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**Conference Paper**

## Economic Growth and Infrastructure in Brazil: A Spatial Multilevel Approach

54th Congress of the European Regional Science Association: "Regional development & globalisation: Best practices", 26-29 August 2014, St. Petersburg, Russia

**Provided in Cooperation with:**

European Regional Science Association (ERSA)

*Suggested Citation:* Almeida, Eduardo; Guimarães, Pablo (2014) : Economic Growth and Infrastructure in Brazil: A Spatial Multilevel Approach, 54th Congress of the European Regional Science Association: "Regional development & globalisation: Best practices", 26-29 August 2014, St. Petersburg, Russia, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/124249>

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# ECONOMIC GROWTH AND INFRASTRUCTURE IN BRAZIL: A SPATIAL MULTILEVEL APPROACH

## 1. Introduction

The international literature had its attention aroused by the role of infrastructure on economic performance by the American productivity crisis of the seventies and eighties. The explanation from some authors for such a collapse rested on the decrease of infrastructure spending (Aschauer, 1989; Munnell, 1992; Prud'homme, 1996). Other authors, on the other hand, found evidence that showed that the influence of infrastructure on production is null from the statistical point of view (Holtz-Eakin, 1994; Kelejian and Robinson, 1997). The controversy has been, however, essentially around the presentation of empirical evidence.

It is theoretically expected that infrastructure supply exerts influence on economic performance in various forms. First, the presence of infrastructure reduces the cost of intermediate inputs, thus decreasing the cost of production and tending to increase local income (Krugman, 1991). Second, the adequate provision of infrastructure increases labor productivity, elevating its respective supplies and, consequently, creating potential conditions for the increase of production (Fourier, 2006). Third, infrastructure minimizes transaction costs by enabling better access to products and technology (World Bank, 2006). Fourth, the allocation of infrastructure creates significant positive externalities in productivity (Martin, 2001). Finally, Carmignani (2003) points out that the provision of infrastructure promotes the increase of physical connectivity, developing regional markets and strengthening informational flows across borders.

Besides the impact on economic development, infrastructure can exert influence on equity. The distribution of activities complementary to production, such as telecommunications and transportation infrastructure, may lead to development concentrated in certain regions (Venables, 2001).

In the literature, there are papers that highlight the relation between infrastructure and income convergence. For example, Nagaraj, Varoudakis and Véganzonès (1998) expound on the limitations of competitiveness in certain regions due to the lack of infrastructure, explaining a large part of the output gap with respect to steady-state. Finally, the authors point out that the efficacy of public investment could be improved by means of the concentration of investment efforts in physical infrastructure, which apparently exerts a significant impact on growth (electrical energy, irrigation and roads). Reinforcing this idea, Silva and Fortunato

(2007) claim that the absence of minimal infrastructure in less-developed regions ultimately compromises the potential for growth.

In Brazil, studies on the influence of infrastructure have also gained notoriety by considering that they would help economic growth, consequently reducing the regional inequalities in Brazil (Azzoni et al 2000; Haddad, 2004; De Negri and Salerno, 2005). As for the relation between transportation and regional equality, Almeida et al (2010) found that improvements in transportation infrastructure in poor regions promoted a drop in regional equality, but when these improvements occur in rich regions, a considerable increase in the regional income inequality is observed.

As noted, there are several theoretical arguments that justify taking into consideration infrastructure stock as one of the determinants in studies on economic growth and income convergence. Thus the absence of infrastructure as an independent variable in the right side of the equation of income convergence may lead to the serious econometric problem of omission of a relevant variable, making the estimation inconsistent.

In spite of there being theoretical justification for taking infrastructure into account in studies on economic growth and equity, there is a difficulty in obtaining infrastructure data at a more disaggregated regional level. Frequently, the decisions on infrastructure investment are taken in the sphere of the federal government or of the state governments. Due to this, the data are usually available only at the state level.<sup>1</sup>

In view of this, there are two alternatives for doing an analysis of income convergence for Brazil. One alternative would be to do the income convergence analysis only at the state level. However, the sample size would be small ( $n=27$ ), making it not reach the asymptotic properties of the estimators, among other limitations.

The other alternative would be to perform the analysis of income convergence only at the municipal level. However, as much information on infrastructure is available at the state level, the researcher would take his chance of omitting variables of infrastructure relevant to analysis, creating bias and inconsistency to the estimator.

Taking this situation into account, the methodological solution involves the adoption of hierarchical models for dealing with infrastructure within the analysis of income convergence, using the data available from Brazilian statistical agencies.

The multilevel approach is justified when attempting to reconcile this hierarchical structure of necessary data in order to perform the analysis of conditional income

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<sup>1</sup> Brazil was composed of 27 states and 5507 “municípios” (municipalities) in 2005.

convergence, including infrastructure as an important determinant. The strategy undertaken here, thus, involves working with the specification of the model of conditional income convergences at the first municipal level. The infrastructure stock, defined at the second level, exerts a direct influence on the equation of income convergence at the first level.

In terms of the analysis of income convergence via the approach of multilevel models, the literature has few works. As far as we know, there are two papers covering this focus.

Fazio and Piacentino (2001) observe that there is an interest in the literature for works that focus on the convergence in its more aggregate aspect. However, the authors claim that, as the macroeconomic analysis is subjacent to the microeconomic issues, the convergence should be analyzed in a more disaggregated point of view. By adopting hierarchical models, the authors obtained the parameters of convergence at the regional micro and macro levels and concluded, by means of an analysis of Italian provinces, that there is a convergence of labor productivity at more disaggregated levels, but such a result is not repeated in macro-regions.

Differently from Fazio and Piacentino, who analyzed the income convergence in its broader aspect, Chasco and Lopéz (2009) studied the role of regional decentralization on income growth, given that each geographical unit presents peculiarities regarding the promotion of decentralizing measures of innovation and economic growth. The analysis done for Europe occurs by the estimation of the coefficient of convergence  $\beta$  both at the level of country and at a more regionalized level (NUTS 2). The results obtained show that a decentralization of the European Union does not guarantee higher rates of income growth. Neither of these papers, however, did an extension to incorporate spatial dependency into the hierarchical model.

Within this context, this article has a double objective, one being of empirical nature and the other of methodological nature. Empirically, it is intended to answer the following question: do stocks of road and electrical energy infrastructure exert influence on income convergence in Brazilian “municípios” (municipalities)? Methodologically, it is intended to develop a multilevel model of conditional income convergence with various types of control. First, the control for variables that condition the income convergence is done. Second, the control for the non-observed characteristics in the municipalities is performed. Third, variables of infrastructure are included, measured at the state level, in order to avoid relevant omitted variable bias. Fourth, it is explicitly controlled for spatial autocorrelation.

