Global Divergence in Growth Regressions*

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Abstract

This paper tries to reconcile the result of 'conditional convergence' of growth regressions with the findings that the distribution of output per capita across countries tends to diverge over time. The paper extends the growth regression model by adding an assumption that a country follows the global technology frontier either fully or partially. The paper then estimates this extended model and reaches three main results. First, it shows that although a country converges to its long-run growth path, this path can diverge from the global frontier and for most countries it indeed diverges. Second, we estimate growth dynamics without controlling for additional variables. Third, our method enables us to disentangle the effects of various explanatory variables on the long-run rate of growth from their overall effects.

Keywords: Economic Growth, Growth Regressions, Global Frontier, Divergence, Convergence.

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* The views in this paper are those of the authors and do not necessarily represent their affiliated institutions.

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1. Introduction

A major tool in the empirical research of economic growth across countries is growth regressions, which follow the seminal contribution of Barro (1991). Over the years growth regressions have been criticized on various grounds. One main criticism has been their result of 'conditional convergence,' namely that output per capita of each country converges to its own steady state. Hence, the distribution of output per capita across countries should converge to some limit distribution. But another line of research that began with Bernard and Durlauf (1995, 1996), which examines directly the dynamics of the distribution of output per capita, has found that this distribution diverges over time. This paper presents an extension of the growth regression model, which can reconcile growth regressions with these results of divergence. Another major criticism of growth regressions has been that the choice of control variables, which are used in the estimation of convergence, is ad-hoc. Our extended model handles this criticism too, as we estimate the dynamic parameters of economic growth without the use of control variables.

Our contribution builds on the canonical growth regression model, as presented in the authoritative survey of this literature, Durlauf, Johnson and Temple (2005) (hereafter DJT). According to this model the ratio between output per worker and productivity converges to some long-run value. The speed of convergence is denoted b, which is usually assumed to be equal across countries. We add to this model a new assumption on how productivity itself changes over time. While previous models assume that productivity grows at a constant rate, which is usually equal across countries, we assume that productivity follows the global frontier, but might follow it partially.[1] More specifically, a country adopts in each period only *d* of the new technologies per period, where *d* is a country specific parameter between 0 and 1. If *d* is equal to 1 the country's long-run growth path follows the global frontier fully, but if *d* is less than 1, its long-run path diverges away from the frontier.

When we embed this assumption in the convergence model, we get a dynamic relationship between the level of output per worker, lagged output per worker and the global frontier, which completely describes the dynamics of output per worker over time. Within this dynamic framework the parameter *b*, which is the measure of 'conditional convergence' in the standard growth regression model, should be interpreted somewhat differently. It measures the convergence of the country to its long-run growth path, but this path itself might diverge away from the global frontier and from the countries at the frontier, if *d* is smaller than 1. Hence, *b* is actually a measure of 'self convergence' and does not exclude global divergence. The full dynamics of convergence and divergence can be revealed only after by finding both *b* and *d* of a country.

We estimate our extended model with data on output per capita and using the US GDP per capita as a proxy to the global technology frontier. Since the levels of output per capita are non-stationary we apply appropriate estimation methods, namely panel cointegration or regression of differences. With these methods we estimate *b* and *d* for each country. We find that *b* is indeed quite similar across countries, around 4%, but *d* differs significantly across countries with an average of 0.7. Interestingly, our measure of *b* is close to previous measures. But more important is the finding that the long-run paths of most countries diverge away from the frontier. Therefore, our assumption, that

[1] A similar assumption is made by Philips and Sul (2007, 2009), but is used differently, as discussed below.

countries might follow the frontier only partially, is supported by the data. We also find that the two methods of dynamic estimation, panel cointegration and regression of differences, yield similar results for *d*, which shows robustness.

It is important to stress that the dynamic country's parameters *b* and *d* are estimated without the control variables used in previous growth regressions, like geography, education, institutions, ethnic diversity, fiscal policy and more. These variables might affect the estimated parameters, but there is no need to control for them in the dynamic estimation itself. Thus, our extended model is prone to the critique that the choice of control variables in the measurement of convergence is ad-hoc. We actually apply such variables only in the second stage of the empirical analysis, which tests their effect on the country's parameter *d*. This regression examines which variables affect the ability of the country to follow the frontier. Namely, our approach can separate the long-run effect of each explanatory variable from the short-run effect. Indeed, the empirical tests in Section 8 show that some variables, which affect growth in general, have no effect on the long-run rate of growth. This separation is, therefore, another result of our extended growth regression model.

The main literature this paper is related to is growth regressions, which began with Barro (1991), Mankiw, Romer and Weil (1992), Barro and Sala-i-Martin (1992) and developed into a huge literature.[2] One of the main results of this literature is that the distribution of output per capita across countries tends to converge to some limit distribution.[3] Our paper tries to reconcile this result with the findings of another empirical approach, by Bernard and Durlauf (1995, 1996), Quah (1996) and others, that

[2] Earlier papers that influenced growth regressions are Baumol (1986) and Kormendi and Meguire (1985).
[3] A more recent example of finding even stronger convergence is Rodrik (2013).

examines directly the dynamics of this distribution and finds global divergence.[4] Growth regressions are also criticized for the arbitrary choice of control variables in the estimation of convergence.[5] An excellent summary of growth regressions and their critiques is DJT.

As explained above, our paper tries to reconcile growth regressions with the results of distributional dynamics, by extending the model to account for following the global frontier. This can be interpreted as treating countries as open economies. Each country does not invent most of its technologies, but adopts them from the growing set of global technologies. Thus, growth of a country depends not only on its own variables, but it should also depend on the expanding global frontier. This view follows a large literature, beginning with Krugman (1979).[6] Recently it also gained support from data on technology adoption, collected and analyzed by Comin and others.[7] Our paper is also strongly related to Phillips and Sul (2007, 2009), who make a similar assumption on partial adoption of technologies. But they use this assumption mainly to show that countries diverge, as a critique of growth regressions. This paper instead embeds this assumption within the growth regression model and tries to reconcile it with the findings of divergence. Another closely related research is Dowrick and Rogers (2002). It also shows that rates of technical change differ significantly across countries, but it uses data on capital, while our model enables us to show it with data on output only.

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[4] Other articles in this direction are Pesaran (2007a) and Philips and Sul (2007, 2009). See also Henderson and Russell (2005) and Di Vaio and Enflo (2011). Also related are the 'varying parameters models' by Liu and Stengos (1999), Durlauf *et al.* (2001) and Lee *et al* (1997, 1998).

[5] Note the title of Sala-i-Martin (1997), "I Just Ran 2 Million Regressions." See also Durlauf (2009).

[6] See also Parente and Prescott (1994), Zeira (1998), Eaton and Kortum (1999), and Acemoglu, Aghion and Zilibotti (2006).

[7] Examples are Comin and Hobijn (2010) and Comin and Mestieri (2013).

Another application of the open economy framework in our paper is the justification of convergence, or the gradual adjustment of output, by adjustment costs to investment rather than the closed economy model of Mankiw et al (1992), where investment is constrained by savings. This approach is both more realistic and it also leads to a better prediction of the size of the parameter b, as shown in the Appendix.

It is important to stress that estimation of our extended growth regression model has been made possible only recently, once data have become sufficiently long to enable us a dynamic estimation of the coefficient d. The initial growth regressions had only 25 years of data, while we use 60 years of data and for some countries even 140 years of data. Recent years have seen more use of this data in panel growth regressions, but these studies were also criticized, as shown in DJT, for the high variability of output relative to the low variability of most explanatory variables. We avoid this criticism by conducting the dynamic estimation without control variables. The second stage estimation of d with respect to explanatory variables is actually a cross-section estimation.

The paper is organized as follows. Section 2 presents our extension of the growth regression model. Section 3 describes the estimation and the data. Section 4 presents the panel cointegration estimation of convergence and divergence in 1950-2008. Section 5 estimates the panel cointegration model for a group of countries with data since 1870. Section 6 presents the results of estimation by differences. Section 7 contains various robustness checks. Section 8 presents the estimation of the effects of some explanatory variables on the long-run rate of growth. Section 9 summarizes while the Appendix presents a theoretical model of convergence in an open economy with adjustment costs to investment.

2. The Extended Growth Regression Model

To explain our contribution, we use the canonical representation of the growth regression model, as presented in DJT. We describe it first and then extend it.

2.1 The Canonical Growth Regression Model

Assume first that the production function in country *i* in period *t* is equal to:

(1) $$Y(i,t) = K(i,t)^{\alpha}\left[A(i,t)L(i,t)\right]^{1-\alpha},$$

where $Y(i,t)$ is output, $L(i,t)$ is labor, $K(i,t)$ is the amount of capital invested prior to *t* and $A(i,t)$ is labor augmented productivity. Labor increases at a constant rate $n(i)$:

(2) $$L(i,t) = L(i,0)\exp[n(i)t],$$

and productivity rises at a constant rate $g(i)$:

(3) $$A(i,t) = A(i,0)\exp[g(i)t].$$

The rates of growth $g(i)$ and $n(i)$ can differ across countries.[8]

We next define output per worker in country *i* at time *t* as $y(i,t) = Y(i,t)/L(i,t)$ and efficiency output per worker as $y^E(i,t) = Y(i,t)/[A(i,t)L(i,t)]$, namely the ratio between output per worker and productivity. The basic assumption in the growth regression literature is that efficiency output per worker converges gradually to a long run value $y^E(i,\infty)$. There are two possible explanations to this gradual adjustment of output. One is derived from the Solow model, where capital accumulation is bounded by savings, since the economy is closed.[9] We think that this assumption does not fit well cross-

[8] According to DJT, most growth regression studies assume, explicitly or implicitly, that *g* is equal across countries.

[9] The Solow model was used by Mankiw, Romer and Weil (1992) and later by many others, as described in DJT. Barro and Sala-i-Martin (1992) used the Ramsey-Cass model, but are also of a closed economy.

country empirical studies. An alternative explanation is gradual adjustment of capital in open economies due to adjustment costs to investment. We pursue this latter explanation in this paper. A full model of adjustment costs is presented in the Appendix, and its implications with respect to convergence are presented below in this Section.

