DECOMPOSING THE SPEED OF CONVERGENCE OF GDP PER WORKER: WHICH INPUT DRIVE US FASTER TO THE STEADY-STATE?

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Abstract:

The paper proposes a simple way to analyze the speed of convergence of a panel of countries to their own steady-states. Due to Durlauf and Bernard (1996) definition of convergence in a time series context and based on Phillips and Sul (2007) *log t* test, we show how to decompose the speed of convergence of the GDP per capita through elements associated with macroeconomic inputs, i. e. TFP, stock of capital and quality of labor force. Our results suggest that the convergence of these inputs are able to accelerate the speed of convergence of the GDP per capita to its steady-state in 12%, 40% and 48%, respectively. This suggests that the quality of workforce and its share in the product are crucial components to drive the GDP per capita faster to its steady state.

1 – INTRODUCTION

Barro and Sala-i-Martin (1992) seminal paper open a research agenda centered on the convergence hypothesis. A direct concept that emerge from that was the speed of convergence. The empirical counterpart of this concept tries to measure, in time periods, the speed at which a country should reach its stead-state position.

Barro and Sala-i-Martin contend it is important to know the speed of convergence of the transitional dynamics. If a group of countries experience a fast rate of convergence, then they should be near their steady state position, otherwise, the growth experience of these countries would be dominated by the transitional dynamics.

The maintenance of an economy in a position near its own steady state is convenient for a reason: from the simplest neoclassical definition of steady state, we have that all variables growth at zero rate, e.g., this means that the society reach its point of satisfaction and so its economic maturity. Another reason is that, once we are getting closer to the steady state, the business cycle has been controlled. This suggests that, at least in theory, the economy will be faced with a lesser degree of risk and volatility.

For these reasons, understand what accelerate the speed of convergence, and how, may be very important questions for macroeconomics and growth. If one takes the basic neoclassical growth model, for example, the speed of convergence is completely determined by parameters. So, the only way to accelerate the speed of convergence is reducing the capital-share parameter or increasing the rates of population growth, technological progress or depreciation.[1]

In the nineties, we saw how more complex models could help us to get convergence rates explained by additional parameters. Also, a strong debate succeed around the plausibility of the speed of convergence implied by the calibrated value of these parameters.[2] Nonetheless, it is important to note that all these parameters are deep, structural, or policy-invariant. A direct implication of this is that it is quietly difficult to accelerate the speed of convergence of an economy in the short run through economic policy.

[1] At Barro and Sala-i-Martin's Growth text book, for example, the term $\beta = (1-\alpha)(x+n+\delta)$ of the basic Solow-Swan model indicates how rapidly an economy's output per effective worker approaches its steady state value. The parameters described are: α, capital-share on product; x, rate of technological progress; n, rate of population growth and; δ, depreciation rate.

[2] See Turnovsky (2002), for example.

This paper challenges this point of view. We propose a simple way to illustrate how what we call macroeconomic inputs (the level of technology, the stock of capital, and the quality of the workforce, and their share on output) would influence the GDP per capita convergence process. As these inputs may be planned, this approach makes possible to economics policy contribute to accelerate the speed of convergence.

A second contribution is to construct an analytical tool to accommodate this subject. If we discard the Quah idea of distribution dynamics, we see that convergence literature has focusing on beta and sigma convergence tests. Note that, while the former is applied mostly to cross-sectional data, the latter generally uses time series. Bernard and Durlauf (1996) suggest that an important advance over both approaches would be the combination of transition information in the cross-section approach and the steady state information in the time series methodology to creating a more broad empirical method.

This paper takes this suggestion seriously and gather central ideas of stablished studies and new ones to construct a unified framework. More specifically, we depart from a beta convergence perspective suggested in Barro and Sala-i-Martin (1992) and show how the concept of speed of convergence may be strongly connected with the time series extracted from *log t* convergence test proposed by Phillips and Sul (2007). This connection is based on the distance of the GDPs per capita of a country to its steady state values. As present below, this distance generates a time-varying metric for the speed of convergence to steady-state.[3]

Next, we work with Durlauf and Bernard (1996) definition of convergence in a time series context to split the convergence process of GDP per capita into convergence processes associated with its macroeconomic inputs. Then, we collect this metric for a panel of countries and illustrate how to decompose it in order to examine which inputs are able to accelerate the convergence process, and how.

The empirical analysis is made through the application of the *log t* test on a Penn World Table 8.0 sample of 74 countries from 1970 to 2011 to extract time series that quantify the distances of the relevant variables to their steady states. As we discuss bellow, the PWT 8.0 dataset has several advantages to our analysis. We construct a panel data with these distances and propose a panel data regression to analyze how the convergence processes of these inputs may influence the speed of convergence of output.

[3] It is important to note that, while the metric for the speed of convergence is time invariant in Phillips and Sul (2007, 2009) and captured as an estimated coefficient for a group of countries, our approach generate a time series metric for each one of the countries.

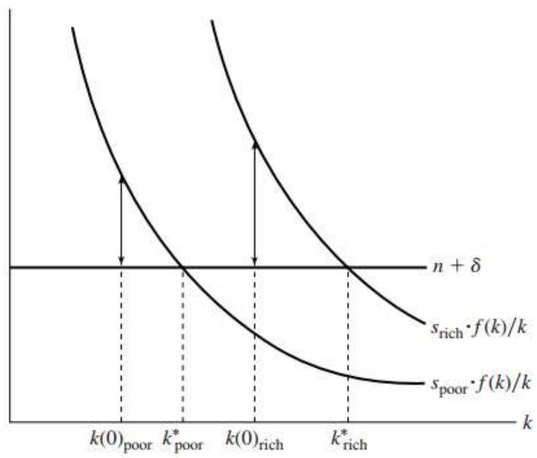
Our results suggest that an average reduction of 10% in the distance between the TFP and your steady state value should reduce the distance of the GDP per capita to its steady state in 1.2%. This same percentage reduction of the distance between the stock of capital input and its steady-state is able to accelerate the speed of convergence of the GDP per capita in 4%. Moreover, an equal reduction of the distance of the labor input should generate an average speed of convergence 4 times faster than the TFP one. This suggests that the quality of workforce and its share in the output are crucial components to drive the GDP per capita faster to its steady state.

