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NÍCOLAS VOLGARINE SCARABOTO

Dois ensaios sobre pobreza e desenvolvimento econômico nos municípios brasileiros

Orientador: Prof. Dr. Luciano Nakabashi

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Banca Examinadora:

Prof. Dr. Luciano Nakabashi
Orientador

Prof. Dr. Marcelo Justus dos Santos
Avaliador 1

Prof. Dr. Fernando Salgueiro Perobelli
Avaliador 2

Prof. Dr. Luiz G. D. da Silva Scorzafave
Avaliador 3

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RESUMO

SCARABOTO, Nícolas Volgarine. *Dois ensaios sobre pobreza e desenvolvimento econômico nos municípios brasileiros*. 2021. 61f. Dissertação – Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto, 2021.

Apesar de experimentar queda nas últimas décadas, o número de pessoas vivendo abaixo da linha da pobreza é alarmante. De acordo com o IBGE, em 2015, o número de pessoas abaixo da linha de pobreza era de 13.5 milhões de brasileiros, em torno de 6,5% da população. Além das privações materiais impostas aos indivíduos, pobreza pode prejudicar o desenvolvimento cognitivo e sócio-emocional, especialmente das crianças, com reflexos no capital humano. Deste modo, a compreensão da dinâmica da pobreza é uma necessidade para se encontrar soluções para superação da mesma. O presente trabalho é constituído de dois ensaios. O primeiro estuda os efeitos da pobreza na qualidade da educação observada pelas notas do SAEB. Para estudantes de 5º ano do ensino fundamental, o efeito da mudança de um ponto percentual na incidência de pobreza chega a reduzir em 1,2% a performance escolar. Para estudantes de 9º ano, esse efeito chega a 1,1%. O segundo ensaio fundamenta-se no trabalho de Ravallion (2012). O objetivo é avaliar porque não vemos convergência da pobreza nos municípios brasileiros. Isto é, porque municípios mais pobres não estão experimentando uma redução mais acentuada da pobreza. Os resultados sugerem que a própria distribuição incidência inicial da pobreza afeta negativamente tanto o crescimento da renda per capita quanto o processo de redução da pobreza.

Palavras-chave: pobreza; educação; renda per capita.
JEL: O11, O15, I25, C21

ABSTRACT

SCARABOTO, Nícolas Volgarine. Two essays on poverty and economic development in brazilian municipalities. 2021. 61f. Dissertation – Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto, 2021.

Although expermenting decline over the past decades, the number of people living below the poverty line is still alarming. According to IBGE, in 2015, the number of people below the poverty line was 13.5 million Brazilians, around 6.5% of the population. In addition to the material deprivations imposed on individuals, poverty can impair cognitive and socio- emotional development, especially of children, with reflections on human capital. Thus, understanding the dynamics of poverty is a necessity in order to find solutions to overcome it. This paper is composed of two essays. The first studies the effects of poverty on the quality of education as observed by the SAEB scores. For 5th grade students, the effect of a one percentage point change in the incidence of poverty reduces school performance by 1.2%. For 9th grade students, this effect reaches 1.1%. The second essay builds on the work of Ravallion (2012). It aims to assess why we do not see poverty convergence across brazilian municipalities. That is, why poorer municipalities are not experiencing a sharper reduction in poverty. The results suggest that the initial incidence distribution of poverty itself negatively affects both the growth of per capita income and the poverty reduction process.

Keywords: poverty; education; per capita income.
JEL: O11, O15, I25, C21

LISTA DE ILUSTRAÇÕES

Figura 1 – Spatial distributions 25
Figura 2 – Moran's I plots 26

Figura 3 – Spatial distributions 42
Figura 4 – Poverty variation and initial poverty 47

LISTA DE TABELAS

Tabela 1 – Descriptive Statistics 22
Tabela 2 – Global Moran's I Statistics 25
Tabela 3 – L.M. tests 26
Tabela 4 – Cross Section Estimations 5th grade students: 2011-2015. OLS and SAC . . 29
Tabela 5 – Cross Section Estimations 5th grade students: 2011-2017. OLS and SAC . . 30
Tabela 6 – Cross Section Estimations 9th grade students: 2011-2015. OLS and SAC . . 32
Tabela 7 – Cross Section Estimations 9th grade students: 2011-2017. OLS and SAC . . 34
Tabela 8 – Cross Section Estimations for the same cohort grade students: 2011-2015. OLS and SAC 35
Tabela 9 – Cross Section Estimations for the same cohort grade students: 2011-2017. OLS and SAC 37

Tabela 10 – Descriptive Statistics 41
Tabela 11 – Correlations 42
Tabela 12 – Global Moran's I Statistics 43
Tabela 13 – Testing advantage of backwardness 45
Tabela 14 – Testing advantage of growth 46
Tabela 15 – Regressions of Growth Rates on Initial Mean and Initial Headcount Index of Poverty 48
Tabela 16 – Regression for per capita income growth rates on the initial poverty rate augmented with extra control variables 50
Tabela 17 – Regressions for proportionate change in poverty rate as a function of the growth rate and initial poverty rate 51

Tabela 18 – Total effects of Table 13 59
Tabela 19 – Total effects of Table 14 59
Tabela 20 – Total effects of Table 15 59
Tabela 21 – Total effects of Table 16 60
Tabela 22 – Total effects of Table 17 61

SUMÁRIO

INTRODUCTION 11

1 POVERTY AND EDUCATION IN BRAZILIAN MUNICIPALITIES . 13
1.1 Introduction 13
1.2 Literature review 16
1.2.1 Poverty and economic development 16
1.2.2 Human capital and economic development 17
1.2.3 Poverty and cognitive development 17
1.3 The Model 18
1.4 Methodology 20
1.4.1 Empirical Strategy and Dataset 20
1.4.2 Spatial Effects 21
1.4.3 Spatial data analysis 24
1.5 Results 27
1.5.1 Different Cohorts Results 27
1.5.2 Same Cohort Results 33
1.6 Conclusion 36

2 POVERTY CONVERGENCE IN BRAZILIAN MUNICIPALITIES . . 38
2.1 Introduction 38
2.2 Literature Review 39
2.3 Methodology and data 40
2.3.1 Data and Descriptive Statistics 40
2.3.2 The choice of the spatial model 43
2.4 Empirical results 44
2.4.1 Testing for Convergence in average income and poverty 44
2.4.2 Initial poverty incidence and income growth 46
2.4.3 Initial poverty and the growth elasticity of poverty reduction . . 49
2.4.4 The reasons we do not see poverty convergence 52
2.5 Conclusions 53

CONCLUSIONS 54

REFERÊNCIAS 55

APÊNDICE A – SLX WITH PARAMETRIC SPATIAL MATRIX . . 58

APÊNDICE B – SDEM'S TOTAL EFFECTS 59

INTRODUCTION

Despite experiencing a decline in recent decades, the number of people living below the poverty line is alarming. According to the IBGE, in 2015, the number of people living below the poverty line was 13.5 million brazilians, around 6.5% of the population. In this scenario, understanding the dynamics of poverty and its relationship with the determinants of economic development is something of great importance for public debate and the creation of public policies.

The authors of this work believe that little attention has been given to understanding the relationship between poverty and the determinants of economic development for the brazilian case, particularly with respect to education. Education is one of the central human capital measures to explain economic growth (NELSON; PHELPS, 1966; ROMER, 1990; MANKIW; ROMER; WEIL, 1992). If poverty can affect economic growth (RAVALLION, 2012) then it stands to reason that one of the main channels is human capital (education).

The first essay of this work seeks to understand how poverty affects the quality of education in Brazilian municipalities. The study is motivated by evidence found in the medical literature indicating that poverty can affect children's cognitive and socio-emotional development with repercussions on learning ability (ABER et al., 1997; ENGLE; BLACK, 2008). This paper therefore aims to analyze whether these effects of poverty incidence on human capital (education) found in microdata studies are relevant at the municipal level to support public policy. The quality of education and measures of cognitive skills have gained relevance in the literature as important variables in promoting economic development (HANUSHEK, 2013; WOESSMANN, 2016). In this sense, it was decided in this first essay to adopt average Saeb scores as a measure of human capital. Such scores reflect students' ability to not only assimilate content but also adapt it to new contexts, thus being closer to a measure of cognitive ability.

Based on Lucas (1988) model, the results indicate a relevant effect of poverty on the school performance of public school students. An increase of 10% in the incidence of municipal poverty is associated with a reduction of 2% to 6% in the school performance of 5th grade students and of 3% to 9% of 9th grade students. These results are robust to possible spatial correlations in the model.

The second essay of this work aims to study why we do not observe poverty convergence across Brazilian municipalities. The essay is based on the seminal work of Ravallion (2012), in which he sought to explain why poverty convergence is not observed in developing countries. This question is relevant for understanding how poverty is related to the direct and indirect mechanisms of economic growth and human development.

Ravallion (2012) argues that poverty is the most relevant variable to explain the difficulty in overcoming poverty itself and not inequality and size of the middle class as previous works have defended. The second essay, therefore, follows along this same line adding as a robustness test, an appropriate spatial treatment, with little attention in Ravallion (2012). The results suggest that the initial poverty level negatively affects per capita income growth and how per capita income growth translates into poverty reduction.

1 POVERTY AND EDUCATION IN BRAZILIAN MUNICIPALITIES

Abstract

This paper studies the effects of poverty incidence on educational quality in Brazilian municipalities. This study aims to explore if municipalities with higher average poverty levels have worse school performance. The results suggest that poverty negatively affects average school performance. For students in the 5th grade of primary school, an increase of one percentage point in poverty incidence reduces average school performance by 1.2%. For students in the 9th grade of primary school, a one percentage point rise in poverty incidence reduces school performance by 1.1%.

Keywords: Poverty Incidence; School Performance; Brazilian Municipalities.

Resumo

Este artigo estuda o efeito da incidência de pobreza sobre a qualidade da educação nos municípios brasileiros. Buscamos explorar se municípios com altos níveis de pobreza têm piores desempenhos escolares. Os resultados sugerem que a pobreza afeta negativamente desempenho escolar. Para estudantes do 5º ano do ensino fundamental, o efeito da mudança de um ponto percentual na incidência de pobreza chega a reduzir em 1.2%. Para estudantes do 9º ano do ensino fundamental, o efeito da alteração de 1 ponto percentual na incidência de pobreza reduz em 1.1% a performance escolar.

Palavras-chaves: Pobreza; Desempenho Escolar; Municípios brasileiros.

1.1 Introduction

Although experimenting decline over the past decades, the number of people living below the world's poverty line is still alarming. The World Bank claims that 10 percent of the world's population lived on less than two dollars a day in 2015. According to IBGE, in the same year, the number of people living below this poverty line was 13.5 million in Brazil, representing 6.5% of its population. In addition to the material deprivations that poverty imposes on individuals and households, it can harm cognitive and socio-emotional development, especially of children (ABER et al., 1997; ENGLE; BLACK, 2008).

The economic growth and development literature has highlighted the effects of poverty incidence on economic development in recent years. Ravallion (2012) seminal paper shows that the initial incidence of poverty across countries may explain why we do not see poverty convergence, as expected by the income convergence theory. According to Ravallion (2012), countries with higher initial poverty incidence tend to experience a lower growth rate, controlling their initial income level. Also, for countries with a high poverty rate, poverty reduction due to economic growth is smaller. These two effects work against the convergence effect, leaving little or no correlation between the initial poverty incidence and the subsequent economic growth.

Other studies aim to explore the effects of poverty on development directly. To name a few, Nindi e Odhiambo (2015) explore the causal relationships between poverty and economic development in Swaziland. Their study shows that economic growth does not Granger-cause poverty reduction in Swaziland – either in the short run or in the long run. Instead, it finds a causal relationship from poverty reduction to economic growth in the short run. Nakabashi (2018) aims to study the effects of poverty incidence on the Brazilian states' economic development represented by income per worker. The study shows that poverty and extreme poverty are essential to understand differences in income per worker across the Brazilian states and over time, with higher relevance for the extreme poverty indicators.

One potential channel linking poverty incidence and economic development is the former's effects on human capital accumulation. This factor of production is critical in promoting economic development, as pointed out by the economic growth and development literature (UZAWA, 1965; LUCAS, 1988; ROMER, 1989; ROMER, 1990; BENHABIB; SPIEGEL, 1994; PELINESCU, 2015). There are three main ways in which human capital affects economic growth: via labor productivity (ROMER, 1989; MANKIW; ROMER; WEIL, 1992); innovation of technology (ROMER, 1990); and dissemination of technology (NELSON; PHELPS, 1966; PISTORIUS, 2004; SIGGEL; SSEMOGERERE, 2004). Also, there are several empirical studies relating human capital quality to economic growth and development. Hanushek (2013) and Woessmann (2016) explores how cognitive skills promote economic development, and Nakabashi e Salvato (2007) employ indicators of educational quality to measure its impacts on workers' wages in the Brazilian States.

The studies measuring the effects of poverty incidence on economic growth and development have been increasing. At the same time, the importance of human capital on the latter is already well established. However, we are not aware of any studies relating poverty incidence and human capital, especially for Brazil. Our premise is that if poverty helps to explain economic growth and development, it is reasonable to expect that one of the main channels is through human capital. Also, numerous studies suggest that childhood poverty incidence affects cognitive and educational development at a micro-level.

Early childhood poverty can affect cognitive and socio-emotional development, reflecting on learning difficulties and school dropouts (ABER et al., 1997; ENGLE; BLACK, 2008). Other studies in the medical literature associate the incidence of early childhood poverty with low brain development (grey mass volume) and, consequently, learning problems (HANSON et al., 2013; HAIR et al., 2015; CHAUDRY; WIMER, 2016; WISE, 2016)). Thus, this study aims to analyze whether these effects of poverty incidence on human capital (cognitive development and learning) found in micro-data studies are substantial with aggregated data at the municipal level. It is crucial to measure poverty's aggregate impact on educational outcomes to support public policies aiming to reduce poverty incidence. If poverty has a relevant effect on children's aggregate cognitive skill development, public policies targeted at poverty reduction become even more important.

The present paper aims to evaluate how the average cognitive skills in a municipality are affected by poverty incidence, the initial level of human capital, the amount of time spent on schooling, among other variables, following the human capital equation proposed by Lucas (1988). If the effects found in the microeconomic studies and medical literature are valid at the aggregate level, we would expect that municipalities with higher poverty rates have worse average school performance.

In an attempt to dialogue with the microeconomic and medical literature, the present study focuses on pupils' public school performance. We focus on school-aged youth because they are usually the target audience in the studies mentioned above, as in Hair et al. (2015) and Engle e Black (2008). The school performance data is also available only for students enrolled in public schools, such as the Basic Education Assessment System (SAEB) scores, the Basic Education Development Index (IDEB), and the School Census.

