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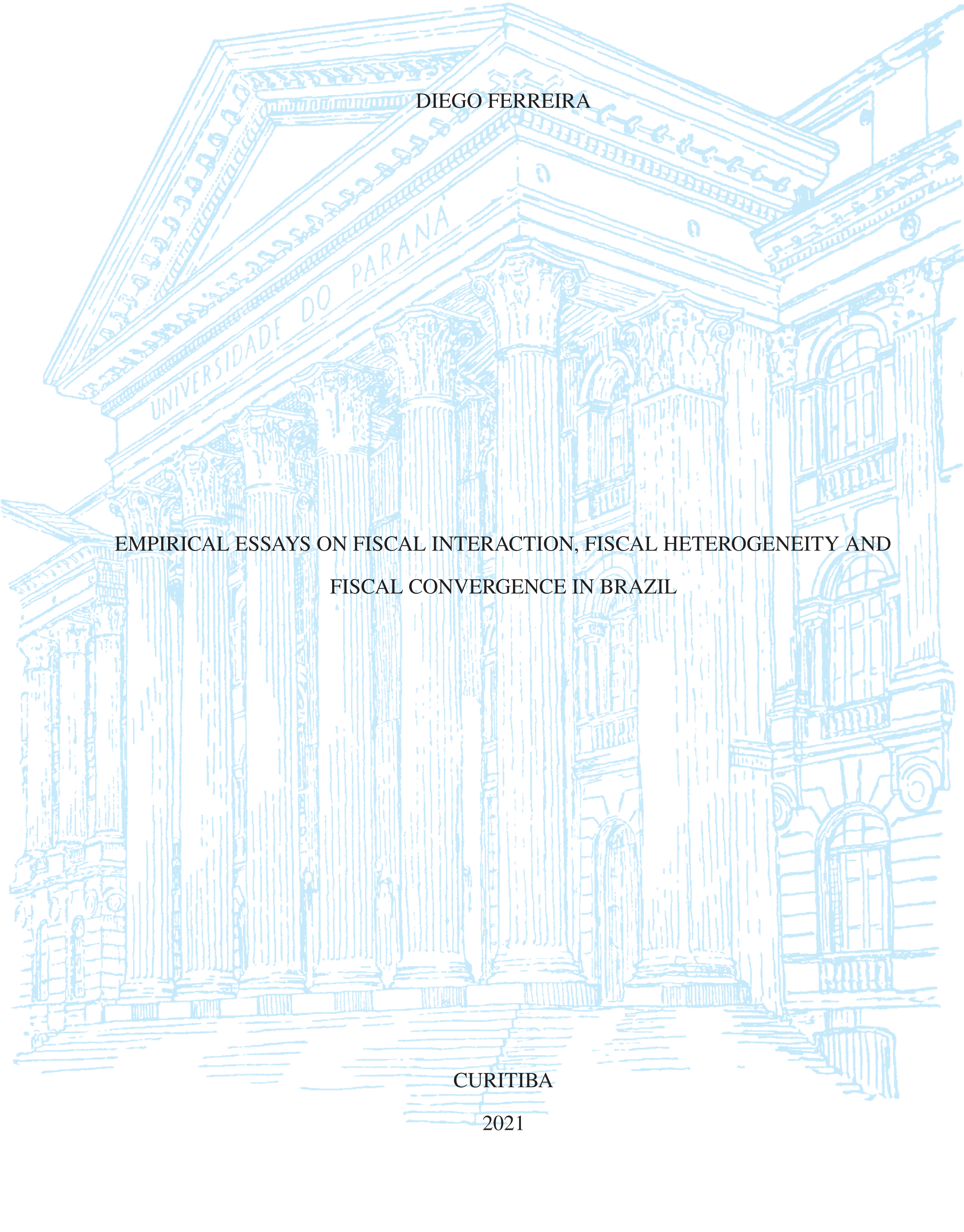

DIEGO FERREIRA

EMPIRICAL ESSAYS ON FISCAL INTERACTION, FISCAL HETEROGENEITY AND FISCAL CONVERGENCE IN BRAZIL

CURITIBA

2021

DIEGO FERREIRA

EMPIRICAL ESSAYS ON FISCAL INTERACTION, FISCAL HETEROGENEITY AND FISCAL CONVERGENCE IN BRAZIL

Tese apresentada como requisito parcial à obtenção do grau de Doutor em Desenvolvimento Econômico, no Curso de Pós-Graduação em Desenvolvimento Econômico, Setor de Ciências Sociais Aplicadas, da Universidade Federal do Paraná..

Orientador: Prof. Dr. Fernando Motta Correia.

CURITIBA

2021

FICHA CATALOGRÁFICA ELABORADA PELA BIBLIOTECA DE CIÊNCIAS SOCIAIS APLICADAS – SIBI/UFPR COM DADOS FORNECIDOS PELO(A) AUTOR(A)
Bibliotecário: Eduardo Silveira – CRB 9/1921

Ferreira, Diego
Empirical essays on fiscal interaction, fiscal heterogeneity and fiscal convergence in Brazil. – 2021.
76 p.

Tese (Doutorado) - Universidade Federal do Paraná. Programa de Pós-Graduação em Desenvolvimento Econômico, do Setor de Ciências Sociais Aplicadas.

Orientador: Fernando Motta Correia.

Defesa: Curitiba, 2021.

1. Desenvolvimento econômico. 2. Setor público. 3. Despesa pública. 4. Municípios. I. Universidade Federal do Paraná. Setor de Ciências Sociais Aplicadas. Programa de Pós-Graduação em Desenvolvimento Econômico. II. Correia, Fernando Motta. III. Título.

CDD 336.39

MINISTÉRIO DA EDUCAÇÃO
SETOR DE CIÊNCIAS SOCIAIS E APLICADAS
UNIVERSIDADE FEDERAL DO PARANÁ
PRÓ-REITORIA DE PESQUISA E PÓS-GRADUAÇÃO
PROGRAMA DE PÓS-GRADUAÇÃO DESENVOLVIMENTO ECONÔMICO - 40001016024P0

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To Maria Ramos and Rafael Maciel.

ACKNOWLEDGEMENTS

This Ph.D. thesis is the product of 4 years of work as a Developement Economics graduate student at the Federal University of Paraná (UFPR), Brazil. Throughout this period, I have met a lot of incredible people who have inspired and enabled me to flourish as a person and a researcher. I would like to thank you all for your constant support in this endeavor. Such accomplishment would not be possible without your valuable suggestions and comments.

I would first like to thank my mother, Maria Aparecida Ramos, for her continual and unconditional support. Walking up this path has been a challenging experience, yet your love and kindness were always there, providing the necessary strength to carry on. I am deeply grateful for everything.

I am equally grateful to Fernando Motta, my supervisor and friend, for his kind help, useful comments, encouragement and support. Even though we have known each other for more than 8 years, your constant wisdom and knowledge, not only in Economics but also regarding life itself, never ceased to amaze me. Thank you.

Next, I would like to thank my thesis committee members Augusta Pelinski Raiher, Luiz Carlos Ribeiro Neduziak, Terciane Sabadini Carvalho and Vinicius de Almeida Vale for accepting to be part of this committee and for their invaluable comments and suggestions. Furthermore, I thank the faculty of the Graduate Program in Development Economics at the Federal University of Paraná, especially Paulo de Andrade Jacinto, for sharing their knowledge. I would also like to mention the Coordination for the Improvement of Higher Education Personnel (CAPES), whose financial aid was essential for achieving the goal of writing the present Ph.D. thesis.

Although Economics has been a passion during the last 12 years, I must confess this thesis would not have been possible if I had not enjoyed my life to the fullest. Would it not be for the love and incredible times I have had with my friends, I do think I would never be able to accomplish the task of writing this thesis. Hence, I would like to thank you all for the support, especially Andreza Palma, Géssica Diniz, Maríndia Brites and Tailiny Ventura. This journey would not be the same without you all. Despite the arduous hours of study and research, the friendship born from them has been and will always be the most rewarding of all. You will always have a friend in me.

Returning to Curitiba was not an easy task at first. Despite all hardship and uncertainty, such experience was also incredibly refreshing and exciting. Thank you Monique Stephany, Thábata Schossler, Gabriela Heller and Thais Brandalize for the laughs and love, for the parties and the house gatherings, for the honesty and support. Thank you for embracing me and making me feel like I belonged.

As constantly stated in this thesis, Brazil is a continental country. Yet, although distance has kept us apart, Maíra Diogo has always been present throughout this whole period, being the most outstanding friend one could ever hope for. For more than 13 years, we have laughed, cried, lived and loved. You are more than just a friend to me, more than a sister: you are my person.

Last but not least, I would like to express my deepest appreciation to my love, friend and husband, Rafael Maciel. Thank you for always being there for me in times of need, for understanding my eventual absence, both physically and emotionally, and for daring to dream this dream with me. Even though the carousel never stops turning, and we can't get off, riding this emotional roller coaster was only remotely possible because you were always by my side. Thank you.

RESUMO

A presente tese de doutorado consiste em três capítulos sobre Economia do Setor Público aplicados aos municípios brasileiros. O primeiro capítulo analisa a relação entre gasto municipal em pessoal e transferências do fundo de participação dos municípios, também controlando por atividade econômica municipal e receita corrente. Os dados constituem um painel para o período 2013-2017. Resultados para o I de Moran indicaram a existência de autocorrelação espacial nos dados. Portanto, modelos espaciais de dados em painel foram estimados e testados para a melhor especificação. Os resultados sugeriram que o modelo Durbin espacial foi a especificação com melhor aderência aos dados. Os impactos cumulativos estimados mostraram que o grau de dependência fiscal dos municípios brasileiros apresentou um efeito direto positivo na despesa com pessoal, apesar do efeito indireto ser negativo. PIB e receita tributária apresentaram efeitos diretos e indiretos positivos. Finalmente, as estimativas dos efeitos diretos confirmaram a presença do efeito *flypaper*. O segundo capítulo discute os potenciais efeitos da não-estacionariedade espacial na relação entre o despesa com pessoal e as variáveis fiscais, econômicas e demográficas para os municípios brasileiros. Nesse sentido, estima-se um modelo de regressão ponderada geograficamente (RPG) com autocorrelação espacial (SAR) de modo a considerar tanto a dependência espacial quanto a não-estacionariedade espacial. As estimativas dos parâmetros locais indicaram que as relações fiscais locais no Brasil variam no espaço. Particularmente, há evidência de que governos locais com baixa dependência fiscal apresentam correlações relativamente mais baixas entre as transferências intergovernamentais e a despesa municipal com pessoal. Além disso, dinamismo econômico é positivamente correlacionado com a folha de pagamentos municipal. No que tange ao comportamento estratégico, os parâmetros locais sugerem interações fiscais tanto positivas quanto negativas entre os municípios brasileiros. Finalmente, demonstra-se que o efeito *flypaper* é mais intenso em governos locais com dependência fiscal relativamente mais altas e/ou com maior densidade populacional. O terceiro capítulo analisa a convergência da despesa com pessoal nos munícipios brasileiros controlando para a potencial presença de dependência espacial. Enqaunto a análise exploratória de dados espaciais forneceu evidências preliminares acerca da validade da hipótese de convergência do gasto público local no Brasil, diferentes padrões macrorregionais foram observados. Adicionalmente, modelos espaciais de dados em corte transversal foram estimados de modo a fornecer evidência estatística acerca de tal processo de convergência. As estimativas obtidas através do modelo Durbin espacial confirmaram a β-convergência condicional da despesa com pessoal *per capita* municipal durante o período de 2013 a 2017. Em termos de processos macrorregionais, foram identificados dois grupos baseados na similaridade de sua velocidade de convergência: um primeiro grupo com as menores velocidades de convergência constituído pelas regiões Norte, Nordeste e Sudeste e um segundo grupo com as maiores velocidades de convergência constituído pelas regiões Sul e Centro-Oeste. Por fim, a decomposição dos efeitos totais em efeitos diretos e indiretos revelaram que a interação fiscal estratégica foi um importante fator em reduzir o inerente processo de convergência da despesa com pessoal *per capita* municipal nas regiões Nordeste e Sudeste.

Palavras-chave: Despesas públicas locais. Municípios brasileiros. Modelos econométricos espaciais.

ABSTRACT

This Ph.D. thesis consists of three chapters about Public Sector Economics applied to Brazilian municipalities. The first chapter analyzes the relationship between municipal personnel expenditure and government transfers, also controlling for municipal economic activity and tax revenue. We make use of a panel data set for the period 2013-2017. Results for the Moran's I statistic indicated the existence of spatial autocorrelation in the data. Therefore, spatial panel data models were estimated and tested for the appropriate specification. The results suggested that the spatial Durbin model was the specification favored by the data. Cumulative impacts showed that the degree of fiscal dependency of the Brazilian municipalities presented a positive direct effect on personnel expenditure even though the indirect effect was found to be negative. GDP and tax revenue presented positive direct and indirect effects. Finally, the estimated direct effects confirmed the flypaper effect. The second chapter discusses the potential effects of spatial nonstationarity on the relationship between personnel expenditure and budgetary, economic and demographic variables among the Brazilian municipalities. To this end, we estimate a geographically weighted regression (GWR) model with spatial autocorrelation (SAR) in order to consider both spatial dependence as well as spatial nonstationarity. Local parameter estimates indicate that local fiscal relations in Brazil vary across space. Particularly, there is evidence of local governments with low fiscal dependency ratios having relatively lower correlations between intergovernmental grants and local personnel expenditure. In addition, economic dynamism is also positively correlated with the local wage bill. In terms of strategic behavior, the obtained local parameters suggest both positive and negative fiscal interactions among the Brazilian municipalities. Finally, the flypaper effect is more intense in local governments with higher fiscal dependency ratios and/or higher population density. The third chapter analyzes the convergence of personnel expenditure across the Brazilian municipalities controlling for the potential presence of spatial dependence. While exploratory spatial data analysis provided preliminary evidence on the validity of local public spending convergence hypothesis in Brazil, different macro-regional patterns were observed. In addition, cross-sectional spatial models were estimated as to provide statistical evidence on such convergence process. The obtained estimates from the spatial Durbin model confirmed the conditional β-convergence of municipal *per capita* personnel expenditure during the period 2013-2017. In terms of macro-regional processes, two groups based on the similarity of their speed of convergence were found: a first group with the lowest speed of convergence comprising the North, Northeast and Southeast regions and a second group with the highest speed of convergence comprising the South and Central-West regions. Finally, decomposition of total effects into direct and indirect effects revealed that fiscal strategic interaction was an important factor in weakening the inherent convergence process of municipal *per capita* personnel expenditure in the Northeast and Southeast regions.

Keywords: Local public spending. Brazilian municipalities. Spatial econometric models.

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1 LOCAL PUBLIC SPENDING AND FISCAL INTERACTIONS: SPILLOVER EFFECTS AMONG BRAZILIAN MUNICIPALITIES

1.1 INTRODUCTION

The debate on fiscal interactions within a federal governmental system accounts for the behavior of individuals in similar fashion to consumers that seek the best goods at the best prices. Tiebout (1956) proposes a model of local public goods financed by revenues where the local residents of each jurisdiction are free to maximize the optimal amount of public goods for a given set of favorable taxes.

Countries with a pronounced regional and territorial dimension such as Brazil tend to exhibit horizontal fiscal imbalances which result from the concentration of tax collection sources as well as the regional dispersion of the demand for public goods. Due to the regional imbalances, the mechanism of government transfers aims to internalize the positive externality to other jurisdictions in an attempt to not only avoid an insufficient supply of a given public good that may aid neighboring units, but also mitigate the inefficiencies on the equilibrium supply of public goods.

The literature has provided evidence that intergovernmental transfers have a more expansionary effect on the expenses of receiving jurisdictions compared to equivalent increases in the income of their taxpayers (Gramlich and Galper, 1973; Fisher, 1982; Wyckoff, 1991; Strumpf, 1998; Amusa et al., 2008). The strategy adopted by these empirical studies consists of specifying a demand for public goods as a function of the income of the median voter, the price of the public goods, the municipality socioeconomic characteristics and the intergovernmental transfers.

The fiscal decentralization in economies with different tax liabilities and expenditure executions consequently engenders fiscal interactions from the existing horizontal externalities of assorted mechanisms of fiscal equalization in federal governmental systems. Fiscal interactions are usually considered as the resulting effects of both public expenditure and interjurisdictional fiscal competition (Revelli, 2005).

By reason of fiscal decentralization, federal governmental systems are able to present fiscal interactions among jurisdictional units similarly to the model developed by Tiebout (1956). However, the empirical literature has mainly focused its attention on two particular types of fiscal interactions: (i) spatial interaction in the tax structure and (ii) the spatial interaction in the expenditure structure.

Under the hypothesis of fiscal competition, the tax burdens in a jurisdiction are independent of those in neighboring jurisdictions. The literature investigating the intertwined relationship among different fiscal variables in the US counties is rather substantial (Case et al., 1993; Besley and Case, 1995; Frederiksson et al., 2004; Crowley and Sobel, 2011). Likewise, empirical studies examine the extent of tax interdependence among jurisdictional units for the euro area (Büttner, 1999, 2001; Solé-Ollé, 2003; Bordignon et al., 2003; Feld and Reulier, 2009). As for the spatial interactions concerning the expenditure structure, the literature is essentially interested in the importance of local expenditure decisions given the low taxing competence of local governments. Even though the results on tax interactions is rather established in the literature, there still is no consensus on the effects of expenditure interactions (Case et al., 1993; Redoano, 2007; Frère et al., 2014; Qu et al., 2016).

The existence of a federal governmental structure where fiscal decentralization is reflected not only by the effects of intergovernmental transfers on the expenditure of jurisdictional units, but also by the different spatial interactions – either in the tax structure or in the spatial expenditure interaction – should make it possible to identify and estimated spatial panel data models. Such econometric framework is chosen due to the fact that standard (non-spatial) panel data models neglect the structure of spatial dependence and, therefore, generate biased and inconsistent estimates.

This study empirically investigates the extent of horizontal fiscal interactions among Brazilian municipalities in which the neighboring effects of intergovernmental transfers on personnel expenditure is accounted for. More precisely, we first describe the Brazilian municipal fiscal data set used in our estimations as well as the data transformations performed. Baseline results are generated through standard non-spatial panel data models (pooled OLS and fixed effects models). However, given that Brazil is a country profoundly characterized by regional heterogeneity, we also investigate the potential existence of global spatial interdependence in the considered fiscal variables in order to properly assess model structure. Then, four different spatial panel data models are estimated and tested as to establish which one best describes the spatial association pattern in the data set. Finally, the obtained estimates from the chosen model are compared to the baseline results, highlighting the role of neighboring spillover effects.

1.2 DATA AND SPATIAL AUTOCORRELATION TESTS

The subsequent empirical analyses were conducted with panel data covering all Brazilian municipalities for the period 2013–2017.[1] The chosen timespan is due to data availability. Fiscal municipal data were collected from the FINBRA (Finances of Brazil – Account Data of Municipalities) database made available by the Brazilian National Treasury Secretariat (STN). The categories of local fiscal measures examined include: total personnel expenditure, tax revenue and Municipal Participation Fund (*Fundo de Participação dos Municípios* – FPM) grants. For municipal GDP, data from 2013 to 2017 were obtained from the Brazilian Institute of Geography and Statistics (IBGE) database. All variables were deflated by the Extended National Consumer Price Index (IPCA, base: 12/2017), taken from the IBGE database. Municipal GDP, total personnel expenditure, FPM grants and tax revenue were converted into *per capita* terms using the annual estimates of municipal population from the IBGE database. Finally, the municipal shares of population under 14 years old and over 65 years old were estimated using the 2010 Brazilian Census and the IBGE projections for population structure of the Brazilian states.

However, given the continental size of Brazil and its bureaucratic intricacies regarding municipal fiscal data, missing data were observed in the data set for total personnel expenditure, tax revenue and FPM grants. The common practice of removal of municipalities with missing values would impair the applicability of spatial econometric methods. Hence, in order to circumvent such restraint, data imputation was performed instead.[2] Table 1.1 summarizes the descriptive statistics of the Brazilian municipal variables for the period 2013–2017. Noteworthy is the great dispersion of the fiscal measures and *per capita* GDP across the considered municipalities, a result of the extensive regional heterogeneity which characterizes the Brazilian federation.

Arising from such regional heterogeneity, it is pivotal to investigate whether *per capita* personnel expenditure presents any pattern of spatial interdependence. To this end, univariate

[1]Even though there were 5,570 Brazilian municipalities in 2017, this paper grouped the ten new municipalities that were legally emancipated after 2005 with their respective municipalities of origin. Such aggregation was performed due to the lack of more recent polygonal shapefiles for Brazilian municipalities. In addition, two island municipalities (Ilhabela/SP and Fernando de Noronha/PE) were removed from the data set. Therefore, the final data set covers 5,558 Brazilian municipalities.

[2]For technical details on the data imputation procedure, see Appendix A.

Table 1.1: Descriptive statistics

Variable	Mean	Std. dev.	Min.	Max.
Per capita personnel expenditure (R$)	1,572.73	686.29	29.33	9,294.86
Per capita GDP (R$)	21,919.34	24,370.31	388.64	1,060,548.00
Per capita FPM grants (R$)	1,185.29	859.12	21.32	10,229.18
Per capita tax revenue (R$)	231.32	311.83	12.79	9,157.58
Share of population under 14 years old (%)	22.80	4.50	6.52	48.40
Share of population over 65 years old (%)	9.73	2.98	1.06	26.14

Notes: The terms "FPM grants" and "Std. dev." refer to the Municipal Participation Fund grants and the standard deviation, respectively. *Sources:* FINBRA/STN and IBGE. Compiled by the author.

Moran's I statistics are computed as to assess the degree of global spatial autocorrelation among the Brazilian municipalities.[3] Three spatial weighting criteria were used in order to ensure robustness: Queen, k-nearest neighbors and inverse distance. The Queen criterion defines neighbors as spatial units which share a common vertex or edge.[4] On the other hand, the k-nearest neighbors criterion establishes the arc distance between the centroids of spatial units as a neighboring measure. By explicitly limiting the number of neighbors to k, the neighborhood of a spatial unit i is then defined as those k spatial units whose centroids are the nearest ones to that of i. In this study, k is set to be either 4, 6 or 8.[5] Finally, the inverse distance matrix, with weights equal to $({}^{1}/_{d_{ij}})$, assumes a distance-decay weighting scheme for the spatial units. Note that d_{ij} is the arc distance between spatial units i and j. Unlike the former two matrices, this specification allows taking into account global effects given that all units receive non-zero weights.[6] The pseudo p-value for the Moran's I statistics is derived *via* numerical simulation, with 9,999 random permutations. Here, inference consists of testing the null hypothesis of spatial randomness.