The paper was organized as follows: next section present our methods, section 3 brings the results of the empirical research and, section 4 concludes.

2 - METHODS

2.1 - Speed and Convergence

The figure bellow depicts the transitional dynamics of two economies, a rich and a poor one.[4] These economies are conditional converging to their steady states, denoted by k^*. We suppose the same structural parameters to these economies, but the initial capital stock and the saving rate are different for them. To keep things simple, despise the human capital initially. So, the production function in per capita terms is $f(k,h) = f(k)$ and the horizontal line $(n+\delta)$ is equal to the sum of population growth rate and the depreciation rate.[5]



[4] For a detailed discussion, see Barro and Sala-i-Martin (1992) text book.

[5] Throughout the text, we will consider an aggregate output in per-worker terms that can be described according to: $y = Ak^{\alpha}h^{1-\alpha}$, where y is the country's GDP per worker; A represents the Total Factor Productivity (TFP), k is the capital-labor ratio and h is the quality of workforce, namely the human capital of an average worker. α is the share of capital in the production and its complementary is the share of human labor.

The vertical distances from $k(0)$ to the declining lines are seen as $\gamma_k = \frac{d[\log(k)]}{dt}$. The declining lines are not linear, and is usual to get an approximation around the steady state. In doing so, we will have $\gamma_k \cong -\beta.\log\left(\frac{k}{k^*}\right)$, where $\beta = (1-\alpha)(n+\delta)$.

The parameter β is measured by how much the growth rate declines as the capital stock increases in a proportional sense, i.e. it provide a quantitative assessment of how fast the economy approaches its steady state.

Due to the linearization, as the saving rate do not alter the convergence rate, and as we have the same structural parameters to both economies, so we must have the same β to rich and poor economies.

Reiss (2000) and Mathunjwa and Temple (2006) investigate the speed of convergence focusing on its behavior away from the steady-state. Their analysis reveals that convergence rates are likely to be heterogeneous in systematic ways. In particular, the second paper shows that, for log-linearized models of the kind commonly used in empirical work, rates of convergence are faster for economies that converge from below than for economies that converge from above.

Reiss (2000) define speed of convergence as follows: let $y(t)$ be the differentiable time-path of the GDP per capita of an economy converging to its balanced growth equilibrium, y^*, which is constant over time. In this terms, the speed of convergence is given by:

$$\beta_y(t) \equiv -\frac{d\big(y^* - y(t)\big)/dt}{y^* - y(t)} \tag{1}$$

Equation (1) suggests that the speed of convergence is a function of y^*, which is completely determined by saving rate and structural parameters, and it is a function of $y(t)$, which can be modeled as a production function. This means that the macroeconomic inputs utilized to generate the macroeconomic output, or the GDP per worker, are able to influence the speed of convergence.

2.2 - Steady States

It is also interesting to note that equation (1) is completely determined by $\big(y^* - y(t)\big)$, i.e. the speed of convergence is totally determined by the distance of the GDP per worker to its steady state position and, moreover, this distance is time-varying.

This point matches well with the relative transition coefficients proposed in Phillips and Sul (2007). Under technological heterogeneity, for a group of N economies (we discuss heterogeneity and group formation bellow), the relative transition coefficient for an economy i in the instant t may be modeled as:

$$h_{it} = \frac{\widehat{w}_{it}}{N^{-1}\sum_{i=1}^{N}\widehat{w}_{it}}, \qquad (2)$$

where $\widehat{w}_{it}$ is the HP filtered series of $\ln(y_{it})$, e.g. the series without the cyclical component.

Equation (2) suggests that the long run trend of the GDP per capita of a country i is a crucial element to measure not only its own steady state, as the steady state for the entire group of economies, i.e. this steady state is common to all countries which belong to the group. So, convergence implies that $h_{it} \to 1$ as $t \to \infty$, i.e. the N economies of the group converge to their steady state position as time evolve.

In practice, Equation (2) requires a technique to identify properly convergence clubs. One suggestion is to use the Phillips and Sul (2007) log t test recursively to a panel of countries. Another one would be the approach suggested in Su, Shi and Phillips (2014), for example.

Technological heterogeneity is a key word for equation (2). The introduction of this concept in a standard neoclassical growth models may be seen in Phillips and Sul (2007), which suggests that each country's technological level, $\log(A_{it})$, may be split into initial technology accumulation, $\log(A_{i0})$, and an idiosyncratic participation on the aggregate level of technology, $\gamma_{it}\log(A_t)$:[6]

$$\log(A_{it}) = \log(A_{i0}) + \gamma_{it}\log(A_t), \qquad (3)$$

It is possible to bring Howitt and Mayer-Foulkes (2005) idea of club formation and adapt it on Equation (3): this authors provide a theoretical explanation, based on Schumpeterian growth theory, for the divergence in per-capita income. The idea is based on technological frontier and they show that a highest group will converge to an "*R&D steady state*", while those in the intermediate group converge to an "*Implementation steady state*".

These different steady state positions for technology generate different steady states for GDP per capita, which explain club formations inside the convergence process. The idea that different levels of technology may lead to club convergence also is accepted

[6] More specifically, $\gamma_{it}\log(A_t)$ captures the distance of country i technology from publicly available advanced technology, $\log(A_t)$, at time t, where γ_{it} means this distance may vary over time and across country.

by Parente and Prescott (1994), who work with concepts of technology adoption and barriers.

2.3 - Convergence Clubs

In practical terms, there are some methodologies to identify groups of countries that share the same steady-state. The convergence test of Phillips and Sul (2007), for example, seems to work well for technology and GDP per capita series. In fact, the test may be apply to several panels of variables. The idea behind their test is based on the follow semi-parametric regression, also called log t test:

$$log\frac{H_1}{H_t} - 2\log[\log t] = \alpha + \gamma \log t + u_t \quad \text{para} \;\; t = T_0, \dots, T \quad , \tag{4}$$

where, H_1/H_t is the relation of the cross-section variance, that can be stated as $H_t = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2$ and h_{it} is just like the describe in (2).

