Journal of Human Development
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/cjhd19

Using Spatial Statistics to Analyze Intra-urban Inequalities and Public Intervention in São Paulo, Brazil

Mônica A. Haddad & Zorica Nedović-Budić
Published online: 22 Jan 2007.

Journal of Human Development
Vol. 7, No. 1, March 2006

Routledge
Taylor & Francis Group

Using Spatial Statistics to Analyze Intra-urban Inequalities and Public Intervention in São Paulo, Brazil

MÔNICA A. HADDAD and ZORICA NEDOVIĆ-BUDIĆ
Mônica A. Haddad is Assistant Professor in the Department of Community and Regional Planning at Iowa State University, and Zorica Nedović-Budić is Associate Professor of Urban Planning and GIS at the University of Illinois at Urbana-Champaign

Abstract Like many cities in developing countries, São Paulo, Brazil, is characterized by major intra-urban inequalities with respect to human development. The center-periphery spatial regimes are the most obvious spatial manifestation of this phenomenon. In this paper we apply confirmatory spatial data analysis to examine these inequalities and their relationship to public interventions. Using district-level data, we examine the relationship between public interventions and the level of human development, while controlling for population density, spatial heterogeneity and spatial autocorrelation. Our results suggest that public interventions reinforce the existing differences between center and periphery. Specifically, public services and utilities and social programs are allocated more intensively in districts with higher human development levels. These findings call for a more careful consideration of distribution of societal resources and effectiveness of public programs and policies.

Key words: Spatial statistics, Intra-urban inequality, Public programs, Urban policy, Developing countries, Human development, Economic growth, Spatial autocorrelation, Spatial heterogeneity

Introduction

Urban areas are characterized by heterogeneous spatial patterns, which are often related to distribution of population, their ethnicity, race, and socio-economic attributes. Urban heterogeneity, however, tends to be associated with intra-urban inequalities, particularly in developing countries. There, the ''differential in wealth … and its associated problems are increasingly

ISSN 1464-9888 print/ISSN 1469-9516 online/06/010085-25 © 2006 United Nations Development Programme
DOI: 10.1080/14649880500502102

more visible and … more intense in urban settlements. A large — or rather the largest — number of rich and poor people are physically concentrated in relatively small geographical areas'' (Werna, 2000, p. 2). Brazilian cities exemplify this uneven spatial distribution of rich and poor people and the heterogeneous spatial patterns. *Favelas* (Brazilian slum areas) and expensive condominiums are adjacent to each other in many metropolitan regions in the country. The income variable, which is probably the major determinant of intra-urban inequalities in Brazilian cities, is also manifested in the differential provision of and access to public infrastructure (Lima, 2001).

Previous studies on the relationship between intra-urban inequalities and public intervention suggest that the success of such interventions depends on local politics as much as on the approach taken to address them. For example, Werna concludes that the public sector's attention to intra-urban differences in the municipality of São Paulo ''has been extremely variable, entailing an oscillation between governments with a strong concern with such differentials and others with different primary interests'' (1995, p. 134). More generally, projects, grants, and interventions for improving human condition in developing countries focus on economic growth, assuming that it generates income gains for the poor and promotes welfare benefits such as access to school and health care. However, there is accumulating evidence that ''economic growth alone does not ensure access for all basic needs, and can in turn increase inequality'' (Devas *et al.*, 2001, p. 6) in urban and rural communities alike (Shah and Sah, 2004).

Extending on efforts to overcome the dominance of economic variables, income in particular, in understanding intra-urban inequalities and promoting overall development, we subscribe to a broader view of development based on the human development paradigm. In addition to income, this paradigm focuses on social, cultural, and political factors, but others are also proposed. For example, Arimah suggests inclusion of ''public expenditures on education, primary school enrollment, female educational enrollment, expenditure on health and good governance'' (2004, p. 399).

In this study we conduct spatial econometric analysis of the intra-urban inequality among the districts of São Paulo municipality (SPM) as the variation in the Human Development Index (HDI) devised by the United Nations Development Programme. We explore the relationship of this index with the provision of public services and utilities and investments in social programs. To achieve these objectives we use confirmatory spatial data analysis (CSDA) methods, which control for spatial heterogeneity (e.g. between center and periphery) and for spatial autocorrelation. Such analytical techniques can be used to evaluate the spatial distribution of societal resources and effectiveness of existing programs and to help policy-makers and decision-makers at the local, regional and national levels address inequalities.

Development and public intervention

Human development–economic growth linkage

Human development is closely interlinked with the overall development and economic growth in urban areas, and thus requires direct attention (Ranis *et al.*, 2000). Even when successful, developments aimed at economic growth only have ''contributed with disturbing regularity to increase inequality, conflict, unemployment'' (Alkire, 2002, p. 14). Conversely, education and health are found to support generation of economic growth (Anand and Sen, 2000). Regardless of this close association between the human and economic development, the two phenomena have been treated and measured independently. The HDI is a widely accepted measure of human development. It summarizes several variables into three indicators: *education*, which is represented by adult literacy rate and gross enrollment ratio; *longevity*, which is represented by life expectancy at birth; and *income*, which is represented by the Gross Domestic Product (GDP) per capita (Purchasing Power Parity (PPP) in US dollars), an established measure of economic strength. Alkire (2002), however, identifies aspects of development, such as human capital and health for which GDP is an inadequate proxy. Foster *et al.* (2005) point to the deficiencies with regard to sensitivity of the indices to distribution of human development.

To address this recognized inadequacy of the GDP, Haq (1998) introduced the human development paradigm, which is defined by four components: equity, sustainability, productivity, and empowerment. He suggests four ways of linking economic growth and human development: emphasis on investment in the education, health, and skills of people; more equitable distribution of income and assets; well-structured social expenditures by government; and the empowerment of people. The author considers equity as crucial for enlarging people's choices, and suggests that equitable access to opportunities is necessary for its achievement. He states that the ''emphasis on investments in the education, health and skills of the people can enable them to participate in the growth process as well as to share its benefits, principally through remunerative employment'' (Haq, 1998, p. 21).

Sen's (1999) capability approach is also useful for understanding urban inequalities and relating the expansion of human capabilities to public interventions. He defines a person's capability ''as the alternative combinations of functionings that are feasible for her to achieve. Capability is thus a kind of freedom: the substantive freedom to achieve alternative functioning combinations (or, less formally put, the freedom to achieve various lifestyles)'' (Sen, 1999, p. 75). A sample of capabilities we apply to this study includes school attendance, adequate health care, sufficient income (without child labor), access to safe water and sanitation, electricity, safe environment, and nourishment. The achieved functionings are represented by variables, which allow us to measure of the effects of public interventions. Student-teacher ratio, proportion of dwelling with bathroom, proportion of dwellings with public sewage connection, and home-based health services are examples of functionings.

Assessing public intervention needs and effects

The empirical work on the relationships between the human development and public interventions to expand human capabilities is scarce. Previous research relates inequalities to the impacts of globalization processes, the effects of the implementation of neoliberal economic policies that advocate a smaller public sector, and other macro-economic initiatives (Burgess *et al.*, 1997; Musterd and Ostendorf, 1998; Marcuse and Van Kempen, 2000, 2002; Andersen and Van Kempen, 2001). With more sensitivity to the local context of São Paulo municipality, Sposati (1996, 2000) applies the Social Exclusion/Inclusion Index to identify districts in need of social assistance. In examining the districts of São Paulo municipality, Torres and Oliveira (2001) find differential access to primary education and conclude that the absence of land regulation creates difficulties in constructing infrastructure in the periphery.

Most studies, however, are descriptive and rely primarily on maps, graphs, or tables to display data and their spatial distribution. These studies tend to ignore spatial associations, or are too general to assess public intervention. Instead, they present only the outcomes of various forces that shape urban space and quality of life. Statistical analyses and tests that increase the reliability of findings are rarely performed. For example, Torres and Marques (2004) only map social indicators to display spatial concentrations of rich and poor people in São Paulo metropolitan area. Departing from this descriptive approach, Ramos' (2002) exploratory spatial data analysis demonstrates how the visualization and analyses of metropolitan level data can be useful in guiding decision-making processes; Câmara's *et al.* (2003) CSDA and mapping of Social Exclusion/Inclusion variables reveals social dynamics at the district level. However, these authors too do not relate the mapped indices to public interventions or any other explanatory factor.

