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GLOBAL DIVERGENCE IN GROWTH REGRESSIONS

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ABSTRACT

Global Divergence in Growth Regressions*

This paper extends the standard growth regression model by adding an assumption that a country follows the global technology frontier either fully or partially. This additional assumption changes significantly the growth regression model and its results in three main ways. First, it shows that although a country converges to its long-run growth path, this path can diverge from the countries at the global frontier. We measure the degree of divergence for each country and find that most indeed diverge from the frontier. Second, we estimate growth dynamics without controlling for additional variables. Third, our new method enables us to disentangle the effects of the explanatory variables on the long-run rate of growth from the short-run effects.

JEL Classification: O40, O47 and O57
Keywords: convergence, divergence, economic growth, global frontier and growth regressions

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Global Divergence in Growth Regressions

1. Introduction

In 1996 Caselli, Esquivel and Lefort published a paper that presented an innovation to growth regressions. At the time this literature was fairly new, but it had already gone through an explosion of research. In their paper they tell that the reaction they received in many seminars was "not another growth regression!" And here, after 17 years and many more articles in this area, we come up with yet another suggestion how to improve growth regressions.[1] How can we justify it? We have at least three justifications. The first and main one is that this paper indeed presents a significant change to growth regressions. It shows that a very simple and very plausible extension of the underlying theoretical model can help to overcome many of the drawbacks of previous growth regressions and can lead to many interesting results. Second, this extension is motivated, among other things, by the gradual accumulation of international output data over time and it offers a new way to take advantage of this longer data set. Third, although research in recent years focused more on explaining differences in levels of output than differences in rates of growth, especially after Hall and Jones (1999), we show that the dynamics of economic growth are still highly informative.

Our main contribution can be explained as treating each country in the sample as an open economy rather than as closed. This has two major implications. The main one is that a country in the global economy does not invent most of its technologies, but adopts

[1] The amazing size of this literature is reflected in the authoritative survey of growth regressions by Durlauf, Johnson and Temple (2005), which is 123 pages long, of which 15 pages alone are references.

them from the growing set of new global technologies. Thus, the growth of a country cannot depend only on its own characteristics, and it should also depend on the expanding global set of technologies, namely on the global technological frontier.[2] The second implication of assuming that countries are small open economies is that the gradual adjustment of output is no longer a result of investment being constrained by saving, but rather a result of adjustment costs to investment.

To state our main contribution more precisely, note that according to the canonical representation of growth regressions in Durlauf, Johnson and Temple (2005), efficiency output per worker converges to some long-run value, where efficiency output is the ratio between output per worker and productivity, which is assumed to be labor augmenting. The speed of this convergence is denoted by b, and is usually assumed to be the same for all countries. Our main point of departure from the previous growth regression models is the assumption on how productivity changes over time. These models have assumed that productivity grows at a constant rate, which is usually assumed to be constant across countries. We instead assume that productivity follows the global frontier, but might follow it partially. More specifically, a country adopts in each period only d of the new technologies introduced in each period, where d is a country specific parameter that should be between zero and one. Thus, if d is equal to 1 the country's long-run growth path should fully follow the global frontier, but if d is less than 1, its long-run path diverges away from the frontier.

When we substitute this assumption in the otherwise standard model of convergence, we get a dynamic relationship between the level of output per worker, lagged output per worker and the global frontier, which completely describes the

[2] For this insight see also Acemoglu, Aghion and Zilibotti (2006).

dynamics of output per worker over time. In these dynamics the parameter *b*, which used to be the measure of convergence in the standard growth regression model, should be interpreted in a narrower way. It only 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, what usually measures 'convergence' 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 we find both *b* and *d* of a country.