It is important to note that the *log t* test is not directly applied on the series, but on the relative transition coefficients, formulated as h_{it}. As h_{it} has to be in accordance with the test properties, i.e. it has to be able to capture the long-term trend of the series, it is necessary to smooth the series through the HP filter, as suggested by Phillips and Sul.

Under the null hypothesis, the coefficients of (4) can be tested based on a unilateral test robust to heteroskedasticity and autocorrelation. For a 5% level, for example, the null hypothesis of convergence should be rejected if $t_\gamma < -1.65$, where t_γ represents the t-statistic associated with γ estimated in (4). The rejection of the null hypothesis of convergence for the entire panel indicates the existence of separate points of equilibrium or multiple steady states. When this occurs, one can have divergence of some members of the panel and / or convergence clubs formation. In this context, Phillips and Sul (2007) propose an algorithm that applies the test sequentially and allows identification of convergence clubs without the use of observable characteristics for the club grouping (e.g., education level, stock of capital, access to credit, etc.).

2.4 - Disaggregation

Bernard and Jones (1996) also discuss how technology affects convergence. In fact, they launched an inquiry that, in our view, seems to have not been appropriately answered by the Academia: How much of the observed convergence of per capita income is due to the convergence of technology process between economies, and how much is due to the convergence process of capital per worker relations?

A simple way to analyze how the technology may influence the convergence process can be seen through the definition of Bernard and Durlauf (1996). In a time series context, they formalize that the GDPs per worker of economies i and j converge if the long-term forecast for their difference becomes zero, $\lim_{k\to\infty} E\left(log\, y_{it+k} - log\, y_{jt+k}\, |\pi_t\right) = 0$, where π_t denotes all information available on time t.

We use a less formal notation and assume that two economies converge if $\lim_{k\to\infty}\left(log\, y_{it+k} - log\, y_{jt+k}\right) = 0$. Pesaran (2007) argue that this condition is too strong to be satisfied as it requires the two economies to be identical almost in every aspects, including their saving rates and initial endowments. In this sense, it is easier to observe that $\lim_{k\to\infty}\left(log\, y_{it+k} - log\, y_{jt+k}\right) = C > 0$, where C is a positive constant. Here we will call the former definition of strong convergence and the latter of weak convergence.

Now, suppose that if a steady state exists, it can be approximated by:

$$y_t^* = A_t^* + \alpha_t^* ln(\, k_t^*) + (1 - \alpha_t^*) ln(h_t^*), \tag{5}$$

where the star superscript means a steady state position.[7]

If the specification (5) is true, and if the functional form of a production function can be correctly described by a Cobb-Douglas technology, $y_t = A_t + \alpha_t ln(k_t) + (1 - \alpha_t) ln(h_t)$, then an economy i converges to its own steady state if:

$$\lim_{k\to\infty}(log\, y_{it+k} - log\, y^*_{it+k})$$
$$= \lim_{k\to\infty}\left\{\begin{array}{c}(ln\, A_{it+k} - ln\, A^*_{it+k})\\ +(\alpha_t\, ln\, k_{it+k} - \alpha_t^*\, ln\, k^*_{it+k})\\ +((1-\alpha_t)\, ln\, h_{it+k} - (1-\alpha_t^*)\, ln\, h^*_{it+k})\end{array}\right\} = C \tag{6}$$

Note that, besides simple, the disaggregation proposed in (6) bring to the convergence analysis important questions as discussed earlier:

i) In fact, Equation (6) indicates that the convergence of the GDP per worker to its own steady state is governed by the convergence processes of three ***macroeconomic inputs*** (a technology factor, a stock of capital per worker,

[7] Caselli (2005) points out that the greater the understanding of the composition of k and the behavior of α the greater the understanding of the differences in per capita GDPs across economies. The PWT version 8.0 has time-varying labor share. Evidence that this parameter is decreasing on time can be seen at Neiman (2014), for example. We take advantage of this dataset and use it on our empirical analysis, next section.

and a quality of the labor force), each one to their own relative steady state position; [8]

ii) It is important to note that when we analyze the evolution of macroeconomic inputs - like capital and labor - and as they share is increasing (decreasing) over time, it suggests that they share may be a very important element to the convergence process;

iii) The distance of the GDP per worker to its steady state position is completely determined by the distances of these macroeconomic inputs to its steady states, and these distances are all time-varying. This permits that the macroeconomic inputs become able to influence the GDP per worker speed of convergence;

iv) This disaggregation accommodate different steady state positions for technology across different economies, and this may explain club formations inside the GDP per worker convergence process; In fact, this manner to split the convergence process permit us to have different steady state positions for each one the macroeconomic inputs, and across different economies. This opens a new window to understand the process of formation of convergent clubs;

v) Last, but not at least, if convergence clubs are convenient identifiable, it is possible to use the relative transition coefficient explain in (2) to measure the distances describe in (6). As it can be done for all countries on a sample, and for each point in time, it is possible to create a panel of distances and use this panel to understand how the macroeconomic inputs affect the GDP per capita speed of convergence.

2.5 - Construction of Panels

From the definition of h_{it} expressed in (2), a suitable position to a steady state of a group of economies can be calculated approximately by $N^{-1}\sum_{i=1}^{N}\widehat{w}_{it}$, i.e. the average path of one variable given an identified club without the cyclical component of it. So, if ones apply the Phillips and Sul (2007) test, or other test to identify convergence clubs, it is possible to compute relative transition coefficients for the GDP per capita as long as for each macroeconomic input.

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[8] Formaly, what we call "***macroeconomic input***" are $H_t = (1-\alpha_t)\, ln\, h_{it}$ and $K_t = \alpha_t\, ln\, k_{it}$, i.e. the share of the input multiplied by its log.

