MUNICIPAL ECONOMIC GROWTH IN BRAZIL, 1970-2000: A QUANTILE REGRESSION APPROACH

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Abstract: The motivation of this paper was to check if Andrade et al. (2003) results for the quantile regressions (a negative coefficient for the initial per capita income for all quantiles) were not driven by the omission of variables, since they only include initial income and regional dummies as control variables. The results show that albeit Andrade et al. (2003) results were not driven by omitted variables, the explanatory variables incorporated in the empirical model were important to explain Brazilian economic growth between 1970-2000 at the municipal level, implying the existence of different steady states levels. Finally, the dynamics of some municipalities of the North and of the Northeast are different from the rest of Brazil, even when they have similar fundamentals, what may be an evidence in favor of the club convergence hypothesis, which is found by Laurini (2007).

Keywords: Economic growth. Income Convergence. Quantile regression.

JEL Code: C30, O40, O54.

Resumo O objetivo deste artigo é testar se os resultados obtidos por Andrade et al. (2003) para as regressões quantílicas (um coeficiente negativo para a renda per capita para todos os quantis) não eram condicionados pela omissão de variáveis, uma vez que eles só incluíram a renda inicial e dummies regionais como variáveis de controle. O estudo mostra que embora os resultados de Andrade et al. (2003) não estejam condicionados pelas variáveis omitidas, as variáveis explicativas incorporadas no modelo empírico são importantes para explicar o crescimento econômico brasileiro entre 1991-2000 em nível municipal, implicando a existência de diferentes níveis de estado estacionário. Finalmente, as dinâmicas de alguns municípios do Norte e do Nordeste são diferentes do resto do Brasil, mesmo quando eles têm fundamentos similares, o que pode ser uma evidência em favor da hipótese de clubes de convergência, encontrada em Laurini (2007).

Palavras-chave: Crescimento econômico. Convergência de renda. Regressão quantílica.

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1 Introduction

An interesting feature of Brazil is the economic and cultural diversity of its states and municipalities[1]. But some regularity can be found in this landscape: on average, poor states and poor municipalities have grown faster than richer ones, while economic growth was fostered in areas with higher human capital and favourable demographical behaviour. Urbanization and availability of social infrastructure seem also to be important to determine economic performance in these areas. In the economic growth terminology, it has been said that there is conditional convergence in the case of states and of the municipalities in Brazil.

Recently, Ferreira (2000), Gondin et al. (2004) and Coelho & Figueiredo (2007) are contesting the above interpretation, when collecting evidence that initial conditions are critical to determine regional income (and dynamic) differences inside Brazil. Furthermore, Laurini et al. (2005) found that municipalities with lower income, inside an intermediate level range, would not grow faster to their steady state levels, what accords with the club convergence hypothesis. On the other hand, using quantile regression, Andrade et al. (2003) usually found evidence in favour of conditional convergence. Precisely, using quantile regression for the 1970-1996 period, in Barro-type equations, they found, initially, that the coefficients of the initial per capita income were different among some (few) quantiles. When controlling for regional dummies, the coefficients were not statistically different any more. However, Laurini (2007) rejects the hypothesis of β-convergence and confirms the results of divergence and formation of convergence clubs using a nonparametric form of

[1] In 2000, Brazil had 27 states and 5,507 municipalities.

quantile regression in the dataset of per capita GDP of Brazilian municipalities between 1970 and 1996.

We want to contribute for the problem of identification between the club x conditional hypothesis, checking the robustness of Andrade et al (2003) results to the inclusion of other regressors, since they have only used the initial per capita income level and regional dummies in their estimation. The initial level of per capita income is correlated with several other relevant (to this discussion) economic aspects as the initial level of human capital or the initial level of urbanization. In this case, omitted variables problems could be biasing the coefficients of the initial level of per capita income. On the other hand, there should be an effort to explain what the dummy variables are capturing. Finally, if the coefficients of the other regressors come to be significant, we could also add to the understanding of what initial conditions are important to the case of Brazil.

As can be inferred in Durlauf & Johnson (1995), if different "basin of attraction" exists, differences in growth rates would be driven not by differences in the level of their determinants, but by differences in their marginal impacts, which by its turn would be due to differences in initial conditions. As a consequence, if the estimated coefficients are different among groups of regions (selected by the relevant initial conditions), this is evidence in favour of the club convergence hypothesis. If the coefficients are significant, but similar among groups, this is evidence in favour of the conditional convergence hypothesis. Durlauf et al. (2004) also highlights the importance of testing for parameter heterogeneity. We employ a quantile regression approach to test if the marginal impacts of the explanatory variables on economic growth are different among groups of Brazilian municipalities between 1970 and 2000.

The paper is organized as follows. In section 2 we develop an empirical growth model and describe the dataset.

Section 3 presents the empirical results. Finally, conclusions are offered.

2 Empirical model and data

We wish to construct an empirical model in order to help us to interpret our results. Our model is based in Mankiw, Romer & Weil (1992), Jones (1999), and also sharing features with McDonald & Roberts (2002).