Summary of the literature base

Haq's human development paradigm and Sen's capability approach form the theoretical basis of this study. Both approaches track the intra-urban inequalities to the lack of equitable access to opportunities. In this paper we demonstrate the intra-urban inequality as the variation in human development between districts of SPM. If 'pro-equality' forces dominated the SPM urban policy agenda, public intervention would reduce intra-urban inequalities by targeting the areas with lower human development levels. Therefore, the assessment of public investments can be used to examine to what extent the public sector intervention is related to the process of 'enabling' people and reducing intra-urban inequalities.

We find that most empirical assessments of the relationship between public interventions and their intended consequences are largely devoid of spatial dimension and statistical analysis. Inclusion of spatial effects in assessing intra-urban inequalities and application of statistical tests would allow for more reliable discovery and comprehension of urban processes. The insights from the spatially enabled statistical analysis might help direct public intervention and allocation of investments in a more strategic and effective manner. In the next section we provide a detailed account of our application of the confirmatory spatial data analysis in studying intra-urban inequalities among São Paulo's districts and their relationship to the provision of public infrastructure and social programs.

Research framework and methodology

Research framework

This study is based on three assumptions: there are some basic capabilities that should be part of everyone's life (for instance, the capability to attend elementary school); urban economic growth is necessary but not a sufficient condition to improve human development level and to reduce intra-urban inequalities; and in most developing countries the public sector still plays an important role in providing these basic capabilities, although other actors also produce and provide them.

The central element of the research framework (Figure 1) is the human development that is either equally or unequally distributed. It is influenced by public intervention — the provision of public services and utilities and investments in social programs. A feedback loop is

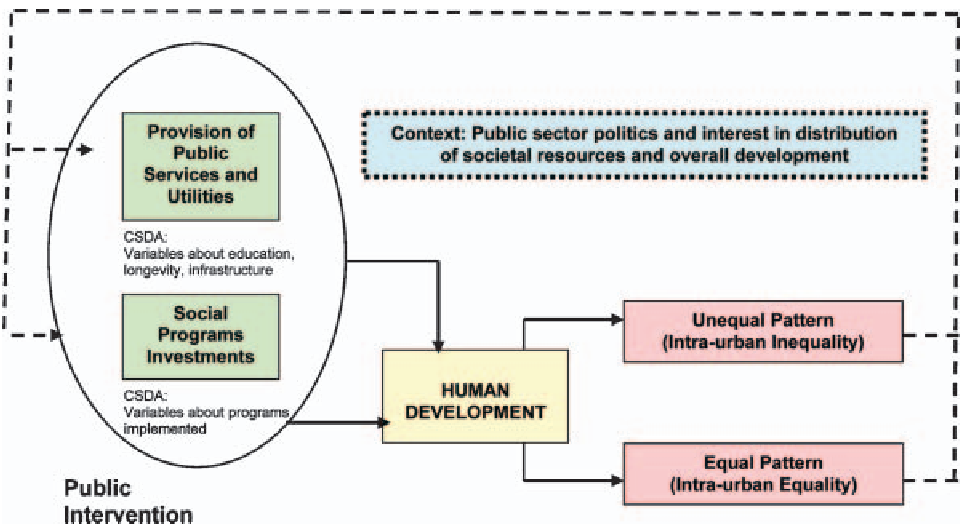

FIGURE 1. Research framework.

constructed to allow for adjustments in public policies to the changed levels of human development.

In this study we ask the following questions: What is the relationship between provision of public services and utilities and human development level? Are the investments in social programs allocated in districts that need them the most?

Data

This study is undertaken with data for SPM, which is part of the São Paulo metropolitan area, the largest in Brazil, and contains 39 municipalities. SPM has over 10.5 million inhabitants, representing more than 10% of the national population. In 2000, about 17% of the National GDP and approximately 21% of the industrial domestic product were generated in SPM. There is a large presence of the public sector in SPM, with about 150000 public employees directly working for the municipal government, and about an additional 50 000 employees working for other public sector entities (Werna, 2000). The municipal government is decentralized into 96 administrative districts, 31 *Sub-Prefeituras* (sub-administrations), 13 *Núcleos de Educação* (Education Nuclei), and 39 *Distritos de Saúde* (Health Districts).

An analysis of regional inequalities with respect to human development at the municipal level in the Brazilian state of São Paulo indicates that SPM is well above other municipalities within the state (Haddad, 2003). That is not surprising given that SPM is the most affluent municipality in the country. However, we suspect that aggregated municipal human development data may be masking the intra-urban variability that occurs even inside the wealthy municipalities. As Portnov alerts, ‘‘similarly to spatial disparities in regional development, intra-urban inequalities, once occurring, may become persistent and self-perpetuating’’ (2002, p. 149). Therefore, a change in the scale of analysis is applied to assess intra-urban inequalities.

Table 1 compares HDI levels and two measures of inequality — Gini and Theil indices — for Brazil, São Paulo state, SPM, and other municipalities within São Paulo state. The HDI for the SPM is above the Brazilian average and São Paulo state average. Within the state, SPM ranks above the 75th percentile (0.802). Gini and Theil indices for SPM have

Table 1. The HDI and the Gini and Theil Indices, 2000

	HDI 2000	Gini 2000	Theil 2000
Brazil	0.766	0.650	0.760
São Paulo State	0.820	0.590	0.610
São Paulo Municipality	0.841	0.620	0.680
Minimum within São Paulo state	0.645	0.420	0.290
Maximum within São Paulo state	0.919	0.730	1.060
Average within São Paulo state	0.779	0.530	0.470

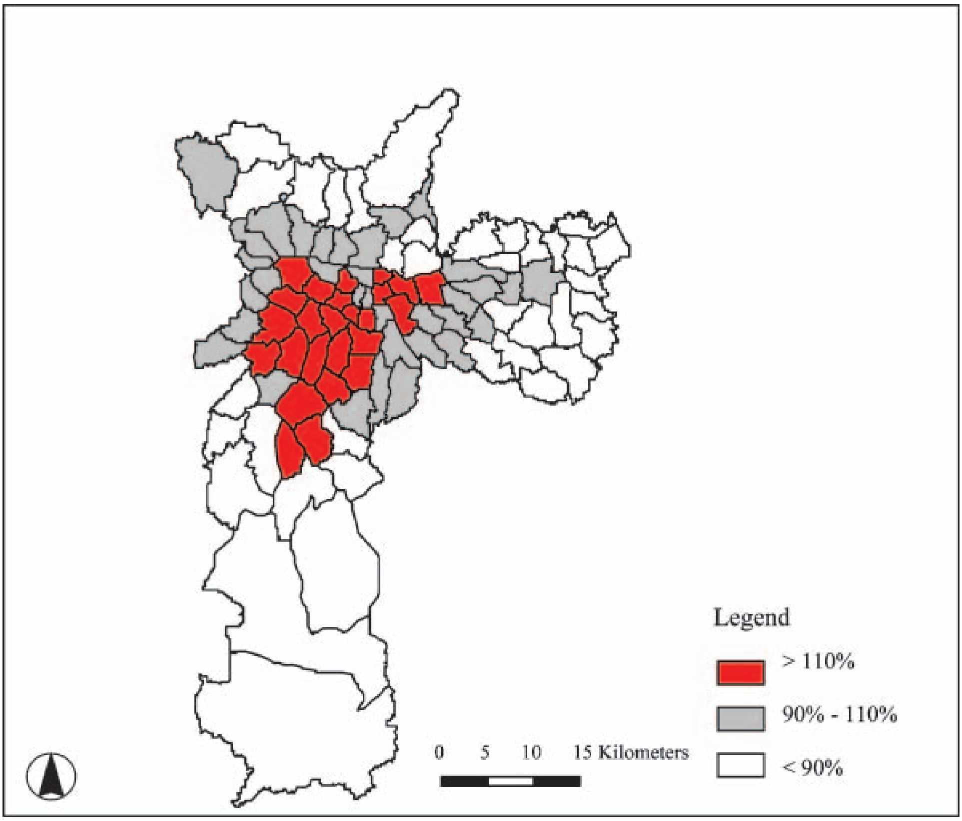

FIGURE 2. HDI relative to the sample average of SPM Districts, 2000.

values close to the Brazilian average and higher than the São Paulo state average. Within the state, they rank below the 90th percentile (0.590 and 0.580, respectively), showing a high level of inequality.