The gradual adjustment is formulated in DJT by:[10]

$$\ln y^E(i,t) = \{1-[1-b(i)]^t\}\ln y^E(i,\infty) + [1-b(i)]^t \ln y^E(i,0). \tag{4}$$

The parameter $b(i)$ measures the rate of convergence of efficiency output to its long-run value. Most growth regressions assume that this parameter is equal across countries.[11] Note that equation (4) implies that output per worker $y(i,t)$ converges to a long-run growth path, along which it follows productivity $A(i,t)$.

Next, equation (4) is used, by calculating the average growth rates in country i over T periods, to derive the following equation:

$$\begin{aligned} \frac{\ln y(i,T)-\ln y(i,0)}{T} &= g(i) + \frac{1-[1-b(i)]^T}{T}\ln A(i,0) + \\ &+ \frac{1-[1-b(i)]^T}{T}\ln y^E(i,\infty) - \frac{1-[1-b(i)]^T}{T}\ln y(i,0). \end{aligned} \tag{5}$$

Equation (5) is the classical cross-section growth regression.[12] Its estimation enables us to find the rate of convergence b, if it is equal across countries from the regression coefficient of initial output per worker, $\ln y(i,0)$. Note that since countries differ with respect to $g(i)$, to initial productivity $A(i,0)$ and to the long-run efficiency output y^E, which are all unobservable, there is a need to add more variables to the regression, in order to control for these unobserved variables. Examples for such variables have been

[10] Equation (4) is exactly the same as equation (1) in DJT, except for approximating 1 – exp(-b) by b.
[11] A non-parametric study that differs with this assumption is Henderson (2010).
[12] This is equation (8) in DJT.

educational attainment, political stability, the rate of saving, geographical characteristics, quality of institutions, ethnic diversity, religion, and many more. These additional variables are sometimes called 'explanatory variables,' since they can be viewed as explaining differences in growth rates across countries.[13]

Actually, there has been quite a proliferation of such explanatory variables in the literature and their total number has already passed 150. The arbitrariness of the choice of these control variables poses a significant problem to growth regressions and their estimation of convergence. Another problem with using such explanatory variables in the estimation of (5) is that even if their effect on $y^E(i,\infty)$ can be isolated, we are left with their overall effects on the sum $g(i)+[1-(1-b)^T]T^{-1}A(i,0)$. Hence, we cannot tell whether the variables affect $g(i)$, or $A(i,0)$, or both. In other words, such a regression does not distinguish between the effects of the explanatory variables on the level of output and on the long-run rate of growth.

Over the years, as data kept accumulating, researchers have tried to reap the benefits from the longer data sets by using panel estimation. The panel equation is derived directly from the convergence model (4):

(6) $$\ln y(i,t) = g(i) + b(i)\ln y^E(i,\infty) + [1-b(i)]\ln y(i,t-1) + b(i)\ln A(i,t-1).$$

Such a panel regression uses more data, but does not yet solve all the problems of growth regressions, as shown in DJT. It actually creates new problems. One difficulty is that output varies much over time, while most of the explanatory variables, like geography, ethnic diversity, political stability, institutions, etc., change little over time. Another problem in a panel regression is that the explanatory variables are highly correlated with

[13] On the problems in relating the effects of these variables with theories of economic growth see Durlaouf, Kourtelos and Tan (2008).

the countries' fixed effects. Using differences, as done by Caselli, Esquivel and Lefort (1996), solves some of these problems but not all.

2.2. The Extended Growth Regression Model

This paper's point of departure from the canonical growth regression model is to change the assumption on the dynamics of productivity A, in a way that gives a richer structure to the estimation and solves some of the problems discussed above. We therefore replace (3) with the assumption that a country's productivity A follows the global technological frontier F, but not necessarily fully. More precisely, assume that:

$$\ln A(i,t) = a(i) + d(i)\ln F(t). \tag{7}$$

The parameter $d(i)$ satisfies $d(i) \le 1$. If it is equal to 1, productivity follows the global frontier fully, and if $d(i) < 1$ it diverges away from the global frontier. Assume also that the global technological frontier is growing at a fixed average rate:

$$\ln F(t) = \ln F(t-1) + g + v(t), \tag{8}$$

where g is the average rate of growth of the frontier and $v(t)$ is a white noise.

Substituting (7) and (8) in (4) yields:

$$\begin{aligned} \ln y(i,t) &= d(i)g + b(i)a(i) + b(i)\ln y^E(i,\infty) + \\ &+ [1-b(i)]\ln y(i,t-1) + b(i)d(i)\ln F(t-1) + d(i)v(t). \end{aligned} \tag{9}$$

This is therefore the dynamic equation that describes the evolution of output over time and across countries in the extended model.

2.3. Dynamic Implications of the Extended Model

To study the dynamics of equation (9) further, subtract from each side of this equation the term $d(i)\ln F(t) + a(i) + \ln y^E(i,\infty)$ and get:

$$\ln y(i,t) - d(i)\ln F(t) - a(i) - \ln y^E(i,\infty) = \tag{10}$$
$$= [1 - b(i)][\ln y(i,t-1) - d(i)\ln F(t-1) - a(i) - \ln y^E(i,\infty)].$$

Equation (10) implies that output per worker converges to a long-run growth path, which is described by $d(i)\ln F(t) + a(i) + \ln y^E(i,\infty)$. The rate of convergence to this path is given by *b*(*i*). But the long-run path itself can diverge from the frontier if $d(i) < 1$, since country *i* follows only *d*(*i*) of the global frontier. This divergence can be quite significant. In the recent two centuries the frontier countries have grown by 20, so a country with *d* equal to 0.5 has diverged from the frontier by a factor of 4.5, a country with *d* of 0.3 has diverged by 8, and a country with *d* of 0.8 diverged by 2. What the extended model (10) implies is that the parameter *b* can no longer be the single measure for convergence in the broad sense of this word. It is better described as a measure of 'self convergence.' Actually, the parameter *d* is just as important, if not more, in classifying the growth path of the economy. We call it a measure of 'divergence' or 'global divergence.' The main part of the paper is dedicated to measure the parameters *d*(*i*).

2.4. Empirical Implications of the Open Economy Assumption

As mentioned above, in this paper the growth regression model is derived not from the Solow model of a closed economy, but from an open economy model, where capital accumulation is gradual due to adjustment costs. This modeling is not only more realistic, but it also leads to different empirical implications. The full theoretical model is presented in the Appendix, and here we present its main conclusions. The first conclusion is that in small open economies the steady state of efficiency output per worker $y^E(i,\infty)$ is equal approximately across countries, as shown in equation (A.16) in the appendix, to:

$$\ln y^E(i,\infty) \cong \frac{\alpha}{1-\alpha}\left[\ln\alpha - \ln(r+\delta)\right]. \tag{11}$$

Note that the real interest rate r is equal to all countries, and so are α and the rate of depreciation δ. Hence, the long-run efficiency output per worker should be similar for all countries. This result is very different from the implications of the closed economy Solow model, which is used in many growth regressions.

Furthermore, equations (A.18) and (A.20) from the adjustment costs model imply that the rate of capital accumulation depends on the marginal productivity of capital:

$$\ln K(t+1) - \ln K(t) = n + g + \frac{b}{1-\alpha}\frac{MPK(t) - r - \delta}{r+\delta}, \tag{12}$$

where b is the above convergence coefficient. Hence, b is equal to:

$$b = (1-\alpha)(r+\delta)\frac{\partial[\ln K(t+1) - \ln K(t)]}{\partial MPK(t)}. \tag{13}$$

This equation enables us to roughly estimate the expected size of b. We can assume, for example by comparing China today with the US, that the effect of *MPK* on the rate of growth of capital should be somewhere between 0.5 and 1.5. According to standard assumptions $r+\delta$ is between 0.10 and 0.15 and $1-\alpha = 0.65$. Hence, the rate of self convergence b should be somewhere between 3% and 15%. Note that most estimates of b in growth regressions are within this range.[14]

3. Estimation of the Extended Model

From equation (9) we get, by adding an error term, the basic empirical equation of the extended growth regression model:

$$\begin{aligned} \ln y(i,t) = {} & d(i)g + b(i)\ln y^E(i,\infty) + b(i)a(i) + \\ & + [1-b(i)]\ln y(i,t-1) + b(i)d(i)\ln F(t-1) + d(i)v(t) + u(i,t). \end{aligned} \tag{14}$$

[14] In a meta-analysis study by Abreu *et al.* (2005), the average of the estimated convergence parameters are 4.3%, while the average of 13 estimates reported by Caselli, Esquivel and Lefort (1996) is 6.2%.

The error term $u(i, t)$ is assumed to be independent over time and across countries. Since the levels of output on both sides of equation (14) and also the global frontier are supposed to grow over time, these variables are clearly non-stationary. To overcome this difficulty, equation (14) is estimated by use of two alternative techniques, one is panel cointegration, and the other is by differences.

In order to better understand the cointegration implied by (14) subtract from each side the term $d(i)\ln F(t)$ and get:

$$\text{(15)} \qquad \begin{aligned} &\ln y(i,t) - d(i)\ln F(t) = b(i)[\ln y^E(i,\infty) + a(i)] + \\ &+ [1-b(i)][\ln y(i,t-1) - d(i)\ln F(t-1)] + u(i,t). \end{aligned}$$

Equation (15), which is similar to (10), implies that output in country i is cointegrated with the global frontier, and the coefficient of cointegration is $d(i)$. Actually, equation (15) describes also the error correction model of this cointegration, where the parameter $b(i)$ measures the rate of convergence of country i toward the cointegrated path. The long run difference between output per worker and the cointegrated path is $\ln y^E(i,\infty) + a(i)$. Estimating equation (15) should yield three country specific parameters: the rate of self convergence $b(i)$, the coefficient of divergence from the frontier $d(i)$, and the distance from the cointegrated path $\ln y^E(i,\infty) + a(i)$, which we denote by $e(i)$. The second method of dynamic estimation by differences is explained below.

