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Thesis

Convergence in Colombia 1990-2015: War and Clubs

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Abstract

This document tests whether there has been convergence in the per-capita income across regions in Colombia between 1990 and 2015. It also discusses the role of war in that context and tests for the existence of convergence clubs. The results display that Colombia has been a successful case of both conditional and unconditional convergence, closing the gap between poor and rich departments in approximately 1.6% per year. Furthermore, no significant impact of war over convergence was found. Lastly, evidence suggests that several groups of Colombian departments have created convergence clubs, in which the speed of convergence is 6.8% per year.

Key words: Absolute convergence, conditional convergence, war, convergence clubs.

Contents

1 Introduction

Economic convergence has been widely studied over the last decades. In particular, researches have relied in neoclassical growth theory[1]to address the following questions: have income disparities across countries/regions widened or narrowed? Have the poorest economies, within and between nations, caught up the richest ones? Although empirical approaches have found puzzling to obtain consistent evidence of economic convergence between countries[2] (Barro, 1991)(Mankiw et al., 1992), there has been successful cases of cross-regional convergence. For instance, Barro and Sala-i Martin (1992)(2004) showed that it is the case for The United States in the period 1880-1988, European regions during 1950-1985, and industries in Japan in the postwar period. However, Barro (1991) also pointed out several distortionary issues that may potentially hinder the finding of convergence evidence when analyzing for developing countries. The main troubles relate to lack of long-sight data, disparities in estimation techniques and particular institutional characteristics (Serra, Pazmino, Lindow, Sutton, & Ramirez, 2006).

Despite this fact, Cárdenas and Pontón (1995), following Barro's framework[3], found that Colombia was a successful case of economic convergence between 1950 and 1990, with evidence of an average catching up rate[4] of 4% per year. However, Empirical literature over the latter period (post 1990) in Colombia is ambiguous and contradictory. Bonet and Meisel (2006)(2009), for instance, found that differences between regions have deepened ever further while Serra et al. (2006), displayed evidence of convergence speed of approximately 1% from 1990 to 2002. This discrepancies preclude policy makers from taking sound decisions of political economy focused on reducing the income and development gap of Colombian departments.

The importance of cross-departmental analysis is found in its utility to design and propose ideal policies that speed up economic growth, leading to improvements of living standards and welfare of the population. This document, thus, is presented as an effort to complement the literature of convergence in the context of developing countries, offering up to date estimations of economic convergence in Colombia using a cross-departmental data for the period 1990-2015. Also, it can be seen as an effort to reconcile previous results. In particular, I test for conditional and unconditional β convergence[5]. Additionally, this research controls for two specific variants that are relevant for the Colombian context: The influence of war over regional convergence, and the existence of convergence

[1] Specially in the one developed by Solow (1956).

[2] Mankiw, Romer, and Weil did not found evidence of convergence at a world's level nor at an oil-producing countries' level.

[3] This framework is detailed under section 3

[4] The rate at which the income gap is reducing over time.

[5] These concepts are explained under section 2.

clubs[6].

On the one hand, Colombia has performed in a context of war approximately for the last six decades[7]. Over the years, the conflict happened principally over rural, isolated areas of the country that were partially or totally abandoned by the state. As a matter of fact, some of these regions turned into a sort of sub-state under the control of rebel groups. Such conditions led, among other consequences, to the gravitation of the labor force towards illegal activities related to drug trafficking, and to the systematic destruction of infrastructure during military combat. Consequently, conflict in such regions took away institutional stability reducing physical and human capital accumulation to infimum levels. As these last two have been proven to be important determinants of growth (Barro & Sala-i Martin, 1992), it appears reasonable to conclude that war has a potential influence over regional disparities of Colombia. In particular, the document intends to answer the question: Has war played a role on the regional convergence of Colombia?

On the other hand, Colombia is a very diverse country in its geography, culture, and economic activities. This fact shapes a country where the resource endowment across regions is so different, that centralized policy making often fails to be effective in promoting an even competitiveness and development throughout the territory. Naturally, the principal economic activity of each department depends on the geographical characteristics that condition them. Among this characteristics, for example, are the height above the sea level, climate, rain rates, access to ocean and location[8]. Interestingly enough, border regions that share such conditions seem to have created sub-cultural groups within Colombia, to the point that not only coincide in economic activity, but also share patterns of behavior and costumes such as accent, traditional diet, music and fashion. This shared characteristics, in both economic and social terms, facilitate labor and capital mobility within the groups, but also might create barriers between them. Therefore, it is reasonable to believe that different groups of departments converge to sub-national levels of steady state. Specifically, this research addresses the question: Is there evidence of regional convergence clubs in Colombia?

Results display evidence that Colombia is still a successful case of both conditional and unconditional convergence. Poor regions of Colombia have closed the income per-capita gap with the rich ones in 1.6% each year between 1990 and 2015. Conditional results present at even higher speed of 3.4%. Regarding war, there is no statistical proof suggesting that it has had a considerably big

[6] "Sub-national levels of steady state around principal cities to which states within each region appear to have converged"(Serra et al., 2006).

[7] A peace agreement between the government and the oldest rebel group of Colombia and Latin America: FARC-EP, was signed during the second half of 2016.

[8] In zones of the country with high density of jungles and mountains, transaction costs are higher.

effect on convergence dynamics. Finally, This research found evidence supporting the existence of convergence clubs in Colombia with an increase of catching up speed to 6.9%. However, not every sub-national group appears to be one. Including regional determinants of the steady state played a key role in the results.

This document is divided in six sections. Section 2 defines key concepts and offers insight of the theories that are essential for the research. Section 3 describes the methodology. It also comments on the potential issues faced by the econometric framework. Section 4 presents the sources of data and briefly explains the construction of proxies. Section 5 displays results and section 6 concludes.

2 Literature Review

This section briefly reviews the neoclassical Solow model of growth on which the technical methodology is based on. Right after, it shows the development from the Solow model towards the econometric equations of convergence used in this research. To do so, it is necessary to go through the augmented model with human capital of Mankiw et al. (1992) to finally detail the econometric test for convergence used by Barro and Sala-i Martin (1992). This document uses the same framework, but includes two expansions in the conditional case. Specifically, I focus on detailing the derivation of the log-linear equations of the steady state level with and without human capital in order to later show how they can be incorporated into the regression function. Additionally, this section clarifies key concepts for the understanding of the estimations. In particular, discusses about conditional and unconditional β convergence[9].

2.1 The Neoclassical Solow Model of Growth

In his classic 1956 article, Solow starts by assuming a standard neoclassical production function with decreasing returns to capital. There are two non-perfect substitutes inputs, capital and labor, which are multiplied by a parameter of technology A. Each input, in equilibrium, is paid its marginal value. The model assumes exogenous the investment rates, population growth and technological progress. Production at time t is given by:

$$Y(t) = K(t)^{\alpha}(A(t)L(t))^{1-\alpha} \tag{1}$$
$$0 > \alpha > 1$$

Effective units of labor $A(t)L(t)$ are assumed to grow at an exogenous rate $n + g$. Where n is the population growth rate and g the technological progress. Furthermore, the model also assumes that a total fraction sY with $0 < s < 1$ is invested on physical capital, so that the evolution of capital per effective worker $\dot{k(t)}$ is given by:

$$\dot{k(t)} = sy(t) - (n + g + \delta)k(t) \tag{2}$$

Where

$$k = \frac{K}{AL};\ y = \frac{Y}{AL}$$

At the steady state, the level of investment is just as high as the delusion factor $n + g + \delta$, such that the stock of capital remains constant. That is to say, additional capital perfectly replaces the depreciated one, corrected by technological progress and population growth. δ is the depreciation rate. When in the steady state, the evolution of capital $\dot{k(t)}$ is equal to 0. Therefore, combining equations

[9] More precisely, they are defined in section 2.3.