The unit of analysis for this study is an administrative district with its intra-urban diversity and human development level, which substitute for Sen's focus on interpersonal diversity and individual preferences, respectively. The HDI for the 96 administrative districts is calculated by the *Secretaria Municipal do Desenvolvimento, Trabalho e Solidariedade* (SMDTS, 2002) using the United Nations Development Programme's methodology (Figure 2). The Secretariat's report states that ''40 percent of the districts of the richest city in the country present low levels of human development'' and that ''the HDI for SPM districts reach values that can be found in both Europe and Africa at the same time'' (SMDTS, 2002, p. 12). Thirty-eight districts have very low HDI (below 0.5), thus ''forming poverty pockets across the municipality'' (SMDTS, 2002, p. 4). The HDI in districts with low human development, located in the east, north, and south, is less than 90% of the sample average; the HDI in districts with high human development, located in the center of the municipality, is over 110% of the sample average. These facts suggest substantial intra-urban inequalities and variability of human development within SPM.

Data on the provision of public services and utilities are derived from three sources: education data from the *Censo Escolar* 2000, from the Ministry of Education; longevity data from *Pesquisa de Assistência Médico-Sanitária* 1999, conducted by the *Instituto Brasileiro de Geografia e Estatística* (IBGE, Brazilian Bureau of Statistics); and infrastructure data (water, sewerage, garbage collection, electric power, and others), from *Censo Demográfico* 2000, also conducted by IBGE.

Data on investments in social programs come from four federal sources: *Programa Bolsa Alimentação* (Nutrition Children Program) supplements the monthly salary of low-income families with funds to be used to feed children up to the age of 6 and their mothers during the pregnancy period and the child's first year; *Programa Merenda Escolar* (School Snack Program) provides nutritional meals for children that attend municipal schools; *Programa Saúde da Família* (Family Health Program) brings health professionals to low-income families by providing basic care in their homes; and *Programa Renda Mínima* (Minimum Wage Program) targets low-income families with children of school age to furnish an income supplement and allow the children to attend school instead of working to help increase their family income (SMDTS, 2003).

Spatial weight matrix

Spatial statistical analysis requires a spatial weight matrix **W**. This matrix is a formal expression of spatial adjacency between observed districts. Its selection affects the results of diagnostic tests (Le Gallo and Ertur, 2003, p. 180) and we use three matrices to test the robustness of the results. By examining the empirical work on the types of spatial weight matrices, the context in which they are used, and their applicability to this study (Anselin, 1995; Talen and Anselin, 1998; Pereira *et al.*, 1998; Messner *et al.*, 1999; Baller *et al.*, 2001; Baumont *et al.*, 2003, 2004; Le Gallo and Ertur, 2003; Guillain *et al.*, 2006), we opted for the simple binary queen contiguity and two *k*-nearest-neighbors matrices.

The simple binary queen contiguity matrix has two values: if district i has a common border and/or vertex with district j, then they are neighbors and $w_{ij}=1$; and if district i does not have a common border and /or vertex with district j, then they are not neighbors and $w_{ij}=0$. The diagonal elements are set to 0. The *k*-nearest-neighbors weight matrix is defined as:

$$\begin{cases} w^*_{ij}(k)=0 & \text{if } i=j \\ w^*_{ij}(k)=0 & \text{if } d_{ij}\leq d_i(k) \quad \text{and} \quad w_{ij}(k)=w^*_{ij}(k)\Big/\sum_j w^*_{ij}(k) \\ w^*_{ij}(k)=0 & \text{if } d_{ij}>d_i(k) \end{cases} \tag{1}$$

where $d_i(k)$ is a critical cut-off distance defined for each district i; $d_i(k)$ is the kth order smallest distance between districts i and j such that each district i has exactly k neighbors. For this study, $k=5$ and $k=6$ are applied. These values are chosen because they represent the highest frequency in the distribution of connection between SPM districts, based on the examination of the simple binary queen contiguity matrix; that is, the majority of SPM districts have five or six neighbors (22 and 23 districts, respectively). All matrices, the two k-nearest neighbors and the simple binary queen contiguity are row standardized so that each row sums up to 1.

Confirmatory spatial data analysis and models

To better understand intra-urban inequalities and their relationship to human development and public intervention, we introduce spatial dimension in our analyses. Spatial dependence and spatial heterogeneity are found to characterize the distribution of HDI across the SPM districts (Haddad, 2003). Spatial dependence occurs when the values of observations in spatial units that are close or adjacent are similar or correlated (Anselin, 1998). This association can be measured by different statistics; one of them is the Moran's I statistic. This statistic gives a formal indication of the degree of linear association between HDI values and HDI spatially lagged values, calculated as spatially weighted averages of neighboring values. For the SPM districts, the Moran's I statistic for the HDI, based on 999 permutations, is 0.6569 ($p=0.001$) when using the simple binary queen contiguity matrix, is 0.6004 ($p=0.001$) when using the six-nearest-neighbors matrix, and is 0.6293 ($p=0.001$) when using the five-nearest-neighbors matrix. It indicates a positive spatial autocorrelation in the distribution of HDI: districts of high (or low) HDI are surrounded by districts of high (or low) HDI, respectively.

Spatial heterogeneity implies unstable relationships between values of observations, and detectable spatial regimes. These relationships may be described by multiplicity of functional forms and parameters that vary across the data set (Anselin, 1988). In this paper, following Le Gallo and Dall'Erba (2006), we use the Getis-Ord statistics to measure local spatial autocorrelation and to detect the presence of spatial heterogeneity among the SPM districts. As Le Gallo and Ertur suggest, ''these statistics are based on spatial accumulations and can thus help to deepen the analysis for detecting spatial clusters around each [district] i without being affected by the value taken by the variable in that [district] i'' (2003, p. 178). Getis-Ord statistics are calculated for each district. The spatial distribution of HDI is not stable across SPM districts and forms a characteristic spatial pattern of human development displayed as center–periphery spatial regimes: a cluster of districts with positive Getis-Ord statistics (the center) and a cluster of districts with negative Getis-Ord statistics (the periphery). Figure 3 displays these spatial regimes.