Let us assume the augmented neoclassical production function, as proposed by Mankiw, Romer & Weil (1992), which includes human capital as one of the economy's input. Instead of only consider the education aspect of human capital (S), let us also consider its health aspect (H), as in McDonald & Roberts (2002).

$$Y_{it} = K_{it}{}^{\alpha} (A_{it} H_{it})^{\beta} (AS_{it})^{1-\alpha-\beta} \qquad (1)$$

Production (Y) is a function of capital (K), technology (A), health (H) and education (S). The index (i) stands for region and (t) for time.

$$H_{it} = \varepsilon^{\delta m_i} L_{it} \qquad (2)$$

$$h_i = \varepsilon^{\delta m_i} \qquad (3)$$

$$S_{it} = \varepsilon^{\phi u_i} L_{it} \qquad (4)$$

$$s_i = \varepsilon^{\phi u_i} \qquad (5)$$

Equations (2)-(5) follow the simple specification proposed by Jones (1999), where the accumulation of human capital follows the rate of population (L) growth (n). The population level, on the other hand, will be higher if people have better health – higher m_i , and a higher education, higher u_i..

Expressing (1) efficient units of labour - the hat variables, (dividing (1) by AL)

$$\hat{y}_{it} = \hat{k}_{it}^{\alpha} h_i^{\beta} s_i^{1-\alpha-\beta} \qquad (6)$$

Following the usual Solow hypothesis – constant saving rate (sr), constant effective depreciation rate (n+g+δ)),

$$\hat{k}_i^* = \left(\frac{sr_i h_i^{\beta} s_i^{1-\alpha-\beta}}{n_i + g + \delta} \right)^{\frac{1}{1-\alpha}} \quad \text{(7a) and}$$

$$\hat{y}_i^* = \left(\frac{sr_i h_i^{\beta} s_i^{1-\alpha-\beta}}{n_i + g + \delta} \right)^{\frac{\alpha}{1-\alpha}} \quad \text{(7b)}$$

The equilibrium per capita income will be:

$$y_{it}^* = A_{it} \left(\frac{sr_i h_i^{\beta} s_i^{1-\alpha-\beta}}{n_i + g + \delta} \right)^{\frac{\alpha}{1-\alpha}} h_i^{\beta} s_i^{1-\alpha-\beta}$$

$$y_{it}^* = A_{it} \left(\frac{sr_i}{n_i + g + \delta} \right)^{\frac{\alpha}{1-\alpha}} h_i^{\frac{\beta}{1-\alpha}} s_i^{\frac{1-\alpha-\beta}{1-\alpha}} \quad (8)$$

Taking logs:

$$\ln y_{it}^* = \ln A_{it} + \frac{\alpha}{1-\alpha} \ln sr_i - \frac{\alpha}{1-\alpha} \ln(n_i + g + \delta) + \frac{\beta}{1-\alpha} \ln h_i + \frac{1-\alpha-\beta}{1-\alpha} \ln s_i \quad (9)$$

Let us assume that technology has three determinants: external economies of scale due to the original level of urbanization (urb) and due to the regions' social infra-structure (social) determine the region initial technological level; a common constant and exogenous growth rate explains its growth (g), while it is also subject to a stochastic error.

$$\ln A_{it} = \ln A_{i0} + gt + \mu_{it} \quad (10)$$

$$\ln A_{i0} = \kappa_1 urb_{i0} + \kappa_2 social_{i0}$$

From (9) and (10) we have our empirical model:

$$\ln y_{it}^* = \kappa_1 urb_{i0} + \kappa_2 social_{i0} + gt + \frac{\alpha}{1-\alpha} \ln sr_{it} - \frac{\alpha}{1-\alpha} \ln(n_i + g + \delta)_t + \\ + \frac{\beta}{1-\alpha} \ln h_{it} + \frac{1-\alpha-\beta}{1-\alpha} \ln s_{it} + \mu_{it} \quad \text{(11a)}$$

or, using (3) and (5):

$$\ln y_{it}^{*} = \kappa_1 urb_{i0} + \kappa_2 social_{i0} + gt + \frac{\alpha}{1-\alpha}\ln sr_{it} - \frac{\alpha}{1-\alpha}\ln(n_i + g + \delta)_t + \\ + \frac{\beta}{1-\alpha}\delta m_{it} + \frac{1-\alpha-\beta}{1-\alpha}\varphi u_{it} + \mu_{it} \qquad (11b)$$

But we should consider Durlauf & Johnson (1995) warning that, accordingly to their level of development, regions could have different responses to the economic impulses. It is possible that regions that did not reach some threshold levels of the human capital variables – h and s, could have different income elasticities with respect to these variables.

Log-linearizing the above equation around the steady state value:

$$\gamma_{\hat{k}} \cong (\alpha - 1)(\delta + g + n)\left[\log \hat{k} - \log \hat{k}^{*}\right] \qquad (12),$$

where the right-hand side variable is the growth rate of capital per efficient units, which will be, in a Cobb-Douglas specification, the growth rate of income per efficient units.