(1) and (2), the model implies that the steady state level of income per effective worker is of the form:

$$y^* = \left(\frac{s}{n+g+\delta} \right)^{\frac{\alpha}{1-\alpha}} \tag{3}$$

The per capita income level depends positively on investment rate and negatively on population growth rate, technological progress and depreciation rate. Taking logs, per-capita income in the steady state at a given time can be expressed as:

$$ln\left(\frac{Y(t)}{L(t)}\right) = lnA + g(t) + \frac{\alpha}{1-\alpha}ln(s) - \frac{\alpha}{1-\alpha}ln(n+g+\delta) \tag{4}$$

Eequation (4) has now a form for the steady state level of the basic Solow model that can be incorporated to a regression equation.

2.2 Augmented Model With Human Capital: Mankiw, Romer & Weil

The authors first tested whether the theoretical predictions of the Solow model regarding the steady state level of per-capita income were consistent with empirical evidence. They concluded that the directions of the effects of investment rate and population growth over the steady state, positive and negative respectively, are in line with predictions. However, the magnitudes of the effects seemed to be overestimated in compare to the predicted values.

To account for it, Mankiw, Romer & Weil (1992) augmented the Solow model by incorporating human capital as a factor of production. In particular, they argue that omitting this variable is the source of the bias that overestimates the coefficients of the basic model. This, because it appears to be correlated with the investment rate and population growth. The accumulation of human capital increases with income. Therefore, at a given level of human capital, any change in s or n that leads to a variation of income will end-up modifying the human capital level and, hence, the levels of investment rate and population growth. For this reason, accounting for both physical and human capital accumulation potentially vanishes the inconsistencies on the estimations of the coefficients. Concluding, the inclusion of such a variable fixes the fitting problems of the Solow model over magnitudes. The complete augmented Solow model with human capital is described with the following equations:

$$Y(t) = K(t)^{\alpha} H(t)^{\beta} (A(t)L(t))^{1-\alpha-\beta} \tag{5}$$

$$0 > \alpha > 1$$

$$0 > \beta > 1$$

$$\alpha + \beta < 1$$

$$\dot{k(t)} = s_k y(t) - (n+g+\delta)k(t) \tag{6}$$

$$\dot{h(t)} = s_h y(t) - (n+g+\delta)k(t) \tag{7}$$

Where

$$k = \frac{K}{AL};\ h = \frac{H}{AL};\ y = \frac{Y}{AL}$$

In equation 5, $H(t)$ is the human capital level at time t and the other variables are the same as in the basic Solow model. To sustain decreasing returns to all capital, $\alpha+\beta < 1$ is assumed. The evolution of both kinds of capital in levels per effective worker is given by equations (6) and (7). Depreciation rate is assumed equal for any kind of capital. The model also assumes that the same production is divided in proportions between investment in physical capital s_k, investment in human capital s_h and consumption, so that they can be exchanged at no cost. Following the same procedure as in the basic Solow model, interacting equations (5), (6) and (7) gives a steady state level per effective worker of the form:

$$y^* = \left(\frac{s_k^{\alpha} s_h^{\beta}}{(n+g+\delta)^{\alpha+\beta}} \right)^{\frac{\alpha}{1-\alpha-\beta}} \tag{8}$$

Taking logs, per-capita income in the steady state for a given time is expressed by:

$$\begin{aligned} ln\left(\frac{Y(t)}{L(t)}\right) &= lnA + g_t + \frac{\alpha}{1-\alpha-\beta} ln(s_k) + \frac{\beta}{1-\alpha-\beta} ln(s_h) \\ &\quad - \frac{\alpha+\beta}{1-\alpha-\beta} ln(n+g+\delta) \end{aligned} \tag{9}$$

Eequation (9) is then the one that has the form for the steady state level with human capital that can be incorporated into a regression equation.

2.3 From the Theory to the Regression Equation

Recalling from previous sections, the Solow model is based in a neoclassical production function with diminishing returns to capital. This characteristic implies that for low levels of capital, the marginal productivity is higher and thus should contribute at a bigger extent to the level of production. Moreover, as the capital stock increases, its marginal productivity becomes exponentially lower. Then, there should be an optimum level of capital in which any additional unit of it will no longer increase production. In line, in the Solow model "the per capita growth rate tends to be inversely related to the starting level of output or income per person"(Barro & Sala-i Martin, 1992). Consequently, the Solow model predicts that economies converge to the steady state level of output per-capita expressed in equations (4) and (9).

In particular, if for a set of economies that share similar preferences and technology, the initial level of output is negatively and significantly correlated with the speed at which economies reduce the short and long run income gap, then we say there is absolute β convergence[10]. In other words, if poor regions grow faster than rich ones, the gap will vanish over time. Note that conditions on the symmetry of economies are key for this analysis. Therefore, this type of convergence necessarily assumes that economies evolve towards the same steady state.

Furthermore, it might not be the case that economies converge to the same steady state. In fact, the Solow model only predicts that income per-capita in a given economy convergences to its own steady state which is traced by its determinants. Therefore, we say that there is conditional β convergence if the economies are approaching to their own steady state. The convergence is conditional in that it accounts for different levels of s and n across economies. This document tests for both conditional and unconditional β convergence.

The equation in the Solow model that captures the dynamics around the steady state is the one of the growth rate of k as a function of the capital stock itself[11].

$$\frac{\dot{k}}{k} = s_k^{\alpha-1} - (n + g + \delta) \tag{10}$$

$\frac{\dot{k}}{k}$ is the growth rate of capital and the other variables are as described before. Note that the growth rate of capital depends negatively on its stock level. Therefore, it is an equation that captures the dynamic of convergence. When the amount of k is large enough so the invested capital is perfectly diluted by depreciation, population growth and technology progress, the growth rate of its stock is 0. Then, we conclude that it is the steady state level k^*. However, note that equation (10) is nonlinear in k so that working with this model is rather difficult. Therefore, in order to simplify the calculations, it is replaced by:

$$\frac{\dot{k}}{k} = \lambda(lnk^* - lnk) \tag{11}$$
$$s_k^{\alpha-1} - (n + g + \delta) \approx \lambda(lnk^* - lnk)$$

Equation (11) is a log-linear approximation that captures the main characteristics of the one of Solow (10). The parameter λ is the speed of convergence or convergence rate, the speed at which the gap reduces over time. Consequently, it appears multiplying the gap in levels itself between short and long run income. Introducing this equation allows us to work with a linear relation between the

[10]It is also known as unconditional convergence. It is unconditional in that it does not consider the differences in the determinants of economies' steady states.

[11]This equation is obtained by dividing equation (2) by k in both sides.

growth of capital $\frac{\dot{k}}{k}$ and the log of capital lnk.

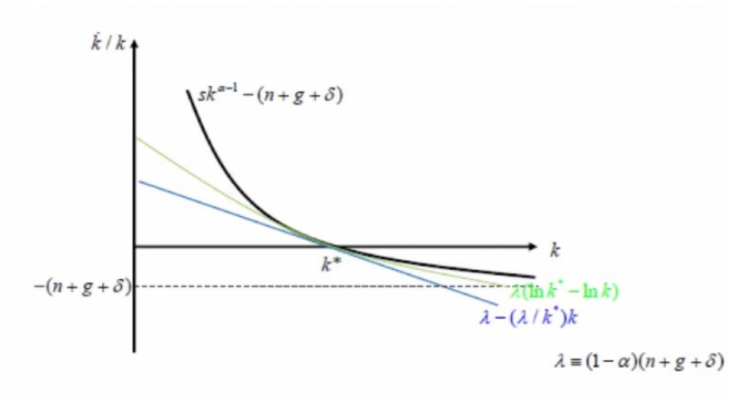

Figure 1: Fit of Best Guess

Figure 1 displays the fit between the linear equation and the original one. It shows that the approximation works especially well for levels of capital that are close to the steady state. The equation in blue, $\lambda - (\frac{\lambda}{k^*})k$, is the actual log-linearization of the true model, but it turns out to be not as accurate as (11).

