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Boris Branisa, Adriana Cardozo

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Platz der Göttinger Sieben 3 · 37073 Goettingen · Germany · Phone: +49-(0)551-398172 · Fax: +49-(0)551-398173
e-mail: uwia@gwdg.de · http://www.iai.wiwi.uni-goettingen.de

Revisiting the Regional Growth Convergence Debate in Colombia Using Income indicators *

Boris Branisa† **Adriana Cardozo**‡

University of Goettingen
Department of Economics
Platz der Goettinger Sieben 3
37073 Goettingen, Germany

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Abstract. This paper investigates growth convergence across Colombian departments during the period of 1975 to 2000, following both the regression and the distributional approaches suggested in the literature, and using two income measures computed by Centro de Estudios Ganaderos (CEGA). We also discuss issues related to data provided by Departamento Administrativo Nacional de Estadısticas (DANE) used by previous convergence studies. Our results show no evidence supporting convergence using per capita gross departmental product, but rather persistence in the distribution. Using per capita gross household disposable income, we find convergence, but only at a low speed, close to one percent per year. Furthermore, we find no evidence of the existence of different steady states for the two variables considered.

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† bbranis@uni-goettingen.de
‡ acardoz@uni-goettingen.de

1 Introduction

One of the most interesting and disputed questions in the economics discipline during the last half century has been whether or not poor countries tend to catch up with wealthier ones over time or if, on the contrary, the gap between the rich and poor widens. This question also reflects an interest in understanding the distribution of outcomes across countries and, implicitly, the determinants of growth (Durlauf, Johnson, and Temple, 2005).

Empirical research on this topic is based upon macroeconomic aggregates and has concentrated on testing the neoclassical growth model of Solow (1956) using the estimation method proposed by Barro and Sala-i-Martin (1991) to investigate whether economies with lower capital per person at a certain initial point in time tend to grow more quickly than economies with higher capital per person. If this is the case, there is convergence among economies over the long run.

The convergence question has also been studied within particular countries to analyze how much regional disparities diminish over time. The difference with cross-country convergence analysis is that in such cases it is risky to make assumptions across countries on key model parameters, such as technology, savings, and population growth rates. On the contrary, within a single country, it is plausible to assume that regions exhibit similarities in these and other variables, such as language, institutions, and preferences. This presumed homogeneity has lead researchers to assume that convergence is more likely to hold within, rather than across, countries (Barro and Sala-i-Martin, 2004).

Empirical research supports regional convergence within industrial countries over the long run. Typical examples are given by Barro and Sala-i-Martin (1992b) who find convergence across U.S. states between 1880 and 2000, across Japanese prefectures between 1930 and 1990, and between regions in eight European countries between 1950 and 1990 (see also Barro and Sala-i-Martin (1992a)).

In the case of Colombia, a heterogeneous country at the department level in economic, geographic, and cultural aspects, existing research is contradictory. While some authors argue that Colombia was a successful case of convergence in the second half of the twentieth century, others argue for the persistence of regional disparities.

The objective of this study is to investigate whether or not Colombia was a case of convergence at the department level between 1975 and 2000 using two different income variables: gross departmental product and gross personal disposable income. We consider that the second variable is more appropriate for measuring convergence in well-being.

The study is constructed around three main questions. First, the study evaluates whether departments converged between 1975 and 2000 and if so, if convergence results obtained using the regression approach contradict the results obtained with the distributional approach suggested by Quah (1997), using bivariate Kernel density estimators. Second, we determine if the assumption of a common steady state for all departments holds or whether there is evidence of heterogeneity in the model parameters. Finally, the study evaluates whether the presence or absence of convergence occurs simultaneously in gross departmental product and in gross personal disposable income.

An important contribution of the study is the first ever test of the convergence hypothesis using time-series cross-sectional data with different specifications to check the robustness of results. The results are based upon data from Centro de Estudios Ganaderos (CEGA) because those data provide the longest time series (25 years) computed with a consistent methodology.[1]

To summarize our results, we do not find convergence in gross departmental product and find no evidence of different steady states across departments using that variable. When using gross personal disposable income, we find convergence, but a very slow one, and no evidence of different steady states. For both variables, when using the regression approach, we find that the best estimators can be achieved using pooled time-series cross-section data and assuming homogeneity in the parameters. Furthermore, considering both variables, we do not find a contradiction in results obtained using the regression and the distributional approaches. Using bivariate kernel density estimators, we find persistence in the distribution of gross departmental product and slight convergence in gross personal disposable income.

One important policy implication of our results is the need to periodically review whether or not departmental disparities diminish over time based on consistent time se-

[1] CEGA was a large research center financed by a private financial institution in Colombia.

ries constructed under a single methodology. We explicitly warn that linking different time series computed with different methodologies can lead to incorrect conclusions for interventions, such as poverty-alleviating policies and growth strategies. In keeping with previous studies on this topic (e.g. Bonet and Meisel, 2006a), we consider important the need to have an explicit regional policy in Colombia to foster growth in departments lagging behind national averages, after conducting case studies to assess which policies could be most effective in each case.

2 Motivation and Background

2.1 Economic Background

One remarkable characteristic of Colombia is the large income inequality which exists at different levels-between individuals, between rural and urban areas, and between departments. The country is currently divided into 32 departments and the capital district of Bogotá. Departments may also be grouped into 5 regions: the Caribbean Region comprising departments with access to the Caribbean Sea; the Pacific Region, with departments in the weast coast to the Pacific Ocean; the Central Region, covering the three branches of the Andes mountain chains; Orinoquia, comprising large plains to the south-east of the country; and Amazonia in the south, comprising the Colombian part of the Amazon rainforest (see the map of Colombia in Figure 1).

Economic growth over the last 30 years, which was low but stable compared to other countries in the region, comes together with a combination of a high incidence of poverty, inequality, and violence. In 2004, the percentage of people living below the poverty line (headcount index) was 52 percent and the Gini coefficient was 0.58. The homicide rate was 63 per 100,000 people. Evidence shows that growth slowed compared to long-term historical trends after 1970. In fact, after having achieved in 1970 a growth rate of 3.1 percent in per capita gross domestic product, growth between 1980 and 1990 occured at an average annual rate of only 1.2 percent due primarily by the adverse effects of Latin America's debt crisis. In the 1990s, the average growth rate was similar (1.1 percent), driven by a boom and bust cycle throughout the decade, which concluded in a severe recession in 1999 (per capita GDP contracted by 5.5 percent (Table 1). On the contrary, in the present decade, favorable external conditions, especially high commodity prices and confidence due to the easing of internal conflict, have contributed to the acceleration of the economy (Tenjo G. and López E., 2003; Cárdenas, 2007).

The heart of economic activity in Colombia lies in the Central or Andean Region which concentrates the largest proportion of population within the major cities. Bogotá and the departments of Cundinamarca and Antioquia account for 42 percent of total GDP with Bogotá having a high level of participation in total production (22 percent). This area concentrates not only manufacturing industry and commerce near the cities, but also coffee plantations and other large-scale agricultural areas.

The GDP of departments in the Caribbean Region is based upon mining, small-scale agriculture, and cattle farming. La Guajira and Cesar are the two largest producers of coal, while Córdoba is the largest nickel producer. Despite having some departments rich in minerals, this region nevertheless has a high incidence of poverty, particularly in Córdoba and Sucre.

The Pacific Region comprises, relative to the Colombian average, three poor departments and one wealthy one (Valle del Cauca). Chocó, which is the poorest department in this region and in the country, is predominantly rural and sparsely populated, with large tropical rain forests and humid areas. It is known as the rainiest area in the country (and even one of the rainiest worldwide) and is geographically isolated from the rest of the country due to a chain of mountains to the east and the ocean to the west. Transport of population living in the department is largely done by way of its abundant affluents and rivers; road infrastructure is minimal. The scarce literature explaining socio-economic factors in this department argues that the current distribution of population and the quality of institutions may largely be explained by the early settlement of an extractive economy during colonization, at which time colonizers brought slaves to exploit gold mines but did not establish themselves in the department (Bonet, 2007). As opposed to Chocó, Valle del Cauca is the third largest departmental economy in the country after Bogotá and Antioquia and has some of the most productive agricultural areas, as well as a high level of participation in the manufacturing sector.

During the last 30 years, production was driven in some departments by the discovery of important mineral resources, as is the case for the departments of Arauca and Casanare, which have the largest oil fields in the country.[2] The same applies for La Guajira, which has the largest open coal mine in Latin America.

According to Meisel (2007b), the burden of poverty in Colombia is geographically located in the coastal departments and inequality is greater between departments than within them. Meisel argues that the urban-versus-rural divide is not the relevant dimension upon which to design poverty-alleviating programs, but the departmental one. Moreover, Meisel affirms that the already-large disparities have increased over the past 15 years and will not spontaneously disappear merely as a result of market forces.

The level of empirical research addressing regional disparities in Colombia has increased gradually since the early nineties, inspired by the international debate on convergence and the methodology proposed by Barro and Sala-i-Martin (1991). Since then, approximately 20 papers have investigated whether departments, regions, or even major cities have converged over time. Important shortcomings in this field arise due to the absence of consistent time-series data allowing for a long-term perspective. As a consequence, results frequently depend upon how the researcher combined the available time series, as well as on the methodology and control variables used, with no robust and undisputed evidence concerning departmental convergence.

Debate in this field revolves around two issues: first, a methodological discussion as to whether or not to rely on the methodology proposed by Barro and Sala-i-Martin (1992a) or on the distributional approach proposed by Quah (1993b), and second, whether one should use information generated by Departamento Nacional de Estadísticas (DANE), rather than by Centro de Estudios Ganaderos (CEGA).[3]

Early studies used Barro-type regressions. The pioneer work of Cárdenas and Pontón (1995), combining early GDP data by department from the National Planning Department

[2] These departments are included in our sample as one group named Nuevos Departamentos (Nuevos), meaning new departments. The so-called New Departments are distributed in the south-east lowland plains, the Amazon Region, and the Caribbean islands. Excepting the islands, these departments are large in extension but have low population densities.

[3] DANE is the official statistical agency in Colombia (http://www.dane.gov.co/).

with those produced by DANE, concluded that between 1950 and 1990, Colombia was a successful case of convergence with a 4-percent speed of convergence, and that migration played an insignificant role in convergence. Alternative combinations of data from DANE yield different results, despite using the same methodology. For instance, Barón (2003) finds convergence during the eighties but not during the nineties. Research using kernel density estimators concluded that Colombia was a case of polarization with the existence of three groups: a wealthy one that diverges from the average national income, a middle income one that shows convergence inside the group, and a third one that grows more impoverished over time (Birchenall and Murcia, 1997). Using CEGA data, research points to polarization in favor of the capital district of Bogotá, to the detriment of departments located in the peripheries (Bonet and Meisel, 2006b). Almost all studies focus only upon convergence in income, while only three ask for convergence in living standards using social indicators.[4]

The reader is than confronted with the question of whether Colombia is a successful case of convergence or rather an example of hopeless persistence unless strong regional redistributive policies are adopted.[5]

Intuitively, when observing the different geographic conditions of the country and the agglomeration processes around the largest cities, as well as the differences in infrastructure, it is unrealistic to expect that poor departments can catch up with leading departments in terms of per capita product, given that they lack basic infrastructure and have a minor manufacturing and government presence.

However, there are mechanisms that could have promoted convergence among departments in recent years. One of them is fiscal equalization through central government transfers. Starting in the mid eighties, the government implemented a decentralization program to reduce the burden of spending by the central government. This process accelerated with the new constitution of 1991 which established a new system of transfers in

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[4] A comprehensive list of convergence studies in Colombia can be found in Aguirre (2008). We deal with regional convergence in social indicators in Colombia in a companion paper (Branisa and Cardozo, 2009).

[5] Research using alternative methodologies and looking for linkages among regions found that Colombia has limited spatial interdependency (Haddad, Perobelli, Bonet, and Hewings, 2008).

order to increase the efficiency of social expenditures, as well as the supply of social services, compensated municipalities with weak financial capacities, and increased political power and the participation of local governments in the implementation of health and educational policies (Departamento Nacional de Planeación DNP, 2002; Rojas, 2003; Barrera and Domínguez, 2006). As a result, social spending increased from 7 to 15 percent between 1991 and 2001. Moreover, starting in the eighties, the model of industrialization through import substitution changed to the policy of liberalization of the economy, reduction of tariffs, and integration into the world markets in order to increase competitiveness, productivity, and economic growth. This shift also accelerated after the constitutional reform.

Another possible mechanism for convergence is migration. In general, the country underwent an important urbanization process in recent decades encouraged by industrialization around urban centers and a higher orientation towards export markets. Labor mobility was a combination between voluntary migration for economic gain (which profited from increasing returns to scale in the manufacturing sector) and forced migration due to violence, which migration helped enlarge informal markets. Migration from rural to urban areas accelerated during the twentieth century. The percentage of population which is urban changed from 59 percent in 1973 to 75 percent in 2005 due not only to a transformation from a predominantly agriculture-based economy to a services and industry-based one, but also due to conflict, violence, and a lack of opportunities in rural areas (Murad R., 2003).

In this context, the substantive question we try to empirically answer in this study is whether or not Colombia was a case of convergence at the department level between 1975 and 2000. Thus, if poor departments had greater growth rates than wealthy ones over time and the gap between them decreased. Our interest relies upon closing the debate on the existence of convergence across departments in Colombia by analyzing methodological issues and data sources that may have had affected results up to now. One important motivation of this study is the policy implication that can result as a consequence of wrongly assuming that departments converge automatically over time.

In order to explain the importance of the data used and the possible combinations of time series, we explain in the next subsection the available data sources and the relevance of two variables, gross departmental product and gross personal disposable income, arguing that the second one is more appropriate for measuring convergence for well-being.

2.2 Data Issues Affecting Convergence Results in Colombia

There are two different data sources of departmental accounts in Colombia: Department of Statistics (DANE) and Centro de Estudios Ganaderos (CEGA).

DANE provides per capita GDP by department for three different periods: one for 1980 through 1996 in constant prices as of 1975, one for 1994 through 2000 in constant prices as of 1994, and a final one for 2000 through 2005 in constant prices as of 2000. The first period was calculated applying concepts of the System of National Accounts of 1986 (SNA-86) and used an indirect method for collecting information. The second period was calculated using the System of National Accounts of 1993 (SNA-93) and combined direct and indirect methods for collecting information.[6] The third period did not include illicit crops in its estimation and is also based upon SNA-93. The classification of sectors, transactions, concepts, and methodology changed considerably in the SNA-93 and allowed for the inclusion of illegal activities as part of the GDP (DANE, 2008).[7]

It must be noted that statistical offices use different techniques to produce consistent time series of national accounts, particularly when international guidelines change.[8] For instance, most (OECD) countries make regular revisions for short time periods (usually of about twenty years) to incorporate new available information and benchmark revisions, in order to provide users with consistent time series. In Latin America, only Chile and Perú offer consistent large time series of regional per capita GDP using statistical or interpolation methods (Serra, Pazmino, Lindow, Sutton, and Ramirez, 2006).