The results obtained show that only road infrastructure, as a conditional variable, exerts impact upon income convergence. The controls for the non-observed idiosyncratic characteristics of the municipalities and for spatial dependence have the greater effect upon the estimation of  $\beta$ -convergence. The estimated coefficient for  $\beta$  in this work is quite different from typical  $\beta$  coefficients calculated in the Brazilian literature on convergence.

Beyond this introduction, the paper is organized in the following form. In the next section, multilevel models are presented, as well as their extension to control spatial dependence. In the third section, the database in the two hierarchical levels adopted (municipal and state) is described. In the fourth section, the results of the estimation are presented and discussed. The last section concludes.

## **2. Spatial Multilevel Analysis**

### *2.1. General Ideas*

In multilevel modeling, each hierarchical level has its own specification, also denominated as submodels.<sup>2</sup> These submodels express the relations between the variables that make up a certain level, and specify how variables at a level exert influence upon the results of another level. According to Raudenbush and Bryk (2002), this is characterized in the form of a hierarchy of data, in which systems may be structured into various levels with different explanatory variables defined in each hierarchical level.

The multilevel methodology incorporates in its analysis at least two hierarchical levels. One level is related to more disaggregated behavior, normally individual. The other level refers to the level of the context, be it a group (classes, schools, hospitals, etc.) or a geographical region. In this paper, the interest lies with the special case in which the hierarchical levels are of geographical aspect, the first level involving regions defined in a more disaggregated way than the regions of the second level. In other words, the first level will be specified for municipalities, whereas the second level will be defined for states.

At first it is important to check whether the variance of the error term can be better explained by being incorporated in a higher hierarchical level, namely the state level. In order to ascertain whether the incorporation of information at the state level helps explain the variability of the data in the income convergence equation, the null hierarchical model is estimated. Later, the intraclass correlation ( $r$ ) is computed, which reports how much of the

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<sup>2</sup> Multilevel model and hierarchical model will be used indistinctly as synonymous in this paper.

variation in the data on economic growth rate (*GROW*) lies within and among the States. The null hierarchical model is specified in the first model in the following manner:

$$GROW_{ij} = \alpha_{0j} + e_{ij} \quad (1a)$$

The specification at the second level assumes the form:

$$\alpha_{0j} = \mu_{00} + v_{0j} \quad (1b)$$

where the indices  $i$  and  $j$  denote the municipal and state levels, respectively, being that  $i=1, 2, \dots, n$  municipalities within state  $j$  and  $j=1, 2, \dots, J$  states. The term is  $\alpha_{0j}$  the intercept that varies with the state, therefore, the subscript  $j$ , while the error term  $e_{ij}$  represents the deviation of municipality  $i$  in relation to the mean state  $j$ . The error term is assumed to have zero mean and variance  $\sigma_e^2$ .

Substituting (1b) in (1a), the complete model is obtained:

$$GROW_{ij} = \mu_{00} + v_{0j} + e_{ij} \quad (1c)$$

where  $\mu_{00}$  is the grand mean, while  $v_{0j}$  is the random error term, with a zero mean and constant variance. It is assumed that there is no correlation between the first level random term and the random term of the second hierarchical level.

The calculation of the intraclass correlation coefficient ( $r$ ) is given by the following formula:

$$r = \frac{\sigma_{v_0}^2}{(\sigma_{v_0}^2 + \sigma_e^2)} \quad (2)$$

The coefficient is the proportion of second level variance compared to total variance. If this coefficient is zero, then, this indicates that  $\sigma_{v_0}^2 = 0$ , in other words, there is no variability of the second level data with respect to the groups. This means that there is no evidence of differences between groups existing, so it is possible to assume a classical regression model instead of a multilevel model (Snijders and Bosker, 1999).

The multilevel model of conditional income convergence is specified for two levels of analysis, the first one containing municipal variables:

$$\begin{aligned} GROW_{ij} = & \alpha_{0j} + \alpha_{1j}IGDP_{ij} + \alpha_{2j}TAX_{ij} + \alpha_{3j}CAP_{ij} + \alpha_{4j}EXP_{ij} + \alpha_{5j}FUND_{ij} \\ & + \alpha_{6j}GAP_{ij} + \alpha_{7j}HUM_{ij} + \alpha_{8j}ROY_{ij} \\ & + \varepsilon_{ij} \end{aligned} \quad (3a)$$

where *IGDP* is initial income; *TAX* represents tax burden, *CAP* is physical capital; *EXP* symbolizes current expenditures of the municipal government; *FUND* denotes municipal participation fund resources; *GAP* is a variable of the productivity gap; *HUM* is human capital; *ROY* are resources received due to petroleum royalties; and, finally,  $\varepsilon$  denotes the error term.

The second level is specified with the infrastructure variables for state data:

$$\alpha_{0j} = \mu_{00} + \mu_{01}ROAD_j + \mu_{02}ENERGY_j + v_{0j} \quad (3b)$$

It can be seen that in Equation (3b) the intercept of the first level model was specified with a fixed component ( $\mu_{00}$ ), with the variables for road infrastructure ( $ROAD$ ) and electrical energy ( $ENERGY$ ), besides a random component ( $v_{0j}$ ).

For the other coefficients of the first level model only a fixed component was specified, namely,  $\alpha_{1j} = \beta$ ;  $\alpha_{2j} = \mu_{20}$ ;  $\alpha_{3j} = \mu_{30}$ ;  $\alpha_{4j} = \mu_{40}$ ;  $\alpha_{5j} = \mu_{50}$ ;  $\alpha_{6j} = \mu_{60}$ ;  $\alpha_{7j} = \mu_{70}$ ;  $\alpha_{8j} = \mu_{80}$ .

Finally, the complete conventional multilevel model for conditional income convergence is expressed as:

$$\begin{aligned} GROW_{ij} = & \mu_{00} + \mu_{01}ROAD_j + \mu_{02}ENERGY_j + v_{0j} + \beta IGDP_{ij} + \mu_{20}TAX_{ij} \\ & + \mu_{30}CAP_{ij} + \mu_{40}EXP_{ij} + \mu_{50}FUND_{ij} + \mu_{60}GAP_{ij} \\ & + \mu_{70}HUM_{ij} + \mu_{80}ROY_{ij} + \varepsilon_{ij} \end{aligned} \quad (4)$$

## 2.2. Spatial Multilevel Model for Income Convergence

The multilevel model for income convergence, expressed by Equation (4), can involve several econometric problems, such as heteroscedasticity, the potential endogeneity of the variables of infrastructure stock, the non-control of characteristics not observed in the first level of the analysis and the possible spatial autocorrelation.