This means that, if we define the distance of an economy to its steady state position as $d_{it}^{x} = |h_{it}^{x} - 1|$, for $x = y, A, K$ and H, it is possible to create a panel for each one of these variables. With this panels at hands it is possible to run the following restricted panel regression:

$$d_{it}^{y} = \mu_0 + \mu_i + \mu_1 d_{it}^{A} + \mu_2 d_{it}^{K} + (1 - \mu_1 - \mu_2) d_{it}^{H} + \varepsilon_{it}, \tag{7}$$

where d_{it}^{x} are the distances defined above, μ_i is a fixed effect, μ_j ; $j = 0, 1, 2$ are coefficients and ε_{it} is the error term, with mean zero and finite variance.

It is interesting to note that the steady state of all variables is normalized to unit, and this can be done to all different clubs of output or macroeconomic inputs. This permits to compare how distant an economy was from its own steady state position in all dimensions, i.e. inside a group of output, inside a group of inputs, and between different groups of output and inputs.

As those distances are directly comparable quantities, and as we have logs on both sides of regression (7), the estimated coefficients are interpreted as elasticities. Note that, due to the coefficients restrictions, they sum one. Moreover, this coefficients measures a reduction of the distance of GDP per capita to its steady state due to a reduction of the distance of a macroeconomic input to its own steady state. This demonstration comes from the fact that, we have:

$$\mu_1 = \frac{\partial d_{it}^{y}}{\partial d_{it}^{A}} = \frac{\partial |h_{it}^{y} - 1|}{\partial |h_{it}^{A} - 1|} = \frac{\partial\left(\left|\frac{\hat{y}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{y}_{it}} - 1\right|\right)}{\partial\left(\left|\frac{\hat{A}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{A}_{it}} - 1\right|\right)} = \frac{\partial(\log y_{it} - \log y_{it}^{*})}{\partial(\ln A_{it} - \ln A_{it}^{*})} = \frac{\partial \beta_y(t)}{\partial \beta_A(t)} \tag{8}$$

$$\mu_2 = \frac{\partial d_{it}^{y}}{\partial d_{it}^{K}} = \frac{\partial |h_{it}^{y} - 1|}{\partial |h_{it}^{K} - 1|} = \frac{\partial\left(\left|\frac{\hat{y}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{y}_{it}} - 1\right|\right)}{\partial\left(\left|\frac{\hat{K}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{K}_{it}} - 1\right|\right)} = \frac{\partial(\log y_{it} - \log y_{it}^{*})}{\partial(\alpha_t \ln k_{it} - \alpha_t^{*} \ln k_{it}^{*})} = \frac{\partial \beta_y(t)}{\partial \beta_K(t)} \tag{9}$$

$$\mu_3 = \frac{\partial d_{it}^{y}}{\partial d_{it}^{H}} = \frac{\partial |h_{it}^{y} - 1|}{\partial |h_{it}^{H} - 1|} = \frac{\partial\left(\left|\frac{\hat{y}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{y}_{it}} - 1\right|\right)}{\partial\left(\left|\frac{\hat{H}_{it}}{N^{-1}\sum_{i=1}^{N}\hat{H}_{it}} - 1\right|\right)} = \frac{\partial(\log y_{it} - \log y_{it}^{*})}{\partial((1-\alpha_t) \ln h_{it} - (1-\alpha_t^{*}) \ln h_{it}^{*})} = \frac{\partial \beta_y(t)}{\partial \beta_H(t)} \tag{10}$$

We have several caveats: Each coefficient give us a direct metric of how faster each one of the inputs are able to accelerate the convergence process, and these metrics are directly comparable. Depending on hypothesis and data, regression (7) should be estimated by restricted panel least squares. Regression (7) also deals essentially with the conditional beta convergence seen on Solow's regressions, because we are controlling for different steady-states positions.

Also, is imperative to discern that the error term should capture all the effect of the variation in the GDP per capita convergence process due to the evolution of the factors and output that are not the country specifics ones. This error should not vanish completely. First, because there is a little degree of dependence and, second, because the formal concept of convergence is taken to the limit.

Our analysis also captures not only the contributions of the physical and human capital stocks, but also the contributions of their shares on the product, and this process should be a very complex one, because it still has to take into account the evolution of these variables for the other countries.[9]

3 - EMPIRICAL ANALYSIS

3.1 - Data:

We use a set of variables from Penn World Table version 8.0 to conduct our empirical analysis. This new dataset have a substantial improvement in the measurement of several variables, like a country-specific labor share which is time variant, and new series of investment that take into account up to six different types of assets and respective depreciation rates.[10] This allows to obtain initial capital stocks more accurately and consequently more precisely evolutions of these series.[11]

The PWT identifies potential outliers that may have problems with the adequacy of the PPP. They are: Burundi, Bermuda, Brunei, Guinea-Bissau, Mozambique and El-Salvador. These countries have been removed from the sample with the aim of not biasing the results. We also exclude Kuwait, Iraq and Tobago Trinidad due to wars and natural disasters. Nepal and Bangladesh are neighbor countries and as it is known, Nepal is a land of ancient and spiritual culture, which tends to put the share of labor in the product at a very high scale, so we take it as an outlier too and take it out of our sample.

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[9] If we take Hong Kong and United States, for example, we see that the stock of capital per worker of the first catches up the United States, but the capital share of Hong Kong is decreasing faster if one compares it to the United States. This may explain why Hong Kong was pushed away to a K convergence club below the United States convergence club, i.e. G6 instead G4 (see next Section for more details).

[10] More specifically, the PWT 8.0 takes into account structures (residential and non-residential), transport equipment, computers, communication equipment, software and other machinery and assets.

[11] As pointed in Feenstra, Inklaar and Timmer (2013), these, and several other improvements bringing with this new generation of PWT permits better comparisons of the evolution of the factors across countries and over time.

Our sample takes into account 78 countries (listed in appendix A) from 1970 to 2011. We form four panel data (y, A, K and H), as indicated below. Besides the PWT provides the TFP series based on national accounts, we extract it simple as a residual, i. e. $ln(A_t) = ln(y_t) - \alpha_t \, ln(k_t) - (1 - \alpha_t) ln(h_t)$. In doing so, all the source of convergence of the GDP per worker can be explained due to the convergence processes of these three inputs.