Stepping forward, the final equation[12] that captures the convergence dynamics, based on the previous derivation, and rewritten in terms of y, is expressed as:

$$\frac{d[ln(y_t)]}{dt} = -\lambda(lny_t - lny^*) \tag{12}$$

Equation (12) states that, for a given t, the rate in which income approximates to its steady state, the growth of per-capita income, depends negatively on the gap in levels between the observable income y_t and the steady state level y^*. It shows consistency with the Solow model in that the bigger the level of the gap the higher the growth rate.

In order to turn such equation into a regression model that can be estimated, it is necessary to find a solution for the ordinary differential equation (12), re-write it in terms of logs, and accommodate it by subtracting $lny_{(0)}$ in both sides[13].

[12] This form is obtained by substituting equation (10) production function and taking logs. Then, applying the same approximation as equation (11) in terms of y and presenting it as a derivative with respect to time

[13] One can confirm this resulting equation by finding equation (12) when taking the first derivative with respect to time of equation (13).

The resulting equation is then:

$$ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right) = (1 - e^{-\lambda t})lny^* - (1 - e^{-\lambda t})lny_i(0) \tag{13}$$

This equation then expresses the average growth in per-capita income between time 0 and time t as a function of the initial level $lny_{(0)}$ and the steady state level y^*. The sub-index i is an indicator for economies. Also note that the steady state does not have the sub-index, that is, it is assumed equal for all i. Therefore, if the initial level of income per-capita is negatively and significantly correlated with the average growth rate of per-capita income between time 0 and time t, we argue that there is absolute β convergence. In other words, that poor economies grow faster than rich ones.

To test for conditional convergence, based committedly on the Solow model, we have to account for the particular determinants of economies' steady states. To do so, it is enough to replace y^* for equations (4) and (9) found in sections 2.1 and 2.2 respectively. By doing that, we get a form that now depend on the investment rate in physical capital (for the basic model), the investment rate on human capital (for the augmented model) and the population growth proper of each economy i. Finally the resulting equations that account for conditional convergence are:

For the basic Solow model:

$$\begin{aligned} ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right) = (1 - e^{-\lambda t})\left(\frac{\alpha}{1-\alpha}ln(s_i) - \frac{\alpha}{1-\alpha}ln(n+g+\delta)\right) \\ -(1 - e^{-\lambda t})lny_i(0) \end{aligned} \tag{14}$$

And for the Augmented model with human capital:

$$\begin{aligned} ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right) = (1-e^{-\lambda t})\left(\frac{\alpha}{1-\alpha-\beta}ln(s_{ki}) + \frac{\beta}{1-\alpha-\beta}ln(s_{hi}) - \frac{\alpha+\beta}{1-\alpha-\beta}ln(n+g+\delta)\right) \\ -(1 - e^{-\lambda t})lny_i(0) \end{aligned} \tag{15}$$

Note: The factors that multiply the variables will then be captured by each coefficient $\beta_i \; with \; i \in [0, \infty]$ resulting from the regressions.

In both cases, the initial level and growth of technology is going to be assumed part of the error term, so there is no need to present them in such equations. They will not be present in the tables of section 5 either.

Finally, it is important to mention that the potential issues of using this framework rely on its assumptions. Specifically, it assumes that economies at time t are very close or already in the steady state. Also, that it does not account for differences in economies' specific $A(0)$ that can potentially bias the results. Therefore, in order to use this framework empirically, it is necessary to give an argumentative validation for these assumptions to hold. This is taken into account in the up-coming section.

3 Methodology

Following the framework of Barro and Martin (2004), I use the following regression model to test for regional absolute β convergence in Colombia. Note that it is obtained from equation (13).

$$ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right) = \alpha + \beta_1 lnY_{i(0)} + u \qquad (16)$$

In (16), u is the error term, $ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right)$ is the average growth rate of output per-capita between time 0 and time t, a is a constant that captures technological parameters of the model, and $lnY_{i(0)}$ is the log of income per capita at time 0. The sub-index i denotes departments of Colombia. The speed of absolute convergence is implied by the coefficient β_1. Depretiation rate δ and growth of technology g are assumed to be the same throughout the national territory. Furthermore, when it comes to absolute convergence, the steady state level is assumed to be equal for all regions, therefore, these variables are not present in the regression model.

This model, however, introduces a technical difficulty. If regions have structural differences on their initial level of technology $A(0)$, they will have an important relation with the initial level of per-capita income $lnY_{i(0)}$. As these effects are captured in the error term, the model would experience heteroscedasticity and the coefficients would be biased. Fortunately, cross-regional analysis deal better with this issue due to the fact that regions are framed under the same institutional structure. Inter-regional capital and labor mobility are more flexible within a country. Therefore, it is reasonable to assume that technological progress spreads uniformly across regions, so that differences in $A(0)$ are not significantly big. Having said that, I assume that the initial levels of technology are equal for all regions $a_i = a$.

Subsequently, I also test for conditional β convergence to assess whether regions of Colombia converge to their own steady state. To do so, determinants of the steady states are incorporated into the model (16). Therefore, In line with equation (15), the resulting econometric model to test for conditional convergence is:

$$ln\left(\frac{y_{i(t)}}{y_{i(0)}}\right) = \alpha + \beta_1 lnY_{i(0)} + \beta_2 S_k + \beta_3 S_h + \beta_4 n + u \qquad (17)$$

Note that this model considers the steady state equation predicted in the augmented Solow model with human capital. To account solely for the basic Solow model, variable s_{hi} must be dropped from the model. These two resulting regression equations for conditional convergence make the same assumption over the level of initial technological across regions. That is $a_i = a$.

In the particular case of Colombia, the incidence of human capital can be distortionary in the sense that capital accumulation is not necessarily captured by the region that invested in it. That is to say, since labor mobility within a country is less costly, it is very likely that, once a person in a poor region has accumulated human capital, he/she decides to move to wealthier regions searching for opportunities. However, I argue that the barriers to labor mobility produced by cultural differences across the sub-regional groups of the country make the introduction of human capital worth to examine. Moreover, an alternative way to control for conditional convergence comes from introducing regional dummies to the regression model (Serra, 2006). In this way it would account for different steady states. Both techniques are used in this research. In any of the regression models presented above, the speed of convergence λ implied by the coefficient β_1 can be obtained in the following way:

$$\beta_1 = -(1 - e^{-\lambda t}) \tag{18}$$

$$\lambda = -\frac{ln(1+\beta_1)}{t}; \longrightarrow \lambda\% = -100\frac{ln(1+\beta_1)}{t} \tag{19}$$

Moving onto testing for the influence of war over convergence, I include a dummy variable δ_i which takes value 1 when regions have been directly affected by war and 0 otherwise. Moreover, I include the interaction between this dummy variable and the initial output level so that the effect of convergence conditional to war is captured. Tests on war then addition $\beta_2\delta_i + \beta_3(\delta_i * lnY_{i(0)})$ to the previous models (16) and (17). The resulting coefficient for the effect on $lnY_{i(0)}$ over the dependent variable is obtained by taking the first derivative of the model with respect to it. Therefore, the total effect now will be captured by $\beta_1 + \beta_3\delta_i$

Similarly, in order to test for the existence of convergence clubs, I allocate regions into sub-national groups by using dummy variables. In particular, Colombia has 32 departments that are divided into six groups: Atlantic region, central region, eastern region, pacific region, new departments or "intendencias" and the capital district. As Bogota C.D. accounts for approximately 20% of total national GDP and population, it is separated from its department Cundinamarca and included alone as a category. Tests for convergence clubs are run omitting information from San Andres. The principal reason is that it is an island isolated from the country so it does not fit in any of the groups. Moreover, its level of GDP is not important enough to make it a new category. The way in which clubs of convergence will be tested is the same as the one used by the IMF (Serra et al., 2006). All 6 regional dummies will be included in the model clustering results to the mean by dropping out the constant term. The existence of convergence clubs is confirmed if the speed of convergence after controlling by the regional dummies significantly increases with respect to the original model.