In Colombia, DANE collected information for some overlapping years using both

[6] Direct methods take departmental information by product whenever data sources are available. Indirect ones use national aggregates and assign each department a percentage of those aggregates.

[7] The main changes concern the measurement of value-added taxes, the reclassification of transactions in the government sector, changes to the capital account, and productivity levels for the banking, energy, and insurance sectors.

[8] Techniques can be broadly classified into four groups: detailed reworking, proportion methods, interpolation between benchmarks, and indicator methods.

methodologies, but did not construct a consistent time series based only upon one. Although users do not have enough information to consistently recompute long time series, they tend to rebase series and connect them using growth rates, which can be problematic.[9]

Comparison of the series for the overlapping years shows different departmental growth rates and a different evolution of the logarithm of the standard deviation, explaining why convergence results change depending on how and when the researcher linked the different data series. Note in Figure 6 that the annual standard deviation of the logarithm of GDP of the three series of DANE yields different patterns. In the series of 1980 to 1996, the standard deviation increases sharply starting in 1990, while in the series from 1990 to 2005, it remains close to 0.36 until 1997 and falls thereafter. Concerning the third time series (2000 to 2005), the trend is similar to the series for 1990 through 2005, but the level of the standard deviation is higher.

The CEGA project compiled information at the departmental level in Colombia from 1975 to 2000 using SNA-93 and presented a simplified system of national accounts. The project used mixed methods for collecting information, classified some particular products differently than DANE, and did not include illicit crops in the agriculture category. Departmental results coincide between CEGA and DANE from 1990 onwards because both use SNA-93 (there are, however, important differences before 1990). CEGA produced consistent time series of two key variables relevant for convergence analysis, gross departmental product, which we will call henceforth PDB, and gross departmental income, which we will refer to as IDB. The first variable reflects production by residents in each department, while the second reflects the primary income received by those residents. The difference between these variables is the net external income of residents. CEGA also provided time series of gross household disposable income by department, which we will call IDBH, and which is the result of households' income after subtracting taxes on property and rental income and net payments to the social security, and adding

[9] For instance, the Canadian statistical office explicitly prohibits users from simply rebasing series using growth rates due to the large methodological differences derived from changing to SNA-93, and argues that only the statistics office in charge may comply series using detailed accounting and recomputing information according to the new procedures (Lal, 1999).

other net current transfers. This variable is a more accurate measure of a population's welfare than per-capita PDB, as it reflects household income after paying taxes and having received transfers from public and private social projects.[10]

Due to the advantages provided by the CEGA database, and as this database is the only consistent time series covering a long time span, we present results and discussion on convergence for per capita PDB and IDBH.[11] Our final data set covers the period of 1975 to 2000 for 23 departments, the capital district of Bogotá, and the nine "New Departments" grouped into one observation, for a total of 25 units and 25 years. [12]

To calculate per capita figures of both PDB and IDBH, we use the latest available population data, computed after reconciliation of the census of 2005 with previous censuses. According to the census of 2005, population is less than what had been forecasted using the 1993 census due to a lower birth rate and increased external migration (DANE, 2007). Although in most of the departments population was overestimated, there are some particular cases in which the contrary situation applies. We use yearly population data at the departmental level from DANE (2007) for the years 1985 to 2000, and for the years 1975 to 1985, we interpolated departmental population using the annual growth rate from 1973 to 1985 based on the 1973 census. The obtained values show a consistent evolution of population by department once connected to the official estimates from 1985 onwards.

Box plots of per capita PDB and IDBH in logs are shown in Figures 2 and 3. Box plots of relative PDB and relative IDBH in logs are shown in Figures 4 and 5. By relative we mean that the variables are expressed as ratios to the national average of the corresponding year. We can see that the ordering of departments is similar in both types of graphs, in levels and relatively, particularly in the upper and lower ends. The five departments with the lowest per capita PDB are Chocó, Sucre, Córdoba, Nariño, and Cauca, four of these being located on the Pacific Coast. Bogotá, Valle, Antioquia, Nuevos Departamentos, and

[10] The abbreviations used refer to the original names in Spanish are Producto Departamental Bruto (PDB), Ingreso Departamental Bruto (IDB) and Ingreso Departamental Bruto (disponible) de los Hogares (IDBH).

[11] As will be explained in the next section, it would be best to work with data expressed as per unit of effective worker, but due to data availability, researchers often use per capita figures.

[12] The New Departments have existed formally since the 1991 constitutional reform when nine former intendancies and commissariats were acknowledged as departments (Amazonas, Arauca, Casanare, Guainía, Guaviare, Putumayo, San Andrés y Providencia, Vaupés, and Vichada).

Cundinamarca have the five highest PDBs. Concerning per capita IDBH, departments with the lowest values are almost the same, excepting Santander instead of Nuevos. The box plots show large variability in per capita figures of Guajira in both PDB and IDBH and low variability for Bogotá. This pattern is accentuated in figures relative to the average, as well as for the group of Nuevos and observing PDB. On the contrary, the log of per capita IDBH shows less variation and dispersion of values, but a higher difference between the richest and the poorest departments. Note also that the group of Nuevos Departamentos has large variability in PDB. That variability is not visible in IDBH. In the following two sections, we present two well-known approaches for testing for convergence-the classical approach to convergence analysis and the distributional approach.

3 The Solow Model and Its Estimation

3.1 The Solow Model

Empirical testing of convergence across economies is based upon the neoclassical growth model developed by Solow (1956)[13] in which economies have a transition dynamic towards the *steady state*, defined as a situation in which all variables per unit of effective worker remain unchanged over time. In the steady state, the ratio of capital to labor is constant given that the capital stock expands at the same rate as the labor force, and the capital expansion is sufficient to compensate for it.

The neoclassical growth model assumes diminishing returns to factors and constant returns to scale. Due to this assumption, real returns of factors adjust to bring about full employment of labor and capital. Technology is exogenous and is the only force that explains changes in output and capital per worker. Any capital-to-labor ratio different than the one needed in the steady state readjusts as time passes so that economies tend towards the steady state. The speed at which this happens is known as the convergence rate and is inversely related to the distance from the steady state (Durlauf, 1996).

Robert Barro and Xavier Sala-i-Martin suggest that smaller initial values of the capital-to-labor ratio k, under the framework of the neoclassical growth model, are associated

[13] The neoclassical model was also developed in the original works of Ramsey (1928) and Cass (1965).

with greater growth rates of the ratio production per worker (Barro and Sala-i-Martin, 1991, 1992a,b, 2004; Sala-i-Martin, 1996). They tested whether economies with lower capital per worker at a certain initial point in time grew more quickly in per-worker terms, using the following equation:

$$\log[\hat{Y}(t)] = (1-\exp^{-\beta^{*}t})\log(\hat{Y}^{*}) + \exp^{-\beta^{*}t} log[\hat{Y}(0)]), \tag{1}$$

where t represents time, β^{*} indicates how rapidly an economy's output per effective worker $\hat{Y}$ approaches its steady-state value $\hat{Y}^{*}$ in the neighborhood of the steady state. The corresponding definition of β^{*} with a constant saving rate s is $\beta^{*} = (1-\alpha)(x+n+\delta)$, where α is a constant representing the share of capital in production, n is the rate of population growth, x is the rate of exogenous growth, and δ is the depreciation rate. The speed of convergence is measured by how much the growth rate decreases as the capital stock increases in a proportional manner.[14] Equation 1 implies that the average growth rate of per-capita output Y over an interval from an initial time 0 to any future time T (higher than 0) is

$$\frac{\log[Y(T)/Y(0)]}{T} = x + \frac{(1-\exp^{-\beta T})}{T}\log[\hat{Y}^{*})/\hat{Y}(0)], \tag{2}$$

where x is the rate of technological progress or the steady-state growth rate.[15] Equation 2 also shows that the effect of the initial position $\hat{Y}(0)$ is conditioned on the steady-state position $\hat{Y}^{*}$ (conditional convergence) (Barro and Sala-i-Martin, 2004). The approach suggested by Barro and Sala-i-Martin (2004) is known as the regression approach or as the classical approach to convergence analysis (Sala-i-Martin, 1996; Magrini, 2004). There are two alternatives for applying this concept-testing for absolute convergence or for conditional convergence.

[14] Note that β^{*} is not the same as $\hat{\beta}$. It is the convergence rate in the proximity of the steady state and is determined by $(1-\alpha)$ for given values of x, n, and δ.

[15] Equation 2 indicates that the coefficient $(1-\exp^{-\beta T})/T$ declines, the higher T is for a given β, and as long as β is positive. Therefore, the average growth rate of Y decreases as $T \to \infty$ (and thus x) dominates the average growth rate. In contrast, for a given T, a higher β implies a higher coefficient $(1-\exp^{-\beta T})/T$.

3.2 Absolute Beta-Convergence

The concept of absolute beta-convergence (also known as unconditional convergence) is relevant for a group of closed economies that are structurally similar; they have the same values of the parameters x, s, n, and δ, and thus they have the same production function steady-state values k^* and Y^*. The only difference is the initial quantity of capital per person $k(0)$, which reflects past disturbances (wars, transitory shocks to production, etc.). Hence, economies with lower values of $k(0)$ and $Y(0)$ have unambiguously greater growth rates of k and Y. The estimation equation for absolute convergence is equation 2, omitting the $\hat{Y}^*$ term:

$$\frac{\log[Y_{i,t}/Y_{i,t-T}]}{T} = a - \frac{(1-\exp^{-\beta T})}{T}\log[Y_{i,t-T}] + w_{it,T}, \tag{3}$$

where $w_{it,T}$ represents the effect of the error terms w_t between dates t and T, i is the corresponding subscript for each region or country, and $a = x + (1-\exp^{-\beta T})\log(\hat{Y}^*)$. Absolute convergence arises when the term multiplying the initial income is negative, and implies that poor economies tend to grow more quickly than wealthy ones. One can estimate a regression with non-linear least squares (NLLS) to obtain the speed of convergence β directly.

3.3 Conditional Convergence

Conditional beta-convergence arises by allowing for heterogeneity across economies, particularly by dropping the assumption that all economies have the same parameters and the same steady state.[16] The main idea is that the further an economy is from its own steady-state value, the more quickly it grows:

$$\frac{\log[Y_{i,t}/Y_{i,t-T}]}{T} = a - \frac{(1-\exp^{-\beta T})}{T}\log[Y_{i,t-T}] + \gamma X_i + w_{it,T}, \tag{4}$$

[16] Under the assumption of different parameters, Equation 3 would provide biased estimates because the steady-state level of income $\hat{Y}_i^*$ would be correlated with the explanatory variable $\log[Y_{i,t-T}]$. To solve this problem, Barro and Sala-i-Martin (1992a) suggest incorporating into the regression a set of variables X_i as proxies for the steady-state level of income ($\hat{Y}_i^*$) and testing for conditional convergence.

where X_i is a set of variables that proxy for the steady-state level of income ($\hat{Y}_i^*$). Empirical studies show little evidence of unconditional convergence for large and heterogeneous samples of countries. Instead, they tend to find conditional convergence in economies with similar structural characteristics (Barro and Sala-i-Martin, 1991) with speeds of convergence usually around 2 percent. However, there is no agreement on which variables to include as proxies for the steady state, and their selection depends mostly upon the researcher interest. An extensive review made by Durlauf et al. (2005) shows a list of about 145 different regressors used in convergence literature and points out that most of them have been found to be statistically significant. These regressors are classified by Durlauf et al. (2005) into 43 distinct growth theories or growth determinants, raising doubts about their usefulness.

3.4 Parameter Heterogeneity: Are There Different Steady States?

An alternative way to estimate conditional beta-convergence is to remove the assumption of parameter homogeneity, as suggested by Canova and Marcet (1995) and Maddala and Wu (2000), using time-series cross-sectional (TSCS) data.[17]Advocates of this approach argue that the Barro-type growth regressions create biases in the estimated coefficients by pooling data whenever there is heterogeneity in the parameters. Moreover, cross-sectional regressions lead to a waste of information, since they ignore unit-specific time variations in growth rates and prevent the estimation of a steady state for each region or country separately (e.g. Lee, Pesaran, and Smith, 1997; Temple, 1999; Pritchett, 2000; Durlauf, 2001; Brock and Durlauf, 2001; Masanjala and Papageorgiou, 2004).[18]

Canova and Marcet (1995) propose a way to model heterogeneity and calculate steady states for each unit without proxying for the steady state of income with additional vari-

[17] For a description of time-series cross-sectional data, see, for example, Beck (2001) and Beck and Katz (2007).

[18] As indicated by Masanjala and Papageorgiou (2004), parameter heterogeneity in growth regressions has at least three interpretations: there are(i) multiple steady states, i.e., the parameters of a linear growth regression are not constant across countries (e.g. Durlauf, 1996), (ii) omitted growth determinants (e.g. Durlauf and Quah, 1999), and (iii) nonlinearities of the production function, i.e., the identical Cobb-Douglas aggregate production function may be unsuitable. After investigating the third interpretation, Masanjala and Papageorgiou (2004) conclude that using more general constant elasticity of substitution aggregate production functions does not explain away heterogeneity across countries, and they consequently suggest shifting attention to the other two interpretations.

ables. The model allows calculation of the speed of adjustment for each unit to its own steady state. A weakness of the approach is the need for the time dimension t to be large; otherwise, estimates will have large standard errors and their small sample distribution may strongly deviate from the asymptotic one. Using cross-country data, they find an average speed of adjustment to be close to 11 percent, but reject the hypothesis of equal steady states for all cross-sectional units.[19] Using an iterative Bayesian approach with a similar cross-country data set, Maddala and Wu (2000) find average annual convergence rates of around 5 percent and further argue in favor of different steady states for each country.