The control for heteroscedasticity is done by the calculation of the robust standard errors of the estimates by the White matrix. The control for potential endogeneity of the road and electrical energy infrastructure stocks is done by utilizing infrastructure variables from the previous period (1998) in the time span adopted in the definitions of economic growth rates (1999-2005).

The control for non-observed characteristics in the first level is done with the definition of the first level variables in differences, dividing the time span of 1999 to 2005 into two subperiods: 1999 to 2002 and 2002-2005. The differenced data were calculated in the following manner:

$$GROW_{ij} = (GROW_{ij,2005} - GROW_{ij,2002}) - (GROW_{ij,2002} - GROW_{ij,1999}) \quad (5a)$$

$$X_{ij} = (X_{ij,2005} - X_{ij,2002}) - (X_{ij,2002} - X_{ij,1999}) \quad (5b)$$

Note that  $X_{ij}$  is the set of explanatory variables of the first hierarchical level, that is,  $X_{ij} = [IGDP_{ij}, TAX_{ij}, CAP_{ij}, EXP_{ij}, FUND_{ij}, GAP_{ij}, HUM_{ij}, ROY_{ij}]$ . Thus, for each of these

variables formula (5) was applied to calculate the differences, in order to remove the fixed effects.

The control for spatial dependence is possible by expanding the conventional multilevel model for income convergence, adding a set of spatial lags:

$$\begin{aligned}
GROW_{ij} = & \alpha_{0j} + \alpha_{1j}IGDP_{ij} + \alpha_{2j}TAX_{ij} + \alpha_{3j}CAP_{ij} + \alpha_{4j}EXP_{ij} + \alpha_{5j}FUND_{ij} \\
& + \alpha_{6j}GAP_{ij} \\
& + \alpha_{7j}HUM_{ij} + \alpha_{8j}ROY_{ij} + \alpha_{9j}WGROW_{ij} + \alpha_{10j}WIGDP_{ij} + \alpha_{11j}WTAX_{ij} + \\
& + \alpha_{12j}WCAP_{ij} + \alpha_{13j}WEXP_{ij} + \alpha_{14j}WFUND_{ij} + \alpha_{15j}WGAP_{ij} + \\
& + \alpha_{16j}WHUM_{ij} + \alpha_{17j}WROY_{ij} \\
& + \xi_{ij}
\end{aligned} \tag{6a}$$

$$\xi_{ij} = \alpha_{18j}W\xi_{ij} + e_{ij} \tag{6b}$$

It is possible to specify several spatial models starting from the restrictions imposed on the spatial parameters in Equations (6a) and (6b). For example, by imposing the restrictions that  $\alpha_{9j} = \alpha_{10j} = \alpha_{11j} = \alpha_{12j} = \alpha_{13j} = \alpha_{14j} = \alpha_{15j} = \alpha_{16j} = \alpha_{17j} = 0$  e  $\alpha_{18j} \neq 0$ , we have the multilevel SEM model. The multilevel SAR model is defined by imposing the restrictions that  $\alpha_{10j} = \alpha_{11j} = \alpha_{12j} = \alpha_{13j} = \alpha_{14j} = \alpha_{15j} = \alpha_{16j} = \alpha_{17j} = \alpha_{18j} = 0$  e  $\alpha_{9j} \neq 0$ . The multilevel SDM model is obtained with the coefficients  $\alpha_{9j}$ ,  $\alpha_{10j}$ ,  $\alpha_{11j}$ ,  $\alpha_{12j}$ ,  $\alpha_{13j}$ ,  $\alpha_{14j}$ ,  $\alpha_{15j}$ ,  $\alpha_{16j}$  e  $\alpha_{17j}$  being nonzero and  $\alpha_{18j} = 0$ . The multilevel SDEM model is specified with the imposition of the following restrictions:  $\alpha_{10j}$ ,  $\alpha_{11j}$ ,  $\alpha_{12j}$ ,  $\alpha_{13j}$ ,  $\alpha_{14j}$ ,  $\alpha_{15j}$ ,  $\alpha_{16j}$ ,  $\alpha_{17j}$  and  $\alpha_{18j}$  being nonzero and  $\alpha_{9j} = 0$ . The multilevel SLX model is determined with  $\alpha_{9j}$ ,  $\alpha_{10j}$ ,  $\alpha_{11j}$ ,  $\alpha_{12j}$ ,  $\alpha_{13j}$ ,  $\alpha_{14j}$ ,  $\alpha_{15j}$ ,  $\alpha_{16j}$  e  $\alpha_{17j}$  being nonzero and  $\alpha_{9j} = 0$  and  $\alpha_{18j} = 0$ .

In the second level, it is also possible to model spatial dependence, specifying the intercept of the first-level model as:

$$\begin{aligned}
\alpha_{0j} = & \mu_{00} + \mu_{01}ROAD_j + \mu_{02}ENERGY_j + \mu_{03}WROAD_j + \mu_{04}WENERGY_j \\
& + v_{0j}
\end{aligned} \tag{6c}$$

It should be pointed out that the spatial lags *WROAD* and *WENERGY* in this specification were included in order to capture spatial spillovers localized in the infrastructure stocks at the state level. It is possible to explain the other first-level coefficients with spatial lags.<sup>3</sup>

For the other of the coefficients of the first-level model only one fixed component was specified, that is,  $\alpha_{1j} = \beta$ ;  $\alpha_{2j} = \mu_{20}$ ;  $\alpha_{3j} = \mu_{30}$ ;  $\alpha_{4j} = \mu_{40}$ ;  $\alpha_{5j} = \mu_{50}$ ;  $\alpha_{6j} = \mu_{60}$ ;  $\alpha_{7j} = \mu_{70}$ ;  $\alpha_{8j} = \mu_{80}$ ;  $\alpha_{9j} = \rho$ ;  $\alpha_{10j} = \mu_{100}$ ;  $\alpha_{11j} = \mu_{110}$ ;  $\alpha_{12j} = \mu_{120}$ ;  $\alpha_{13j} = \mu_{130}$ ;  $\alpha_{14j} = \mu_{140}$ ;  $\alpha_{15j} = \mu_{150}$ ;  $\alpha_{16j} = \mu_{160}$ ;  $\alpha_{17j} = \mu_{170}$ .

<sup>3</sup> This was the adaptation done by Morenoff (2003) to treat the spatial dependence in multilevel models.