Following Durlauf et al (2004) in developing the expression for per capita income growth rate, this can be expressed by:

$$\log y(t) - \ln y(0) = (1-\varepsilon^{-\lambda t})\kappa_1 urb_{i0} + (1-\varepsilon^{-\lambda t})\kappa_2 social_{i0} + \\ + (1-\varepsilon^{-\lambda t})gt + (1-\varepsilon^{-\lambda t})\frac{\alpha}{1-\alpha}\ln sr_{it} - (1-\varepsilon^{-\lambda t})\frac{\alpha}{1-\alpha}\ln(ni + g + \delta)_t + \\ + (1-\varepsilon^{-\lambda t})\frac{\beta}{1-\alpha}\delta m_{it} + (1-\varepsilon^{-\lambda t})\frac{1-\alpha-\beta}{1-\alpha}\varphi u_{it} + \mu_{it} \qquad (13),$$

where $\lambda=(\alpha-1)(\delta+g+n)$.

Basically, there are at least three problems when Ordinary Least Square (OLS) regressions are used to study economic growth, such as in Equation (13): parameter homogeneity[2], "Galton's Fallacy"[3], existence of outliers[4]. The quantile regression estimator gives, potentially, one solution to each quantile. So, this methodology can deal with these problems altogether.

Quantile regression is a method for estimating functional relations between variables, such as in Equation (13), for all portions of a probability distribution[5]. Koenker & Hallock (2001) demonstrated that minimizing a sum of asymmetrically weighted abso**lute** residuals yields the quantiles. In sum, t**he** estimates of the conditional quantile functions are obtained by solving:

$$\min_{\xi \in \Re p} \sum_{i=1}^{n} \rho_\tau (y_i - \xi(x_i, \beta)) \,. \qquad \textbf{(14)}$$

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[2] Parameter homogeneity implies that the marginal effect of a change in any of the explanatory variables will be the same for all regions. However, there is nothing on the theory of growth saying that the effect of an increase in human capital, for example, should be the same across regions. In fact, we expect it to depend on the specifics of each economy such as its level of development or its growth rate (Mello & Perreli, 2003).

[3] This means that a negative coefficient in the traditional OLS regression may not indicate that economies are converging to the same long-run steady-state, but it can only signal regression to the mean. Friedman (1992) and Quah (1993) point out that sub-sample of countries or regions has a different mean growth rate and average initial income, which ultimately determines whether the economy is converging or not. So, the analysis convergence based on a regression of growth rates on levels depends explicitly on the sample selection. However, using quantile regression it is possible to obtain different coefficient estimates for each chosen quantile, as well as allow the estimates to indicate convergence or not for each one of them.

[4] The existence of outliers is one of the problems in estimating and interpreting classical growth regressions that have been well documented [see Temple (1999)]. Outliers can bias the coefficient estimated from the OLS regression. Quantile regression is robust to outliers with the added benefit that it allows us to better understand the behavior of the unusual observations.

[5] See Koenker & Bassett (1978) for the seminal article, and Koenker & Hallock (2001) and Koenker (2005) for recent surveys on quantile regression.

where the function $\rho_\tau(\cdot)$ is the tilted absolute value function that yields the τ th sample quantile as its solution. The resulting minimization problem, when $\xi(x,\beta)$ is formulated as a linear function of parameters, can be solved very efficiently by linear programming methods[6].

Our null hypothesis will be that there is club convergence, in which case a region dynamics is influenced by its initial conditions and/or is subject to different regimes (Durlauf & Johnson, 2005 and Johnson & Takeyama, 2001).

If our null hypothesis is correct, we should expect that regions with the same fundamentals – technology, sr, n, g, δ, m, κ_1, κ_2 and u, could have different per capita income growth rates, what can happen if they respond differently to these variables, in which case the estimated coefficients of equation (13) will differ among quantiles. We will consider that the alternative hypothesis of conditional convergence is the correct one if the coefficients are different from zero, but not different among quantiles. We use dummy variable to proxy for regional differences in the saving behaviour and in the depreciation rate.

Concerning the dataset, it was necessary to make some adjustments in the data because the number of municipalities increased from 3920 municipalities in 1970 to 5,507 municipalities in 2000. To address this problem, we merged municipalities into 3659 Minimum Comparable Areas (MCAs) – consisting of sets of one or three municipalities whose borders were constant over 1970 to 2000. All data have then been aggregated to match these MCAs.

The data used in this paper comes from the Brazilian Population Census for growth rates of per capita (household)

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[6] In this paper, we use Stata software. Buchinshy (1998) presents and discuss several alternative estimators for the covariance matrix of the quantile regression estimates. Our estimates are via *bootstrap*.

income between 1970 and 2000[7], initial per capita (household) income, urbanization rate, average years of schooling, piped water, and infant mortality rate. All explanatory variables are measured in 1970. Per capita income information are monthly data, deflated to Real (R$) in 2000. Finally, the econometric model includes regional dummies for each one of the four Brazilian macro-regions[8]: Northeast, Center-West, Southeast and South.

3 Empirical results

The OLS and quantile results for the test of absolute convergence are displayed in Table 1. The coefficients of OLS for (log of) per capita income are always significant and negative for all the period analyzed, 1970-2000. Concerning the quantile estimates, all the coefficients of the initial per capita income variable are negative and significant, for all quartiles, reflecting the faster growth of the poorest municipalities within any percentile. On the other hand, the magnitudes are different across percentiles, showing faster convergence for the fast-growing ones[9]. In the Appendix, Figure 1 shows results for quantiles 05, .10, , .15, .20, , .25, .30, , .35, .40, , .45, .50, , .55,

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[7] Differently of Andrade et al. (2003), Laurini et al. (2005) and Laurini (2007) that employ the Gross Domestic Product (GDP) variable estimated by IPEA for the period 1970-1996, we use household income information from Brazilian Censuses of 1970 and 2000. We prefer to use Census data given the overall quality of it is better than the GDP information for the period analyzed.