The estimation relies upon transforming equation 2 in discrete time as follows:

$$\log(y_{i,T}) = \alpha + \rho_T \log(y_{i,0}) + \gamma X_i + u_i, \tag{5}$$

where $y_{i,t}$ is *relative* output per worker, which will be defined below, $\rho_T = \exp^{-\beta T}$, $t = 0, 1, 2, \ldots, T$, and the variables X_i are introduced to allow for shifts in the limit of the steady state means of y_i. The key to allow for parameter heterogeneity relies in dropping the assumptions that $\beta_i = \beta$ and $\alpha_i = \alpha \; \forall_i$. The first assumption is expressed by $\rho_i \neq \rho$; that is to say, the convergence rates among all economies are allowed to be different. After grouping $\alpha_i = \alpha + \gamma X_i$, the final estimation is

$$\log(y_{i,t}) = \alpha_i + \rho_i \log(y_{i,t-1}) + u_{i,t}. \tag{6}$$

Note that both Canova and Marcet (1995) and Maddala and Wu (2000) use relative per worker (capita) output $y_{i,t}$ for the estimation, defined as $Y_{i,t}$, i.e., per capita output of region i in period t, divided by the national average of output per capita in year t. A value higher (or lower) than 1 means that the region has a higher (or lower) per-capita output than the national average. Using $y_{i,t}$ instead of $Y_{i,t}$ has the advantage that the linear trend term disappears, as it is assumed that in steady state all $y_{i,t}$ should grow at the same rate of technological progress, although the levels may vary. It also corrects for problems of serial and residual cross-unit correlation and avoids specifying a process for growth, that

19 According to Shioji (1997) their convergence rates are high due to the type of Bayesian approach and the short period used (10 years).

is, whether it is trend or unit-root with drift (Maddala and Wu, 2000).

For each region, Equation 6 is an AR(1) process of $log(y_{i,t})$. If $|\rho| < 1$, the time series is stationary and given that $E(log(y_{i,t})) = E(log(y_{i,t-1}))$, the mean of $log(y_{i,t})$ converges in a mathematical sense to $\frac{\alpha_i}{1-\rho_i}$ as $t \to \infty$. If $|\hat{\rho}| < 1$, one could estimate the expected value as

$$\hat{E}(log(y_{i,t})) = \frac{\hat{\alpha}_i}{1-\hat{\rho}_i}, \tag{7}$$

where $\hat{\alpha}_i$ and $\hat{\rho}_i$ are obtained from regressions based on Equation 6.

According to Maddala and Wu (2000), the condition $|\rho| < 1$ ensures that region i converges towards its own steady state and is equivalent to the definition of beta-convergence in Barro and Sala-i-Martin (1992a). As long as $|\rho| < 1$, the speed of adjustment of each unit to its own steady state is given by $1-\rho_i$.

Concerning the empirical estimation, and as discussed by Maddala and Wu (2000), equation 6 can be estimated by (i) pooling the data and assuming that $\forall_i\ \alpha_i = \alpha$ and $\rho_i = \rho$, (ii) running 25 separate regressions, one for each department, allowing for 25 α_i and ρ_i, or (iii) through shrinkage estimators that assume that α_i and ρ_i have two components, one fixed and one random. Additionally, one could estimate Equation 7, assuming that there is a fixed number of groups, allowing, for example, for three values of α and ρ, in other words, α_1, α_2, α_3 and ρ_1, and ρ_2 and ρ_3. The departments that belong to each group should be identified with the appropriate method.

We will estimate equation 6 following all the alternatives presented.

3.5 Sigma-Convergence

An alternative to evaluating beta-convergence is to focus on whether there is a reduction over time in the dispersion of real per-capita income across entities, indicating a more equitable distribution of income. This is called sigma-convergence and arises when for $T > 0$

$$\sigma_{t+T} < \sigma_t, \tag{8}$$

where σ_t is the standard deviation of real per-capita income in period t (Sala-i-Martin, 1996). The existence of beta-convergence tends to generate sigma-convergence. However, there are cases in which shocks affecting each entity differently lead to the existence of beta-convergence but the lack of sigma-convergence. The example given by Sala-i-Martin (1996) in this regard is clear. Assume two economies, one rich and one poor. The initial poor economy grows so quickly that in the final period its distance from the rich one is the same as before, except that now the poor economy is the wealthier. In such a case, the resulting standard deviation would be the same in the initial and final period. One would observe beta-convergence, given that the poor economy is growing more quickly than the rich one, but no sigma-convergence. Hence, sigma-convergence is an indicator of dispersion of the overall entities, but does not tell much about mobility of each one. Beta-convergence is thus a necessary, but not sufficient, condition for observing sigma-convergence.

4 Distributional Approach: Quah's Critique

One important critique to the standard regression approach was raised by Danny Quah (Quah, 1993a,b, 1996, 1997), who argues that neither beta nor sigma-convergence can deliver useful answers to the question of whether poor countries or regions are catching up to wealthier ones. Quah argues that the classical approach does not give any information about mobility, stratification, or polarization, and suggests that the typically obtained 2-percent speed of convergence is a statistical artifact that arises in moderate size samples for reasons other than convergence (Durlauf et al., 2005). In his analysis using cross-country data, Quah finds some evidence of convergence clubs, but also evidence of poor countries becoming progressively poorer and wealthy countries, even wealthier.

Quah initially suggested working with a sequence of income distributions and, after discretizing the space of income values, counting the observed transitions into and out of the distinct cell values to construct a transition probability matrix (Quah, 1993a,b). Later, Quah (1997) argued that the discretization could distort dynamics if the underlying observations are indeed continuous variables. He proposed thinking of the distinct cells as tending towards infinity and towards the continuum, with the transition probability matrix tending to a matrix with a continuum of rows and columns, that is, becoming a stochastic kernel.[20]

The methodology is based upon tracking the evolution over time of the entire cross-sectional distributions across regions through the estimation of kernel densities for "relative" variables, which means that the variables of interest are expressed as being relative to the national average, allowing abstraction from changes in the mean when one evaluates how the distribution changes.

Before we define how we proceed to test for convergence using the distributional approach, we briefly present some concepts needed for our estimation.[21]

For the distributional approach, all variables are expressed relative to the Colombian value. Additionally, we take the logarithm of the relative variable, as it facilitates the comparison to the national level. Expressed in logs, a relative value equal to 0 indicates that the department has the same value as the country, while a value that is, for example, equal to -0.05 means that the value of the department is 5 percent lower than the national value.

A univariate kernel density estimate may be regarded as a generalization of a histogram:

$$\hat{f}_h(q) = \frac{1}{mh} \sum_{i=1}^{n} \kappa \left(\frac{q - Q_i}{h} \right), \tag{9}$$

where κ is a kernel, m is the number of observations, and $h > 0$ is the bandwidth, also called the smoothing parameter.[22] In the context of growth convergence, we are interested in checking whether we find unimodality or multimodality in the estimated densities of the logarithm of relative income, and in what way the estimated densities change between the starting and the final period.

Bivariate kernel density estimation requires two-dimensional data and a two-dimensional

[20] For a technical derivation of a stochastic kernel see Quah (1997, section 4).

[21] A review of the statistical principles of univariate and multivariate kernel density estimations can be found, for example, in Härdle, Müller, Sperlich, and Werwaltz (2004).

[22] Kernel refers to any smooth function satisfying the conditions $\kappa(q) > 0$, $\int \kappa(q)dq = 1$, $\int q\kappa(q)dq = 0$, and $\sigma_\kappa^2 \equiv \int q^2\kappa(q)dq > 0$ (Wasserman, 2006).

kernel. Here, $Q = (Q_1, Q_2)^T$ and the kernel K maps $\mathbb{R}^2$ into $\mathbb{R}_+$. The estimate is

$$\hat{f}_H(q) = \frac{1}{m} \sum_{i=1}^{m} \frac{1}{det(H)} K\{H^{-1}(q - Q_i)\}, \tag{10}$$

where K is a bivariate kernel function, m is the number of observations, and H is a symmetrical bandwidth matrix.

For the analysis of convergence, we estimate the bivariate kernel density for the relative variable in two periods and check whether or not a large portion of the probability mass remains clustered around the 45-degree diagonal, which would indicate persistence in the distribution. We present the 3D representation of the estimated bivariate density and a contour plot showing the highest density regions.

5 Empirical Estimation and Results

We empirically test for convergence in PDB and IDBH, using both the classical and distributional approaches to convergence, as we are interested in checking if, in the Colombian case, there is a contradiction of the results obtained when employing both approaches, as suggested by the existing literature on Colombia. We do not use population weights in our calculations, as we are interested in investigating whether or not departments that were lagging behind have been able to catch up, and consider this to be a pertinent question in the Colombian case where departments are important political entities, with elected local governments and separate department assemblies.

Our empirical analysis begins with the classical approach, testing for sigma and beta-convergence. In the case of beta-convergence, we test absolute and conditional convergence. Conditional convergence is tested with cross-sectional regressions with control variables and also with AR(1) regressions using time-series cross-sectional data for relative income, starting with a pooled model that assumes homogeneity in the parameters and then allows for heterogeneity.

We then follow the distributional approach and compute univariate and bivariate kernel density estimators for relative income in 1975 and 2000.

5.1 Sigma-Convergence

Results of sigma convergence are presented in Figure 7. As may be observed, there exists evidence of sigma-convergence in IDBH but not in PDB. From 1975 to 1984, the standard deviation of the log of both variables remains close to 0.40. From 1985 onwards, IDBH decreases and has a value close to 0.32 in 2000. On the contrary, PDB remains around 0.40. Thus, the distribution of IDBH has become more equitable, while the distribution of PDB has not.

5.2 Absolute Beta-Convergence

Figure 8 shows a weak inverse relationship between the growth rate of per-capita PDB between 1975 and 2000 and its value in 1975. Cross-sectional regression results based upon Equation 3 and using NLLS are shown in Table 2. We use HC3 robust standard errors as proposed by Davidson and MacKinnon (1993) to account for possible heteroscedasticity, considering that the number of observations is small (Long and Ervin, 2000). The estimated speed of convergence is 0.7 percent, but it is not significantly different from 0 at the 5 percent level. The adjusted R-squared of the regression is extremely low (0.01) suggesting that this model does not explain departmental PDB growth rates. These results do not change if one excludes Chocó, Nuevos, and Guajira, which have a large influence on results, as suggested by Cook's distance computed after the first regression (Figure 9).

In the case of IDBH, Figure 10 shows a stronger negative relationship between the growth rate of per-capita IDBH between 1975 and 2000 and its value in 1975. This is confirmed with the regression presented in Table 3, where the estimated speed of convergence is 1.2 percent and statistically significant. The adjusted R-squared is 0.35. Excluding Guajira, as suggested by Cook's distance, and then rerunning the regression yields similar results.

Hence, we find evidence of absolute beta-convergence using IDBH, but not using PDB.

5.3 Conditional Beta-Convergence Using Control Variables

As explained in Subsection 3.3, one may drop the assumption that all economies have the same parameters, and hence the same steady state, and try to proxy for the steady-state level of income with a set of variables X_i, running regressions based upon Equation 4.

There is no agreement as to which variables to include as proxies for the steady state with cross-sectional data (Durlauf et al., 2005). We use variables that are based upon theoretical arguments and our choice is limited by data availability at the departmental level. We use the logarithm of population growth and a variable based upon saving rates.[23] Additionally, we use three variables proxying for human capital: log of life expectancy in 1975, log of literacy in 1973, and log of net enrolment rate in 1985. Several specifications for the average growth rate of per-capita PDB are shown in Table 4 and for per-capita IDBH in Table 5.[24]

Results for PDB show that the speed of convergence remains statistically insignificant in all the specifications, including the variables proxying for the steady state, as was the case with absolute convergence. We find no evidence of conditional convergence using PDB data.

In the case of IDBH, where we find evidence of absolute convergence, once we include variables X_i proxying for the steady-state level of income, the speed of convergence turns insignificant. We find no evidence of conditional convergence using IDBH data.

5.4 Beta-Convergence Using Time-Series Cross-Sectional Data

Recall that with TSCS data, the regression is based upon Equation 6, defined in subsection 3.4 as

$$\log(y_{i,t}) = \alpha_i + \rho_i \log(y_{i,t-1}) + u_{i,t},$$

which uses the measure of relative income $y_{i,t}$, that is, income of each department expressed as the ratio to the national average. One may estimate the equation in several

[23] As the saving rates that are available from CEGA (2006b,a) include values that are negative, we add a constant to all values, so that the transformed data are all positive and we can compute the logs.

[24] The number of departments included depends upon data availability

ways. First, we begin by pooling the data, assuming homogeneity in the parameters. Second, we use linear mixed models where the parameters are assumed to have a fixed component, common to all departments, and a random part. Third, we estimate 25 separate ordinary least squares(OLS) regressions for each entity. Finally, we assume that there are several groups of departments which share the same α and ρ, and explore this issue with finite mixture models.

In all cases, the key issue is whether the estimated value for ρ is lower than 1, which would suggest that there is economic convergence.

5.4.1 Pooled Data and OLS

The assumption of $\alpha_i = \alpha$ and $\rho_i = \rho \ \forall_i$ in Equation 6 is equivalent to assuming that there is a common steady state to all departments. Hence, the results are comparable to those obtained using cross-sectional data when we tested for absolute beta-convergence in subsection 5.2.

Tables 6 and 7 present the results for PDB and IDBH using TSCS pooled data and estimating with OLS. In both cases, the estimated ρ is less than 1 (0.989 for PDB and 0.986 for IDBH). However, it must be noted that while the value 1 is not included in the 95 percent confidence interval of ρ for IDBH, it is included for PDB, confirming the evidence of absolute convergence in IDBH, but not in PDB.

For IDBH the implied estimated speed of convergence β, computed with the estimated ρ value, is 1.4 percent, slightly higher than the one observed using cross-sectional data in Section 5.2.

5.4.2 Mixed Models

We follow here a frequentist approach for the estimation of Equation 6. Following Maddala, Trost, Li, and Joutz (1997) and using matrix notation, we define

$$Z_i = \begin{pmatrix} \log(y_{i,1}) \\ \vdots \\ \log(y_{i,T}) \end{pmatrix}, \quad X_i = \begin{pmatrix} 1 & \log(y_{i,0}) \\ \vdots & \vdots \\ 1 & \log(y_{i,T-1}) \end{pmatrix}, \quad b_i = \begin{pmatrix} \alpha_i \\ \rho_i \end{pmatrix}, \text{ and } \quad U_i = \begin{pmatrix} u_{i,1} \\ \vdots \\ u_{i,T} \end{pmatrix},$$

with $i = 1, \ldots, N$, where N is the number of regions in the data.

We consider the autoregressive regression model

$$Z_i = X_i b_i + U_i, \qquad i = 1, \ldots, N, \tag{11}$$

with the assumptions $U_i \sim N(0, \sigma_i^2 I)$, and $b_i \sim N(\mu, \Sigma)$, where I is the identity matrix and Σ is a nonzero covariance matrix. [25] We further assume that the U_i are independent across the N equations, and that b_i and U_i are independent for different regions.