We next estimate our extended model using data on output per capita and using GDP per capita of the US as a proxy to the global technology frontier. Since the levels of output per capita are non-stationary we need to apply appropriate estimation methods, such as panel cointegration or regression of differences. Using these methods enables us to estimate *b* and *d* for each country. We find that *b* is quite similar across countries, around 4%, but *d* differs significantly across countries with an average of 0.7. These results have two implications. The first is that our measurement of b is close to previous ones, but its meaning is only a measure of the 'speed of self convergence.' The second implication is that most countries diverge away from the frontier. Namely our initial assumption that countries might follow the frontier only partially is supported by the data. Interestingly, the two methods used for dynamic estimation, panel cointegration and regression of differences, yield similar results, which shows robustness.

Note that the dynamic country's parameters *b*, *d* are estimated without any use of explanatory variables, like geography, human capital, 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. The explanatory variables are used only in the second stage of the empirical analysis, which tests their effect on each country's parameter *d*. This regression enables us to find which variables affect the ability of the country to follow the frontier. In other words, we are able to separate the effect of each variable on the long-run rate of growth from short-run effects. The estimation shows that some of the variables that have a strong effect on growth in general, have no effect on the long-run rate of growth. Hence, this separation is real.

The main literature this paper should be related to is of course growth regressions, which followed the seminal contribution of Barro (1991) and have been used extensively since then, in order to understand international differences in output and output growth across countries.[3] But over the years growth regressions have been criticized on various grounds. One criticism is that the need to use control variables adds an ad-hoc element in the choice of such variables, which makes it quite arbitrary.[4] Another criticism has been that while growth regressions pointed at convergence, other statistical methods pointed at divergence between countries.[5] The attempt to use longer data for growth regressions by panel estimation also drew criticism due to the high variability of output relative to low variability of most explanatory variables. An excellent summary of this literature and of its critiques appears in Durlauf, Johnson and Temple (2005).

As already explained above, the current paper departs from this literature in a number of ways. First, we extend the single measure of convergence to a richer picture

[3] Growth regressions have been influenced strongly by Baumol (1986). The initial papers in this literature were Barro (1991), Barro and Sala-i-Martin (1991, 1992), and Mankiw et al (1992). Another early but less known contribution was Kormendi and Meguire (1985). For recent surveys of this literature see Durlauf, Johnson and Temple (2005) and Durlauf (2009).

[4] The title of Sala-i-Martin (1997), "I Just Ran 2 Million Regressions," reflects this arbitrariness.

[5] See Bernard and Durlauf (1995, 1996), Quah (1996), and Pesaran (2007a). See also the 'varying parameters models' by Liu and Stengos (1999), Durlauf *et al.* (2001) and Lee *et al* (1997, 1998).

that also includes possible divergence from the frontier in the long-run. This lays a bridge over the gap described above, between growth regressions and other dynamic empirical studies, which have detected divergence between countries. Second, this paper estimates the dynamic parameters without use of any control variables. This reduces significantly the arbitrariness of previous convergence models. Third, while standard growth regressions find only the overall effect of various variables on output growth, we can separate the effects of explanatory variables on the long-run rate of growth from the overall effects. In our humble view each of these improvements is quite significant.

The paper is organized as follows. Section 2 presents the extension we introduce to 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 extends the analysis to a group of countries with data since 1870. Section 6 presents the results of estimation by differences. Section 7 estimates a variant of the model with output net of human capital. Section 8 shows how the model identifies the effects of explanatory variables on the long-run rate of growth. Section 9 summarizes while Appendix I presents a theoretical model of convergence in an open economy and Appendix II discusses robustness of the results.

2. Extending the Growth Regression Model

To explain our contribution, we use the canonical representation of growth regressions, as presented in the monumental survey of this literature by Durlauf, Johnson and Temple (2005). We first describe shortly this canonical representation and then show how our contribution fits into 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) $$L(i,t) = L(i,0)\exp[n(i)t].$$

Assume also that 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.[6]

We next define output per worker in country i at time t as $y(i,t) = Y(i,t)/L(i,t)$ and the efficiency output per worker as $y^{E}(i,t) = Y(i,t)/[A(i,t)L(i,t)]$. 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.[7] Since this explanation assumes that the economy is closed, we think that it does not fit well cross-country empirical studies. An alternative explanation is gradual adjustment of capital in open economies due to adjustment costs. We pursue this latter explanation in this paper. The model of convergence due to adjustment costs is presented in Appendix I, and its implications with respect to convergence are presented below in this Section.