Our dynamic estimation uses data on output per capita, which is PPP adjusted, from the Groningen Growth and Development Centre (2013). We use output per capita instead of output per worker as these data cover a much longer period, especially for less developed countries. Specifically, we use real GDP per capita, in PPP adjusted Geary-Khamis 1990 US$, for 139 countries over the years 1950-2008. Although data are available up to 2010 for many countries, we end the period of analysis at 2008, to include all countries. For a smaller set of 30 countries the data are much longer and span over 140 years, from 1870 to 2010. The main reason we use the Groningen data set and not other PPP adjusted data sets, like Penn World Tables, is the ability to use this particular data set that is 140 years long. It fits our main idea, namely to better characterize the long-run dynamics of economic growth. In Section 7 we show that using an alternative data set of PPP adjusted output, Penn World Tables, does not alter the main results of the paper.[15]

For the global frontier we use as a proxy the US output per capita, which has grown quite steadily over more than a hundred and forty years and is also the highest among the developed large countries. The stability of the growth rate of the US economy is demonstrated in Figure 1, which plots the natural logarithm of US GDP per capita over the years 1870-2010. The US growth trend was disturbed only during the years 1929-1945, due to the great depression and to World War II.

[Insert Figure 1 here]

To further examine the use of US GDP per capita as a measure of the global frontier, we test whether it satisfies equation (8). We run the regression of the growth rate on a constant dummy of 1, for the periods 1870-2010 and 1950-2010, and find that the coefficient is equal exactly to the mean growth rate, namely it is equal to 1.8% for the entire period 1870-2010 and to 1.95% for the sub-period 1950-2010. We also run a unit root test and find that the first differences are stationary, for each sub-period examined.

[15] We have just learned that the two data sets are going to be merged. We hope to use the merged data set in the next versions of this paper.

In the panel cointegration estimation we use 5 years moving averages of output per capita to reduce cyclical high-frequency autocorrelations of output. We therefore calculate for each year the following geometric average:

$$\ln y_5(i,t) = \frac{1}{5}\left[\ln y(i,t) + \ln y(i,t-1) + \ln y(i,t-2) + \ln y(i,t-3) + \ln y(i,t-4)\right].$$

We calculate similarly the averages of output per capita of the US, which is the global frontier. We then estimate the error correction model (15) for these variables. In Section 7 we examine the choice of 5 years' by testing the model for other time lengths, like 1, 3 or 10 years. The results are similar, which shows robustness.

The other method we apply to estimate (14) is differences, following Caselli, Esquivel and Lefort (1996). As in the estimation of cointegration, here we also use 5 years averages to remove cyclical effects.[16] We use the following notation for 5 years average rates of growth: $g_5(i,t) = \left[\ln y(i,t) - \ln y(i,t-5)\right]/5$ and get:

$$\begin{aligned} &g_5(i,t) = [1-b(i)]g_5(i,t-1) + c(i)g_5(US,t-1) + \\ &+ d(i)\left[v(t) - v(t-5)\right]/5 + [u(i,t) - u(i,t-5)]/5, \end{aligned} \tag{16}$$

where $c(i) = b(i)d(i)$. Note that we estimate (16) using annual observations for all t, except for the first 5 years. Hence, if our data span over T periods of time, we can use T – 5 observations. Note also that the moving average nature of the error term in equation (16) induces a correlation with the right-hand side lagged rate of growth, which requires the use of instrumental variables. Finally, (16) does not estimate d directly, but only b and c. The divergence coefficient d is calculated as a ratio: $d(i) = c(i)/b(i)$. Since calculation of such a ratio might depend on the denominator, which is rather small, we also apply

[16] If we do not take 5-year averages we obtain similar qualitative results, but with lower d. Hence, the procedure of averaging the data even strengthens our main claim, that d is lower than 1 for most countries.

another test to whether d is smaller or equal to 1, as $d(i) < 1$ if and only if $1 - b(i) + c(i) < 1$. Namely, if the sum of coefficients of (16) is significantly smaller than 1, then the country diverges from the frontier.

4. Convergence and Divergence in 1950-2008: Cointegration

We begin our estimation of the dynamic model with a panel cointegration test of equation (15) for 139 countries over the period 1950-2008. The results for the whole sample are presented in Table 1 and are very clear. The coefficient b is around 4% and significantly higher than 0, which is in line with most previous growth regressions. This result means that each country converges to its own long-run growth path. Table 1 also shows that most of these long-run paths are diverging from the global frontier, since the coefficient d is equal on average to 0.69, it is significantly lower than 1 and it is significantly heterogeneous across countries. Hence, our results succeed in reconciling the conditional convergence result of growth regressions with the divergence result of studies of the dynamics of distributions.

[Insert Table 1 here]

We have tested the ADF of the cointegration for the various countries and the results came out very supportive. Except for 5 countries the probability of not being cointegrated was lower than 10% and only for 9 countries the probability of not being cointegrated was higher than 7%. Most of these countries suffered from intense conflicts and severe interruptions of economic activity.[17] We therefore treat these countries as outliers from here on. An additional group of countries that deserves attention are the oil-

[17] The countries not cointegrated with probability above 10% are Bangladesh, Indonesia, Kenya, Laos and Vietnam. The countries with probability between 10% and 7% are Ghana, Cambodia, Nepal and Senegal.

producing countries, which experienced very high levels of output in the 1970s and declining output since then.[18] Such countries might bias *d* downward.[19] Table 1 also presents the results of the panel cointegration without the outliers and without the oil-producing countries. The second column in Table 1 shows that removing these countries indeed increases *d*, but not by much and it is equal to 0.71 and is still significantly lower than 1.

[Insert Figure 3 here]

Figure 3 plots the results of the panel cointegration analysis and further amplifies the results of Table 1. It shows that *d* is quite dispersed across countries. The variability of the coefficient *b* is much smaller and it is closely clustered around its average of 4%. Hence, these results justify our main assumption that countries can differ in following the global frontier. Note that we did not constraint the coefficient *d* to be between 0 and 1 as the theory implies. The main reason is the possibility of misspecification in the estimation of (15), especially if the coefficient *a* is changing during the period of the estimation, which might appear as a different *d*. We therefore follow Eberhardt and Teal (2013), who claim that unconstrained heterogeneous estimation is preferred, since it reduces bias of average estimates, where the noise created by misspecification at the country-level is filtered out.

[Insert Table 2 here]

A further examination of the results indicates that *d* follows a regional pattern to some extent. This is shown in Table 2. The regions are the same as in Figure 2: OECD,

[18] Mankiw, Romer and Weil (1992) have eliminated these countries from their analysis.

[19] We define countries as oil producers if their oil rents exceed 30% of GDP in 1975-2000. The countries are Bahrain, Republic of Congo, Equatorial Guinea, Gabon, Ghana, Kuwait, Libya, Nigeria, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

SSA, LAC, SEA and Other Countries, which are mainly MENA and the EEC. Table 2 paints a clear regional picture of divergence from the frontier. While the OECD countries follow the frontier with *d* very close to 1, and while in South East Asia *d* is higher than 1, around 1.6, which is discussed below, the rest of the world lags behind the frontier. Not surprisingly the most miserable region is South Saharan Africa, but Latin American countries are lagging quite behind as well and so are the other countries in MENA and in East Europe. This supports our main assumption, that *d* is significantly lower than 1 for many countries and it is quite variable across countries.

At this point we should discuss the problem caused by the famous Asian Tigers: Hong Kong, Korea, Singapore and Taiwan. These countries went through a rapid 'catch up' through much of the period. In terms of equation (7) this can be interpreted as a change in $d(i)$, but also changing their position relative to the US by raising $a(i)$ over these years. We guess that this biases our estimates of the parameter *d* for these countries, which is on average equal to 2.5. Without the Asian Tigers the estimated average of *d* in the whole sample goes down to .58 and it is lower for South East Asia as well. We therefore treat the high values of *d* of in this region with some caution in some of the tests below.

In addition to the estimation of $b(i)$ and $d(i)$, our panel cointegration enables us to estimate for each country also the parameter $e(i)$, which is the long-run difference between $\ln y(i,t)$ and $d(i)\ln F(t)$. This parameter is equal to $\ln y^E(i,\infty)+a(i)$, as shown above. Since under the open economy assumption $\ln y^E(i,\infty)$ should be quite similar across countries, our estimated $e(i)$ is a good proxy for $a(i)$. Note that according to equation (7): $a(i)=\ln A(i,t)-d(i)\ln F(t)$. Hence, if the global frontier is normalized to 1 at some period R, namely if $\ln F(t) = \ln y(US,t) - \ln y(US,R)$, the parameter $a(i)$ is equal to the productivity of the country at this reference period R.

5. Long-Run Convergence and Divergence: 1870-2010

In this section we extend the analysis further to the past. Our data allow us to examine patterns of economic growth over a longer period of time, 1870-2010, although for a smaller set of 30 countries, in addition to the US.[20] Most of these countries are now developed, namely OECD countries. Note that this period has experienced not only significant economic growth, but also two World Wars and the Great Depression. The results of the panel cointegration regression are presented in Table 3.

[Insert Table 3 here]

Table 3 shows that the developed countries indeed follow the global frontier and do not diverge from it. The average *d*, if we take out Sri Lanka, which is an outlier in this estimation, is 0.99 and not significantly different than 1. The only countries in the long-run sample that deviate and diverge from the frontier, namely that their *d* is less than 0.75, are: Argentina with *d* equal to 0.61, India with *d* equal to 0.02, New Zealand with *d* equal to 0.73, Uruguay with *d* equal to 0.59, and South Africa with *d* equal to 0.7. Interestingly, the other Latin American countries in this sample, Brazil, Chile, Columbia, Peru and Venezuela, follow fully the global frontier. We know that Latin American countries have grown better until WWII and much worse later. This might be one reason

[20] The sample for 1870-2010 includes Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Denmark, Finland, France, Germany, Greece, India, Indonesia, Italy, Japan, Netherlands, New Zealand, Norway, Peru, Portugal, South Africa, Spain, Sri Lanka, Sweden, Switzerland, United Kingdom, Uruguay and Venezuela.

for the differences between the estimation in 1950-2008 and the estimation over the longer period 1870-2010 in Latin America.