The equivalent notation of this paper in terms of PWT Data is what follows.

Panel	**Paper**	**PWT 8.0**
y	$ln\, y_{it}$	$\log\left(\frac{rgdpna}{emp}\right)$
A	$A_{it} = y - K - H$	-
K	$\alpha_t \, ln\, k_{it}$	$(1 - labsh) * \left(\frac{rkna}{emp}\right)$
H	$(1 - \alpha_t)\, ln\, h_{it+k}$	$(labsh) * (hc)$

Variable	**Definition**
emp	Number of persons engaged (in millions)
hc	Index of human capital per person, based on years of schooling (Barro/Lee, 2012) and returns to education (Psacharopoulos, 1994)
$rgdpna$	Real GDP at constant 2005 national prices (in mil. 2005US$)
$rkna$	Capital stock at constant 2005 national prices (in mil. 2005US$)
$rtfpna$	TFP at constant national prices (2005=1)
$labsh$	Share of labour compensation in GDP at current national prices

3.2 - Convergence Groups

Initially, it is necessary to apply a method of clustering panels into club convergence groups. We apply the Phillips and Sul (2007) algorithm to panels y, A, K and H. The details of the test results are in appendix B.[12]

Next we rank the countries by the GDP, than by TFP groups, by K, and by H groups. We can see from it that there is no relationship between groups of output and inputs. There are cases in which countries in the highest GDP group also belongs to either low A groups, such as India, or to low H groups, such as Taiwan, for example. In the

[12] If one compares our results for GDP per capita and those from Phillips and Sul (2003), one should find differences. But, It is important to note that this results are not directly comparable, because their panel data have different dimensions. Phillips and Sul (2003) use 120 countries from 1950 to 1992 and find 6 convergence clubs. We use 78 countries from 1970 to 2011 and find 8 convergence clubs and five countries diverging from these clubs.

remaining GDP groups, the same heterogeneity in the results becomes stronger and no pattern can be identified. The same diversity is true for the divergent countries.

CONVERGENT CLUBS BY GDP AND MACROECONOMIC INPUTS

Country	***y***	***A***	***K***	***H***
Barbados	DIV	G3	G6	G6
China	DIV	G3	G1	G5
Korea, Republic of	DIV	G4	G1	G6
Niger	DIV	G3	G6	G1
Zimbabwe	DIV	G6	G2	G5
India	G1	G8	G1	G4
Malta	G1	G3	G2	G5
Thailand	G1	G4	G2	G5
Taiwan	G1	G4	G1	G6
Egypt	G2	G3	G2	G1
Indonesia	G2	G3	G2	G4
Sri Lanka	G2	G3	G1	G6
Bulgaria	G3	G3	G2	G6
Cyprus	G3	G2	G5	G5
Hong Kong	G3	G1	G5	G5
Malaysia	G3	G4	G1	G5
Poland	G3	G3	G2	G7
Singapore	G3	G2	G4	G4
Turkey	G3	G3	G3	G3
Hungary	G4	G4	G1	G6
Ireland	G4	G2	G5	G6
Austria	G5	G4	G2	G6
Belgium	G5	G3	G4	G6
Chile	G5	G3	G5	G5
Dominican Republic	G5	G7	G1	G6
Spain	G5	G3	G4	G4
Finland	G5	G4	G1	G7
France	G5	G4	G2	G5
United Kingdom	G5	G3	G3	G6
Iceland	G5	G2	DIV	G5
Japan	G5	G5	G2	G7
Morocco	G5	G4	G3	G1
Norway	G5	G6	G1	G7
Panama	G5	G4	G3	G6
Portugal	G5	G3	G3	G5
Sweden	G5	G3	G2	G6
Tunisia	G5	G4	G3	G2

Tanzania	G5	DIV	G2	G5
Argentina	G6	G6	G2	G7
Australia	G6	G7	G1	DIV
Brazil	G6	G4	G3	G2
Germany	G6	G4	G2	G5
Denmark	G6	G2	G6	G6
Greece	G6	G3	G4	G6
Italy	G6	G5	G2	G6
Luxembourg	G6	G5	G2	G8
United States	G6	G3	G3	G7
Bolivia	G7	G4	G3	G5
Canada	G7	G5	G2	G7
Switzerland	G7	G3	G4	G7
Cameroon	G7	G5	G3	G3
Colombia	G7	G4	G3	G5
Costa Rica	G7	G4	G3	G5
Ecuador	G7	G8	G3	G6
Guatemala	G7	G4	G4	G4
Honduras	G7	G3	G6	G3
Iran	G7	G8	G3	G3
Iraq	G7	G1	DIV	DIV
Israel	G7	G3	G3	G6
Jordan	G7	G4	G3	G4
Kenya	G7	G4	G1	G4
Mexico	G7	G7	G3	G5
Netherlands	G7	G4	G2	G7
New Zealand	G7	G4	G2	G8
Peru	G7	DIV	G1	DIV
Philippines	G7	G5	G3	G6
Paraguay	G7	G2	G6	G3
Senegal	G7	G2	G6	G2
Uruguay	G7	G5	G3	G6
Bahrain	G8	G8	G4	G4
Cote d`Ivoire	G8	G7	G2	G2
Jamaica	G8	G3	G6	G4
Venezuela	G8	G5	G5	G5
South Africa	G8	DIV	G2	G5