Every test described in this section will be estimated using cross-departmental data for the period between 1990 and 2015. They account for 32 departments and the capital district, for a total of 33 observations (except from the one of convergence clubs). To better deal with the already discussed potential heteroscedasticity. The regressions are estimated using nonlinear least squares (Newey West).

4 Data

The data base used in this research was built up from different sources: The regional accounts from the Colombian National Department of Statistics DANE[14], the World Bank, the center of data “CEDE” of the economics faculty of ”Universidad de los Andes”, and the data base used by Professor Juan Fernando Vargas in his paper “Regional inequity in Colombia”(2012).

Regional data on the real income per-capita, available in the national accounts, is constant to a different base year’s price level every 15 years. In particular, data from 1990 to 2005 is constant at a 1994‘s price level; and data from 2000 until 2015 is constant at a 2005‘s price level. Given this condition, the series for the first 15 years was converted into constant at a 2005‘s price level using a multiplier obtained out of the overlapping years (2000-2005). This offers then a complete series of real income per-capita for the whole length of time between 1990 and 2015, constant at a 2005’s price level.

When accounting for conditional β convergence, data about the average share of GDP that is invested per year in physical and human capital is needed. To account for this values I constructed two proxies.

The investment in physical capital makes reference to the introduction of any kind of new fixed capital that contributes to technological improvements for production as well as the replacement and repairs of the existing one. Based on this, the proxy for the variable s_{ki} is constructed by, first, summing up the per year participation on total GDP of the industrial production of machinery and fixed capital, infrastructure construction, civil works and maintenance of road network. Second, finding the average per year for the whole time length of the joint participation of these activities on GDP. The resulting value, I argue, is a valid proxy for the average level of investment in physical capital during the relevant period.

Similarly, the human capital “makes reference to stock of knowledge, habits, social and personality attributes, including creativity, embodied in the ability to perform labor”(Becker, 1962). Therefore, every activity that somehow contributes positively to the productivity of labor should be counted as contributor to the accumulation of human capital. Based on this, the variable s_{hi} is constructed by, first, summing up the per year participation on total GDP of market and non-market education, market and non-market cultural activities, health and social activities. Second, finding the average per year for the whole time length of the joint participation of these activities on GDP. The resulting value, I argue, is a valid proxy for the average level of investment in human capital during the relevant period.

[14]From its acronym in Spanish.

Note: Departmental data to construct these proxies is only available from 1994 to 2007, therefore the average obtained for this period is assumed to be the same for the whole period of analysis 1990-2015.

The data contains several dummies that are essential when testing for war and convergence clubs. On the one hand, the dummy of war includes Antioquia, Arauca, Caqueta, Cauca, Choco, Guaviare, La guajira, Meta, Nariño, Norte de Santander, Putumayo, Valle, Vaupes and Vichada. The regions assigned to this dummy were selected under the criteria of being the most vulnerable to conflict or that have been systematically affected by war over time. On the other hand, to test for clubs of convergence 6 regional dummies are present, one per each sub-national group. Altantic, includes Atlantico, Bolivar, Cesar, Cordoba, La Guajira, Magdalena and Sucre. Pacific, includes Choco, Cauca, Nariño and Valle. Central includes Antioquia, Caldas, Risaralda, Quindio, Tolima, Meta and Huila. Eastern includes Boyacá, Cundinamarca, Norte de Santander and Santander. Finally New departments includes Amazonas, Arauca, Caqueta, Casanare, Guainia, Guaviare, Putumayo, Vaupez and Vichada.

5 Discussion and Results

In the late 80's, Colombia was stocked in an economic slow-down produced by the global crisis of the beginning of the decade. As an effort to overcome this, and in line with the globalization trend of the world, the country set a series of institutional reforms that opened up the economy for international trade. In the early 90's, Colombia reduced notably not only the import tariffs but also the non-tariff barriers of trade. As a matter of fact, this last type of barriers, among which there were quotas, subsidies and technical and quality barriers, were reduced by approximately half.

The Year 1990 represents the breaking point of the economy towards an import substitution industrialization. The reforms that led to it, represent themselves a structural change for Colombia. Having said that, and keeping in mind that disparities in Colombia in that year were still important, it is possible to conclude that these reforms potentially affected differently each of its regions changing the pattern of convergence found previously. As Colombia started competing in the foreign market, poor regions with less competitive advantage must have been hampered while rich ones boosted. That is the reason why it is of great importance the analysis of the latter period 1990-2015.

Interestingly enough, table 1 displays a significant negative correlation between the initial level of income per-capita in 1990 and the average growth rate between 1990 and 2015. Results in column (I) show that Colombia is still a successful case of absolute β convergence, but that the speed of catching up of 1.6% per year between 1990 and 2015 is lower in compare to the approximately 4% of the previous period (Cárdenas & Pontón, 1995). On the other hand, the implied speed of convergence of 1.6% per year is higher but yet in line with those found by Serra et al. (2006) of 0.6% between 1980 and 2002. Therefore, this evidence suggests that poorer regions of Colombia have been steadily and systematically catching up the richest ones for the last 60 years.

Moreover, columns (II) and (III) display results for conditional β convergence using the basic and the augmented model respectively. This columns show estimations to test whether regions are converging to their own steady state based on their determinants. The analysis of these columns can be done through two different approaches: the theory fit and the economic interpretation.

In the one hand, it is to highlight that the signs of the coefficients for per-capita income in 1990, the investment in capital as a percentage of GDP, and the population growth are negative, positive and negative respectively. This goes in line with those predicted by the Solow model. In particular, the negative sign of the initial level of income displays evidence of convergence. Also, the positive sign of investment share shows that, empirically, Colombian departments grow faster as their saving rates are higher. Lastly, as the variable of interest is per-capita income, any increase in population growth naturally should decrease the share of income per-person. This effect is also effectively captured by the estimation.

Table 1:

Estimation for regional conditional and unconditional β convergence

Dependent Variable: Average growth of GDP per capita 1990-2015			
	(I)	(II)	(III)
	Absolute-Unconditional	Conditional	
Model Variables:	Basic model	Basic model	Augmented model
Y(90)	-0,33915	-0,30591	-0,58700
	(0,071)	(0,087)	(0,003)
s_k		1,72738	1,188147
		(0,018)	(0,116)
n		-11,13408	-5,7998
		(0,131)	(0,536)
s_h			-4,01251
			(0,013)
Implied λ	0,01656	0,0146	0,0354
Adjusted R^2	0,1312	0,2843	0,5270
$Prob > F$	0,0713	0,0163	0,0009

Note:
Estimator: Nonlinear Least Squares (Newey West).
P values in pharentheses
Y90 is the Real GDP per-capita in 1990
Number of observations: 33

In contrast, when it comes to the coefficient for the share of investment in human capital, displayed in column (III), the sign appears to be negative. This result is opposite from the one expected in theory. However, the sign can be intuitive for the context of Colombia. The main explanation is that, as every region in the country is framed under the same institutional structure, labor mobility across regions is very flexible. As Colombians share language, infrastructure and letter of law, for example, citizens will not face high transaction costs[15] different from

[15] I make reference to the costs implied in learning another language, adapting to a new culture, tax differences and so on that individuals have to experience when, for example, moving to a different country.

the ones involved in the transportation and installment. Adding to it, the regions that lead the ranking of income such as Bogota, Antioquia and Atlantico, demand more highs kill workers relative to low income departments. Therefore, the rate of return of human capital in such departments is higher.