We work with a linear mixed model (McCulloch and Searle, 2001). If we write b_i as $b_i = \mu + \eta_i$, with $\eta_i \sim N(0, \Sigma)$, we can rewrite $Z_i, (i = 1, \ldots, N)$ as

$$\begin{aligned} Z_i &= X_i(\mu + \eta_i) + U_i \\ &= X_i\mu + X_i\eta_i + U_i \qquad (12) \\ &= X_i\mu + w_i, \qquad (13) \end{aligned}$$

with $w_i \sim N(0, \Omega_i)$, Ω_i being the variance covariance matrix defined as

$$\Omega_i = X_i \Sigma X_i' + \sigma_i^2 I. \tag{14}$$

In Equation 12, the vector μ represents the fixed effects and η_i represent the random effects. In linear mixed models, fixed effects are used for modeling the mean of the response variable and the random effects are used to model the variance-covariance structure of it (McCulloch and Searle, 2001). The parameters in our linear mixed model are then μ, Σ, and σ_i^2. The last two parameters are in fact variance components, as presented in Equation 14.

One can obtain an estimator for μ and best-linear unbiased predictors for the random effects η_i with maximum likelihood or restricted maximum likelihood (REML). [26] Here, we prefer REML for three reasons: (i) the estimators are based upon taking into account the degrees of freedom for the fixed effects in the model, (ii) because of its unbiasedness in the case of balanced panels, and (iii) as REML estimators seem to be less sensitive to outliers in the data.[27] With the obtained values for μ and η_i, one could compute the

[25] The results of the estimation assume no special structure of the matrix Σ.

[26] For the algorithms used for obtaining maximum likelihood and restricted maximum likelihood estimates in the case of a linear mixed model, see Pinheiro and Bates (2000).

[27] For a review of linear mixed models and a discussion of the estimation with maximum likelihood and

estimated values for the N differently from α_i and ρ_i.

We are interested in the estimation of the fixed effects. As was mentioned before, the literature suggests that in some cases, the estimated β can be substantially higher than the one obtained by assuming there are no random effects. We also compare the results with those assuming homogeneity in the parameters using likelihood ratio tests and the Akaike information criterion (AIC) in order to investigate if a more flexible model allowing for heterogeneity in the parameters should be preferred.

Results for PDB are presented in Table 8. The estimated coefficients for the fixed effects are similar to the coefficients estimated when assuming homogeneity in the parameters (Table 6). In the case of ρ, the estimated value for the linear mixed model is 0.984, close to the value 0.989 obtained with OLS and assuming no random effects. It must be noted that the standard error of the fixed effect of ρ is higher than for the coefficient estimated in the model assuming homogeneity in the parameters. The estimated standard deviations of both random effects are quite low, especially the one for α, with a value close to 0, suggesting there is no evidence of different steady states. The value for the Akaike information criterion for the linear mixed model is larger than for the simpler model, assuming parameter homogeneity, and hence the simpler model is preferred. This is also corroborated by a likehood ratio test.

Table 9 shows the results for IDBH. Once again, the coefficients for the fixed effects are close to the ones obtained with the model in the previous section, in which we assumed parameter homogeneity (Table 7), with ρ equal to 0.986 in both cases. The estimated standard deviations of both random effects are low, in particular the one for α, which is close to 0, giving no support for the existence of different steady states. The AIC suggest that the simpler model is better, which is confirmed with a likelihood ratio test.[28]

REML, see McCulloch and Searle (2001).

[28] Although it is possible to calculate the implied speed of convergence for each department, the interpretation is difficult. For illustrative purposes, we present them in Tables 10 for PDB and 11 for IDBH. The associated speeds of convergence have a larger variability for PDB than for IDBH. The average speed of convergence is 1.6 percent for PDB and 1.4 percent for IDBH).

5.4.3 Separate Regressions for Each Department

We also treat all departments as separate entities and run an AR(1) regression for each one. These separate regressions shed light upon the effect of past values on current values, but due to the low amount of observations for each department (25 years), estimations are not reliable. In Table 12, we present results for PDB. The slope coefficient ρ is lower than 1 for all departments but has large standard errors and is not significant at the 5-percent level for Cauca and Boyacá.[29] The resulting speeds of convergence are implausibly high with values ranging from 10 to 60 percent in the case of PDB, a result influenced by the fact that the period only covers 25 years. Results for IDBH are similar (Table 13).

The graphical analysis of each time series is more informative. In Figure 12, we plot the individual time series for relative PDB in logs for all departments. We observe that in almost all departments, the values change little over time and the series seem stationary. They remain either above or below the national average with the exception of Guajira and Nuevos. The time series do not become closer to the national value over time, except for Guajira, indicating a lack of economic convergence among departments.

Results for IDBH (Table 12) show that most of the time series seem stationary. Interestingly, the wealthiest department, Bogotá, moves slightly closer to the national average, as does as the poorest department, Chocó. Guajira, although becoming closer to the national average, still remains below it.

5.4.4 Mixture Models

In the previous sections, we estimated a model assuming that α and ρ are the same for all departments. We then allowed these parameters to be different for each department, in the context of a linear mixed model, where the parameters are assumed to have a fixed component, common to all departments, and a random part. Then, we estimated 25 separate AR(1) regressions, one for each department.

Another possibility is that there are several groups of departments which share the same α and ρ. We explore this possibility with a finite mixture model, as described

[29] The expected value can be calculated when $|\rho| < 1$ and is relevant if $t \to \infty$, so that $E(log(y_{i,t}))$ approaches $\frac{\alpha_i}{1-\rho_i}$.

in Leisch (2004) and Grün and Leisch (2008). These types of models can be applied, assuming that observations originate from various groups, where the group affiliations are unknown. Finite mixture models with a fixed number of components are estimated with the expectation-maximization (EM) algorithm within a maximum likelihood framework.

We assume three groups and fit the model with the statistical software R (R Development Core Team, 2008) and the package *flexmix* (Leisch and Grün, 2008). Results for PDB and IDBH are presented in Tables 14 and 15. We show estimated α and ρ for each group of departments, as well as the departments composing each group.

Results for PDB (Table 14) show that Group 1 includes many of the poorest departments (e.g., Chocó, Sucre, Nariño, and Córdoba), Group 2 is composed of Nuevos Departamentos and La Guajira, and Group 3 includes the richest departments (e.g., Bogotá, Valle, and Antioquia).[30] Estimated values for α and ρ are similar for Groups 1 and 3, with α being negative and close to 0 and ρ being close to 0.99, a result that is similar to the estimated value obtained in subsection 5.4.1, assuming homogeneity in the parameters. The implied speed of convergence for these two groups is close to 1 percent. If one believes in the validity of the estimated expected value of the time series, one would expect that departments belonging to Group 1 would remain well below the national average over time, while those from Group 3 would remain below, as well, but would be closer to it. As was discussed before, Nuevos Departamentos and La Guajira experienced high growth rates between 1975 and 2000, associated with the production of oil and coal. The model captures this, suggesting that both departments are far from their steady states, showing a large implied speed of convergence (10 percent), and predicting that both would remain above the national average.

Concerning IDBH (Table 15), the grouping of departments is similar as above, with Group 1 including many of the poorest departments and Group 3 including the richest ones. Group 2 now includes Nuevos Departamentos, La Guajira, and Sucre. Groups 1 and 3 have values for the estimated α that are quite similar to one another, and close to 0. Values for the estimated ρ are also similar with 0.98 for Group 1 and 0.99 for Group 3,

[30] Mixture models are only identifiable up to a permutation of the component labels (Leisch, 2004). The names, Group 1, Group 2, etc., have no special meaning here, and the order of the groups is irrelevant.

both being close to the estimated value obtained, assuming homogeneity in the parameters (Subsection 5.4.1). Nuevos Departamentos, La Guajira, and Sucre have values for α and ρ that are different than those from the other two groups (-0.01 for α and 0.96 for ρ). Once again, the model suggests that these departments are far from the steady state, with an implied speed of convergence of 4 percent, which speed is greater than that for Groups 1 (2 percent) and 3 (1 percent). Once again, with an analyzed time period of only 25 years, it is questionable whether one should rely upon the estimated expected values.

5.5 Kernel Density Estimators

All the results for kernel density estimations were computed with the statistical software R (R Development Core Team, 2008) and the package *ks*.[31] For both univariate and bivariate kernel density estimations, we use Gaussian kernels and smoothed cross validation bandwidth selectors[32] (Jones, Marron, and Park, 1991; Duong and Hazelton, 2005). In the bivariate case, the smoothed cross validation is unconstrained, meaning that we do not impose that the (nonsingular) bandwidth matrix H has to be diagonal in Equation 10. Hence, we are able to handle correlation between components, as we allow kernels to have an arbitrary orientation (Wand and Jones, 1995). As we are especially interested in checking whether a large portion of the probability mass remains clustered around the 45-degree diagonal, this flexibility is relevant for us. If we were to impose a diagonal matrix H, only kernels which are oriented to the coordinate axes would be allowed.

Univariate kernel density estimations of the logarithm of relative departmental PDB for the years 1975 and 2000 are shown in Figure 16. Both densities seem unimodal and are very similar. Thus, according to this figure, there were almost no changes in the distribution. Bivariate kernel-density estimators are presented in Figures 17 and 18. Both figures make clear that most of the mass is concentrated along the 45-degree diagonal and hence support persistence in the distribution. Departments with a relative GDP that was above (or below) average in the year 1975 tend to remain above (or below) average

[31] *ks* is currently the most comprehensive kernel density estimation package in R (Duong, 2008). All the estimations were done with the function *kde*.

[32] We have also tried direct plug-in methods as suggested by Sheather and Jones (1991) and obtained results that are not very dissimilar.

in 2000. Two interesting cases are La Guajira and Nuevos Departamentos, as they show some mobility. Nuevos Departamentos was close to the national average in 1975 and is clearly above the average in 2000, while La Guajira was clearly below the national average in 1975 and is quite close to it in 2000.

Turning to results using the logarithm of relative departmental IDBH, Figure 19 presents the univariate kernel estimators for the years 1975 and 2000, showing a slight shift of the distribution to the right in 2000. The distribution narrowed between 1975 and 2000 and the two modes observed in 1975 in the left and right tails of the distribution almost disappeared in 2000. Bivariate kernel density estimators in Figures 20 and 21 show some mobility, as well. In the contour plot (Figure 21), the mass of the distribution rotates slightly clockwise, suggesting mild convergence in the distribution.

6 Conclusions

Returning to the questions raised at the beginning of the study, we do not find absolute or conditional convergence in PDB using the regression approach. The distributional approach shows persistence in the distribution, i.e., relative to the average, each department remains in the position where it was located in 1975. Results of both methods point in the same direction-there is no convergence but persistence in PDB does exist.

Analysis of IDBH shows absolute convergence using the regression approach. After testing different models allowing for parameter heterogeneity, we found that there is no evidence of the existence of different steady states. The pooled model using TSCS provides our preferred estimators. Bivariate kernel density estimators show some improvements in the distribution. However, the changes are small and consistent with the low speed of convergence of around 1.4 percent.

Different factors explain our results. Differences in geography, infrastructure, and population density among departments are relevant factors to explain lack of convergence in PDB, as are differences in production structures and value added by department. Excepting for the mining departments, the different production structures remained almost unchanged between 1975 and 2000 (Table 16).[33] However, mineral exploitation in Colombia is relatively recent, going back only to the mid eighties, and this fact explains why the group of Nuevos and the department of La Guajira are the only initial poor departments that grew more quickly than the wealthier departments, according to PDB data. Previous literature had already pointed to the fact that once the mining departments are excluded, any hint of convergence disappears (Birchenall and Murcia, 1997) and that departments with a high share of agricultural production had the lowest growth rates (Bonet, 1999). Three departments concentrated at least 50 percent of PDB in both evaluated years: Antioquia, Bogotá, and Valle del Cauca. These three departments combined produced 65 percent of the manufacturing output in 1975 and 60 percent in 2000. The stability of the shares in other sectors is also remarkable, indicating departmental concentration and low mobility of production factors across the country.

At least two of the assumptions of the Solow model, which is the usual theoretical framework for studying convergence, seem problematic for application to the Colombian case. First, the neoclassical model assumes mobility of factors, which is in this case constrained by geographic, climatic, and infrastructural issues, as well as by the internal conflict issue. For instance, several productive sectors periodically suffer from attacks by violent groups, not only on physical capital, but also human capital through kidnapping and extortion. Second, the assumption of constant returns to scale is an oversimplification that does not hold for all sectors in the economy. As has been argued by World Bank (2009), while returns to scale in agriculture tend to be constant, those in manufacturing and services are increasing.

The slow convergence observed in IDBH can be explained by recent redistributive policies, particularly higher public spending in social sectors and infrastructure. Literature dealing with the direct link between convergence and public spending is scarce, but suggests that it affected the relative position of some departments, although not the distribution as a whole (Ardila Rueda, 2004), and that efficiency of public spending has been decreasing over time, mainly due to political interests and corruption.

[33] Nuevos Departamentos increased its participation from 11 percent of the total in 1975 to 55 percent in 2000.

Summary of Results

	Per capita income measure used	
	PDB	IDBH
Classical Approach: Convergence?		
Sigma	No	Yes
Absolute Beta	No	Yes
Conditional Beta Cross Sections	No	No
Conditional Beta Pooled TSCS assuming homogeneity of parameters	No	Yes
Distributional Approach		
Univariate Kernel Estimators	Distribution Unchanged	Dispersion Decreases
Bivariate Kernel Estimators	Persistence in the Distribution	Suggests slow Convergence

Note: Results for conditional beta convergence with TSCS data and for the distributional approach based on relative values, i.e., ratios to the national level.

Increased social spending has also benefited from mining sector revenues which are distributed across all departments through the fiscal system.[34] IDBH of mining departments is still very low and did not exhibit the high growth rates observed in PDB.[35] One reason for this is that fiscal decentralization began in the late eighties and the reforms are thus still too recent to be fully evaluated. A second reason is that financial resources from mining sectors are not efficiently spent because of corruption and are not sufficient to compensate for the low starting point in income of these departments. Recall that in 1975, La Guajira was the second poorest department in Colombia and that a large part of its population is indigenous and poorly linked to the departmental economy. Previous

[34] Oil revenues are divided between direct and indirect revenues and correspond to about eight to 25 percent of total extracted crude oil income. Direct revenues are those given to producing departments, municipalities, and ports of exports basically to finance investment in social sectors, and account for about 76 percent of oil revenues. Indirect revenues are those distributed among non-producing departments (Hernández, 2004).