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[6] According to Durlauf, Johnson and Temple (2005), most growth regression studies have assumed, explicitly or implicitly, that g is equal across countries.

[7] The use of the Solow model originated in Mankiw, Romer and Weil (1992) and was followed by many other papers, as described by Durlauf, Johnson and Temple (2005). Barro and Sala-i-Martin (1992) used the Ramsey-Cass version of the Solow model, but are also based on the premise of the closed economy.

The gradual adjustment is formulated in Durlauf, Johnson and Temple (2005) by:[8]

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

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. 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.[9] 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 educational attainment, political stability, 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.

[8] Equation (4) is exactly the same as equation (1) in Durlauf, Johnson and Temple (2005), except for approximating $1 - \exp(-b)$ by b.
[9] This is equation (8) in Durlauf, Johnson and Temple (2005).

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 $g(i)+[1-(1-b)^T]T^{-1}A(i,0)$. But 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 the effect 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 Durlauf, Johnson and Temple (2005). It actually creates new problems. One problem is that in the 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 the countries' fixed effects. Using differences, as done by Caselli, Esquivel and Lefort (1996), solves some of these problems but not all.

<u>2.2. The Extended Growth Regression Model</u>

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 many 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 $g > 0$ is the average rate of the frontier's technical change and $v(t)$ is white noise. The parameter $a(i)$ in (7) is not exogenous. To see this assume that the global frontier F is normalized to 1 at some reference year, which is denoted R. Then $\ln F(R) = 0$, and equation (7) implies that $a(i) = \ln A(i,R)$. Hence, $a(i)$ depends on the period of reference and on the country's parameter $d(i)$. We return to this issue below.

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

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

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 it the term $d(i)\ln F(t) + a(i) + \ln y^E(i,\infty)$ and get:

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

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. Since in the recent two centuries the frontier countries have grown by 20, 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 only 2. What the extended model (10) implies is that the parameter *b* can no longer be a single measure for convergence in the broad sense of this word. It should better be called the 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*) and to understand what makes them different across countries.

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 Appendix I, and here we present only its main conclusions. The first conclusion is that in a small open economy the steady state efficiency output per worker $y^E(i,\infty)$ is equal approximately, as shown in equation (A.16) in the appendix, to:

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

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.

From the adjustment cost model of Appendix I, equations (A.18) and (A.20), we also deduce that 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 of the 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.[10]

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:

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

[10] 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 *et al*. (1996) is equal to 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 $e(i)$. Note that the choice of R, the reference year for normalizing F, does not affect $b(i)$ or $d(i)$, but does affect the estimated $e(i)$. The second method of dynamic estimation by differences is explained below.

The 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 are of higher quality, 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 is 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 data set that is 140 years long. It fits our main idea, namely to better characterize the long-run dynamics of economic growth. In Appendix II we show that using an alternative data set of PPP adjusted output, Penn World Tables, does not alter the main results of the paper.

For the global frontier we use as a proxy the US output per capita, which has grown 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 period 1870-2010 and to 1.95% for 1950-2010. We also run a unit root test and find that the first differences are stationary, for each sub-period examined. Hence, in our estimations the global frontier is defined as $\ln F(t) = \ln y(US,t) - \ln y(US,R)$, where R is the year of reference, when the frontier is normalized. This normalization is relevant only to the estimation of e, where we have tried to normalize F both initially, $R = 1950$, and at the end of the period, $R = 2008$.

In the panel cointegration estimation we try to avoid the cyclical high-frequency autocorrelations of output. We do it by using 5 years' moving averages 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 then estimate the error correction model (15) for these variables. In Appendix II 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 that our results are robust.