Taking into consideration these two facts, the sign of the coefficient suggests that people with considerable accumulation of human capital, tend to gravitate toward these poles of economic growth rather than staying productive in their native region. Consequently, the effort put into the accumulation of this kind of capital for low and medium income departments appears to harm growth rather than improve it: The productivity accumulated in such regions ends up boosting growth of the richest ones, widening the gaps. These results also neglect the hypothesis that inter-cultural differences, and the potential barriers for mobility they bring along, play a role in keeping workers in their native region.

Switching to the second approach, columns (II) and (III) display that Colombian regions are converging to their own steady state with significant implied speed of convergence of 1.4%, for the basic model, and 3.4% for the augmented model. However, when human capital is introduced, the R^2 increases from 28.4% to 52.7%, and the confidence level of both the coefficient for y(90) and the joint effect of the controls over the dependent variable (F test), goes from 90% to 95%. That is to say, the augmented model explains 52.7% of the economic growth of regions between 1990 and 2015 and present a more accurate coefficient of speed. Consequently, results display that Colombian regions converge conditional to their own determinants of steady state at a higher speed (3.4%), in compared to the model in column (I) (1.6%).

Furthermore, Colombia has been performing in a context of war for approximately 50 years, table 2 contains information of the results testing the effect of war over regional convergence. Section 4 listed the exact regions that were assigned to the dummy "War" for being the most directly affected by the conflict. The test was designed to measure the difference in the convergence speed between the two groups: affected and non-affected. In this model, the effect of initial income over growth is composed by the direct coefficient of Y(90) and the differential captured by conditioning it by the dummy. That is to say, the coefficient of the interaction between the dummy and Y(90). The implied speed of convergence for the group affected by war is the sum of the two coefficients while the speed of the remaining group is captured solely by the coefficient of Y(90).

Contrary from expected, in both unconditional and conditional convergence the negative coefficient of the interaction suggests that those regions most affected by war have a speed of convergence higher than the one for those non-affected. Interestingly enough, when testing for absolute convergence the estimations reveal that only the regions in concern are actually experiencing convergence at a speed of 3.4% while there is no evidence of convergence among the non-affected

Table 2:

Influence of war on convergence

Dependent Variable: Average growth of GDP per capita 1990-2015		
Model	(I) Absolute-Unconditional	(II) Conditional
Variables:		
Y(90)	-0,019433	-0,322611
	(0,928)	(0,068)
War	8,270292	7,156643
	(0,073)	(0,034)
War*Y(90)	-0,5545693	-0,473695
	(0,069)	(0,033)
s_k		1,05311
		(0,15)
n		-1,21646
		(0,902)
s_h		-3,86704
		(0,009)
Implied $\lambda War = 1$	0,0341	0,0636
Implied $\lambda War = 0$	.	0,01558
Adjusted R^2	0,3066	0,6045
$Prob > F$	0,0599	0,0003

Note:
Estimator: Nonlinear Least Squares (Newey West).
P values in pharentheses
Y90 is the Real GDP per-capita in 1990
Number of observations: 33
Dummy War is 1 if state affected by war and 0 otherwise

group of regions.

When testing for conditional convergence including accumulation of human capital, the coefficient for Y(90) becomes significant at a 10% level, with P value of 0.068, whereas the one of the interaction passes to be significant at a 5% level, with a P value of 0.033. In this case, it is to highlight that these coefficients imply a speed of conditional convergence of 1.6% for the least affected and an even faster catching up rate of 6% for the affected regions in compare to the absolute model. Note that the speed of convergence for the first group, however, remains very close to the one found in the unconditional case of column (I). This suggests that 1.6% is indeed a steady ground rate of convergence among high income regions. Note also that the group of war is mainly composed by the poorest departments, so results suggest that the higher catching up rate of 6% is indeed being individually experienced by the regions with the lowest income. It is to mention that the joint effect of the independent variables over the dependent one remains significant in both in both conditional and unconditional, with $prob > F = 0.059$ and $prob > F = 0.0003$ respectively. Figure 2 further restates these differences in speed between the two groups. The dummy has value 1 when effected by war and 0 otherwise.

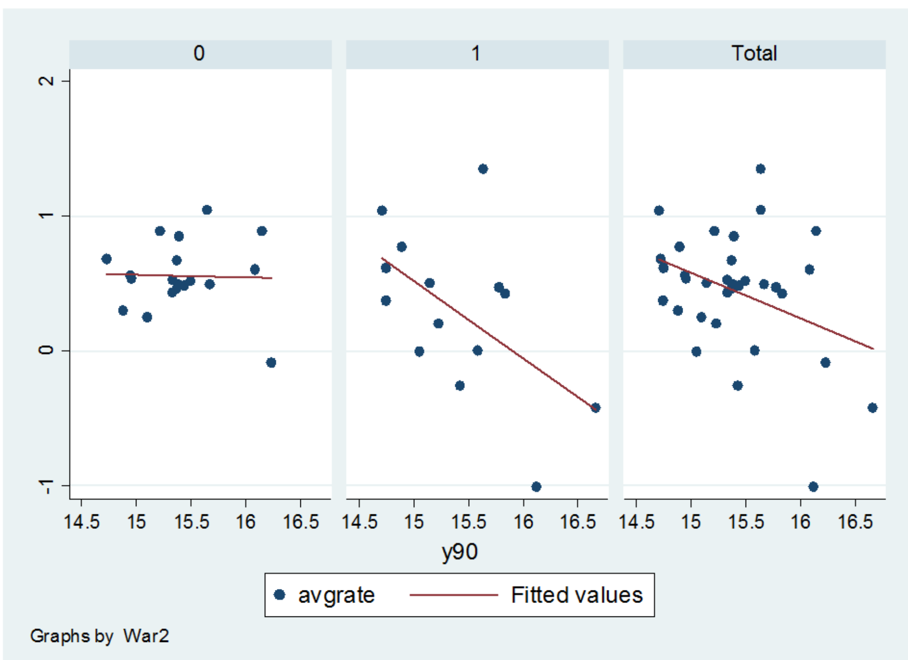

Figure 2: Average growth rate against $y_{(90)}$. Sorted by War.

Regarding the effect of war, the model did not capture any significant effect that lowers or prevents regions from converging to their steady state. However, two comments have to me made. In the first place, it is possible that the effect of war does not overweighting the high growth rate due to low income, but yet decreases it. If that is the case, the test does not capture nor measures that effect. In second place, departments of Colombia include many cities and municipalities and are big in land extension. Therefore, departments directly affected by war in just few of those municipalities might not be significantly affected as a department.

Based on that, it is possible that a regional approach is not the most appropriate to study for such effects. Thus, further analysis is needed to truly grasp the role of war over growth. For example, using municipal data to test for the determinants of departmental growth for each region of Colombia could complement this study. Despite, what indeed can be concluded from the test presented in this research is that, at a regional level, the effect of war over convergence rate was not big enough to nullify it between 1990 and 2015.

Finally, table 3 presents formal estimations for the existence of convergence clubs. In this test, 6 regional dummies are included in the model. In particular, if the implied speed of convergence of the model improves significantly when controlling for groups of regions, then the country is said to grow within local sub-levels of steady state rather than at a national wide one. Successful evidence of convergence clubs has been previously found for countries like Brazil and Peru(Serra et al., 2006). The estimation is clustered around the mean, so that taking out the constant from the model allows me to introduce all 6 dummies to the model without facing collinearity.