As for the estimation of the multilevel SAR model, the econometric problem that needs to be confronted is the endogeneity of the spatially lagged dependent variable ( $WGROW_{ij}$ ). One way to do this is to eliminate the endogeneity from the  $WGROW_{ij}$  variable at the first level by means of an auxiliary regression in which it is attempted to be instrumentalized, using the spatial lag of the explanatory variables as instruments. In other words, the multilevel SAR model must be estimated by a kind of two stage least squares. In the first stage, the auxiliary regression is estimated by ordinary least squares (OLS) with data of the first hierarchical level:

$$WGROW_{ij} = X_{1ij}\delta + WX_{1ij}\tau + \eta_{ij} \quad (7)$$

where  $WX$  represents the spatial lags of the explanatory variables ( $X$ ),  $\tau$ ,  $\delta$  are vectors of the coefficients of the instruments and  $\eta_{ij}$  is an error term.

In the second stage, the predicted values of the spatial lag of the dependent variable are inserted into the regression at the first hierarchical level, that is,  $\widehat{WGROW}_{ij}$ , and, finally, the mixed multilevel model is estimated.

The estimation of the multilevel SDM model involved the endogenous variable  $WGROW$  in the right side of equation (8). To circumvent this, it is necessary to eliminate the endogeneity from the variable  $WGROW$  by means of the auxiliary regression at the regional hierarchical level, using now as instruments the spatial lag of the spatial lags of the explanatory exogenous variables,  $W^2X$ :

$$WGROW_{ij} = X_{ij}\delta + WX_{ij}\tau + W^2X_{ij}\phi + \eta_{ij} \quad (8)$$

in which  $\delta$ ,  $\tau$  and  $\phi$  are vectors of the coefficients to be estimated, being that the rest of the notation remains the same. In the second stage, the predicted values of the variable ( $\widehat{WGROW}_{ij}$ ) are introduced into the model in the first hierarchical level and the model is estimated.

The multilevel SEM model can be estimated by Generalized Method of Moments (GMM). Using the estimation procedure of Kelejian and Prucha (1998), the model is estimated in the first level to obtain a consistent  $\lambda$ . In the second step, the variables of the first level are spatially filtered in the following way:

$$GROW^* = GROW - \lambda WGROW \quad (9a)$$

$$X^* = X - \lambda WX \quad (9b)$$

Afterwards, the  $GROW^*$  variables and the set of spatially filtered explanatory variables  $X^*$  should be included in the model in order to estimate this transformed equation.

The multilevel SDEM model is specified in the first hierarchical level, the estimation procedure of which is also based on GMM, as shown for the SEM model, only additionally filtering the spatially lagged explanatory variables, besides those previously filtered:

$$WX_1^* = WX_1^* - \lambda W^2 X_1^* \quad (10)$$

In the final stage of the procedure, the transformed equation with the spatially filtered variables is estimated.

In the multilevel SLX model, as  $WX_{ij}$  are considered exogenous explanatory variables in the first level, the estimator can be that adopted by the basic multilevel model.

In order to obtain the most adequate model for representing the generating data process, the specification procedure proposed by Hox (2002) was extended here to incorporate spatial dependence:

- a) Specify the model at the most disaggregated level;
- b) Adopt the null model and calculate the coefficient of intraclass correlation. The closer to 1 (one) the coefficient is, the better the specification of the second level of the model at explaining the variance of the data;
- c) Specify the fixed part and the random part in the most aggregated level, in such a way as to explain the variability of the coefficients at that most disaggregated level;
- d) Adopt the substitution method to obtain the complete model;
- e) Estimate the complete multilevel model;
- f) Verify the spatial autocorrelation in the residuals of the complete model. If there is spatial autocorrelation, proceed to the next step; if there is not spatial autocorrelation, adopt the specification of the conventional multilevel model;
- g) Estimate the spatial multilevel models (SAR, SEM, SDM, SDEM and SLX) respecifying the model so as to control the spatial autocorrelation, including spatial lags in the first level and/or in the second level;
- h) Select the model that consecutively meets the two criteria. First, choose the model that has corrected the spatial autocorrelation in the residuals of the complete model. Afterwards, select that model that presents the fewest information criteria;

### 3. Database

#### 3.1. Variables at the Municipal Level

The dependent variable under study is the rate of per capita income growth for Brazilian municipalities (*GROW*). In order to construct this variable data from the Brazilian Institute of Geography and Statistics (IBGE) were used, regarding municipal GDP and estimates of the population residing in each municipality. The construction of the variable is done in the following way:  $GROW_{it} = \ln(GDP_{it}/GDP_{it-1})$ . The period of analysis is from 1999 to 2005.

The variable of interest is the initial level of per capita income (*IGDP*), represented by variable natural logarithm of the municipal per capita GDP, and obtained from IBGE.

The description of the variables used to condition the income convergence analysis is done below.

As to the Human Capital (*HUM*) variable, the natural logarithm of the number of people with, at least, a high school education who are in the formal job market was used, taken from the RAIS database from the Ministry of Labor and Employment. The proxy for Physical Capital (*CAP*) is given by the natural logarithm of the ratio of municipal capital expenditure to the GDP of each municipality. The measurement of public spending is the Current Expenses (*EXP*) of the municipal governments, calculated as being the ratio of current expenses to GDP. Tax burden (*TAX*) is represented by the natural logarithm of the ratio of municipal tax burden to *GDP*. In tax burden, land and urban property taxes (IPTU), services tax and other taxes related to taxes received by the municipalities are included, such as the tax on the transfer of real estate (ITBI). The source of these data is the Secretary of the Treasury. The Municipal Participation Fund (*FUND*), which represents the municipality's share in the revenue of the States and of the Union, is calculated by the natural logarithm of the ratio of shares of the Fund and the number of inhabitants of the municipality. The data referring to the shares are taken from the database of the Secretary of the Treasury. To get a proxy for the productivity gap (*GAP*), the variable of productivity (*PROD*) was calculated a priori, which represents the ratio "municipal manufacturing GDP with respect to the total of hours worked in manufacturing industry." The manufacturing sector was chosen for being considered the radiating center of innovations in the economic system. The gap indicates the distance between the productivity of each municipality with respect to the greatest productivity. Thus, the variable *GAP* is mathematically represented by:

$$GAP = 1 - \frac{PROD_i}{PROD_m} \quad (11)$$

in which  $PROD_i$  of municipality  $i$  and  $PROD_m$  is the productivity of the municipality with the highest productivity. The data related to industrial GDP were taken from an IBGE database and the total of hours worked from a RAIS database.