We have employed the Development Atlas Dataset (PNUD) to measure poverty incidence, i.e., the proportion of the municipality's population classified as poor. The poverty line is based on the minimum income needed to consume a sufficiently nutritious basket, the same criterion adopted in different studies in the area, as in Hair et al. (2015) and Hanson et al. (2013). We use the human capital accumulation function developed by Lucas (1988) since his definition of human capital is similar to the studies cited above (ABER et al., 1997; ENGLE; BLACK, 2008).

The empirical strategy consists of estimations via Ordinary Least Squares (OLS) with robust standard errors and spatial econometric methods since there is a considerable spatial correlation across municipalities. We have employed two empirical strategies in our analysis. The first one evaluates poverty's effect on school performance of "the same" cohort of students in different grades. The second assesses this relationship for students of "different cohorts" in the same grade.

The results indicate that the effects of poverty on human capital accumulation are relevant. For example, considering the "different" cohort students in the 5$^{\text{th}}$ grade, a 10 percentage points increase in extreme poverty incidence negatively impacts average school performance from 2% to 6%, and for those in the 9$^{\text{th}}$ grade from 3% to 9%, depending on the estimation method and time spam. Without the Bolsa Família income transfer program, extreme child poverty in 2010 would rise 27 percentage points on average, with a decline in school performance from 5.4% to 16.2% for the fifth graders, and from 8.1% to 24.3% for the ninth graders. These results point to poverty reduction public policies' relevance to improve school performance and, therefore, subsequent economic growth and development.

Besides this introduction, we present the literature review and theoretical structure in the next two sections. Section 1.4 reports the dataset, methodology, and some preliminary results. The last section brings and discuss the empirical results.

1.2 Literature review

The literature review is organized to show the relationship: poverty affects human capital, which in turn affects economic development. Some papers find that poverty may be important in the economic development process and explore the channel of poverty affecting human capital. Thus, section 1.2.1 discusses the relationship between poverty and economic development; section 1.2.2 discusses human capital and economic development. Finally, section 1.2.3 discusses the channel we want to study – poverty and human capital.

1.2.1 Poverty and economic development

An important subject on the economic growth and development literature is poverty convergence. There are two stylized facts about economic development. In a comparison between two similar countries, the one with lower initial income tend to have a higher rate of income growth (income convergence), and a higher income tends to be associated with a lower absolute poverty incidence. Under the assumption that the dynamic processes of growth in the mean and poverty reduction are not related to the initial level of poverty, we should also see poverty convergence. However, this is not the case. (RAVALLION, 2012)

Evidence suggests we do not see poverty converge because there is something about the initial distribution of poverty across countries that is offsetting both the advantage of backwardness and the advantage of growth. According to Ravallion (2012), that something is poverty incidence. The paper shows an negative effect of poverty on income growth, that is countries with higher initial poverty incidence tend to experience a lower growth rate, for a given initial income level. Another effect is that for countries with a high poverty rate, the effect of economic growth on poverty reduction is smaller. These effects harms the convergence effect, leaving almost zero correlation between the initial poverty incidence and the economic growth.

Nakabashi (2018) aims to study the effects of poverty incidence on the economic development of the Brazilian states represented by income per worker. Since poverty can affect output and vice versa, there is a problem of reverse causality. To deal with this problem, Nakabashi (2018) uses the GMM Arellano-bond estimator and panel estimation for fixed effects. The study shows that the incidence of poverty and extreme poverty are essential to understand differences in income per worker across the Brazilian states and over time, with higher relevance for the extreme poverty indicators.

Nindi e Odhiambo (2015) study the causal relationship between poverty reduction and economic growth in Swaziland using modern time-series techniques like ARDL-bounds testing approach to co-integration and the ECM-based Granger causality model. This study shows that there are not Granger-causality from economic growth to poverty reduction in Swaziland – either in the short run or in the long run. Instead, it finds a causality from poverty reduction to economic growth in the short run. Also, the study shows that there are distinct short and long-run causal flows from economic growth to financial development in Swaziland and there are Granger-causality from financial development to poverty reduction in the short run.

1.2.2 Human capital and economic development

Following Pelinescu (2015), there is well-established literature showing that human capital is one of the main factors explaining economic growth and development. There are three main ways in which human capital affects economic growth: via labor productivity (MANKIW; ROMER; WEIL, 1992; ROMER, 1989), the innovation of technology (ROMER, 1990), and via competitive advantage through the dissemination of technology (PISTORIUS, 2004; SIGGEL; SSEMOGERERE, 2004; NELSON; PHELPS, 1966).

Considering labor productivity, Benhabib e Spiegel (1994) run growth accounting regressions with a Cobb-Douglas production function using cross-country estimates of physical and human capital. The results indicate that human capital has significant power to explain per capita output growth rates.

Recent studies suggest a more significant concern with the quality of human capital. According to Hanushek (2013), recent evidence shows the importance of cognitive skills in promoting economic growth and may explain why there are uncertainties in the role of human capital on growth, because the cognitive skills, and not just years of schooling, are strongly related to individual earnings, income distribution, and economic growth. Hanushek (2013) argues that developing countries have been effective in reducing the schooling gap compared to developed ones. However, they have not been successful in reducing the deficit in cognitive skills.

Considering the Brazilian dataset, Nakabashi e Salvato (2007) point to the relevance of the human capital quality on income per worker. Based on the augmented version of the Solow model (MANKIW; ROMER; WEIL, 1992), the authors use different regression methods, having as a proxy for the human capital quantity the average years of schooling of the population over 25 (IPEA) and as a proxy for the quality of human capital an index of educational quality. The human capital proxy considers quantitative and qualitative aspects of this factor. With fixed effects regression, an increase of one percent in the human capital proxy results in an income per worker rise of 4.32%. According to the authors, the direct impact of human capital seems smaller than predicted in other studies. Still, it remains crucial in determining the level of product per worker.

1.2.3 Poverty and cognitive development

It is unusual to find studies with aggregate data analyzing poverty incidence and human capital accumulation – measures of cognitive skills in the present study. In other research areas, the focus is on microdata.

Engle e Black (2008) argue that the effects of poverty on child development and school performance work through direct, moderate, mediated, and transactional channels. As a direct effect, consider nutrition. Children from more impoverished families may suffer from malnutrition or even obesity due to a lack of adequate alimentary education. Moderate effects depend on the particular characteristics of families. More educated families tend to invest more in their children's education and health. Mediated effects are those that lead to family disorganization.

Poverty associated with economic hardship can lead to negative emotional impacts leading parents to be unable to provide the necessary care for their children. Finally, the transactional effects arise from the interaction between parents' characteristics and those of their children. For example, parents of temperamental children are more susceptible to depressive symptoms and, consequently, pay less attention to their children.

Engle e Black (2008) consider that poverty is crucial to child development and school performance. Child development refers to interdependent skills such as sensory and motor, cognitive, linguistic, and socio-emotional that are dependent on the family and social context. Educational outcomes include school performance and retention, dropout, and years of schooling.

Aber et al. (1997) study the impacts of poverty on children's health and development. Like Engle and Black (2008), the authors seek a more precise definition of poverty to analyze its dynamic behavior. For the authors, factors such as economic cycles and fluctuations in income, taxation, and public services make it difficult to establish a reference poverty line. Aber et al. (1997) claim that poverty, directly and indirectly, affects child development through mechanisms such as stress, family behavior, and family processes such as divorces and separations.

Considering the relationship between poverty, brain development, and learning, Hair et al. (2015) show that poverty affects several areas of the brain associated with school performance, in a study of 823 magnetic resonances in 389 children and adolescents from 4 to 22 years old. The grey mass volume of children living in poverty regions with an income of 150% of the Federal Poverty Level (FPL) was 3 to 4 percent below the expected norm. An even more significant gap of 8 to 10 percent for children in households below the federal poverty level. Also, Hair et al. (2015) show that, on average, low-income household children scored from 4 to 7 points lower on standardized tests, with 20 percent of the gap on the test scores explained by delays in the frontal and temporal lobe maturation in early childhood development.

Hanson et al. (2013) obtained similar results. Using the random effects method, the authors found that children from low-income families have lower volume and brain grey mass than children from high socioeconomic level families. The authors found that children in poor or vulnerable to poverty households (which incomes are below 200% FPL) have significantly lower total gray matter in comparison to children from higher household income. According to the authors, the grey mass is critical for information processing and task execution. In that way, children with lower gray matter are more prone to have worse school performance. Wise (2016) and Chaudry e Wimer (2016) find similar results.

1.3 The Model

Based on Robert Solow and Edward Denison's growth models, Lucas (1988) developed an economic growth model where human capital accumulation is the critical variable to promote sustainable growth. In his model, there are N workers with skill levels $h_i \in [0, \infty)$ so $N = \int N(h)dh$. He assumes that a worker with skill h_i devotes a fraction $u(h_i)$ of his non-leisure time to current production and the remaining time $1-u(h_i)$ to human capital accumulation. Then the effective workforce in production is given by $N^e = \int u(h_i)N(h_i)h_i dh$.

Lucas (1988) treats all workers in the economy as identicals, so they have the same skill level h. Then the time dedicated to human capital accumulation is simply $1-u(t)$. The author links the effort $1-u(t)$ devoted to human capital accumulation to its rate of change:

$$\dot{h}(t) = h(t)^{\zeta} G[1-u(t)] \tag{1.1}$$

Where G is increasing in $1-u(t)$ with $G(0)=0$. Equation (1.1) says that human capital accumulation depends on the human capital level and the time spent at school. This model does not consider human capital depreciation.

Assuming that $h(t) > 0$, and $0 < u(t) < 1$[1], we can take the natural logarithm on both sides of equation (1.1) to obtain

$$\log \dot{h}(t) = \zeta h(t) + \log G[1-u(t)] \tag{1.2}$$

Note that the function G determines the efficiency of the time spent on human capital accumulation. Suppose that this function is in a multiplicative form:

$$G[1-u(t)] = \delta(c,p,\varepsilon)(1-u(t))^{\eta} \tag{1.3}$$

Unlike Lucas (1988), we will not consider the efficiency term (δ) as a constant. In that way, equation (1.2) becomes

$$\log \dot{h}(t) = \zeta h(t) + \log \delta(c,p,\varepsilon) + \eta \log[1-u(t)] \tag{1.4}$$

where c is a constant, p is a poverty incidence measure, and ε is the error term[2]. The assumption is that poverty incidence reduces the efficiency of the hours allocated to developing cognitive skills. Children living in poverty and extreme poverty are subject to family instability, low learning stimulus, lower cognitive development, among other effects (ABER et al., 1997; ENGLE; BLACK, 2008). Therefore, municipalities with high poverty incidence tend to have low education quality, giving the quantity of schooling (time spent on cognitive skills development).

Following Mankiw, Romer e Weil (1992), but for the human capital function instead of the production function, we assume:

$$\log \delta(c,p(t),\varepsilon(t)) = c + \beta p(t) + \varepsilon(t) \tag{1.5}$$

Then, considering (1.5) into (1.4) and discrete time:

$$\log(h_{t+1} - h_t) = c + \zeta \log h_t + \beta p_t + \eta \log[1-u(t)] + \varepsilon_t \tag{1.6}$$

[1] It is reasonable to assume that the workers dedicate some time to human capital accumulation and, therefore, have some amount of human capital and some time spent on final output production.

[2] We assume that other variables influencing time efficiency in human capital accumulation enter in the parameter c and the error term ε.

We use equation (1.6) as the specification to estimate the regressions. However, variables other than poverty can impact the efficiency of hours allocated to learning, and we consider this in the estimations. In our analysis, the initial period (t) is 2010 since we have to use census data to measure poverty across municipalities, and these data are only available every ten years. Also, the mean schools' tests score across municipalities (our human capital measure – cognitive skills) are available every two years starting in 2005.

1.4 Methodology

1.4.1 Empirical Strategy and Dataset

Our empirical analysis uses two central databases: the Human Development Atlas (PNUD) to measure poverty and extreme poverty incidence; and the Brazilian standard test results dataset as indicators of cognitive skills from the National Institute for Educational Studies and Research Anísio Teixeira (INEP).

"The Human Development Atlas in Brazil is a consultation platform for the Municipal Human Development Index (M-HDI) of the 5,565 Brazilian municipalities, 27 Federal Units, 20 Metropolitan Regions, and their respective Human Development Units (HDU). Along with M-HDI, the Atlas has over 200 indicators of democracy, education, income, labor, housing, and vulnerability with data extracted from the Demographic Censuses of 1991, 2000, and 2010"[3].

The data is measured as the percentage of extremely poor, poor, and vulnerable to poverty households across the Brazilian municipalities. For example, in 2010, the rate of extremely poor, poor, and vulnerable children is the proportion of individuals aged up to 14 years old living in households with per capita income equal to or lower than R$70.00, R$140.00, and R$255.00 per month, respectively. The advantage of these thresholds is that microdata studies frequently use them, as Hair et al. (2015) and Hanson et al. (2013).

The Brazilian standardized exam (Prova Brasil) and the National System for the Evaluation of Basic Education (SAEB) are the sources of the present study's educational datasets. They evaluate the school quality in the Brazilian educational system through standard exams and socioeconomic questionnaires. These standard tests cover almost all the Brazilian municipalities, and they allow us to compare school performance over time and space. The data availability is biennial, starting in 2005. The mean SAEB score of a municipality – a measure of mean cognitive skills – is our human capital measure.

One challenge is to encounter a proxy for the non-leisure time dedicated to human capital accumulation $(1-u(t))$. We should compute all the time devoted to education at and outside of school. However, due to its complexity and lack of availability, we decided to use the average class hours provided by INEP.

The Gini index from PNUD was employed as a regressor to test the robustness of the results. The inclusion of this variable is to check if the municipalities with higher income ine-

[3] http://atlasbrasil.org.br/2013/en/o_atlas/o _atlas_/, acessed 13 july 2020.

quality have a worse performance at the educational tests. Income inequality may be important on average students' performance since high inequality precludes part of the population from investing in their children. Besides, it is a more traditional control variable than poverty in economic growth and development analysis (BREUNIG; MAJEED, 2020).

Since the SAEB scores are our human capital measure, we may write equation (1.6) as:

$$\log(\Delta SAEB_i) = c + \zeta \log SAEB_{i,2011} + \beta Poverty_{i,2010} + \eta \log[Class\ Hours_{i,2011}] + \varepsilon_{i,t} \tag{1.7}$$

Where i indicates the municipality, $\Delta SAEB$ is the SAEB indicator variation between two periods, $SAEB$ is the exam performance, *Poverty* is a poverty incidence measure of households with children up to 14 years old from PNUD, and *Class Hours* is the average hours of students in the classroom. The poverty incidence measures are for 2010, not for 2011, given the data availability. However, this is not a problem since poverty incidence changes slowly over time. We deal with the potential reverse causality problem between poverty and cognitive skills evolution by measuring the effects of prior poverty incidence (2010) on subsequent SAEB variation (2011-2015; 2011-2017).