[8] We exclude one of the dummy variables (North dummy) from the regressions to avoid perfect multicollinearity.

[9] It is worth noting that those municipalities with higher growth rates belong to the higher quantiles, since quantile regression ordinates the municipalities by the dependent variable, i.e, the average growth rate between 1970-2000.

.60, , .65, .70, , .75, .80, , .85, .90, , .95. Also, it shows the 95% confidence interval for the quantile regression estimate, and the OLS estimate on the initial per capita income (dashed line). As expected, this unconditional (absolute) convergence result is very similar to the Andrade et al. (2003) one since it shows that municipalities in the quantiles 25% and 50% are converging at a slower rate.

Table 1 – Unconditional Convergence – OLS and Quantile Regression

Dependent variable: average growth rate of per capita income between 1970 and 2000			
Variable	τ	Coef.	Std. Err.
Constant	0.25	0.0484	0.0016
	0.50	0.0618	0.0011
	0.75	0.0769	0.0013
	OLS	0.0648	0.0013
Initial per capita income	0.25	-0.0025	0.0004
	0.50	-0.0041	0.0003
	0.75	-0.0065	0.0003
	OLS	-0.0052	0.0003

Own elaboration.
Note: The table reports estimates of the slope coefficient of the following equation $(1/T)*\ln(y_{T,i}/y_{0,i}) = \alpha + \beta \ln(y_0) + \varepsilon_i$, where $y_{T,i}$ and $y_{0,i}$ are, respectively, the final period and the initial period household income per capita, T is the time period, and ε_i error term.

Table 2 shows the OLS and quantile results for the conditional convergence test. Using OLS method, conditional convergence cannot be rejected, since the per capita income coefficient is negative and significant at 1% confidence level, with higher absolute value than in the unconditional convergence case, as it is usual to find in the literature.

Furthermore, OLS coefficients of the other explanatory variables are statistically significant: higher urbanization rates are related to higher growth rates; higher human capital – higher average years of schooling and lower infant mortality rates – is good for growth, while a better social infra-structure, proxied by access to water, also foster economic growth.

Table 2 also shows the results for the quantile regressions for the conditional case. Contrary to the unconditional case, the coefficients of the initial per capita income are quite stable among quantiles. The coefficients of the other explanatory variables are also stable among quantiles. In the Appendix, Figures 3-6 show the quantile coefficients, the respective 95% confidence intervals and the OLS results, from which we can observe that the quantile coefficients are not significantly different from the OLS results.

Mello & Perreti (2003) found, similarly to our results for the unconditional case, that fast-growing countries would converge quicker to their steady state value, when testing for unconditional convergence. When controlling for other determinants, the coefficients were much more similar to the OLS ones, also resembling our findings.

Our results also imply, similarly to the rest of the Brazilian literature, that several determinants are playing a role in the determination of per capita income, as human capital, urbanization rate and social infra-structure, since the results of the conditional case (OLS and quantile) are better than the unconditional case ones.

The behavior of the dummy variables is quite interesting both for the OLS and quantile estimates. Center-West, Southeast and Southern dummies are positive and significant, implying a better behavior of these regions with respect to the Northern one (the excluded dummy). Also, it seems clear that the behavior of the Northern and Northeastern municipalities is similar, confirming the results found in the Brazilian literature. The picture we have is of the existence of two regions (North and Northeast) that have a worse performance than the rest of Brazil. Among the municipalities of these regions, there are different dynamics for per capita income.

Table 2 – Conditional Convergence – OLS and Quantile Regression

Dependent variable: average growth rate of per capita income between 1970 and 2000							
Variable	τ	Coef.	Std. Err.	Variable	τ	Coef.	Std. Err.
constant	0.25	0.118910	0.002488	Urbanization	0.25	0.000151	0.000010
	0.50	0.119854	0.002433	rate	0.50	0.000139	0.000013
	0.75	0.129032	0.003267		0.75	0.000125	0.000010
	OLS	0.120964	0.001764		OLS	0.000094	0.000010
Initial per capita income	0.25	-0.028666	0.000646	Dummy	0.25	0.005432	0.001075
	0.50	-0.027067	0.000671	Northeast	0.50	0.004614	0.001004
	0.75	-0.026654	0.000686		0.75	-0.000023	0.002506
	OLS	-0.025833	0.000454		OLS	0.000758	0.000761
Mortality rate	0.25	-0.000031	0.000006	Dummy	0.25	0.017745	0.001185
	0.50	-0.000031	0.000005	Southeast	0.50	0.018995	0.001095
	0.75	-0.000033	0.000005		0.75	0.014661	0.002454
	OLS	-0.000026	0.000004		OLS	0.014546	0.000721
Years of	0.25	0.005725	0.000347	Dummy	0.25	0.023377	0.001157
schooling	0.50	0.005535	0.000411	South	0.50	0.022187	0.000984
	0.75	0.005653	0.000416		0.75	0.016726	0.002442
	OLS	0.006032	0.000335		OLS	0.018331	0.000771
Piped water	0.25	0.010713	0.001289	Dummy	0.25	0.022527	0.001254
	0.50	0.004772	0.001451	Center-West	0.50	0.019988	0.001117
	0.75	0.002389	0.001097		0.75	0.015346	0.002511
	OLS	0.006222	0.001231		OLS	0.017318	0.000849

Source: Own elaboration.