The variable  $ROY$  concerns the volume of royalties received by a municipality due to oil exploration. The variable used is given by the natural logarithm of the ratio of the volume of royalties received/GDP. The data concerning royalties have as their source the National Petroleum Agency (ANP) and the Getúlio Vargas Foundation (FGV). Table 1 shows an explanatory synthesis of the variables used in this study and their principal characteristics.

Table 1: Variables for the Study of Income Growth Rate at the First Hierarchical Level

Variable	Description	Expected Sign	Units of Measurement	Source
<i>GROW</i>	Per capital income growth rate		R\$ (thousand)/Population	IBGE
<i>IGDP</i>	Initial per capital income	-	R\$ (thousand)/Population	IBGE
<i>HUM</i>	Per capital level of Human Capital	+	Population with, at least, a high school education/Population	RAIS and IBGE
<i>TAX</i>	Total Tax Burden by $GDP_{i,t}$	-	Percentage of municipal GDP	Secretary of the Treasury and IBGE
<i>CAP</i>	Capital Expenditures by $GDP_{i,t}$	+	Percentage of municipal GDP	Secretary of the Treasury and IBGE
<i>EXP</i>	Current Expenses by $GDP_{i,t}$	-	Percentage of municipal GDP	Secretary of the Treasury and IBGE
<i>FUND</i>	Fundo de Participação Municipal <i>per capita</i>	+	R\$ (thousand)/Population	Secretary of the Treasury and IBGE
<i>GAP</i>	Productivity Gap		R\$ (thousand)/Hours Worked	IBGE and RAIS
<i>ROY</i>	Volume of <i>Royalties</i> received by $GDP_{i,t}$	-	Percentage of municipal GDP	InfoRoyalties, from data from ANP and from FGV and IBGE

Source: prepared by the author.

Table 2 displays the descriptive statistics of the municipal variables.

Table 2 - Descriptive Statistics of the Municipal Level Variables

Statistics	<i>GROW</i>	<i>IGDP</i>	<i>HUM</i>	<i>TAX</i>	<i>FUND</i>	<i>CAP</i>	<i>EXP</i>	<i>GAP</i>	<i>ROY</i>
Mean	1.13	4.20	0.21	1.44	178.83	22.74	91.03	1.00	20.40
Standard Deviation	0.35	4.58	2.15	1.33	192.57	32.81	84.23	0.02	894.35
Minimum	0.13	0.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	13.03	132.74	97.60	10.82	2373.26	506.62	565.76	1.00	89044.71
N	5507	5507	5507	5507	5507	5507	5507	5507	5507

Source: prepared by the author.

Spatial autocorrelation, Moran  $I$  and Geary  $c$  statistics were calculated. According to Table 3, one can see the presence of spatial autocorrelation in the first hierarchical level, such that the null hypothesis of spatial randomness of the income growth rate was rejected in Brazilian municipalities for both statistics ( $I$  and  $c$ ).

Table 3 - Indicators of Spatial Autocorrelation for Income Growth Rate

Indicator	Coefficient	Mean	Standard Deviation	Z-Value	P-Value
Moran $I$	0.311	0.000	0.019	16.321	0.000
Geary $c$	0.703	1.000	0.020	-14.328	0.000

Source: prepared by the author.

### 3.2. Variables at the State Level

Given that one of the objectives of this study rests on the investigation of the influence exerted by state infrastructure on municipal income convergence, for the second geographical level initial infrastructure stocks are specified, in other words, infrastructure stocks from the year 1998 were used, prior to, therefore, the period of analysis of the municipal growth rate (1999-2005). Table 4 clarifies the variables used in the second level.

Table 4: Second Level Hierarchical Variables

Variable	Description	Expected Sign	Units of Measurement	Source
<i>ENERGY</i>	Stock of Energy Infrastructure per capita	+	MwH/Population	ANEELand IBGE
<i>ROAD</i>	Stock of Road Infrastructure per capita	+	Kilometers of paved roads /Population	DNIT and IBGE

Source: prepared by the author.

In Table 5 descriptive statistics of the initial stocks of the state infrastructure variables that will be used in the second level hierarchy are shown.

Table 5: Descriptive Analysis of the State Variables

Statistics	<i>ROAD</i>	<i>ENERGY</i>
Mean	3,771.36	4,544.57
Standard Deviation	5,302.19	3,982.66
Minimum	43.26	441.40
Maximum	18,153.89	18,254.40
n	27	27

Source: Prepared by the author.

#### 4. Results and Discussion

We begin with a presentation of the model's estimates of conditional income convergence in a single hierarchical level. In Table 6, the estimates of the model of conditional income convergence are reported with data in cross-section, without controlling for fixed effect, and in data in differences, controlling for fixed effects. It can be clearly seen that, after controlling for non-observed municipal characteristics, the estimated value of the beta convergence coefficient is substantially increased from -0.05 to -1.14, making the speed of convergence much faster. There are also changes of magnitude, level of significance and even of sign in other conditional variables, showing the importance of controlling for non-observed municipal characteristics.

The next step is to examine whether the increase of the other hierarchical level of analysis, namely, the state level, is justified in order to explain a larger proportion of the variable of the data and to control for the per capita stocks of infrastructure (*ROAD* and *ENERGY*). To answer this, the coefficient of intraclass correlation is calculated. The calculation of the coefficient of intraclass correlation takes the value = 0.61, meaning that 61% of the variance of the per capita income growth rate occurs among the States. The coefficient of intraclass correlation justifies the incorporation of the state level in the analysis to be performed, as well as helping to better explain the variation of the data, when considering only the municipal level.

Table 6: Estimation of the Spatial Models at the Municipal Level

Dependent variable: <i>GROW</i>		
Independent variables	SEM (cross-section)	SEM (in differences)
Constant	-0.0605 (0.1593)	0.0305 (0.0029)*
<i>IGDP</i>	-0.0472 (0.0074)*	-1.1380 (0.0135)*
<i>TAX</i>	0.0056 (0.0055)	0.0190 (0.0038)*
<i>CAP</i>	0.0117 (0.0053)**	0.0032 (0.0031)
<i>EXP</i>	-0.0254	0.0009

	(0.0083)*	(0.0036)
<i>FUND</i>	0.0203	0.0093
	(0.0070)*	(0.0027)*
<i>GAP</i>	0.2304	-0.1680
	(0.1940)	(0.0761)**
<i>HUM</i>	0.0034	0.0041
	(0.0106)	(0.0408)
<i>ROY</i>	0.0054	0.0185
	(0.0035)	(0.0105)

Source: Prepared by the author.

Note: \* significant at 1%; \*\* significant at 5%.