Lines 1 and 2 in table 3 display results for the basic model when the regional dummies are included. In this case, although the R^2 notably increases from 13% to 69%, the implied speed of convergence barely changed, staying again around the steady ground level of 1.6% per year. Since the coefficient didn't increase importantly, these results suggest that there is no evidence of convergence clubs in Colombia, outcome that is in line with the findings of Serra et al. (2006) in their working paper for the IMF.

Furthermore, note that the way in which the test of the first raw is designed can be called conditional in that the different coefficients of the dummy variables will add up to the constant and the error term. When clustered to the mean, therefore, the test analyzes whether regions converge to an average level of steady state modified by the different coefficients of the dummies. Put differently, each regional dummy conditions the regression offering a different level of steady state proper of its departments, but the test checks whether they converge to the resulting average level between the six groups. Such a test in a country like Colombia might be inconclusive since it does not control for the

Table 3:

Convergence Clubs

Dependent Variable: Average growth of GDP per capita 1990-2015			
Variables:	(I) Coefficient Y(90)	(II) Implied λ	(III) Adjusted R^2
Model:			
Basic Model	-0,33915 (0,071)	0,01656	0,13120
Basic model with regional dummies	-0,333335 (0,158)	0,01621	0,69010
Augmented model with regional dummies	-0,8193807 (0.005)	0,06845	0,8020

Note:
Estimator: Nonlinear Least Squares (Newey West)
The model includes the 6 regional dummies, Omitting the constant
San Andres excluded
P values in pharentheses
Y90 is the Real GDP per-capita in 1990
Number of observations: 32

individual determinants of the steady state per department. It might be the case that sub-national groups of regions are converging within them at a much higher speed but the steady state towards which they gravitate as a group is far away from the resulting average one, so that the evidence is deluded. To get a more accurate test that accounts for this possibility, therefore, the determinants of the steady state should be included in the model.

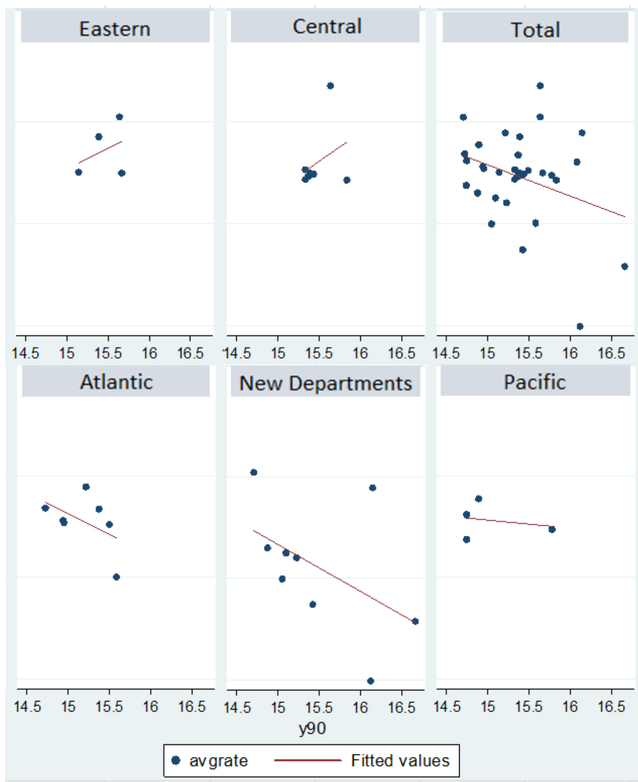

Figure 3: Average growth rate against $y_{(90)}$ of each sub-national group

Before moving onto the formal test, figure 3 offers insight about the particular dynamics of convergence within each group. This figure displays the correlation of the initial level of per-capita income and the average growth rate between 1990 and 2015 for each sub-group. It also includes the total correlation when accounting for the 33 departments found before. It is very important to clarify that this figure is only intended to graphically represent the directions of the effects of $y_{(90}$ over the average growth rate per region, but that they have no statistical power due to lack of observations.

As it is depicted, the sub groups eastern and central, located in the top part of figure 3, do not present signs of inner convergence. The relationship between growth rate and initial level of income is positive rather than negative. On the other hand, regions displayed on the bottom, atlantic, pacific and the new departments, present the negative relationship that suggests proper inner convergence. Furthermore, when visually comparing the top and bottom plots, it seems that the joint effect of high convergence within sub-groups is greater than the one of non-convergence. Not only they include more regions, but also the slopes and length of the fitted values suggest higher coefficients of Y(90). Finally the graph on the top right corner further restates the findings presented previously of the negative relationship when accounting for all regions.

Moving onto formally test for convergence clubs accounting for different determinants of steady state , I included in the model the average share of investment of both kinds of capital, altogether with the 6 regional dummies. I use the same methodology as the one in the working paper of the IMF (Serra et al., 2006). Therefore, the constant is also dropped out from the model. In this way I account for different levels of steady state while examining the regional sub-division of the country. Doing that, will generate a new and more accurate mean to which the regression will be clustered to. The third raw of table 3 presents outcomes of this tests. Interestingly, introducing the determinants of the steady state not only kicks up the speed of convergence to 6.9% but also presents a coefficient for Y(90) significant at a 1% level (P=0.005). Additionally the model displays an R^2 of 0.8. Based on this, results suggest that there is indeed evidence of convergence clubs in Colombia. The important change in the speed of convergence passing from 1.6% to 6.9% stands as the evidence to make such statement.

When analyzing the econometric results in contrast to the information displayed in figure 3, few comments have to be made. In the first place, although convergence within sub-groups of regions appears to be high, figure 3 suggests that not all of them are experiencing it. That is to say, economic convergence clubs do exist in Colombia, but not all of the regions accounted for in this research is one. Specific speed of convergence of each sub-group couldn't be captured significantly due to the lack of observations. Moreover, it is to highlight that the region of the highest evidence of convergence in figure 3 corresponds to the group new departments. Also, departments of that region are majority in the list of the most affected by war. Taking this two facts into account it is not surprising, yet interesting, that he speed of catching up when analyzing for convergence clubs is very similar to the one implied for the regions with war.

6 Conclusions

There has been an increasingly used argument in politics that points at opening up the economy in the 90's as the source of income per-capita disparities across regions. This research contradicts this argument and presents evidence of that, on the contrary, Colombia has been a successful case of economic convergence between 1990 and 2015, presenting a catching up speed of 1.6% per year. Moreover, the speed is even higher (3.4%) when testing for conditional convergence. Adding up this document to the literature allows to state that the poorest Colombian regions have consistently caught up the richest ones for the past 60 years.

Contrary to what was expected, this research show that there is no evidence of importantly harmful effects of war over economic growth. In fact, these regions showed the highest speed of convergence. One reason is due to the fact that most of the regions included in "war" corresponds to the poorest ones. Another one, is that as departments are big in extension and contain different cities and municipalities, it might be the case that when these municipalities are small relative to the department as a whole, the effect of war gets deluded. What indeed can be concluded from this research is that the effect of war on growth rate does not importantly affect the speed of convergence.

Lastly, Colombia displayed that the convergence process happens more rapidly around different economic poles than when testing for a uniform national wide steady state level. This fact implies the existence of different convergence clubs in Colombia. However, not all the sub-national groups of regions display patterns of convergence. In particular, nor central nor eastern groups displayed evidence of economic convergence.