Andrade et al. (2003) have also concluded, running separated quantile regressions for each region, that the differences observed between the OLS and the quantile estimation were due to some quantiles of the North and of the Northeast. They subsequently run the full sample regression controlling for these regional areas, concluding for the existence of conditional beta convergence, since the coefficients of the initial per capita income were always negative.

The results of Andrade et al (2003) could be due to omission of variables, what we partially corrected in these exercises. Their results are sustained. We could also not identify which specific determinant/initial condition is driving the different behavior of the Northern and Northeastern municipalities. It seems not to be differences in urbanization, social infra-structure, average year of studying or infant mortality rates, since all explanatory variable coefficients are also stable among quantiles.

However, our results may also imply the existence of club convergence in Brazil, restricted to a range of municipalities in the North and in the Northeast, since as discussed by Laurini (2007) the linear functional form assumed in the estimate of the growth regression using quantile regression is the main reason for the no-rejection of the conditional beta-convergence hypothesis. Thus, both hypotheses, beta-conditional and club convergence, cannot be rejected in the case of Brazil. Moreover, the results for the explanatory variables seem to be dependent of the linearity assumption, they should be reassessed using a nonparametric form of quantile regression.

Finally, Table 3 shows the speed of convergence and the implied half-life for the unconditional convergence case and conditional case as well.

The half-life is the number of years that the economy takes to transit half way to its steady-state level of income per capita. From the initial income per capita coefficient, the speed of convergence and the half-life (HL) are calculated according to the following formulas, respectively: $-(1-\mathrm{e}^{-\beta T})/T = b$ and $-\ln(2)/\beta = HL(years)$, where b is the OLS (or quantile) estimate of the initial income coefficient, T is the sample period (in the case of this study T=1, since the dependent variable is already calculated annually) , and β is the speed of convergence. The speed of convergence found for the OLS conditional estimate is a speed of convergence of 2.6% per annum, which corresponds to a half-life of around 27 years, differently to the results found for the unconditional case (see Table 3, for details).

Table 3: Speed of Convergence – OLS and Quantile Regression

Quantile	Unconditional speed of convergence (%)	Unconditional half-life (years)	Conditional speed of convergence (%)	Conditional half-life (years)
q5	0.5%	139	2.8%	24
q10	0.2%	326	2.8%	25
q15	0.2%	362	2.7%	25
q20	0.2%	319	2.7%	25
q25	0.2%	278	2.7%	26
q30	0.3%	239	2.7%	26
q35	0.3%	216	2.6%	26
q40	0.3%	198	2.6%	26
q45	0.4%	188	2.6%	27
q50	0.4%	168	2.5%	27
q55	0.4%	154	2.5%	27
q60	0.5%	135	2.5%	27
q65	0.5%	130	2.6%	27
q70	0.6%	117	2.5%	27
q75	0.7%	106	2.5%	27
q80	0.7%	98	2.5%	27
q85	0.7%	92	2.6%	27
q90	0.8%	83	2.5%	28
q95	1.0%	70	2.5%	28
OLS	0.5%	134	2.6%	27

Own elaboration.

Moreover, using quantile method for the conditional case the half-lives estimated are very stable across quantiles ranging from 24 years for quantile 5% to 28 years for quantiles 90% and 95%.

4 Conclusion

The motivation of this paper was to check if Andrade et al.(2003) results (a negative coefficient for the initial per capita income for all quantiles) were not driven by the omission of variables, since they only include initial income and regional dummies as control variables (allowing also for different coefficients among regions). Introducing explanatory variables, we could also contribute to identify what is driving the differences in the behaviour of the Brazilian municipalities.

Our main conclusions in this paper are five. First, per capita income growth rates react similarly to chocks in human capital variables (average years of schooling and infant mortality rates), urbanization rate and social infra-structure, proxied by access to water; Second, human capital, social infrastructure and urbanization rate are important determinants of the steady state income values, implying the existence of different steady states levels; Third, Andrade et al (2003) results were not driven by omitted variables; Fourth, the dynamics of some municipalities of the North and of the Northeast are different from the rest of Brazil, even when they have similar fundamentals, what may be an evidence in favor of the club convergence hypothesis, which is found by Laurini (2007).