6. Convergence and Divergence in 1950-2008: Method of Differences

In this section we turn to the second method of estimation of the parameters *b* and *d*, namely estimation of the time differences instead of panel cointegration. Our approach follows Caselli, Esquivel and Lefort (1996), but our analysis differs by adding the new variable of the global frontier and also by not using any additional explanatory variable. Since we assume that countries follow the global frontier differently, we cannot use the Arellano-Bond (1991) method, as in Caselli, Esquivel and Lefort (1996). To estimate different coefficients for each countrywe follow the method of Pesaran and Smith (1995), and we use it with instrumental variables, as done in Bond *et al.* (2010).[21]

As noted above, lagged growth rates are endogenous, so we use instrumental variables to control for them. The instruments are growth rates lagged by more than 5 years: $g_5(i,t-6)$, $g_5(i,t-7)$, $g_5(i,t-8)$, $g_5(i,t-9)$ and $g_5(i,t-10)$ for country *i*, and $g_5(US,t-6)$, $g_5(US,t-7)$, $g_5(US,t-8)$, $g_5(US,t-9)$, and $g_5(US,t-10)$ for all countries. The results are reported in Table 4.

[Insert Table 4 here]

The results of the estimation by differences in Table 4 support the results obtained from the panel cointegration estimation. The estimate of short run convergence *b* is slightly higher, 11% instead of 4%, but the estimates of *d* are quite close. The average *d*

[21] We also tried I.V., GMM and Pesaran-Smith estimations on differences. In I.V. and GMM we get a lower *d*, while mean pooled estimation is similar to our results. This implies that the problems of endogeneity and residual autocorrelations are not crucial. The Arellano-Bond results bias *b*, due to heterogeneity, as pointed out in Hauk and Wacziarg (2009).

is between 0.68 in the whole sample and 0.66 in the sample without the outlying countries. In order to examine how different the estimates of *d* are for each method, we present in Figure 4 a scatter diagram of the various countries where on the horizontal axis is the *d* estimated by differences and on the vertical axis is the *d* estimated by panel cointegration. As Figure 4 shows, most countries are close to the diagonal, namely the two estimations yield very similar estimates for *d*. In addition to Figure 4, we also run a Kolmogorov-Smirnov test to check how different the two distributions of *d* are from one another. The null hypothesis of the test is that the two sets of *d* are drawn from the same continuous distribution, and we find that the null cannot be rejected at P=0.88. Hence, the two methods of estimation lead to very similar results with respect to *d*. Due to this similarity we keep Panel Cointegration as our main method of analysis, because it enables us to estimate *d* more accurately, not as a quotient, but directly, and also because it enables us to estimate also the coefficient *e* in addition to *b* and *d*, which we cannot estimate by differences.

[Insert Figure 4 here]

7. Robustness Checks

In this Section we run a number of tests in order to check the robustness of our main results on convergence and divergence. First, we examine the effect of the source of data on our results. As explained above, we use the Groningen data set mainly due to its long time span, but we have also applied our main test to an alternative data set, Penn World Tables (PWT) 7.1, which is used in many growth regressions. The comparison requires adjustment of the time span and sets of countries, due to availability of data. The PWT has data on only 58 countries since 1950. We therefore compare the two data sets for the period 1960-2008 for 100 common countries, and eliminate from both data sets China and Nepal, which are outliers in PWT and Bangladesh, which is an outlier in our data. The estimation of the panel cointegration with the Groningen data set for these countries yields an average *d* of 0.667 (standard error 0.082) and average *b* of 0.049 (standard error 0.003). The estimation of the panel cointegration with the PWT 7.1 data set for these countries yields an average *d* of 0.673 (standard error 0.105) and average *b* of 0.057 (standard error 0.004). Hence the results are quite similar across the two data sets and the choice of Groningen does not have a significant effect on the main results.

As explained above, our dynamic regressions use moving averages of logarithm of output per capita over periods of 5 years. Next we examine how restrictive this is by using averages over different time lengths: one year, three years, and ten years. We also examine whether the initial year matters, namely what happens if we begin to calculate the 5 (or 3 or 10) years averages at 1955 or at 1956, etc. The tests are conducted for the whole sample excluding the Oil Producing Countries and the other outliers. Their exclusion is done mainly for the 1 year average, to avoid extreme values of *d* in tests that do not smooth data at all. Table 5 presents the results of these tests and shows that the main results of the paper hold for other choices of timing as well.

[Insert Table 5 here]

Table 5 reveals a few additional interesting results. First, the rate of convergence *b* declines as the data is averaged over longer periods, from 9% for annual data, to 6% for 3 years averages, 4.5% for five years averages, to 3.5% for 10 years averages. This means that output depends less and less on lagged output as it is averaged over longer periods of time. This means that there is a significant amount of cyclical autocorrelation and averaging indeed removes this effect. This indeed justifies the averaging of data as done in this paper. Note also that *d* changes very little as averaging changes and it is somewhere between 0.65 and 0.7. Only in the case of annual data, without averaging, the value of *d* falls slightly below 0.6, but it is of course lower than 1. Hence, the choice of averaging over 5 years is not a restrictive procedure and it is justified as it reduces the effect of cyclicality.

Our estimation of each country's *d* implicitly assumes that this coefficient does not change much over time. We conduct a simple test of this assumption by running our dynamic estimation over a sub-period, the years 1980-2008, namely for the second half of our period. We find that indeed the average *d* for the later sub-period is 0.869, which is higher than for the entire period, but still significantly lower than 1. Figure 5 presents a scatter diagram for all countries, where the horizontal axis is *d* from the full period estimation in 1950-2008 and the vertical axis is *d* from the sub-period estimation in 1980-2008. The scatter diagram also shows that there were changes in *d* for some countries, but most countries are still located close to the diagonal, namely the estimated coefficients in the second half of the period did not change by much for most countries. Note that the differences can also stem from estimation over a shorter period, which is less accurate. This test, therefore, shows that treating the country coefficient $d(i)$ as stable over time is a reasonable first-order approximation.

[Insert Figure 5 here]

The final test we present combines our model with the method of 'development accounting.' This method decomposes total factor productivity (TFP) into human capital and all the rest by calculating human capital from data on years of schooling. This method is surveyed in Caselli (2005).[22] To apply 'development accounting' to growth regressions assume that output is described by the following production function, which replaces (1):

(17) $$Y(i,t) = K(i,t)^{\alpha}\left[A(i,t)h(i,t)L(i,t)\right]^{1-\alpha}.$$

The variable $h(i,t)$ is the average amount of human capital in country i at time t. The variable $A(i,t)$ is no longer total productivity, but the residual after subtracting human capital, which can be assumed to be mainly technical change. We next keep assumptions (4), (7) and (8) of our model, but assume that (7) holds for A only. We next define output per worker and per human capital in the following way:

(18) $$y^{H}(i,t) = \frac{Y(i,t)}{h(i,t)L(i,t)}.$$

Applying this variable to the model we derive the same dynamics as in (9) or (10), except that output per worker $y(i,t)$ is replaced by $y^{H}(i,t)$.

In the calculation of h we use the coefficients derived from many labor studies, as summarized by Caselli (2005): each year of schooling increases ln$h$ by 0.13 in the first 4 years of education, by 0.1 in the next 4 years and by 0.07 in the years 8 to 12. The data on schooling are taken from Barro and Lee (2013). We then run the panel cointegration test on $y^{H}(i,t)$ and the global frontier $y^{H}(US,t)$. The results are summarized in Table 6.

[Insert Table 6 here]

The results of Table 6 are quite illuminating. The self convergence coefficient b comes out around 4%, as in the benchmark estimation. The d coefficients are much

[22] First famous papers in this direction are Klenow and Rodríguez-Clare (1997), and Hall and Jones (1999).

lower. The main reason for that is that although many countries did not grow as fast as the US, they increased their human capital by much more, mainly because their initial education in 1950 was very low. There can be another explanation to this result. It is possible that more education in many developing countries does not translate fully to higher productivity, as there is need to invest more capital, to create the required jobs, and to create the environment that enables people to fully materialize their education.

8. Effects of Explanatory Variables on Global Divergence

In this paper we succeed in estimating the convergence and divergence of output across countries without using any control variable. The reason for this success can be understood from equation (14). If it is estimated without using the global frontier F then in order to estimate b one needs to control for d and a, which differ by country, and this is done by using explanatory variables as controls. Once we add the global frontier F, we estimate directly the country parameters d and a and thus we do not have to use any control variable. But since d and a depend on various explanatory variables, we can conduct a second stage test on how such variables affect d and a. Hence our method can decompose the effects of explanatory variables to long and short-run effects.

This section presents an example of such second stage empirical analysis, which estimates the effects of some explanatory variables on the coefficient d, as estimated by panel cointegration for the years 1950-2008. We compare the results of this estimation with a standard growth regression and show that the results differ significantly. Namely, some variables that affect growth according to the standard regression do not affect the parameter d, while one variable that is insignificant in the growth regression, has an effect on *d*. This means that our method indeed succeeds in separating the long-run effect from the overall effect.

It is important to stress that this section does not try in any way to enter the big debates on what are the true explanations to economic growth, or what are the right explanatory variables that should be included in the empirical tests. We just try to show that our approach enables us to separate the effects of explanatory variables to short and long-run effects. For that goal, we picked a set of variables, which are used in many growth regressions. Here is the list of the variables:

1. TROPIC is the share of land in a country that is tropical (Gallup *et al.*, 2010).
2. COAST is the share of land in a country that is within 100 km from a coast or from a navigable river (Gallup *et al.*, 2010).
3. Y_50 is the natural logarithm of the GDP per capita in the country at 1950.
4. ETHNIC is a measure for ethnic fractionalization in a country.
5. EDU is average years of schooling of people above age 15 over the period 1950-2010 (Barro and Lee, 2013).
6. OPEN is a measure of openness of a country. It is a measure of trade policy over the years 1965-1990, which has been introduced by Sachs and Warner (1995).[23]
7. ICRG is average measure of quality of institutions during the period 1982-1997 according to the International Country Risk Guide (Knack and Keefer, 1995).
8. G/Y is the share of public expenditures in GDP, averaged in the years 1950-1960, taken from Feenstra, Inklaar, and Timmer (2013).