The other method we apply to estimate (14) is differences, following Caselli et al (1996). Similar to the estimation of cointegration, here we also take the difference over 5 years in order to average growth rates and to remove cyclical effects.[11] Dividing the differences by 5 and using the following notation for 5 years average rates of growth: $g_5(i,t) = \left[\ln y(i,t) - \ln y(i,t-5)\right]/5$ we get:

(16) $$g_5(i,t) = [1-b(i)]g_5(i,t-1) + c(i)g_5(US,t-1) + [u(i,t) - u(i,t-5)]/5.$$

Note that we estimate (16) using annual observations except for the first 5 years. Hence, if our data span over T periods of time, we can use $T - 5$ observations. This seems better than using data only in intervals of 5 years, which uses only N/5 observations. Note also that the moving average nature of the error term in equation (17) induces a correlation with the right-hand side lagged rate of growth, which requires use of instrumental

[11] 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.

variables. Finally, (16) does not estimate *d* directly, but only *b* and *c*. We can calculate *d* as a ratio: $d(i) = c(i)/b(i)$. Actually, we can also test whether *d* is smaller or equal to 1, since $d(i) < 1$ 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 is diverging 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. This result is in line with most previous growth regressions, but the meaning is different here, as it measures convergence of each country to its own long-run growth path. Table 1 also shows that most of these long-run paths are not converging to the frontier, namely most countries do not experience global convergence. This is since the coefficient *d* is equal on average to 0.69, it is significantly lower than 1 and it is significantly heterogeneous across countries. This is, therefore, the main result of this paper: countries diverge from the frontier and thus from each other.

[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.[12] We therefore treat these countries as outliers from here on. An additional group of countries that deserves attention are the oil-producing countries, which experienced very high levels of output in the 1970s and declining output since then.[13] Such countries might bias *d* downward.[14] Table 1 presents the results of cointegration without the outliers and the oil-producing countries as well. The second column in Table 1 shows that eliminating 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 clustered around its average of 4%. Hence, these results justify our main assumption that countries can differ in following the global frontier. A further examination of the results indicates that *d* follows a regional pattern to a large extent. This is shown in Table 2. The regions are the same as in Figure 2: OECD, SSA, LAC, SEA and Other Countries, which are mainly MENA and the EEC.

[Insert Table 2 here]

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

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[12] The countries not cointegrated with probability avove 10% are Bangladesh, Indonesia, Kenya, Laos and Vietnam. The countries with probability between 10% and 7% are Ghana, Cambodia, Nepal and Senegal.
[13] Mankiw, Romer and Weil (1992) have eliminated these countries from their analysis.
[14] 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.

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 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 changing their position relative to the US by raising their $a(i)$ 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 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. As we have shown, under the open economy assumption $\ln y^E(i,\infty)$ is similar for all countries. Hence, our estimated $e(i)$ is a good proxy for $a(i)$, namely for the initial level difference between a country and the global frontier. The average value of the estimated *e* across all countries is 0.23. We return to this parameter below in Section 8.

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.[15] These countries are mainly developed, namely what we now call OECD countries. Note that this period has been not only a period of significant economic growth, but also of great crisis. It includes two World Wars and the Great Depression. The results of the panel cointegration regressions 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 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: Differences

In this section we turn to the second method of estimation of the parameters *b* and *d*, which is estimation of the time differences instead of panel cointegration. Our approach follows Caselli et al (1996), who were the first to estimate growth regressions by

[15] 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.

differences. Our addition to their analysis is the new variable of the global frontier and that we do not use any additional explanatory variable. Since we assume that countries can follow the global frontier differently, we cannot follow the Arellano-Bond (1991) method, which is used by Caselli et al (1996), but we need to use a method that enables us to estimate different coefficients for each country. Hence, equation (16) is estimated by use of instrumental variables following Pesaran and Smith (1995), in order to obtain country specific coefficients as in Bond *et al.* (2010).[16]

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, as presented 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* 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 compute the difference between the two estimates and present the distribution of this difference in Figure 4. As the figure shows the difference is very small and its distribution is quite clustered around 0. In addition to Figure 4, we have also run a

[16] 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).