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Appendix A:

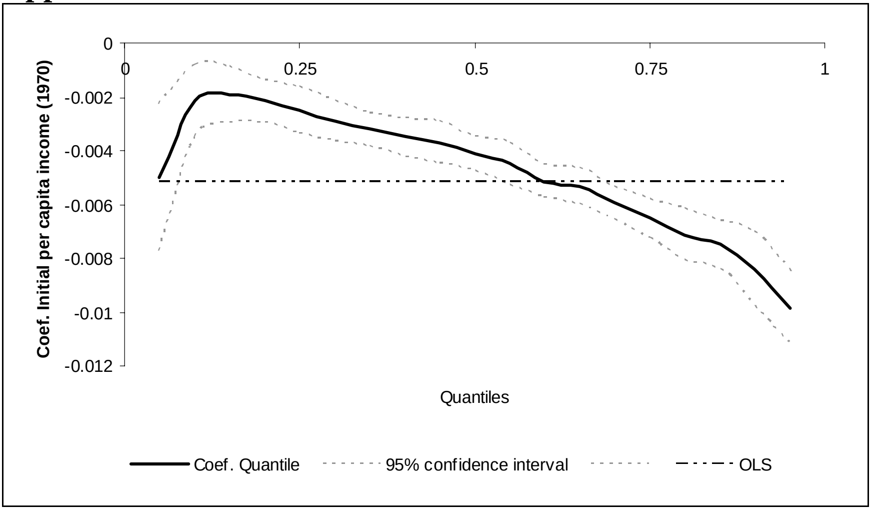

Figure 1 - Unconditional Convergence (1970-2000), Initial per capita income

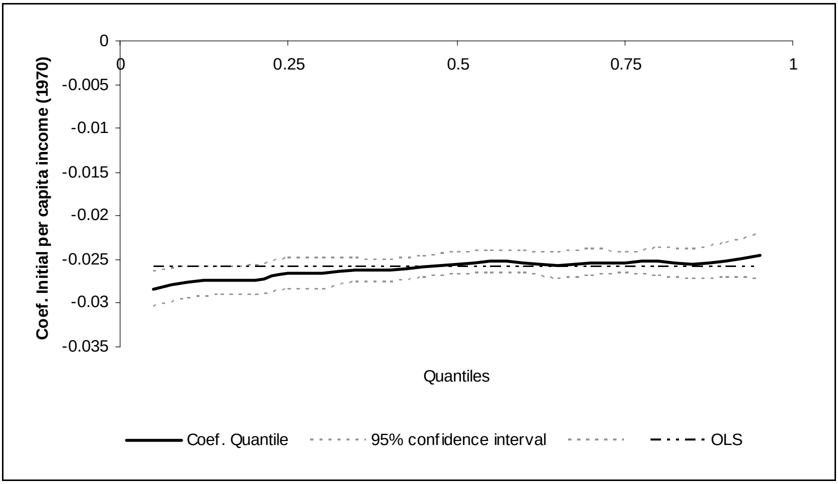

Figure 2 - Conditional Convergence (1970-2000), Initial per capita income

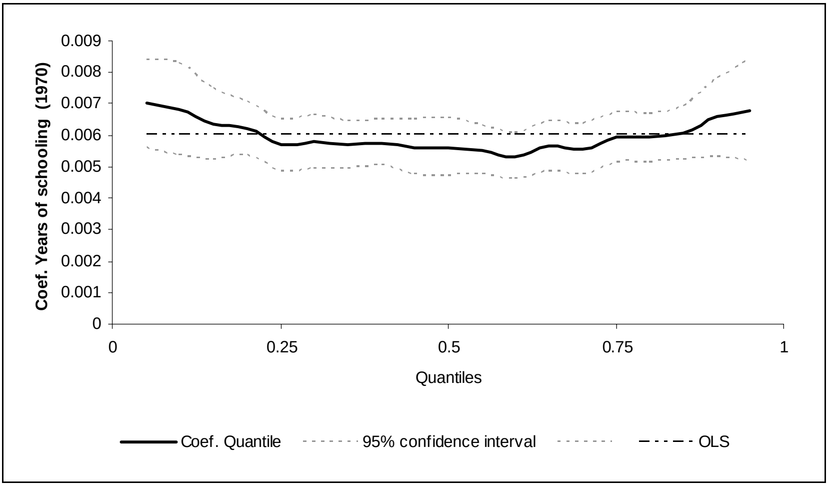

Figure 3 - Conditional Convergence (1970-2000), Years of schooling