[23] This is a variable that classifies an economy as closed according to the following five criteria: (i) if its average tariff rate exceeded 40%; (ii) if its non-tariff barriers covered more than 40% of imports; (iii) if it had a socialist economic system; (iv) if it had a state monopoly of major exports; or (v) if its black-market premium exceeded 20% during either the decade of the 1970s or the decade of the 1980s.

Note that variables 1-2 reflect the geographical explanation to growth. Variables 3-4 reflect the history of the country, namely its initial conditions, both economic and social. Variable 5 is human capital and variables 6-8 reflect institutional explanations to economic growth. As mentioned above, these variables were chosen not only because they are used in many growth regressions, but also because they are potentially related to following the global technology frontier, which lies at the heart of this paper. As explained by Sachs (2001), geography is a barrier to technology transfer, since technology might be region-specific, especially in agriculture or health. This is also implied by Parente and Prescott (1994) and by Zeira (1998). Human capital also affects the ability to adopt new technologies, as pointed by Galor and Moav (2000) and Zeira (2009). Institutions are crucial to adoption of technology, as claimed by Acemoglu, Johnson and Robinson (2005) and others, especially institutions that affect international trade, as stressed by Grossman and Helpman (1991).

[Insert Table 7 here]

Before we turn to the direct estimation, we present the matrix of correlations between these variables in Table 7. This table can already give us some preliminary insights into the relationship between these variables and economic performance. For example, being in the tropics is strongly negatively correlated with most other variables, like education and institutions. It is also clear that the quality of institutions is strongly correlated with openness and with initial output. This is probably the reason that some of these variables come out insignificant in the regressions. As a result, we omit in the following analysis the variable ICRG.

The regressions are presented in Tables 8 and 9. The first one, Table 8, presents the results of the estimation where the dependent variable is the average rate of growth over the years 1950-2008, which we denote by AVG. Since Initial output in 1950 is one of the explanatory variables, this is a standard growth regression, and we include it as a point of reference, that enables us to compare it to the results of the other regression. Table 9 presents the regressions with d as the dependent variable. These regressions therefore show how the explanatory variables affect the rate of divergence from the frontier, namely how they affect the long-run rate of growth of a country. We also report in the text on the regressions with e as the dependent variable.

All the regressions in the two tables include constants and are OLS in a cross-section of countries. In each table we present three separate regressions. One is with all the countries for which the data is available without outliers. Data availability reduces the number of countries in the regression to 90. In the next regression we omit the South East Asian countries, and in the third we omit both the SEA countries and the OECD countries. The reasons for these omissions are as following. First, there is a bias in the estimation of d among the SEA countries and it is too high above 1. This is mainly because most of the rapid growth in these countries happened toward the end of the period explored, and thus the cointegration procedure tends to confuse the convergence in these countries with a new trend. Another reason for considering omission of these countries is that they are clearly countries that change their pattern of growth during the period covered by the data. Since they change their d and probably also change their coefficient a, it is preferred not to include these countries when testing for a statistical regularity between explanatory variables and these coefficients. For very different reasons we also find the inclusion of the OECD countries as problematic in the estimation of the effects on *d*. The main reason is that in these countries *d* is around 1, which is a corner solution, since in the long-run countries cannot adopt technologies at a higher rate than the frontier. Being at such a corner, therefore, might make these countries insensitive to the explanatory variables. The OECD countries may have more or less education, larger or smaller government, better or worse institutions, but they all have *d* around 1, since it is a corner solution. Thus, including the OECD countries in the estimation reduces its ability to identify relationships between *d* and the explanatory variables. Hence, the third regressions in Tables 8 and 9 omit not only the SEA countries, but the OECD countries as well.

[Insert Table 8 here]

Table 8 presents the results of the standard growth regression on this set of explanatory variables for the three sets of countries, full, without SEA and without SEA and OECD. There are 6 variables that are significant throughout, in addition to the constant. These variables are TROPIC, which reduces growth, proximity to coast, which increases growth, initial output Y_50, which has a negative effect on economic growth as expected, education, which has a positive effect on growth, openness, also with a positive effect on growth and the share of government in GDP, which has a negative effect on economic growth. These results resemble results of many other studies. Ethnic fractionalization appears to be insignificant.

[Insert Table 9 here]

Table 9 presents the effects of the same explanatory variables on the long-run coefficient *d* and we can compare these results to those in Table 8. One variable that still has a negative significant effect is the tropics. Note that its effect is increasing as we narrow the set of countries in the test. In the most relevant group, without South East Asia and OECD, the effect of TROPIC is around half. Namely being in the Tropics can reduce *d* by almost 0.5 relative to the developed countries. Hence, this variable can account for much of the divergence of Africa and Latin America. Another variable that affects *d* positively and significantly is openness. Hence, it has a significant positive effect on growth both in the short and in the long-run. But for the other variables the results in Table 9 differ significantly from the results in Table 8. Initial output becomes less and less significant as we narrow the sample. Education and the share of government in output become insignificant once we begin to narrow the set of countries. The result on education is quite surprising.[24] One possible interpretation is that education affects only the level of output but not its long-run rate of growth. Another interesting result is that although ethnic fractionalization does not affect growth in the standard growth regression, it has a negative significant effect on *d*, namely on long-run growth.

Thus, Tables 8 and 9 demonstrate that the dynamic estimation suggested in this paper enables us to differentiate between short-run and long-run effects of various explanatory variables on economic growth. Of the variables used in this Section, which is to a large extent an arbitrary set of variables, we found that initial output, education and fiscal policy do have an effect on economic growth in a standard growth regression, but do not have a significant effect on the long-run rate of growth, while ethnic fractionalization does not have a significant effect in a growth regression, but tends to have a significant effect on long-run growth.

[24] For similar results and a more through analysis of the effect of education on growth see Delgado, Henderson, and Parmeter (2014).

In addition to the test of the coefficient *d* on the explanatory variables we also tested the effects of these variables on the coefficient *a*, as some measure of short-run growth. As explained above this coefficient depends significantly on the year for which the variable *F* is normalized. If it is normalized to be 1 in year *R*, then $a(i) = A(i, R)$, namely it is equal to the level of productivity in that year. We tried to normalize the global frontier both in 1950 and in 2008. The results were similar and somewhat disappointing. Most variables had no significant effect on a. When including all countries in the regression, only G/Y had a significant negative effect, but excluding SEA made it insignificant, while openness became significant instead with a negative sign. We could therefore learn little from these regressions. Obviously, this Section presents only preliminary results and just shows that here is a tool that can help us to decompose the effects of various variables to long-run versus overall effects. The main important question, namely which variables should be included in these tests and how to test whether they have a causal effect, remains beyond the scope of this study.

9. Conclusions

Durlauf (2009) claims that one of the problems of early growth regressions was that they were used as empirical tests to judge between two conflicting theories, neoclassical growth and endogenous growth. He is right of course, because endogenous growth theory focuses mainly on global technical change, while growth regressions test economic growth across countries. Thus they are not really comparable. But this paper claims that the two phenomena, global technical change and individual countries' growth performances, are strongly related, because each country adopts global technologies. The big question is how much.

In a world where the global technology expands continuously and countries can choose whether to adopt a new technology or not, the growth path of each country reflects, among other things, how much it follows the global technology frontier. The main claim in this paper, hence, is that growth regressions should include the global technology frontier. Note, that we do not criticize previous studies for not including this variable, since previous data spanned much shorter time, during which changes in the global frontier were relatively small. Nowadays, that the data cover much longer time periods, the global frontier cannot be left outside any more.

This paper adds the global technology frontier in growth regressions by specifying explicitly how a country might adopt global technologies either fully or partially. We then estimate this specification and find that most countries run more slowly than the frontier. We show that this finding reconciles the results of growth regressions with the results on the dynamics of the distribution of output across countries. Another benefit of our approach is that we can estimate convergence and divergence without controlling for explanatory variables, which avoids some of the critiques on growth regressions. We also show how our approach can help in separating the effects of explanatory variables on growth into long-run and short-run effects. Our regressions demonstrate that this difference is significant.

This paper is of course quite preliminary and might lead to various potential research lines. One possible direction can be estimation of the dynamic coefficients by use of alternative methods to panel cointegration or differences, like non-parametric estimation, rolling regressions, or other methods. Another possible direction of research is to extend the second stage regressions to more explanatory variables and to take better care of endogeneity problems. All such potential extensions are waiting for future research.

Appendix: Convergence in a Small Open Economy

Consider a small open economy with full capital mobility facing a constant global interest rate r. Output in the economy in period t is described by the following Cobb-Douglas production function:

$$Y(t) = K(t)^{\alpha}\left[A(t)L(t)\right]^{1-\alpha}, \tag{A.1}$$

where $Y(t)$ is output, $L(t)$ is labor and $K(t)$ is the amount of capital invested prior to t. Capital depreciates at a rate δ. Productivity A and population N increase at constant rates:

$$A(t) = A(0)e^{gt}, \text{ and } N(t) = N(0)e^{nt}, \tag{A.2}$$

where g and n are positive numbers.[25] Each person supplies 1 unit of labor per period. Investment has adjustment costs, which are assumed to be quadratic and of CRS:

$$a(t) = \frac{1}{2z}\frac{[K(t+1) - K(t)]^2}{K(t)}. \tag{A.3}$$

The parameter z is an inverse measure of the intensity of these costs.