From the results on Table 1.2, the univariate Moran's I statistics for *per capita* personnel expenditure provide evidence of a generalized positive global spatial autocorrelation (at the 1% level of statistical significance) throughout the whole period, regardless of the adopted spatial weights matrix. This positive spatial interdependence implies that municipalities in Brazil tend to cluster, so that spatial areas with high (low) *per capita* personnel expenditure are likely to be surrounded by other areas with high (low) *per capita* personnel expenditure. Despite fluctuating during the period, the pattern of global spatial autocorrelation remained rather stable.

By rejecting the null hypothesis of spatial randomness, traditional panel data models are then unsuitable econometric methods to estimate the potential space-dependent relationship

[3]The univariate Moran's I statistic was initially proposed by Moran (1948) and is defined as the cross-product between a mean-centered variable and its spatial lag, that is, $I_U = ({}^{n}/_{s_0})\left({}^{\sum_i \sum_j w_{ij}(x_i-\mu)(x_j-\mu)}/_{\sum_i (x_i-\mu)^2}\right)$, where n is the number of observations; x is the variable of interest; μ is the mean of x; w_{ij} is the ij-element of the spatial weights matrix with zeroes on the diagonal (i.e., $w_{ii} = 0$); and s_0 is the sum of all the weights (i.e., $s_0 = \sum_i \sum_j w_{ij}$). Note that $-1 \leq I_U \leq 1$, with $I_U = 1$ corresponding to perfect positive global spatial correlation and $I_U = -1$ suggesting perfect negative global spatial autocorrelation.

[4]The Queen contiguity weights are constructed based on a first order contiguity assumption, that is, only the spatial units that directly share a common vertex or edge with a given spatial unit are considered as neighbors. For instance, a second order contiguity assumption would imply that two spatial units are neighbors if they directly share a vertex or an edge or if they have a common neighbor with which they directly share a vertex or an edge.

[5]Summary statistics for the Queen weights matrix showed that, on average, a Brazilian municipality is surrounded by 6 neighbors, with a standard deviation value of two. Therefore, the k is set to represent the latter mean and one standard deviation to either of its sides.

[6]Further technical details on distance-based spatial weights can be found on Le Gallo and Ertur (2003), Haining (2003) and Anselin and Rey (2014).

Table 1.2: Global spatial autocorrelation – univariate Moran's I statistic

Variable	Spatial Weights Matrix	2013	2014	2015	2016	2017
Per Capita Personnel Expenditure	W_Q	0.287	0.283	0.305	0.306	0.302
	W_4	0.315	0.311	0.334	0.332	0.331
	W_6	0.312	0.308	0.329	0.324	0.322
	W_8	0.302	0.301	0.318	0.317	0.314
	W_I	0.191	0.194	0.207	0.217	0.229

Notes: The terms "W_Q", "W_4", "W_6", "W_8" and "W_I" refer to the Queen, the 4 nearest neighbors, the 6 nearest neighbors, the 8 nearest neighbors and the inverse squared distance weights matrices, respectively. A pseudo p-value of 0.0001 was obtained for all univariate Moran's I statistics, therefore rejecting the null hypothesis of spatial randomness. Compiled by the author.

between Brazilian local expenditure and its determinants. In fact, as discussed in Anselin (1988) and Anselin and Bera (1998), even though standard panel data analysis may be capable of controlling for time-wise autoregression, cross-sectional heteroscedasticity, simultaneity and endogeneity, neglecting the structure of spatial dependence would generate bias and inconsistent estimates. In order to circumvent these issues, spatial panel data models are therefore adopted as the econometric framework in this study. The details on such models are presented in the subsequent section.

1.3 SPATIAL PANEL DATA MODELS

Panel data (also longitudinal data) is a data structure in which the behavior of individual units are observed over multiple time periods. Compared to pure cross-sectional or time series models, the use of panel data provides more information and more variability (from combining variation both between and within regions), less collinearity among the variables, and higher estimate efficiency due to more degrees of freedom (Hsiao, 2003; Baltagi, 2005). Yet, despite controlling for time-invariant unobservable individual (i.e., unit-specific) effects, the standard specifications of panel data models are not capable of accounting for another form of unobserved heterogeneity: the one arising from the spatial interdependence among cross-sectional units. Even though Spatial Econometrics has been widely explored in single equation cross-sectional settings, empirical research has recently focused its attention on integrating spatial effects into traditional panel data regression models (Millo and Piras, 2012; Elhorst, 2014a,b).

In the absence of spatial interdependence among cross-sectional units, standard (non-spatial) individual-specific effects models for panel data would emerge as a natural and straightforward class of econometric methods to deal with the unobserved heterogeneity arising from spatial independent effects. Formally, the model is expressed as

$$\boldsymbol{y}_{nt} = \boldsymbol{X}_{nt}\beta + \boldsymbol{c}_n + \boldsymbol{v}_{nt} \tag{1.1}$$

where $t = 1, 2, \ldots, T$; $\boldsymbol{y}_{nt} = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ is an $(n \times 1)$ vector of observations on the dependent variable for time period t; $\boldsymbol{X}_{nt}$ is an $(n \times k)$ matrix of observations on the nonstochastic exogenous regressors for time period t; $\boldsymbol{c}_n$ is an $(n \times 1)$ vector of individual effects (or heterogeneity); and $\boldsymbol{v}_{nt} = (v_{1t}, v_{2t}, \ldots, v_{nt})'$ is an $(n \times 1)$ vector of disturbances. Note that v_{it} is $i.i.d.$ across i and t with zero mean and variance σ_0^2. In this setting, the $\boldsymbol{c}_n$ would thus capture the referred spatial specific effects. Defining whether Equation (1.1) corresponds to a fixed or random effects model depends upon the assumption of $\boldsymbol{c}_n$ being or not correlated with the observed regressors $\boldsymbol{X}_{nt}$ (Cameron and Trivedi, 2005).

However, as in standard cross-sectional models, non-spatial panel data analysis assumes cross-sectional independence, that is, individuals are assumed to be independent from one another. Violation of such hypothesis due to spatial interactions would then induce bias and generate inconsistent estimates (Anselin, 1988; Anselin and Bera, 1998). Spatial autocorrelation is taken into account in panel data models by extending them to consider spatially autocorrelated errors and/or spatially lagged variables.

Following Lee and Yu (2010a), a SAR panel model with individual-level effects and SAR disturbances (often called spatial autoregressive with spatially autocorrelated errors model – SARAR) is given by

$$\begin{aligned} \boldsymbol{y}_{nt} &= \lambda \boldsymbol{W} \boldsymbol{y}_{nt} + \boldsymbol{X}_{nt}\beta + \boldsymbol{c}_n + \boldsymbol{u}_{nt} \\ \boldsymbol{u}_{nt} &= \rho \boldsymbol{M} \boldsymbol{u}_{nt} + \boldsymbol{v}_{nt} \end{aligned} \tag{1.2}$$

with $\boldsymbol{u}_{nt}$ being an $(n \times 1)$ vector of spatially lagged disturbances; and $\boldsymbol{W}$ being an $(n \times n)$ nonstochastic spatial weights matrix in which spatial dependence on $\boldsymbol{y}_{it}$ among cross-sectional units is defined. Similarly, $\boldsymbol{M}$ is an $(n \times n)$ spatial weighting matrix for the disturbances. Note that, in practice, $\boldsymbol{W}$ and $\boldsymbol{M}$ need not necessarily be different from each other. All other terms are characterized as in Equation (1.1).

In this study, the individual effect $\boldsymbol{c}_n$ is treated as fixed.[7] We also set $\boldsymbol{W}$ to be time invariant. Estimation follows the quasi-maximum likelihood estimator (QMLE) derived by Lee and Yu (2010a).[8] In order to remove the fixed effects $\boldsymbol{c}_n$, an orthogonal transformation is performed. Let $\left[\boldsymbol{F}_{T,T-1}, ({}^{1}/\sqrt{T})\, \boldsymbol{l}_T\right]$ be the orthonormal eigenvector matrix of $\left(\boldsymbol{I}_T - \frac{1}{T}\boldsymbol{l}_T\boldsymbol{l}_T'\right)$, where $\boldsymbol{I}_T$ is a $(T \times T)$ identity matrix and $\boldsymbol{l}_T$ is a $(T \times 1)$ vector of ones, and $\boldsymbol{F}_{T,T-1}$ be a $(T \times (T-1))$ submatrix corresponding to the eigenvalues of one. Consequently, for any $(n \times T)$ matrix $[z_{n1}, z_{n2}, \ldots, z_{nT}]$, the transformed $(n \times (T-1))$ matrix is expressed as $\left[\tilde{z}_{n1}, \tilde{z}_{n2}, \ldots, \tilde{z}_{n,T-1}\right] = [z_{n1}, z_{n2}, \ldots, z_{nT}]\, \boldsymbol{F}_{T,T-1}$. Therefore, the transformed version of the model described in Equation (1.2) reads as

$$\begin{aligned} \tilde{\boldsymbol{y}}_{nt} &= \lambda \boldsymbol{W} \tilde{\boldsymbol{y}}_{nt} + \tilde{\boldsymbol{X}}_{nt}\beta + \tilde{\boldsymbol{u}}_{nt} \\ \tilde{\boldsymbol{u}}_{nt} &= \rho \boldsymbol{M} \tilde{\boldsymbol{u}}_{nt} + \tilde{\boldsymbol{v}}_{nt} \end{aligned} \tag{1.3}$$

where $t = 1, 2, \ldots, T-1$. Given that $(\tilde{\boldsymbol{v}}_{n1}', \ldots, \tilde{\boldsymbol{v}}_{n,T-1}')' = (\boldsymbol{F}_{T,T-1}' \otimes \boldsymbol{I}_n)(\tilde{\boldsymbol{v}}_{n1}', \ldots, \tilde{\boldsymbol{v}}_{nT}')'$ and v_{it} are $i.i.d.$, Lee and Yu (2010a) emphasize that $\tilde{v}_{it}$ are uncorrelated for all i and t, with $\tilde{v}_{it}$ being the i-th element of $\tilde{\boldsymbol{v}}_{it}$. This lack of transformed disturbance correlation stems from the fact that $\mathbb{E}\left\{(\tilde{\boldsymbol{v}}_{n1}', \ldots, \tilde{\boldsymbol{v}}_{n,T-1}')'(\tilde{\boldsymbol{v}}_{n1}', \ldots, \tilde{\boldsymbol{v}}_{n,T-1}')\right\} = \sigma_0^2(\boldsymbol{F}_{T,T-1}' \otimes \boldsymbol{I}_n)(\boldsymbol{F}_{T,T-1} \otimes \boldsymbol{I}_n) = \sigma_0^2\boldsymbol{I}_{n,T-1}$, where $\mathbb{E}$ is the expected value operator and $\otimes$ is the Kronecker product.

Accordingly, the log-likelihood for the transformed model in Equation (1.3) follows as

[7]Based on the procedure developed by Mundlak (1978), the fixed effects specification was found to better fit the data. Technical details on such approach are later discussed in this section. For the obtained results, see Section 1.4.

[8]Conversely, estimation of spatial panel data models with random effects is based on a maximum likelihood estimator (MLE). Technical details on model specification and the estimation procedure can be found on Lee and Yu (2010b).

$$\ln L_{nT}(\theta) = -\frac{n(T-1)}{2}\ln(2\pi\sigma^2) + \\ + (T-1)\left[\ln|\boldsymbol{S}_n(\lambda)| + \ln|\boldsymbol{R}_n(\rho)|\right] - \frac{1}{2\sigma^2}\sum_{t=1}^{T-1}\tilde{\boldsymbol{v}}'_{nt}(\psi)\tilde{\boldsymbol{v}}_{nt}(\psi) \tag{1.4}$$

with $\tilde{\boldsymbol{v}}_{nt}(\psi) = \boldsymbol{R}_n(\rho)[\boldsymbol{S}_n(\lambda)\tilde{\boldsymbol{y}}_{nt} - \tilde{\boldsymbol{X}}_{nt}\beta]$; $\boldsymbol{S}_n(\lambda) = \boldsymbol{I}_n - \lambda\boldsymbol{W}$; $\boldsymbol{R}_n(\rho) = \boldsymbol{I}_n - \rho\boldsymbol{M}$; $\theta = (\beta', \lambda, \rho, \sigma^2)'$; and $\psi = (\beta', \lambda, \rho)'$. The QMLE is the extremum estimator derived from the maximization of Equation (1.4). For technical details on the first and second derivatives of the latter log-likelihood function, refer to Lee and Yu (2010a).

By considering both spatially autocorrelated errors and a spatially lagged endogenous variable, the SARAR model described by Equation (1.2) represents one of the most comprehensive spatial specification for panel data analysis. Still, one might be interested in analyzing nested reduced models. By imposing $\rho = 0$ and $\lambda \neq 0$, the SARAR model is simplified to the spatial autoregressive (SAR) model. If $\rho \neq 0$ and $\lambda = 0$, a spatial error model (SEM) is obtained. In the limiting case of $\rho = 0$, $\beta = 0$ and $\lambda \neq 0$, the SARAR model would then be reduced to a pure SAR model, that is, $\boldsymbol{y}_{nt} = \lambda\boldsymbol{W}\boldsymbol{y}_{nt} + \boldsymbol{u}_{nt}$.

Selecting the appropriate spatial model is an essential but still controversial part of Spatial Econometrics. Even though a plethora of hypothesis testing procedures have been suggested, spatial econometricians have yet to reach a consensus on the appropriate strategy. The debate mainly revolves around whether pursuing a specific-to-general or a general-to-specific approach (Florax et al., 2003; Mur and Angulo, 2009). In this study, we follow a three-step mixed model selection strategy similar to the one outlined in Elhorst (2014b). In the first (specific-to-general) step, non-spatial panel data models with or without spatial fixed effects are estimated so that poolability tests and Hausman specification tests are performed. Once the poolability hypothesis is rejected and the form of individual-level effect is determined, SAR, SEM and SARAR models are estimated and linear Wald tests are performed as to evaluate the potential presence of spatially autocorrelated error terms and/or a spatially lagged dependent variable (Elhorst, 2010, 2014a,b). These Wald tests follow a χ^2 distribution with q degrees of freedom, where q is the number of restrictions to be tested. In the occurrence of a non-spatial model being rejected in favor of any spatial counterpart, we proceed to the next step.

The second (general-to-specific) step consists of considering the spatial Durbin model (SDM) and testing whether it can simplified to the SAR model and/or to SEM (Burridge, 1981). Given that the SDM nests both these models, its general specification can be tested for the exclusion of variables *via* likelihood ratio (LR) and Wald tests (LeSage and Pace, 2009; Elhorst, 2010). More specifically, let the SDM with individual-level effects be specified as

$$\boldsymbol{y}_{nt} = \lambda\boldsymbol{W}\boldsymbol{y}_{nt} + \boldsymbol{X}_{nt}\beta + \boldsymbol{W}\boldsymbol{X}_{nt}\delta + \boldsymbol{c}_n + \boldsymbol{v}_{nt} \tag{1.5}$$

where $\boldsymbol{W}\boldsymbol{X}_{nt}$ is an $(n \times k)$ matrix of spatially lagged exogenous covariates.[9] The estimated parameters of the model in Equation (1.5) are then subjected to (linear and nonlinear) Wald tests as well as LR tests in order to evaluate the hypotheses $\mathrm{H}_0 : \delta = 0$ and $\mathrm{H}_0 : \delta + \lambda\beta = 0$. These LR tests follow a χ^2 distribution with k degrees of freedom, where k is the rank of the

[9]In this study, all exogenous covariates $\boldsymbol{X}_{nt}$ enter Equation (1.5) as their spatially lagged counterparts. However, one could define a subset $\boldsymbol{Z}_{nt} \subset \boldsymbol{X}_{nt}$ as the exogenous covariates to be spatially lagged in the model, i.e., $\boldsymbol{y}_{nt} = \lambda\boldsymbol{W}\boldsymbol{y}_{nt} + \boldsymbol{X}_{nt}\beta + \boldsymbol{W}\boldsymbol{Z}_{nt}\delta + \boldsymbol{c}_n + \boldsymbol{v}_{nt}$.

(co)variance matrix. Rejecting both hypotheses would indicate that the SDM is the model that best fits the data. On the other hand, if $H_0 : \delta = 0$ cannot be rejected, then the appropriate spatial specification should be the SAR model, provided that $H_0 : \delta + \rho\beta = 0$ was rejected. Failing to reject $H_0 : \delta + \lambda\beta = 0$ would statistically imply that the SEM is favored by the data, provided that $H_0 : \delta = 0$ was rejected. If one of these conditions are not satisfied, then the spatial Durbin model should be adopted as it generalizes both the spatial autoregressive and the spatial error model (Elhorst, 2014b). Alternatively, one might also be interested in comparing the SDM and the SARAR model. Since these models are nonnested, Belotti et al. (2017) suggests adopting the modified Akaike's information criterion (AIC) developed by Burnham and Anderson (2004) as a measure to assess which model best describes the data.

The third (and final) step consists in evaluating whether the individual-specific effects should be modeled as random effects (RE) or fixed effects (FE). To this end, this study employs the econometric procedure proposed by Mundlak (1978), adapted to the spatial case.[10] More precisely, the spatial panel data model is augmented to also include the panel-level averages of the time-varying covariates in their direct and spatially lagged forms. Then, their joint significance is tested using a Wald test. Rejecting the null hypothesis of the coefficients being jointly zero implies the existence of correlation between the time-invariant unobservables and the regressors, which satisfies the fixed effects assumptions. Conversely, if the null hypothesis of the coefficients being zero cannot be rejected, the time-invariant unobservables and the regressors display no statistically significant correlation, satisfying the random effects assumptions.

Once the appropriate spatial panel data model is chosen, drawing economic reasoning from its estimated parameters is not as straightforward as it is with its non-spatial counterpart (Kim et al., 2003; Kelejian et al., 2006; Anselin and Le Gallo, 2006). Traditionally, regression coefficients represent the marginal and separate effects of regressors on the dependent variable. Yet, by considering the intricate spatial dependence structure among cross-sectional units, Spatial Econometrics depart from the sole use of point estimates in order to also account for spillover effects. According to LeSage and Pace (2009), in the presence of endogenous and/or exogenous spatial interactions, shocks in a cross-sectional unit associated with any given independent variable would affect not only the cross-sectional unit itself (direct effect) but potentially also all the other neighboring units indirectly (spillover effect).[11] Neglecting such feedback mechanism would likely lead to erroneous economic – and even econometric – conclusions.[12] Therefore, estimation of direct, indirect (or spillover) and total marginal effects follow the partial derivative procedure outlined in LeSage and Pace (2009).

1.4 EMPIRICAL RESULTS

In order to assess whether unobserved heterogeneity should be accounted for, poolability tests were performed considering both fixed and random effects. The results for the non-spatial panel data models are presented in Table 1.3. Regressions (1), (2) and (3) are those for the pooled OLS (no fixed nor random effects) and one-way (individual) fixed and random effects, respectively.

[10] Even though Belotti et al. (2017) proposes a robust Hausman specification test for spatial panel data models, obtaining such statistic for large data sets (as it is the case of this study) is rather computationally infeasible. Yet, both the robust Hausman test and the Mundlak (1978) procedure are asymptotically equivalent.

[11] As the (panel) SEM model considers neither the endogenous ($\boldsymbol{W}\boldsymbol{y}_{nt}$) nor the exogenous ($\boldsymbol{W}\boldsymbol{X}_{nt}$) spatial interactions, only the direct effect can be observed.

[12] In an econometric illustration relating regional total factor productivity and regional knowledge stock for the 48 contiguous US states, LeSage and Pace (2009, p. 68-75) estimated a spatial Durbin model and showed that the coefficient for the spatially lagged knowledge stock was found to be negative and insignificant even though its spatial spillover effect was positive and significant.

Here, the terms *spatial* fixed effects and *spatial* random effects refer to individual cross-sectional effects, in which no spatial interdependence is considered. For the fixed effects model, the poolability test relies on an F-test regarding the statistical significance of the estimated spatial effects. More precisely, the latter test evaluates H_0: *pooled OLS model is favored by the data* against H_1: *spatial fixed effects model is favored by the data*. The results ($F = 13.42$, with 5,557 numerator and 22,227 denominator degrees of freedom [*df*], $p < 0.01$) indicate that the hypothesis of poolability (H_0) must be rejected. However, testing poolability against a spatial random effects model is based on the LM test developed by Breusch and Pagan (1980). Similarly to the fixed effects case, null hypothesis H_0: *pooled OLS model is favored by the data* is tested against its alternative H_1: *spatial random effects model is favored by the data*. Again, poolability is rejected ($LM_{BP} = 25,367.05$, 1 *df*, $p < 0.01$). Overall, both tests underscore the importance of accounting for unobserved heterogeneity across Brazilian municipalities.

Table 1.3: Estimation results using panel data models without spatial interaction effects

Determinants	(1) Pooled OLS	(2) Spatial fixed effects	(3) Spatial random effects
ln(*Per Capita* GDP)	0.1738*	0.0991*	0.1528*
	(50.72)	(15.15)	(34.67)
ln(*Per Capita* FPM Grants)	0.3925*	0.2163*	0.3123*
	(153.57)	(26.06)	(73.70)
ln(*Per Capita* Tax Revenue)	0.1214*	0.0779*	0.0865*
	(50.71)	(32.98)	(39.68)
ln(Share of Population under 14 years old)	0.2767*	0.3397*	0.0438***
	(19.36)	(4.38)	(1.77)
ln(Share of Population over 65 years old)	0.0440*	0.7646*	0.1181*
	(5.81)	(16.60)	(8.62)
Intercept	1.3331*		
	(17.58)		
σ^2	0.2363	0.1266	0.1266
R^2	0.6041	0.3294	0.5789
Log-Likelihood	654.81	21,096.27	13,039.67
Akaike Information Criterion (AIC)	-1,297.62	-42,180.53	-26,063.35
Bayesian Information Criterion (BIC)	-1,248.23	-42,131.14	-25,997.49
Hausman test			1,732.62*

Notes: t-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Inference for the Hausman test was based on a chi-squared (χ^2) distribution with 4 degrees of freedom. Compiled by the author.

Furthermore, a Hausman specification test was also conducted in order to determine whether spatial random effects provided a better fit to the data than spatial fixed effects. The results ($H_{spec} = 1,732.62$, 5 *df*, $p < 0.01$) suggest that spatial random effects must be rejected. Indeed, both the Akaike and the Bayesian information criteria in Table 1.3 favor the spatial fixed effects specification. Accordingly, subsequent analyses will rest on the assumption of spatial fixed effects.

As discussed in Section 1.3, neglecting spatial interdependence would lead to model misspecification and, therefore, to bias and inconsistent estimates. The Moran's I statistics in Table 1.2 provided a preliminary evidence for the presence of spatial autocorrelation within the data. Yet, we still need to formally test for such form of interaction effects. Following the specific-to-general approach, SAR, SEM and SARAR models with spatial fixed effects were estimated to statistically test the (joint) significance of the spatially lagged dependent variable (i.e., λ) and/or the spatially autocorrelated error term (i.e., ρ). The results are reported in Table 1.4.