Kolmogorov-Smirnov test to check how different the two distributions 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 similarity of results in the two methods we stick to Panel Cointegration as our main method of analysis, mainly 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. Adding Development Accounting to Growth Regressions

In the last decade economists have used extensively a method called 'development accounting' in the analysis of economic growth. One of the main contributions of this method is the decomposition of total factor productivity (TFP) into human capital and all the rest. Human capital is calculated from data on years of schooling by use of parameters that describe the effect of schooling on productivity, which have been measured in many labor studies. This method is extensively described and surveyed in Caselli (2005). We next show how we can apply this method to growth regressions.

Assume that output in the country is described by the following production function, which replaces (1):

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

Where $h(i,t)$ is the average amount of human capital in country *i* at time *t*. The variable $A(i,t)$ is not longer total productivity, but only the residual after subtracting human capital. We can assume that A describes mainly technical change. We next keep assumptions (4), (7) and (8) of our model, but assume that (7) holds only for technology A. We next define output per worker and per human capital in the following way:

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

Applying this variable to the model we get the same summary dynamics as in (9) or (10), except that output per worker $y(i,t)$ should be replaced by output per worker and per human capital $y^H(i,t)$.

In the calculation of h we use the results of many previous microeconomic tests on the effect of schooling on wages. These studies were summarized by Caselli (2005) in the following way: 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 same panel cointegration on $y^H(i,t)$ and the global frontier $y^H(US,t)$. The results of the panel cointegration are summarized in Table 5.

[Insert Table 5 here]

The results of Table 5 are quite illuminating. The self convergence coefficient b comes out around 4%, as in the benchmark estimation. The d coefficients are much 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. These results might also indicate to another possibility, that increasing levels of education in many countries do not translate fully to higher productivity, as there is need to invest the required capital, to create the required jobs, and to create the environment that enables people to fully materialize their higher education.

8. Effects of Explanatory Variables on Global Divergence

In this section we present the second stage of our empirical analysis, which estimates the effects of various explanatory variables on the coefficients d, which were estimated by panel cointegration for the years 1950-2008. These regressions identify the effects of the explanatory variables on the degree of divergence from the frontier. As shown in equation (5) in Section 2, standard growth regressions estimate the combined effect of these explanatory variables on both long-run growth rate and short-run output. Estimating the effects of these variables on d enables us to divide this effect to the long-run effect and to a short-run effect. Indeed our estimation shows that there are significant differences in the results and some explanatory variables have qualitative different effects on long-run growth than what a standard growth regression shows. In this Section we also test the effects of the same explanatory variables on the coefficient e, namely on a. This is not the main focus of this Section, since the parameter e varies with the year of reference, as explained above, but we still learn something from the estimation of the effects on e as well.

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 effect of many explanatory variables, as used in standard growth regressions, to short and long-run rate of growth effects. For that goal, we picked a set of variables, which are used in many growth regressions, and focused on variables that should have an effect on technology adoption, as it is a key element in our story. 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. ED_PRIM is the average years of primary schooling of people above age 15 over the period 1950-2010 (Barro and Lee, 2011).
6. ED_SEC is the average years of secondary schooling of people above age 15 over the period 1950-2010 (Barro and Lee, 2011).
7. ED_TERT is the average years of tertiary schooling of people above age 15 over the years 1950-2010 (Barro and Lee, 2011).
8. 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).[17]
9. ICRG is average measure of quality of institutions during the period 1982-1997 according to the International Country Risk Guide (Knack and Keefer, 1995, 1997).
10. G/Y is the share of public expenditures in GDP in the years 1950-1960, taken from Durlauf et al (2008).