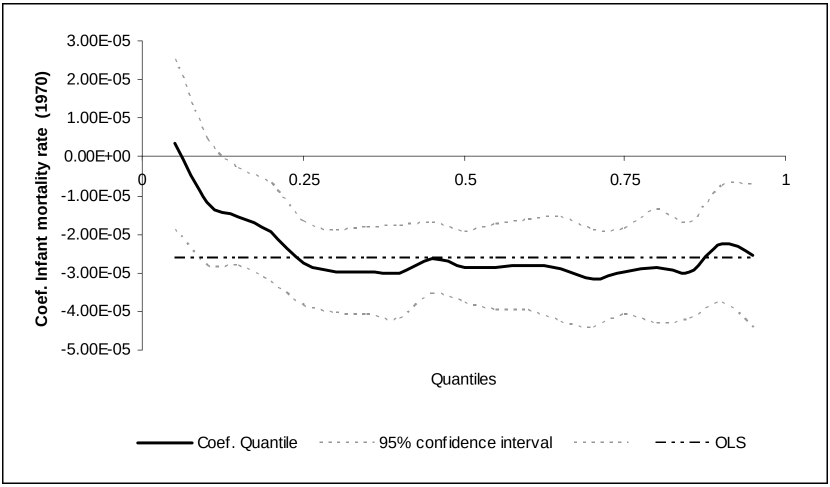

Figure 4 - Conditional Convergence (1970-2000), Infant mortality rate

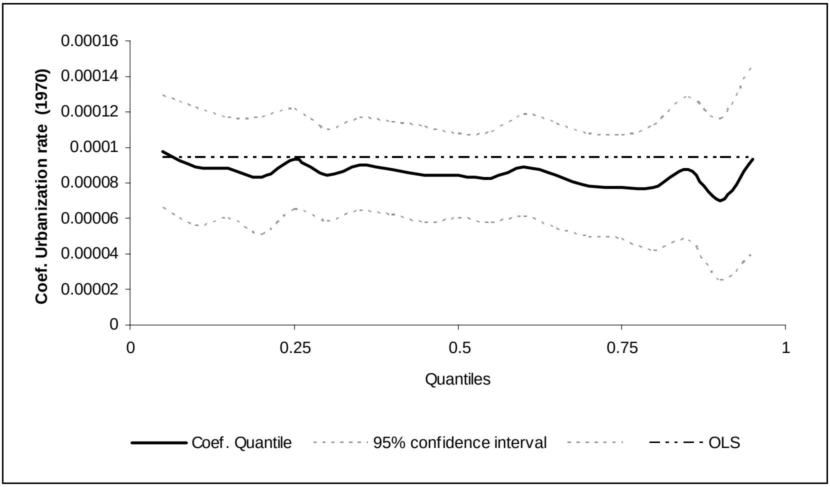

Figure 5 - Conditional Convergence (1970-2000), Urbanization rate

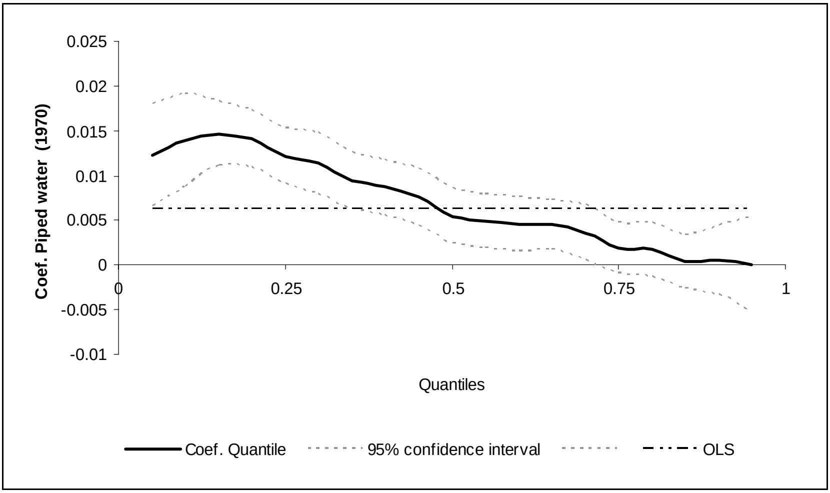

Figure 6 - Conditional Convergence (1970-2000), Piped water provision

Note: Quantiles between 0.75 and 0.95 are not statistically significant at 10% level for piped water provision.