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A Data Base

Table 4:

i	State	ppGDP1990	ppGDP2015	n	sk%	sh	War2
1	Amazonas	3602942	4629933	0,02	1,79	20,78	0
2	Antioquia	7507710	11455944	0,01	20,49	9,64	1
3	Arauca	17260706	11299392	0,03	3,43	3,76	1
4	Atlántico	5380563	9020819	0,01	18,46	10,16	0
5	Bogotá D. C.	9691825	17737511	0,02	16,95	10,38	0
6	Bolívar	4734483	9242018	0,01	28,92	7,78	0
7	Boyacá	4839976	11360796	0,00	16,45	9,43	0
8	Caldas	4815172	7889748	0,00	18,17	11,69	0
9	Caquetá	4105854	5016309	0,01	8,12	13,36	1
10	Casanare	10296449	25084227	0,02	7,33	2,26	0
11	Cauca	2933812	6369778	0,01	16,22	13,01	1
12	Cesar	4050993	9870832	0,01	6,61	8,00	0
13	Chocó	2527705	3675316	0,01	6,57	18,07	1
14	Córdoba	3084804	5403464	0,02	7,27	9,35	0
15	Cundinamarca	6376773	10449840	0,02	20,57	8,22	0
16	Guainía	2892254	3905308	0,03	10,45	30,13	0
17	Guaviare	10037220	3664686	0,02	12,54	18,28	1
18	Huila	4726673	7530458	0,02	14,52	9,86	0
19	La Guajira	5862683	5892689	0,03	4,55	6,82	1
20	Magdalena	3120291	5338849	0,01	8,63	13,62	0
21	Meta	6189984	23872036	0,02	9,39	6,22	1
22	Nariño	2532516	4689754	0,01	14,00	13,76	1
23	Norte Santander	3769392	6217791	0,01	11,97	13,98	1
24	Putumayo	2440618	6923442	0,01	5,52	14,31	1
25	Quindío	4551043	7024464	0,01	16,63	12,92	0
26	Risaralda	5053119	8195783	0,01	18,98	12,16	0
27	San Andrés	11204311	10295387	0,01	3,48	11,73	0
28	Santander	6206322	17657256	0,01	30,52	6,41	0
29	Sucre	2480142	4903026	0,01	13,20	13,71	0
30	Tolima	4547846	7690986	0,00	13,98	10,99	0
31	Valle	7114950	11408020	0,01	17,21	10,29	1
32	Vaupés	3443031	3435246	0,02	7,22	35,59	1
33	Vichada	4996247	3862506	0,03	5,26	15,21	1

Note:
ppGDP stands for per-capita GDP

Table 5:

i	State	Atlantic	Pacific	Central	Eastern	Newdepto	Bogota C.D
1	Amazonas	0	0	0	0	1	0
2	Antioquia	0	0	1	0	0	0
3	Arauca	0	0	0	0	1	0
4	Atlántico	1	0	0	0	0	0
5	Bogotá D. C.	0	0	0	0	0	1
6	Bolívar	1	0	0	0	0	0
7	Boyacá	0	0	0	1	0	0
8	Caldas	0	0	1	0	0	0
9	Caquetá	0	0	0	0	1	0
10	Casanare	0	0	0	0	1	0
11	Cauca	0	1	0	0	0	0
12	Cesar	1	0	0	0	0	0
13	Chocó	0	1	0	0	0	0
14	Córdoba	1	0	0	0	0	0
15	Cundinamarca	0	0	0	1	0	0
16	Guainía	0	0	0	0	1	0
17	Guaviare	0	0	0	0	1	0
18	Huila	0	0	1	0	0	0
19	La Guajira	1	0	0	0	0	0
20	Magdalena	1	0	0	0	0	0
21	Meta	0	0	1	0	0	0
22	Nariño	0	1	0	0	0	0
23	Norte Santander	0	0	0	1	0	0
24	Putumayo	0	0	0	0	1	0
25	Quindío	0	0	1	0	0	0
26	Risaralda	0	0	1	0	0	0
27	San Andrés	0	0	0	0	0	0
28	Santander	0	0	0	1	0	0
29	Sucre	1	0	0	0	0	0
30	Tolima	0	0	1	0	0	0
31	Valle	0	1	0	0	0	0
32	Vaupés	0	0	0	0	1	0
33	Vichada	0	0	0	0	1	0

B Do File

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import excel "C:\Users\tomas_000\Desktop\Thesis\Test.xlsx", sheet("Sheet1") firstrow
//generated variables//
gen avgrate= ln(ppGDP2015/ppGDP1990)
gen y90= ln(ppGDP1990)
gen intwar1y90= War1*y90
gen intwar2y90= War2*y90
gen intAtlanticy90= Atlantic*y90
gen intPacificy90= Pacific*y90
gen intCentraly90= Central*y90
gen intEasterny90= Eastern*y90
gen intNewdeptoy90= Newdepto*y90
gen intbogotay90= BogotaCD*y90



//unconditional convergence//
reg avgrate y90, vce(robust)
graph twoway (lfit avgrate y90) (scatter avgrate y90)

//conditional convergence//
reg avgrate y90 sk n1ln, vce (robust)
reg avgrate y90 sk sh n1ln, vce (robust)
//war//
reg avgrate y90 War1 intwar1y90, vce(robust)
reg avgrate y90 War2 intwar2y90, vce(robust)
reg avgrate y90 sk sh n1ln War1 intwar1y90, vce(robust)
reg avgrate y90 sk sh n1ln War2 intwar2y90, vce(robust)
scatter avgrate y90 || lfit avgrate y90 ||, by(War1, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(War2, total row(1))
//
//
//convergence clubs//
drop if i==27
reg avgrate y90 Atlantic Pacific Central Eastern Newdepto BogotaCD, noconstant vce(robust)
reg avgrate y90 sh sk n1ln Atlantic Pacific Central Eastern Newdepto BogotaCD, noconstant 
vce(robust)
scatter avgrate y90 || lfit avgrate y90 ||, by(Atlantic, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(Pacific, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(Central, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(Eastern, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(Newdepto, total row(1))
scatter avgrate y90 || lfit avgrate y90 ||, by(BogotaCD, total row(1))
```

C Log File

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                       Tilburg University

Notes:
      1.  Unicode is supported; see help unicode_advice.

 1 . import excel "\\studfiles.campus.uvt.nl\files\home\home02\u1273530\tomas ramir
> ez\Tesis\Data base\Test.xlsx", sheet("Sheet1") firstrow

 2 . do "C:\Users\u1273530\AppData\Local\Temp\STD01000000.tmp"

 3 . //generated variables//
 4 . gen avgrate= ln(ppGDP2015/ppGDP1990)

 5 . gen y90= ln(ppGDP1990)

 6 . gen intwar1y90= War1*y90

 7 . gen intwar2y90= War2*y90

 8 . gen intAtlanticy90= Atlantic*y90

 9 . gen intPacificy90= Pacific*y90

10 . gen intCentraly90= Central*y90

11 . gen intEasterny90= Eastern*y90

12 . gen intNewdeptoy90= Newdepto*y90

13 . gen intbogotay90= BogotaCD*y90

14 .
15 .
16 .
17 . //unconditional convergence//
18 . reg avgrate y90, vce(robust)
```

Linear regression

Number of obs	=	**33**
F(1, 31)	=	**3.49**
Prob > F	=	**0.0713**
R-squared	=	**0.1312**
Root MSE	=	**.4291**

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	**-.33915**	**.1815676**	**-1.87**	**0.071**	**-.7094596**	**.0311596**
_cons	**5.668256**	**2.754129**	**2.06**	**0.048**	**.0511721**	**11.28534**

```
19 . graph twoway (lfit avgrate y90) (scatter avgrate y90)

20 .
21 . //conditional convergence//
22 . reg avgrate y90 sk n1ln, vce (robust)
```

Linear regression

Number of obs	=	33
F(3, 29)	=	4.04
Prob > F	=	0.0163
R-squared	=	0.2843
Root MSE	=	.40266

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	-.3059139	.17262	-1.77	0.087	-.6589615	.0471336
sk	1.72738	.6900315	2.50	0.018	.3161076	3.138653
n1ln	-11.13408	7.165847	-1.55	0.131	-25.78988	3.521724
_cons	5.110377	2.611642	1.96	0.060	-.2310301	10.45178

```
23 . reg avgrate y90 sk sh n1ln, vce (robust)
```