We use CSDA methods to examine the development level measured by the HDI, provision of utilities and services, and administration of social

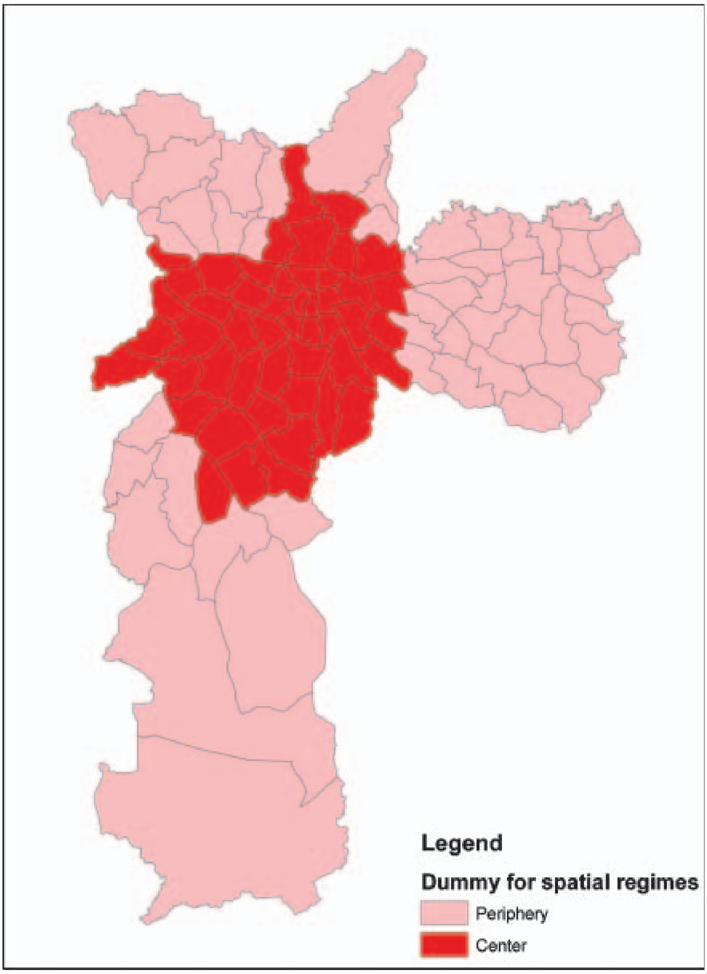

FIGURE 3. Spatial regimes — center and periphery — calculated based on the Getis-Ord statistics.

programs in each district by taking into account its geographic location relative to other districts in the municipality. The CSDA methods enable specification of spatially-explicit regression models that incorporate spatial autocorrelation and spatial heterogeneity. These methods help avoid misspecifications of models, inefficient coefficients, and erroneous statistical inferences that happen when spatial dependency and spatial heterogeneity are not addressed (Anselin and Rey, 1991).

To examine the relationship between the public interventions and human development levels, we use the following three regression models: the education model (M-EDU), the social programs model (M-SP), and the infrastructure model (M-IS). The HDI is the dependent variable in all three models. Also, to control for districts' population distributions, all models have a density variable calculated by dividing the total population of a district by its area.

- M-EDU has the following independent variables: density and public school variables — number of students per classroom, number of students per computer, level of education of teachers (e.g. teachers with bachelor's degree), and proportion of students per teacher.
- M-SP has the following independent variables: density and ratios between the population that received the program benefits and the target population of the four social programs — Nutrition Children, School Snack, Family Health, and Minimum Wage.[1]
- M-IS has the following independent variables: density, infrastructure development, and health development — the two latter variables are derived from 12 variables by a factor analysis.[2]

We take the following steps in specifying the models, addressing Florax's *et al.* (2003) ''specific to general'' model specification approach. Because the steps are the same for all models, we illustrate the process using the M-EDU model with only two independent variables. Step 1 is a simple non-spatial regression model estimated by:

$$HDI_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i \quad i = 1, \ldots, 96 \text{ and } \varepsilon \sim \mathrm{N}\left(0, \sigma_\varepsilon^2 I\right) \tag{2}$$

where HDI_i is the Human Development Index for each district I, x_{1i} and x_{2i} are independent variables representing the number of students per computer and the number of students per classroom, and β_0, β_1, and β_2 are the unknown parameters to be estimated; ε is the vector of errors.

In Step 1 we carry out tests to detect the presence of spatial dependence, which lead us to further apply the spatial error model or the spatial lag model. For all three models, the tests reveal that the spatial lag model is the most appropriate. Step 2 is also an ordinary least squares (OLS)-based regression model that controls for spatial heterogeneity. Therefore the spatial regimes — center and periphery, identified by calculating the Getis-Ords statistics — are introduced in the regression:

$$\begin{aligned} HDI_i = {} & \beta_{0C} D_C + \beta_{0P} D_P + \beta_{1C} x_{1i} D_C + \beta_{1P} x_{1i} D_P + \beta_{2C} x_{2i} D_C + \beta_{2P} x_{2i} D_P + \varepsilon_i \\ & i = 1, \ldots, 96 \ \text{ and } \ \varepsilon \sim \mathrm{N}\left(0, \sigma_\varepsilon^2 I\right) \end{aligned} \tag{3}$$

where all other elements are defined as previously, but divided in two groups; that is, for each element, there is one dummy variable for the 'center' D_C and one for the 'periphery' D_P.

In Step 3 the spatial lag model is applied to include the spatial dependence in the model specification, as an additional covariate in the model, the so-called spatial lag. The coefficients of the spatial lag model are estimated by the Maximum Likelihood (ML) method and the Instrumental Variables (IV) method (the latter only if the assumption of the normality of errors is rejected based on the results of Jarque-Bera test).[3] For M-EDU, the spatial lag model in matrix form is written as:[4]

$$HDI = \beta_0 S_{(Nx1)} + \rho WHDI_{(Nx1)} + \beta_1 x_{1(Nx1)} + \beta_2 x_{2(Nx1)} + u_{(Nx1)} \quad u \sim \mathrm{N}\left(0, \sigma_\varepsilon^2 I\right) \quad (4)$$

where *HDI* is a vector of dimension n=96 of the Human Development Index for each district i, $x_{1(Nx1)}$ and $x_{2(Nx1)}$ are vectors containing values for independent variables (e.g. students per computer and students per classroom in 2000), S is the sum vector, β_0, β_1, β_2, and ρ are the unknown parameters to be estimated, and ρ is the spatial autoregressive parameter that indicates the extent of interaction between the observations according to the spatial pattern exogenously introduced by means of the standardized weight matrix **W**. The spatial lag variable $WHDI_{(Nx1)}$ contains the HDI multiplied by the weight matrix: for a district i of vector $HDI_{(Nx1)}$, and the corresponding line of the spatial lag vector contains the spatially weighted average of HDI. u is the vector of errors with the usual properties.

Finally, in Step 4 the spatial lag model is enhanced by including the center-periphery spatial regimes to the equation:

$$\begin{aligned} HDI = \rho WHDI + \beta_{0C} SD_C + \beta_{0P} SD_P + \beta_{1C} x_1 D_C + \beta_{1P} x_1 D_P \\ + \beta_{2C} x_2 D_C + \beta_{2P} x_2 D_P + u_{(Nx1)} \quad u \sim \mathrm{N}\left(0, \sigma_\varepsilon^2 I\right) \end{aligned} \quad (5)$$

where all the elements are defined as previously, but divided into two groups; that is, for each element there is one dummy variable for the 'center' D_C and one for the 'periphery' D_P.

If after controlling for the spatial regimes there is a remaining problem of heteroskedasticity, the model has to be estimated using groupwise heteroskedasticity. Groupwise heteroskedasticity means that the variance across error terms in the center regime is different from the one across error terms in the periphery regime.

Results

In this section we present the results of model estimations based on the six-nearest-neighbors weight matrix. Reporting the models estimates based on the simple binary queen contiguity and the five-nearest-neighbors weight matrices would be redundant as they led to the same results. This fact points to the robustness of our results with regard to the choice of the spatial weight matrix. It is important to emphasize that for all three models the Akaike Information Criterion and the Schwartz Criterion show that the spatial models perform better than the non-spatial models. For all models, the tables display the results of the OLS (non-spatial) model and the more appropriate spatial specification.[5] Finally, because there is no time lag between data for the dependent variable and the independent variables, the models do not measure the effects of the selected public services, utilities and social programs on human development, but only verify if they are located where the needs are.

Regression results for the education model (M-EDU)

As displayed in Table 2, the OLS model coefficients for 'students per classroom,' 'students per computer,' 'education teachers' and 'students per teacher' are all significant, indicating that a high HDI coincides with a lower number of students per classroom and students per computer and with a higher level of teachers' education and higher number of students per teacher. The model's R^2-adjusted value is close to 30% but, because of the presence of spatial autocorrelation, the OLS estimators are inefficient and inconsistent. The Jarque-Bera test rejects the assumption of normality of errors, and therefore, when specifying the spatial lag model, the IV method is used in addition to ML to estimate the lag model and confirm that the ML-based estimates are reliable. The White test and the Breusch–Pagan test reject homoskedasticity. We presume that the heteroskedasticity is possibly associated with structural instability across regimes, and address this by estimating a spatial regime lag model specified with dummies for center and periphery.