[17] 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. Variables 5-7 reflect human capital. Variables 8-10 represent 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 is in many cases region-specific, as in agriculture or health. This is also implied indirectly 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 et al (2005) and many others, and especially institutions that affect international trade, as stressed by Grossman and Helpman (1991).

[Insert Table 6 here]

Before we turn to the direct estimation, we present the matrix of correlations between these variables in Table 6. 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 all educational variables are highly correlated between themselves and also 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 variables ED-SEC, ED-TERT, and ICRG.

The regressions are presented in Tables 7, 8 and 9. The first one, Table 7, 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 therefore 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 regressions. Table 8 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. Table 9 presents the regressions on the explanatory variables with *e* as the dependent variable, with 2008 as a year of reference.

All the regressions in all three 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 and without outliers. Data availability reduces the number of countries in the regression to 88. 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 and convergence 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 the patterns of growth. 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 7, 8 and 9 omit not only the SEA countries, but the OECD countries as well.

[Insert Table 7 here]

As mentioned above, Table 7 presents the results of the standard growth regression on this set of explanatory variables. There are five variables that are significant throughout, in addition to the constant. These variables are TROPIC, which reduces growth and is significant at 1%, initial output Y_50 with a negative effect on economic growth as expected, which is also significant in all specifications. Primary education has a positive effect on growth and it is significant and similar in size for all specifications and so is openness. The share of government in GDP has a negative and significant effect on economic growth, as is found in many studies.

[Insert Table 8 here]

Table 8 shows that some of the variables that affect growth in general also affect long-run growth. Being in the tropics has a negative effect on *d* that becomes more and more significant as we narrow the set of countries. In the most relevant group, without South East Asia and OECD, the effect of TROPIC is significant at 1% and its size 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 in Africa and Latin America. Another variable that affects *d* significantly is the initial output. Hence this variable has a negative effect not only in the short-run but in the long-run as well. Openness also increases *d*, namely it has a significant strong effect on growth both in the short and in the long-run. But for some variables the results of Table 8 differ significantly from the results in Table 7. This holds for education and for the share of government. Although education has a significant effect on growth in general, as shown in Table 7, it does not have a significant effect on *d*. Hence, it seems not to have a significant effect on long-run growth. This is a very surprising result. One possible interpretation is that that education affects only the level of output but not its long-run rate of growth. Another interesting result is the effect of G/Y on *d*. Although it is negative and significant in the full sample it becomes less significant as the problematic countries are removed from the sample and in the final regression it is insignificant. It therefore implies that the negative effect of government on growth from Table 7 is rather a short-run effect but not a long-run effect.

[Insert Table 9 here]

In Table 9 we present the effects of the explanatory variables on *e*, which is estimated for the reference year 2008, namely by the end of the sample. As explained above, *e* is a proxy for the country's level of technology at the reference year. Note first that the three regressions of *e* on the explanatory variables are not of high quality. The R^2

is rather low and the F probability is high. Note also that most variables come out insignificant, especially in the regression without SEA and OECD. But note also that for *e*, unlike for *d*, there is no need to eliminate the OECD countries from the estimation and thus we can focus on the first two columns of Table 9. Still the picture is quite unclear and most variables are insignificant and their effect changes from one regression to the other, sometimes even in sign. One interesting result that emerges from the Table is the strong negative effect of G/Y on e in the whole sample. This strengthens our above guess that the negative effect of this variable in many growth regressions reflects a level effect and not a long-run growth effect. Interestingly this result is similar when e is estimated with reference year 1950, namely when it reflects initial output instead of final period output.

To summarize this Section shows that the dynamic estimation suggested in this paper enables us to differentiate between the 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, we found that education and fiscal expenditures do not have a significant effect on the long-run rate of growth, even if a standard growth regression finds that they have an effect on economic growth in general. It is therefore likely to be a level effect.