[35] Producing departments are obliged to spend at least 50 percent of the received mining revenues on social investment until having achieved certain minimum thresholds for infant mortality, health care, education, water, and sanitation. Indirect revenues are distributed according to projects presented through territorial entities (Law 141 of 1994).

research suggests that even if revenues of coal exports in La Guajira were distributed efficiently and without any corruption-related loss (corruption levels seem to be particularly high in mining departments), IDB of that department would still be about 60 percent of national IDB in 2000(Meisel, 2007a).

Although overall public spending has increased, the transfer system bears some disadvantages for poor departments. Evidence shows that after totaling all public revenue (not only that directed to social sectors), there is no fiscal equalization in Colombia and the system is regressive; wealthy municipalities have the highest shares of public funds.

Two other issues have to be taken into consideration for interpreting the results of both PDB and IDBH. One is that in 2000, our last year of analysis, the country was experiencing a large economic crisis which affected public and private finances. Transfers from the central government were thus also affected by the crisis. A second issue is related to the domestic conflict. Between 1998 and 2002, violence escalated dramatically when the groups involved in the war were fighting one other for control of strategic areas. Sánchez and Palau (2006), who deal directly with this last issue, argue that decentralization policies, political and fiscal, affected the interests of armed groups and even strengthened them through the sharp increase in local resources. The higher political autonomy at the local level increased the ability of armed groups to intimidate politicians and to extract rents from public funds. Guerrillas relocated in strategic zones with greater levels of prosperity, the facility for processing illicit drugs, and an intimidated local population (Sánchez and Palau, 2006).

One of the policy implications of this study is the necessity of monitoring the efficiency of social spending and enforcing decentralization policies so that a faster convergence in IDBH can be achieved. Concerning convergence in PDB, reallocation of productive sector resources is not easy to achieve and could yield to efficiency losses, but the state can, for example, encourage the accumulation of human capital and improve infrastructure in lagging departments, which would help attract investments in the long run. Additionally, it is crucial to find a way out of the internal conflict to foster factor mobility in Colombia, particularly in those areas without significant state presence. We consider it vital to have an explicit regional policy in Colombia to foster growth in departments lagging behind national averages, after conducting case studies to assess which policies could be most effective in each case.

Finally, for monitoring convergence across departments in the future, it is essential to have consistent time series constructed under a single methodology. Unfortunately, the work done by CEGA for the period 1975 to 2000 did not continued for the years after 2000. Such a project is of high policy relevance for the country.

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Tables and Figures

Table 1: Colombia. Gross Domestic Product (Constant Million Pesos of 1994), Per Capita GDP and Population. 1980-2006.

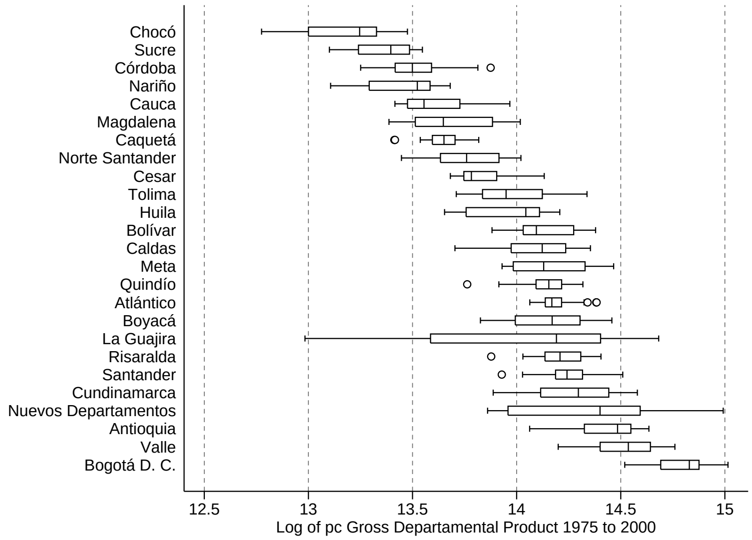
Year	**GDP (million)**	**Per capita GDP**	**Growth rate**	**Population**	**Growth rate**
1980	40822304	1503335		27154504	
1981	41846404	1503069	-0.02	27840636	2.53
1982	42160220	1476873	-1.74	28546950	2.54
1983	42820420	1462737	-0.96	29274176	2.55
1984	44217404	1472781	0.69	30023068	2.56
1985	45475604	1476748	0.27	30794424	2.57
1986	48189708	1533078	3.81	31433316	2.07
1987	50775504	1582200	3.20	32091720	2.09
1988	52808848	1611804	1.87	32763808	2.09
1989	54544940	1630958	1.19	33443488	2.07
1990	56873928	1666658	2.19	34124536	2.04
1991	58222936	1671462	0.29	34833548	2.08
1992	60757528	1710026	2.31	35530176	2.00
1993	64226880	1773819	3.73	36208244	1.91
1994	67532864	1832015	3.28	36862624	1.81
1995	71046216	1895088	3.44	37489664	1.70
1996	72506824	1904234	0.48	38076640	1.57
1997	74994024	1940536	1.91	38646044	1.50
1998	75421328	1923949	-0.85	39201320	1.44
1999	72250600	1817821	-5.52	39745712	1.39
2000	74363832	1846071	1.55	40282216	1.35
2001	75458112	1849177	0.17	40806312	1.30
2002	76917224	1861165	0.65	41327460	1.28
2003	79884488	1908947	2.57	41847420	1.26
2004	83772432	1977279	3.58	42367528	1.24
2005	87727928	2045484	3.45	42888592	1.23
2006	93881688	2162904	5.74	43405388	1.20

Source: Own calculations based on National Accounts and Census 2005, DANE

Figure 1: Map of Colombia.

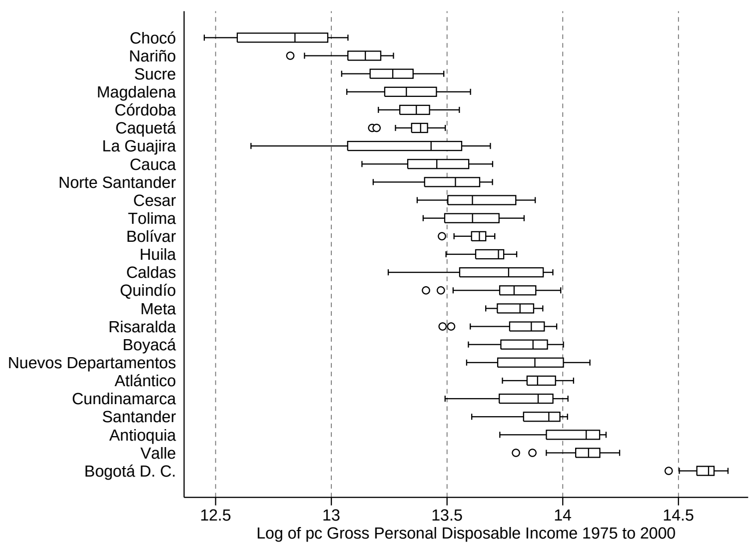
Source: Instituto Geográfico Agustín Codazzi.
Labels in its order of appearance: International Limit, Departmental Limit, Country Capital, Capital District, River, Water.

Figure 2: Box Plot: Log of Per Capita PDB. 1975-2000.



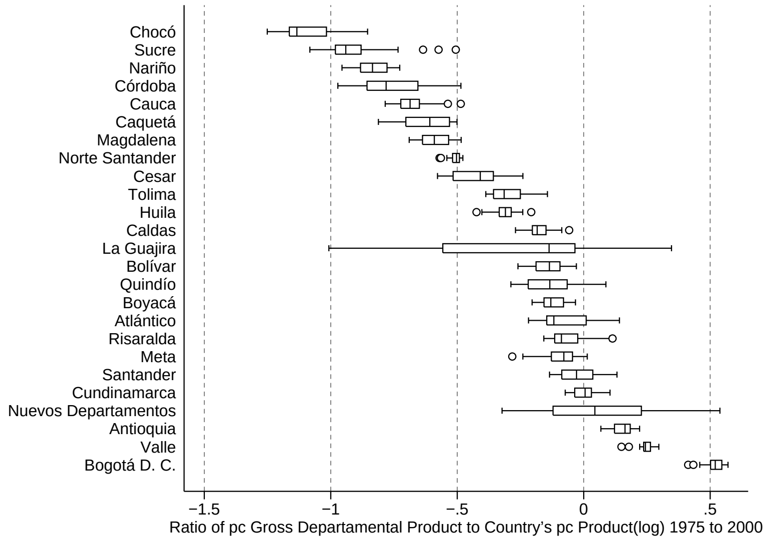
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 3: Box Plot: Log of Per Capita IDBH. 1975-2000.



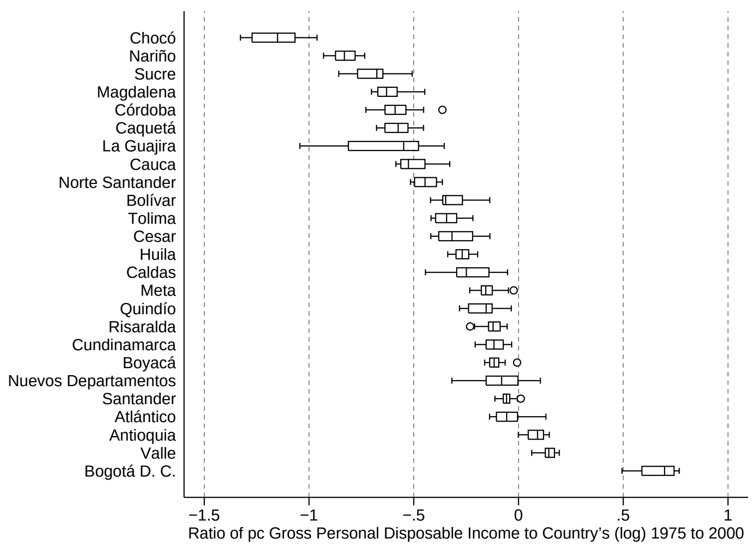
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 4: Box Plot: Log of Relative Per Capita PDB. 1975-2000.



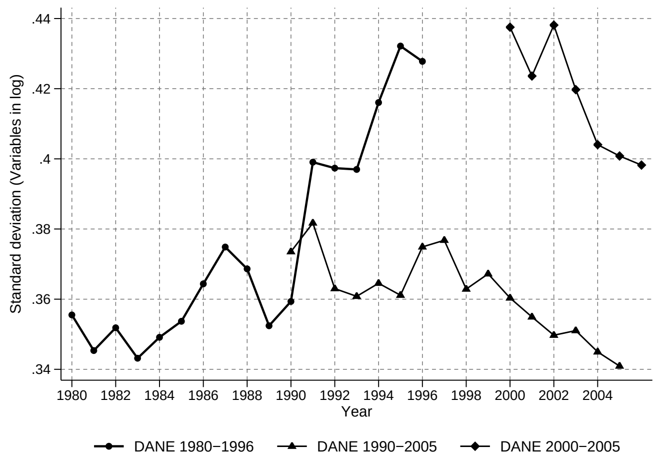
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 5: Box Plot: Log of Relative Per Capita IDBH. 1975-2000.



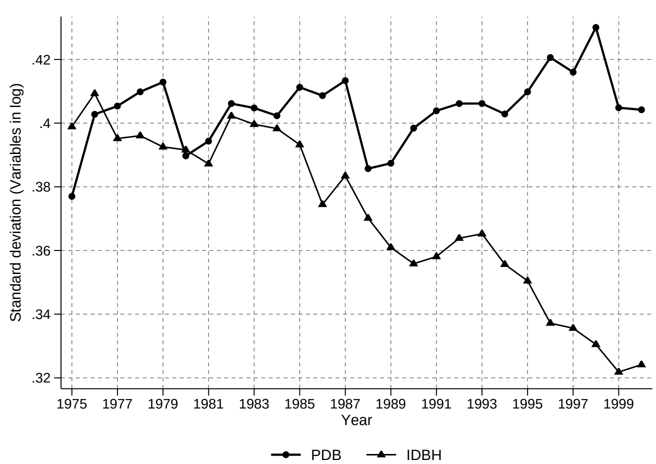
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 6: Sigma Convergence. GDP by Department.



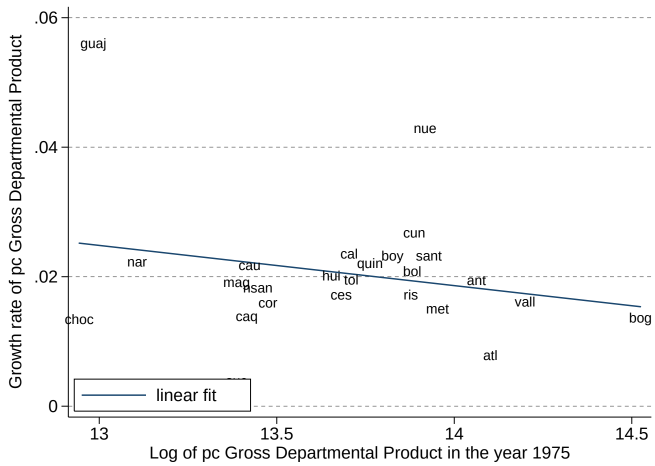
Source: Own calculations based on data from DANE.

Figure 7: Sigma Convergence. Per Capita Gross Departmental Product (PDB) and Gross Personal Disposable Income (IDBH). 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 8: Beta Convergence. Per Capita PDB. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

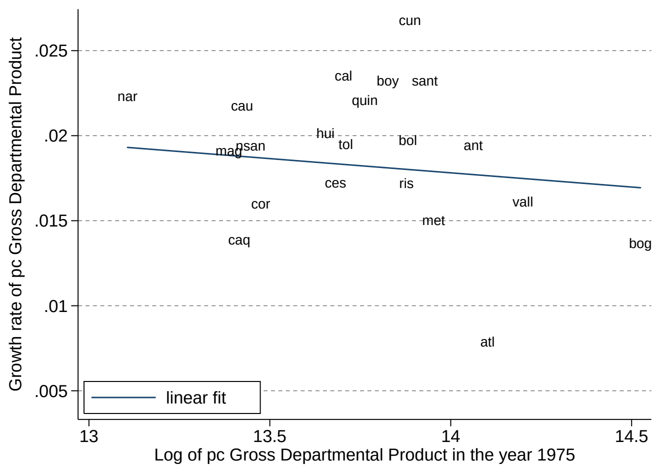
Table 2: Beta Convergence Using Cross-sections and Non Linear Least Squares. Dependent Variable: Average Growth Rate of pc PDB 1975-2000.