Table 2. Estimation results for the education model for São Paulo municipality Districts, 2000

Estimation	Non-spatial OLS	Spatial (ML)	
		Center	Periphery
β_0 (constant)	0.389	0.19	0.225
	(0.001)	(0.102)	(0.113)
β_1 (density)	−0.0000006	−0.000005	0.0000008
	(0.757)	(0.062)	(0.436)
β_2 (students/classroom)	−0.003	−0.0004	−0.0003
	(0.000)	(0.591)	(0.479)
β_3 (students/computer)	−0.0002	0.0002	−0.0003
	(0.084)	(0.121)	(0.000)
β_4 (education teachers)	0.283	0.197	0.078
	(0.000)	(0.004)	(0.400)
β_5 (students/teacher)	0.01	0.001	0.001
	(0.020)	(0.783)	(0.598)
R^2-adjusted	0.299	–	
Spatial lag	–	0.467	
		(0.000)	
Akaike information criterion	−156.892	−250.709	
Schwarz information criterion	−141.506	−217.373	
Jarque–Bera estimated residuals normality test	18.607	–	
	(0.00009)		
Spatially-adjusted Breusch–Pagan test for heteroskedasticity	28.320	–	
	(0.00003)		
Likelihood Ratio test	–	20.976	
		(0.000)	
White test for heteroskedasticity	58.775	–	
	(0.00001)		

Note: p values presented in parentheses.

Further testing of the spatial regime lag model with the Lagrange Multiplier Test on Spatial Error Dependence indicates the presence of omitted spatial autocorrelation. Also, the spatially-adjusted Breusch–Pagan heteroskedasticity test versus the dummy center is significant, suggesting that there is remaining heteroskedasticity in the specification. Finally, the Chow–Wald test strongly rejects the joint null hypothesis of structural stability, requiring an estimate of a spatial regime lag model with groupwise heteroskedasticity. The Likelihood Ratio and the Chow–Wald tests reveal a significant presence of groupwise heteroskedasticity that is also associated with structural instability across regimes.

The spatial regime lag with groupwise heteroskedasticity model (ML) takes into account the fact that public intervention could be different within each of the two regimes. The spatial lag coefficient is positive and significant, revealing that there is spatial autocorrelation between HDI levels in neighboring districts, which is not captured by the covariates used in the OLS-based model. At the periphery regime the only significant (and negative) coefficient is for 'students per computer,' showing that lower numbers of students per computer are associated with higher HDI, as expected. At the central regime, two coefficients are significant — 'education teachers' (positive) and 'density' (negative) — suggesting that higher HDI is associated with higher level of teachers' education and with lower density districts, respectively.

Table 3 shows that the Chow–Wald test strongly rejects the joint null hypothesis of structural stability for the spatial regime lag with groupwise heteroskedasticity model (ML). When examining the tests of stability of the individual coefficients, 'density' and 'students per computer' coefficients turn significantly different across regimes. These results indicate that the correct model for M-EDU is a spatial lag with heterogeneity taking the form of spatial regimes and groupwise heteroskedasticity. In other words,

Table 3. Chow–Wald tests for overall stability and individual stability, education model

	Spatial (ML)
Chow–Wald overall stability	37.947
	(0.000)
β_0 (constant)	0.042
	(0.837)
β_1 (density)	4.074
	(0.043)
β_2 (students/classroom)	0.018
	(0.891)
β_3 (students/computer)	10.91
	(0.000)
β_4 (education teachers)	1.04
	(0.307)
β_5 (students/teacher)	0.01
	(0.920)

Note: *p* values presented in parentheses.

public intervention concerning education (when controlling for 'density') in central districts is significantly different from the peripheral districts. In examining the significance and signs of the four public intervention variables in the center and in the periphery, we cannot affirm that the public sector intervention is driven by 'pro-equality' forces. The only significant coefficient for the 'students per computer' variable has a negative sign and points to a possible bias in allocation of school-related funds toward districts with higher HDI.

Regression results for the social programs model (M-SP)

In interpreting the signs of the M-SP coefficients, we assume that they are positive if the programs are implemented in districts that have a high HDI (i.e. where they are not needed); the coefficients are negative if the programs are implemented in districts that have a low HDI (i.e. where they are needed). The model estimation by OLS has an R^2-adjusted value of just over 46% and results in two significant coefficients — 'minimum wage' with the negative sign and 'nutrition children' with a positive sign (Table 4). We specify the spatial lag model using both ML and the IV methods. However, the Breusch–Pagan test detects heteroskedasticity, which we consider possibly associated with structural instability across regimes. To address that, we estimate the spatial regime lag model, including the dummies in the specification — one for center and one for periphery.

Further tests do not indicate the presence of omitted spatial autocorrelation, but do suggest heteroskedasticity (spatially-adjusted Breusch–Pagan against the dummy center is significant) and structural instability (Chow–Wald is significant)(Table 5). Based on the results of the spatially-adjusted Breusch–Pagan and Chow–Wald tests for the spatial regime lag model, there is a need to estimate a spatial regime lag with groupwise heteroskedasticity model. The model results, based on the Likelihood Ratio test and on the Chow–Wald test, reveal the significant presence of groupwise heteroskedasticity and structural instability. Indeed, heteroskedasticity is associated with structural instability across the center–periphery regimes.

The spatial regime lag model with groupwise heteroskedasticity (ML) has several significant coefficients. The spatial lag coefficient is positive and significant. Two coefficients are significant at the periphery regime: 'school snack' is negative and significant (i.e. allocated in districts with low HDI), and 'family health' is positive and significant (i.e. allocated in districts with high HDI). One coefficient is significant in the center regime: the 'minimum wage' coefficient is negative and significant, revealing that this program is being allocated in districts of low HDI. This program, however, is not significant in the periphery where the overall level of human development is lower than in the center and more resources for the 'minimum wage' program are needed. Finally, the tests of stability of

Table 4. Estimation results for the social programs model for São Paulo municipality districts, 2000

Estimation	Non-spatial OLS	Spatial (ML)	
		Center	Periphery
β_0 (constant)	0.582	0.184	0.148
	(0.000)	(0.003)	(0.002)
β_1 (density)	−0.000002	−0.000003	0.0000004
	(0.211)	(0.104)	(0.700)
β_2 (minimum wage)	−0.228	−0.213	−0.043
	(0.000)	(0.000)	(0.112)
β_3 (school snack)	−0.057	0.111	−0.135
	(0.412)	(0.294)	(0.000)
β_4 (family health)	−0.0000005	0.000008	0.000006
	(0.919)	(0.353)	(0.014)
β_5 (nutrition children)	0.058	0.018	0.027
	(0.000)	(0.129)	(0.294)
R^2-adjusted	0.462	–	
Spatial lag	–	0.68	
		(0.000)	
Akaike information criterion	−182.372	−272.603	
Schwarz information criterion	−166.986	−239.266	
Jarque–Bera estimated residuals normality test	10.290	–	
	(0.005)		
Spatially-adjusted Breusch–Pagan test for heteroskedasticity	15.667	–	
	(0.007)		
Likelihood Ratio test	–	13.513	
		(0.000)	
White test for heteroskedasticity	35.216	–	
	(0.018)		

Note: p values presented in parentheses.

Table 5. Chow–Wald tests for overall stability and individual stability, social programs model

	Spatial (ML)
Chow–Wald overall stability	20.06
	(0.002)
β_0 (constant)	0.373
	(0.541)
β_1 (density)	2.566
	(0.109)
β_2 (minimum wage)	7.825
	(0.005)
β_3 (school snack)	4.778
	(0.028)
β_4 (family health)	0.065
	(0.797)
β_5 (nutrition children)	0.109
	(0.748)

Note: p values presented in parentheses.

individual coefficients point to the 'minimum wage' and 'school snack' coefficients as significantly different across the center-periphery regimes.