Due to the constant returns to scale of the production and the adjustment cost functions, the value of each firm is proportional to its capital and marginal q is equal to average q, as shown in Hayashi (1982). Hence, the market value of capital $V(t)$ satisfies:

$$V(t) = q(t)K(t+1), \tag{A.4}$$

where $q(t)$ is the economy wide value of one unit of capital. Denote the wage rate in period t by $w(t)$. Then, firms maximize:

$$\begin{aligned} &K(t)^{\alpha}L(t)^{1-\alpha} - w(t)L(t) + q(t)K(t+1) - K(t+1) + (1-\delta)K(t) - \\ &\qquad - \frac{K(t)}{2z}\left[\frac{K(t+1) - K(t)}{K(t)}\right]^2 \end{aligned} \tag{A.5}$$

[25] Note that this open economy model fits the canonical growth regression model of Section 2.1, but it can be applied also to the extended model, as done in Section 2.2.

The two first order conditions of (5) determine the labor demand:

(A.6) $$w(t) = (1-\alpha)K(t)^{\alpha} A(t)^{1-\alpha} L(t)^{-\alpha},$$

and the rate of capital accumulation:

(A.7) $$\frac{K(t+1) - K(t)}{K(t)} = z[q(t) - 1].$$

We next introduce the equilibrium conditions. Labor market equilibrium requires:

(A.8) $$L(t) = N(t).$$

Due to capital mobility and lack of risk we get that the returns on capital and on lending are equal, so that:

(A.9) $$q(t)(1+r) = MPK(t+1) + q(t+1) - d + \frac{z}{2}[q(t+1) - 1]^2,$$

Where the marginal product of capital is:

(A.10) $$MPK(t) = \alpha K(t)^{\alpha-1}[A(t)N(t)]^{1-\alpha}.$$

We next turn to describe the dynamics of the economy. First, we transform the dynamic variables to better fit the empirical model. Instead of the price of capital we use: $Q(t) = q(t) - 1$, and instead of marginal productivity of capital we use its natural logarithm: $x(t) = \ln[MPK(t)]$. From (A.9) we get:

(A.11) $$Q(t)(1+r) = \exp[x(t+1)] + Q(t+1) - (r+\delta) + \frac{z}{2}Q(t+1)^2.$$

The dynamics of x are derived from (A.2) and (A.7):

(A.12) $$x(t+1) = x(t) + (1-\alpha)\{g + n - \ln[1 + zQ(t)]\}.$$

It is clear that this dynamic system has a saddle path solution that is described by the function: $Q(t) = Q[x(t)]$, where Q is monotonic increasing. Using a linear approximation of ln we get that the steady state of the system is described by:

(A.13) $$Q^* = \frac{g+n}{z},$$

And:

(A.14) $$x^* = \ln(r+\delta) + \ln\left[1 + \frac{g+n}{z}\frac{r-(g+n)/2}{r+\delta}\right].$$

Note that the second term of the RHS of (A.14) is close to 0 for realistic values of *g*, *n* and *r*. To see this assume that *g* is around 2 percent annually, *n* is around 1 percent, *r* is around 3 percent and the rate of depreciation is around 10 percent. To such specifications we get that $x^* = \ln(r+\delta) + \ln[1 + 0.0035/z]$. Since z cannot be below 0.1 we get: $\ln(r+\delta) \le x^* \le \ln(r+\delta) + 0.0344$. Note that 0.0344 is extremely small and is negligible relative to $\ln(r+\delta) = -2.04$. Hence we can assume that the steady state marginal productivity of capital is equal approximately to $r+\delta$ and it does not depend on the country's specific parameters *g*, *n* and *z*.

We next turn to connect the model more to the growth regression model. Note that efficiency output per worker, $y^E(t)$, satisfies:

(A.15) $$\ln y^E(t) = -\frac{\alpha}{1-\alpha}[x(t) - \ln\alpha].$$

Hence, efficiency output per worker converges to a steady state $\ln y^E(\infty)$ along the saddle path. The steady state can be calculated from (A.14) and (A.15) and is equal to:

(A.16) $$\ln y^E(\infty) = \frac{\alpha}{1-\alpha}\left\{\ln\alpha - \ln(r+\delta) - \ln\left[1 + \frac{g+n}{z}\frac{r-(g+n)/2}{r+\delta}\right]\right\} \cong$$
$$\cong \frac{\alpha}{1-\alpha}[\ln\alpha - \ln(r+\delta)].$$

Note that since r is the same for all countries, and α and δ are technological parameters that should also be the same for all countries, $\ln y^E(\infty)$ should also be equal across countries if they are small open economies.

From (A.12) and (A.15) we derive the dynamics of efficiency output per worker:

(A.17) $$\ln y^E(t+1) = \ln y^E(t) + \alpha z Q\left[\ln\alpha - \frac{1-\alpha}{\alpha}\ln y^E(t)\right] - \alpha(g+n).$$

Hence, the coefficient of convergence of y^E can be derived from (A.17) and in the neighborhood of the steady state it is equal to:

(A.18) $$b = (1-\alpha)zQ'(x^*).$$

One way to find b is to calculate the slope of the saddle path at the steady state, $Q'(x^*)$. This slope is the positive solution of the following quadratic equation:

(A.19) $$(1-\alpha)z(1+g+n)[Q'(x^*)]^2 + \left[r-g-n+(1-\alpha)ze^{x^*}\right]Q'(x^*) - e^{x^*} = 0.$$

Yet another way to estimate b is to examine the dynamics of capital accumulation using a first order approximation around the steady state. We get:

(A.20) $$\ln K(t+1) - \ln K(t) = n + g + zQ'(x^*)\frac{MPK(t) - MPK^*}{MPK^*}.$$

Hence:

(A.21) $$b = (1-\alpha)MPK^*\frac{\partial[\ln K(t+1) - \ln K(t)]}{\partial MPK(t)} \cong (1-\alpha)(r+\delta)\frac{\partial[\ln K(t+1) - \ln K(t)]}{\partial MPK(t)}.$$

Note that the right hand side of equation (A.21) can be estimated and thus supply some idea on the expected size of b, as done in Section 2.4.