In order to apply the procedure delineated in the second section of the paper, the first multilevel model to be estimated does not include any spatially lagged variable in the right side of the regression. Thus, the conventional multilevel model of conventional income convergence was estimated, with only the variables in differences to remove the fixed effects. In relation to this equation, the distinctive element was the control for fixed effect by transforming the municipal variables in differences according to equation 5. The results are reported in the third column of table 7 (conventional multilevel model). The estimated value of the coefficient accompanying the initial income variables (*IGDP*) assumes the magnitude of -1.13, very similar to that obtained by the model of conditional income convergence with data in differences, using only the municipal hierarchical level. When this multilevel model is estimated, including the infrastructure variables of the state hierarchical level, the coefficient of the road infrastructure variable (*ROAD*) is shown to be significant at 5%, whereas the coefficient of the electrical energy variable (*ENERGY*) does not prove to be significant. It can be concluded that the incorporation of infrastructure stocks by itself alone had not effect upon the magnitude of the coefficient that indicates beta convergence, remaining stable with respect to that estimation of beta, controlling for fixed effects, with data in differences, reported in Table 6.

The residuals of this equation were checked for the presence of spatial autocorrelation by the Moran *I* test, showing the presence of spatial dependency at a significance level of 0.1%. After estimations of several multilevel spatial models (SAR, SEM, SDM, SDEM and SLX), spatial autocorrelation was eliminated only by the multilevel SAR model.

Table 7 shows the values of the multilevel SAR model of conditional income convergence. The estimated coefficient of beta convergence ( $\beta_{10}$ ) was -1.13 and highly significant. Its negative sign corroborates the hypothesis of conditional income convergence. Coefficient  $\rho$  was statistically significant at 5%, and because it is positive it indicates that the economic growth rate of neighboring regions (*WGROW*) holds a direct relationship with the

growth rate of region  $i$ , in other words, a high (low) value of  $GROW$  in neighboring regions increases (decreases) the value of  $GROW$  in region  $i$ .

But the fundamental issue is about the magnitude of the impact of the convergence process. If we consider only the sign of  $(\beta_{10})$ , this entails taking into consideration only the direct effects of income convergence, leaving aside the indirect effects represented by the spatial interaction among the regions in the form of migration of labor, movements of capital, technology transfers and trade in merchandise.

Since it deals with an SAR model in which there are global spatial spillovers, the total impact of the initial income variable on the economic growth rate ( $GROW$ ) must take into account all of these indirect effects, denoted by the coefficient  $\rho$ , and not only the direct effect, given by the coefficient  $\beta_{10}$ . Thus, the total impact is calculated as  $(1 - \rho)^{-1} * \beta_{10}$ , making the direct and indirect effects assume the magnitude of -1.74.<sup>4</sup>

Table 7: Estimation of the Multilevel Models of Income Convergence

Dependent variable: GROW			
Independent variables	Coefficients	Conventional	SAR
<i>Constant</i>	$\mu_{00}$	0.0582 (0.0200)*	0.0732 (0.0301)**
<i>ROAD</i>	$\mu_{01}$	1.0876 (0.5028)**	1.1460 (0.4759)**
<i>ENERGY</i>	$\mu_{02}$	0.0271 (0.0271)	0.0126 (0.0281)
<i>WROAD</i>	$\mu_{03}$		-0.3925 (0.4847)
<i>WENERGY</i>	$\mu_{04}$		-0.0163 (0.0341)
<i>IGDP</i>	$\beta$	-1.1289 (0.0417)*	-1.1285 (0.0137)*
<i>TAX</i>	$\mu_{10}$	0.0151 (0.0052)*	0.0151 (0.0037)
<i>CAP</i>	$\mu_{20}$	0.0021 (0.0031)	0.0021 (0.0030)
<i>EXP</i>	$\mu_{30}$	-0.0011 (0.0042)	-0.0011 (0.0035)
<i>FUND</i>	$\mu_{40}$	-0.0058 (0.0037)**	-0.0058 (0.0026)**
<i>GAP</i>	$\mu_{50}$	-0.1437 (0.1762)	-0.1437 (0.0750)

<sup>4</sup> For reference to the calculation of the total impact of spatial models, taking into account the direct and indirect effects, see LeSage and Pace (2009).



<i>HUM</i>	$\mu_{60}$	0.0341 (0.0343)	0.0341 (0.0408)
<i>ROY</i>	$\mu_{70}$	0.0080 (0.0099)	0.0080 (0.0104)
<i>WGROW</i>	$\rho$		0.3534 (0.0885)*

Source: Prepared by the author.

Note: \* significant at 1%; \*\* significant at 5%.

At the second hierarchical level, the coefficients of the per capita spatial infrastructure gaps, both road and electric, were not statistically significant at 5%, as was the coefficient of electrical infrastructure stock. Only the coefficient of road infrastructure was significant at 5%, making that variable exert a positive influence on the intercept of the income growth rate. However, in general, the control for per capita infrastructure stocks by means of the incorporation of the state hierarchical level does not engender a significant impact to alter the magnitude of the estimated convergence coefficient ( $\beta_{10}$ ).

To look at the effects of several controls done in the estimations, table 8 was prepared.

Table 8: Impact of Several Controls on the Estimate of  $\beta$

Types of Controls	Estimate of $\beta$
Without controls	-0.0472
Controlling for FE	-1.1380
Controlling for FE/Infrastructure	-1.1289
Controlling for FE/Infrastructure/Spatial Autocorrelation	-1.7376

Source: Prepared by the author.

The greatest impact occurs when controlling for non-observed municipal characteristics: the coefficient “jumps” from -0.05 to -1.14. When the joint control for fixed effects and state infrastructure is done within a multilevel model, the coefficient remains practically constant at about -1.14, indicating that there was not an impact on the estimate of beta of considering variables of road infrastructure and electrical energy in the model. However, when jointly controlling for fixed effects, state infrastructure and spatial autocorrelation, the coefficient takes another leap, increasing to -1.74.

It is interesting to compare these estimates with those found up to the present in the literature on income convergence in Brazil. Table 9 shows a descriptive analysis of the  $\beta$  coefficients found in the domestic literature, according to the regional levels most frequently adopted.

Table 9: Descriptive Analysis of the  $\beta$  Coefficients Estimated in the Literature<sup>5</sup>

Regional Levels	N	Mean	Median	SD	Maximum	Minimum
State	22	-0.0822	-0.0484	0.0890	0.0290	-0.2440
AMC	20	-0.2220	-0.0325	0.3490	-0.0012	-1.2990
Microregions	11	-0.1559	-0.0359	0.3811	0.0284	-1.3007
Municipalities	17	-0.1599	0.0066	0.3515	0.0393	-1.0190

Source: Prepared by the author.