Therefore, the correct model for M-SP too is a spatial lag with heterogeneity model taking the form of spatial regimes and groupwise heteroskedasticity. The model shows that the implementation of social programs (when controlling for 'density') among central districts is significantly different from the implementation among peripheral districts. When examining the social programs variables in the center and in the periphery, we find evidence of the public sector's 'pro-equality' concerns in distributing program recourses among SPM districts only in the 'school snack' program. There is some evidence of targeting the 'minimum wage' program toward districts with low HDI, but only within central districts. Overall, except for the 'school snack,' social programs are not implemented where the needs are. If this were the case (i.e. if the programs are well targeted toward the districts in need), all of the social programs coefficients would be significant and negative in the periphery regime. This may suggest that in SPM, as a provider of social programs, the public sector's efforts are insufficient and mis-targeted to enhance human development levels and reduce intra-urban inequalities.

Regression results for the infrastructure model (M-IS)

The OLS coefficient estimates for 'infrastructure development' and 'health development' are significant and have positive signs, indicating that the HDI is higher in districts with higher levels of infrastructure and health development (Table 6). The model fit is good with R^2-adjusted values close to 60%, but with inefficient and inconsistent OLS estimators due to the presence of spatial autocorrelation. As in the previous two models, after estimating the spatial lag and performing further diagnostic tests, we detect heteroskedasticity that we suspect is due to the center–periphery instability, and estimate the spatial regime model by including the dummies for center and periphery in the specification.

For this model the tests also point to the presence of omitted spatial autocorrelation and structural instability, and a spatial regime lag with groupwise heteroskedasticity model has to be estimated (ML). The Likelihood Ratio test for this model estimation points out the significant presence of groupwise heteroskedasticity. The spatial lag coefficient is positive and significant. The public intervention variables — 'infrastructure development' and 'health development' — are positive and significant at both the center and periphery. This reveals that the better the provision of physical infrastructure and health services is associated with higher overall level of human development across all the districts in the center and in the periphery. Population density is significant and inversely related to the HDI only in the periphery, indicating that the HDI in lower-density districts is on average higher than in more dense districts.

Table 6. Estimation results for the infrastructure model for São Paulo municipality districts, 2000

Estimation	Non-spatial OLS	Spatial (ML)	
		Center	Periphery
β_0 (constant)	0.6	0.315	0.307
	(0.000)	(0.000)	(0.000)
β_1 (density)	−0.000004	−0.000003	−0.000002
	(0.005)	(0.128)	(0.079)
β_2 (infrastructure development)	0.054	0.111	0.036
	(0.000)	(0.071)	(0.000)
β_3 (health development)	0.079	0.049	0.071
	(0.000)	(0.000)	(0.000)
R^2-adjusted	0.598	–	
Spatial lag	–	0.467	
		(0.000)	
Akaike information criterion	−212.153	−279.270	
Schwarz information criterion	−201.895	−256.191	
Jarque–Bera estimated residuals normality test	27.226	–	
	(0.00000)		
Spatially-adjusted Breusch–Pagan test for heteroskedasticity	16.492	–	
	(0.0008)		
Likelihood Ratio test	–	23.572	
		(0.000)	
White test for heteroskedasticity	22.468	–	
	(0.007)		

Note: p values presented in parentheses.

From Table 7 one can observe that the Chow–Wald test does not reject the joint null hypothesis of structural stability, and the tests of the individual coefficient stability are not significantly different across the center–periphery regimes. In other words, the 'infrastructure development' and 'health development' (when controlling for 'density') among central districts are not significantly different from those among peripheral

Table 7. Chow–Wald tests for overall stability and individual stability, infrastructure model

	Spatial (ML)
Chow–Wald overall stability	5.878
	(0.208)
β_0 (constant)	0.05
	(0.822)
β_1 (density)	0.311
	(0.112)
β_2 (infrastructure development)	2.511
	(0.112)
β_3 (health development)	0.949
	(0.329)

Note: p values presented in parentheses.

districts. These results suggest that the public sector serves the whole municipality with infrastructure and health services without discriminating between center and periphery, and equally distributing the investments across them. However, we would expect that, given the inequalities in the level of human development, more resources should be invested in the periphery and in districts with low HDI.

Summary remarks

Two out of the three models for SPM presented in this section — education, and social programs — show that the public interventions are different across the center–periphery regimes. The modeling results also show that, except for 'school snack,' the valuable public resources set aside for education, social programs, and infrastructure are not always targeted toward the population in the most needy districts.

Predicted value maps for the M-EDU, M-SP and M-IS (Figure 4) show the predicted values for HDI-EDU, HDI-SP, and HDI-IS based on the independent variables for public intervention (while controlling for 'density'). These predicted values indicate the distribution and intensity of the outcomes of the public attention to specific conditions across the SPM districts. Higher predicted values indicate more intensive public intervention. Assuming that the public intervention is intended to expand people's capabilities and create more equitable access to opportunities, we expect that the higher values for the predicted HDI would be in the districts located in the periphery. The three maps in Figure 4 display a common trend — higher values in the central districts, and lower values in the southern and eastern districts — perpetuating the existing disparities in human development among SPM districts. However, a positive trend towards the districts surrounding the central area can be noticed more strongly in the HDI-IS, and moderately in the HDI-EDU.

Conclusion

In this paper we examine the relationship between intra-urban inequalities in the level of human development and public intervention in the SPM. We apply CSDA that accounts for the location of the 96 municipal districts and dependency among the neighboring districts. The empirical evidence from the CSDA leads to a few conclusions about the public intervention in SPM. The valuable public investments in education and social programs are allocated differentially among the central and peripheral districts, with central districts on average benefiting more from those investments. Investments in infrastructure and health services are allocated without distinction across the whole municipality, but more prominently in districts with higher HDI. Knowing that the needs vary across the SPM territory, this finding indicates that the funds for these services are unlikely