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Figures and Tables

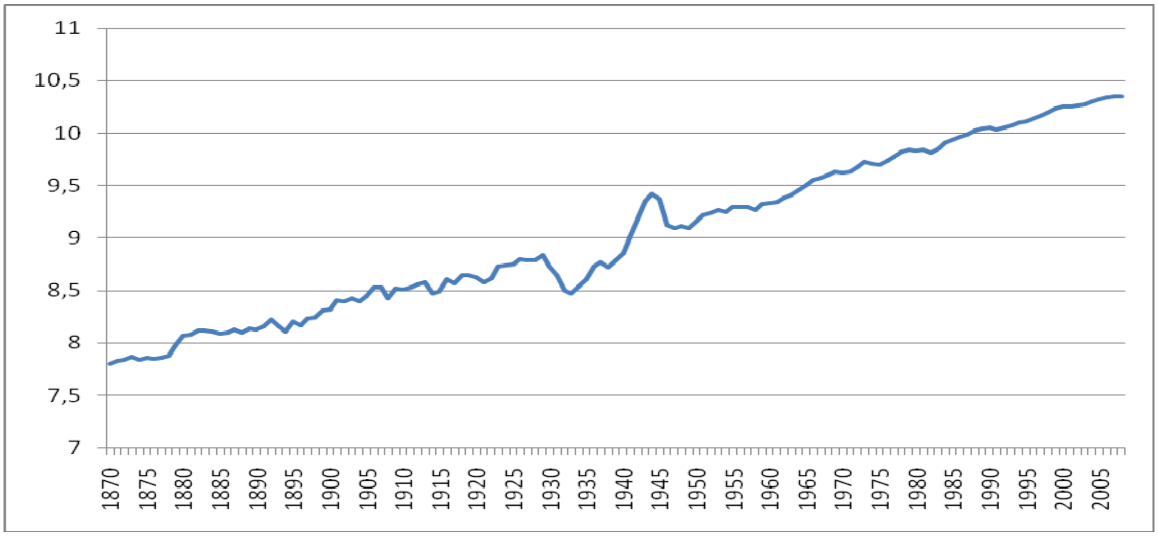

Figure 1: Natural Logarithm of US GDP per capita in 1870-2010

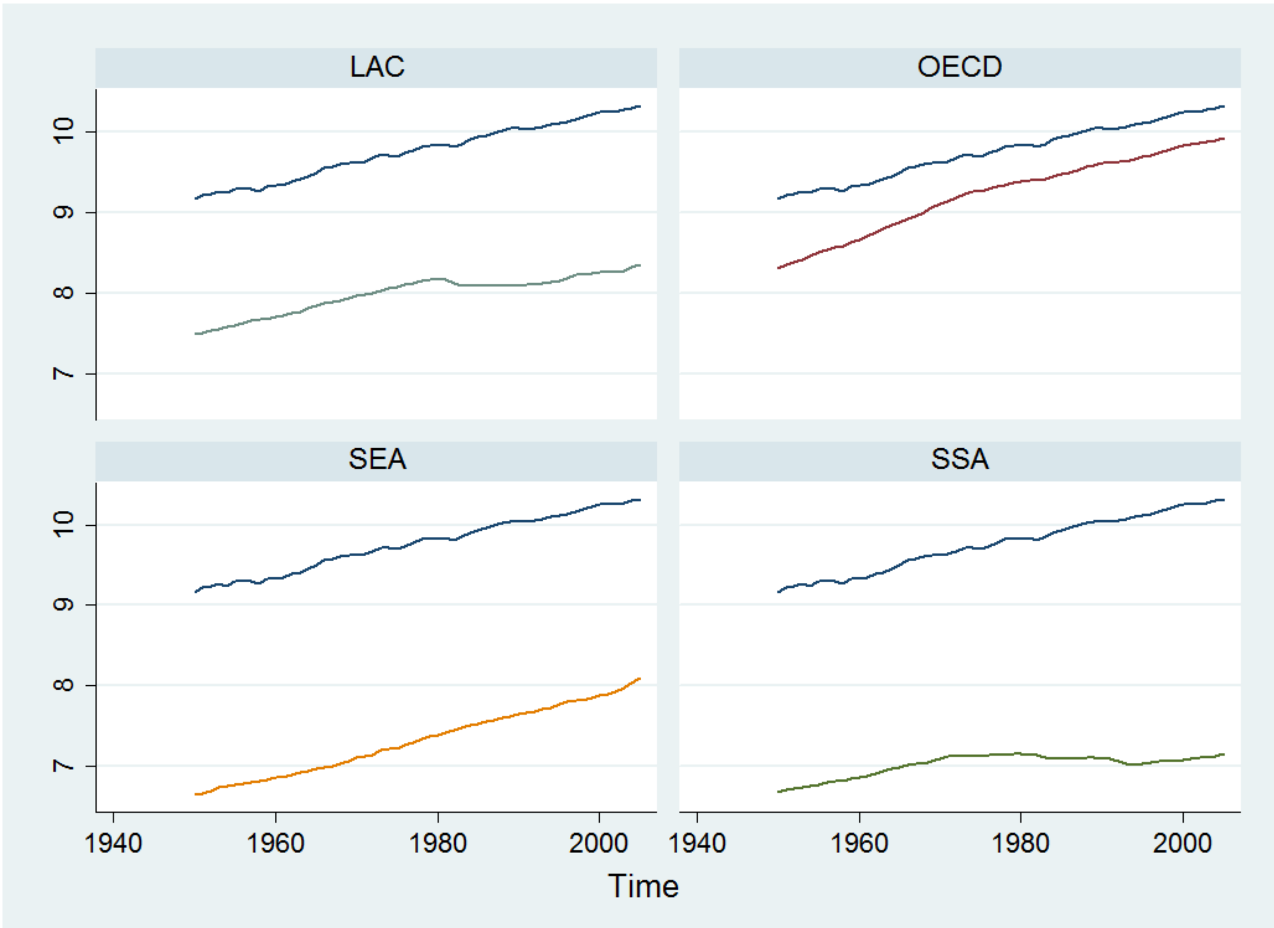

Figure 2 : Ln of Output per Capita in Different Regions over 1950-2005

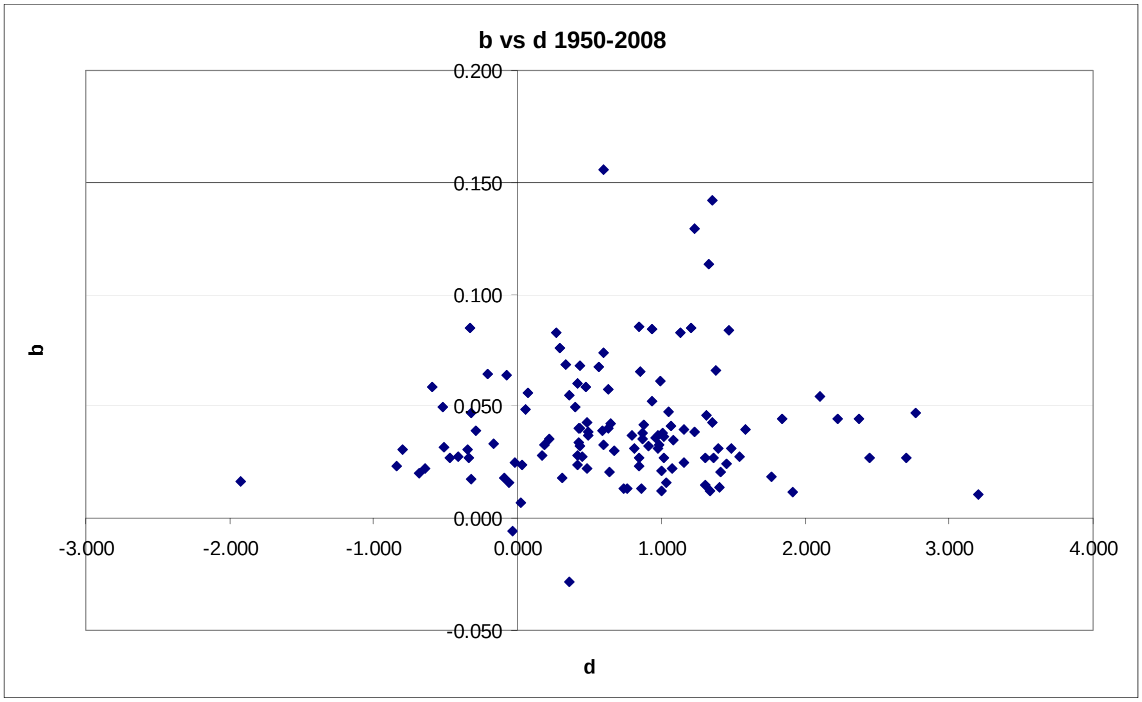

Figure 3: A Scatter Diagram of b vs. d 1950-2008

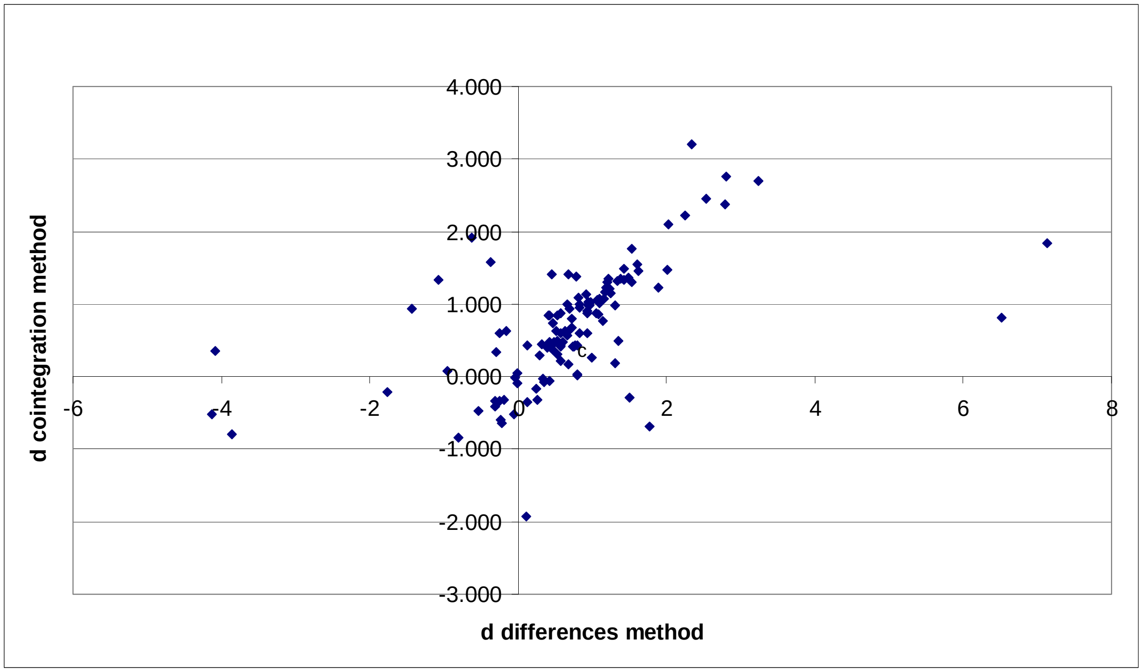

Figure 4: Correlation Between *d* in The Two Estimations: Cointegration and Differences