Table 1.4: Estimation results using panel data models with spatial fixed effects and spatial interaction effects

Determinants	(1) SAR	(2) SEM	(3) SARAR	(4) SDM
Main structure				
ln(*Per Capita* GDP)	0.0840*	0.0856*	0.0846*	0.0850*
	(6.92)	(6.73)	(6.67)	(6.61)
ln(*Per Capita* FPM Grants)	0.21474*	0.2417*	0.2420*	0.2420*
	(6.11)	(6.10)	(6.10)	(6.11)
ln(*Per Capita* Tax Revenue)	0.0720*	0.0714*	0.0709*	0.0710*
	(12.85)	(12.66)	(12.61)	(12.54)
ln(Share of Population under 14 years old)	0.1390***	-0.0098	-0.0188	-0.2402
	(1.65)	(-0.07)	(-0.13)	(-1.31)
ln(Share of Population over 65 years old)	0.2727*	0.7515*	0.6330*	0.6520*
	(5.03)	(7.75)	(6.02)	(5.85)
Spatial structure				
λ	1.1015*		0.7610*	0.8639*
	(26.71)		(3.10)	(51.82)
ρ		1.2497*	1.1969*	
		(129.54)	(41.28)	
W × ln(*Per Capita* GDP)				-0.0694
				(-0.66)
W × ln(*Per Capita* FPM Grants)				-0.3070*
				(-4.68)
W × ln(*Per Capita* Tax Revenue)				-0.0256
				(-0.43)
W × ln(Share of Population under 14 years old)				0.7749***
				(1.83)
W × ln(Share of Population over 65 years old)				-0.5433**
				(-2.33)
σ^2	0.0157	0.0156	0.0155	0.0157
R^2	0.0705	0.3091	0.1026	0.0963
Log-Likelihood	14,635.54	14,700.96	15,053.00	15,101.37
Akaike Information Criterion (AIC)	-29,257.07	-29,387.92	-30,090.00	-30,178.75
Bayesian Information Criterion (BIC)	-29,201.01	-29,331.86	-30,025.93	-30,082.64

Notes: t-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Coefficients are bias corrected following Lee and Yu (2010a). Compiled by the author.

Overall, t-tests show that both spatial lag and spatial error effects are individually significant at the 1% level. Also, based on the SARAR model, the Wald test for joint significance of ρ and λ ($W_{LT} = 1,732.33$, 2 *df*, $p < 0.01$) corroborates the latter results by rejecting the null hypothesis of $H_0 : \rho = \lambda = 0$. Thus, a model specification with both spatial fixed effects and spatial interaction effects may be favored over a non-spatial panel data model with only spatial fixed effects.

To further evaluate the appropriate spatial model specification, we proceed to the general-to-specific model selection step. According to Elhorst (2014b), this step consists of performing Wald and LR tests on a spatial Durbin panel model. Formally, we test both null hypotheses $\mathrm{H}_0 : \delta = 0$ and $\mathrm{H}_0 : \delta + \lambda\beta = 0$. Estimation results for the SDM model with spatial fixed effects are presented in Table 1.4. The linear Wald test for the joint significance of the spatially lagged covariates ($W_{LT} = 95.30$, 5 *df*, $p < 0.01$) rejects the null hypothesis of $\mathrm{H}_0 : \delta = 0$. Consequently, there is no statistical evidence that the SDM model can be simplified to the SAR model. A similar result was found when comparing the SDM and the SEM models. Indeed, based on a nonlinear Wald test, the null hypothesis of $\mathrm{H}_0 : \delta + \lambda\beta = 0$ was rejected at the 1% level ($W_{NLT} = 15.74$, 5 *df*, $p < 0.01$), suggesting that the SDM is the appropriate model specification in contrast to the SEM. As an extension, we also compare the SDM and the SARAR models. However, given that they are nonnested, information criteria is used for such comparison. Both AIC and BIC imply that the SDM overperforms the SARAR model.

Even though the Hausman test indicated the spatial fixed effects as the appropriate specification for the non-spatial panel data models (Table 1.3), we must assess the suitability of such form of individual-level effect in a spatial panel data model as well. As discussed in Section 1.3, this third (and final) step regarding model selection is based on the econometric procedure outlined in Mundlak (1978), adapted to the spatial case. Table B.1 in Appendix B reports the SDM model with spatial random effects and panel-level averages of the time-varying covariates. The linear Wald test ($W_{LT} = 2,329.00$, 10 *df*, $p < 0.01$) rejects the null hypothesis of the coefficients associated with the panel-level means – in their direct and spatially lagged forms – being jointly zero. This result indicates that time-invariant unobservables and the regressors are correlated, satisfying the fixed effects assumptions. Therefore, we provide further statistical evidence of the SDM model with spatial fixed effects being the appropriate specification given the data.

However, relying on point estimates from spatial models might induce practitioners to misleading conclusions. In order to account for the spatial feedback mechanism inherent in panel SDM models, cumulative impacts are computed according to the partial derivative procedure outlined in LeSage and Pace (2009). These results are reported in Table 1.5. Despite the point estimates of the SDM main (non-spatial) structure (Table 1.4) and the direct effects being similar in magnitude, comparison between the spatially lagged estimates and the indirect effects show that the former overestimates the influence of neighboring areas. These differences are due to the estimated coefficient of the spatially lagged dependent variable (i.e., λ) as well as the estimated coefficients of the spatially lagged time-varying covariates.

We observe positive direct and indirect effects of *per capita* GDP on the expenses in personnel (Table 1.5). In this sense, increases in either the location i or its neighboring ones would lead to increases in personnel expenditure in location i. This result suggests that demand pressures within Brazilian municipalities positively spillover to neighboring areas, increasing their amount of publicly provided goods and, therefore, their expenses in personnel. Such phenomenon is consistent with the free rider behavior, in which citizens in one location would make use of public services in other locations as to avoid bearing their costs in the form of higher taxes.

Higher FPM grants in one location is also associated with higher personnel expenditure. Yet, the indirect effect in table 1.5 shows personnel expenditure in location i decreases as FPM grants within neighboring areas increase. Therefore, there is statistical evidence of strategic behavior regarding expenses in personnel given changes in the amount of resources received from the central government. In fact, the obtained results suggest that, as FPM grants increase in location i, the provision of public goods within the location also increases, which triggers

Table 1.5: Cumulative impacts from the SDM model with spatial fixed effects

Determinants	Effect		
	Direct	Indirect	Total
ln(*Per Capita* GDP)	0.0851*	0.3107**	0.4058**
ln(*Per Capita* FPM Grants)	0.2420*	-0.1519*	0.0900*
ln(*Per Capita* Tax Revenue)	0.0712*	0.6802**	0.7514**
ln(Share of Population under 14 years old)	-0.2390	4.7241***	4.4851***
ln(Share of Population over 65 years old)	0.6526*	2.3501***	3.0027**

Notes: The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. By definition, the total effect corresponds to the sum of both direct and indirect effects. Since both endogenous and exogenous variables are considered in their natural logarithmic forms, the obtained effects may be interpreted as direct, indirect and total elasticities. The estimated variance of the impacts is calculated according to the Delta method. Estimation results based on an inverse distance spatial weights matrix. Compiled by the author.

neighboring local governments to scale down their own expenses as citizens can potentially benefit from the services provided in location i.

Tax revenue is also positively correlated with personnel expenditure, both directly and indirectly (Table 1.5). Yet, one must carefully evaluate these results. First, the relatively low elasticity of personnel expenditure with respect to tax revenue in location i is intrinsically related to the restricted local tax base within the Brazilian municipalities. Moreover, the apparent high indirect effect is due to it being measured as the cumulative result of concurrent increases in tax revenue in *all* neighboring areas of location i. Such positive indirect effect further underscores the occurrence of free rider behavior among the Brazilian municipalities.

The obtained estimates also provides evidence in favor of the flypaper effect in the Brazilian municipalities. More specifically, the the estimated direct elasticity of personnel expenditure with respect to *per capita* GDP is lower than the one with respect to *per capita* FPM grants (Table 1.5). In fact, an one percent increase in *per capita* FPM grants would induce an increase in *per capita* personnel expenditure 0.16 percentage points higher, on average, than the same increase in *per capita* GDP. From the theoretical perspective of the median voter framework, such effect is an empirical anomaly given that, in the presence of normal goods, increases in disposable income and the citizen's share of fiscal transfers should lead to the same increase in public spending. In practice, such distortionary effect might impose challenges to fiscal equalization since it can potentially lead to disincentives in increasing tax collection efficiency. Overall, these findings are in line with the previous Brazilian literature on the matter (see e.g. Cossio and Carvalho (2001), Nascimento (2010), Sakurai (2013), Costa and Castelar (2015), Ribeiro (2015), Araújo and Siqueira (2016), Nojosa and Linhares (2018), Martins (2020), among others).

1.5 CONCLUSION

This chapter represents an attempt at understanding fiscal interactions and potential spillover effects among the Brazilian municipalities. To this end, we estimate spatial panel data models in order to take into account both time and specific effects as well as the inherent spatial data structure.

Our results show that geographical location is pivotal when dealing with local public finances in Brazil. Comparison of different classes of models revealed that the spatial Durbin model (SDM) is favored by the data. Based on its parameter estimates, direct and indirect effects are provided. First, positive direct and indirect effects of *per capita* income on *per capita* personnel expenditure are observed. The presence of positive spillover effects of income on a given location from its neighbors suggests the occurrence of free rider behavior among the Brazilian local governments. Second, despite the positive direct effect of FPM grants on local expenses in personnel, there is evidence of a negative indirect effect. Such phenomenon indicates that local governments behave strategically regarding their expenses. In fact, as FPM grants increase in neighboring areas, the local government tends to scale down their provision of public goods as a response. Third, the positive direct and indirect elasticities of personnel expenditure with respect to tax revenue further underscore the free rider behavior among the residents within the Brazilian municipalities. Finally, as for the flypaper effect hypothesis, there is statistical evidence of its presence across Brazil.

Overall, this chapter provides further evidence on horizontal fiscal interactions among the Brazilian municipalities. Since subnational governments often behave strategically in terms of their spending decisions, analyzing such behavior is essential in order to effectively design fiscal equalization policies.

2 LOCAL PUBLIC SPENDING AND FISCAL HETEROGENEITY IN BRAZIL: ADDRESSING SPATIAL DEPENDENCE IN THE PRESENCE OF SPATIAL NONSTATIONARITY

2.1 INTRODUCTION

Brazil is one of the most decentralized governments in the world (Baiocchi, 2006). Under the aegis of the 1988 Constitution, the three-tiered federalism adopted in Brazil has endowed each federative entity with political, legislative, administrative, and financial autonomy. Particularly, article 30 of the Federal Constitution establishes the municipal sovereignty regarding not only the creation and collection of taxes, but also revenue allocation within their jurisdiction (Brazil, 2019). Yet, given inter-regional socioeconomic imbalances and restricted local tax bases across the country, Brazilian local governments are still highly dependent on transfers from states and the Union as one of their primary sources of budgetary revenue.

From the seminal study of Tiebout (1956) on local governance and the free rider problem in the provision of public goods, the fiscal federalism literature has provided both normative and positive analyses on the intertwined relations among subnational governments [for a recent literature survey, refer to Vo (2010)]. Market-preserving federalism advocates that fiscal dependency is a byproduct of intergovernmental transfers as they induce soft-budget constraints (Weingast, 2009). Moreover, in the context of federative systems with low quality in the distribution of their competencies, spatial fiscal interactions might emerge as the result of local free-riding behavior, in which spillover effects lead to a higher demand for publicly provided goods in neighboring jurisdictions.

Empirical research on spatial fiscal interactions in local public spending decisions has substantially increased over the last decades (Case et al., 1993; Kelejian and Robinson, 1993; Solé-Ollé, 2006; Redoano, 2007; Frère et al., 2014; López et al., 2016, among others). However, the conventional spatial regression models applied by these papers intrinsically assume spatially-invariant intra- and inter-jurisdictional fiscal relationships. By disregarding the potential presence of spatial nonstationarity due to spatial heterogeneity, the obtained parameter estimates might be biased and not reflect the true data generating process. Hence, this chapter explores the importance of considering spatial nonstationarity in the analysis of horizontal fiscal interactions among local governments, with a study of the Brazilian case. Even though some studies tackled the issue of spatial variability in the context of local public finances in Brazil (Cossio and Carvalho, 2001; Nojosa and Linhares, 2018), to the best of our knowledge, this is the first study to consider both spatial dependence and spatial nonstationarity.

The obtained results underscore the importance of considering Brazil's inter-regional imbalances when studying its fiscal relations. Particularly, there is evidence of local personnel expenditure *per capita* being positively correlated with income *per capita*, FPM grants *per capita* and tax revenue *per capita*. Yet, local parameter estimates display different spatial patterns across Brazil. First, local governments with low fiscal dependency ratios tend to present lower correlations between intergovernmental grants and local wage bills. Second, jurisdictions with higher economic dynamism present higher levels of personnel expenditure. As for horizontal fiscal interactions, we observe both negative and positive statistically significant parameters across space, corroborating the notion of Brazilian local governments behaving strategically in their spending decisions. The flypaper effect is also detected in most local governments, with its intensity being in jurisdictions with higher fiscal dependency ratios and/or higher population density.

The rest of this chapter is organized as follow. Section 2 briefly presents the heterogeneous nature of local fiscal finances in Brazil. The GWR-SAR model is outlined in section 3 and the subsequent empirical results are discussed in section 4. Finally, section 5 concludes.

2.2 HORIZONTAL FISCAL HETEROGENEITY IN BRAZIL

Brazil is a continental country comprising 26 states, a Federal District (Brasilia), and 5,570 municipalities. Despite being the world's ninth largest economy in terms of GDP (IMF, 2019), Brazilian income distribution is still considered one of the most unequal on the planet – a Gini coefficient of 0.539 in 2018 (World Bank, 2019). Such level of inequality is even more striking when analyzing inter-regional and intra-regional disparities. For instance, in 2016, 41.91% of the Brazilian residents were located in the Southeast region, which was responsible for 53.17% of the country's GDP, whereas the Northeast region generated 14.33% of the national GDP with 27.62% of the country's population (IBGE, 2019). Also, in terms of life conditions, the 2016 Human Development Index (HDI) for the Northeast region was 0.633 *vis-à-vis* a value of 0.766 for Southeast region (PNUD, 2016). As for social vulnerability, while 24.9% of the Northeast population were below the poverty line in 2015, 13.8% and only 5% of the Southeast and South residents, respectively, were considered poor in Brazil (Rocha, 2019).

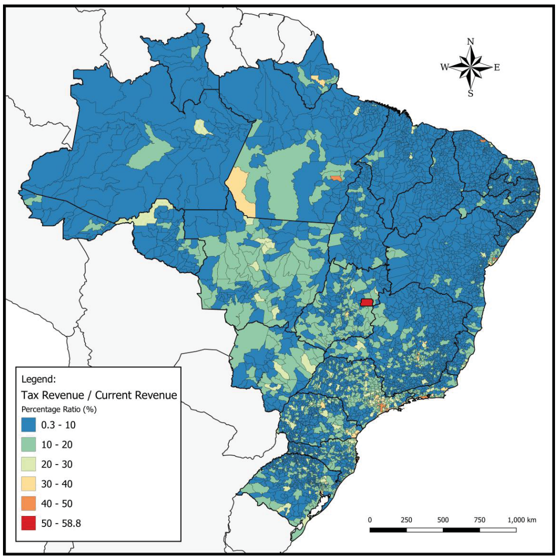
The profound economic and social heterogeneity in Brazil is translated into its subnational fiscal structure mainly through inter-regional imbalances in the tax base and in the dependence on transfers from the federal government in a context of virtually no access to financing (Bornhorst et al., 2018).

As shown in figure 2.1(a), municipalities with low tax collection capacity were mostly concentrated in the North and Northeast regions during the 2013-2017 period. In fact, among those below the 10% threshold, 46.84% were located in both regions, which corresponds to 93% of all Northern and Northeastern local governments. Conversely, in terms of Municipal Participation Fund (FPM) grants as a percentage of current revenue, the highest fiscal dependency ratios were observed in the Northeastern municipalities as well as those from the states of Tocantins (North) and Minas Gerais (Southeast) during the period (Figure 2.1(b)). On average, 39.6% of current revenue in the latter municipalities consisted of such federal transfer between 2013 and 2017.

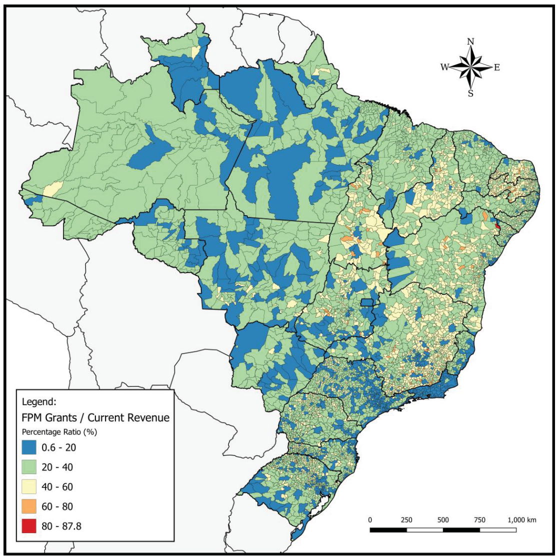
In terms of public expenditure, the wage bill poses a challenge for the Brazilian local governments. In a macroeconomic context, the Fiscal Responsibility Law (FRL) aims to impose a homogeneous pattern in the behavior of public budgets for different federative entities by establishing fiscal targets for some budgetary indicators. For instance, in the case of municipal governments, personnel expenditure is limited at a maximum threshold of 60% of net current revenue, with 54% being considered a prudential limit. During the 2013-2017 period, on average, 15.9% (884) of total Brazilian municipalities were in excess of the prudential limit whereas 4.7% (262) were beyond the 60% threshold. As shown in figure 2.2(a), local governments beyond the FRL limits are mostly located in the North and Northeast regions. Such geographical distribution exposes the difficulty of these latter municipalities in complying with the FRL targets.

Associating public spending with economic activity is not a new exercise in the economic literature. From the so-called Wagner's Law, the size of the public sector is conditional on economic dynamism, with public spending growth being higher than income growth. For a sample of 17 countries, Tanzi and Schuknent (2000) demonstrated that the share of public spending on GDP increased substantially between the end of the 19th century and the end of the

Figure 2.1: Budgetary profile of Brazilian municipalities (Average values, 2013-2017)

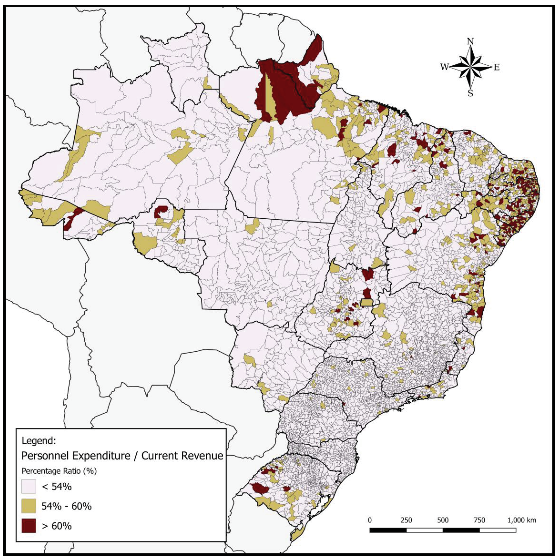


(a) Tax revenue / current revenue (%)

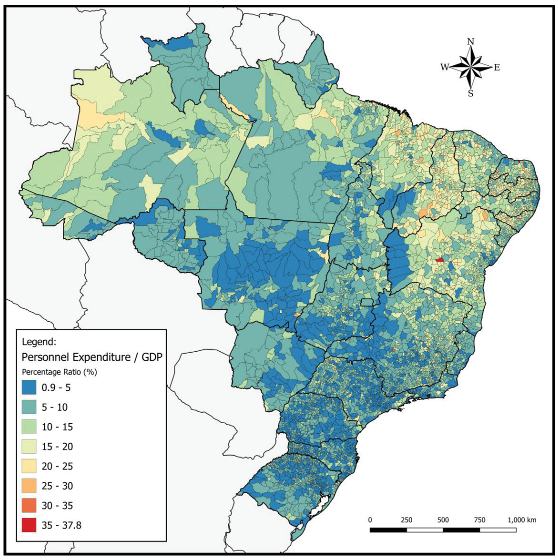


(b) FPM grants / current revenue (%)

Figure 2.2: Personnel expenditure in the Brazilian municipalities (Average values, 2013-2017)



(a) Personnel expenditure / current revenue (%)



(b) Personnel expenditure / GDP (%)

20th century. Other papers also validate such phenomenon for different economies and periods (Gupta, 1967; Musgrave, 1969; Goffman and Mahar, 1971; Bird, 1971; Ganti and Kolluri, 1979; Abizadeh and Gray, 1985; Islam, 2001; Al-Faris, 2002; Loizides and Vamvoukas, 2005; Akitoby et al., 2006; Magazzino, 2012; Keho, 2015, among others).

In the case of Brazil, local governments with lower economic dynamism, such as those in the North and Northeast regions, have higher expenses in personnel. In fact, the lowest percentage ratios between *per capita* personnel expenditure and GDP are located in the South-Central region of the country. Two potential explanations for these inter-regional divergences are: (i) the displacement effect hypothesis of Peacock and Wiseman (1961), in which discontinuous government expenditure growth is a function of tolerable tax burden; and (ii) predictions from the Theory of Public Choice, particularly the median voter theorem, in which the level of government expenditure is determined by the median voter (Bowen, 1943; Downs, 1957; Black, 1958). In the first case, given that local tax bases in the North and Northeast are relatively more restricted than other Brazilian regions, government expenditure is also relatively lower in these areas. As for the second one, since income is the criterion to assess the distribution of voters and is unequally distributed across the Brazilian regions, public expenditure might as well be unequally distributed given that public decisions are based on elections under the majority system.

In summary, the Brazilian structure of local public finances is inherently correlated with the country's socioeconomic and geographical characteristics. Regions with lower development and population density are associated with more restricted tax bases – and consequently higher fiscal dependency ratios – as well as greater levels of personnel expenditure. As discussed in the following sections, considering such inter-regional imbalances is essential in order to effectively comprehend local fiscal relations across Brazil.

2.3 GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) WITH SPATIAL AUTOCORRELATION (SAR)

Conventional regression models intrinsically assume spatially-invariant relationships between the dependent and independent variables within a study area. These so-called *global* regressions calibrate the values of parameter estimates in a single equation framework and assign these estimated responses to every location. However, by disregarding the potential presence of spatial nonstationarity due to spatial heterogeneity, the use of standard econometric techniques might lead to the misspecification of the underlying data generating process (Fotheringham et al., 2002). In order to circumvent such limitation and explicitly incorporate the extraneous variation from the geographically varying aspects of the association structure, Brunsdon et al. (1996) proposed the geographically weighted regression (GWR) model – an extension to the ordinary regression model – which consists of deriving location-specific coefficient estimates through the estimation of a kernel-based non-parametric linear regression.