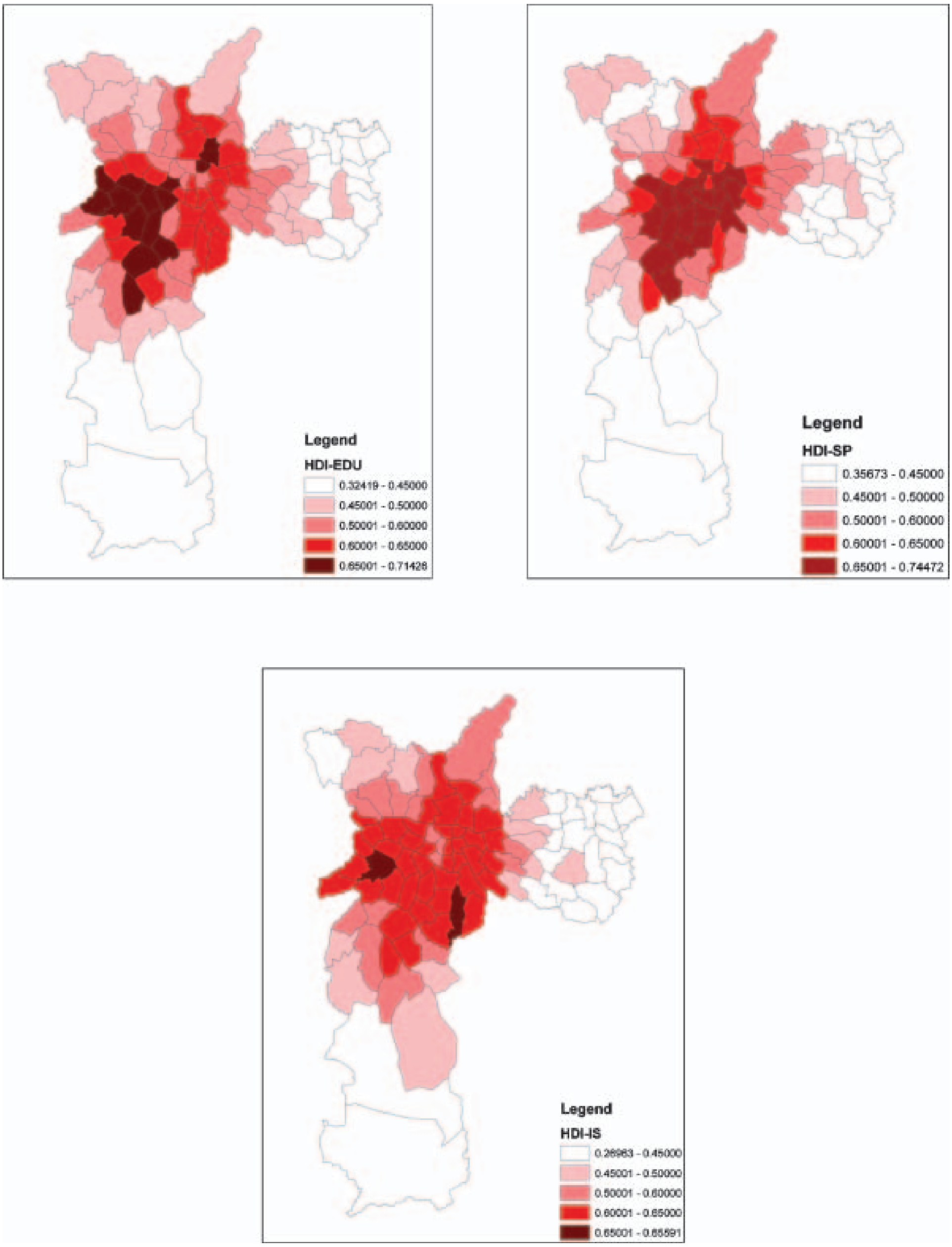

FIGURE 4. HDI predicted maps based on the M-EDU, M-SP, and M-IS models.

to be allocated in districts where they are needed. Mapping of the predicted HDI values for all three models, in general, demonstrate that the manner in which public interventions are distributed (when controlling for population 'density') is unlikely to address the observed inequalities since they largely still follow the center–periphery regimes.

When examining the difference between center and periphery, we find based on the M-EDU model that, on average, the central districts with higher HDI have teachers with higher education, and that in the periphery the districts with higher HDI values have smaller ratio of students per computer. The M-SP model suggests that the 'minimum wage' program is allocated in the center, in districts of lower HDI and hence higher need. However, it is important to highlight that this program is not significant in peripheral districts, where it is also needed. The 'school snack' program is correctly allocated in the periphery, in districts of higher needs (i.e. lower human development level). The M-IS model indicates that 'infrastructure development' and 'health development' have a positive association with the HDI in both the center and the periphery, showing that the periphery is not neglected.

To examine the idea of expansion of capabilities and its link with public intervention we consider only the peripheral districts. This idea is manifested with regard to the 'school snack' variable, which is the only one displaying a desirable direction, with the number of program recipients increasing as the HDI gets lower. Other social programs and provisions of public services and facilities do not contribute significantly to expanding the capabilities of those affected by the intra-urban inequalities. The models suggest that already affluent and well-developed central districts perhaps benefit more from the public investments than the peripheral districts where the needs are more prominent.

We offer a few possible explanations of the discovered reinforcement of the center–periphery regimes by public intervention. First, in SPM it is not unusual to see 'wealthy people influencing government officials to attract public investments and services to the neighborhoods they live in, at the expense of low-income neighborhoods'' (Werna, 2000, p. 4). These wealthy people tend to live in the center of the municipality. Second, the inequalities in human development are also related to the ''processes of political representation, [and] action rationale of the bureaucratic segments responsible for service provision'' (Torres and Oliveira, 2001, p. 16). Most of the time, residents of the less developed districts do not have enough education and power to participate in political processes. Third, the southern part of the municipality is characterized by a high level of urban violence and homicides that are ''concentrated in the periphery of the Municipality of São Paulo, spilling over the borders to neighboring municipalities of the Metro area'' (Cardia, 2000, p. 11). This condition may present an obstacle to public intervention. Fourth, the geography of the municipality probably contributes to this condition by partially isolating the southern districts with a body of water. This physical barrier may affect the decisions regarding the geographical allocation of public investments. Fifth, three of the four examined social programs are universal (i.e. they serve all the districts). Only one program (Minimum Wage) is based on allocation to the districts in need. However, according to the M-SP model results, the peripheral districts do not benefit from it. Finally, the *Strategic Master Plan of the São Paulo Municipality 2002–2012* (SEMPLA, 2004) points out that the peripheral districts had the highest population growth in the past decade. This plan also designates these districts as zones for environmental protection (*macrozona de proteção ambiental*). Clearly, there are multiple and conflicting forces at work in these districts — population growth pressures, the demands for environmental protection, and an already existing low level of human development.

We conclude that policies and programs which explicitly target less developed areas are more likely to be more effective and successful in reducing intra-urban inequalities. If the public sector is willing to achieve 'pro-equality' goals, attention to spatially-oriented social policies is needed. If the allocation of public resources is decided by power politics and ability to participate in the decision-making processes, then the less educated and poor will continue to be on the shorter end of the distribution. The inequalities identified in this paper are probably due to these kind of issues, although without time-series data this study could not determine the causes of specific outcomes of public intervention and its correlates. To evaluate the effectiveness of public policies and programs and to identify the factors that are causally linked to their outcomes, future studies should rely on data collected at multiple periods of time.

Acknowledgements

The authors are grateful for the comments and suggestions provided by three anonymous referees. They would also like to thank Julie Le Gallo for her comments and suggestions on an earlier version of this paper, the Brazilian institutions for their help with data acquisition and, last but not least, Geoffrey Hewings and Sandy Dall'Erba for their comments and suggestions along the way. The support by the Hewlett Program of the University of Illinois is greatly appreciated. However, the authors remain solely responsible for any opinions, errors or misconceptions.

Notes

1 For Children Nutrition, one group is targeted: children from 0 to 6 years old in families with per-capita income lower than US$ 30.00 per month. For School Snack the target population was not provided by the program coordinators, so we assumed that it includes children from 4 to 14 years old in families with an income of three minimum wages or less (around US$ 240.00). For Family Health we assumed that the target population is families with an income of three minimum wages or less. For Minimum Wage the target population is children from 0 to 15 years old in families with an income of three minimum wages or less (Pochmann, 2002, p. 100).

2 A list of all the variables used in the factor analysis and the factors they belong to is as follows:

Proportion of dwellings with water supply from the public network	Infrast.
Proportion of dwellings with water supply from spring or well	Infrast.
Proportion of dwellings with sewage services from the public network	Infrast.
Proportion of dwellings with sewage services using concrete cesspit	Infrast.
Proportion of dwellings with garbage collection from the public network	Infrast.
Proportion of dwellings with garbage collection by collective tanks	Infrast.
Proportion of dwellings with bathroom (toilet)	Infrast.
Proportion of dwellings with eletric power and TV	Infrast.
Nutrition Program for children between 0 and 6 years of age	Health
Nutrition Program for pregnant women between 15 and 49 years of age	Health
Snack Program for children between 4 and 14 years of age	Health
Medical equipments/district population ratio (public and private)	Health

3 For all three models, there was a need to estimate using both methods, ML and IV. For all three models, the results for the IV models confirm the signs of the coefficients and their significance are consistent with the results of the ML models.

4 According to Anselin, ''a spatial lag is constructed as a weighted average (using the weights in the spatial weighted matrix) of the values observed for the neighbors of a given location'' (1998, p. 260). This type of model suggests a possible diffusion process: events in one place predict an increased likelihood of similar events in neighboring places. In this model, spatial dependence is best described with reference to the influence of the dependent variable in neighboring locations. If this form of spatial autocorrelation is ignored, the results are similar to the consequences of omitting a significant explanatory variable in the regression model.

5 The three models do not present problems of multicolinearity, having the following multicolinearity condition numbers: 36.86 (M-EDU); 10.43 (M-SP); and 4.68 (M-IS). Concerning endogeneity, Hausman tests were performed and only two variables are endogenous at 1%: 'school snack' and 'children nutrition.' The other variables are all exogenous.