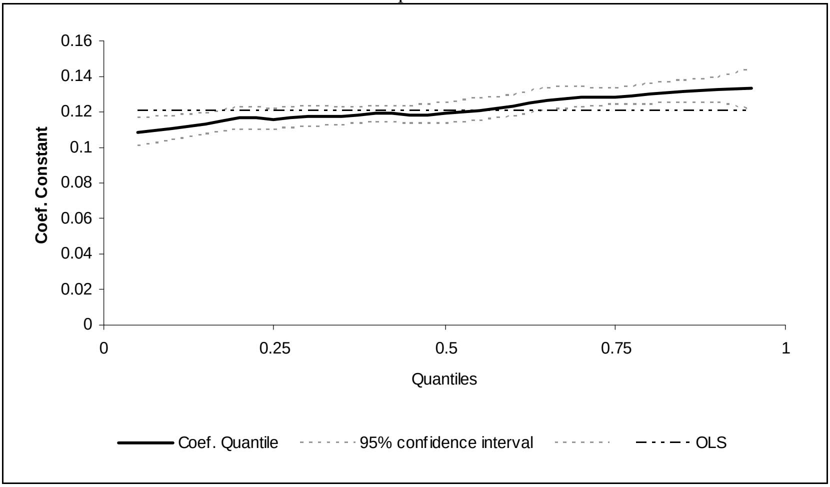

Figure 7 - Conditional Convergence (1970-2000), Constant term

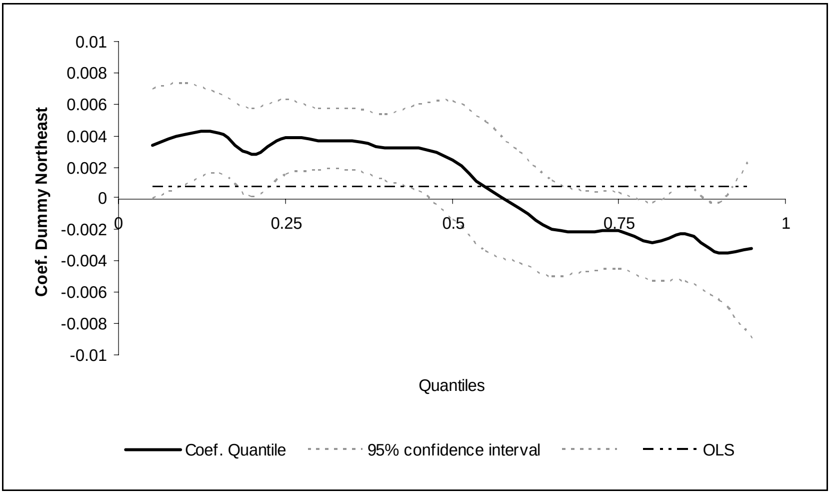

Figure 8 - Conditional Convergence (1970-2000), Dummy Northeast

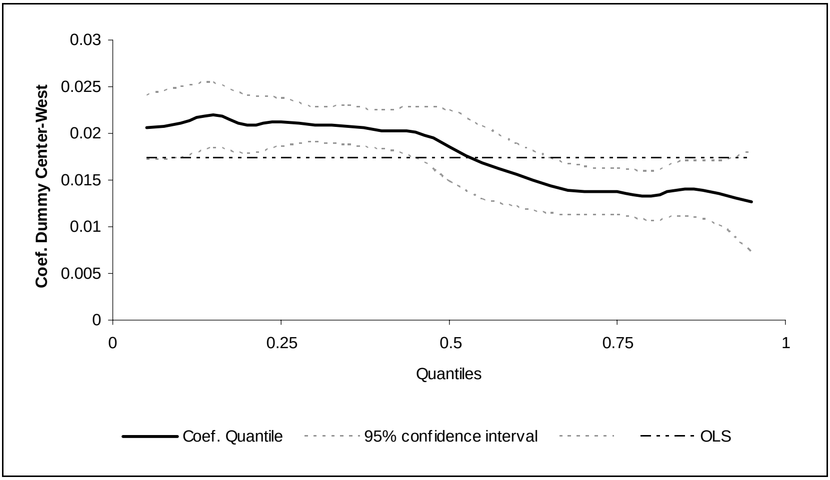

Figure 9 - Conditional Convergence (1970-2000), Dummy Center-West

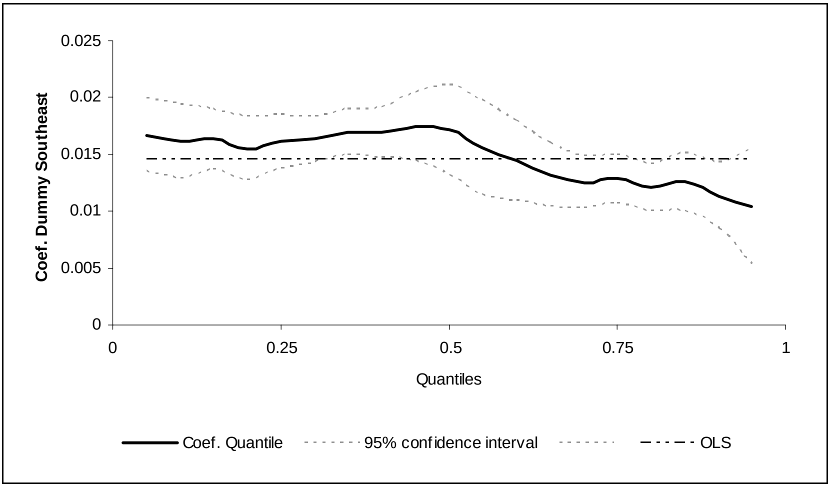

Figure 10 - Conditional Convergence (1970-2000), Dummy Southeast

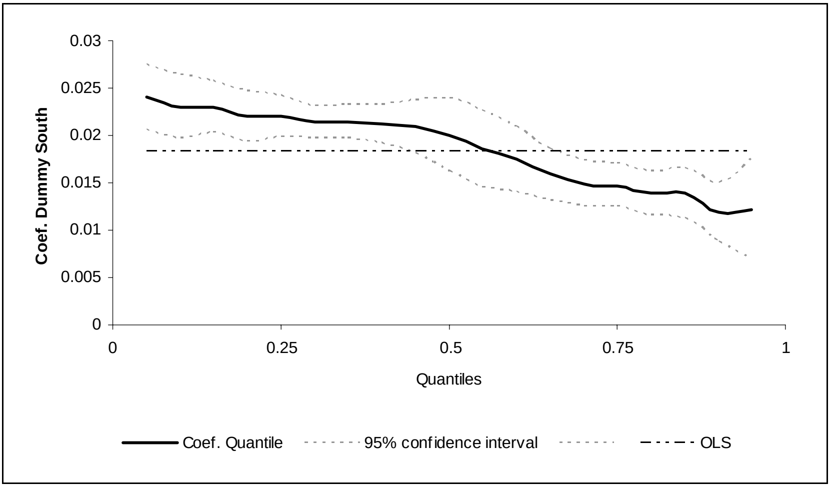

Figure 11 - Conditional Convergence (1970-2000), Dummy South