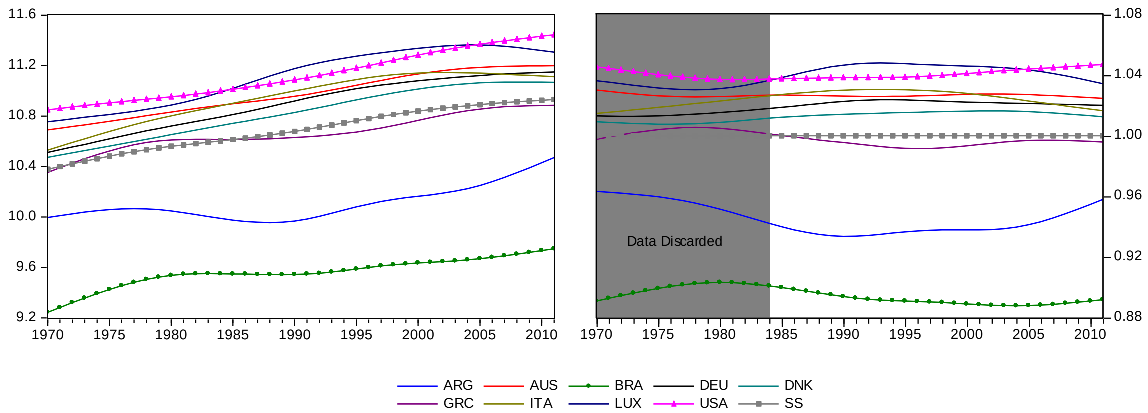
3.3 - Controling for Steaady States

For each one of these groups, we compute the transition path to the steady-state as a time series approximated by $h_{it} = \hat{w}_{it}/N^{-1}\sum_{i=1}^{N}\hat{w}_{it}$. In doing so, the steady-state can be merely approximated by 1, because $h_{it} \rightarrow 1$ as $t \rightarrow \infty$. If a country is diverging, we set $h_{it} = 1$. This suggests that the diverging country has his own evolution path, and this transition is approximated by its own HP filtered GDP per worker series. The results of the *log t* test applied on the GDP per worker, y, and on the three aforementioned inputs, A, K, and H, are present in the appendix B.

To illustrate how the relative transition coefficient works, we present the evolution of the filtered series of y and the relative transition coefficients for the United States' Group of RGDP per worker. We will use the notation $USA \in G_y^6$, meaning that USA belongs to a sixth group of RGDP per worker.

The recursive application of the *log t* test to a panel data permits identify groups of countries that share a common trend and the test suggests that the cross section variance tends to reduce in a long run.[13] In the USA case, the $\log t$ test procedure suggests that USA takes place in G_y^6, G_A^3, G_K^4 and G_H^7. Below we present the pattern of the sixth group of GDP per worker.

Graphic 1: $\hat{y}$ and Relative Transition Coefficients for G_y^6 members



There are several positive points to construct those diagrams, but one is fundamental: as we discuss earlier, the construction of the coefficient permit us to normalize the steady state position to the unit and this can be done to all different clubs of macroeconomic inputs. This suggests that is possible to compare how distant an

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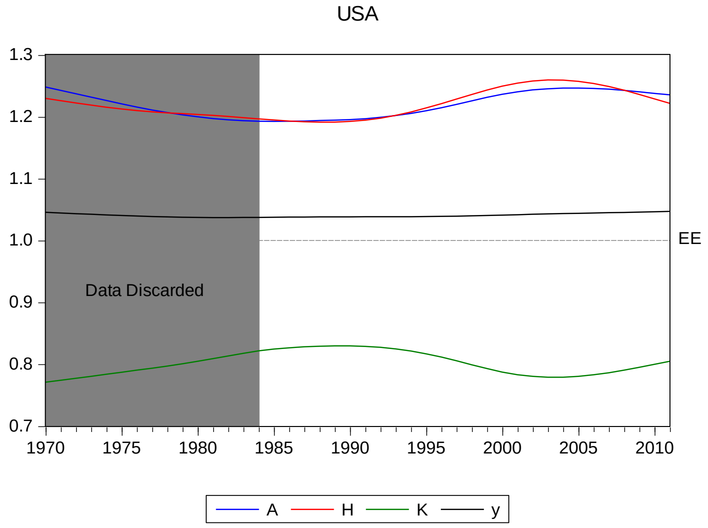
[13] As Phillips and Sul pointed out, it is convenient to discard 1/3 of the initial sample before apply the log t test. The suggestion comes from the fact that the procedure takes into account the series normalized by the initial observations. They conduct Monte Carlo experiments to mitigate the effect of this initial normalization and observe that the cut of 1/3 of the sample is the one more desire in terms of size and power to the log t test.

economy was from its own steady state position in all dimensions, e.g. inside a group of output or input (as we see in the panel (b) of graph 1 for the GDP per capita), and between groups of different output and macroeconomic inputs, as we can see in the next graph.

Graphic 2: Relative Transition Coefficients for Output and Factors (USA)



From the graphic above we see that the GDP per capita of United States (y) is closer to its steady state position than their inputs (A, K and H), and that the transition paths of the TFP and the human capital input to its steady states are very close.

We then collect the distances of an economy to its steady state position. Creating the variables $d_{it}^{x} = |h_{it}^{x} - 1|$, for $x = y, A, K$ and H, it is possible to create a panel for each input and output variables. With this panels at hands, we run the panel regression (7).[14] The result of this regression is what follows:

$$d_{it}^{y} = -0.124 + \beta_i + 0.12 * d_{it}^{A} + 0.40 * d_{it}^{K} + 0.48 * d_{it}^{H}$$
$$(-155.65) \quad (12.60) \quad (33.27) \quad (40.22) \qquad R^2 = 0.8435$$

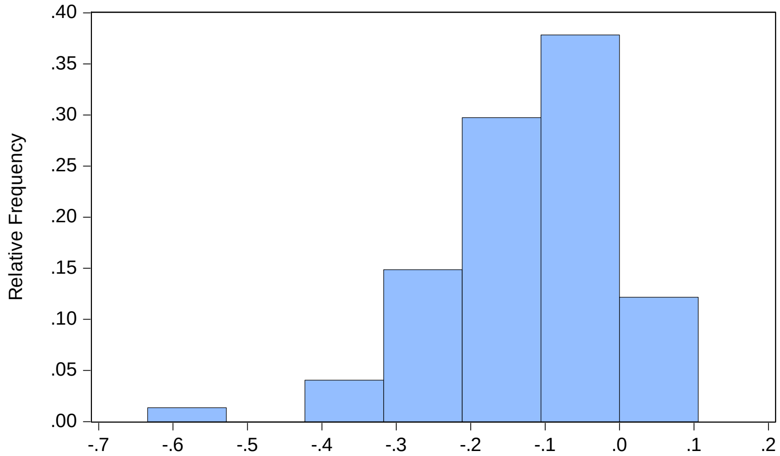
We see that all coefficients has the expect signs and are all statistically significant. The R^2 also indicates a good fit for a panel regression. The regression's outcome suggests that the effects of the TFP, the stock of capital per worker adjusted for the capital participation on the product, and the quality of labor adjusted for the labor participation on the product are 12%, 40% and 48%, respectively.