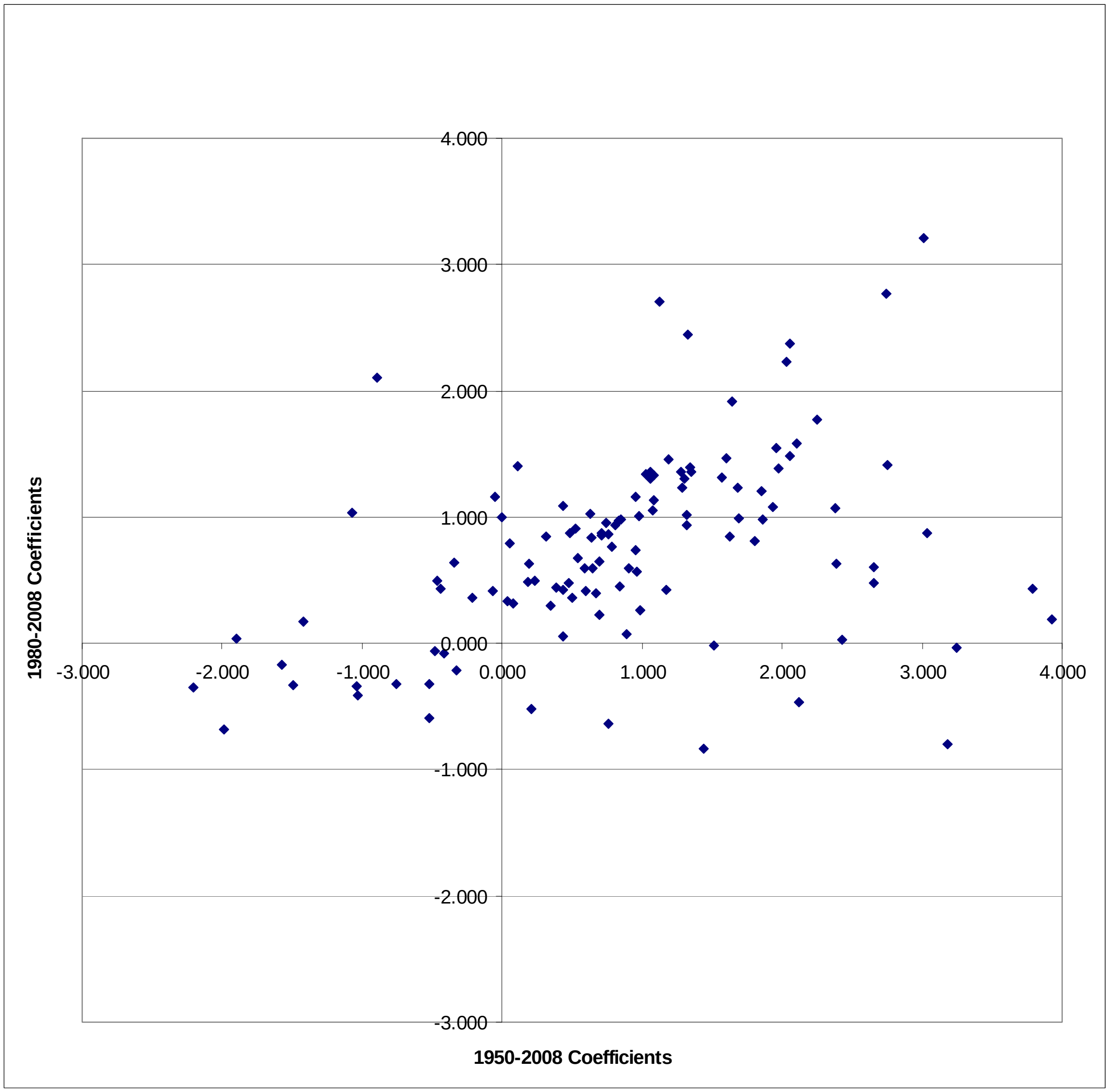

Figure 5: Correlation between *d* in 1950-2008 and in 1980-2008

Coefficient	Whole Sample	Without Oil & Outliers
b	0.0389*** (0.002)	0.0405*** (0.002)
d	0.688*** (0.093)	0.708** (0.072)
Test for $d = 1$	χ^2=23.95 P=0.00	χ^2=16.63 P=0.00
Hausman Test for Heterogeneity	χ^2=2.80 P=0.094	χ^2=9.23 P=0.002
Countries	139	124

1. Standard errors in parenthesis.
2. Hausman null hypothesis: difference in coefficient not systematic.

Table 1: Panel Cointegration of *b* and *d* 1950-2008

Coefficient	OECD	SSA	LAC	E_SEA	Other Countries
b	0.0344*** (0.006)	0.0424*** (0.005)	0.0468*** (0.004)	0.0348*** (0.006)	0.0438*** (0.007)
d	1.060*** (0.078)	0.201* (0.115)	0.634** (0.098)	1.617*** (0.322)	0.623*** (0.177)
Test for $d = 1$	χ^2=0.59 P=0.4425	χ^2=48.54 P=0.000	χ^2=14.05 P=0.000	χ^2=3.67 P=0.056	χ^2=4.31 P=0.038
Hausman Test for Heterogeneity	χ^2=0.54 P=0.464	χ^2=1.18 P=0.277	χ^2=7.33 P=0.007	χ^2=-43.00 P=0.0000	χ^2=9.71 P=0.002
Countries	21	42	23	13	25

Table 2: Panel Cointegration of *b* and *d* by Regions, 1950-2008

Parameter	**Coefficient**	**z**	**P>z**	**Test *d* = 1**	**Hausmann Test for Heterogeneity**
b	0.0232 (0.004)	6.51	0.000		
d	0.993 (0.060)	16.49	0.000	χ^2 (1)=0.01 P>χ^2(1): 0.908	χ^2 (2)=2.86 P> χ^2 (2): 0.091
1. Standard errors are in parenthesis.					

Table 3: Panel Cointegration Estimation of *b* and *d*, 1870-2010

Coefficient	**Pesaran-Smith I.V. Estimates**	
	Full Sample	Without Oil and Outliers Countries
1-*b*	0.890*** (0.013)	0.890*** (0.014)
c	0.075*** (0.012)	0.073*** (0.012)
1-*b*+*c*	0.965	0.963
d=*c*/*b*	0.682	0.664
Number of Observations	139	124

1. Instruments for the lagged GDP variable are the lags from 6 to 9 of the GDP and the US GDP in order to avoid overlapping with the 5 years average.
2. The IV estimation for the whole sample has value for Hansen statistics p=0.21 (H0: instruments are exogenous and cannot be rejected).
3. The under-identification tests have a p-value of 0.000 (H0: instruments are relevant for the RHS rejection of the null implies the model is rejected).
4. The Kleibergen-Paap rk Wald F statistics for weak instruments' test is 62.56, which implies rejection of the null hypothesis that instruments are weakly identifies at a p-value of 0.000.

Table 4: Estimation of *b* and *c* by Differences, 1950-2008

	Annual data			
	1951-2006	**1952-2007**	**1953-2008**	**1951-2008**
b	-0.091*** (0.007)	-0.089*** (0.007)	-0.090*** (0.006)	-0.085*** (0.006)
d	0.494*** (0.096)	0.534*** (0.094)	0.594*** (0.090)	0.597*** (0.099)
Test $d = 1$	χ^2=28.01 (0.000)	χ^2=24.48 (0.000)	χ^2=20.17 (0.000)	χ^2=18.86 (0.000)
	3 years averaged data			
	1951-2004	**1953-2006**	**1955-2008**	**1951-2008**
b	-0.058*** (0.004)	-0.060*** (0.004)	-0.059*** (0.003)	-0.054*** (0.003)
d	0.616*** (0.079)	0.656*** (0.073)	0.669*** (0.073)	0.685*** (0.073)
Test $d = 1$	χ^2=23.99 (0.000)	χ^2=23.03 (0.000)	χ^2=20.71 (0.000)	χ^2=18.65 (0.000)
	5 years averaged data			
	1951-2000	**1955-2004**	**1959-2008**	**1951-2008**
b	-0.045*** (0.003)	-0.049*** (0.003)	-0.047*** (0.003)	-0.040*** (0.002)
d	0.634*** (0.100)	0.689*** (0.099)	0.679*** (0.072)	0.708*** (0.072)
Test $d = 1$	χ^2=13.35 (0.000)	χ^2=9.82 (0.002)	χ^2=19.92 (0.000)	χ^2=16.63 (0.000)
	10 years averaged data			
	1951-1998	**1961-2008**		
b	-0.031*** (0.003)	-0.034*** (0.020)		
d	0.686*** (0.135)	0.700*** (0.078)		
Test $d = 1$	χ^2=5.36 (0.021)	χ^2=14.76 (0.000)		
Observations	124			

Table 5: Averaging over Different Periods of Time

Parameter	Total Sample	OECD	LAC	SSA	SEA	Other
b	0.04 (0.002)	0.039 (0.006)	0.0467 (0.005)	0.0411 (0.005)	0.038 (0.005)	0.0352 (0.003)
z	18.2	6.47	8.95	8.56	7.06	11.0
P>z	0	0	0	0	0	0
d	0.367 (0.102)	0.781 (0.089)	0.12 (0.131)	-0.063 (0.234)	1.317 (0.256)	-0.002 (0.21)
z	3.6	8.75	0.91	-0.27	5.145	-0.01
p>z	0	0	0.363	0.87	0	0.99
Number of countries	118	21	22	31	20	24

Table 6: Estimation of b and d with y^H

	TROPICS	**COAST**	**ETHNIC**	**Y_50**	**EDU**	**OPEN**	**G/Y**
TROPICS	1.0000						
COAST	-0.1794	1.0000					
ETHNIC	0.5729	-0.5279	1.0000				
Y_50	-0.4754	0.3517	-0.3811	1.0000			
EDU	-0.5709	0.4554	-0.5503	0.7405	1.0000		
OPEN	-0.3205	0.3301	-0.3812	0.4930	0.5353	1.0000	
G/Y	-0.0466	-0.2029	0.1393	-0.2273	-0.0785	-0.2162	1.0000
ICRG	-0.5740	0.4079	-0.5705	0.6879	0.7884	0.7054	-0.1777

Table 7: Correlations between the Explanatory Variables

Dependent Variable: AVG			
Explanatory Variable	(1) Whole sample	(2) Without SEA	(3) Without SEA and OECD
TROPIC	-0.704*** (0.235)	-0.938*** (0.242)	-0.906*** (0.281)
COAST	0.008*** (0.003)	0.007*** (0.003)	0.007** (0.004)
Y_50	-0.857*** (0.178)	-0.648*** (0.194)	-0.529*** (0.222)
ETHNIC	-0.766* (0.452)	-0.569 (0.422)	-0.530 (0.574)
EDU	0.149*** (0.059)	0.123** (0.060)	0.156** (0.076)
OPEN	1.109*** (0.231)	0.754*** (0.234)	1.190*** (0.471)
G/Y	-2.558*** (0.898)	-1.707** (0.859)	-1.883** (0.986)
CONST.	8.012*** (1.267)	6.527*** (1.343)	5.509*** (1.566)
R^2	0.61	0.60	0.52
F PROB.	0.0000	0.0000	0.0000
OBS.	90	77	57

1. Robust standard errors in parentheses.
2. Significance levels of 99%, 95% and 90% are denoted by ***, **, and * respectively.

Table 8: Effect of Explanatory Variables on growth rate 1950-2010

Dependent Variable: ***d***			
Explanatory Variable	(1) Whole sample	(2) Without SEA	(3) Without SEA and OECD
TROPIC	-0.287** (0.152)	-0.389*** (0.133)	-0.459*** (0.144)
COAST	0.004** (0.002)	0.002 (0.002)	0.003 (0.002)
Y_50	-0.468*** (0.127)	-0.240** (0.122)	-0.225* (0.137)
ETHNIC	-0.432* (0.282)	-0.417** (0.218)	-0.574** (0.304)
EDU	0.088** (0.039)	0.053 (0.038)	0.048 (0.043)
OPEN	0.591*** (.150)	0.319** (0.150)	0.875*** (0.291)
G/Y	-1.290** (0.578)	-0.483 (0.513)	-0.927 (.680)
CONST.	4.051*** (0.946)	2.517*** (0.835)	2.580*** (0.966)
R^2	0.45	0.44	0.48
F PROB.	0.0000	0.0000	0.0000
OBS.	90	77	57

3. Robust standard errors in parentheses.
4. Significance levels of 99%, 95% and 90% are denoted by ***, **, and * respectively.

Table 9: Effect of Explanatory Variables on *d*