Denote y_i as the dependent variable at location i and x_{ik} as the k-th explanatory variable at location i. The GWR model may be written as

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i \tag{2.1}$$

where p is the number of independent variables; β_{i0} is the intercept coefficient at location i; β_{ik} is the local coefficient for the k-th independent variable at location i; and ε_i is the independent normally distributed error term with zero mean at location i.[1] The $(p+1) \times 1$ vector of location-specific parameter estimates associated with location i is

$$\hat{\boldsymbol{\beta}}_i = [\boldsymbol{X}'\boldsymbol{M}_i\boldsymbol{X}]^{-1}\boldsymbol{X}'\boldsymbol{M}_i\boldsymbol{Y} \tag{2.2}$$

with $\boldsymbol{X} = [\boldsymbol{X}_1', \boldsymbol{X}_2', \ldots, \boldsymbol{X}_n']'$ being a $n \times (p+1)$ design matrix of observations for the explanatory variables, which includes a column of ones for the intercept; $\boldsymbol{Y}$ being a $n \times 1$ vector of observations for the dependent variable; and $\boldsymbol{M}_i = diag[M_{i1}, \ldots, M_{in}]$ being a $n \times n$ diagonal local spatial weights matrix. According to Geniaux and Martinetti (2018), for each observation $i \in \{1, \ldots, n\}$, the $n \times n$ weight matrix $\boldsymbol{M}$ is such that $m_{ij} = K(d_{ij}, d_{iB})$, for any $j \in \{1, \ldots, n\}$, with $K()$ being a distance-decay kernel function of the Euclidean distance d_{ij} between location i and location j as well as a bandwidth d_{iB}. Note that equation (2.2) represents a locally weighted least squares procedure in which data from observations closer to location i have a stronger influence on the local regression (Wheeler and Páez, 2010).

Yet, equation (2.1) may be augmented as to consider the possibility of nonstationary spatial autocorrelation. Such feature is rather compelling when modeling the potential interaction among agents in neighboring locations in the presence of a spatially-varying density of observations throughout the study area. Following Páez et al. (2002), the GWR with spatial autocorrelation (GWR-SAR) model is specified as

$$y_i = \beta_{i0} + \rho_i \sum_{j=1}^{n} w_{ij} y_j + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i \tag{2.3}$$

where ρ_i is a spatially-varying spatial autocorrelation coefficient associated with location i; and w_{ij} is the ij-th element of a known $n \times n$ spatial weights matrix $\boldsymbol{W}$.[2]

The inclusion of such spatially-lagged dependent variable as a regressor in the GWR framework introduces a source of endogeneity from its usual correlation with the error term ε_i. While Brunsdon et al. (1999) and Páez et al. (2002) suggest estimation based on local maximum likelihood techniques, these are found to be computationally intensive (Geniaux and Martinetti, 2018). The instrumental-variable (IV) method of spatial two-stage least squares (S2SLS) regression is considered an alternative estimation procedure when dealing with this class of models (Anselin, 1988; Kelejian and Prucha, 1998). The first stage consists of regressing the spatially-lagged dependent variable $\boldsymbol{WY}$ on the set of instruments $H = [\boldsymbol{X}, \boldsymbol{WX}_{-1}]$, where $\boldsymbol{X}_{-1}$ denotes the design matrix of covariates without the column of ones for the intercept. Based on the fitted values of $\boldsymbol{WY}$ from the first stage, equation (2.3) is then estimated in the second stage.

2.3.1 Selection of kernel function and kernel bandwidth

For both GWR and GWR-SAR models, the local weights matrix, $\boldsymbol{M}$, is calibrated according to a distance-decay kernel function (for a detailed discussion, see Fotheringham et al. (2002) and Wheeler and Páez (2010)). In this paper, a bi-square kernel is adopted, which provides a continuous, near-Gaussian weighting scheme (Fotheringham et al., 2002). By assigning zero

[1] In this study, geographical indexation is based on spherical coordinates (i.e. latitude and longitude) of areal centroids.

[2] Three classes of spatial weights matrix are tested in order to define the neighboring structure in $\boldsymbol{W}$, namely, the contiguity-based weights matrix, the inverse-distance weights matrix, and the K-nearest neighbor weights matrix.

weight to any observation outside of a given bandwidth, the bi-square kernel nullifies their impact on the estimation of the location-specific coefficients.

As to the selection of kernel bandwidth in the context of GWR and GWR-SAR models, the procedure is based on optimization by either distance (fixed bandwidth) or the number of neighboring data points (adaptive bandwidth). Fotheringham et al. (2002) argues that, in the presence of sparsely located data, fixed bandwidths might induce large standard errors and a "undersmoothed" parameter surface (in extreme cases, model estimation might become unfeasible). Conversely, in the adaptive framework, bandwidth size is conditional on variation in the distribution of data points across space, so that its value at each regression point represents the optimal proportion of neighboring observations. Given the spatially-varying nature of data density across our geographical area, an adaptive bandwidth is chosen.

The bi-square nearest-neighbor kernel function is written as

$$m_{ij} = K(d_{ij}, d_{iB}) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{d_{iB}}\right)^2\right]^2 & \text{if } j \text{ is one of the } B\text{-th nearest neighbors of } i; \\ 0 & \text{otherwise.} \end{cases} \tag{2.4}$$

with d_{ij} being the Euclidean distance between locations i and j; and d_{iB} being the kernel bandwidth, that is, the distance to the B-th nearest neighbor from location i. Note that d_{iB} is adjusted at each location i as to consider B nearest data points around it. Consequently, proper bandwidth selection is an essential step in fully establishing the data-borrowing scheme. Following Fotheringham et al. (2002), optimal bandwidth is chosen by minimizing the corrected Akaike information criterion (AICc) based on a golden section search routine.[3]

2.3.2 Inference on local parameter estimates

Both GWR and GWR-SAR models rely on data-borrowing schemes to generate local parameter estimates. Given the overlapping nature of these procedures, multiple hypothesis testing based on the classic t-test are likely to produce a set of false positives since local sub-samples will not be independent. In order to account for such dependency issue, Da Silva and Fotheringham (2015) proposed a GWR-specific correction to the significance level (α) as to derive more conservative critical t-values. Hence, hypothesis testing is carried out using

$$\alpha = \frac{\xi}{\frac{p_e}{p}} \tag{2.5}$$

where ξ is the desired joint type I error rate (e.g. 0.05); p_e is effective number of independent parameter estimates, defined by $p_e = 2\mathrm{tr}(\boldsymbol{S}) - \mathrm{tr}(\boldsymbol{S'S})$; and p is the number of parameters in the model. Note that the ratio $\frac{p_e}{p}$ ($p_e \geq p$) is proportional to the number of multiple tests. In the specific case of $p_e = p$ (infinitely large bandwidth), equation (2.5) reduces to $\alpha = \xi$, thus resulting in the equivalence of the t-tests for GWR and for a global regression.

[3]According to Gollini et al. (2015), in the context of GWR and GWR-SAR models, given a bandwidth d_{iB}, the AICc is obtained by

$$\mathrm{AICc}(d_{iB}) = 2n\ln(\hat{\sigma}) + n\ln(2\pi) + n\left[\frac{n + \mathrm{tr}(\boldsymbol{S})}{n - 2 - \mathrm{tr}(\boldsymbol{S})}\right]$$

where n is the local sample size defined by d_{iB}; $\hat{\sigma}$ is the estimated standard deviation of the error; and $\mathrm{tr}(S)$ is the trace of the hat matrix $\boldsymbol{S}$.

2.3.3 Inference on spatial (non)stationarity

Once either GWR or GWR-SAR is estimated, inference on each surface of parameter estimates can be performed via Monte Carlo methods. As discussed in Brunsdon et al. (1998), the spatial variability test consists of evaluating the null hypothesis of $H_0 : \beta_{ik} = \beta_k$ for all $i \in (1, \ldots, n)$ against the alternative hypothesis of $H_1 : \beta_{ik}$ not being all the same for all $i \in (1, \ldots, n)$. Note that under the null hypothesis, β_{ik} is assumed to be location invariant for a fixed variable x_k so that no significant difference in the patterns of the respective local parameter estimates should be detected if the model were to be re-calibrated on randomized data. Thus, failing to reject H_0 implies that the observed pattern of data distribution across space does not affect the obtained parameter estimates for variable x_k – that is, β_{ik} are fixed over space (spatially stationary). In other words, such Monte Carlo significance test assesses whether each explanatory variable in the local regression model should be characterized as spatially nonstationary or not.

Following Oshan et al. (2019), 1,000 iterations were performed in order to construct the pseudo p-values. A pseudo p-value larger than 0.05 indicates that the surface of parameter estimates for a given variable exhibits no significant local variation (i.e. it is spatially stationary).

2.3.4 Detection of local multicollinearity

Despite Fotheringham and Oshan (2016) demonstrating the robustness of GWR models regarding the effects of multicollinearity in the context of large sample sizes, there still is no consensus on the issue. Among the potential negative effects of high collinearity between covariates, one should mention (i) estimate instability, (ii) imprecise estimates with counter-intuitive signs or implausible magnitudes, (iii) loss of statistical power due to inflated parameter standard errors, and (iv) high R^2 diagnostics in the presence of few or no significant parameter estimates (Besley et al., 1980; O'Brien, 2007). Therefore, as a precautionary assessment, local variance inflation factors (VIF) are evaluated for all explanatory variables – including the spatial autocorrelation parameter.

As outlined in Wheeler (2007), the local VIF for a given variable x_k at location i is

$$\text{VIF}_k(i) = \frac{1}{1 - R_k^2(i)} \tag{2.6}$$

with $R_k^2(i)$ being the coefficient of determination at location i when x_k is regressed on the remaining covariates for the same location. As a rule of thumb, multicollinearity is considered to be problematic when local VIF values are higher than the threshold of 10 (Besley et al., 1980; Wheeler and Tiefelsdorf, 2005; O'Brien, 2007; Wheeler, 2007; Oshan et al., 2019).

2.4 EMPIRICAL RESULTS

In order to take into account both fiscal interaction and fiscal heterogeneity when analyzing the budgetary, economic and demographic determinants of *per capita* municipal expenses in personnel, a GWR-SAR model was calibrated using the average municipal values of *per capita* tax revenue, *per capita* FPM grants, *per capita* GDP, the share of population under 14 years old, and the share of population over 65 years old for the 2013-2017 period as explanatory variables. The study area consisted of 5,558 Brazilian municipalities.[4] Averaged values were used not only

[4]Even though there were 5,570 Brazilian municipalities in 2017, this paper grouped the ten new municipalities that were legally emancipated after 2005 with their respective municipalities of origin. Such aggregation was performed due to the lack of more recent polygonal shapefiles for Brazilian municipalities. In addition, two island

because of the cross-sectional nature of the econometric procedure but also to smooth eventual data spikes during the period.

Estimation results and their discussion are presented in three steps. First, global estimates from OLS and SAR models are provided in Table 2.1 as a baseline for the GWR-SAR results. Differently from the OLS specification, the possibility of fiscal interaction is considered in the SAR model by including of a spatial autocorrelation coefficient. Both the spatially lagged personnel expenditure variable and its respective instruments were constructed with an inverse-distance weighting scheme. In a second step, the estimation strategy is augmented as to consider the potential existence of spatial nonstationarity. The summary statistics for the GWR-SAR parameter estimates are outlined in Table 2.2. The last step consists of assessing the so-called flypaper effect in the Brazilian municipalities, exploring its potential spatial nonstationarity.

2.4.1 OLS and SAR model estimates

The estimation results of the classic OLS model indicate the importance of the budgetary, economic and demographic variables in explaining municipal expenses in personnel (Table 2.1. Besides all regressors being statistically non-zero for a significance level of 0.01, the model produces a relatively high R^2 (0.68) even in the presence of a rather large sample size. In particular, increases in both tax revenue and FPM grants are associated with a higher level of personnel expenditure per municipal resident. The respective estimated elasticities are 0.142 and 0.404. In terms of *per capita* GDP, the estimated elasticity is 0.164, which indicates that local governments with higher income are prone to present higher levels of personnel expenditure. The positive elasticities for the demographic variables represent the indirect effect of higher demand pressures on the provision of public goods within jurisdictions with relatively lower shares of economically active population.

Table 2.1: Global results from OLS and SAR models

Variable	OLS	SAR
Intercept	1.138*	1.239*
ln(Tax revenue *per capita*)	0.142*	0.142*
ln(FPM grants *per capita*)	0.404*	0.404*
ln(GDP *per capita*)	0.164*	0.165*
ln(Share of population under 14 years old)	0.314*	0.287*
ln(Share of population over 65 years old)	0.039*	0.047*
Spatial autocorrelation (λ)		-0.009*
Number of observations	5,558	5,558
AICc	-2,105.85	-2,112.47
Adjusted R^2	0.680	0.681

*Notes: * one percent level of significance. W: inverse-distance weights matrix.*

Imposing a global spatial dependence structure in the model specification leads to little variation in the estimated parameters from the OLS model. Despite being statistically non-zero for a significance level of 0.01, the spatial autocorrelation coefficient is -0.009, suggesting the effects of fiscal interaction are virtually nonexistent (Table 2.1). However, this result should be considered with caution. By not accounting for local heterogeneity, the SAR model imposes a spatially-invariant structure that is potentially not observed from the data.

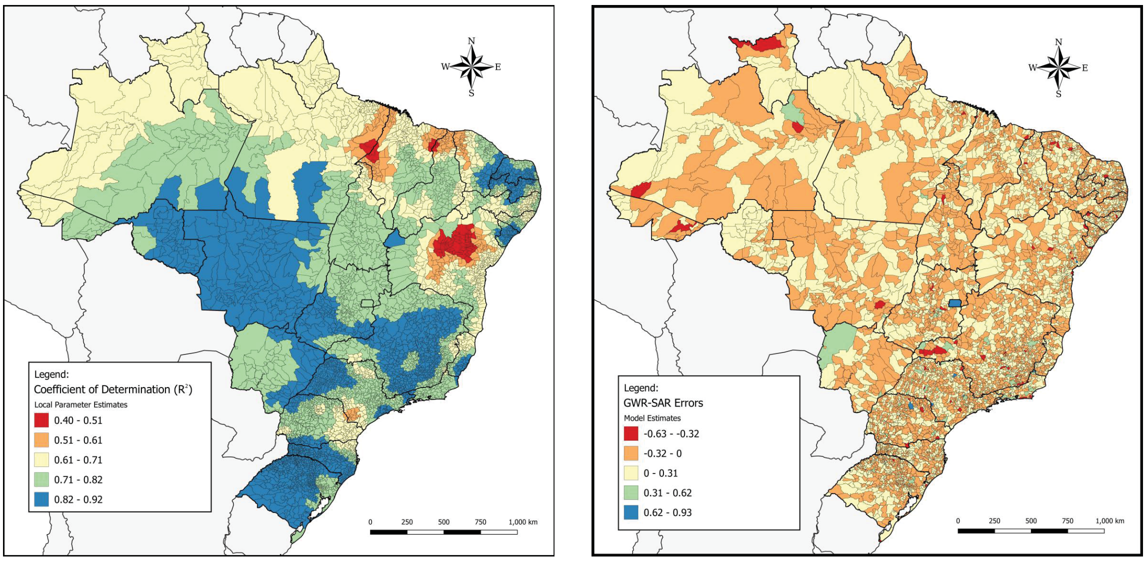
municipalities (Ilhabela/SP and Fernando de Noronha/PE) were removed from the data set. Therefore, the final data set covers 5,558 Brazilian municipalities.

2.4.2 GWR-SAR model estimates: Fiscal responsiveness in the context of spatial nonstationarity

Even though Brazil is a country profoundly characterized by fiscal heterogeneity across space, a Monte Carlo spatial variability test is performed as to formally assess the presence of spatial nonstationarity for each explanatory variable. The last column of table 2.2 presents the test results. At the one percent level of significance, all regressors should be characterized as local, including the spatial autocorrelation coefficient. Therefore, the choice of a GWR-SAR model is statistically supported by the data.

With the same set of variables used in the global SAR specification, the adaptive bi-square kernel of the GWR-SAR model was calibrated with a relatively local optimal bandwidth: 141 nearest neighbors. The average R^2 increased to 0.832 in the GWR-SAR model, a 22% increase compared to the global SAR model. Figure 2.3(a) maps the local R^2. Overall, the selected variables are capable of explaining most of the variation in the municipal personnel expenditure throughout Brazil. More specifically, local R^2 ranges from 0.71 to 0.92 for the South-Central Brazilian municipalities, with few exceptions (the North region of Espírito Santo, the South region of São Paulo and the East region of Paraná). Lower local R^2 are mainly concentrated in the North and Northeast region, especially in Bahia and Maranhão, suggesting budgetary decisions regarding personnel expenditure in these regions are determined by further factors to those considered in our specification (e.g. political and institutional variables, such as political-party alliance between governor and mayor, the type – first or second – of mandate of elected mayor, electoral performance in the municipality measured by the margin of victory over the runner-up candidate, and others).

Figure 2.3: Selected results from the estimated GWR-SAR model



(a) Coefficient of determination (R^2)

(b) GWR-SAR residuals

Before proceeding to the analysis of the GWR-SAR estimates, one must evaluate whether the spatial correlation structure is properly captured by the model. After controlling for spatial autocorrelation and spatial nonstationarity, the presence of spatial patterns in the distribution of regression residuals indicates misspecification, leading to bias and inconsistent estimates. GWR-SAR residuals are mapped in figure 2.3(b). Visual inspection suggests the estimated residuals are randomly distributed. Yet, formal statistical testing is still required. The estimated Moran's I statistic is -0.001 [E(I) = -0.000, SD(I) = 0.001, Z = -0.822] with a pseudo p-value of 0.411, based on 9,999 permutations.[5] By failing to reject the null hypothesis of randomly distributed residuals at the 0.01 level of significance, there is statistical evidence of the estimated GWR-SAR model properly capturing the inherent spatial correlation in the data.

Based on the summary statistics in table 2.2, the average values of the parameters of the GWR-SAR model are rather similar to those obtained with the OLS and SAR models. Exceptions are the average results for the share of population over 65 years old and for the spatial autocorrelation term. In the case of the former, a negative relationship between the proportion of the elderly in the population and the expenses in personnel is observed. As for spatial autocorrelation, the negative relation previously found is considerably enhanced. However, the relatively high standard deviation associated with the GWR-SAR coefficients reveals the extent of spatial variation. Apart from the estimates for the *per capita* FPM grants, the estimated local parameters range from negative to positive values (Table 2.2). Overall, these results represent a preliminary evidence of the complexity of local public finances across Brazil.

Table 2.2: Summary statistics for GWR-SAR parameter estimates

Variable	Mean	SD	Min	Median	Max	Significant cases (α = 5%)	Cases with local VIF > 10	MC-SV
Intercept	1.017	1.824	-5.781	1.237	5.808	23.62%	0.00%	SNS
ln(Tax revenue *per capita*)	0.161	0.090	-0.054	0.154	0.409	79.60%	0.00%	SNS
ln(FPM grants *per capita*)	0.468	0.089	0.156	0.481	0.642	100.00%	0.00%	SNS
ln(GDP *per capita*)	0.186	0.080	-0.001	0.182	0.437	78.77%	0.00%	SNS
ln(Share of population under 14 years old)	0.202	0.376	-0.661	0.158	1.415	21.00%	0.36%	SNS
ln(Share of population over 65 years old)	-0.011	0.166	-0.594	-0.021	0.862	14.11%	0.00%	SNS
Spatial autocorrelation (λ)	-0.040	0.131	-0.695	-0.033	0.393	25.10%	0.00%	SNS
Number of observations					5,558			
AICc					-4,904.48			
Adjusted R^2					0.832			

Notes: adjusted critical t-value (95%) *is equal to* 3.463. *MC-SV corresponds to the Monte Carlo test for spatial variability. SNS denotes spatial nonstationarity at one percent level of significance. Optimal bandwidth:* 141.

However, further analyzes on the local parameters are required. First, the average values of parameter estimates in table 2.2 are not tested for statistical significance. Consequently, conclusions regarding the behavior of municipal public finances solely based on these average values and their respective standard deviation might not appropriately reflect the fiscal reality within local governments. Following the correction procedure proposed by Da Silva and Fotheringham (2015), the adjusted critical t-value at the 0.05 significance level is 3.463, a more conservative value than the standard 1.96 critical t-value. Second, the sole analysis of average local estimates does not fully present the inherent extent of spatial variation. Thus, in order to simultaneously tackle both issues as to provide a better understanding of the spatially-varying nature of fiscal relations among Brazilian municipalities, the surfaces of statistically significant local parameter estimates are mapped in figures 2.4 and 2.5.[6]

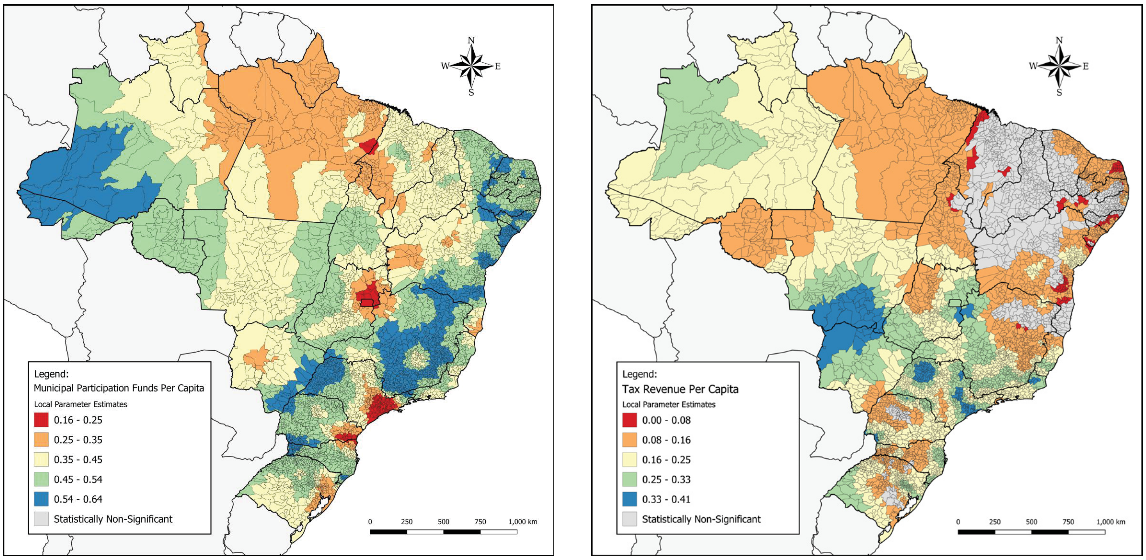
Local parameter estimates associated with the *per capita* FPM grants are statistically significant at the five percent adjusted significance level for all Brazilian municipalities (Table 2.2). Figure 2.4(a) displays the respective parameter surface. Despite inter-regional differences in the magnitude of local parameters, in terms of *per capita* values, municipal expenses in personnel

[5]Moran's I test statistic was based on a two-tail test with an inverse distance weights matrix.