Table 1 brings the descriptive statistics of the variables. Considering the same grade from 2011 to 2017, the Saeb mean score has been rising. The opposite pattern happens to its standard deviation. The poverty measures have a high mean and standard deviation, showing that poverty is a critical problem in Brazil. The mean Gini index (ranging from 0 to 100) is high and with a low standard deviation concerning its mean, indicating that income inequality is a relevant problem in most of the Brazilian municipalities. The data for some variables are not available for all 5564 municipalities.

1.4.2 Spatial Effects

Tobler (1970) asserts that "everything is related to everything else, but near things are more related than distant things". According to Anselin e Bera (1998), spatial correlation is an unobservable geographical factor that varies systematically in space. For economic data, spatial dependence may be due to factors such as economies of agglomeration and regional dynamics of labor attraction (KALENKOSKI; LACOMBE, 2008). For local data, the determination of some variables may take place on a broader regional level than the municipal one. In the present study, we use the spatial econometric method because poverty and school performance are usually associated with regional characteristics beyond municipalities' boundaries. They are influenced by public policies undertaken at the state and federal levels, for example.

When the spatial correlation is present but ignored using the OLS estimation method, the estimators are biased and inconsistent (ARBIA, 2014). To detect the presence of spatial correlation, we have used the Moran's I statistic. It is a correlation coefficient measuring the spatial correlation of the variables in the model or the error term, and it ranges from -1 (perfect dispersion) to 1 (perfect clusterization).

Tabela 1 – Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Saeb 5^{th} gr (2011)	5,226	196.13	21.97	140.13	178.64	212.41	289.60
Saeb 9^{th} gr (2011)	5,355	241.11	18.28	188.81	228.09	253.92	315.88
Δ Saeb 5^{th} gr (2011-15)	5,081	12.45	12.77	−72.54	4.93	19.61	102.39
Δ Saeb 5^{th} gr (2011-17)	5,189	17.99	13.84	−58.79	9.65	25.84	106.54
Δ Saeb 9^{th} gr (2011-15)	5,115	7.28	12.27	−71.19	−0.09	14.65	81.75
Δ Saeb 9^{th} gr (2011-17)	5,276	10.97	13.86	−84.32	2.46	19.59	83.61
Δ Saeb (2011-15)	5,093	51.73	13.81	−32.87	43.21	60.98	128.71
Δ Saeb (2011-17)	4,982	64.38	17.55	−33.10	53.73	75.65	144.27
C. hrs 5^{th} gr (2011-15)	5,531	4.43	0.60	3.45	4.00	4.50	9.20
C. hrs 5^{th} gr (2011-17)	5,529	4.40	0.57	3.55	4.00	4.50	9.05
C. hrs 9^{th} gr (2011-15)	5,556	4.53	0.59	3.20	4.20	4.65	9.20
C. hrs 9^{th} gr (2011-17)	5,560	4.52	0.56	3.30	4.20	4.60	8.75
C. hrs (2011-15)	5,532	4.47	0.55	3.40	4.15	4.55	9.00
C. hrs (2011-17)	5,515	4.50	0.56	3.50	4.15	4.70	8.20
EPOV (2010)	5,564	16.03	15.35	0.00	3.02	27.24	72.43
POV (2010)	5,564	33.73	21.99	0.00	13.48	54.04	84.66
VPOV (2010)	5,564	58.98	22.82	2.45	39.71	80.57	95.44
GINI (2010)	5,564	49.44	6.61	28	45	54	80

Notes: **Saeb y^{th} 20xx** are the saeb performance of students of the y^{th} grade in the 20xx year. **Δ Saeb x^{th} (20yy-20zz)** are the variation in saeb between the years 20yy and 20zz for x^{th} grade. **Δ Saeb (20yy-20zz)** are the variation in saeb between the years 20yy and 20zz for the same students in the 5^{th} grade (2011), 9^{th} grade (2015) and 3^{rd} highschool grade (2017). **C. hrs y^{th} (20yy-20zz)** are average class hours of y^{th} grade students in the years 20yy and 20zz. **VPOV** is the proportion of children vulnerable to poverty (2010). **POV** is the proportion of children living in poverty (2010). **EPOV** is the proportion of children living in extreme poverty (2010). **GINI** is the inequality measure for municipalities (2010).

The Moran's I statistic, was estimated with all the main spatial weights matrix criterion. By the Queen criterion, if the municipalities share at least one point of their border, they are considered neighbors. The Rook criterion considers as neighbors municipalities that share a straight segment of their border. The K-5 and K-10 criteria attribute the 5 and 10 closest municipalities as neighbors, respectively. Finally, the distance based criterion considers the distance among all centroids in kilometers or miles to determine the spatial effects in each other.

The next step is to check if the spatial correlation appears in the dependent variable, the independent variables, or the error term. When the spatial correlation occurs only in the explanatory variables, it is possible to "correct" the OLS estimations by including a matrix of lagged explanatory variables (SLX). If the spatial correlation is in the regressand, we use the Spatial Autoregressive Model (SAR) that includes the neighbors' dependent variables as regressors. If the spatial correlation arises in the error term, the Spatial Error Model (SEM) is the most appropriate, which adds the neighbors' error term in the estimations.

It is also possible for the spatial correlation to happen in more than one term. The Spatial Autocorrelation (SAC/SARAR) model is a combination of the SAR and SEM models. It is indicated when the spatial autocorrelation is present in the dependent variable and the error term simultaneously. The Spatial Durbin Model (SDM) is a combination of SLX and SAR, and it is appropriate when the spatial correlation occurs in the independent and dependent variables simultaneously. The Spatial Durbin Error Model (SDEM) is a combination of SLX and SEM, and it is employed when the spatial correlation happens in the regressors and the error term. Finally, the General Nesting Spatial (GNS) model combines SLX, SAR, and SEM (LESAGE; PACE, 2009).

Equation (1.8) captures the above-cited possibilities of spatial autocorrelation.

$$\begin{aligned} y &= \alpha + \rho W y + X\beta + W X \theta + u \\ u &= \lambda W u + \varepsilon \end{aligned} \tag{1.8}$$

Where W is the spatial weight matrix. If $\rho = 0$, the appropriate model is the SDEM. If $\lambda = 0$, the resulting model is the SDM. When $\theta = 0$ the SAC model is the suitable one. Considering $\rho = \lambda = 0$, we have the SLX model. If $\theta = \lambda = 0$ the chosen one is SAR. Finally, if $\rho = \theta = 0$, the resulting model is SEM.

There are two strategies to determine the spatial model. The first is to go from the most specific to the most general model to choose the most parsimonious one. The second begins with the complete spatial model [equation 1.8], reducing it using proper statistical tests.

The first strategy has the advantage of starting with the simplest OLS model, and through Lagrange Multiplier tests, choose a compact spatial effect structure. The disadvantage is that the criteria to select the proper model may lead to ambiguities. The second strategy leads to an adequate inferential sequence since it starts with the three types of spatial dependencies. The disadvantage is that the GNS model in (1.8) is not the most general specification. We could add lags to the spatial matrices, and the error term can display local or global spatial autocorrelations. Moreover, there is weak statistical identification with three or more spatial dependences (COOK; AULT; SMERDON, 2015).

Vega e Elhorst (2015) show evidences that the first model to study spatial effects when we do not have a prior motive or underlying theory should be the SLX model associated with a parameterized weight matrix. The SLX model together with the SDEM, SDM and GNS models have the advantage of be able to produce different spillover effects from one explanatory variable to another relative to their direct effects. As the SLX model is the more simple, it is a natural point of departure and to the estimation of the spatial matrix.

The use of a parameterized spatial weight matrix is interesting because we seldom have a good idea of how the spatial dependence between units diminishes as the distance increases. The parameterized spatial matrix W have the form

$$W = (w_{ij}) \in \mathbb{R}^{n \times n}; \quad w_{ij} = \begin{cases} 0, & \text{if} \quad i = j \quad \text{or} \quad d_{ij} > \bar{c} \\ \dfrac{1}{d_{ij}^{\gamma}}, & \text{if} \quad i \neq j \quad \text{and} \quad d_{ij} \leq \bar{c} \end{cases} \tag{1.9}$$

where n is the number of regions, d_{ij} is the distance between regions i and j, γ is the decay parameter to be estimated and $\bar{c}$ is a maximum distance cut-off[4]. The algorithm to estimate the decay parameter together with the SLX model is explained in appendix A.

Cook, Ault e Smerdon (2015) provide a useful guide for the treatment of spatial effects. They analyze the bias on the estimation of β, θ, ρ and λ by Monte Carlo simulations, with the following conclusions:

1. SAC and SDEM are appropriate models to avoid spurious correlations and to obtain unbiased β estimators;

2. for researchers more interested in the estimation of β than in the spatial structure, the SDM should be used (ELHORST, 2011);

3. the GNS model is usually not recommended.

In the present study, we adopted a combination of the first strategy and the guide provided by Cook, Ault e Smerdon (2015) using a parametric W (VEGA; ELHORST, 2015). The first step is to estimate the parametric W matrices. The second step is to use the Lagrange Multiplier tests to check for spatial autocorrelation in the dependent variable and the error term. The third step is to use the Bayesian Information Criterion (BIC) to decide among the models.

1.4.3 Spatial data analysis

Figure 1 shows the spatial distribution of the main variables of the present study. We divide the variables into quantiles, with the darkest colors indicating regions in the higher quantiles. In (a) is the distribution of the SAEB variation between the years 2011 and 2015. In (b) is the distribution of the SAEB scores of 5^{th} grade students in 2011. Part (c) of the figure brings the average class hours of 5^{th} grade students in 2011. In (d), the incidence of extreme child poverty in 2010.

Visually, we can distinguish patterns of spatial correlation across the municipalities. For the 5^{th} grade SAEB scores, a and b, and the average class hours, c, the country's Southeast region concentrates the municipalities in the highest quantiles. For the child poverty indicator, d, there is a concentration in the highest quantiles in Brazil's North and Northeast regions.

Table 2 reports the Moran's I statistics for the variables in Figure 1[5]. The tests indicate spatial autocorrelation with all neighborhood criteria, and the correlation coefficients are quite similar. The two highest spatial correlations are for the Saeb score, and the incidence of children up to 14 living in holseholds in extreme poverty.

Figure 2 shows the scatter plots of the spatial correlation of the standardized variables in Table 2 using the parametric W[6]. The observations are concentrated in the second and third quadrants, supporting the Moran I tests' positive spatial correlation in Table 2. In a and c, the

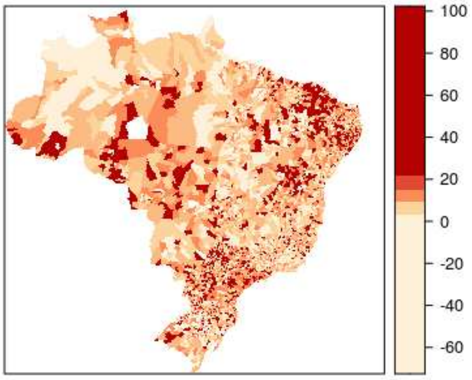
4 It is a common practice choose the cut-off arbitrarily. In this paper the cut-off is the minimun distance as such all municipalities have at least one neighbor.

5 The other variables have similar spatial autocorrelation. Thus the tests and plots are not presented.

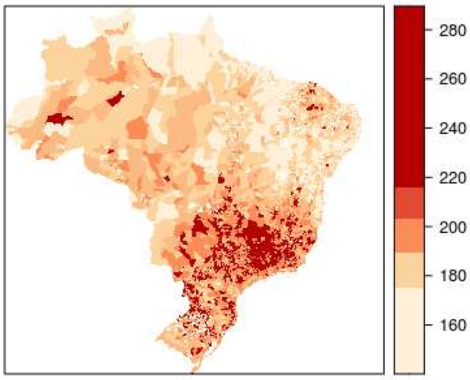
6 The figures was generated using the parametric W, but similar pattern is found using the other criteria.

Figura 1 – Spatial distributions

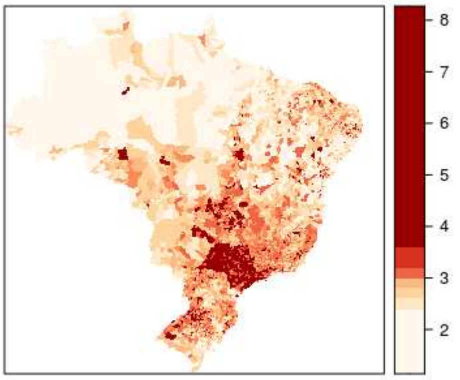
(a) Saeb 5th grade variation



(b) Saeb 5th grade



(c) Average Class hours 5th grade



(d) EPOV

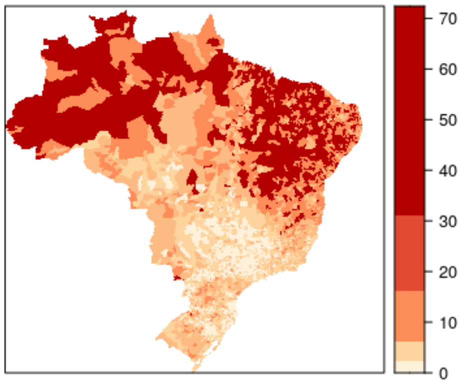


Tabela 2 – Global Moran's I Statistics

Criterion	Saeb 5th gr variation (2011-2015)	Saeb 5th gr (2011)	Average class hours 5th gr (2011-2015)	EPOV (2010)
Queen	0.205***	0.735***	0.331***	0.809***
Rook	0.207***	0.735***	0.334***	0.809***
Dist (30km)	0.165***	0.626***	0.303***	0.634***
K-5	0.202***	0.734***	0.332***	0.808***
K-10	0.183***	0.72***	0.318***	0.791***
Parametric	0.183***	0.712***	0.3***	0.782***

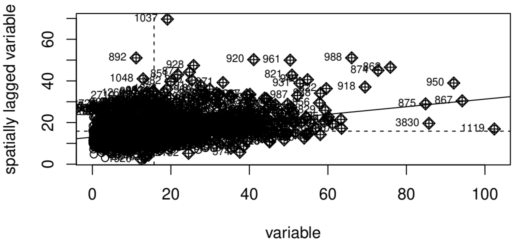
patterns are not so clear as in the other quadrants. In Table 2, we see that the SAEB 5th grade variation and the 5th grade average class hours have smaller Moran I statistics.