As robustness check, we depart again from the idea of convergence, which suggests that the GDP per capita of an economy is converging if this distance to steady

[14] We may impose constant returns to scale (restricted least squares) because we are strictly based on this hypothesis and due to the construction of the PWT variables, which also is based on this.

state is reducing over time. To see if this definition is matching with our approach it is necessary to check if the distances of the GDP per workers are decreasing or becoming zero. This suggests that the sums of the intercept and the fixed effects should be negative or at least zero for the great majority of our sample (unless for countries those are in fact diverging like Barbados, China, Korea, Niger and Zimbabwe). This is exactly what we see in the next graph.

Graphic 4: Relative Frequency of the Intercept plus Fixed Effect



4 – CONCLUDING REMARKS

Our comprehension about the convergence of RGDP per worker is in-depth in economics. We already have a good idea about convergence clubs and about the influences of capital and the quality of labor force. Besides this knowledge, new techniques and econometric approaches always bring new evidence, sometimes challenging our theories and findings or reinforcing the old ones, making them more robust.

In this sense, the contribution of our research is twofold. First, our analysis is conducted on a set of variables from Penn World Table, version 8.0. This new dataset gave us a possibility to work with time variant country specifics labor and capital shares, and we show how to bring this feature and its influence to the analysis of the convergence process. Likewise, we argue that if this piece is misleading, then the influence of the macroeconomic inputs on the RGDP convergence process may be misrepresentative.

Second, the whole idea of the investigation process is quietly naïve and intuitive: Given the existence of convergence clubs (of RGDP per workers and of macroeconomic inputs), a comprehensive way to check how the convergence process of the inputs impact the output's one is to observe how the distances to steady state of each input are influencing the distance to the steady state of the RGDP per worker. [15]

Based on the idea of relative transition coefficients proposed in Phillips and Sul (2007) and based on a sample of 74 countries for the years 1970-2011, we show that the convergence of the GDP per worker do not follow a standard behavior when analyzing the factors that comprise it: the convergence clubs of GDP per worker have no linkage with the process of formation of convergence clubs of the capital stock per capita, human capital nor TFP. This is an evidence that has not been presented by the literature and impose additional investigations to the studies conducted so far.

The exercise conducted here invokes a dialogue between a number of issues presented in Caselli (2005), a technique of decomposition of the factors of convergence (Bernard and Durlauf, 1996), a methodology of time series that allows to analyze the convergence process taking into account nonlinearities, heterogeneity and the formation of convergence clubs (Phillips and Sul, 2007), and a recent database that has a number of advantages for the analysis (PWT, 8.0).

Through this exercise, we show that the importance of the quality of workforce is four times greater than the TFP for the RGDP convergence process, a result that goes against the initial analyzes of Klenow and Rodrigues-Clare (1997) and Easterly and Levine (2001), for example.

It is also important to distinguish the analysis conducted here from the analyzes conducted so far. Our paper deals with the influence of the convergence of factors on the convergence of the RGDP per worker, instead of the mere influence of the factors on the RGDP. This caveat is important because sometimes we are interested in how we could catch up economies that belong to a group with higher RGDP per capita. Our research does not enter in issues like that. Here we are interesting in how an economy may reach its own steady state position unlike the steady state of other economies. We still believe

[15] Besides these distances are relatively abstract due to the idea of steady state of the variables, Phillips and Sul (2007) propose an interesting way to deal with that: a steady state position can be identified based on the mean of the filtered series belonging to each group. In feature research it should be interesting to check if the validity of our results remains stable compared to alternative ways to identify convergence clubs, for example, using the methodology proposed in Su, Shi, and Phillips (2014).

that TFP has a very important effect in this second case, but future research on the field should pay more attention to these issues and their details.

APPENDIX A – SAMPLE AND COUNTRY CODE

1	ARG	Argentina	40	ITA	Italy
2	AUS	Australia	41	JAM	Jamaica
3	AUT	Austria	42	JOR	Jordan
4	BEL	Belgium	43	JPN	Japan
5	BGR	Bulgaria	44	KEN	Kenya
6	BHR	Bahrain	45	KOR	Korea, Republic of
7	BOL	Bolivia	46	KWT	Kuwait
8	BRA	Brazil	47	LKA	Sri Lanka
9	BRB	Barbados	48	LUX	Luxembourg
10	CAN	Canada	49	MAR	Morocco
11	CHE	Switzerland	50	MEX	Mexico
12	CHL	Chile	51	MLT	Malta
13	CHN	China	52	MYS	Malaysia
14	CIV	Cote d`Ivoire	53	NER	Niger
15	CMR	Cameroon	54	NLD	Netherlands
16	COL	Colombia	55	NOR	Norway
17	CRI	Costa Rica	56	NZL	New Zealand
18	CYP	Cyprus	57	PAN	Panama
19	DEU	Germany	58	PER	Peru
20	DNK	Denmark	59	PHL	Philippines
21	DOM	Dominican Republic	60	POL	Poland
22	ECU	Ecuador	61	PRT	Portugal
23	EGY	Egypt	62	PRY	Paraguay
24	ESP	Spain	63	QAT	Qatar
25	FIN	Finland	64	SAL	Saudi Arabia
26	FRA	France	65	SEM	Senegal
27	GBR	United Kingdom	66	SGP	Singapore
28	GRC	Greece	67	SWE	Sweden
29	GTM	Guatemala	68	THA	Thailand
30	HKG	Hong Kong	69	TUN	Tunisia
31	HND	Honduras	70	TUR	Turkey
32	HUN	Hungary	71	TWN	Taiwan
33	IDN	Indonesia	72	TZA	Tanzania
34	IND	India	73	UKR	Ukraine
35	IRL	Ireland	74	URY	Uruguay
36	IRN	Iran	75	USA	United States
37	IRQ	Iraq	76	VEM	Venezuela
38	ISL	Iceland	77	ZAF	South Africa
39	ISR	Israel	78	ZWE	Zimbabwe