[6]Given the lack of economic reasoning regarding the interpretation of the intercept term, its respective parameter surface is presented in Appendix C. As for the demographic control variables, local parameter estimates are statistically significant in only a few cases (21% for the share of population under 14 years old and 14.11% for the share of population over 65 years old) and do not display an explicit pattern of geographical distribution. Since these variables were included as controls in order to lessen the likelihood of omitted-variable bias, their local parameter surfaces are also presented in Appendix C.

are positively correlated with FPM grants in Brazil. Yet, higher local correlations are mainly observed throughout municipalities relatively near coastal regions. The lowest values (0.16 - 0.25) are concentrated in regions with low fiscal dependency ratios, that is, local governments in which FPM grants do not represent a significant share of their current revenue. Given the procyclical nature of such intergovernmental transfer, municipalities with higher correlations are more prone to the weakening of their public finances during economic downturns than those whose fiscal dependency ratios are low. Hence, in a fiscal setting of expenditure limits and relative local expenditure rigidity, such dependence on intergovernmental grants as a source of revenue might potentially hinder the ability of these municipalities in satisfying the fiscal constraints imposed by the FRL.

Figure 2.4: Local parameter estimates from the GWR-SAR model for FPM grants *per capita* and tax revenue *per capita*



(a) FPM grants *per capita* (b) Tax revenue *per capita*

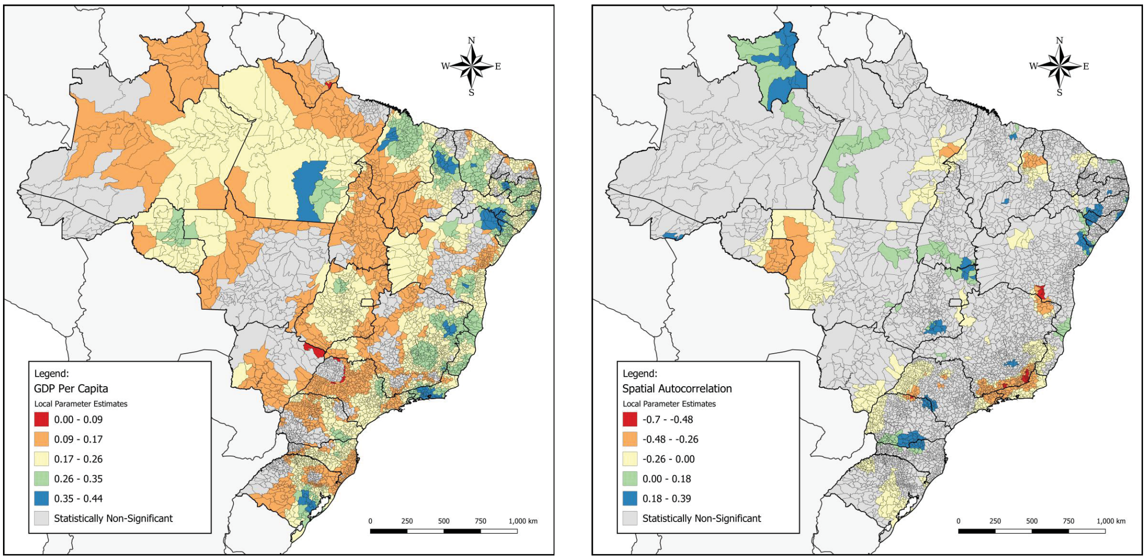
Tax revenue and personnel expenditure are also positively correlated across Brazil. Even though the respective local parameters in table 2.2 range from negative to positive values, only positive coefficients are statistically significant at the adjusted 0.05 significance level. The approximately 20% of statistically non-significant cases (1,134 municipalities) are predominantly situated in the Northeast region.[7] In general, lower parameter values are mostly observed in municipalities with low tax collection capacity. The lower estimated elasticities range from 0.00 to 0.16, which suggests that an one percent increase in local tax revenue would lead to a maximum increase of 0.16% in local personnel expenditure within these municipal governments. In the context of tax base restriction, the latter low responsiveness is expected since marginal increases in tax revenue would not potentially induce a budget recomposition effect capable of providing effective bases for substantial expansion of the municipal wage bill.

The joint analysis of both figure 2.4(a) and 2.4(b) provides evidence in favor of another expected result: local personnel expenditure presents a higher degree of responsiveness towards FPM grants than tax revenue. According to Bonet and Fretes Cibils (2013), in Latin America, the fiscal decentralization process has increased the responsibility of local governments regarding the provision of public goods without considering the existent disparities in tax administration among these subnational entities as well as the small scale at which most of them operate. Thus,

[7]Statistically non-significant local parameters are also found in the north of Minas Gerais.

in the absence of a stable local tax base, budgetary decisions regarding the wage bill are more sensitive to intergovernmental *lump-sum* grants from the central government since subnational governments are highly dependent to such sources of revenue.

Figure 2.5: Local parameter estimates from the GWR-SAR model for GDP *per capita* and the spatial autocorrelation term



(a) GDP *per capita* (b) Spatial autocorrelation term

Figure 2.5(a) maps the local parameter surface associated with municipal GDP *per capita*. Statistical significance is confirmed for 78.77% of cases, which corresponds to 4,378 municipalities (Table 2.2). Despite the presence of only positive values, the estimated coefficients show considerable spatial variation across Brazil. Similarly to the results for FPM grants, municipal governments located near coastal areas are more likely to display higher local correlations between expenses in personnel and income *per capita*. Since the development process of the Brazilian economy was mainly concentrated across the country's coastal area, a historically higher population density is observed. Given the intrinsic indivisibility of public goods in small local governments (in terms of population), provision of these services are concentrated in larger cities as their respective tax prices are comparatively lower (Oates, 1988; Sampaio de Souza et al., 2005; Mendes and Sampaio de Souza, 2006). Consequently, the greater provision of public goods in economically more dynamic municipalities is concurrent to a relatively higher level of personnel expenditure in these locations.

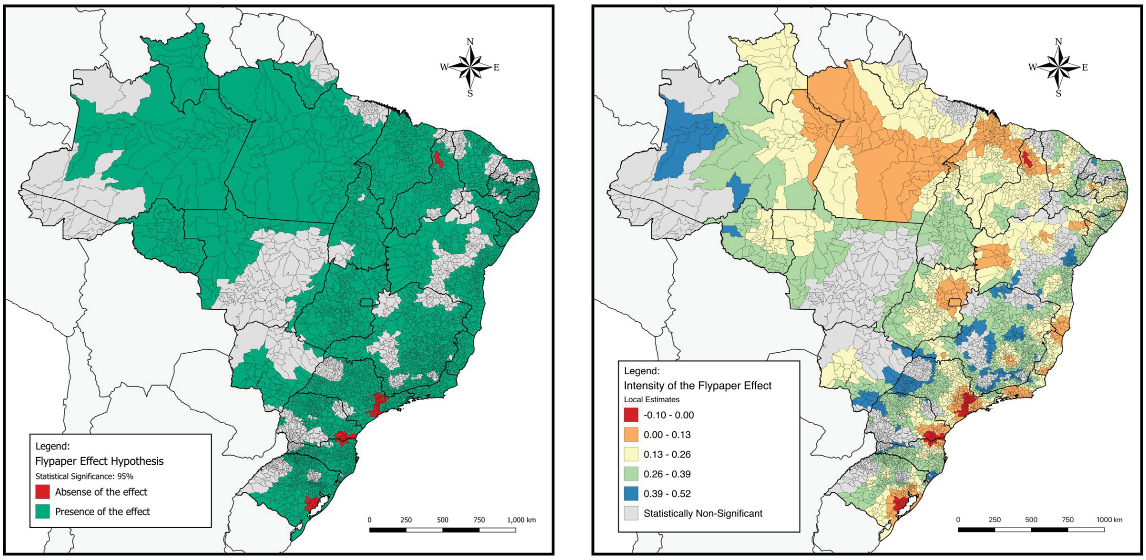
Fiscal interaction among the Brazilian municipalities is empirically assessed by estimating the degree of local spatial autocorrelation in the data. Statistical significance tests show that only 25.1% of cases (1,395 municipalities) are statistically non-zero for an adjusted 0.05 significance level (Table 2.2). Parameter surface is mapped in figure 2.5(b). Even though such interactions are not observed for all municipal governments, the statistically significant local coefficients reveal an interesting phenomenon: both positive and negative spatial autocorrelation are detected. Although identifying the driving forces of the observed geographical distribution is beyond the scope of this essay, such inter-regional differences in the sign and magnitude of the spatially-varying spatial autocorrelation terms further accentuate spatial nonstationary nature of fiscal interactions across Brazil. A negative spatial autocorrelation term suggests personnel expenditure in a given Brazilian municipality and its neighboring counterparts are substitutes. On the other hand, complementarity is observed when spatial autocorrelation is positive. Therefore, in some extent, there is statistical evidence of strategic behavior by Brazilian local governments as to the decision of their own expenditure levels.

Finally, local multicollinearity is evaluated. The effects of local multicollinearity on locally weighted regressions is still an ongoing debate. Despite recent literature providing statistical evidence of GWR resiliency regarding local multicollinearity, especially in large samples (Páez et al., 2011; Fotheringham and Oshan, 2016), local VIF are computed for each variable in each location as a form of precautionary assessment. The estimated statistics are outlined in table 2.2. Based on the threshold value of 10 (Besley et al., 1980; Oshan et al., 2019), the problem of collinearity is only detected for the share of population under 14 years old. Yet, the relatively high multicollinearity (local VIF > 10) for the latter variable is clustered in a small area of the North region – more specifically, 20 municipalities located in Acre. Therefore, the aforementioned conclusions are robust to such issue.

2.4.3 Revisiting the flypaper effect in Brazil: Evidence from the spatially-varying estimates

Empirically, the flypaper effect is observed in local governments whose elasticity of public spending with respect to unconditional grants-in-aid is relatively greater than the income elasticity of demand for publicly provided goods (Megdal, 1987). Local parameter estimates from the GWR-SAR model allow the assessment of the latter fiscal puzzle across the Brazilian municipalities. Figure 2.6(a) presents the obtained results. Note that the flypaper effect hypothesis is only evaluated in local governments whose both elasticities are statistically non-zero for an adjusted significance level of five percent.

Figure 2.6: Geographical distribution of local flypaper effect in Brazil



(a) Flypaper effect hypothesis

(b) Intensity of the flypaper effect

Overall, the flypaper effect is detected in 77% of Brazilian municipalities (4,281), which corresponds to 97.8% of all local governments with both elasticities being statistically significant (green areas in figure 2.6(a)). In fact, statistical evidence against the effect is only observed in 97 local governments (red areas in figure 2.6(a)). The presence of the flypaper effect in most Brazilian municipalities suggests a potential displacement between the supply and demand for local public services in these locations. As the response of personnel expenditure to variation on unconditional grants is relatively higher than that from the same variation on income, the observed levels of expenditure might be beyond those rationally desired. Given that tax policies adopted by these local governments do not represent the real marginal cost of public expenditure, their distortionary nature leads to inefficieny in terms of optimal government decisions (Logan, 1986; Oates, 1988; Turnbull, 1998). In the Brazilian case, Mattos et al. (2011) argue that the flypaper effect is also associated with lower efficiency in local tax collection.

Regarding the intensity of the flypaper effect, it is measured as the differential value between the elasticity of personnel expenditure with respect to FPM grants and the income elasticity of personnel expenditure. Figure 2.6(b) maps the obtained results. Even though the effect's spatial distribution presents distinctive inter-regional patterns across Brazil, two conclusions are drawn: first, as fiscal dependency ratio increases, the intensity of the flypaper effect also increases; second, populous regions tend to have less intense flypaper effects. While the former is explained by the distortionary nature of intergovernmental *lump-sum* grants, the latter is associated with relatively less restricted tax bases in local governments with higher population density.

Yet, four negative clusters are identified, with the intensity of the flypaper effect ranging from 0.00 to -0.10. Consequently, within these clusters, the responsiveness of personnel expenditure associated with changes in local income *per capita* is (at most) 0.1 percentage points greater than those related to identical changes in FPM grants *per capita*. Such contrasting results are mainly driven by two complementary characteristics: in comparison to their neighboring regions, the local governments within these clusters have (i) relatively lower fiscal dependency ratios; and (ii) substantially higher economic dynamism.

2.5 CONCLUSION

This chapter intended to present an analysis of the heterogeneous fiscal profile of the Brazilian municipalities and its potential effect in the responsiveness of personnel expenditure. To this end, we estimated a GWR-SAR model, in which the parameters are allowed to locally vary across space.

Our results show that there are substantial inter-regional differences in the sensitivity of the local wage bill. First, optimal kernel bandwidth reveals that the data generating process is rather local. Second, local parameter estimates for *per capita* FPM grants are positive and statistically significant for all Brazilian municipalities, with higher values concentrated near coastal regions. Local governments with low fiscal dependency ratios tend to present lower correlations. Third, tax revenue is also positively correlated to personnel expenditure across Brazil. Notice that the responsiveness of local public spending is higher for FPM grants than for tax revenue. Fourth, there is statistical evidence in favor of local personnel expenditure being higher in municipalities with higher economic dynamism. Finally, the results associated with fiscal interactions among the Brazilian municipalities show that local personnel expenditure can behave as either a substitute or a complement in relation to neighboring expenditure. Hence, we provide evidence of strategic behavior by Brazilian local governments as to the decision of their own expenditure levels.

The occurrence and intensity of the flypaper effect is also assessed. By comparison of the estimated elasticity of personnel expenditure with respect to FPM grants and the estimated income elasticity of personnel expenditure, there is evidence in favor of the flypaper effect hypothesis throughout Brazil. The absence of such effect is found only in four relatively small clusters, comprising 97 local governments (1.75% of the total number of Brazilian municipalities). Despite not presenting explicit spatial patterns, two conclusions are drawn from the results regarding the intensity of the flypaper effect: first, local areas with higher fiscal dependency ratios tend to present more intense flypaper effects; second, populous regions tend to have less intense flypaper effects.

Overall, this chapter underscores the importance of considering Brazil's inter-regional imbalances when studying its fiscal relations. Given that local municipalities respond differently to budgetary recompositions and to their economic performance, Brazilian policy-makers should consider such regional disparities when designing fiscal policy. Despite potentially decreasing the influence of political factors when transferring resources to local governments, the imposition of homogeneous rules for intergovernmental grants neglects regional specificities, compromising the fiscal commitment to the FRL and, ultimately, failing to effectively promote equalization. Coupled with the substantial distortionary effects of the Brazilian unconditional grants-in-aid system, fiscal equalization measures should therefore gravitate towards inducing higher efficiency in local tax collection as to enhance self-generating revenue capacity and, consequently, decrease the relevance of the flypaper effect within these local governments.

3 CONVERGENCE OF PUBLIC SPENDING AND SPATIAL DEPENDENCE ACROSS LOCAL GOVERNMENTS: EVIDENCE FROM THE BRAZILIAN MUNICIPALITIES

3.1 INTRODUCTION

Convergence has been a recurrent topic in both theoretical and empirical economic research. Based on the predictions of neoclassical growth theory (Solow, 1956; Swan, 1956), the seminal papers of Baumol (1986) and Barro and Sala-i-Martin (1992) introduced the concept of *income β-convergence* in which economies initially poor would grow faster than the initially more affluent ones. Since publicly provided goods and services not only generate positive externalities to the private sector but also redistribute income, the long-run path of income growth is then partially recognized as a reflection of public spending decisions (Barro, 1990; Skidmore et al., 2004). Granted that voter preferences are similar across regions and that factor endowments, which initially differ spatially, migrate to jurisdictions with higher marginal product, spatial convergence of income *per capita* levels and income distributions would therefore induce the spatial convergence of the associated *per capita* levels and patterns of government revenues and expenditures (Scully, 1991).

Even though several cross-country and regional studies have empirically assessed both absolute and conditional income "catching-up" hypotheses (see e.g. Sala-i-Martin (1996), Ferreira (2000), Goddard and Wilson (2001), Cunado et al. (2003), Le Gallo and Dall'erba (2008), Tan (2010), Alexiadis (2013) and Johnson and Papageorgiou (2020)), the existing literature on fiscal convergence is rather limited. Despite not explicitly testing for convergence in public expenditure, earlier work by Scully (1991) for the US state and local governments found that income equalization led to the increase in the rate of taxation and, consequently, in the public sector size during the period 1960-1980. Following the standard assumptions of the neoclassical growth model as developed by Solow (1956), Annala (2003) reported that both tax revenues and most categories of government expenditure had effectively β-converged across the US states over the period 1977 to 1996. The study of Skidmore and Deller (2008) supported the latter findings using detailed municipal expenditure data from Wisconsin for the period 1990-2000.

While these preceding studies have generated compelling empirical insights on local public spending convergence, the role of strategic fiscal interaction among local governments has been virtually ignored. For instance, under the preference interaction hypothesis, expenditure spillovers would stem from the idea that publicly provided services in a given jurisdiction directly affect the welfare function of neighboring areas (Gordon, 1983; Revelli, 2005). By extending Scully (1991) and Annala (2003) frameworks to allow for both substantive and nuisance spatial dependence, Coughlin et al. (2007) argued that the estimates from formerly non-spatial fiscal convergence models were subject to bias and inconsistency as they implicitly assumed that cross-sectional units are independent of each other. In fact, besides reporting that state and local fiscal policies had been converging faster than output among the US states over the period 1977 to 2002, the authors not only demonstrated that output growth and revenue growth were spatially autocorrelated but also that state expenditure growth was dependent on expenditure growth of economically and demographically similar states.

In the particular case of the Brazilian municipalities, empirical findings on fiscal convergence are even more scarce. In a study for the state of Minas Gerais using a dynamic panel data model, Santolin et al. (2009) found preliminary evidence on the convergence of municipal *per capita* personnel and investment expenditure during the period 1995-2005. Recently, in an assessment of both absolute and conditional β-convergence hypotheses for a fiscal management index of municipal personnel expenditure, Giovanini and Almeida (2019) identified that Brazilian local governments have been converging their expenses in personnel toward the limits imposed by the Fiscal Responsibility Law in the last few years. However, by ignoring the potential existence of spatial interdependence, it is unclear as to whether the latter results properly reflect the extent of local fiscal convergence across Brazil.

In this chapter, convergence of local public spending in the presence of spatial dependence is evaluated using municipal data on personnel expenditure over the period 2013-2017.[1] To date, this is the first study to employ spatial econometric models to assess local fiscal convergence in Brazil. Model specification is mainly based on the theoretical formulations developed by Case et al. (1993), Skidmore et al. (2004) and Frère et al. (2014). Moreover, a quasi-maximum likelihood procedure with robust standard errors is employed in order to estimate the parameters from the spatial cross-sectional models as in Lee (2004).

We contribute to the growing debate over the Brazilian public finances in several ways. First, exploratory spatial data analysis revealed that municipal *per capita* personnel expenditure is spatially correlated in Brazil, with distinctive macro-regional clustering processes. Further, besides the "core-periphery" spatial pattern observed in the North, Northeast and Southeast regions, preliminary evidence in favor of the β-convergence hypothesis is observed as local governments within these regions are mostly associated with low spending values in 2013 (initial year). On the other hand, even though preliminary evidence of convergence is also observed in the Central-West and South regions, their respective municipal wage bills have considerably increased at rates superior to the national average. Second, estimates of the total effect from the spatial Durbin model validated the hypothesis of real municipal *per capita* personnel expenditure converging in Brazil throughout the period. Third, based on the estimated direct and indirect effects, there is evidence of free riding behavior from local policymakers regarding the effects of tax revenue and FPM grants. Finally, at the macro-regional level, while expenses in personnel have converged in all regions, the speed of convergence has not been homogeneous.

The rest of this chapter proceeds as follow. Section 3.2 proposes a theoretical model of public spending convergence in the presence of spatial dependence as to underscore the importance of fiscal strategic interaction among neighboring jurisdictions. Besides an exploratory analysis of the spatial association patterns of local *per capita* personnel expenditure across the Brazilian municipalities, Section 3.3 also provides preliminary evidence regarding the validity of the convergence hypothesis. In Section 3.4, the spatial econometric procedure is outlined and the convergence hypothesis is formally assessed. Finally, Section 3.5 concludes.

3.2 PUBLIC SPENDING CONVERGENCE IN THE PRESENCE OF SPATIAL DEPENDENCE: A THEORETICAL APPRAISAL

Let G_i represent the level of government spending of jurisdiction i. As discussed in Revelli (2005), given the existence of horizontal externalities of assorted mechanisms of fiscal equalization in federal governmental systems, such spending level is also affected by the spending choices of

[1] Even though the sample period might be considered rather limited, convergence regressions are still valid granted that they rely on an approximation around the steady-state and are mainly used to understand the inherent dynamics revolving around such steady-state (Islam, 1995; Durlauf and Quah, 1999; Alexiadis, 2013).

neighboring jurisdictions, G_j. Consequently, the objective function faced by each municipality can be depicted as

$$U(G_i, G_j, X_i) \tag{3.1}$$

where X_i represents a vector of socioeconomic variables associated with jurisdiction i. Accordingly, the optimal public spending level of municipality i is then chosen by maximizing equation (3.1) with respect to its own level of public spending (i.e. $\partial U / \partial G_i = 0$). Frère et al. (2014) argue that such maximization problem yields a reaction function of municipality i's spending decision relative to its neighbors' spending choices and the structural properties of its own economy. Formally, the aforementioned solution can be described as

$$G_i = R(G_j, X_i) \tag{3.2}$$

Yet, the fiscal strategic interaction outlined in equation (3.2) can also be expressed in terms of growth rates. Particularly, the evolution of public spending over time at location i can be defined as a function of its neighbors' spending levels and its own socioeconomic factors, as reflected in equation (3.3) below:

$$\ln\left(\frac{g_{i,t}}{g_{i,t-1}}\right) = \phi\left(g_{j,t}, Z_i\right) \tag{3.3}$$

where lower case letters represent *per capita* values and Z_i consists of a vector comprising characteristics of municipality i that affect the rate of its public spending growth.