Table 9 shows a very different among the values of  $\beta$  obtained in the literature, at the distinct regional hierarchical levels. The magnitude of their standard deviations, as well as the distance between the mean and the median and the amplitude of the estimates denote the several specifications of models of  $\beta$ -convergence. For the municipal level, which was the first hierarchical level of the multilevel model developed in this paper, the mean of 17 estimates found in the literature was -0.16, while the minimum value was -1.02. For the state level, the mean of 22 estimates of beta found was -0.08, while the minimum value found was -0.24. The smallest minimum value was found in a study on the microregional level with a value of -1.30. It is worth noting the difference between this value and the estimate of  $\beta$  -1.74, when all of the controls done in this study are used. The difference for typical results, represented by means, is abyssal, denoting that there is an overestimation of income convergence in the Brazilian literature.

## 5. Final Considerations

The objective of this paper was the analyze multilevel modeling, ascertaining whether the incorporation of infrastructure data in the second hierarchical level exerts influence on the convergence of income of Brazilian municipalities, manifested in the estimated value of the coefficient of  $\beta$ -convergence. Various sources of estimation inconsistency were dealt with, such as controlling for non-observed municipal characteristics, heteroscedasticity, the omission of relevant infrastructure variables and spatial autocorrelation. To do the last control, it was necessary to adapt the conventional hierarchical model to be able to treat spatial dependency in its framework.

<sup>5</sup> For municipalities, the estimates were compiled from the following studies: Grolli et al (2006), Perobelli et al (2006), Maranduba Jr. (2007), Barreto and Almeida (2008), Vieira et al (2008), Ribeiro (2010), Silveira et al (2010) and Menezes and Azzoni (2000); for microregions, the estimates were obtained from the following studies: Vergolino (1996), Silva et al (2004), Harfuch and Santos Filho (2005), Vieira et al (2008); for AMCs, the studies consulted were: Monastério and Ávila (2004), De Vreyer and Spielvogel (2005), Reis (2008), Ribeiro (2010); for states, the estimates came from the following studies: Ferreira and Ellery Jr. (1996), Azzoni et al (2000), Nunes and Nunes (2005), Cravo and Soukiazis (2006), Abitante (2007), Barreto and Almeida (2009), Silveira Neto and Azzoni (2008) and Costa (2009).

The results revealed that there is evidence that only the stock of road infrastructure has a positive impact as a constraint of income convergence among Brazilian municipalities, whereas an effect from the electric energy infrastructure stock was not found.

Following several controls in the conditional convergence equation, it was perceived that the control for non-observed characteristics and the control for spatial autocorrelation are those that exert the greatest impacts upon the estimated value of  $\beta$ -convergence in this paper, around -1.74. It is worth emphasizing that the magnitude of this estimated value is much less than the means estimated for income convergence in Brazil. Furthermore, it is much lower than the lowest estimate found in the literature until then. From this fact, it can be concluded that the literature tends to overestimate the value of  $\beta$ , independent of the spatial scale adopted. The reason for this is mainly the lack of control over non-observed characteristics of the municipalities and/or the lack of spatial control in the majority of studies done on income convergence in Brazil.

## 6. References

- ABITANTE, K.G. Desigualdade no Brasil: um estudo sobre convergência de renda. **Pesquisa & debate**, vol. 18, n.2 (32), pp. 155-169, 2007.
- ALMEIDA, E. S., HADDAD, E. A. e HEWINGS, G. J. D. The transport-regional equity issue revisited. **Regional Studies**, v. 44, p. 1387-1400, 2010.
- AUSCHAUER, D. A. (1989). Is public expenditure productive? **Journal of Monetary Economics**, vol. 23, p. 177-200.
- AZZONI, C., MENEZES FILHO, N., MENEZES, T. e SILVEIRA NETO, R. **Geografia e Convergência de Renda entre os Estados Brasileiros**. IPEA, 2000.
- BARRETO, R. C. S. ; ALMEIDA, E. S. . A contribuição da pesquisa para convergência e crescimento da renda agropecuária no Brasil. **Revista de Economia e Sociologia Rural** (Printed), v. 47, p. 719-737, 2009.
- BARRETO, R. C. S.; ALMEIDA, E. S. Crescimento econômico e convergência de renda no Brasil: a contribuição do capital humano e da infra-estrutura. **In: VI Encontro Nacional da Associação Brasileira de Estudos Regionais e Urbanos - VI ENABER**, 2008, Aracaju. Anais do VI ENABER, 2008a.
- CARMIGNANI, F. The Road to Regional Integration in Africa: Macroeconomic Convergence and Performance in COMESA. **Journal of African Economies**, 15, 212-250, 2006.
- CHASCO, C.; LÓPEZ, A. M. Multilevel models: an application to the Beta-convergence model. **Région et Développement**, 2009.
- COSTA, L. M. **Análise do processo de convergência de renda nos estados brasileiros: 1970-2005**. (Masters Dissertation) – Rio de Janeiro, RJ – Escola de Pós-Graduação em Economia – EPGE, Fundação Getúlio Vargas, 2009.
- CRAVO, T. e SOUKIAZIS, E. O Capital Humano como Fator Determinante para o Processo de Convergência entre os Estados do Brasil. In: Encontro Regional de Economia/Nordeste: Estratégias de Desenvolvimento Regional. **Anais**. 2006.
- DE NEGRI, J. A. e SALERMO, M. (eds.) **Inovação, padrões tecnológicos e desempenho das firmas industriais brasileiras**. Rio de Janeiro:Ipea. 2005

FAZIO, G.;PIACENTINO,D. **Testing for Convergence from the Micro-Level**. Università degli Studi di Palermo. Università di Napoli "Parthenope", 2011. Available at: <[http://www.gla.ac.uk/media/media\\_197524\\_en.pdf](http://www.gla.ac.uk/media/media_197524_en.pdf)>. Accessed on: 6/7/2011.

DE VREYER P.; SPIELVOGEL, G. **Spatial externalities between Brazilian municipalities and their neighbours**. Ibero America Institute for Econ. Research, IAI Discussion Papers 123, 2005.

FERREIRA, P.C. e ELLERY Jr, R. Convergência Entre a Renda *per Capita* dos Estados Brasileiros. **Revista de Econometria**, 1996.

FOURIER, J. Economic Infrastructure: A Review Of Definitions, Theory And Empirics. **South African Journal Of Economics** (74), 530-556, 2006.