The next step is to determine the spatial correlation model. For this, we have estimated conventional and robust Lagrange Multiplier tests (L.M.) for all regressions using a parametric spatial matrix as discussed in section 1.4.2. Table 3 reports the results using students' performance in the same grade (5th grade)[7] in different years ("distinct" cohorts). Both conventional and robust L.M. tests rejected the null hypothesis of no spatial correlation in the error term and the dependent variable. These results suggest that the SAC model is the most appropriate. Ad-

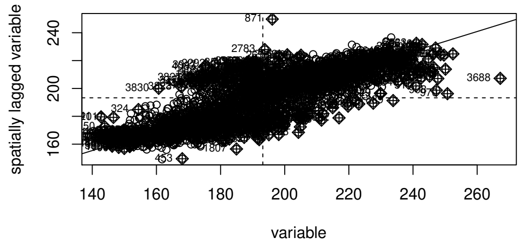
[7] The tests of the other regressions are similar, and we omit them because of space constraints. The results are available with the authors upon request.

Figura 2 – Moran's I plots

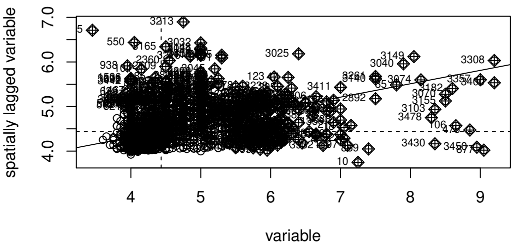
(a) Saeb 5th grade variation



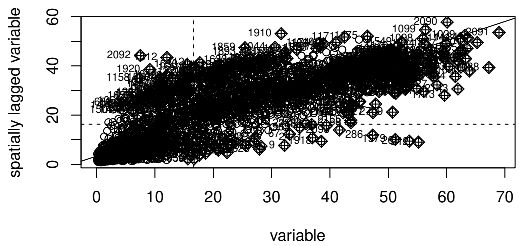
(b) Saeb 5th grade



(c) Average Class hours 5th grade



(d) EPOV



ditionally, the BIC criterion supports the SAC model ($BIC = 10274.2$) instead of the SDEM model ($BIC = 10380.2$).

Tabela 3 – L.M. tests

	Statistic	p.value
LMerr	334.84	0.00
LMlag	231.90	0.00
RLMerr	153.02	0.00
RLMlag	50.07	0.00
γ	2.50	0.00

Note: γ is the decay parameter.

The last step in the spatial model selection is to decide whether to include a matrix of lagged explanatory variables. The inclusion of the explanatory variables would turn it into the GNS model. It has two major issues, according to Vega e Elhorst (2015). The first is that this model does not have formal proof stating under which conditions its parameters are identified. The second is the problem of overfitting. Therefore, we have opted to use the SAC model.

Therefore, the specification to estimate the regressions is:

$$\log(\Delta SAEB_i) = \alpha + \rho \sum_j W_j \log(\Delta SAEB_{j,2011}) + \zeta \log(SAEB_{i,2011}) + \\ + \eta \log(Class\ Hours_{i,2011}) + \beta Poverty_{i,2010} + \varepsilon_{i,t} \\ u = \lambda \sum_j W_j \varepsilon_i \quad (1.10)$$

Where j represent the neighbors and W is the parametric spatial matrix.

1.5 Results

As discussed in Section 1.4, our empirical strategy is to evaluate the influence of poverty incidence and other variables on cognitive skills measured by Saeb performance across the Brazilian municipalities. We assess this effect using two different samples. In the first one, we estimate the change in cognitive skills over time of students in the same grade and "different cohorts". It captures the scores change at the same school grade over time. In the second, we measure the variation of cognitive skills over time of students in the "same cohort". In this sample, we assume that the vast majority of the 5$^{\text{th}}$ grade students in year t will be in the 9$^{\text{th}}$ grade in $t+4$ and the 3$^{\text{rd}}$ year of high school in $t+7$. This last exercise evaluates the poverty incidence effects on the "same" children's school performance over time. All the regressions have controls for the average classroom number of students, the proportion of teachers with a graduate degree, the adult population's educational level, and the urbanization rate. Their estimated coefficients were omitted for the sack of space.

1.5.1 Different Cohorts Results

This section presents and discusses the results using the first sample ("different cohorts"). Tables 4 and 5 bring the results for the 5$^{\text{th}}$ grade students, and Tables 6 e 7 for the 9$^{\text{th}}$ grade students. The difference in the first and last three columns results is the OLS and SAC estimation method, respectively. With the same estimation method, the difference in each column's results is the poverty measure.

In Table 4, the regressand is the variation of the cognitive skills of the 5$^{\text{th}}$ grade students from 2011 to 2015. In all OLS estimations, the initial performance level (5$^{\text{th}}$ grade Saeb score in 2011) is significant and negative, indicating a relevant convergence process in mean students' performance across municipalities. Because the specification is *log-log* for the initial level of cognitive skills, an increase of 1% in the initial level of students' performance leads to a 3.615% reduction in performance variation from 2011 to 2015. Because the specification is *log-log* for class hours, an increase in 1% in the average class hours leads to a 0.537% increase in performance variation from 2011 to 2015.

Table 4 reports that all the poverty incidence measures hurt school performance over time. Since the relationship between the regressand and the other regressors other than initial school performance and class hours is in log-level, a one percentage point increase in poverty incidence[8] leads to a reduction in school performance from 0.4% to 0.8% from 2011 to 2015, indicating that poverty incidence hampers school performance. The extremely poverty indicator do not show significance. Still, this effect is not so expressive at the municipal level[9]. The Gini index's negative estimated coefficients suggest that income inequality also hurts school performance through time controlled by the poverty indicators. For the regression (3), the Gini index show more expressive effect.

The SAC method results are similar to those from OLS, except for income inequality since its estimated coefficients are not statistically different from zero in the first two regressions results. Poverty and the initial school performance have a negative and more relevant impact on school performance over time than the OLS results. The positive spillover effect of poverty on the regressand means that higher poverty in the neighbors leads to better school performance change. One possible explanation is student migration from poor municipalities to close ones with better public school systems. In future studies, we will perform a more thorough analysis to understand this positive spillover effect.

The spatial parameters ρ, λ and γ are significant. The value of the correlation coefficient, $\rho = -0.64$, in column (4) of Table 4 indicates a negative correlation between the school performance of municipality i and its neighbors, i.e., a negative spillover effect. The positive $\lambda = 0.78$ suggests that random shocks in a spatially omitted variable affecting school performance in the neighborhood can positively impact school performance in municipality i. The distance decay values, γ, greater than 1 suggest that more distant regions are less relevant to the spillovers.

The effects of the SAC estimations are divided into direct and spillover effects. Although the direct effects are higher in absolute values than the OLS regressions results, the spillover effects are negative. Concerning the total effects, we find on mean a smaller influence of poverty and initial school performance on the regressand with the SAC estimation methods.

The Moran's I statistics in Table 4 suggest that the spatial autocorrelation in the residuals is no longer present. Therefore, we have correctly treated the spatial autocorrelation in the OLS estimations using the SAC estimation method.

Table 5 reports the 5$^{\text{th}}$ grade students' school performance change from 2011 to 2017 as the regressand. The OLS results are similar to those of Table 4, with smaller effects of the initial school performance, income inequality. and poverty on school performance.

The SAC results of Table 5 show a significant influence of extreme poverty incidence on school performance different from those of Table 4. The Gini index loss importance to poverty suggesting that the effects of poverty is better capture in a greater period. The direct effects are close to those via OLS, but the indirect effects counterbalance them so that the total effects are slighly smaller in the SAC estimation methods. Furthermore, as in Table 4, child vulnerability

[8] The poverty measures vary from 0 to 100, and they are in percentage points.

[9] This effect may be underestimated because some municipalities, which may be the most affected by poverty, had negative school performance variation from 2011 to 2015 and from 2011 to 2017, and were not considered in the analysis.

Tabela 4 – Cross Section Estimations 5th grade students: 2011-2015. OLS and SAC

	Log Saeb variation from 2011 to 2015 - 5th grade					
		OLS			*SAC*	
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	−3.615***	−3.364***	−3.066***	−4.907***	−4.818***	−4.619***
	(0.192)	(0.193)	(0.186)	(0.233)	(0.226)	(0.229)
Log C. Hours	0.537***	0.524***	0.511***	0.475***	0.491***	0.505***
	(0.119)	(0.120)	(0.120)	(0.135)	(0.130)	(0.133)
Poverty	−0.008***	−0.004***	0.002	−0.009***	−0.006***	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Gini	−0.007**	−0.009***	−0.015***	−0.004	−0.003	−0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag L. Saeb				2.036***	2.001***	1.714***
				(0.134)	(0.145)	(0.195)
Lag L. C. Hrs				−0.197***	−0.204***	−0.188***
				(0.057)	(0.055)	(0.052)
Lag Poverty				0.004***	0.002***	0.001
				(0.001)	(0.001)	(0.001)
Lag Gini				0.002	0.001	0.002**
				(0.001)	(0.001)	(0.001)
Constant	21.419***	19.726***	18.039***	28.731***	28.298***	27.137***
	(1.065)	(1.051)	(1.003)	(1.189)	(1.173)	(1.179)
ρ				-0.64***	-0.67***	-0.58***
λ				0.78***	0.85***	0.88***
γ				2.5	1.98	1.54
Moran's I.	0.13***	0.12***	0.1***	-0.01	0	0
AIC	10,573.5	10,601.8	10,608.6	10,204.5	10,190.3	10,207.7
BIC	10,630.5	10,658.8	10,665.5	10,274.2	10,260	10,277.3
N	4,154	4,154	4,154	4,154	4,154	4,154

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 5th grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of hours of the 5th grade students in 2011 and 2015. ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. AIC and BIC are the Akaike and Schwarts information criteria. N is the number of observation.

Tabela 5 – Cross Section Estimations 5th grade students: 2011-2017. OLS and SAC

	Log Saeb variation from 2011 to 2017 - 5th grade					
		OLS			*SAC*	
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	-2.751^{***}	-2.682^{***}	-2.468^{***}	-4.209^{***}	-4.139^{***}	-4.023^{***}
	(0.154)	(0.154)	(0.149)	(0.184)	(0.177)	(0.182)
Log C. Hours	0.520^{***}	0.515^{***}	0.508^{***}	0.411^{***}	0.411^{***}	0.403^{***}
	(0.102)	(0.102)	(0.102)	(0.114)	(0.111)	(0.112)
Poverty	-0.006^{***}	-0.005^{***}	-0.002	-0.007^{***}	-0.006^{***}	-0.004^{**}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Gini	-0.004^{*}	-0.004^{*}	-0.007^{***}	-0.0004	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag L. Saeb				1.697^{***}	1.625^{***}	1.430^{***}
				(0.121)	(0.130)	(0.158)
Lag L. C. Hrs				-0.166^{***}	-0.161^{***}	-0.143^{***}
				(0.046)	(0.045)	(0.042)
Lag Poverty				0.003^{***}	0.002^{***}	0.001^{**}
				(0.001)	(0.001)	(0.001)
Lag Gini				0.0002	-0.0002	0.0003
				(0.001)	(0.001)	(0.001)
Constant	16.940^{***}	16.363^{***}	15.105^{***}	26.037^{***}	25.414^{***}	24.548^{***}
	(0.849)	(0.836)	(0.799)	(0.964)	(0.937)	(0.938)
ρ				-0.64***	-0.62***	-0.54***
λ				0.87***	0.88***	0.89***
γ				2.01	1.89	1.65
Moran's I	0.13***	0.13***	0.12***	0	0	0
AIC	8,722.000	8,732.900	8,750.200	8,233.100	8,238.800	8,256.100
BIC	8,779.000	8,789.900	8,807.100	8,302.700	8,308.500	8,325.700
N	4,154	4,154	4,154	4,154	4,154	4,154

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 5th grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of hours of the 5th grade students in 2011 and 2017. ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. AIC and BIC are the Akaike and Schwarts information criteria. N is the number of observation.

to poverty (VPOV) and child poverty (POV) have a more substantial influence than extreme child poverty (EPOV) on the regressand.

Table 5 shows a critical convergence process in school performance, where the municipalities with higher initial school performance have slower school performance improvements through time. Moreover, municipalities with high initial school performance neighbors tend to enjoy a more significant improvement in school performance for the 2011-2015 period, in Table 4, and 2011-2017, in Table 5.

To assess the importance of public policies to reduce poverty in Brazil, we identified children from impoverished families who were beneficiaries of the Bolsa Família Program in 2010 using the CadÚnico dataset. We calculated the proportion of children living in households considered extremely poor[10] in relation to the total children population up to 14 years old in the municipalities[11]. If the Bolsa Familia Program ended in 2010, the extreme child poverty in the Brazilian municipalities would, on average, rise 27 percentage points. Since one percentage point increase in extreme poverty incidence leads to a total reduction in school performance of 0.3% in the 2011-2017 period (Table 5 column (6)), a rise in extreme child poverty of 27 percentage points would reduce SAEB performance of the 5th graders by 8.1%, on average. These effect is considerable, and it is even more relevant since the reduction in school performance occurs in children with the lowest performance.

Tables 6 and 7 bring analogous regressions specifications for the 9th grade students. The results are qualitatively equivalent to those of Tables 4 and 5. In Table 6, the regressand is the school performance variation for 9th grade students from 2011 to 2015. The municipalities' initial school performance is significant and negative as previously, but its influence is even more substantial. Hence, for 9th grade students, school performance improvements are even more challenging than for 5th graders. The estimated coefficients of poverty incidence in Table 6 are similar to those of Table 4, and the extreme poverty index is signifcant. Income inequality has smaller effect in the OLS regressions of Table 6. Besides, its estimated coefficients have no significance in SAC regression results of both tables.

The class hours estimated coefficients are not significant in the results of Table 6 and slightly smaller than the results of Table 4. This lack of effect may happen because the class hour proxy does not take into account outside of the classroom or extracurricular activities that are important in the learning process and, therefore, in school performance. An increase in poverty incidence leads to a total decrease in the school performance of roughly 0.4% (direct effects of -0.7% plus a positive spillovers of 0.3%). The initial school performance has a total effect on the regressand of -4.3.

Table 7 shows the results where the regressand is the Saeb variation for 9th graders from

[10] We choose the extreme poverty indicator because it is known that these Bolsa Família beneficiary families receive enough income to leave this condition. For poor and vulnerable families, however, the value of the grant is more complex and may not be enough to lift them out of this condition.

[11] In fact, the CadUnico data are available for 2012 and the total children population up to 14 year old is calculated by the 2010 Demographic Census. Therefore, when comparing the number of extreme poor children to the total number of children may have some difference in population size.