Note that the reaction function $\phi(\cdot)$ only indicates that public spending growth in jurisdiction i depends on its socioeconomic characteristics and public spending decisions of its neighboring local governments, without explicitly imposing a structure for their spatial fiscal interdependence. Therefore, in order to correctly specify a functional form for equation (3.3), one must further comprehend how such fiscal interaction among jurisdictions can be accounted for as well as the driving forces behind the growth in public spending. Following the standard procedures of spatial data analysis, the influence of spatial spillovers across municipal boundaries is usually captured *via* spatially lagged variables, which are constructed based on a spatial weights matrix, W.[2] Yet, such proposition on spatial dependence can take on two major forms: (i) a spatial autoregressive process in the endogenous variable, which rests on the assumption that the rate of public spending growth at jurisdiction i is a function of the rate of public spending growth of its near-by jurisdictions; and (ii) a spatial cross-regressive process, in which spatially lagged values of neighboring jurisdictions' variables are also included as determinants of the rate of public spending growth at jurisdiction i (Anselin, 1988; LeSage and Pace, 2009). It should also be mentioned that spatial dependence may also arise from unobserved latent variables that are spatially correlated. Such third form of spatial dependence is usually referred as nuisance dependence, since it is reflected in the errors from different jurisdictions displaying spatial covariance (Anselin and Rey, 1991; Rey and Montouri, 1999).

By reason of fiscal decentralization, local budgetary decisions are mainly driven by economic performance, self-generating revenue and intergovernmental transfers (Tiebout, 1956; Gramlich and Galper, 1973; Case et al., 1993). From the so-called Wagner's Law, the positive

[2]Note that W is an $(n \times n)$ positive symmetric matrix, whose elements w_{ij} take values according to some preset rules of spatial relations among jurisdictions. For technical details on the different definitions of spatial weights matrices, see e.g. Haining (2003) and Anselin and Rey (2014).

association between the effective size of the public sector and economic dynamism has been extensively discussed in the economic literature (Gupta, 1967; Musgrave, 1969; Goffman and Mahar, 1971; Bird, 1971; Ganti and Kolluri, 1979; Abizadeh and Gray, 1985; Islam, 2001; Al-Faris, 2002; Loizides and Vamvoukas, 2005; Akitoby et al., 2006; Magazzino, 2012; Keho, 2015, among others). Also, based on the assertion that government budgets are a function of past economic performance and are capable of stimulating current output, Skidmore et al. (2004) argue that the rate of growth in current *per capita* public spending at a given location also depends on the levels of past *per capita* public spending. The importance of unconditional transfers from the central government to the local level has also been considerably addressed in the theory of fiscal federalism (Buchanan, 1950; Buchanan and Goetz, 1972; Boadway and Flatters, 1982). Despite being designed to address potential vertical and horizontal fiscal imbalances, these government transfers are usually perceived as one of the most important sources of local public revenue (Weingast, 2009; Vo, 2010; Bornhorst et al., 2018).

Hence, in order to account for spatial dependence and the aforementioned determinants of local public spending, equation (3.3) can be approximated by an econometric model, such as:

$$\begin{aligned} \ln\left(\frac{g_{i,t}}{g_{i,t-1}}\right) &= \alpha + \lambda W \ln\left(\frac{g_{j,t}}{g_{j,t-1}}\right) + \beta \ln(g_{i,t-1}) \\ &\quad + \delta W \ln(g_{j,t-1}) + \tau Z_i + \theta W Z_j + \varepsilon_{i,t} \end{aligned} \tag{3.4}$$

where Z_k is a vector comprising the *per capita* values of local income, self-generating revenue and intergovernmental transfers, in their natural logarithmic forms, with $k \in \{i, j\}$; and ε_i is the error term. Such functional form corresponds to the spatial Durbin model, which simultaneously controls for the potential existence of a spatial autoregressive process in the endogenous variable, a spatial cross-regressive process as well as spatially autocorrelated errors (LeSage and Pace, 2009). Also, note that $g_{i,t-1}$ enters equation (3.4) following the discussion outlined in Skidmore et al. (2004).

Given the premise of diminishing marginal utility in the consumption of publicly provided goods and services, β is expected to negative, which would imply that, *ceteris paribus*, low-spending jurisdictions are more prone to experience higher public spending growth than their high-spending counterparts (Skidmore et al., 2004). Such proposition is analogous to the "catch-up" hypothesis postulated in the seminal works of Baumol (1986) and Barro and Sala-i-Martin (1992) on income convergence. In fact, Scully (1991) provides a theoretical basis for the existence of an intertwined relationship between income convergence and fiscal regime convergence. By assuming that voter preferences are similar across regions and that factor endowments, which initially differ spatially, migrate to jurisdictions with higher marginal product, the author argues the resultant spatial convergence of the income distribution would ultimately lead to the spatial convergence of the level and pattern of government revenues and expenditures.

As equation (3.4) considers public spending growth rates at location i to be a function of a range of factors other than only its own initial public spending level, such functional form intrinsically assumes the validity of the conditional convergence hypothesis. Conversely, if absolute convergence were to hold, all jurisdictions would eventually converge to the same steady state, with equation (3.4) being reduced to the following unconditional model:

$$\ln\left(\frac{g_{i,t}}{g_{i,t-1}}\right) = \alpha + \beta \ln(g_{i,t-1}) + \varepsilon_{i,t} \tag{3.5}$$

Both equations (3.4) and (3.5) can be considered fiscal variants of the so-called β-convergence. While income β-convergence rests on the neoclassical assertion that poor economies grow faster than rich economies due to differentials in capital marginal product (Barro and Sala-i-Martin, 1992), β-convergence of public spending is mostly a byproduct of three phenomena: (i) a higher willingness to pay for additional government goods and services in economies with low levels of public spending; (ii) fiscal strategic interaction among neighboring jurisdictions; and (iii) the equalizing nature of intergovernmental transfers (Besley and Case, 1995; Skidmore et al., 2004). While the inclusion of both spatially lagged public spending growth and public spending level in equation (3.4) allows us to isolate the potential effects of fiscal strategic interaction on the convergence of local public spending, explicitly controlling for unconditional transfers from the central government to the local level may also provide empirical evidences on whether such horizontal equalization mechanism is contributing to the convergence process.

3.3 EXPLORATORY SPATIAL DATA ANALYSIS OF LOCAL PUBLIC SPENDING CONVERGENCE IN BRAZIL

In order to analyze the potential convergence in *per capita* public spending across Brazilian local governments, we use data for 5,558 municipalities over the period of 2013 to 2017.[3] In this study, local public spending is measured by municipal expenses in personnel.[4] The choice of such type of expenditure is due to two main reasons. First, personnel expenditure has been the most relevant component of total current expenditure across Brazilian municipalities over the last two decades. For instance, between 2013 and 2017, the municipal wage bill corresponded, on average, to 59.6% of total current expenditure. Second, in light of the fiscal constraints imposed by the Fiscal Responsibility Law (FRL), understanding the intricate temporal dynamics of local personnel expenditure may provide an alternative perspective on whether the evolution of such public expenses is consistent with the established guidelines for local public finance in Brazil.

As discussed in section 3.2, local fiscal decisions are assumed to be influenced by those of neighboring jurisdictions. A preliminary analysis of such phenomenon is usually carried out by means of the univariate Moran's I statistic.[5] Table 3.1 reports the obtained results for the natural log of real municipal *per capita* personnel expenditure from 2013 to 2017. Despite being rather time-invariant, statistically significant positive spatial autocorrelation is found for all years. This indicates that the distribution of *per capita* personnel expenditure is spatially clustered, so that municipalities with relatively high (low) *per capita* personnel expenditure are more likely to be surrounded by neighboring areas with high (low) *per capita* personnel expenditure than

[3]Even though there were 5,570 Brazilian municipalities in 2017, this paper grouped the ten new municipalities that were legally emancipated after 2005 with their respective municipalities of origin. Such aggregation was performed due to the lack of more recent polygonal shapefiles for Brazilian municipalities. In addition, two island municipalities (Ilhabela/SP and Fernando de Noronha/PE) were removed from the data set. Therefore, the final data set covers 5,558 Brazilian municipalities.

[4]Given the continental size of Brazil and its bureaucratic intricacies regarding municipal fiscal data, missing data were observed in the data set for total personnel expenditure, tax revenue and FPM grants. The common practice of removal of municipalities with missing values would impair the applicability of spatial econometric methods. Hence, in order to circumvent such restraint, data imputation was performed instead. For technical details on the data imputation procedure, see Appendix A.

[5]The univariate Moran's I statistic was initially proposed by Moran (1948) and is defined as the cross-product between a mean-centered variable and its spatial lag, that is, $I = (n/s_0)\left(\sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu) / \sum_i (x_i - \mu)^2\right)$, where n is the number of observations; x is the variable of interest; μ is the mean of x; w_{ij} is the ij-element of the spatial weights matrix with zeroes on the diagonal (i.e., $w_{ii} = 0$); and s_0 is the sum of all the weights (i.e., $s_0 = \sum_i \sum_j w_{ij}$). Note that $-1 \leq I \leq 1$, with $I = 1$ corresponding to perfect positive global spatial correlation and $I = -1$ suggesting perfect negative global spatial autocorrelation.

would be expected if the underlying spatial process was random. From a local public finance perspective, such positive spatial dependence is a first indication of spatial fiscal interaction among the Brazilian municipalities in terms of their expenses in personnel.

Table 3.1: Moran's I statistic for the natural log of real municipal *per capita* personnel expenditure

Year	I	E(I)	sd(I)	z-value	p-value
2013	0.087	-0.000	0.001	149.959	0.000
2014	0.090	-0.000	0.001	156.710	0.000
2015	0.103	-0.000	0.001	177.794	0.000
2016	0.099	-0.000	0.001	172.082	0.000
2017	0.111	-0.000	0.001	191.784	0.000

Notes: Moran's I test statistic was based on a two-tail test, with an inverse distance weights matrix. Pseudo p-*values were numerically estimated with 9,999 permutations.*

Yet, as global measures of spatial dependence only reflect the overall pattern of spatial data distribution, potential local nonstationarity is still to be accounted for. Figure 3.1 contain Moran scatterplots for the natural log of real municipal *per capita* personnel expenditure in 2013 (initial year) and 2017 (terminal year).[6] Visual inspection reveals that Brazilian municipalities are mostly concentrated in the upper-right and lower-left quadrants, which is consistent with the obtained positive Moran's I statistics for both years. Indeed, for the year 2017, 69.3% $(3,855)$ of all Brazilian municipalities were located in these latter two quadrants – an increase of 3.9 percentage points compared to the year 2013. Still, even though dominance of positive spatial dependence is observed, the presence of municipalities in the upper-left and lower-right quadrants also suggests the potential existence of spatial clusters with negative spatial autocorrelation in Brazil.

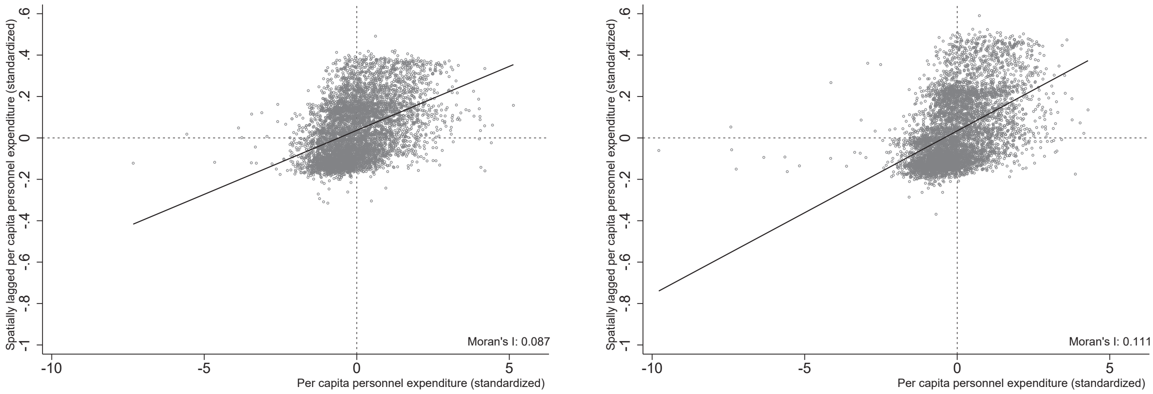
Local indicators of spatial association (LISA) are alternative procedures to Moran scatterplots. Proposed by Anselin (1995), local Moran's I statistics allow not only the identification and mapping of spatial clusters and spatial outliers but also the assessment of their statistical significance.[7] Figure 3.2 maps the obtained local Moran's I statistics for the natural log of real municipal *per capita* personnel expenditure in 2013 (initial year) and 2017 (terminal year).[8] As expected, among the Brazilian municipalities with a significant local Moran's I statistic, 71.8% (2,735) displayed positive spatial autocorrelation in 2013 compared to 75.2% (2,919)

[6]According to Anselin (1996), the Moran scatterplot is a bivariate scatterplot of a standardized spatially lagged variable (Wz) against the original standardized variable (z). Since $I = {}^{z'Wz}/_{z'z}$, the slope of the linear fit to the scatterplot is a direct estimate for Moran's I. The associated four quadrants in the scatterplot box depict different types of spatial dependence. While the upper-right quadrant represents association of high values (above the mean), association of low values (below the mean) is observed in the lower-left quadrant. Consequently, jurisdictions located in either of these two latter quadrants display positive spatial autocorrelation. Conversely, the upper-left and lower-right quadrants are associated with negative spatial autocorrelation, in the sense that low values are surrounded by high values and high values are surrounded by low values, respectively. Note that both Moran scatterplots in figure 3.1 were constructed using an inverse distance weights matrix.

[7]The local Moran's I statistic is defined as $I_i = \left({}^{n(x_i - \mu)}/_{\sum_i (x_i - \mu)^2}\right) \sum_j w_{ij}(x_j - \mu)$, where the summation over j is such that only neighboring values of $j \in J_i$ are considered; n is the number of observations; x is the variable of interest; μ is the mean of x; and w_{ij} is the ij-element of the spatial weights matrix with zeroes on the diagonal (i.e., $w_{ii} = 0$). Given that the sum of local Moran's I statistics is such that $I = {}^{\sum_i I_i}/_{s_0}$, with s_0 being the sum of all the weights (i.e., $s_0 = \sum_i \sum_j w_{ij}$), these local indicators implicitly reflect the contribution of the underlying process of spatial dependence at each location to the overall pattern of spatial association (Anselin, 1995).

[8]The obtained local Moran's I statistics are based on an inverse distance weights matrix. Also, statistical inference is performed under the assumption of total randomization, with 9,999 permutations, and a 5% pseudo-significance level.

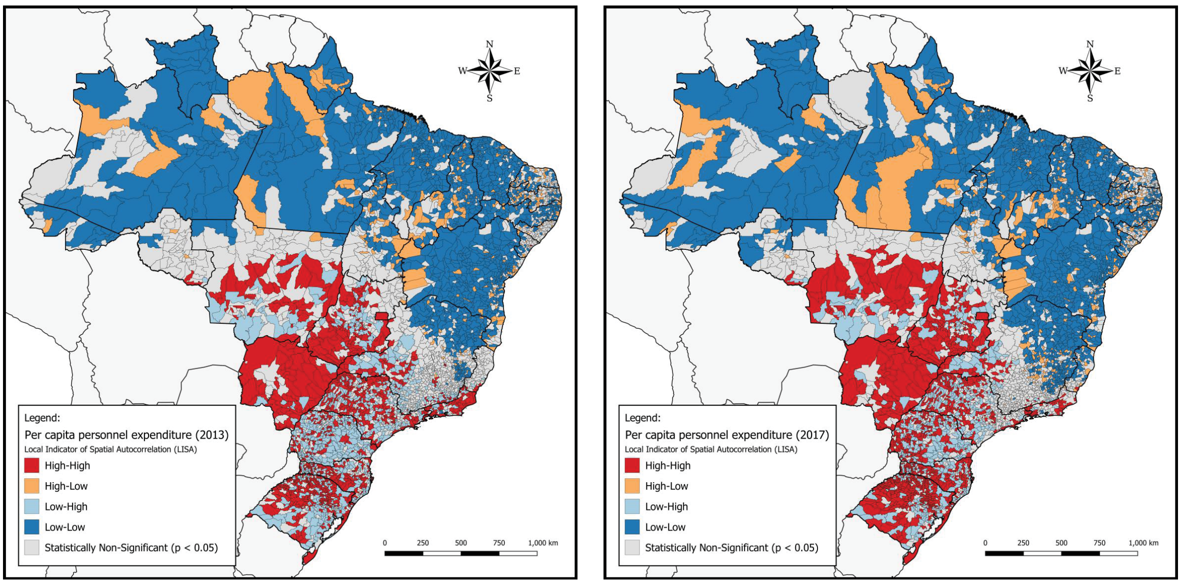
Figure 3.1: Moran scatterplots for the natural log of real municipal *per capita* personnel expenditure



(a) 2013 (initial year) (b) 2017 (terminal year)

in 2017. Despite the 3.4 percentage points increase during the period, the overall structure of spatial dependence remained rather stable. In fact, the distribution of spatial clusters follows a North-South polarization regime, in which high-spending municipalities with high-spending neighbors (i.e., high-high clusters) are concentrated in the Center-South region of Brazil whereas low-spending municipalities with low-spending neighbors (i.e., low-low clusters) are mostly found in the North and Northeast regions. Moreover, since 38.4% of all significant local Moran's *I* statistics, on average, refer to high-high clusters while 34.4% represent low-low clusters, no dominance of a specific form of positive spatial association seems to exist.

Figure 3.2: Local Moran's *I* statistics for the natural log of real municipal *per capita* personnel expenditure ($p < 0.05$)

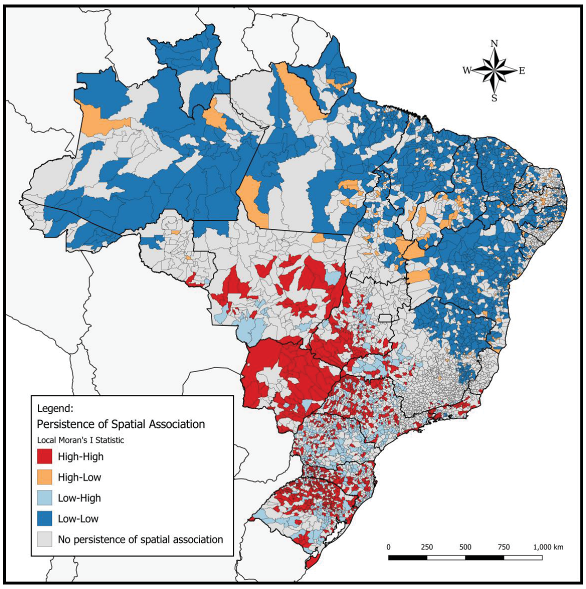


(a) 2013 (initial year) (b) 2017 (terminal year)

Deviations from the global trend are also present in both years. As high-high clusters are concentrated in the South-Central region of Brazil, statistically significant low-high outliers are mainly associated with these jurisdictions. Yet, such transitional regions of nonstationarity, in which low-spending municipalities are surrounded by high-spending municipalities, have decreased over the years. In particular, approximately 14.5% (561) of all significant local Moran's I statistics were low-high outliers in 2017, a decline of 4.8 percentage points in comparison to 2013. Conversely, high-spending municipalities surrounded by low-spending municipalities (i.e., high-low outliers) were mostly found in the North and Northeast regions. However, in contrast to the low-high outliers, the number of Brazilian local governments associated with the latter form of negative spatial autocorrelation increased during the period, going from 8.8% of all significant local Moran's I statistics in 2013 to 10.3% in 2017.

In terms of the persistence of spatial clusters in time, Figure 3.3 presents the Brazilian municipalities in which the form of spatial clustering remained unaltered throughout the whole period.[9] Four strong regional clusters are identified.[10] The first is the Northeast cluster of low-spending municipalities comprising most of the northeastern local governments and those in the north of Minas Gerais. The second is the Amazonian cluster which also consists of Brazilian municipalities with relatively low levels of *per capita* personnel spending. The third cluster, located in the south of the Central-West region, is characterized as a group of high-spending prefectures. Finally, the fourth and rather less evident cluster is the high-high one in the region comprising the north of Rio Grande do Sul and northwest of Santa Catarina. Yet, even though these clusters are regionally located, the North-South polarization regime shown in Figure 3.2 also seems to have persisted over time.

Figure 3.3: Persistence of spatial association in Brazil



While these results provide an overall understanding of the underlying process of spatial dependence, still no conclusion can be drawn with regard to the evolution of municipal *per capita* personnel expenditure across Brazil. In fact, the univariate Moran's I statistic associated with the growth rates between 2013–2017 reveals positive spatial autocorrelation ($I = 0.041$ with $p < 0.001$). In the context of spatial fiscal interactions, this finding suggests that the wage bill of

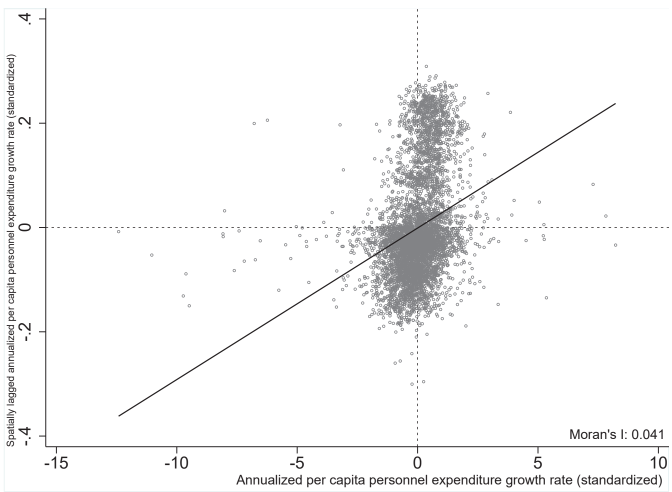
[9]In order to construct Figure 3.3, we performed a two-step procedure. First, we calculated and evaluated the statistical significance of local Moran's I statistics for each year as to classify each municipality according to its form of spatial association. Then, we identified those locations in which the spatial clustering process remained unaltered and statistically significant throughout the whole period.

[10]Note that spatial outliers also persisted across time, particularly those of high-low form in the states of São Paulo and Paraná.

municipalities located near each other evolve rather similarly over time, which is a preliminary indication that Brazilian local governments behave strategically regarding their expenses.

The Moran scatterplot for the annualized growth rates in Figure 3.4 illustrates two general points. First, compared to the Moran scatterplots for the *per capita* personnel expenditure in 2013 and 2017, relatively more spatial instability is found: only 63.2% (3, 513) of Brazilian municipalities exhibit spatial association of similar values. Given that 39.5% (2, 198) of all local governments are situated in the lower-left quadrant of Figure 3.4 in contrast to 23.6% (1, 315) in the upper-right quadrant, the estimated global positive trend appears to be dominated by the low-low form of spatial clustering. Second, despite the positive Moran's I statistic, the presence of municipalities with high growth rates surrounded by neighbors with low growth rates (i.e., high-low outliers) is rather substantial: 27.7% (1, 539). Nonetheless, their influence on the latter global indicator of spatial association is mitigated due to only 9.1% (506) of Brazilian prefectures being located in the upper-left quadrant of Figure 3.4.