Linear regression

Number of obs	=	33
F(4, 28)	=	6.41
Prob > F	=	0.0009
R-squared	=	0.5270
Root MSE	=	.33315

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	-.5870046	.183575	-3.20	0.003	-.9630409	-.2109683
sk	1.188147	.7327466	1.62	0.116	-.3128164	2.68911
sh	-4.012509	1.511265	-2.66	0.013	-7.108195	-.9168225
n1ln	-5.799804	9.26602	-0.63	0.536	-24.78039	13.18078
_cons	9.926126	2.898813	3.42	0.002	3.988176	15.86408

```
24 . //war//
25 . reg avgrate y90 War1 intwar1y90, vce(robust)
```

Linear regression

Number of obs	=	33
F(3, 29)	=	2.88
Prob > F	=	0.0529
R-squared	=	0.3503
Root MSE	=	.38365

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	-.0551823	.1618704	-0.34	0.736	-.3862445	.2758799
War1	8.563652	4.288114	2.00	0.055	-.206526	17.33383
intwar1y90	-.5787489	.2819124	-2.05	0.049	-1.155325	-.0021733
_cons	1.392252	2.46443	0.56	0.576	-3.648073	6.432576

```
26 . reg avgrate y90 War2 intwar2y90, vce(robust)

Linear regression                               Number of obs     =         33
                                                F(3, 29)          =       2.76
                                                Prob > F          =     0.0599
                                                R-squared         =     0.3066
                                                Root MSE          =     .39634

------------------------------------------------------------------------------
             |               Robust
     avgrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         y90 |  -.0194332   .2120108    -0.09   0.928    -.4530441    .4141776
        War2 |   8.270292   4.441437     1.86   0.073    -.8134661    17.35405
  intwar2y90 |  -.5545693   .2931276    -1.89   0.069    -1.154083     .044944
       _cons |   .8579024   3.232805     0.27   0.793    -5.753926     7.46973
------------------------------------------------------------------------------

27 . reg avgrate y90 sk sh n1ln War1 intwar1y90, vce(robust)

Linear regression                               Number of obs     =         33
                                                F(6, 26)          =       7.70
                                                Prob > F          =     0.0001
                                                R-squared         =     0.6320
                                                Root MSE          =     .30495

------------------------------------------------------------------------------
             |               Robust
     avgrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         y90 |  -.3426751   .1373505    -2.49   0.019    -.6250031   -.0603472
          sk |   .8936047   .7511241     1.19   0.245    -.6503531    2.437562
          sh |  -4.085669   1.375662    -2.97   0.006    -6.913384   -1.257955
        n1ln |   .0763379   10.37404     0.01   0.994    -21.24782    21.40049
        War1 |   9.164992    3.19453     2.87   0.008     2.598543    15.73144
  intwar1y90 |  -.6029813   .2102483    -2.87   0.008    -1.035153   -.1708097
       _cons |   6.161565   2.113541     2.92   0.007     1.817119    10.50601
------------------------------------------------------------------------------

28 . reg avgrate y90 sk sh n1ln War2 intwar2y90, vce(robust)

Linear regression                               Number of obs     =         33
                                                F(6, 26)          =       6.39
                                                Prob > F          =     0.0003
                                                R-squared         =     0.6045
                                                Root MSE          =     .31615

------------------------------------------------------------------------------
             |               Robust
     avgrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         y90 |  -.3226108   .1694758    -1.90   0.068    -.6709732    .0257516
          sk |    1.05311   .7107881     1.48   0.150     -.407936    2.514156
          sh |  -3.867036   1.360305    -2.84   0.009    -6.663183   -1.070888
        n1ln |  -1.216457   9.772967    -0.12   0.902    -21.30508    18.87216
        War2 |   7.156643   3.192262     2.24   0.034     .5948545    13.71843
  intwar2y90 |  -.4736954   .2104976    -2.25   0.033    -.9063794   -.0410113
       _cons |   5.840297   2.602674     2.24   0.034     .4904233    11.19017
------------------------------------------------------------------------------
```

```
29 . scatter avgrate y90 || lfit avgrate y90 ||, by(War1, total row(1))

30 . scatter avgrate y90 || lfit avgrate y90 ||, by(War2, total row(1))

31 . //
32 . //
33 . //convergence clubs//
34 . drop if i==27
   (1 observation deleted)

35 . reg avgrate y90 Atlantic Pacific Central Eastern Newdepto BogotaCD, noconstant
   >  vce(robust)
```

Linear regression

Number of obs	=	**32**
F(6, 25)	=	**.**
Prob > F	=	**.**
R-squared	=	**0.6901**
Root MSE	=	**.40286**

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	**-.333335**	**.2291169**	**-1.45**	**0.158**	**-.80521**	**.1385401**
Atlantic	**5.612793**	**3.468822**	**1.62**	**0.118**	**-1.53138**	**12.75697**
Pacific	**5.572583**	**3.449888**	**1.62**	**0.119**	**-1.532595**	**12.67776**
Central	**5.754656**	**3.534291**	**1.63**	**0.116**	**-1.524353**	**13.03366**
Eastern	**5.877016**	**3.546617**	**1.66**	**0.110**	**-1.427378**	**13.18141**
Newdepto	**5.270411**	**3.455208**	**1.53**	**0.140**	**-1.845723**	**12.38655**
BogotaCD	**5.96669**	**3.685756**	**1.62**	**0.118**	**-1.624266**	**13.55765**

```
36 . reg avgrate y90 sh sk n1ln Atlantic Pacific Central Eastern Newdepto BogotaCD,
   >  noconstant vce(robust)
```

Linear regression

Number of obs	=	**32**
F(9, 22)	=	**.**
Prob > F	=	**.**
R-squared	=	**0.8020**
Root MSE	=	**.34324**

avgrate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
y90	**-.8193807**	**.2618408**	**-3.13**	**0.005**	**-1.362405**	**-.2763562**
sh	**-4.915749**	**2.02218**	**-2.43**	**0.024**	**-9.109493**	**-.7220051**
sk	**1.139463**	**.8742172**	**1.30**	**0.206**	**-.6735525**	**2.952479**
n1ln	**-.900006**	**14.75897**	**-0.06**	**0.952**	**-31.50825**	**29.70823**
Atlantic	**13.35253**	**3.963263**	**3.37**	**0.003**	**5.133227**	**21.57184**
Pacific	**13.41641**	**4.002885**	**3.35**	**0.003**	**5.114937**	**21.71789**
Central	**13.61927**	**4.111401**	**3.31**	**0.003**	**5.092748**	**22.1458**
Eastern	**13.64176**	**4.076514**	**3.35**	**0.003**	**5.187585**	**22.09593**
Newdepto	**13.57544**	**4.075483**	**3.33**	**0.003**	**5.123409**	**22.02748**
BogotaCD	**14.11956**	**4.187977**	**3.37**	**0.003**	**5.434232**	**22.8049**

```
37 . scatter avgrate y90 || lfit avgrate y90 ||, by(Atlantic, total row(1))

38 . scatter avgrate y90 || lfit avgrate y90 ||, by(Pacific, total row(1))

39 . scatter avgrate y90 || lfit avgrate y90 ||, by(Central, total row(1))

40 . scatter avgrate y90 || lfit avgrate y90 ||, by(Eastern, total row(1))

41 . scatter avgrate y90 || lfit avgrate y90 ||, by(Newdepto, total row(1))

42 . scatter avgrate y90 || lfit avgrate y90 ||, by(BogotaCD, total row(1))
   (note:  regress could not fit model)
   insufficient observations

43 .
   end of do-file

44 .
```