Tabela 6 – Cross Section Estimations 9th grade students: 2011-2015. OLS and SAC

	Log Saeb variation from 2011 to 2015 - 9th grade					
	OLS			*SAC*		
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	-5.507^{***}	-5.342^{***}	-5.029^{***}	-7.283^{***}	-7.224^{***}	-7.094^{***}
	(0.320)	(0.316)	(0.307)	(0.368)	(0.355)	(0.362)
Log C. Hours	0.102	0.066	0.082	0.260	0.247	0.240
	(0.145)	(0.145)	(0.145)	(0.194)	(0.186)	(0.189)
Poverty	-0.008^{***}	-0.007^{***}	-0.005^{***}	-0.007^{***}	-0.007^{***}	-0.005^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Gini	-0.006^{**}	-0.006^{*}	-0.010^{***}	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag L. Saeb				3.051^{***}	3.061^{***}	3.051^{***}
				(0.227)	(0.232)	(0.234)
Lag L. C. Hrs				-0.109	-0.105	-0.103
				(0.082)	(0.079)	(0.081)
Lag Poverty				0.003^{***}	0.003^{***}	0.002^{*}
				(0.001)	(0.001)	(0.001)
Lag Gini				-0.0004	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Constant	33.469^{***}	32.351^{***}	30.443^{***}	42.314^{***}	41.894^{***}	41.139^{***}
	(1.803)	(1.766)	(1.700)	(1.941)	(1.884)	(1.845)
ρ				-0.66***	-0.68***	-0.7***
λ				0.77***	0.78***	0.8***
γ				2.23	2.15	2.05
Moran's I	0.09***	0.09***	0.09***	0	0	0
AIC	8,777.300	8,785.900	8,799.900	8,564.300	8,561.100	8,562.700
BIC	8,832.300	8,840.900	8,854.900	8,631.400	8,628.300	8,629.900
N	3,308	3,308	3,308	3,308	3,308	3,308

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 9th grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of hours of the 9th grade students in 2011 and 2015. ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. AIC and BIC are the Akaike and Schwarts information criteria. N is the number of observation.

2011 to 2017. The initial school performance is significant and negative, and its influence on the regressand is more sizable than for the 5th graders (Table 4). Compared to Table 4, the poverty measures have a smaller impact on school performance over timeon SAC regressions. In the OLS and SAC regressions, a ten percentage point increase in the vulnerability to poverty measures reduces school performance by 7% from 2011 to 2017 by the first method and 6% by the latter. For the results in Table 7 (columns (3) and (6)), the OLS and the SAC methods show a statistically significant and negative influence of income inequality on school performance from 2011 to 2017. The class hours are positive and significant for the SAC estimation methods. The spillovers are significant only for the initial performance level.

Considering the 2011-2015 period, where the EPOV indicator show significance, one percentage point increase in child extreme poverty would reduce school performance by 0.3% in total effect. Without the Bolsa Família income transfer program, extreme child poverty in 2010 would rise 27 percentage points on average, with a decline in school performance by 8.1% for the ninth graders. These results point to poverty reduction public policies' relevance to improve school performance and, therefore, subsequent economic growth and development.

1.5.2 Same Cohort Results

In this section, we present the results of the second exercise. In Table 8, the regressand is the Saeb's variation for the "same students cohort" in 2011 (5th grade) and 2015 (9th grade). The qualitative results are similar to those in the previous exercise. The initial level of Saeb and poverty incidence measures have a statistically significant and negative influence on school performance through time. However, both have a smaller impact on the regressand than the previous exercise results ("different cohorts"). The class hours variable is not significant in these regressions. In the SAC regressions results, the absolute value of ρ is relatively smaller than in the previous exercise, as we can see in columns (4) to (6), indicating a smaller spillover effect on school performance.

The smaller effects of poverty incidence in the "same cohort" concerning the estimations with "different cohorts" may be due to other variables influencing the performance of the same cohorts of students over time. The data show that school performance has improved more in the 5th grade than the 9th grade scores in the Brazilian municipalities. Therefore, there are other variables not controlled for in the estimations preventing the 9th graders from having better scores over time, leading to a reduced effect of poverty on performance when students go from the 5th grade to the 9th grade.

In Table 9, the regressand is the variation of cognitive skills for the "same cohort" in 2011 (5th grade) and 2017 (3rd high school grade). The results are similar to those of Table 8, but the poverty incidence indicators have a slightly higher impact on students' performance. The class hours estimated coefficients turn to statistically significant and positive. In the spatial regressions results, the Gini index has a positive and significant effect on students' performance over time, contrary to what we would expect.

Tabela 7 – Cross Section Estimations 9th grade students: 2011-2017. OLS and SAC

	Log Saeb variation from 2011 to 2017 - 9th grade					
		OLS			*SAC*	
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	-4.261^{***}	-4.102^{***}	-3.790^{***}	-5.077^{***}	-4.661^{***}	-4.559^{***}
	(0.283)	(0.279)	(0.271)	(0.308)	(0.284)	(0.292)
Log C. Hours	-0.016	-0.049	-0.032	0.377^{**}	0.325^{**}	0.321^{**}
	(0.133)	(0.133)	(0.134)	(0.173)	(0.162)	(0.161)
Poverty	-0.007^{***}	-0.006^{***}	-0.002	-0.006^{***}	-0.004^{*}	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Gini	-0.003	-0.003	-0.007^{**}	-0.005^{*}	-0.005^{*}	-0.006^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag L. Saeb				1.017^{**}	1.078^{**}	1.138^{**}
				(0.469)	(0.479)	(0.440)
Lag L. C. Hrs				-0.076	-0.075	-0.080
				(0.053)	(0.051)	(0.052)
Lag Poverty				0.001	0.001	0.0004
				(0.001)	(0.001)	(0.001)
Lag Gini				0.001	0.001	0.002
				(0.001)	(0.001)	(0.001)
Constant	26.383^{***}	25.341^{***}	23.451^{***}	30.820^{***}	28.530^{***}	27.912^{***}
	(1.592)	(1.562)	(1.504)	(1.716)	(1.629)	(1.591)
ρ				-0.25*	-0.3*	-0.33**
λ				0.88***	0.9***	0.91***
γ				1.07	0	0
Moran's I	0.13***	0.1***	0.1***	0	0*	0*
AIC	7,962.200	7,971.400	7,984.900	7,555.600	7,638.000	7,643.500
BIC	8,017.100	8,026.300	8,039.800	7,622.800	7,705.100	7,710.600
N	3,308	3,308	3,308	3,308	3,308	3,308

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 9th grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of hours of the 9th grade students in 2011 and 2017. ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. N is the number of observation.

Tabela 8 – Cross Section Estimations for the same cohort grade students: 2011-2015. OLS and SAC

	Log Saeb variation from 2011 to 2015					
	OLS			*SAC*		
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	-2.064^{***}	-2.066^{***}	-2.028^{***}	-2.412^{***}	-2.409^{***}	-2.384^{***}
	(0.048)	(0.049)	(0.047)	(0.059)	(0.056)	(0.058)
Log C. Hours	-0.002	-0.005	-0.002	0.055	0.051	0.048
	(0.036)	(0.036)	(0.036)	(0.042)	(0.043)	(0.044)
Poverty	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.003^{***}	-0.002^{***}	-0.002^{***}
	(0.0004)	(0.0004)	(0.0005)	(0.001)	(0.001)	(0.001)
Gini	0.001	0.001	0.001	0.001	0.002^{**}	0.001^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag L. Saeb				0.508^{***}	0.556^{***}	0.590^{***}
				(0.101)	(0.090)	(0.083)
Lag L. C. Hrs				-0.012	-0.012	-0.012
				(0.009)	(0.010)	(0.011)
Lag Poverty				0.001^{***}	0.001^{***}	0.0004^{***}
				(0.0001)	(0.0001)	(0.0002)
Lag Gini				-0.0002	-0.0004^{**}	-0.0003
				(0.0002)	(0.0002)	(0.0002)
Constant	14.868^{***}	14.824^{***}	14.573^{***}	17.582^{***}	17.574^{***}	17.461^{***}
	(0.269)	(0.267)	(0.254)	(0.398)	(0.382)	(0.373)
ρ				-0.26***	-0.29***	-0.32***
λ				0.79***	0.78***	0.78***
γ				1.79	1.87	1.92
Moran's I	0.12***	0.13***	0.13***	0	0	0
AIC	372.500	374.200	383.800	-102.800	-104.300	-92.900
BIC	430.700	432.400	442.000	-31.700	-33.200	-21.800
N	4,748	4,748	4,748	4,748	4,748	4,748

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 5^{th} grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of class hours of the same generation students in 2011 and 2015 (columns 1 to 3) and in the years 2011 and 2017 (columns 4 to 6). ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. AIC and BIC are the Akaike and Schwarts information criteria. N is the number of observation.

In summary, the results of Tables 8 and 9 support the negative influence of the initial cognitive performance and poverty incidence on students' scores through time. Our results support a convergence process on cognitive skills across municipalities and the hypothesis that poverty incidence is crucial to students' cognitive performance using a macroeconomic dataset.

1.6 Conclusion

This study's objective was to evaluate the effect of poverty on students' cognitive performance in the Brazilian municipalities. The study's motivation was based on microeconomic and medical studies that indicate adverse effects of poverty on people's cognitive development and learning, especially children (ABER et al., 1997; ENGLE; BLACK, 2008; HANSON et al., 2013). It is also essential to analize if the poverty influence on school performance is relevant using macroeconomic dataset since the measurement of the aggregate effects is crucial for public policies aiming to fight poverty.

The human capital production function was developed by Lucas (1988), and we used spatial models to estimate the regressions since variables as poverty and students' cognitive skills are determined in a larger geographic areas than the municipality level. Through different exercises, the results support that poverty incidence is crucial to students' cognitive performance across municipalities and time, considering the same and different cohorts of students. This study's results are a step in this research agenda to understand poverty incidence and its relationship with cognitive skills and economic growth and development.

Tabela 9 – Cross Section Estimations for the same cohort grade students: 2011-2017. OLS and SAC

	Log Saeb variation from 2011 to 2017					
	OLS			*SAC*		
	VPOV	POV	EPOV	VPOV	POV	EPOV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Saeb	-1.943^{***}	-2.017^{***}	-1.995^{***}	-2.536^{***}	-2.499^{***}	-2.477^{***}
	(0.046)	(0.046)	(0.045)	(0.055)	(0.052)	(0.054)
Log C. Hours	0.562^{***}	0.564^{***}	0.566^{***}	0.507^{***}	0.505^{***}	0.501^{***}
	(0.032)	(0.032)	(0.032)	(0.037)	(0.038)	(0.038)
Poverty	-0.002^{***}	-0.004^{***}	-0.005^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.0003)	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)
Gini	0.001	0.003^{***}	0.003^{***}	0.002^{**}	0.003^{***}	0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag L. Saeb				0.695^{***}	0.645^{***}	0.710^{***}
				(0.090)	(0.096)	(0.084)
Lag L. C. Hrs				-0.139^{***}	-0.130^{***}	-0.143^{***}
				(0.021)	(0.021)	(0.020)
Lag Poverty				0.001^{***}	0.001^{***}	0.001^{***}
				(0.0002)	(0.0002)	(0.0002)
Lag Gini				-0.0005^{**}	-0.001^{***}	-0.001^{***}
				(0.0002)	(0.0002)	(0.0002)
Constant	13.495^{***}	13.842^{***}	13.647^{***}	18.307^{***}	17.811^{***}	17.774^{***}
	(0.257)	(0.253)	(0.241)	(0.379)	(0.388)	(0.372)
ρ				-0.37***	-0.34***	-0.4***
λ				0.9***	0.9***	0.89***
γ				1.64	1.57	1.65
Moran's I	0.16***	0.15***	0.15***	0.01***	0.01***	0.01***
AIC	9.900	−42.500	−63.400	−853.100	−831.000	−824.800
BIC	68.100	15.700	−5.200	−781.900	−759.900	−753.700
N	4,748	4,748	4,748	4,748	4,748	4,748

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard deviations are in parentheses. Saeb is the school performance for the 5th grade student in 2011. VPOV is the proportion of children vulnerable to poverty (2010). POV is the proportion of children living in poverty (2010). EPOV is the proportion of children living in extreme poverty (2010). Gini is the inequality measure for municipalities (2010). Class hours are the average number of class hours of the same generation students in 2011 and 2015 (columns 1 to 3) and in the years 2011 and 2017 (columns 4 to 6). ρ is the scalar spatially autoregressive parameter. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay estimate. Moran's I is the spatial correlation test on the regression residuals. AIC and BIC are the Akaike and Schwarts information criteria. N is the number of observation.

2 POVERTY CONVERGENCE IN BRAZILIAN MUNICIPALITIES

Abstract

The objective of this paper is to analyze poverty convergence across Brazilian municipalities. Following Ravallion (2012), we study the effects of initial poverty incidence on average per capita income growth and poverty variation. The results suggest that poverty incidence may be hindering poverty convergence across the Brazilian municipalities. We find that per capita income growth decreases poverty and the presence of income convergence in Brazil. However, these effects are counterbalanced by the initial poverty incidence on income growth and poverty reduction.

Keywords: Poverty Incidence; Economic Growth; Brazilian Municipalities.

Resumo

O objetivo deste artigo é analisar porque não observamos convergência da pobreza nos municípios brasileiros. Seguindo Ravallion (2012), estudamos os efeitos da incidência de pobreza inicial sobre o crescimento da renda per capita média e sobre a redução da própria pobreza. Os resultados encontrados sugerem que a própria pobreza pode estar prejudicando a convergência da pobreza. Encontramos que o crescimento da renda per capita média reduz pobreza e a presença da convergência da renda no Brazil. Entretanto, esses efeitos são contrabalanceados pela incidência de pobreza inicial no crescimento da renda e na redução da pobreza.

Palavras-chaves: Pobreza; Crescimento Econômico; Municípios Brasileiros.

2.1 Introduction

Following Ravallion (2012), two stylized facts are highlighted in the economic growth and development literature when comparing countries with different economic development levels: 1) the advantage of backwardness; and 2) the advantage of growth. The first fact states that when comparing two similar countries, the one with lower initial average income will experience higher economic growth. The second suggests that countries with higher economic growth have a more substantial poverty reduction. Therefore, we can infer that countries with lower initial income – those usually having higher poverty incidence – experience higher economic growth. Consequently, they have a more significant poverty reduction.

However, on average, poorer municipalities are not those experiencing the most relevant poverty reduction rates from 1991 to 2010, i.e., there is no sign of poverty convergence, in line with Ravallion (2012) across countries. This enigma points that we are missing something important. Ravallion (2012) considers that the initial poverty incidence may influence per capita income and poverty variations in ways that cancel out the previously cited advantages. To test this hypothesis, he estimates a model in which the initial levels of poverty incidence and per capita income influence subsequent income and poverty variations.