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, by 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 cannot 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 a coefficient *d*, which measures by how much the country's long-run growth path follows the global frontier. We find that for most countries *d* is lower than 1, so that our basic assumption on the possibility of partial adoption of technologies is verified by the data. Another accomplishment of our approach is that we can estimate the dynamic coefficients of convergence and divergence without controlling for explanatory variables and thus we avoid some of the harshest 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 many 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. All such potential extensions are waiting for future research.

Appendix I: Convergence of 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:

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

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

where g and n are positive numbers.[18] Each person supplies 1 unit of labor. Investment in this economy is costly and these costs are assumed to be quadratic and of CRS:

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

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, if $V(t)$ is the market value of capital, it is:

(A.4) $$V(t) = q(t)K(t+1),$$

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:

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

[18] 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.20) can be estimated and thus supply some idea on the expected size of b, as done in Section 2.4.

Appendix II: Additional Robustness Tests

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 wide 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 our choice of data does not have a significant effect of any of the main results of the paper.

We next examine the effect of the choice of timing on the results. As explained in the paper we use moving averages of logarithm of output per capita over periods of 5 years. In the robustness tests we examine using average over different time lengths, one year, three years, and ten years. We also try to 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 found in the data. Their exclusion is done mainly to avoid extreme values of d in the tests that do not smooth data at all, namely the 1 year averages.

Table A1 presents the results of these tests and it shows that the main results of the paper are reached for other choices of timing as well.

[Insert Table A1 here]

Table A1 reveals a few interesting results. First, the rate of convergence 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 fall slightly below 0.6, but it is still not far away from 0.7 and in any case it is clearly 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.