Figure 3.4: Moran scatterplot for the annualized growth rate of real municipal *per capita* personnel expenditure (2013–2017)



The classification in Figure 3.4 also allows a better understanding of the regional growth process of personnel expenditure and its potential implications for convergence. For instance, the Southeast region of Brazil appears to be compatible with a "core-periphery" spatial pattern. More specifically, as 63.9% (1, 065) of all southeastern municipalities belong to the lower-left quadrant of Figure 3.4 (low-low spatial clustering) and 31.4% (524) are in the lower-right quadrant (high-low spatial clustering), the region is characterized by "core" zones in which municipal expenses in personnel have systematically grown above the national average (1.74% per annum) and wider "periphery" zones of relatively low growth. When compared to the pattern of spatial association in the initial level of personnel expenditure in Figure 3.1(a), 74.1% (628) of the southeastern municipalities with high-high or high-low forms of spatial clustering in 2013 displayed growth rates below the national average. Further, among those local governments with relatively low initial spending, 40.9% (335) increased their expenses in personnel at a rate superior to the national average while low-spending levels persisted for 58% (475) due to their growth rates remaining below average. Interestingly, the North and Northeast regions of Brazil also have rather similar results. Besides the distribution of personnel expenditure growth rates being relatively even between high-low and low-low forms of clustering in both regions, these local governments are mostly associated with low spending values in 2013. Although these findings represent a preliminary evidence in favor of the validity of the β-convergence hypothesis in these regions, confirmatory analyses are still required for a definite conclusion.

However, in contrast to the latter results, the Central-West and South regions are mainly typified as zones of persistent above-average levels of *per capita* personnel expenditure. As shown in Figure 3.3, strong high-high clusters remained statistically significant in these regions throughout the whole sample period. In the particular case of the Central-West, 63.9% (296) of all municipalities had initial personnel expenditure levels above average. Among these, while 53.7% (159) were local governments that not only had relatively high expenditure growth rates but were also surrounded by high-growing neighbors, 36.1% (107) corresponded to low-growing municipalities associated with high-growing neighboring jurisdictions. This finding suggests the strengthening of "core" high-spending clusters concomitant with the weakening of surrounding clusters of also high-high spatial association, especially in the state of Mato Grosso do Sul. Moreover, as local governments with low initial levels of expenses in personnel and above-average growth rates are only 25.7% (119) of all municipalities in the region, the coexistence of such opposing trends raises serious questions regarding the nature of the convergence process in the region.

The South region is also emblematic. The first thing to note is that the southern municipalities have considerably increased their wage bill at rates superior to the national average. More specifically, over 78% (935) of all southern local governments had high expenditure growth rates while also being surrounded by neighbors with high growth rates (i.e., falling in upper-right quadrant of Figure 3.4).[11] Such relatively high growth reflects two cumulative phenomena: (i) the strengthening of high-spending clusters along with the emergence of new ones; and (ii) the substantial personnel expenditure increase in municipalities with below-average levels. In fact, while the number of high-high cluster had a net increase of 18.8% (from 682 to 810) during the period, low-high clusters decreased 25.3% (from 506 to 378). Such decline in the number of municipalities with low-spending levels could thus suggest a pattern of regional convergence. Still, since 97.4% (664) of high-high clusters in 2013 remained with the same form of spatial association in 2017, the associated above-average growth rates indicate that these local governments in fact deviated even further from the rest of the region. In the context of this rather diverse spatial association setting, confirmatory spatial data analyses are therefore required as to statistically assess the convergence trend in the region.

3.4 CONFIRMATORY SPATIAL DATA ANALYSIS OF LOCAL PUBLIC SPENDING CONVERGENCE IN BRAZIL

Even though exploratory spatial data analysis provided an overall understanding of spatial association patterns and potential implications for personnel expenditure convergence across the Brazilian municipalities, formal econometric testing of β-convergence is still required for a definite conclusion.

As a preliminary assessment of the validity of both absolute and conditional convergence hypotheses, standard OLS regression models are estimated and their results are presented in Table 3.2. Regression (1) is analogous to equation (3.5) and allows the evaluation of the absolute β-convergence hypothesis by conditioning the annualized growth in municipal *per capita* personnel expenditure over the period 2013-2017 only on the initial levels of municipal *per capita* personnel expenditure. Given that the respective obtained coefficient is negative

[11] When considering only the states of Paraná and Rio Grande do Sul, the proportion of municipalities associated with such high-high form of spatial clustering increases to 83.4% (746).

($\beta = -0.022$) and highly significant ($p < 0.01$), there is strong statistical evidence in favor of an absolute convergence process.

Conditioning the local rates of growth in personnel expenditure on other factors that influence budgetary decisions further confirmed the existence of a convergence process across the Brazilian municipalities. More specifically, regression (2) in Table 3.2 expands the latter model by also considering the initial levels of *per capita* tax revenue, *per capita* FPM grants, *per capita* GDP and the shares of population under 14 years old and over 65 years old.[12] Several conclusions can be drawn from the estimated coefficients. First, the parameter associated with the initial *per capita* personnel expenditure implies a faster rate of convergence, *ceteris paribus*, in comparison to the estimate from regression (1). Second, despite fairly low, the positive relationship between expenditure growth and initial tax revenue suggests that municipalities with relatively less restricted tax bases tend to increase their wage bill at a superior rate than those with lower self-generating revenues. Third, the initial level of *per capita* FPM grants is also positively correlated with personnel expenditure growth. Such result is in line with Alves and Araujo (2021), which showed that increases in FPM grants have induced higher local public expenditure on general administration in Brazil. Fourth, the positive and statistically significant coefficient of *per capita* GDP shows that municipalities economically more dynamic had higher expenditure growth than those with relatively lower dynamism. Finally, as young and elderly populations have a particularly higher demand for locally provided public services, the positive estimates for both demographic variables reflect the increasing costs related to these services in municipalities with greater shares of these age groups.

The analysis of spatial dependence among the residuals of both OLS models is performed by means of a Moran's I test as well as (robust) Lagrange multiplier (LM) tests.[13] The obtained results point to the presence of both spatial lag and spatial error structures in regressions (1) and (2). Hence, the respective estimated coefficients are potentially biased and inconsistent due to model misspecification.

In order to properly account for spatial dependence, we follow a two-step mixed model selection strategy similar to the one outlined in Elhorst (2014b) in which both specific-to-general and general-to-specific selection approaches are considered. The first (specific-to-general) step consists of estimating SAR, SEM and SARAR models and performing linear Wald tests as to evaluate the statistical significance of the respective spatial coefficients. More specifically, consider the spatial cross-section model given by

[12]Note that the demographic variables are included as to take into account the potential indirect effects of the age structure on the provision of publicly provided goods and services.

[13]The Moran's I test for spatial autocorrelation in the residuals is analogous to the standard statistic developed by Moran (1948). In matrix notation, the Moran's I statistic is given by $I = [({}^{n}/_{s_0})({}^{e'We}/_{e'e})]$, with e as a vector of OLS residuals and $s_0 = \sum_i \sum_j w_{ij}$, which corresponds to a standardization factor comprising the sum of all nonzero cross-products of the spatial weights. While the Moran's I test detects the misspecification of the estimated model, it does not suggest which alternative specification is favored by the data. On the other hand, despite only requiring the estimation of the model under the null hypothesis, the Lagrange multiplier (LM) tests are designed as to indicate the source of spatial dependence in the OLS residuals. Originally proposed by Burridge (1980), the LM test against a spatial error alternative is defined as $\text{LM}_{error} = [{}^{e'We}/_{(e'e/n)}]^2/[\text{tr}(W^2 + W'W)]$, where LM_{error} follows an asymptotic χ^2 distribution with one degree of freedom. Developed by Anselin (1988), the LM test against a spatial lag alternative is obtained by $\text{LM}_{lag} = [{}^{e'Wy}/_{(e'e/n)}]^2/D$, with $D = [(WX\beta)'(I - X(X'X)^{-1}X')(WX\beta)/\sigma^2] + \text{tr}(W^2 + W'W)$. Note that LM_{lag} also follows an asymptotic χ^2 distribution with one degree of freedom. According to Anselin (2001), as these tests have power against the other alternative, extended formulations with an asymptotic adjustment were constructed as to be robust to the presence of local misspecification of the other respective form of spatial dependence (Anselin et al., 1996). Yet, robust LM_{error} and robust LM_{lag} statistics are only to be considered if both their standard counterparts reject the null hypotheses.

Table 3.2: Estimation results from OLS regression models

Determinants	(1)	(2)
Constant	0.175*	0.059**
	(16.55)	(2.17)
ln(Initial *per capita* personnel expenditure)	−0.022*	−0.064*
	(−14.94)	(−28.99)
ln(Initial *per capita* tax revenue)		0.003*
		(2.81)
ln(Initial *per capita* FPM grants)		0.024*
		(18.92)
ln(Initial *per capita* GDP)		0.019*
		(15.24)
ln(Initial share of population under 14 years old)		0.013**
		(2.49)
ln(Initial share of population over 65 years old)		0.010*
		(3.82)
Goodness of fit		
Root MSE	0.039	0.037
R^2	0.038	0.149
Log-likelihood	10,033.75	10,372.74
Akaike Information Criterion (AIC)	$-20,063.5$	$-20,731.48$
Bayesian Information Criterion (BIC)	$-20,050.25$	$-20,685.12$
Regression diagnostics for spatial correlation among the residuals		
Moran's *I* test	0.158*	0.116*
LM_{lag} test	298.49*	147.31*
Robust LM_{lag} test	134.53*	17.19*
LM_{error} test	388.29*	211.35*
Robust LM_{error} test	224.33*	81.22*

Notes: t-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Compiled by the author.

$$
\begin{aligned}
y_n &= \lambda W y_n + X_n\beta + u_n \\
u_n &= \rho M u_n + v_n
\end{aligned}
\tag{3.6}
$$

where y_n is an $(n \times 1)$ vector of observations on the dependent variable; X_n is an $(n \times n)$ matrix of observations on the nonstochastic exogenous regressors; W is an $(n \times n)$ spatial weights matrix associated with y_n; M is an $(n \times n)$ spatial weights matrix for the disturbances; u_n is an $(n \times 1)$ vector of spatially lagged disturbances; and λ and ρ are the parameters representing the spatial dependence on y_n and u_n, respectively.[14] Note that equation (3.6) corresponds to the SARAR model, which nests both SAR and SEM specifications. Therefore, such specific-to-general selection procedure evaluates the (joint) significance of λ and ρ. In the occurrence of a non-spatial model being rejected in favor of any spatial counterpart, we proceed to the next step.

The second (general-to-specific) step considers the spatial Durbin model (SDM) and tests whether it can be simplified to the SAR model and/or the SEM specification (Burridge, 1981). Particularly, as the SDM nests both these models, Wald tests can be performed as to evaluate the exclusion of the respective spatial structures (LeSage and Pace, 2009; Elhorst, 2010). Since the SDM specification is described as

$$
y_n = \lambda W y_n + X_n\beta + W X_n\delta + v_n \tag{3.7}
$$

with $WX_n\delta$ being an $(n \times n)$ matrix of spatially lagged exogenous covariates, we test whether the hypotheses $\mathrm{H}_0 : \delta = 0$ and/or $\mathrm{H}_0 : \delta + \lambda\beta = 0$ can be statistically rejected. While failing to reject the former would imply that a SAR model should be estimated, failing to reject the latter suggests the SEM is favored by the data. Consequently, the SDM is considered to be the appropriate spatial specification when both hypotheses are rejected (Elhorst, 2014b).

As the absolute β-convergence hypothesis is rather restrictive since it implicitly considers all Brazilian municipalities would eventually converge to the same steady-state level, we only consider its conditional form hereafter. Model estimation is based on a quasi-maximum likelihood (QML) procedure with robust standard errors.[15] Results from the spatial cross-section models are provided in Table 3.3. Following the specific-to-general model selection step, we analyze the estimated spatial coefficients for the SAR, SEM and SARAR models. Overall, both spatial lag and spatial error coefficients in the SAR and SEM specifications are individually significant at the 1% significance level, respectively. Moreover, regarding the SARAR model, the null hypothesis of $\mathrm{H}_0 : \lambda = \rho = 0$ is also rejected ($W_{LT} = 370.92$, 2 *df*, $p < 0.01$), corroborating the latter results as well as those from the (robust) Lagrange multiplier tests in Table 3.2. Thus, these finding point to the data-generating process being better described by a cross-section regression model with both spatial interaction effects.

From the general-to-specific perspective, we proceed to testing the SDM specification. First, the linear Wald test for the joint significance of the spatially lagged covariates ($W_{LT} = 90.53$, 6 *df*, $p < 0.01$) rejects the null hypothesis of $\mathrm{H}_0 : \delta = 0$. Therefore, there is no statistical evidence to support that the SDM specification can be simplified to a SAR model. The comparison of the SDM and SEM models yields similar results. Based on a nonlinear Wald test, the null hypothesis of $\mathrm{H}_0 : \delta + \lambda\beta = 0$ is rejected at the 1% level ($W_{LT} = 44.25$, 6 *df*, $p < 0.01$), which suggests that the SDM is model specification favored by the data. Note that SDM and SARAR models can

[14]In practice, W and M need not necessarily be different from each other.

[15]The QML estimator is the extremum estimator derived from the maximization of the associated concentrated log-likelihood function of a spatial regression model. Standard errors are estimated considering the possibility of non-normally distributed innovations. For further technical details, refer to Lee (2004).

Table 3.3: Estimation results from the spatial cross-section models

Determinants	(1) SAR	(2) SEM	(3) SARAR	(4) SDM
Main structure				
Constant	0.065**	0.087*	0.114*	0.057**
	(2.41)	(3.01)	(3.82)	(2.10)
ln(Initial *per capita* personnel expenditure)	–0.061*	–0.067*	–0.069*	–0.070*
	(–27.28)	(–29.07)	(–29.06)	(–28.42)
ln(Initial *per capita* tax revenue)	0.002*	0.003*	0.004*	0.004*
	(2.84)	(3.58)	(4.09)	(3.96)
ln(Initial *per capita* FPM grants)	0.023*	0.025*	0.024*	0.026*
	(18.08)	(18.40)	(17.20)	(17.31)
ln(Initial *per capita* GDP)	0.017*	0.018*	0.017*	0.018*
	(13.82)	(13.70)	(13.12)	(12.79)
ln(Initial share of population under 14 years old)	0.012**	0.011**	0.007	0.018*
	(2.38)	(1.97)	(1.23)	(3.11)
ln(Initial share of population over 65 years old)	0.009*	0.011*	0.14*	0.018*
	(3.37)	(3.87)	(4.58)	(5.83)
Spatial structure				
λ	0.241*		–0.428*	0.298*
	(10.38)		(–6.17)	(11.88)
ρ		0.316*	0.626*	
		(12.67)	(13.11)	
W × ln(Initial *per capita* personnel expenditure)				0.041*
				(8.28)
W × ln(Initial *per capita* tax revenue)				–0.007*
				(–3.35)
W × ln(Initial *per capita* FPM grants)				–0.013*
				(–4.69)
W × ln(Initial *per capita* GDP)				–0.004
				(–1.44)
W × ln(Initial share of population under 14 years old)				–0.028*
				(–5.39)
W × ln(Initial share of population over 65 years old)				–0.024*
				(–5.90)
Goodness of fit				
Pseudo-R^2	0.1412	0.1485	0.1487	0.1569
Log-Likelihood	10,426.4	10,453.8	10,471.8	10,474.3
Akaike Information Criterion (AIC)	-20,834.7	-20,889.5	-20,913.6	-20,928.7
Bayesian Information Criterion (BIC)	-20,775.1	-20,829.9	-20,814.2	-20,862.4

Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Results are based on quasi-maximum likelihood estimation. Spatial weights are defined as the inverse arc-distance between polygon centroids. Robust standard errors are computed following Lee (2004). Compiled by the author.

not be directly compared as they are non-nested. Yet, according to both Akaike and Bayesian information criteria, the SDM overperforms the SARAR model.

As both model selection steps indicate the SDM as the appropriate specification given the data, we also formally evaluate whether the spatial correlation structure is properly captured by the chosen model. Given that the global Moran's I statistic for the SDM residuals is 0.0004 [$E(I) = -0.0002$, $SD(I) = 0.0006$, $Z = 0.9835$] with a pseudo p-value of 0.3254, based on 9,999 permutations.[16] Since the null hypothesis of randomly distributed residuals is not rejected at the 0.01 level of significance, there is statistical evidence of the SDM model properly capturing the inherent spatial correlation in the data.

As discussed in LeSage and Pace (2009), relying on point estimates from spatial Durbin models might induce misleading conclusions as spatial feedback mechanisms are not taken into account. Indeed, in the presence of spatially lagged endogenous and/or exogenous variables, shocks in independent variables associated with location i would affect not only the location itself (i.e., direct effect) but potentially also its neighboring locations (i.e., indirect – or spillover – effect). In this sense, the estimated cumulative impacts from the SDM model provided in Table 3.4 illustrate several points. First, the direct effects of all variables are statistically significant at the 1% level of significance and are marginally lower than the point estimates of the non-spatially lagged variables (Table 3.3) due to inherent feedback effects. Yet, only the total effects of initial *per capita* personnel expenditure, FPM grants and GDP are statistically different from zero. More specifically, even though the direct and indirect effects of initial *per capita* tax revenue and the shares of population under 14 years old and over 65 years old are significant, their feedback interaction results in non-significant total effects.

Second, the negative total effect of initial *per capita* personnel expenditure confirms the conditional convergence hypothesis for municipal personnel expenditure across Brazil (Table 3.4). Still, such estimate is higher than the direct effect given the presence of a positive indirect effect. In other words, while a "catching-up" process is directly observed, Brazilian municipalities neighboring those with higher initial expenses in personnel tend to have higher expense growth rates. Such result further indicates that low-high and high-high clusters of initial personnel expenditure (Figure 3.2(a)) have increased their wage bill faster than their high-low and low-low counterparts.

Table 3.4: Cumulative impacts from the SDM model

Determinants	Effect		
	Direct	Indirect	Total
ln(Initial *per capita* personnel expenditure)	-0.0693^{*}	0.0215^{*}	-0.0478^{*}
ln(Initial *per capita* tax revenue)	0.0036^{*}	-0.0065^{*}	-0.0029
ln(Initial *per capita* FPM grants)	0.0261^{*}	-0.0054^{**}	0.0207^{*}
ln(Initial *per capita* GDP)	0.0178^{*}	0.0017	0.0195^{*}
ln(Initial share of population under 14 years old)	0.0173^{*}	-0.0243^{*}	-0.0070
ln(Initial share of population over 65 years old)	0.0172^{*}	-0.0205^{*}	-0.0033

Notes: The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. By definition, the total effect corresponds to the sum of both direct and indirect effects. The estimated variance of the impacts is calculated according to the Delta method. Estimation results based on an inverse distance spatial weights matrix. Compiled by the author.

[16] Moran's I test statistic was based on a two-tail test with an inverse distance weights matrix.

Third, while the total effect of initial *per capita* tax revenue is statistically non-significant, analyzing the direct and indirect effects provide interesting conclusions (Table 3.4). The positive direct effect implies that municipalities with higher tax revenues tend to increase their expenses in personnel at rates superior to those with lower tax revenues. The respective negative indirect effect reflects the potential free rider behavior of Brazilian municipal policymakers: in the presence of neighboring locations with comparatively higher initial tax revenues, local governments increase the wage bill at a rather lower rate due to the cross-border benefits of public provided goods and services. Similar conclusions are obtained from the estimates for initial *per capita* FPM grants, despite the total effect being positive and statically significant at the 1% significance level (Table 3.4).

Fourth, the positive direct effect of initial *per capita* GDP shows that local governments with relatively higher economic dynamism tend to have higher personnel expenditure growth rates (Table 3.4). In terms of the median voter framework, such finding is plausible as economically more dynamic municipalities ultimately reflect higher demand pressures on the provision of public goods and services. Note that, even though the total effect is also positive and significant at the 1% significance level, the indirect effect is found to be statistically non-significant.

Finally, the results for the shares of population under 14 years old and over 65 years old are rather similar: while the positive direct effects reflect the higher demand of young and elderly populations in terms of locally provided public goods and services, the negative indirect effects reinforce the evidences of local policymakers' opportunistic behavior. Note that both aforementioned effects are statistically significant at the 1% significance level despite total effect not being statistically different from zero.

Local public spending convergence within the Brazilian macro-regions

As discussed in Section 3.3, Brazilian municipalities within different macro-regions might have shown different (conditional) convergence processes. Therefore, we econometrically assess such proposition by estimating spatial Durbin models for each of the five Brazilian macro-regions. The estimated direct, indirect and total effects of the initial *per capita* personnel expenditure from these models are presented in Table 3.5.[17]

Apart from the North region, the estimated total effects for the macro-regions are negative and statically significant at the 1% significance level. These findings indicate that municipal *per capita* personnel expenditure has β-converged within each Brazilian macro-region during the period. However, such regional convergence process has not been homogeneous. More specifically, in comparative terms, the Southeast region has shown the slowest speed of convergence (Total effect = −0.0337) whereas the Central-West region has been the fastest one (Total effect = −0.0764). Note that only the South region (Total effect = −0.0608) and Central-West region have converged at a faster pace than the estimated speed for Brazil as a whole (Total effect = −0.0478). Also, the estimated macro-regional speed of convergence can also be divided into two groups based on their similarity: a first group comprising the North, Northeast and Southeast regions and a second group with the South and Central-West regions. This result is in line with the exploratory spatial data analysis in Section 3.3, which provided preliminary evidence of the convergence processes within these groups being rather similar. In the particular case of the second group, the relatively high total effects reflect the high-growing rates of initially low-spending municipalities.

[17] The estimated coefficients of the five macro-regional SDM models are presented in Table B.2 to Table B.6 in Appendix B.

Table 3.5: Cumulative impacts of the natural log of initial *per capita* personnel expenditure from macro-regional SDM models

Brazilian macro-regions	Effect		
	Direct	Indirect	Total
North region	–0.0680*	0.0202	–0.0478**
Northeast region	–0.0947*	0.0487*	–0.0460*
Southeast region	–0.0522*	0.0184*	–0.0337*
South region	–0.0556*	–0.0052	–0.0608*
Central-West region	–0.0990*	0.0226	–0.0764*
Brazil	–0.0693*	0.0215*	–0.0478*

Notes: The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. By definition, the total effect corresponds to the sum of both direct and indirect effects. The estimated variance of the impacts is calculated according to the Delta method. Estimation results based on an inverse distance spatial weights matrix. Compiled by the author.