Variable	**Coefficient**	**Robust HC3 Std. Err.**	**95% conf. interval**	
Intercept	0.1055481	0.1258539	-0.1548005	0.3658967
β	0.0067474	0.0107561	-0.0155033	0.028998
β (%)	0.67			
Number of observations	25			
Adj.R-squared	0.0112			

Source: Own calculations based on data from CEGA. Constant prices of 1994.

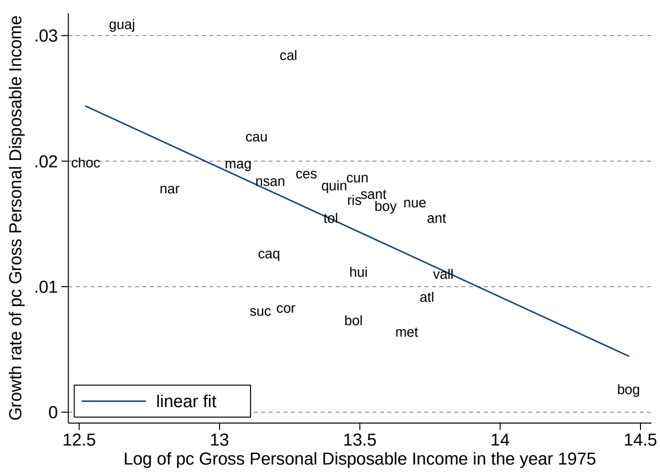
Source: HC3 standard errors calculated according to Davidson and MacKinnon (1993).

Figure 9: Beta Convergence without Nuevos, Chocó and Guajira. Per Capita PDB. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 10: Beta Convergence. Per Capita IDBH. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

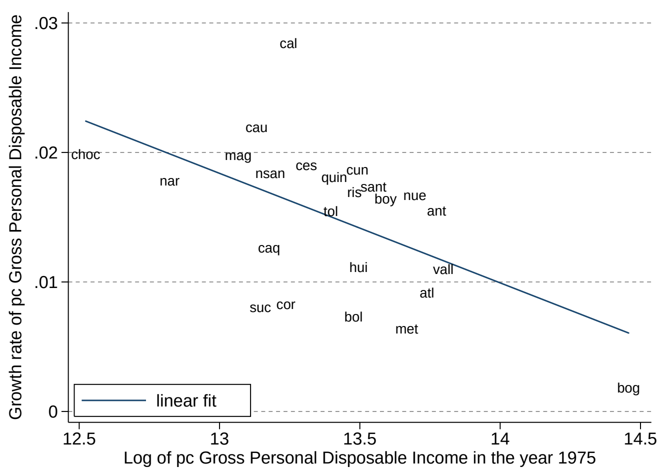
Table 3: Beta Convergence Using Cross-sections and Non Linear Least Squares. Dependent Variable: Average Growth Rate of pc IDBH 1975-2000.

Variable	Coefficient	Robust HC3 Std. Err.	95% conf. interval	
Intercept	0.1533007	0.0392428	0.0721207	0.2344807
β	0.0119014	0.0039056	0.003822	0.0199809
β (%)	1.19			
Number of observations	25			
Adj.R-squared	0.3514			

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Source: HC3 standard errors calculated according to Davidson and MacKinnon (1993).

Figure 11: Beta Convergence without Guajira. Per Capita IDBH. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 4: NLLS Regressions. Dependent Variable Average Growth Rate of pc PDB. 1975-2000.

Regressors	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
constant	0.1157	0.1534	0.3533	0.2753	0.2271
	(0.1306)	(0.4804)	(0.3071)	(0.2533)	(0.3062)
speed of convergence β	0.0076	0.0401	0.0186	0.0226	0.0375
	(0.0114)	(0.0809)	(0.0250)	(0.0278)	(0.0622)
log (life expectancy 1975)		0.0402	-0.0092		
		(0.1344)	(0.0785)		
log (literacy 1973)		0.0355		0.015	
		(0.0645)		(0.0367)	
log (transformed saving rate)		0.0017	0.0047	0.0036	0.0043
		(0.0059)	(0.0064)	(0.0086)	(0.0128)
log (population growth + 0.05)		0.0378	0.032	0.0293	-0.0009
		(0.0443)	(0.0373)	(0.0371)	(0.0313)
log (net enrollment rate 1985)					0.0342
					(0.0414)
Number of observations	24	24	24	25	24
R-square	0.06	0.31	0.28	0.24	0.31
Adjusted R-square	0.02	0.12	0.13	0.09	0.16

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: HC3 robust standard errors (Davidson and MacKinnon, 1993) in brackets.

Table 5: NLLS Regressions. Dependent Variable Average Growth Rate of pc IDBH. 1975-2000.

Regressors	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
constant	0.1574***	0.1272	0.335	0.1400	0.1233
	(0.0402)	(0.2917)	(0.1817)	(0.0962)	(0.1038)
speed of convergence β	0.0123**	0.0282	0.0135	0.0254	0.0262
	(0.0040)	(0.0280)	(0.0110)	(0.0126)	(0.0155)
log (life expectancy 1975)		0.0063	-0.0443		
		(0.0777)	(0.0485)		
log (literacy 1973)		0.031		0.0279	
		(0.0309)		(0.0161)	
log (transformed saving rate)		0.0007	0.0036	0.0009	0.0019
		(0.0033)	(0.0046)	(0.0021)	(0.0055)
log (population growth + 0.05)		-0.001	-0.0079	-0.0037	-0.0227
		(0.0224)	(0.0181)	(0.0183)	(0.0127)
log (net enrollment rate 1985)					0.0241
					(0.0171)
Number of observations	24	24	24	25	24
R-square	0.40	0.58	0.53	0.56	0.64
Adjusted R-square	0.37	0.47	0.43	0.48	0.56

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: HC3 robust standard errors (Davidson and MacKinnon, 1993) in brackets.

Table 6: OLS Linear Regression. TSCS Data. Dependent Variable $log(y_{i,t})$. Relative Per capita PDB. 1975-2000.

Variable	**Coefficient**	**Std. Err.**	**95% conf. interval**	
Intercept	-0.0022949	0.0032097	-0.008598	0.0040083
$log(y_{i.t-1})$	0.9890855	0.0069185	0.975499	1.002672
Implied β	1.09%			
Number of observations	625			
R-squared	0.9730			
AIC	-1632			

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 7: OLS Linear Regression. TSCS Data. Dependent Variable $log(y_{i,t})$. Relative Per Capita IDBH. 1975-2000.

Variable	**Coefficient**	**Std. Err.**	**95% conf. interval**	
Intercept	-0.0013856	0.0017381	-0.0047989	.0020276
$log(y_{i.t-1})$	0.9861798	0.0046479	0.9770525	0.9953072
Implied β	1.38%			
Number of observations	625			
R-squared	0.9867			
AIC	-2183			

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 8: Linear Mixed Model (REML). TSCS Data. Dependent Variable: $log(y_{i,t})$. Relative Per Capita PDB. 1975-2000.

Fixed effects		
Variable	**Coefficient**	**Std. Err.**
Intercept	-0.002679	0.003366
$log(y_{i,t-1})$	0.983587	0.008332
Random effects		
Standard deviation	**Estimate**	
Intercept	6.0571e-09	
$log(y_{i,t-1})$	0.016325	
Number of observations	625	
Number of groups	25	
AIC	-1606	

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 9: Linear mixed model (REML). TSCS Data. Dependent Variable: $log(y_{i.t})$. Relative Per Capita IDBH. 1975-2000.

Fixed effects		
Variable	**Coefficient**	**Std. Err.**
Intercept	-0.001425	0.002192
$log(y_{i,t-1})$	0.985925	0.004710
Random effects		
Standard deviation	**Estimate**	
sd(Intercept)	0.0000000	
$log(y_{i,t-1})$	0.0026213	
Number of observations	625	
Number of groups	25	
AIC	-2155	

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 10: Implied Convergence Rates Using TSCS Data and Linear Mixed Models (REML). Per capita PDB. 1975-2000

Department	Intercept α	Slope ρ	Implied β (%)	Expected Value
Nuevos Departamentos	-0.003	0.976	2.4	-0.111
Antioquia	-0.003	0.984	1.6	-0.168
Atlántico	-0.003	0.983	1.7	-0.156
Bogotá D. C.	-0.003	0.986	1.4	-0.197
Bolívar	-0.003	0.982	1.8	-0.149
Boyacá	-0.003	0.981	1.9	-0.140
Caldas	-0.003	0.981	1.9	-0.137
Caquetá	-0.003	0.990	1.0	-0.265
Cauca	-0.003	0.986	1.4	-0.193
Cesar	-0.003	0.986	1.4	-0.187
Córdoba	-0.003	0.989	1.1	-0.242
Cundinamarca	-0.003	0.983	1.7	-0.161
Chocó	-0.003	0.994	0.6	-0.483
Huila	-0.003	0.983	1.7	-0.162
La Guajira	-0.003	0.957	4.3	-0.063
Magdalena	-0.003	0.986	1.4	-0.194
Meta	-0.003	0.981	1.9	-0.143
Nariño	-0.003	0.988	1.2	-0.220
Norte Santander	-0.003	0.986	1.4	-0.192
Quindío	-0.003	0.977	2.3	-0.119
Risaralda	-0.003	0.982	1.8	-0.148
Santander	-0.003	0.982	1.8	-0.152
Sucre	-0.003	0.998	0.2	-1.095
Tolima	-0.003	0.983	1.7	-0.158
Valle	-0.003	0.985	1.5	-0.174
Mean			1.6	
Median			1.7	

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 11: Implied Convergence Rates Using TSCS Data and Linear Mixed Models (REML). Per capita IDBH. 1975-2000

Department	Intercept α	Slope ρ	Implied β (%)	Expected Value
Nuevos Departamentos	-0.001	0.986	0.0	-0.10
Antioquia	-0.001	0.986	1.4	-0.10
Atlántico	-0.001	0.986	1.4	-0.10
Bogotá D. C.	-0.001	0.986	1.4	-0.10
Bolívar	-0.001	0.986	1.4	-0.10
Boyacá	-0.001	0.986	1.4	-0.10
Caldas	-0.001	0.986	1.4	-0.10
Caquetá	-0.001	0.986	1.4	-0.10
Cauca	-0.001	0.986	1.4	-0.10
Cesar	-0.001	0.986	1.4	-0.10
Córdoba	-0.001	0.986	1.4	-0.10
Cundinamarca	-0.001	0.986	1.4	-0.10
Chocó	-0.001	0.987	1.3	-0.11
Huila	-0.001	0.986	1.4	-0.10
La Guajira	-0.001	0.985	1.5	-0.09
Magdalena	-0.001	0.986	1.4	-0.10
Meta	-0.001	0.986	1.4	-0.10
Nariño	-0.001	0.986	1.4	-0.10
Norte Santander	-0.001	0.986	1.4	-0.10
Quindío	-0.001	0.986	1.4	-0.10
Risaralda	-0.001	0.986	1.4	-0.10
Santander	-0.001	0.986	1.4	-0.10
Sucre	-0.001	0.987	1.3	-0.11
Tolima	-0.001	0.986	1.4	-0.10
Valle	-0.001	0.986	1.4	-0.10
Mean			1.4	
Median			1.4	

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 12: Autoregressive Processes of Order 1. Dependent Variable: $log(y_{i.t})$. Per Capita PDB. 1975-2000.

Department	Intercept (α) Coefficient	Intercept (α) Sdt.Error	Slope (ρ) Coefficient.	Slope (ρ) Std.Error	Regression Adjusted R^2	Expected Value	Implied β (%)
Nuevos Departamentos	0.03	0.03	0.85	0.14	0.62	0.21	14.75
Antioquia	0.06	0.03	0.65	0.16	0.41	0.16	35.48
Atlántico	-0.02	0.01	0.85	0.06	0.88	-0.15	14.99
Bogotá D. C.	0.08	0.09	0.84	0.17	0.52	0.48	16.10
Bolívar	-0.05	0.02	0.69	0.15	0.48	-0.14	31.16
Boyacá	-0.09	0.03	0.29	0.21	0.08		
Caldas	-0.11	0.03	0.39	0.18	0.17	-0.17	61.42
Caquetá	-0.16	0.08	0.76	0.13	0.58	-0.64	24.10
Cauca	-0.26	0.13	0.62	0.18	0.33	-0.68	38.31
Cesar	-0.07	0.04	0.85	0.10	0.77	-0.45	15.34
Córdoba	-0.18	0.09	0.77	0.12	0.66	-0.78	22.95
Cundinamarca	0.01	0.00	0.87	0.13	0.68	0.06	12.51
Chocóó	-0.37	0.17	0.67	0.16	0.45	-1.11	33.14
Huila	-0.11	0.05	0.66	0.16	0.43	-0.31	34.25
La Guajira	0.01	0.03	0.90	0.06	0.92	0.06	10.36
Magdalena	-0.29	0.11	0.52	0.18	0.27	-0.59	48.31
Meta	-0.04	0.02	0.67	0.15	0.48	-0.11	32.80
Nariño	-0.30	0.14	0.63	0.16	0.40	-0.83	36.65
Norte Santander	-0.47	0.11	0.09	0.21	0.01		
Quindío	-0.04	0.03	0.64	0.16	0.41	-0.12	36.26
Risaralda	-0.02	0.01	0.74	0.15	0.52	-0.07	25.89
Santander	0.00	0.01	0.86	0.11	0.71	0.01	13.89
Sucre	-0.24	0.09	0.75	0.10	0.72	-0.96	25.32
Tolima	-0.09	0.05	0.71	0.15	0.51	-0.30	29.06
Valle	0.05	0.05	0.80	0.20	0.41	0.23	19.61
Mean	-0.11		0.68				
Median	-0.07		0.71				

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Note: Expected values ($\alpha/(1-\rho)$) calculated only for ρ significant at 5% level and lower than 1.

Figure 12: Log of Relative PDB by Department. 1975-2000.

Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 13: Autoregressive Processes of Order 1. Dependent Variable: $log(y_{i.t})$. Per capita IDBH. 1975-2000.