GROLI, P. A, OLIVEIRA, C. A. e JACINTO, P. A. Crescimento Econômico e Convergência com a Utilização de Regressões Quantílicas: um estudo para os municípios do Rio Grande do Sul (1970 a 2001). In: XXXIV Encontro Nacional de Economia – ANPEC. **Anais**. 2006.

HADDAD, E. A. **Linking Interregional CGE Models with Geo-Coded Transportation Network Infrastructure Models**. Working Paper Nereus, n.04, 2004.

HARFUCH, L.; SANTOS FILHO, J. I. . Convergência do PIB per capita das Microrregiões Paranaenses. **In: IV ECOPAR**, 2005, Toledo-PR. IV ECOPAR, 2005.

HOLTZ-EAKIN, D. (1994). Public-sector capital and the productivity puzzle. **The Review of Economics and Statistics**, vol. 76, p. 12-21.

HOX, J. **Multilevel Analysis: Techniques And Applications**. Lawrance Erlbaum Associates, New Jersey, 2002

KELEJIAN, H. H. e ROBINSON, D. P. (1997). Infrastructure productivity estimation and its underlying econometric specifications: a sensitivity analysis. **The Journal of the Regional Science Association International**, vol. 76, n.1, p. 115-131.

KELEJIAN, H.; PRUCHA, I. A generalized spatial two stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. **Journal of Real Estate Finance and Economics**, n. 17, p.99–121,1998

KRUGMAN, P.R. **Geography and Trade**. Cambridge: MIT Press, 1991.

LESAGE, J. P. E PACE, R. K. **Introduction to Spatial Econometrics**. CRC Press, Boca Raton, 2009.

MENEZES, T. A. e AZZONI, C. R. Convergência de Renda Real e Nominal entre as Regiões Metropolitanas Brasileiras: uma análise de dados em painel. In: XXVIII Encontro da ANPEC. **Anais**. Campinas, 2000. Available at: <<http://www.nemesis.org.br/artigos/a0024.pdf>>.

MARANDUBA Jr, N. G. **Política Regional, Crescimento Econômico e Convergência de Renda em Minas Gerais**. (Masters Dissertation) – Juiz de Fora, MG – Faculdade de Economia e Administração – UFJF, 2007.

MONASTERIO, L. M. e ÁVILA. R. P. Uma Análise Espacial do Crescimento Econômico do Rio Grande do Sul (1939-2001). **Economia**. Vol. 5, n.2, p.269–296, Jul./Dec. 2004.

MORENOFF, J. D. Neighborhood mechanisms and the spatial dynamics of birth weight. **American Journal of Sociology**, v.108, n.5, p.976-1017, Mar. 2003.

MUNNELL, A. H. Infrastructure investment and economic growth. **Journal of Economic Perspectives**, vol. 6, n. 4, p. 189-198.1992

NAGARAJ, R., VAROUDAKIS, A. e VÉGANZONÈS, M.A. **Long-run growth trends and convergence across Indian states**. OCDE Working Paper n. 131, 1998

NUNES, R. C. e NUNES, S. P. P. O Papel dos Fundos de Participação dos Estados – FPE- na Convergência de Renda *per Capita* dos Estados Brasileiros. **Revista de Economia e Estadística**, Universid Nacional de Córdoba, 2005.

PEROBELLI, F. S. FARIA, W. R. FERREIRA, P. G. C. Análise de convergência espacial do PIB *per capita* em Minas Gerais: 1975-2003. In: Fórum BNB 2006. **Anais**.

PRUD'HOMME, R., Infrastructure And Development, Washington Dc, Paper Prepared For **The ABCDE** (Annual Bank Conference On Development Economics), May 3-5, 2004.

RAUDENBUSH, S e BRYK, A. **Hierarchical linear models: applications and data analysis methods**. London: **Sage Publications**, 2002.

REIS, E. J. . Convergência de renda municipal no Brasil e em Minas Gerais no período 1872-2000. In: **XIII Seminário sobre a Economia Mineira**, 2008, Diamantina, MG. Economia, História, Demografia e Políticas Públicas Diamantina, MG - 26 to 29 of August of 2008. Belo Horizonte. Editora da UFMG, 2008. v. XIII.

RIBEIRO, E. C. B. A. **Convergência De Renda Local Entre Os Municípios Brasileiros Para O Período 2000 A 2005**. (Masters Dissertation) – Juiz de Fora, MG – Faculdade de Economia – UFJF, 2010.

SILVA, E., FONTES, R. e ALVES, L. F. Análise das Disparidades Regionais em Minas Gerais. In: XI Seminário Sobre a Economia Mineira. **Anais**. Diamantina, 2004.

SILVA, G. J. C. ; FORTUNATO, W. L. L. . Infra-Estrutura e Crescimento Regional: uma Avaliação do Caso Brasileiro no Período de 1985-1998. In: Encontro da ANPEC-NE, 2007, Fortaleza. **Anais**.

SILVEIRA NETO, R. M. e AZZONI, C. R. Non-Spatial Policies and Regional Income Inequality in Brazil. In: RSAI Congress. **Anais**. São Paulo, 2008.

SILVEIRA, B. C.; SILVA, R. G.; CARVALHO, L. A.. ANÁLISE DA CONVERGÊNCIA DE RENDA NA REGIÃO NORTE. In: **XLVIII Congresso da Sociedade Brasileira de Economia**, Administração e Sociologia Rural, 2010, Campos Grande. XLVIII Congresso da Sociedade Brasileira de Economia, Administração e Sociologia Rural, 2010.

SNIJDERS, T. E BOSKER, R. **Multilevel analysis: an introduction to basic and advanced multilevel modeling**. Sage Publications, London, 1999.

VENABLES, A.J. **Winners and Losers from Regional Integration Agreements**. Discussion Paper, Centre of Economic Policy Research, London. 2001.

VERGOLINO, J. R. O. A hipótese da convergência da renda: um teste para o Nordeste do Brasil com dados microrregionais: 1970-1993. **Revista Econômica do Nordeste**, Fortaleza, v. 27, n. 4, p. 561-581, 1996.

VIEIRA, N. M.; SONAGLIO, C. M.; CARVALHO, F. M. A. Convergência de renda na Amazônia Legal: Estudo no arco do povoamento adensado. **Revista Brasileira de Gestão e Desenvolvimento Regional**, v. 4, p. 136-171, 2008.

WORLD BANK, The. Infrastructure At The Crossroads : Lessons From 20 Years Of World Bank Experience. Washington Dc: **The International Bank For Reconstruction And Development** / The World Bank, 2006.