Yet, a closer look at the direct and indirect effects reveal further intrinsic convergence mechanisms. For instance, the Northeast region is an interesting case. Given that the estimated negative direct effect for the northeastern municipalities is the second highest one, in the absence of neighboring effects, these local governments would have presented the second fastest convergence process among the five Brazilian macro-regions. However, as the respective positive indirect effect for the region is the highest one, such finding suggests the spatial interaction among these municipalities has effectively weakened the latter inherent convergence process. In contrast, indirect effects are only statistically significant for the Northeast and Southeast regions, which indicates the potential absence of fiscal strategic interaction among neighboring jurisdictions in the North, South and Central-West regions regarding the budgetary planning of their expenses in personnel.

3.5 CONCLUSION

This chapter evaluated the hypothesis of local public spending convergence across the Brazilian municipalities in the presence of potential fiscal interaction among neighboring jurisdictions during the period 2013-2017. To this end, we first analyzed potential spatial autocorrelation processes by means of exploratory spatial data analysis (ESDA) and provide preliminary evidence on the validity of the β-convergence hypothesis. In a second step, we estimated cross-sectional spatial models in which spatial dependence is taken into account by considering – either implicitly or explicitly – the existence of a spatial autoregressive process in the endogenous variable, a spatial cross-regressive process and spatial autocorrelated disturbances.

The obtained results from ESDA show that municipal *per capita* personnel expenditure is spatially autocorrelated in Brazil, with distinctive macro-regional clustering processes. In fact, four strong regional clusters persisted over time: low-low clusters in the Northeast and Amazonian regions as well as high-high clusters in the Central-West and South regions. Further, based on the Moran scatterplot for the annualized growth rates of real municipal *per capita* personnel expenditure, positive autocorrelation was observed with such trend being dominated by the low-low form of spatial clustering. Yet, a closer look at the spatial autocorrelation process of such growth rates revealed potential macro-regional differences in terms of β-convergence. More specifically, besides the “core-periphery” spatial pattern observed in the North, Northeast and Southeast regions, with the distribution of personnel expenditure growth rates being relatively even between high-low and low-low forms of clustering, the local governments within these regions were mostly associated with low spending values in 2013 (initial year). As for the Central-West and South regions, even though preliminary evidence of β-convergence was also observed, their respective municipal wage bills have considerably increased at rates superior to the national average.

In terms of confirmatory spatial data analysis, the spatial Durbin model was chosen as the best econometric representation of the underlying data generating process. In this sense, the potential effects of spatial fiscal interactions on the convergence process were explicitly considered by also controlling for both spatially lagged exogenous and endogenous variables. The obtained estimates confirmed the occurrence of a conditional β-convergence process during the period. Moreover, we also found evidence of free riding behavior from local policymakers regarding the effects of tax revenue and FPM grants. At the macro-regional level, while expenses in personnel have converged in all regions, the speed of convergence was not homogeneous. Particularly, the Southeast region has shown the slowest speed of convergence whereas the Central-West region has been the fastest one. The macro-regions are also divided into two groups based on the similarity of their speed of convergence: a first group comprising the North, Northeast and Southeast regions and a second group with the South and Central-West regions. Finally, by decomposing the total effect into direct and indirect effects, we also observed that fiscal strategic interaction was an important factor in weakening the inherent convergence process of municipal *per capita* personnel expenditure in the Northeast and Southeast regions.

Overall, this chapter provides empirical evidence of local public spending convergence across Brazil while also underscoring the importance of considering the potential effects of spatial fiscal interaction among neighboring jurisdictions. Given the fiscal commitment to the Fiscal Responsibility Law (FRL), understanding the evolution of municipal personnel expenditure is pivotal in the design of local fiscal policy, specially in terms of local budgetary reforms. Hence, even though conditional convergence is observed, the rather fast growth of the Brazilian municipal wage bill, mainly in the Central-West and South regions, raises serious concerns as to whether the FRL constraints have been effectively binding. Future research aims to further analyze the regional specific aspects of such convergence processes as well as better evaluate the macro-regional effectiveness of the FRL in Brazil.

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APPENDIX A – DATA IMPUTATION PROCEDURE

In order to obtain a balanced spatial panel for all the 5,558 Brazilian municipalities considered in this study, missing data in the data set for (i) personnel expenditure, (ii) FPM grants and (iii) tax revenue were imputed through a two-step mean imputation. In the first step, each Brazilian municipality was classified according to its population size. In the second step, state means for each variable of interest were computed according to each population size class. Missing values within each state were finally imputed based on the latter conditional means. This imputation procedure was repeated for each year. Table A.1 presents the population size classes and, for illustration, the distribution of the number of municipalities and their estimated resident population within each these classes in 2017.

Table A.1: Number of Brazilian municipalities and estimated resident population, according to each population size class – 2017

Population Size Class	Number of Municipalities		Estimated Resident Population	
	Total	%	Total	%
Brazil	*5558*	*100*	*207,750,123*	*100*
Less than 5,000	1231	22.15	4,173,179	2.01
From 5,001 to 10,000	1210	21.77	8,626,799	4.15
From 10,001 to 20,000	1350	24.29	19,351,025	9.32
From 20,001 to 50,000	1102	19.83	33,493,023	16.12
From 50,001 to 100,000	355	6.39	24,658,771	11.87
From 100,001 to 500,000	268	4.82	54,622,975	26.29
More than 500,000	42	0.75	62,824,351	30.24

Sources: FINBRA/STN and IBGE. Compiled by the author.

Table A.2 reports the number of imputed data by year and their relative importance in percentage terms. Considering 5,558 cross-sectional observations over 5 years, the full data set is comprised of 27,790 observations for each variable. Considering each year, the amount of missing data ranges from 3.6% (200 observations) to 15.6% (869 observations). Note that both FPM grants and tax revenue had the same amount of imputed values. Indeed, both fiscal measures presented missing data for the same municipalities in each year. Such occurrence is due to the fact the two fiscal measures are subcategories of the total budgetary revenue, for which information was also missing. Yet, when all three variables are jointly considered (83,370 observations), the amount of missing data imputed corresponds to 10.8% (8,959 observations) of the full data set.

In order to evaluate whether the imputation procedure has altered the data distribution, we performed two-sample Kolmogorov-Smirnov tests of the equality of distributions.[1] More specifically, we compared the before- and after-imputation distributions of all three local fiscal

[1]According to (Conover, 1999), given the null hypothesis of equal distributions between two sample groups, the Kolmogorov-Smirnov test is based on the following statistics:

$$D = \max\Big(|D^{+}|, |D^{-}|\Big)$$

in which D is the combined K-S statistic; $D^{+} = \max_x \Big\{F(x) - G(x)\Big\}$; $D^{-} = \min_x \{F(x) - G(x)\}$; and $F(x)$ and $G(x)$ are the empirical distribution functions being compared. Let m and n be the sample sizes for the first and

Table A.2: Missing data in level and percentage terms

Variable	2013	2014	2015	2016	2017	Total
Personnel expenditure	200	470	378	597	582	2227
	(3.6)	(8.5)	(6.8)	(10.7)	(10.5)	(8.0)
FPM grants	366	740	599	869	792	3366
	(6.6)	(13.3)	(10.8)	(15.6)	(14.3)	(12.1)
Tax revenue	366	740	599	869	792	3366
	(6.6)	(13.3)	(10.8)	(15.6)	(14.3)	(12.1)
Total	932	1950	1576	2335	2166	8959
	(5.6)	(11.7)	(9.4)	(14.0)	(13.0)	(10.8)

Notes: Percentage values are in parentheses. Compiled by the author.

variable for each year as to properly identify potential biases to both their mean and variance due to the imputation procedure. Table A.3 provides the combined K-S statistics and the associated p-values. Due to all p-values being higher than the 0.1 significance level, there is statistical evidence on the imputation procedure not effectively altering the distribution of our data since we cannot reject the null hypothesis of equal distributions between the two sample groups. As robustness checks, we also performed standard two-sample t-tests for equality of means and two-sample robust tests for equality of variances (Tables A.4 and A.5). The obtained results corroborated those from the Kolmogorov-Smirnov test.

Table A.3: Two-sample Kolmogorov-Smirnov test of the equality of distributions

Year	Personnel expenditure		FPM grants		Tax revenue	
	D	p-value	D	p-value	D	p-value
2013	0.0022	0.9999	0.0026	0.9999	0.0025	0.9999
2014	0.0072	0.9992	0.0084	0.9914	0.0142	0.6544
2015	0.0035	0.9999	0.0047	0.9999	0.0035	0.9999
2016	0.0062	0.9999	0.0052	0.9999	0.0057	0.9999
2017	0.0025	0.9999	0.0040	0.9999	0.0024	0.9999

Notes: By definition, the Kolmogorv-Smirnov test is based on the null hypothesis of equal distributions between two sample groups. Also, “D” refers to the combined K-S statistic. Compiled by the author.

second sample, respectively, therefore the associated p-value is obtained by evaluating the asymptotic limiting distribution, so that:

$$\lim_{m,n\to\infty} \Pr\left\{\sqrt{\frac{mn}{(m+n)}}D_{m,n} \leq z\right\} = 1 - 2\sum_{i=1}^{\infty}(-1)^{i-1}\exp(-2i^2z^2).$$

Table A.4: Two-sample t-tests for equality of means (p-values)

Year	Personnel expenditure	FPM grants	Tax revenue
2013	0.9674	0.8751	0.9596
2014	0.8758	0.7795	0.8851
2015	0.9331	0.8769	0.9435
2016	0.9284	0.8146	0.9304
2016	0.9608	0.8663	0.9640

Notes: By definition, the standard two-sample t-test for equality of means is based on the null hypothesis of equal means between two sample groups. Compiled by the author.

Table A.5: Two-sample robust test for equality of variances

Year	Personnel expenditure			FPM grants			Tax revenue		
	W_0	W_{10}	W_{50}	W_0	W_{10}	W_{50}	W_0	W_{10}	W_{50}
2013	0.0042	0.0020	0.0017	0.0545	0.0275	0.0269	0.0072	0.0027	0.0026
	(0.948)	(0.964)	(0.967)	(0.815)	(0.868)	(0.870)	(0.932)	(0.958)	(0.959)
2014	0.0585	0.0250	0.0247	0.0888	0.0688	0.0638	0.0679	0.0220	0.0216
	(0.809)	(0.874)	(0.875)	(0.766)	(0.793)	(0.801)	(0.794)	(0.882)	(0.883)
2015	0.0224	0.0074	0.0078	0.0843	0.0419	0.0340	0.0147	0.0053	0.0051
	(0.881)	(0.928)	(0.930)	(0.772)	(0.838)	(0.854)	(0.904)	(0.942)	(0.943)
2016	0.0292	0.0095	0.0096	0.1827	0.0831	0.0702	0.0226	0.0080	0.0078
	(0.864)	(0.920)	(0.922)	(0.669)	(0.773)	(0.791)	(0.880)	(0.929)	(0.930)
2017	0.0078	0.0026	0.0028	0.0429	0.0231	0.0232	0.0061	0.0022	0.0021
	(0.930)	(0.957)	(0.958)	(0.836)	(0.879)	(0.879)	(0.937)	(0.963)	(0.964)

Notes: p-values are in parentheses. By definition, the standard two-sample robust test for equality of variances is based on the null hypothesis of equal variances between two sample groups. Also, while "W_0" refers to the conventional Levene's robust test statistic, which is centered at the mean, "W_{10}" and "W_{50}" are two alternative statistics centered at the 10% trimmed mean and at the median, respectively (Levene, 1960; Brown and Forsythe, 1974). Compiled by the author.

APPENDIX B – AUXILIARY ESTIMATION RESULTS

Table B.1: Estimation results using a panel data model with spatial random effects, spatial interaction effects and panel-level averages of time-varying covariates

Determinants	(1)
	SDM (*Mundlak Approach*)
Main structure	
ln(*Per Capita* GDP)	0.0893*
	(13.39)
ln(*Per Capita* FPM Grants)	0.2422*
	(27.83)
ln(*Per Capita* Tax Revenue)	0.0712*
	(30.11)
ln(Share of Population under 14 years old)	0.0141
	(0.08)
ln(Share of Population over 65 years old)	0.6722*
	(6.22)
ln(*Per Capita* GDP)$_{avg}$	0.1070*
	(10.78)
ln(*Per Capita* FPM Grants)$_{avg}$	0.2015*
	(20.09)
ln(*Per Capita* Tax Revenue)$_{avg}$	0.0927*
	(15.74)
ln(Share of Population under 14 years old)$_{avg}$	0.2081
	(1.23)
ln(Share of Population over 65 years old)$_{avg}$	-0.6380*
	(-5.86)
Spatial structure	
W × ln(*Per Capita* GDP)	-0.6108ˆ*
	(-6.54)
W × ln(*Per Capita* FPM Grants)	-0.3455*
	(-8.76)
W × ln(*Per Capita* Tax Revenue)	-0.3019*
	(-8.72)
W × ln(Share of Population under 14 years old)	-0.5678
	(-1.39)
W × ln(Share of Population over 65 years old)	-1.6940*
	(-7.20)
W × ln(*Per Capita* GDP)$_{avg}$	0.6752*
	(4.62)
W × ln(*Per Capita* FPM Grants)$_{avg}$	-1.5664*
	(-16.14)
W × ln(*Per Capita* Tax Revenue)$_{avg}$	-0.5371*
	(-5.39)
W × ln(Share of Population under 14 years old)$_{avg}$	-0.2177
	(-0.52)
W × ln(Share of Population over 65 years old)$_{avg}$	2.4444*
	(8.47)
λ	0.3818*
	(11.92)
σ^2	0.0155
R^2	0.5725

Notes: t-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. The subscript "*avg*" refers to the panel-level average of the respective variable. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

Table B.2: Estimation results from the spatial Durbin model for the North region

Determinants	(1) SDM
Main structure	
Constant	0.2538**
	(2.08)
ln(Initial *per capita* personnel expenditure)	−0.0683*
	(−5.94)
ln(Initial *per capita* tax revenue)	−0.0008
	(−0.24)
ln(Initial *per capita* FPM grants)	0.0210*
	(3.13)
ln(Initial *per capita* GDP)	0.0152**
	(2.35)
ln(Initial share of population under 14 years old)	−0.0182
	(−0.67)
ln(Initial share of population over 65 years old)	0.0108
	(1.35)
Spatial structure	
W × ln(Initial *per capita* personnel expenditure)	0.0294
	(1.11)
W × ln(Initial *per capita* tax revenue)	0.0085
	(1.07)
W × ln(Initial *per capita* FPM grants)	−0.0152
	(−1.20)
W × ln(Initial *per capita* GDP)	−0.0267**
	(−2.14)
W × ln(Initial share of population under 14 years old)	0.0347
	(1.20)
W × ln(Initial share of population over 65 years old)	−0.0079
	(−0.43)
λ	0.1079
	(1.20)
σ^2	0.0021
R^2	0.1187

Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

Table B.3: Estimation results from the spatial Durbin model for the Northeast region

Determinants	(1) SDM
Main structure	
Constant	0.1313**
	(2.23)
ln(Initial *per capita* personnel expenditure)	−0.0959*
	(−19.93)
ln(Initial *per capita* tax revenue)	0.0021
	(1.36)
ln(Initial *per capita* FPM grants)	0.0341*
	(10.16)
ln(Initial *per capita* GDP)	0.0179*
	(6.22)
ln(Initial share of population under 14 years old)	0.0438*
	(3.33)
ln(Initial share of population over 65 years old)	0.0127***
	(1.94)
Spatial structure	
W × ln(Initial *per capita* personnel expenditure)	0.0689*
	(5.78)
W × ln(Initial *per capita* tax revenue)	−0.0016
	(−0.43)
W × ln(Initial *per capita* FPM grants)	−0.0260*
	(−3.62)
W × ln(Initial *per capita* GDP)	−0.0122**
	(−2.08)
W × ln(Initial share of population under 14 years old)	−0.0559*
	(−4.47)
W × ln(Initial share of population over 65 years old)	−0.0117
	(−1.35)
λ	0.2070
	(4.54)
σ^2	0.0014
R^2	0.1948

Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

Table B.4: Estimation results from the spatial Durbin model for the Southeast region

Determinants	(1)
	SDM
Main structure	
Constant	0.2538**
	(2.08)
ln(Initial *per capita* personnel expenditure)	−0.0524*
	(−12.91)
ln(Initial *per capita* tax revenue)	0.0082*
	(4.35)
ln(Initial *per capita* FPM grants)	0.0222*
	(8.59)
ln(Initial *per capita* GDP)	0103*
	(4.23)
ln(Initial share of population under 14 years old)	−0.0107
	(−1.06)
ln(Initial share of population over 65 years old)	0.0158*
	(2.91)
Spatial structure	
W × ln(Initial *per capita* personnel expenditure)	0.0260
	(3.14)
W × ln(Initial *per capita* tax revenue)	−0.0076**
	(−1.98)
W × ln(Initial *per capita* FPM grants)	−0.0127*
	(−2.66)
W × ln(Initial *per capita* GDP)	−0.0023
	(−0.48)
W × ln(Initial share of population under 14 years old)	−0.0022
	(−0.81)
W × ln(Initial share of population over 65 years old)	−0.0121
	(−1.30)
λ	0.0985**
	(1.98)
σ^2	0.0012
R^2	0.1208

Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

Table B.5: Estimation results from the spatial Durbin model for the South region

Determinants	(1) SDM
Main structure	
Constant	0.0397
	(0.82)
ln(Initial *per capita* personnel expenditure)	−0.0554*
	(−11.52)
ln(Initial *per capita* tax revenue)	0.0093*
	(4.44)
ln(Initial *per capita* FPM grants)	0.0204*
	(7.20)
ln(Initial *per capita* GDP)	0.0127*
	(5.23)
ln(Initial share of population under 14 years old)	0.0164***
	(1.65)
ln(Initial share of population over 65 years old)	0.0125**
	(2.17)
Spatial structure	
W × ln(Initial *per capita* personnel expenditure)	0.0096
	(1.02)
W × ln(Initial *per capita* tax revenue)	−0.0064
	(−1.40)
W × ln(Initial *per capita* FPM grants)	−0.0090***
	(−1.74)
W × ln(Initial *per capita* GDP)	0.0015
	(0.31)
W × ln(Initial share of population under 14 years old)	−0.0086
	(−0.99)
W × ln(Initial share of population over 65 years old)	0.0124
	(1.58)
λ	0.2577
	(5.10)
σ^2	0.0007
R^2	0.1454

Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

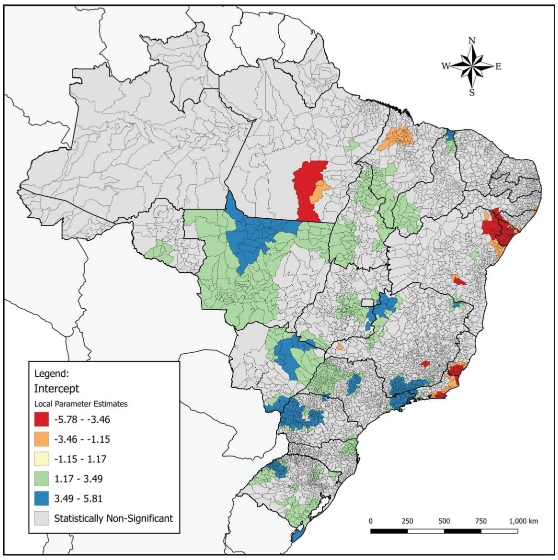
Table B.6: Estimation results from the spatial Durbin model for the Central-West region

Determinants	(1) SDM
Main structure	
Constant	0.2415**
	(2.50)
ln(Initial *per capita* personnel expenditure)	−0.0988*
	(−12.15)
ln(Initial *per capita* tax revenue)	0.0116*
	(2.84)
ln(Initial *per capita* FPM grants)	0.0432*
	(8.86)
ln(Initial *per capita* GDP)	0.0209*
	(4.58)
ln(Initial share of population under 14 years old)	−0.0228
	(−1.04)
ln(Initial share of population over 65 years old)	0.0027
	(0.33)
Spatial structure	
W × ln(Initial *per capita* personnel expenditure)	0.0213
	(0.92)
W × ln(Initial *per capita* tax revenue)	−0.0066
	(−0.63)
W × ln(Initial *per capita* FPM grants)	−0.0185***
	(−1.65)
W × ln(Initial *per capita* GDP)	−0.0003
	(−0.03)
W × ln(Initial share of population under 14 years old)	0.0079
	(0.34)
W × ln(Initial share of population over 65 years old)	−0.0017
	(−0.13)
λ	−0.0734
	(−0.78)
σ^2	0.0015
R^2	0.2595

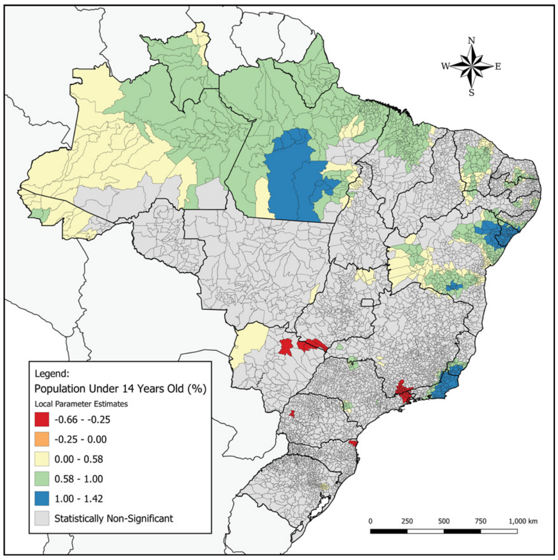
Notes: z-values are in parentheses. The symbols *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively. Both dependent and independent variables are considered in their natural logarithmic form. Estimation results based on an inverse-distance spatial weights matrix. Compiled by the author.

APPENDIX C – SUPPLEMENTARY MAPS

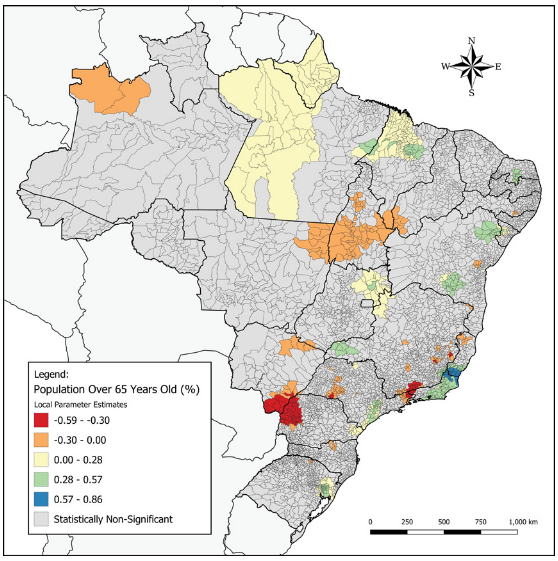
Figure C.1: Local parameter estimates from the GWR-SAR model for the intercept term, share of population under 14 years old and share of population over 65 years old



(a) Intercept term



(b) Share of population under 14 years old



(c) Share of population over 65 years old