In this paper, we follow Ravallion (2012) analysis for the Brazilian municipalities. It is crucial to check if his results hold for regions of the same country since many important variables affecting income and poverty as the institutional setting and macroeconomic policies are more similar than in the comparison across countries. In addition, since poverty is high in many Brazilian municipalities, it is relevant to understand its impacts on economic performance to foster public policies to fight poverty. Also, we consider other aspects that may influence income or poverty variations as income distribution and the middle-class size. Since the variables in the present study are likely to be influenced by public policies and other macroeconomic events that are broader in space than the limits of a municipality, we have considered the potential spatial effects on our estimates. For example, this spatial dependence may be due to economies of agglomeration and regional dynamics of labor attraction (KALENKOSKI; LACOMBE, 2008). When there is a spatial correlation in the data, but it is ignored, the OLS and GMM estimation methods are biased (ARBIA, 2014). In general, our results are in line with those of Ravallion (2012).

Besides this introduction, the following section brings a brief review of the literature. Section 2.3 presents the methodology and data. The following one brings the empirical analysis. The last section concludes.

2.2 Literature Review

Ravallion (2012) emphasizes the effects of initial poverty incidence on economic growth. Lopez e Servén (2006) introduce a minimum subsistence consumption to the model of Aghion, Caroli e Garcia-Penalosa (1999) and find that high poverty incidence implies a lower growth rate. Poverty trap models based on impatience to consume (high time preference associated with low life expectancy) indicate that poverty reduces savings and investment rates (AZARIADIS, 2006; KRAAY; RADDATZ, 2005).

Another way in which poverty affects income is via nutrition and health. Only when in childhood the nutrition is sufficient to cover the basal metabolic rate, the individuals in adulthood will be able to perform work fully. In addition, other aspects of children's development, such as learning and cognitive skill development can be affected by poverty, reducing their future earnings (ABER et al., 1997; ENGLE; BLACK, 2008; HANSON et al., 2013). Therefore, a higher poverty incidence hurts income growth.

Many theoretical studies have also pointed to the importance of initial income distribution on economic growth. High inequality can reduce physical and human capital investments when there are credit constraints (GALOR; ZEIRA, 1993; PEROTTI, 1996; AGHION; BOLTON, 1997). Moreover, high inequality can distort policy responses or restrict efficiency-promoting cooperation so that essential public goods are underprovided or efficiency-enhancing reforms are blocked (BARDHAN; BOWLES; GINTIS, 2000). Thus, many papers include income inequality measures as an explanatory variable for economic growth, and they find adverse effects of inequality on growth (LI; ZOU, 1998; BARRO, 2000; FORBES, 2000).

The literature has focused mainly on the Gini index to measure income inequality (VOITCHOVSKY, 2005). Also, the middle-class size has been used to measure the income distribution influence on income growth. The increase in the middle-class can foster entrepreneurship, consumer demand, growth-promoting policy reforms, and good institutions (DOEPKE; ZILIBOTTI, 2005; SRIDHARAN, 2004; EASTERLY, 2001; BIRDSALL; GRAHAM; PETTINATO, 2000; ACEMOGLU; ZILIBOTTI, 1997; MURPHY; SHLEIFER; VISHNY, 1989).

These arguments suggest that poverty is a crucial variable in explaining income growth. There is also evidence that inequality is relevant in income performance. Therefore, we include both variables in the empirical analysis as regressors.

2.3 Methodology and data

2.3.1 Data and Descriptive Statistics

The municipality is the unit of analysis. The dataset is mainly from the Brazilian Demographic Censuses of 1991, 2000, and 2010. Since the data for the variables are from the same surveys, the comparability problems are minor compared to countries' datasets. Most data are from the Human Development Atlas (PNUD). PNUD uses the Brazilian Demographic Censuses (IBGE) to construct its dataset. All variables values are measured in prices of 2010. The period of analysis focus on the years 1991 and 2010. The 2000 dataset is used for robustness check.

Given the most recent survey for date (t) in municipality i and the earliest available survey for date $(t-\tau)$, the growth rate for variable x is

$$g_i(x_{i,t}) = (x_{i,t} - x_{i,t-\tau})/(\tau x_{i,t-\tau}). \tag{2.1}$$

The headcount index measures poverty $(P_{i,t})$. It is calculated as the proportion of the population living in households with income per capita below a poverty line. There are three poverty lines: extremely poverty; poverty; and vulnerability to poverty. The monthly income thresholds are R\$ 70.00, R\$ 140.00, and R\$ 255.00, in 2010 prices. These income thresholds are used as references to assessment poverty programs. In this paper, we focus on the poverty line as a measure of poverty incidence $P_{i,t}$. Table 10 brings the descriptive statistics. For 1991, poverty incidence range from 0.44% (Fernando de Noronha – PE) to 97% (São Sebastião de Uatumá – AM). One quarter of the sample P_{1991} was below 36.6% while the upper one quarter it was above 76.9 percent.

The Gini index measures income inequality $(G_{i,t})$. It ranges from 0 (most equal income distribution) to 100 (most unequal income distribution). For 1991, the income distribution measure range from 32 (Areiopolis – SP) to 92 (Santa Helena – PB). About one-quarter of the sample had a Gini index below 49, while one quarter had a Gini index above 57. The average Gini index in 1991 was about 53.1, while in 2010, it was 49.5.

In addition, we use three measures of the middle-class size as indicators of income inequality. The first is the share of the population living in households with income between R$ 1,540.00 and R$ 2,813.00 in 2012 prices (BARROS; GROSNER, 2012)[1]. Following Easterly (2001), the second measure is the income share of the households in the middle three quintiles of the income distribution $(MQ_{i,t})$. Finally, the "misery index" proposed by Lind e Moene (2011) is an inverse measure of the middle class. The misery index is given by $P_{i,t}(y_{i,t} - y^P_{i,t})$, where $y_{i,t}$ is the average income, and $y^P_{i,t}$ is the average income of those living below the poverty line.

Tabela 10 – Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	4,491	244.704	145.955	43.700	125.155	327.730	1,185.280
y^P	4,491	73.377	14.902	0.000	62.140	85.331	124.820
P	4,491	55.348	23.593	0.440	36.581	76.895	97.020
G	4,491	53.058	6.578	32.000	49.000	57.000	92.000
MC	4,491	22.086	11.680	0.000	12.336	30.273	60.399
MQ	4,491	37.989	5.243	1.920	34.665	41.630	53.450
$misery$	4,491	6,643.590	2,833.751	200.882	4,391.596	8,546.213	23,695.700
$g(y)$	4,491	6.521	3.162	−0.233	4.427	8.110	30.967
$g(P)$	4,491	−3.362	1.055	−5.216	−4.185	−2.602	21.053
LE	4,491	63.851	4.660	50.970	60.320	67.650	73.610
SA	4,491	70.254	13.398	10.590	62.963	80.015	99.250

Notes: $\mathbf{y}$ is the average per capita income. $\mathbf{y}$ is the average per capita income of the poor. $\mathbf{P}$ is the proportion of people below the poverty line (headcount index). $\mathbf{G}$ is the Gini inequality index. $\mathbf{LF}$ is the life expectation index. $\mathbf{SA}$ is the school attendance rate. $\mathbf{MC}$ is the middle class size (SAE definition). $\mathbf{MQ}$ is the income share commanded by the middle three quintiles. $\mathbf{misery}$ is the misery index. $\mathbf{g}$ variables are the growth rate of the per capita income and the poverty index by the percentual difference (expression 2.1) between 1991 and 2010.

Table 11 shows the correlation coefficients of the variables in 1991. There are some high correlation coefficients amongst them. The Gini index G_{1991} is highly correlated with MQ_{1991} (-0.97). The poverty measure is strongly correlated with the average income y_{1991} (-0.92) and y^P_{1991} (-0.90). The middle-class measure (MC_{1991}) is highly correlated with the poverty measure (-0.95).

Figure 3 brings the spatial correlations of the main variables of the present study for 1991. Panel (a) shows the poverty headcount index (P_{1991}), which shows a clear concentration of high poverty incidence in the municipalities of the North and Northeast of the country. In panels (b) and (c), we have the average per capita income (y_{1991}) and the size of the middle class (MC_{1991}), which shows higher values in the municipalities of the South and Southeast of Brazil. Finally, panel d brings income distribution measured by the Gini index (G_{1991}). The income distribution is better in the municipalities of the South and Southeast of the country, but there many municipalities in the Northeast with good income distribution.

[1] This is the criterion adopted by the Brazilian Bureau of Strategic Affairs (SAE).

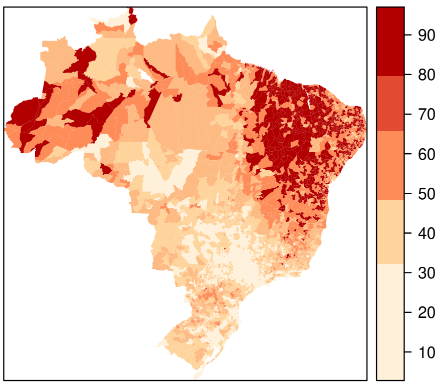
Tabela 11 – Correlations

	y	y^P	P	G	MC	MQ	$misery$	$g(y)$	$g(P)$
y	1	0.799	-0.917	0.093	0.855	-0.151	0.499	-0.506	-0.447
y^P	0.799	1	-0.900	-0.228	0.867	0.117	0.408	-0.479	-0.569
P	-0.917	-0.900	1	0.102	-0.955	-0.043	-0.449	0.463	0.541
G	0.093	-0.228	0.102	1	-0.144	-0.969	0.652	-0.141	-0.062
MC	0.855	0.867	-0.955	-0.144	1	0.092	0.380	-0.469	-0.458
MQ	-0.151	0.117	-0.043	-0.969	0.092	1	-0.682	0.208	0.100
$misery$	0.499	0.408	-0.449	0.652	0.380	-0.682	1	-0.360	-0.474
$g(y)$	-0.506	-0.479	0.463	-0.141	-0.469	0.208	-0.360	1	-0.130
$g(P)$	-0.447	-0.569	0.541	-0.062	-0.458	0.100	-0.474	-0.130	1

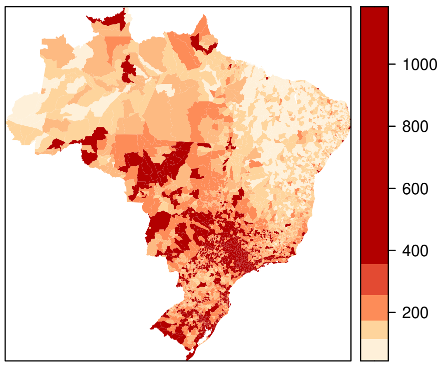
Notes: **y** is the average per capita income. $\mathbf{y^P}$ is the average per capita income of the poor. **P** is the proportion of people below the poverty line (headcount index). **G** is the Gini inequality index. **MC** is the middle class size (SAE definition). **MQ** is the income share commanded by the middle three quintiles. **misery** is the misery index. **g**(.) variables are the growth rate of the per capita income and the poverty index by the percentual difference.

Figura 3 – Spatial distributions

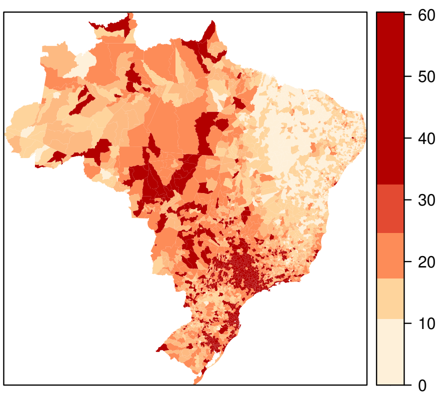
(a) Poverty (P_{1991})



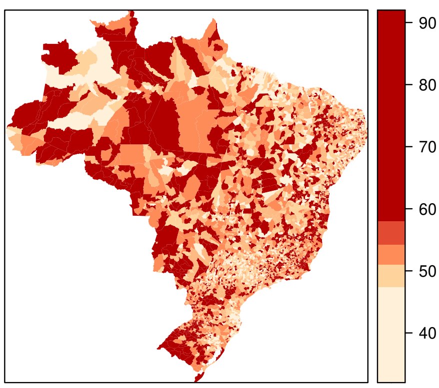
(b) Per Capita Income (y_{1991})



(c) Middle Class (MC_{1991})



(d) Gini (G_{1991})



In Table 12, we have the Moran's I Global Statistics for the variables of Figure 3. The

Moran's I Statistics is a correlation coefficient that measures the spatial autocorrelation of the variables across the neighboring municipalities, and it ranges from -1 to 1. The tests' results indicate the presence of spatial autocorrelation with the most used neighbors' spatial weight matrices, and the spatial correlation coefficients are similar in all of them. The poverty measure and income per capita have the two highest spatial correlations.

Tabela 12 – Global Moran's I Statistics

	P_{1991}	y_{1991}	MC_{1991}	G_{1991}
Queen	0.853***	0.734***	0.79***	0.217***
Rook	0.853***	0.735***	0.789***	0.217***
Dist (30 km)	0.742***	0.62***	0.712***	0.173***
K-5	0.857***	0.706***	0.806***	0.229***
K-10	0.847***	0.701***	0.792***	0.216***

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

2.3.2 *The choice of the spatial model*

According to Vega e Elhorst (2015), unless we have sound theoretical reasoning for modeling spatial dependence, the SLX model with a parametric spatial matrix based on the inverse distance[2] is the most suitable model to start the analysis. The SLX model takes the form:

$$\mathbf{Y} = \alpha \mathbf{i_N} + \mathbf{X}\beta + \mathbf{WX}\theta + \varepsilon \tag{2.2}$$

where $\mathbf{Y}$ represents the $N \times N$ vector of dependent variable, $\mathbf{i_N}$ is an $N \times N$ vector of ones associated with the constant term α, $\mathbf{X}$ is an $N \times N$ matrix of explanatory variables associated with the $K \times 1$ parameter vector β, $\mathbf{W}$ is the spatial weight matrix so that $\mathbf{WX}$ represents the exogenous interaction effects among the explanatory variables associated with the $K \times 1$ parameter vector θ and ε is a vector of iid disturbance with zero mean and variance σ^2.

Following Vega e Elhorst (2015), we use a parameterized spatial weight matrix which has the form

$$W = (w_{i,j}) \in \mathbb{R}^{n \times n}; \quad w_{i,j} = \begin{cases} 0, & \text{if} \quad i = j \quad \text{or} \quad d_{i,j} > \bar{c} \\ \dfrac{1}{d_{i,j}^{\gamma}}, & \text{if} \quad i \neq j \quad \text{and} \quad d_{i,j} \leq \bar{c} \end{cases} \tag{2.3}$$

where n is the number of regions, $d_{i,j}$ is the distance between regions i and j, γ is the estimated decay parameter and $\bar{c}$ is a cut-off distance[3]. The algorithm to estimate the decay parameter (γ) is presented in appendix A.