APPENDIX B – PHILLIPS AND SUL (2007) TESTS

	Groups for $\boldsymbol{y}$	γ	$\boldsymbol{t_\gamma}$	γ	$\boldsymbol{t_\gamma}$
	Whole Sample:	-2.256	-56.817	(rest of group)	
G1	IND, MLT, THA, TWN	0.600	3.619	-2.197	-49.233
G2	EGY, IDN, LKA	0.053	0.231	-2.223	-63.994
G3	BGR, CYP, HKG, MYS, POL, SGP, TUR	0.603	2.537	-2.293	-117.623
G4	HUN, IRL	1.524	8.983	-2.294	-107.985
G5	AUT, BEL, CHL, DOM, ESP, FIN, FRA, GBR, ISL, JPN, MAR, NOR, PAN, PRT, SWE, TUN, TZA	0.099	0.531	-2.370	-277.227
G6	ARG, AUST, BRA, DEU, DNK, GRC, ITA, LUX, USA	0.909	4.366	-2.402	-2452.289
G7	BOL, CAN, CHE, CMR, COL, CRI, ECU, GTM, HND, IRN, IRQ, ISR, JOR, KEN, MEX, NLD, NZL, PER, PHL, PRY, SEN, URY	0.010	0.385	-2.750	-50.456
G8	BHR, CIV, JAM, VEN, ZAF	1.299	2.207	-2.903	-73.604
D	BRB, CHN, KOR, NER, ZWE		(DIVERGENTS)		

	Groups for $\boldsymbol{A}$	γ	$\boldsymbol{t_\gamma}$	γ	$\boldsymbol{t_\gamma}$
	Whole Sample:	-3.722	-32.968	(rest of group)	
G1	HKG, IRQ	-1.840	-1.138	-2.444	148.897
G2	CYP, DNK, IRL, ISL, PRY, SEN, SGP	0.01	0.14	-2.127	-60.523
G3	BEL, BGR, BRB, CHE, CHL, CHN, EGY, ESP, GBR, GRC, HND, IDN, ISR, JAM, LKA, MLT, NER, POL, PRT, SWE, TUR, USA	0.286	1.444	-1.997	-67.519
G4	AUT, BOL, BRA, COL, CRI, DEU, FIN, FRA, GTM, HUN, JOR, KEN, KOR, MAR, MYS, NLD, NZL, PAN, THA, TUN, TWN	0.417	2.444	-2.269	-49.447
G5	CAN, CMR, ITA, JPN, LUX, PHL, URY, VEN	-0.221	-1.035	-2.190	-40.023
G6	ARG, NOR, ZWE	0.312	0.188	-2.115	-38.423
G7	AUS, CIV, DOM, MEX	0.049	0.109	-2.324	-36.546
G8	BHR, ECU, IND, IRN	0.234	1.091	-3.332	-10.540
D	PER, TZA, ZAF		(DIVERGENTS)		

	Groups for $\boldsymbol{K}$	γ	$\boldsymbol{t_\gamma}$	γ	$\boldsymbol{t_\gamma}$
G1	Whole Sample:	-1.932	-143.006	(rest of group)	
G2	AUS, CHN, DOM, FIN, HUN, IND, KEN, KOR, LKA, MYS, NOR, PER, TWN	0.089	1.197	-2.387	-146.730

G3	ARG, AUT, BGR, CAN, CIV, DEU, EGY, FRA, IDN, ITA, JPN, LUX, MLT, NLD, NZL, POL, SWE, THA, TZA, ZAF, ZWE	0.023	0.102	-2.699	-17.507
G4	BOL, BRA, CMR, COL, CRI, ECU, GBR, IRN, ISR, JOR, MAR, MEX, PAN, PHL, PRT, TUN, TUR, URY, USA	0.181	1.687	-3.031	-24.574
G5	BEL, BHR, CHE, ESP, GRC, GTM, SGP	0.374	2.308	-2.714	-40.827
G6	CHL, CYP, HKG, IRL, VEN	0.759	1.248	-2.041	-30.672
G7	BRB, DNK, HND, JAM, NER, PRY, SEN	-0.652	-3.793	-4.564	-2.833
D	IRQ, ISL		(DIVERGENTS)		

	Groups for *H*	γ	t_γ	γ	t_γ
	Whole Sample:	-1.817	-34.630	(rest of group)	
G1	EGY, MAR, NER	0.821	12.328	-1.753	-52.024
G2	BRA, CIV, SEN, TUN	0.358	26.659	-1.743	-41.771
G3	CMR, HND, IRN, PRY, TUR	0.181	1.292	-1.801	128.857
G4	BHR, ESP, GTM, IDN, IND, JAM, JOR, KEN, SGP	0.382	1.828	-1.901	-69.938
G5	BOL, CHL, CHN, COL, CRI, CYP, DEU, FRA, HKG, ISL MEX, MLT, MYS, PRT, THA, TZA, VEN, ZAF, ZWE	0.271	2.139	-2.055	-35.761
G6	AUT, BEL, BGR, BRB, DNK, DOM, ECU, GBR, GRC, HUN, IRL, ISR, ITA, KOR, LKA, PAN, PHL, SWE, TWN, URY	-0.21	-2.229	-2.205	-38.977
G7	ARG, CAN, CHE, FIN, JPN, NLD, NOR, POL, USA	0.665	5.336	-2.293	-47.190
G8	LUX, NZL	-0.299	-2.478	-2.363	-72.983
D	AUS, IRQ, PER		(DIVERGENTS)		

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