References

Alkire, S. (2002) *Valuing Freedoms: Sen's Capability Approach and Poverty Reduction*, Oxford University Press, Oxford.

Anand, S. and Sen, A. (2000) 'Human development and economic sustainability', *World Development*, 28(12), pp. 2029–2049.

Andersen, T. and Kempen, R. (2001) *Governing European Cities: Social Fragmentation, Social Exclusion and Urban Governance*, Ashgate, Aldershot.

Anselin, L. (1988) *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers, Dordrecht.

Anselin, L. (1995) 'Local indicators of spatial association — LISA', *Geographical Analysis*, 27, pp. 93–115.

Anselin, L. (1998) 'Interactive techniques and exploratory spatial data analysis', in P.A. Longley, M.F. Goodchild, D.J. Maguire and D.W. Wind (Eds.), *Geographical Information Systems: Principles, Techniques, Management and Applications*, Wiley, New York.

Anselin, L. and Rey, S. (1991) 'Properties of tests for spatial dependence in linear regression models', *Geographical Analysis*, 23(2), pp. 112–131.

Arimah, B. (2004) 'Poverty reduction and human development in Africa', *Journal of Human Development*, 5, pp. 399–415.

Baller, R., Anselin, L., Messner, S., Deane, G. and Hawkins, D. (2001) 'Structural covariates of U.S. county homicide rates: incorporating spatial effects', *Criminology*, 39(3), pp. 561–588.

Baumont, C., Ertur, C. and Le Gallo, J. (2003) 'Spatial convergence clubs and the European regional growth process, 1980–1995', in B. Fingleton (Ed.), *European Regional Growth*, Springer, Berlin.

Baumont, C., Ertur, C. and Le Gallo, J. (2004) 'Spatial analysis of employment and population density: the case of the agglomeration of Dijon, 1999', *Geographical Analysis*, 36, pp. 146–176.

Burgess, R., Carmona, M. and Kolstee, T. (1997) *The Challenge of Sustainable Cities: Neoliberalism and Urban Strategies in Developing Countries*, Zed Books, London.

Câmara, G., Monteiro, A., Ramos, F., Sposati, A. and Koga, D. (2003) 'Mapping social exclusion/inclusion in developing countries: social dynamics of São Paulo in the 1990s', in M.F. Goodchild and D.G. Janelle (Eds.), *Spatially Integrated Social Science: Examples in Best Practice*, Oxford University Press, Oxford.

Cardia, N. (2000) 'Urban violence in São Paulo', *Comparative Urban Studies Occasional Papers Series*, Woodrow Wilson International Center for Scholars, Washington, DC.

Devas, N., Amis, P., Beall, J., Grant, U., Mitlin, D., Rakodi, C. and Satterthwaite, D. (2001) *Urban Governance and Poverty: Lessons from a Study of Ten Cases in the South*, The School of Public Policy, University of Birmingham, Birmingham.

Florax, R., Folmer, H. and Rey, S. (2003) 'Specification searches in spatial econometrics: the relevance of Hendry's methodology', *Regional Science and Urban Economics*, 33, pp. 557–579.

Foster, J., Lopez-calva, L. and Szekely, M. (2005) 'Measuring the distribution of human development: methodology and an application to Mexico', *Journal of Human Development*, 6, pp. 5–25.

Guillain, R., Le Gallo, J. and Boiteux-Orain, C. (2006) 'Changes in spatial and sectoral patterns of employment in Ile-de-France, 1978–1997', *Urban Studies*, (forthcoming).

Haddad, M. (2003) 'Human development and regional inequalities: spatial analysis across Brazilian municipalities', *PhD Dissertation*, University of Illinois at Urbana-Champaign, Urbana, IL.

Haq, M. (1998) *Reflections on Human Development*, Oxford University Press, Calcutta, India.

Le Gallo, J. and Dall'Erba, S. (2006) 'Evaluating the temporal and spatial heterogeneity of the European convergence process, 1980–1999', *Journal of Regional Science*, (forthcoming).

Le Gallo, J. and Ertur, C. (2003) 'Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980–1995', *Papers in Regional Sciences*, 82, pp. 175–201.

Lima, J.J. (2001) 'Socio-spatial segregation and urban form: Belém at the end of the 1990s', *Geoforum*, 32, pp. 493–507.

Marcuse, P. and Van Kempen, R. (2000) 'Introduction', in P. Marcuse and R. van Kempen (Eds.), *Globalizing Cities: A New Spatial Order?*, Blackwell Publishers, Oxford.

Marcuse, P. and Van Kempen, R. (2002) 'States, cities and the partitioning of urban space: conclusions', in P. Marcuse and R. van Kempen (Eds.), *Of States and Cities: The Partitioning of Urban Space*, Oxford University Press, New York.

Messner, S., Anselin, L., Baller, R.D., Hawkins, D.F., Deane, G. and Tolnay, S.E. (1999) 'The spatial patterning of county homicide rates: an application of exploratory spatial data analysis', *Journal of Quantitative Criminology*, 15(4), pp. 423–450.

Musterd, S. and Osterndorf, W. (1998) *Urban Segregation and the Welfare State: Inequality and Exclusion in Western Cities*, Routledge, London.

Pereira, J.M.C., Carreiras, J.M.B. and Vasconcelos, M.J.P. (1998) 'Exploratory data analysis of the spatial distribution of wildfires in Portugal, 1980–1989', *Geographical Systems*, 5, pp. 355–390.

Pochmann, M. (2002) *Desenvolvimento, Trabalho, e Solidariedade: Novos Caminhos Para a Inclusão Social*, Cortez Editora, São Paulo.
Portnov, B. (2002) 'Intra-urban inequalities and planning strategies: a case study of Be'er Sheva, Israel', *International Planning Studies*, 7(2), pp. 137–156.
Ranis, G., Stewart, F. and Ramirez, A. (2000) 'Economic growth and human development', *World Development*, 28(2), pp. 197–219.
Ramos, R. (2002) 'Análise espacial de estruturas intra-urbanas: o caso de São Paulo', *Masters Thesis*, INPE, São José dos Campos.
SEMPLA, (2004) *Plano Diretor Estratégico do Município de São Paulo 2002–2012*, Senac São Paulo Editora, Prefeitura de São Paulo, São Paulo.
SMDTS, (2002) *Desigualdade em São Paulo: o IDH*, Prefeitura da Cidade de São Paulo, São Paulo.
SMDTS, (2003) *Programas Sociais e Restrições Macroeconômicas*, Prefeitura da Cidade de São Paulo, São Paulo.
Sen, A. (1999) *Development as Freedom*, Anchor Books, New York.
Shah, A. and Sah, D.C. (2004) 'Poverty among tribals in South West Madhya Pradesh: has anything changed over time?', *Journal of Human Development*, 5, pp. 249–263.
Sposati, A. (1996) *Mapa da Exclusão/Inclusão Social da Cidade de São Paulo*, EDUC, São Paulo.
Sposati, A. (2000) *Mapa da Exclusão/Inclusão Social/2000: Dinâmica Social dos Anos 90*, Catholic University, São Paulo.
Talen, E. and Anselin, L. (1998) 'Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds', *Environment and Planning A*, 30, pp. 595–613.
Torres, H. and Marques, E. (2004) 'Políticas sociais e Territorio: Uma abordagem Metropolitana', *Revista São Paulo em Perspectiva*, 18(4), pp. 28–38.
Torres, H. and Oliveira, G.C. (2001) *Primary Education and Residential Segregation in the Municipality of São Paulo: a Study Using Geographic Information Systems*, conference paper, Lincoln Institute of Land Policy, Cambridge, MA.
Werna, E. (1995) 'Urban management and intra-urban differentials in São Paulo', *Habitat International*, 19(1), pp. 123–138.
Werna, E. (2000) *Combating Urban Inequalities: Challenges for Managing Cities in the Developing World*, Edward Elgar, Cheltenham.