Department	Intercept (α)		Slope (ρ)		Regression	Expected	Implied
	Coefficient	**Sdt.Error**	**Coefficient.**	**Std.Error**	**Adjusted R^2**	**Value**	**β (%)**
Nuevos Departamentos	-0.02	0.02	0.71	0.17	0.44	-0.08	29.39
Antioquia	0.02	0.01	0.86	0.11	0.74	0.11	14.22
Atlántico	-0.01	0.01	0.84	0.09	0.78	-0.07	15.57
Bogotá D. C.	-0.04	0.03	1.04	0.04	0.96		
Bolívar	-0.06	0.03	0.83	0.10	0.76	-0.35	16.92
Boyacá	-0.04	0.03	0.60	0.23	0.23	-0.11	39.76
Caldas	0.00	0.02	0.93	0.06	0.91	-0.01	6.81
Caquetá	-0.14	0.08	0.76	0.13	0.59	-0.58	23.54
Cauca	-0.02	0.06	0.95	0.12	0.75	-0.32	5.03
Cesar	-0.01	0.03	0.95	0.10	0.79	-0.19	5.30
Córdoba	-0.13	0.07	0.79	0.11	0.68	-0.60	20.87
Cundinamarca	-0.01	0.01	0.90	0.07	0.88	-0.07	9.80
Chocó	-0.08	0.12	0.92	0.10	0.78	-1.07	7.87
Huila	-0.09	0.04	0.68	0.13	0.52	-0.27	32.45
La Guajira	-0.07	0.05	0.86	0.07	0.86	-0.50	13.79
Magdalena	-0.03	0.07	0.95	0.12	0.73	-0.49	5.46
Meta	-0.05	0.02	0.71	0.10	0.67	-0.17	28.72
Nariño	-0.23	0.13	0.71	0.16	0.46	-0.82	28.68
Norte Santander	-0.05	0.05	0.87	0.10	0.75	-0.40	12.91
Quindío	-0.04	0.02	0.74	0.12	0.61	-0.15	25.57
Risaralda	-0.04	0.02	0.63	0.14	0.47	-0.11	36.51
Santander	-0.02	0.01	0.65	0.18	0.35	-0.05	35.48
Sucre	-0.19	0.09	0.74	0.13	0.60	-0.71	26.37
Tolima	-0.01	0.03	0.96	0.09	0.82	-0.27	3.53
Valle	0.03	0.02	0.79	0.16	0.51	0.14	20.62
Mean	-0.05		0.82				
Median	-0.04		0.83				

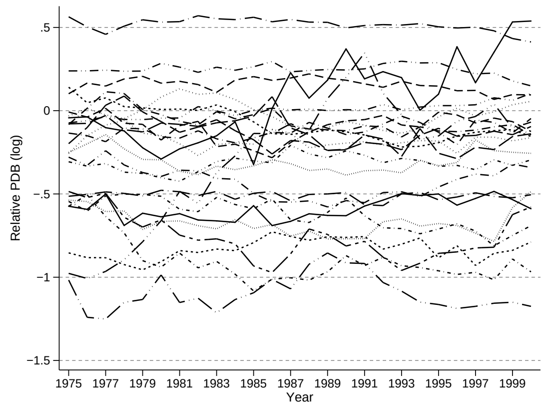
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Note: Expected values ($\alpha/(1-\rho)$) calculated only for ρ significant at 5% level and lower than 1.

Figure 13: Log of relative IDBH by department. 1975-2000.

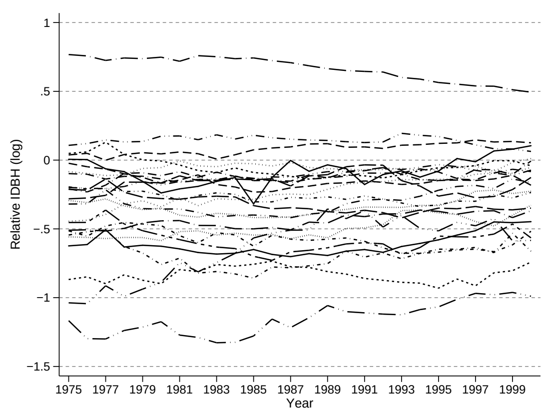
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 14: Log of Relative PDB. All Departments. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 15: Log of Relative IDBH. All Departments. 1975-2000.



Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 14: Mixture Model with 3 Components. Fitted with ML. Dependent Variable: $log(y_{i,t})$. Relative Per capita PDB. 1975-2000.

Department	Group	Intercept α	Slope ρ	Implied β (%)	Expected value
Bolívar	1	-0.007	0.988	1.168	-0.618
Boyacá	1				
Caldas	1				
Caquetá	1				
Cauca	1				
Cesar	1				
Córdoba	1				
Chocó	1				
Magdalena	1				
Meta	1				
Nariño	1				
Quindío	1				
Risaralda	1				
Sucre	1				
Tolima	1				
Nuevos Departamentos	2	0.015	0.900	9.986	0.153
La Guajira	2				
Antioquia	3	-0.001	0.990	1.045	-0.139
Atlántico	3				
Bogotá D.C	3				
Cundinamarca	3				
Huila	3				
Norte Santander	3				
Santander	3				
Valle	3				

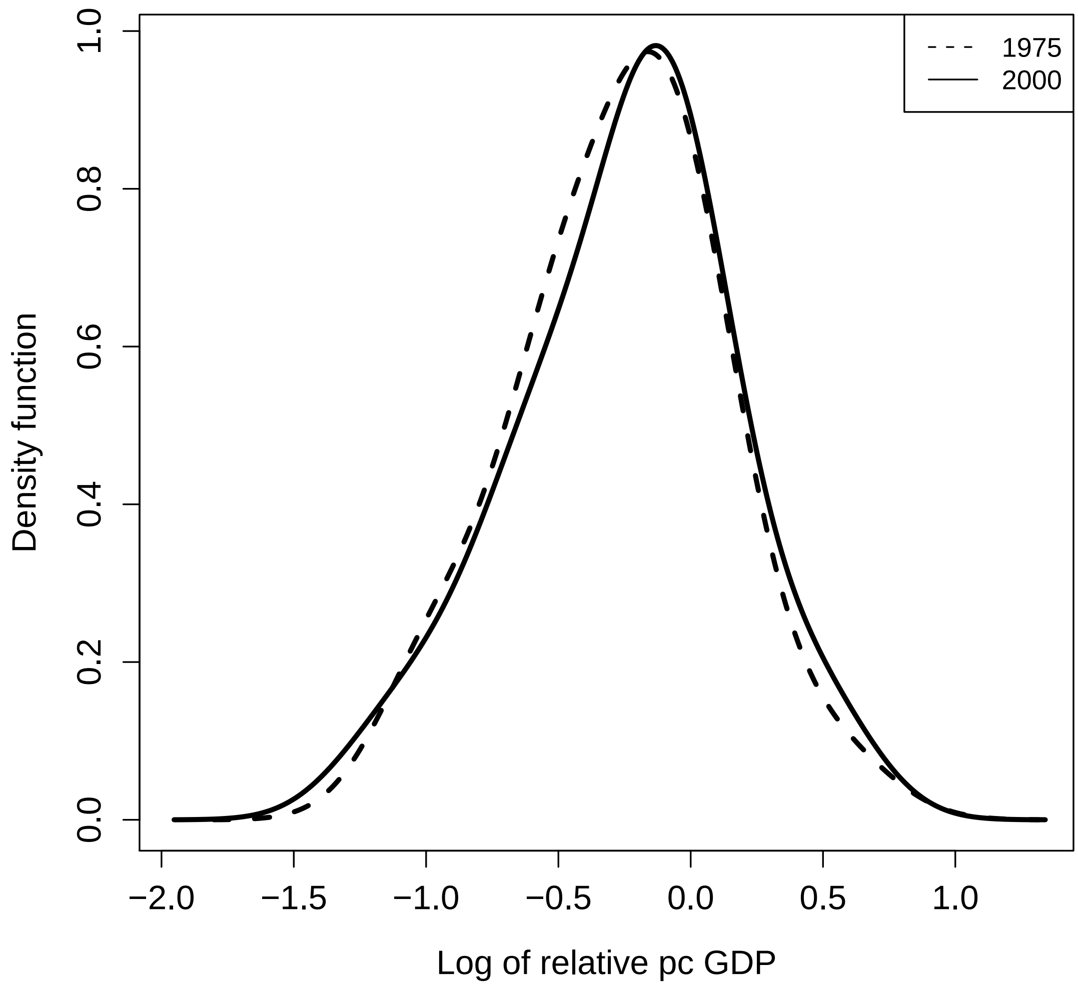
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Table 15: Mixture Model with 3 Components. Fitted with ML. Dependent Variable: $log(y_{i,t})$. Relative Per Capita IDBH. 1975-2000.

Department	Group	Intercept α	Slope ρ	Implied β (%)	Expected value
Bolívar	1	0.000	0.982	1.757	-0.004
Caquetá	1				
Cauca	1				
Cesar	1				
Córdoba	1				
Chocó	1				
Magdalena	1				
Nariño	1				
Quindío	1				
Nuevos Departamentos	2	-0.013	0.961	3.893	-0.325
La Guajira	2				
Sucre	2				
Antioquia	3	-0.003	0.988	1.174	-0.239
Atlántico	3				
Bogotá D.C	3				
Boyacá	3				
Caldas	3				
Cundinamarca	3				
Huila	3				
Meta	3				
Norte Santander	3				
Risaralda	3				
Santander	3				
Tolima	3				
Valle	3				

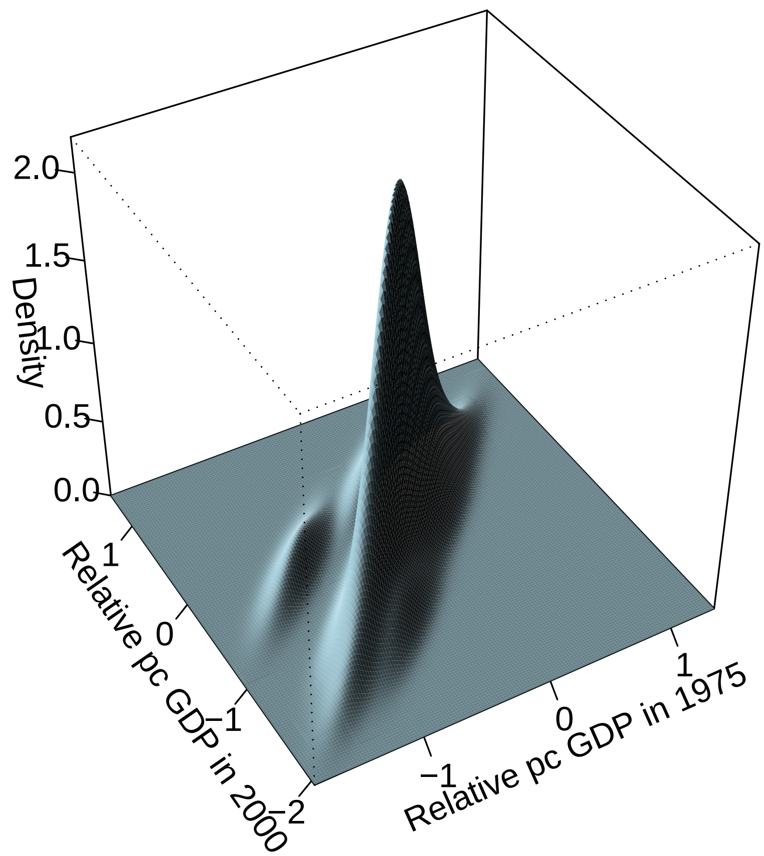
Source: Own calculations based on data from CEGA. Constant prices of 1994.

Figure 16: Univariate Kernel Density Estimators of Relative Per Capita PDB. Years 1975 and 2000. Constant Prices of 1994.



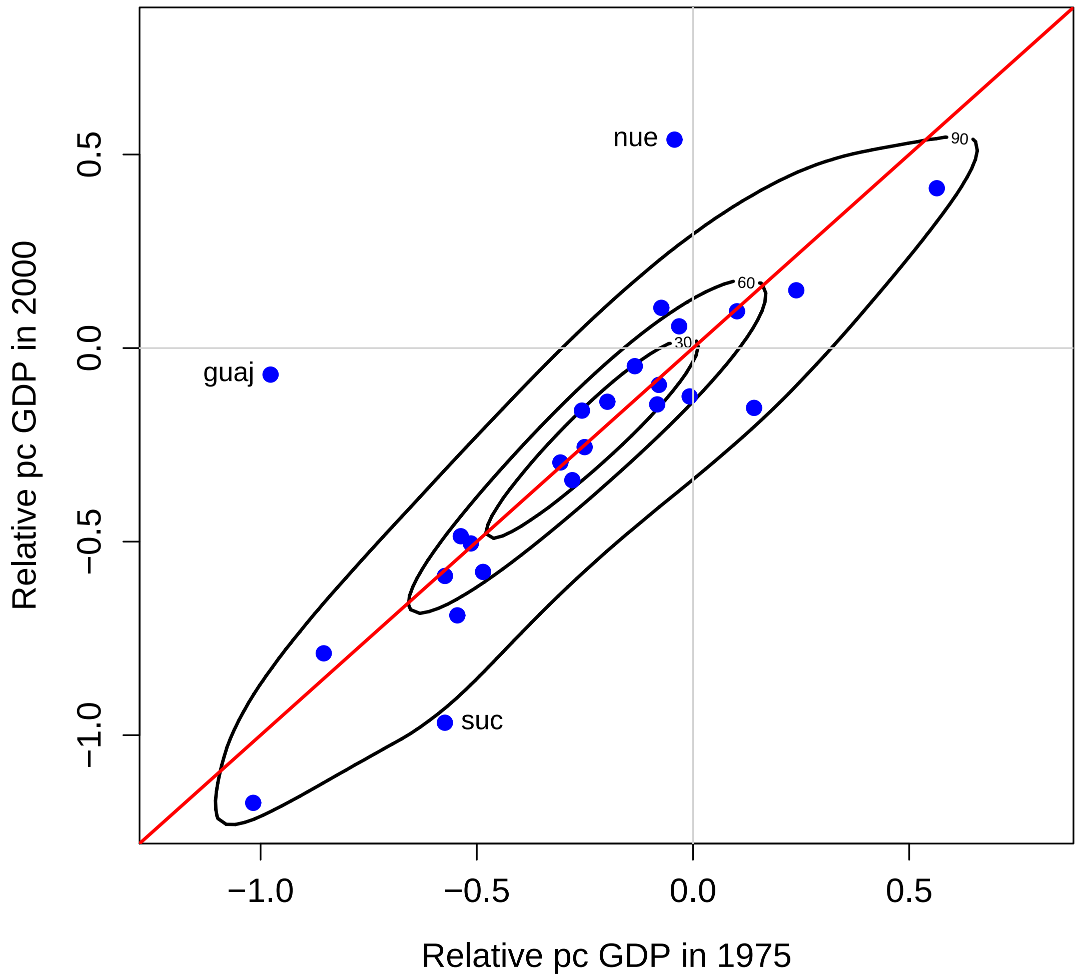
Source: Own calculations based on data from CEGA. Variables in logs

Figure 17: Relative Per Capita PDB Dynamics. Years 1975 and 2000. Constant Prices of 1994.