Amongst the advantages of this approach is that the SLX model does not impose a prior restriction on the ratio between the direct and spillover effects as the SAC and SAR models

[2] The parametric elements of the spatial matrix can be estimated following $w_{i,j} = 1/d_{i,j}$, where $d_{i,j}$ denotes the distance between observations i and j, and γ is the distance decay parameter to be estimated alongside the model. The advantage of using this parametric spatial matrix is that the more information is used to evaluate the spatial effects in comparison with pre-defined matrices (VEGA; ELHORST, 2015).

[3] It is a common practice choose the cut-off arbitrarily. In this paper the cut-off is the minimum distance as such all the municipalities have at least one neighbor. In the present study, this minimum distance is 260km.

(VEGA; ELHORST, 2015). Also, LeSage (2014) emphasizes that most spatial spillovers are local. Thus the preferred models would be the SLX and SDEM.

In the present study, the LM tests, the AIC and BIC criterions and the Moran's I statistics on residuals supports the SDEM model as the preferred model, which have the form

$$\begin{aligned} \mathbf{Y} &= \alpha \mathbf{i_N} + \mathbf{X}\beta + \mathbf{WX}\theta + \mathbf{u} \\ \mathbf{u} &= \lambda W \mathbf{u} + \varepsilon \end{aligned} \tag{2.4}$$

The result tables report the OLS estimates and the direct and spillover effects of the SDEM. The SDEM's total effects are in appendix B.

2.4 Empirical results

2.4.1 Testing for Convergence in average income and poverty

The two stylized facts of income convergence and income growth reducing poverty imply that we should observe poverty convergence. According to Ravallion (2012), in the standard *log-linear* growth models, the speed of convergence is the same for the average income and poverty incidence. To show this, consider the most common growth specification:

$$\Delta \ln y_{i,t} = \alpha_i + \beta_i \ln y_{i,t-\tau} + \varepsilon_{i,t}. \tag{2.5}$$

Where α_i is a municipal-specific effect, β_i is a municipal-specific convergence parameter and $\varepsilon_{i,t}$ is a zero-mean error term.

Now consider the most simple specification for poverty as a function of income per capita:

$$\ln P_{i,t} = \delta_i + \eta_i \ln y_{i,t} + \nu_{i,t}. \tag{2.6}$$

Where δ_i is a municipal-specific effect, η_i is the elasticity of poverty to income and $\nu_{i,t}$ is a zero-mean error term.

From equations (2.5) and (2.6), the implied equation for poverty variation is

$$\Delta \ln P_{i,t} = \tilde{\alpha}_i + \tilde{\beta}_i \ln P_{i,t-\tau} + \tilde{\varepsilon}_{i,t}, \tag{2.7}$$

where $\tilde{\alpha}_i = \alpha_i \eta_i - \beta_i \delta_i$, $\tilde{\beta}_i = \beta = i$ and $\tilde{\varepsilon}_{i,t} = \varepsilon_{i,t}\eta_i + \nu_{i,t} - (1+\beta_i)\nu_{i,t-\tau}$. Comparing (2.5) and (2.7), we see that the "speed of convergence" for the poverty measures, $\partial \Delta P_{i,t}/\partial \ln P_{i,t-\tau} = \beta_i$, is the same as that for income per capita, $\partial \Delta \ln y_{i,t}/\partial \ln y_{i,t-\tau} = \beta_i$.

The data show evidences of income convergence. In columns (1) and (2) of Table 13, we have the standard convergence tests for the mean income based on the following equation:

$$g_i(y_{i,t}) = \alpha + \beta \ln y_{i,t-\tau} + \delta X_{i,t-\tau} + \varepsilon_{i,t} \tag{2.8}$$

where X denotes a vector of controls comprising log school attendance and log life expectancy at birth. The results in Table 13 show evidence of income convergence because the OLS β

coefficient (column 1) is -2.86 without controls and -6.00 with controls. The results are robust to the spatial autocorrelation without additional controls, as we can see in column (2): the direct effect is -3.17, and the spillover effect is 0.26. With additional controls, the direct effects are more relevant (-5.814) and significant. The spillover effect becomes is bigger such that the total effect is smaller compared to the withou additional controls. The decay parameter is significant and near 1 in column (2) and near 0 in column (4), suggesting that the additional controls raise the spillover effects of more distant neighbors. The Moran's I Statistics suggest that the SDEM model almost completely remove the residual spatial correlation.

Tabela 13 – Testing advantage of backwardness

	$g(y)$			
	OLS	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)
$\ln y$	-2.865 t = -42.355^{***}	-4.028 t = -46.025^{***}	-6.000 t = -58.494^{***}	-5.814 t = -52.394^{***}
Lag $\ln y$		0.825 t = 12.375^{***}		2.883 t = 4.135^{***}
Constant	21.791 t = 60.075^{***}	26.164 t = 56.440^{***}	-72.771 t = -25.649^{***}	-37.003 t = -10.346^{***}
λ		1***		0.992***
γ		0.96		0.11
AIC	21576.1	20014.3	20354.5	19685.8
BIC	21595.3	20046.4	20386.5	19685.8
Moran's I Stat.	0.28***	0.05***	0.13***	0.02***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 2.8. Columns (3) and (4) show the estimation of expression 2.8 with additional controls (ln school frequency and ln life expectancy). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

The data also suggests that the advantage of growth occurs, i.e., higher income growth is associated with a more relevant reduction in poverty incidence. Table 14 brings the results with the following equation regression:

$$g_i(P_{i,t}) = \alpha + \beta g_i(y_{i,t}) + \omega X_{i,t-\tau} + \nu_{i,t} \tag{2.9}$$

where X denotes the same vector of controls. In column (1) the significant coefficient -0.043 suggests that a rise in income per capita reduces poverty. With the additional controls, with the results in column (3), the income effect on poverty reduction duplicates. When controlling for the spatial effects, with the result in columns (2) and (4), the total effect is slightly smaller in relation to the OLS results. The spillover in colum (4) is positive[4].

Tabela 14 – Testing advantage of growth

	$g(P)$			
	OLS	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)
$g(y)$	−0.043 t = −9.387***	−0.060 t = −16.849***	−0.092 t = −31.033***	−0.079 t = −26.807***
$Lag\ g(y)$		−0.129 t = −10.210***		0.130 t = 4.286***
Constant	−3.084 t = −91.900***	−2.322 t = −69.904***	34.438 t = 62.315***	21.816 t = 27.309***
λ		0.999***		0.997***
γ		0		0
AIC	12573.9	9040	8362.1	7228
BIC	12593.2	9072.1	8394.2	7228
Moran's I Stat.	0.59***	0.13***	0.13***	0.05***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 2.9. Columns (3) and (4) show the estimation of expression 2.9 with additional controls (ln school frequency and ln life expectancy). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

However, as we see in Figure 4, poverty convergence does not occur for the poverty rate, which is robust to the poverty threshold choice. With the extremely poverty measure, the regression line of Figure 4 has an inclination of almost zero (0.009), and with the vulnerability to poverty measure, the inclination is 0.04.

In summary, similar to what Ravallion (2012) found for countries, our results support both effects of the advantages of growth and backwardness, but no poverty convergence in the Brazilian municipalities.

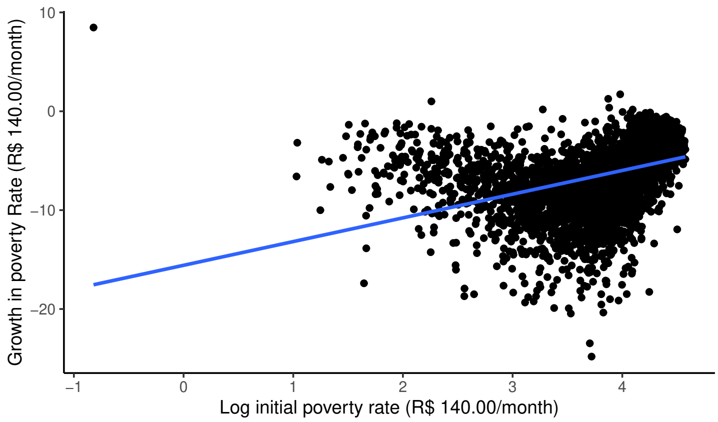
2.4.2 Initial poverty incidence and income growth

This subsection begins with specification in equation (2.10) to test the importance of initial poverty on income growth.

$$g_i(y_{i,t}) = \alpha + \beta \ln y_{i,t-\tau} + \delta \ln P_{i,t-\tau} + \varepsilon_{i,t} \tag{2.10}$$

[4] However, the GMM estimation of the regression shows a less expressive spillover size.

Figura 4 – Poverty variation and initial poverty



In column (1) of Table 15, the OLS results show that the estimated coefficients of the initial poverty incidence are negative and significant, indicating that the initial poverty incidence negatively impacts per capita income growth. A one percentage point increase in P_{1991} is associated with a decline of almost 0.5 p.p. in the income growth rate.

Several alternative specifications might be considered for a robustness check. Column (2) of Table 15 brings the SDEM estimation instead of the OLS one. The initial poverty has a negative direct effect and a stronger negative spillover effect. An increase of 1% in the initial poverty incidence in the neighboring municipalities is associated with a 1.8 p.p. reduction in per capita income growth.

The negative spillover effect of poverty incidence on income growth suggests that poverty and per capita income growth are determined at a broader level than that of the municipalities' borders. One possible explanation is that when the neighboring municipalities' poverty incidence is high, the incentives to engage in productive actives reduce because the average purchasing power of their citizens is low, reducing the demand for goods and services.

Another robustness check uses the three available surveys (1991, 2000 and 2010) to reduce measurement error and smooth short-run variation of the variables using their average in the previous two periods. Equation (2.10) can be rewritten as

$$g_i(y_{it}) = \alpha + \beta \ln \bar{y}_{i,t-\tau} + \delta \ln \bar{P}_{it-\tau} + \varepsilon_{it}, \tag{2.11}$$

where $\bar{y}_{i,t-\tau}$ is the income per capita average of 1991 and 2000, and $\bar{P}_{i,t-\tau}$ is the poverty incidence average of 1991 and 2000. Column (3) of Table 15 gives the results, which are robust to this change in the specification.

In addition, we can use the 1991 dataset as a source of instruments for the variables of 2000. Therefore, the estimated equation is

$$g_i(y_{i,t}) = \alpha + \beta \log \hat{y}_{i,t-\tau} + \delta \log \hat{P}_{i,t-\tau} + \varepsilon_{it}, \tag{2.12}$$

Where $\ln \hat{y}_{i,t-\tau}$ and $\ln \hat{P}_{i,t-\tau}$ are the initial poverty incidence and income per capita – values of 2000 – instrumentalized by the values of the variables of 1991. Column (4) of Table 15 reports

Tabela 15 – Regressions of Growth Rates on Initial Mean and Initial Headcount Index of Poverty

	$g(y)$			
	Two years (1991 and 2010)		Three years (1991, 2000 and 2010)	
	OLS	*SDEM*	*1991-2000 means as initial conditions – SDEM*	*Using IV's from 1991 - SDEM*
	(1)	(2)	(3)	(4)
$\ln y$	-3.297	-4.979	-2.743	-3.848
	t = -23.276***	t = -35.149***	t = -25.605***	t = -9.450***
$\ln P$	-0.493	-0.969	-0.697	-0.520
	t = -3.470***	t = -5.850***	t = -5.725***	t = -1.353
$Lag\ \ln y$		2.023	0.420	0.784
		t = 9.037***	t = 3.682***	t = 3.659***
$Lag \ln P$		-1.764	-0.087	-0.548
		t = -5.865***	t = -0.500	t = -1.662*
λ		0.997***	0.997***	1***
γ		1.11	1.6	0
AIC	21566.1	19901.9	17090.8	
BIC	21591.7	19946.8	17116.4	
Moran's I Stat.	0.3***	0.06***	0.05***	0.26***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. The Table shows the estimation of the expression 2.10. Column (1) is the OLS estimation and the others are robustness test for spatial dependence (2), possible measurement errors (3) and endogeneity (4). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

the Generalized Methods of Moments estimates using $\beta \ln \hat{y}_{i,t-\tau}$ and $\beta \ln \hat{P}_{i,t-\tau}$ as regressors. The results are similar to those of column (3): poverty total effects are negative.

The initial poverty incidence may capture the influence of other variables on subsequent income growth. Therefore, we have added regressors such as income inequality, the income share of the middle three quintiles, the share of the middle class, the misery index, primary school frequency, and life expectancy at birth. Table 16 brings the estimations with these additional control variables. We see that the initial poverty rate remains a negative and significant predictor of income growth in the OLS regression. The SDEM direct effects are similar to those of the OLS estimations, but they are somewhat smaller. The spillover effects are significant and higher than the direct ones. The Gini index is significant in both methods and, contrary to expected, its estimated coefficients are positive. The OLS and direct effect of the SDEM estimates of the middle-class size (MC) are negative, although the total effect is (not significant) positive. In summary, Table 16 suggests that poverty is a better predictor of growth than income inequality and the size of the middle class, in line with Ravallion (2012).

2.4.3 *Initial poverty and the growth elasticity of poverty reduction*

In Section 2.4.2, we saw that municipalities with higher poverty incidence have a lower income growth rate given the initial per capita income. Following Ravallion (2012), we analyze the relationship of the initial poverty incidence, income growth, and poverty reduction in this section.

To test this effect, we use the following equation:

$$g_i(P_{i,t}) = \gamma_1 + \gamma_2 g_i(y_{i,t}) + \gamma_3 \ln P_{i,t-\tau} + \gamma_4[g_i(y_{i,t}) \cdot P_{i,t-\tau}] + \varepsilon_{i,t} \quad (2.13)$$

where $g_i(P_{i,2010-1991})$ is the poverty annualized growth rate between 1991 and 2010. The interaction effect between initial poverty incidence and income growth (γ_4) tests if a higher incidence of initial poverty reduces the influence of income growth on poverty reduction. We can represent equation (2.13) as

$$g_i(P_{i,t}) = \gamma_1 + \gamma_3 \ln P_{i,t-\tau} + (\gamma_2 + \gamma_4 P_{i,t-\tau}) \cdot g_i(y_{i,t}) + \varepsilon_{i,t} \quad (2.14)$$

In equation (2.14), we see that the influence of income growth on poverty reduction changes for distinct proportions of initial poverty. If γ_4 is positive, a higher initial poverty incidence reduces the effect of income growth on poverty reduction. Another way to estimate the interaction effects of initial poverty incidence and income growth is through the following equation:

$$g_i(P_{i,t}) = \tau_1 + \tau_2 \ln P_{i,t-\tau} + \tau_3(1 - P_{i,t-\tau}) \cdot g_i(y_{i,t}) + \varepsilon_{i,t} \quad (2.15)$$

If the initial poverty incidence reduces the economic growth influence on poverty reduction, the coefficient τ_3 should be negative ($\tau_3 < 0$). In equation (2.15), we assume that $\tau_3 = \gamma_2 = -\gamma_4$. This specification makes the interpretation of the interaction effect more straightforward.

