative costs and the local contexts. The local contextual dependence increases the complexity of the local government expenditures, a topic not adequately examined and worth further exploration. Methodologically, it raises concerns about the universal (spatially non-varying) cost structure implicitly assumed in the existing studies on local government efficiencies. More importantly, the dependence of government performance on local contexts has important implications for policy designs and implementation. It helps to differentiate between top-down and bottom-up policies concerning government reforms. Top-down mandates of a universal policy or regulations cannot fully consider the differences in local contexts. They can result in vastly different policy outcomes depending on the local contexts, except for cases with clear evidence of spatial stationarity. In contrast, bottom-up policies take root in local contexts and will be more likely to succeed, even though they are less likely to be generalizable.

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