Source: Own calculations based on data from CEGA. Variables in logs

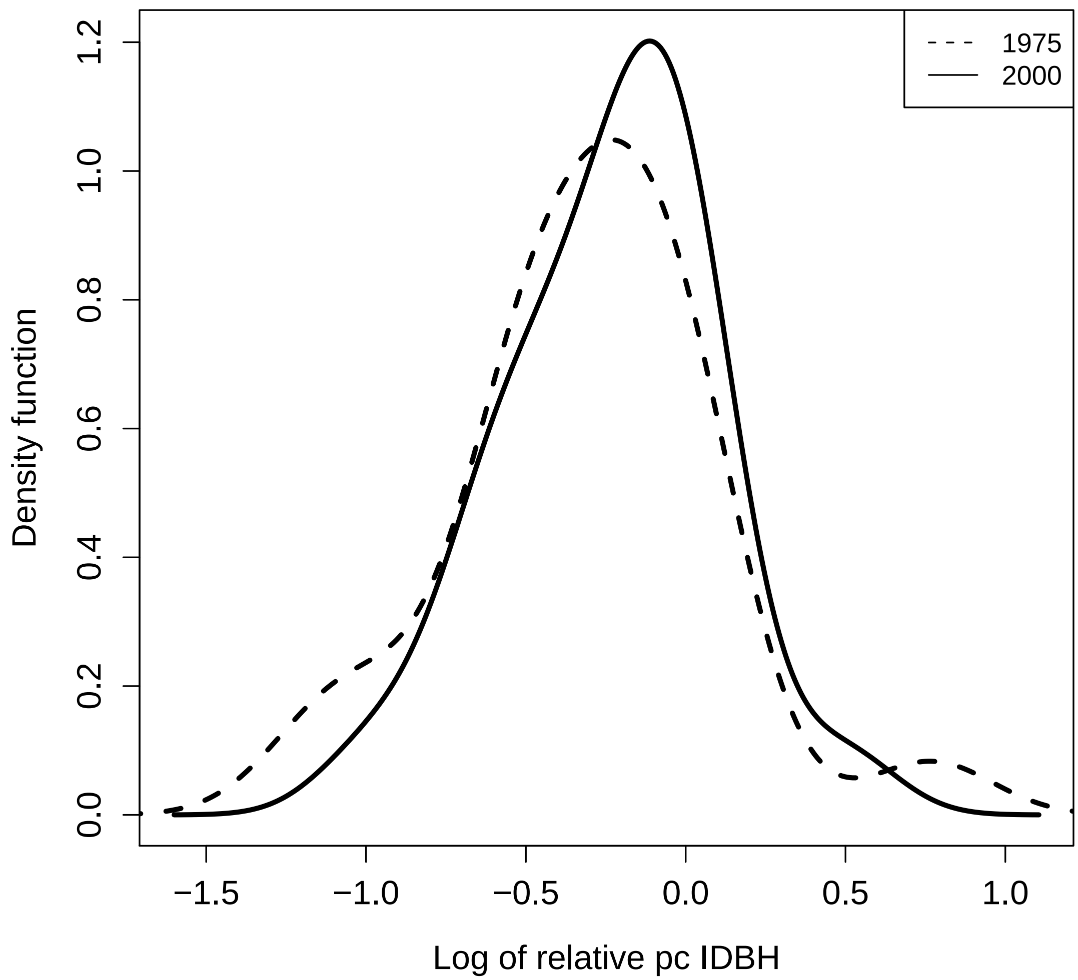
Figure 18: Relative per capita PDB Dynamics: Contour Plot. Years 1975 and 2000. Constant Prices of 1994.



Source: Own calculations based on data from CEGA. Variables in logs

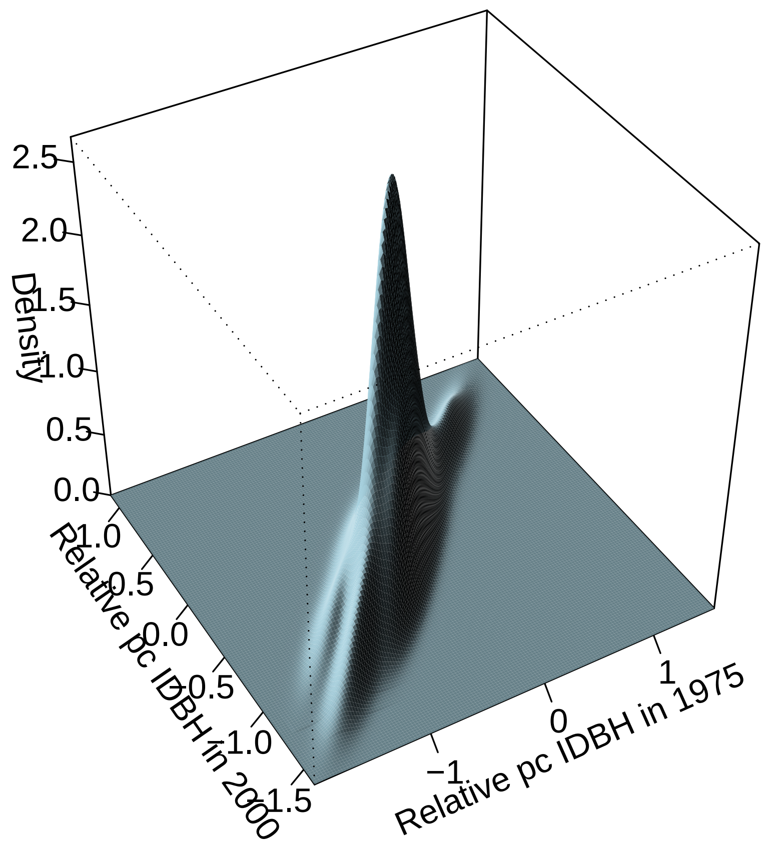
Note: Contours are drawn at 30%. 60%. and 90% which are upper percentages of highest density regions. The points represent the 25 observations. Points outside the 90% contour are identified. A 45 degree line is added to the plot.

Figure 19: Univariate Kernel Density Estimators of Relative per Capita IDBH. Years 1975 and 2000. Constant Prices of 1994.



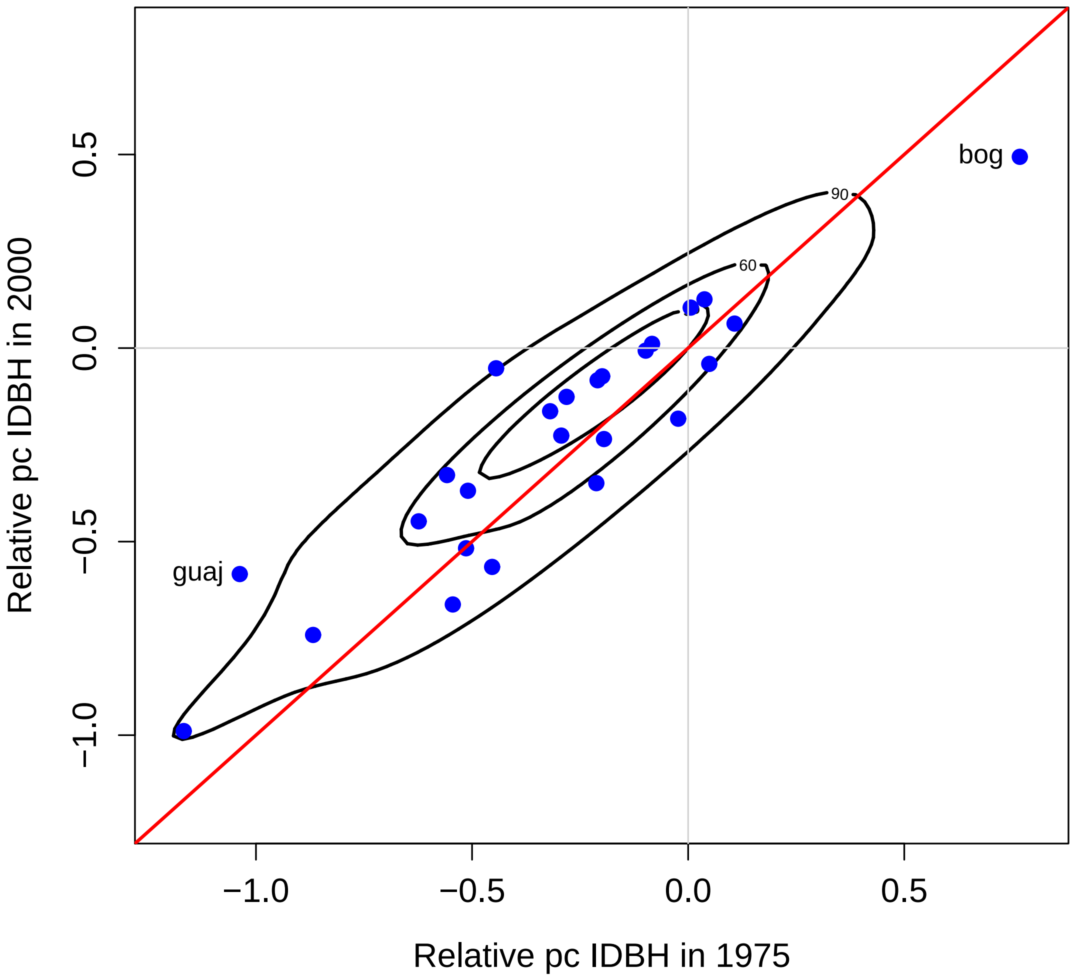
Source: Own calculations based on data from CEGA. Variables in logs

Figure 20: Relative Per Capita IDBH Dynamics. Years 1975 and 2000. Constant Prices of 1994.



Source: Own calculations based on data from CEGA. Variables in logs

Figure 21: Relative per Capita IDBH Dynamics: Contour Plot. Years 1975 and 2000. Constant Prices of 1994.



Source: Own calculations based on data from CEGA. Variables in logs

Note: Contours are drawn at 30%. 60%. and 90% which are upper percentages of highest density regions. The points represent the 25 observations. Points outside the 90% contour are identified. A 45 degree line is added to the plot.

Table 16: Share of Total PDB and Share of selected PDB Sectors by Department. Years 1975 and 2000.

	Percentage of total PDB		Agriculture		Mining		Manufacturing		Financing		Government		Commerce	
Department	1975	2000	1975	2000	1975	2000	1975	2000	1975	2000	1975	2000	1975	2000
Antioquia	15.3	14.4	12.2	13.9	21.3	4.0	21.0	18.0	14.1	15.7	15.5	10.9	18.4	16.9
Atlántico	5.3	4.3	0.8	0.7	0.0	0.0	7.5	6.1	4.8	4.0	2.7	3.4	6.4	5.1
Bogotá D.C	22.4	23.6	0.7	0.0	0.5	0.0	25.4	22.6	40.1	45.6	27.8	24.8	21.2	18.3
Bolívar	4.0	4.1	3.3	2.9	2.3	0.9	4.8	5.6	2.0	1.8	3.4	2.9	4.1	6.3
Boyacá	3.8	2.9	7.2	7.1	13.1	2.8	2.5	1.8	1.9	1.2	3.7	4.6	3.2	2.1
Caldas	2.5	2.0	3.7	2.6	0.7	0.1	2.2	2.0	2.3	1.8	2.4	2.9	2.0	1.9
Caquetá	0.5	0.5	1.2	1.6	0.0	0.0	0.1	0.0	0.1	0.2	0.7	0.9	0.2	0.2
Cauca	1.8	1.9	4.0	3.3	0.5	0.2	1.0	2.2	0.9	0.7	2.3	3.0	1.5	2.3
Cesar	1.6	1.5	3.7	3.0	0.0	5.5	0.6	0.4	1.3	0.5	1.2	1.8	1.5	0.9
Chocó	0.4	0.3	0.5	1.0	6.0	0.3	0.0	0.0	0.2	0.1	1.2	0.7	0.2	0.2
Córdoba	2.0	1.9	6.2	3.7	1.5	2.8	0.1	1.9	1.0	0.7	2.1	2.2	1.2	1.6
Cundinamarca	4.8	5.7	8.4	12.7	7.5	1.2	4.2	8.2	1.6	1.4	4.7	7.1	5.2	8.6
Guajira	0.4	1.3	0.6	0.6	3.6	12.3	0.1	0.0	0.4	0.3	0.6	0.8	0.3	0.1
Huila	1.6	1.7	3.1	2.5	1.5	5.4	0.4	0.6	1.2	1.0	2.0	2.3	1.1	1.1
Magdalena	1.8	1.5	3.6	3.4	1.9	0.0	0.4	0.3	1.1	0.7	1.8	1.9	1.0	0.8
Meta	1.2	1.5	2.4	2.8	0.3	5.1	0.4	0.7	1.2	0.9	1.0	1.3	0.9	1.4
Nariño	1.6	1.6	2.9	3.8	1.0	0.1	0.4	0.4	1.3	1.0	1.7	2.5	1.2	1.1
Norte de Santander	2.0	1.8	3.1	3.3	5.3	0.6	0.9	0.7	1.7	1.4	2.9	2.7	1.3	1.0
Nuevos	1.3	4.7	2.4	3.9	10.7	55.0	0.1	0.1	1.2	1.0	2.0	2.9	0.5	0.8
Quindío	1.2	1.1	2.2	2.3	0.0	0.0	0.6	0.3	1.1	1.1	1.4	1.2	1.2	0.6
Risaralda	2.0	1.9	2.1	1.5	0.1	0.0	2.2	2.3	2.0	1.6	1.6	1.7	2.0	2.0
Santander	5.2	5.0	6.2	6.9	18.9	2.1	5.2	6.5	3.8	3.5	4.0	5.3	5.0	7.7
Sucre	1.0	0.7	3.0	1.6	0.3	0.1	0.2	0.2	0.6	0.3	1.0	0.9	0.6	0.4
Tolima	3.2	2.6	7.0	6.0	0.9	1.3	1.1	1.9	2.3	1.6	4.1	3.1	2.7	2.7
Valle	13.2	11.4	9.3	8.8	2.0	0.3	18.5	17.2	12.0	11.8	7.8	8.3	17.1	16.1

Source: Own calculations based on data from CEGA. Constant prices of 1994.