Table 17 presents both OLS and SDEM estimation results using equations (2.14) and (2.15). In columns (1) and (2), we see that the municipalities with a higher initial poverty rate have a lower income growth effect on poverty reduction since the estimated effect of the interaction between the income growth rate and initial poverty incidence (γ_4) is positive. For both OLS and SDEM models, there is no conditional poverty convergence.

Since the initial poverty incidence does not promote poverty reduction, we exclude the initial poverty incidence as a regressor in the results of columns (3) and (4) of Table 17. The results are very close to those of columns (1) and (2). Then in columns (5) and (6), we adopt the most parsimonious model (equation (2.15) – restricted model). The results indicate that the municipalities with high initial poverty incidence have a lower influence of income growth on poverty reduction. At an initial poverty rate of 22 percent (about one standard deviation below the average), the expression $\tau_3(1 - \ln P_{i,t-1})$ is near -0.4. It falls to -0.16 at a poverty incidence

Tabela 16 – Regression for per capita income growth rates on the initial poverty rate augmented with extra control variables

	$g(y)$		
	OLS	*SDEM - Direct Effects*	*SDEM - Spillover Effects*
	(1)	(2)	(3)
$\ln y$	−11.189 t = −22.047***	−9.563 t = −19.620***	−19.960 t = −3.521***
$\ln P$	−4.988 t = −13.087***	−4.190 t = −11.370***	−14.226 t = −3.096***
$\ln G$	3.330 t = 4.525***	3.034 t = 4.412***	38.266 t = 4.667***
$\ln MQ$	6.276 t = 11.111***	4.553 t = 8.693***	19.566 t = 2.336**
MC	−0.059 t = −6.497***	−0.048 t = −5.521***	0.263 t = 1.409
$misery$	0.001 t = 11.663***	0.0004 t = 7.197***	0.003 t = 4.627***
ln School att.	3.045 t = 15.736***	2.465 t = 12.828***	−1.428 t = −0.530
ln Life expec.	23.250 t = 29.275***	13.355 t = 14.027***	−19.248 t = −1.769*
Constant	−63.099 t = −9.422***	−23.294 t = −3.554***	−23.294 t = −3.554***
λ		0.991***	0.991***
γ		0.64	0.64
AIC	20097.9	19199.7	19199.7
BIC	20162	19321.5	19321.5
Moran's I Stat.	0.13***	0.02***	0.02***
Observations	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) show the estimation of the expression 2.10 with additional controls. Columns (2) and (3) show the SDEM estimation of expression 2.10 with additional controls. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

Tabela 17 – Regressions for proportionate change in poverty rate as a function of the growth rate and initial poverty rate

	$g(P)$ from 1991 to 2010					
	Complete		Dropping initial poverty		Imposing Homogeneity	
	OLS	*SDEM*	*OLS*	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln P$	0.190***	−0.006				
	t = 7.543	t = −0.226				
$g(y)$	−0.464***	−0.312***	−0.489***	−0.314***		
	t = −63.335	t = −38.221	t = −75.034	t = −40.606		
$g(y) \cdot P$	0.005***	0.003***	0.005***	0.003***		
	t = 50.867	t = 30.178	t = 77.238	t = 34.366		
$Lag\ \ln P$		−0.026				
		t = −0.360				
$Lag\ g(y)$		−0.556***		−0.557***		
		t = −12.718		t = −18.790		
$Lag\ g(y) \cdot P$		0.007***		0.007***		
		t = 15.385		t = 15.291		
$g(y) \cdot (1 - P)$					−0.005***	−0.003***
					t = −75.291	t = −43.768
$Lag\ g(y) \cdot (1 - P)$						−0.005***
						t = −18.818
Constant	−3.009***	−2.022***	−2.304***	−2.051***	−2.085***	−1.966***
	t = −31.191	t = −18.382	t = −95.237	t = −73.271	t = −105.993	t = −82.073
λ		0.997***		0.997***		0.997***
γ		0.16		0.09		0
AIC	8724.3	7169.6	8778.8	7185.9	8994.1	7246.1
BIC	8756.3	7227.3	8804.5	7230.8	9013.4	7278.2
Moran's I Stat.	0.17***	0.05***	0.18***	0.05***	0.23***	0.05***
Observations	4,490	4,490	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 2.13. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

of 65 percent (about one standard deviation above the mean). These effects are lower than those of Ravallion (2012) for countries.

The same interaction effects studied in Table 17 can be made for inequality and middle class size to determine which paramenter of initial income distribution is the most relevant to poverty reduction. Using the size of middle class, the OLS regression (robust to spatial analysis) is

$$g_i(P_i) = -2.38 + (0.039 - 0.01 \cdot MC_{i,1991}) \cdot g(y_i) + \hat{\nu}_{i,t} \tag{2.16}$$

which suggests that the interaction effect is more substantial than poverty. (RAVALLION, 2012) found the same, but he showed that the effect is mainly attributable to poverty. In this study this is an open question to further analysis.

Adding the interaction with the Gini index, the OLS regression is

$$g_i(P_i) = -3.08 + (0.01 - 0.001 \cdot G_{i,1991}) \cdot g(y_i) + \hat{\nu}_{i,t} \tag{2.17}$$

which shows an lower effect than the poverty. In addiction, controlling for spatial dependence, the total SDEM effect is even slighly positive (0.06), suggesting that a higher inequality helps reduce poverty for a given income growth rate.

2.4.4 The reasons we do not see poverty convergence

Following Ravallion (2012), we find evidence of income convergence in the Brazilian municipalities and that income growth tends to reduce poverty (section 2.4.1). We found too the adverse effects of the initial poverty incidence on income growth and poverty reduction (sections 2.4.2 and 2.4.3). So, we put together the two effects studied in the last two sections. We test poverty convergence using Ravallion (2012) empirically model:

$$g_i(P_{i,t}) = \eta(1 - P_{i,t-\tau}) g_i(y_{i,t}) + \nu_{i,t} \tag{2.18}$$

$$g_i(y_{i,t}) = \alpha + \beta \ln(y_{i,t-\tau}) + \delta \ln P_{i,t-\tau} + \varepsilon_{i,t} \tag{2.19}$$

Using (2.18) and (2.19), we can derive the following decomposition of the poverty convergence (dropping the subscripts for clearness):

$$\begin{aligned} \frac{\partial g(y)}{\ln P} &= \eta \left[-P g(y) + \frac{\partial g(y)}{\partial \ln P} \cdot (1 - P) \right] \\ &= -\eta P g(y) + \eta (1 - P) \left[\beta \frac{\partial \ln y}{\partial \ln P} + \delta \right] \end{aligned}$$

Rearranging:

$$\frac{\partial g_i(P_{i,t})}{\partial \ln P_{i,t-\tau}} = \underbrace{\eta\beta(1 - P_{i,t-\tau}) \left(\frac{\partial \ln P_{i,t-\tau}}{\partial \ln y_{i,t-\tau}} \right)^{-1}}_{\text{(mean convergence effect)}} + \underbrace{\eta\delta(1 - P_{i,t-\tau})}_{\text{(direct effect of poverty)}} - \underbrace{\eta g_i(y_{i,t}) P_{i,t-\tau}}_{\text{(poverty elasticity effect)}} \tag{2.20}$$

On evaluating all variables at their sample means and using the estimates in the above sections we can calculate the convergence poverty elasticity decomposition. Substituing the values in the expression (2.20) we obtain:

$$\begin{aligned}\frac{\partial g_i(P_{i,t})}{\partial \ln P_{i,t-\tau}} &= (-0.005)\times(-11.19)\times 44.6\times(-0.88)^{-1} + (-0.005)\times(-4.99)\times 44.6 - (-0.005)\times 6.52\times 55.4 \\ &= -2.838 + 1.113 + 1.806 \\ &= 0.081 \qquad (2.21)\end{aligned}$$

where -0.88 is the OLS elasticity of the initial poverty index P_{1991} with respect to the initial per capita income mean. In resume, mean convergence effect is -2.838, while the direct effect of poverty is 1.113 and the poverty elasticity effect is 1.806. So the direct effect of poverty and the poverty elasticity effect works in oppose direction to the mean convergence effect. The resultant effect of initial poverty on the poverty growth is near zero, as found for countries in Ravallion (2012).

Using the SDEM direct effects[5] the calculations in (2.21) return -0.051. This corroborates with the OLS, showing a almost zero convergence effect.

2.5 Conclusions

The advantages of backwardness and growth imply that we should see poverty convergence across the Brazilian municipalities. However, as Figure 4 shows, this is not the case. Following Ravallion (2012), the analysis evaluated how the initial poverty affects per capita income growth at a given initial per capita income and how it influences the relationship between income growth and poverty reduction. The findings suggest that high initial poverty incidence affects both advantages of backwardness and growth, leading to no poverty convergence in the Brazilian municipalities.

5 The calculation with the total effect can be distorcive given the high spillover effects of Table 16.

CONCLUSIONS

Poverty is a crucial variable in determining people's quality of life. Overcoming poverty is a great desire of humanity in its quest for the dignity of life for all. In this sense, understanding its relationship with economic development is very important for public debate and for the adoption of public policies to fight poverty. The present work was structured in two essays that sought to assess the effects of poverty on economic development channels.

In the first essay, we sought to assess whether municipal school performance, an important measure of human capital, is affected by the proportion of poor children in the municipality. The study is motivated by evidence found in the medical literature suggesting that poverty can affect children's cognitive and socio-emotional development, with impacts on their learning abilities (ABER et al., 1997; ENGLE; BLACK, 2008).

Based on Lucas (1988)'s model, the results corroborate those found in the medical literature, suggesting that poverty can significantly affect school performance at the municipal level. For children in the 5^{th} grade of elementary school, a 10% increase in the incidence of poverty is associated with a 2% to 6% reduction in school performance. For children in the 9^{th} grade of elementary school, the effect is around 3% to 9%.

In the second essay, we sought to assess whether poverty affects the convergence of poverty. It is known in the literature that, when comparing similar cities, the one with the lowest per capita income should be observing greater growth in per capita income due to the advantage of backwardness. Through the advantage of growth, municipalities with higher growth should be seeing greater poverty reduction. Therefore, municipalities with lower per capita income, which are generally the poorest, should be growing faster and reducing poverty faster.

As we saw in chapter 2, the poorest municipalities are not the ones that, on average, are reducing poverty the fastest. The results suggest that poverty itself is the variable responsible for reducing the effect of the advantage of backwardness and the advantage of growth leaving little or no sign of convergence, similar to the found in Ravallion (2012) for countries.

Both essays help shed light on the ways in which poverty affects some of the determinants of economic growth and development. It is hoped that this work will open space for new studies and deepenings to be carried out in this important research agenda.

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APÊNDICE A – SLX WITH PARAMETRIC SPATIAL MATRIX

In this section, we give a brief explanation of the algorithms used to calculate the SLX model along with a parametric spatial matrix. The algorithm follows Vega e Elhorst (2015) and in their Matlab codes. The algorithm consists:

1. As a initial guess, define $\gamma = 1$, generate a inverse distance spatial matrix, and normalize it (diving by its maximum eigenvalue).
2. Use a Newton-Raphson or Richardson method to search for a set of parameters $\Theta = (\gamma, \beta_0, \beta_1, \cdots, \beta_K)$ that maximizes the SLX log likelihood. The constraint is $\gamma \geq 0$.
3. Calculate the SLX log likelihood hessian matrix at the optimal Θ, which is an approximation to the Fisher Information Matrix.
4. Update the hessian with the known information matrix $X'X$.
5. For the resultant matrix, search for the nearest positive-definite matrix.
6. For the resultant matrix, calculate the inverse matrix as a estimation of the variance-covariance matrix.
7. Using the variance-covariance matrix, calculate the parameters standard errors, t-values e p-values.
8. Optionally, again normalize the spatial matrix constructed with the optimal γ and run the SLX to obtain the new estimates. According to the Vega e Elhorst (2015), this last normalization "ensures more sensible magnitudes of the spatial lag coefficient estimates".
9. Returns the estimated Θ and it standard erros, t-values and p-values.

The R codes for estimate the SLX with parametric spatial matrix can be found in the page: <https://drive.google.com/drive/folders/12cxTD9N9rJwT_4k7lZbxvMRCA-LhoWzX?usp=sharing>

APÊNDICE B – SDEM'S TOTAL EFFECTS

In this appendix are the total effects of the spatial models of chapter 2.

Tabela 18 – Total effects of Table 13

	$g(y)$	
	(1)	(2)
$\ln y$	-3.203	-2.931
	t = -29.565^{***}	t = -4.325^{***}
Constant	26.164	-37.003
	t = 56.440^{***}	t = -10.346^{***}
Observations	4,490	4,490

Tabela 19 – Total effects of Table 14

	$g(P)$	
	(1)	(2)
$g(y)$	-0.189	0.051
	t = -15.227^{***}	t = 1.703^{*}
Lag $g(y)$	-2.322	21.816
	t = -69.904^{***}	t = 27.309^{***}
Observations	4,490	4,490

Tabela 20 – Total effects of Table 15

	$g(P)$		
	(1)	(2)	(3)
$\ln y$	-2.956	-2.323	-3.064
	t = -11.682^{***}	t = -14.850^{***}	t = -6.367^{***}
$\ln P$	-2.733	-0.784	-1.067
	t = -9.088^{***}	t = -4.413^{***}	t = -2.345^{**}
Observations	4,490	4,490	4,490

Tabela 21 – Total effects of Table 16

	$g(y)$
	OLS
$\ln y$	-29.523
	t = -5.248^{***}
$\ln P$	-18.416
	t = -4.040^{***}
$\ln G$	41.301
	t = 5.048^{***}
$\ln MQ$	24.119
	t = 2.881^{***}
MC	0.215
	t = 1.160
$misery$	0.004
	t = 5.194^{***}
ln School att.	1.036
	t = 0.390
ln Life expec.	-5.893
	t = -0.549
Constant	-23.294
	t = -3.554^{***}
Observations	4,490

Tabela 22 – Total effects of Table 17

	$g(P)$ from 1991 to 2010		
	(1)	(2)	(3)
$\ln P$	-0.033 t = -0.416		
$g(y)$	-0.867^{***} t = -20.502	-0.871^{***} t = -31.369	
$g(y) \cdot P$	0.010^{***} t = 23.760	0.010^{***} t = 24.362	
$g(y) \cdot (1-P)$			-0.008^{***} t = -33.431
Constant	-2.022^{***} t = -18.382	-2.051^{***} t = -73.271	-1.966^{***} t = -82.073
Observations	4,490	4,490	4,490