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Figures and Tables

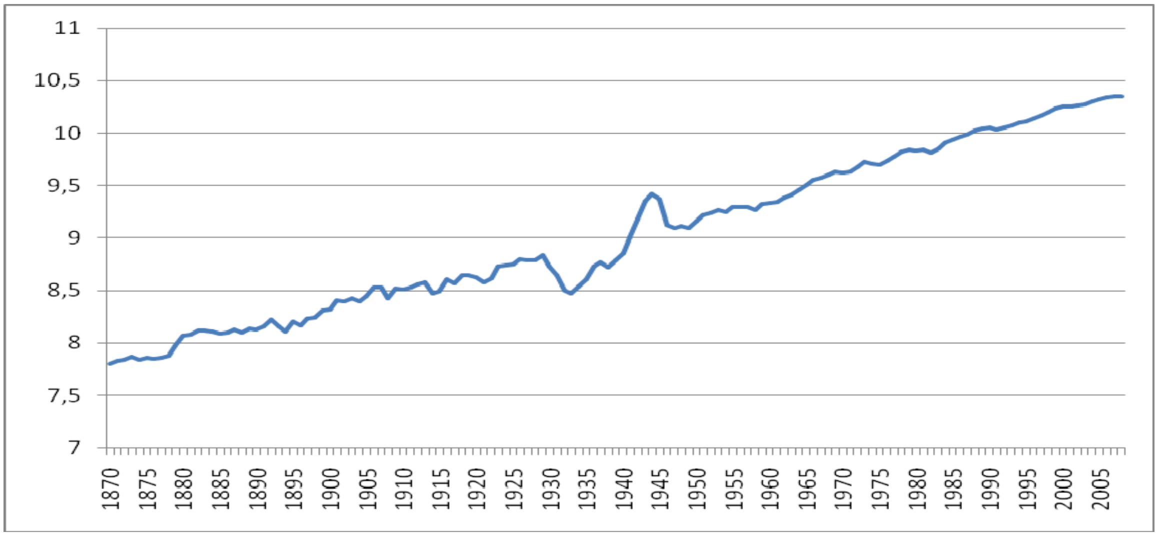

Figure 1: Natural Logarithm of US GDP per capita in 1870-2010

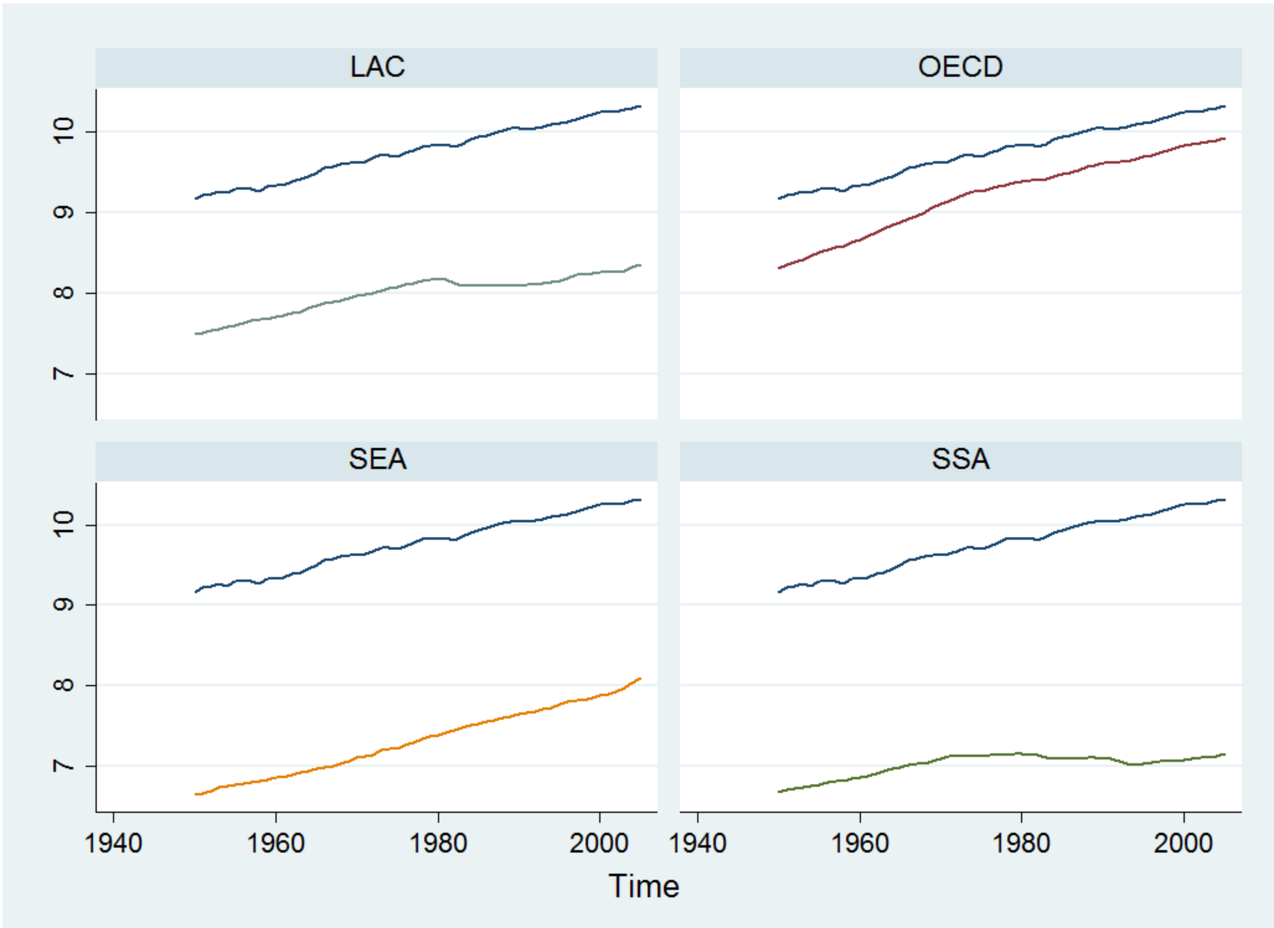

Figure 2 : Ln of Output per Capita in Different Regions over 1950-2005

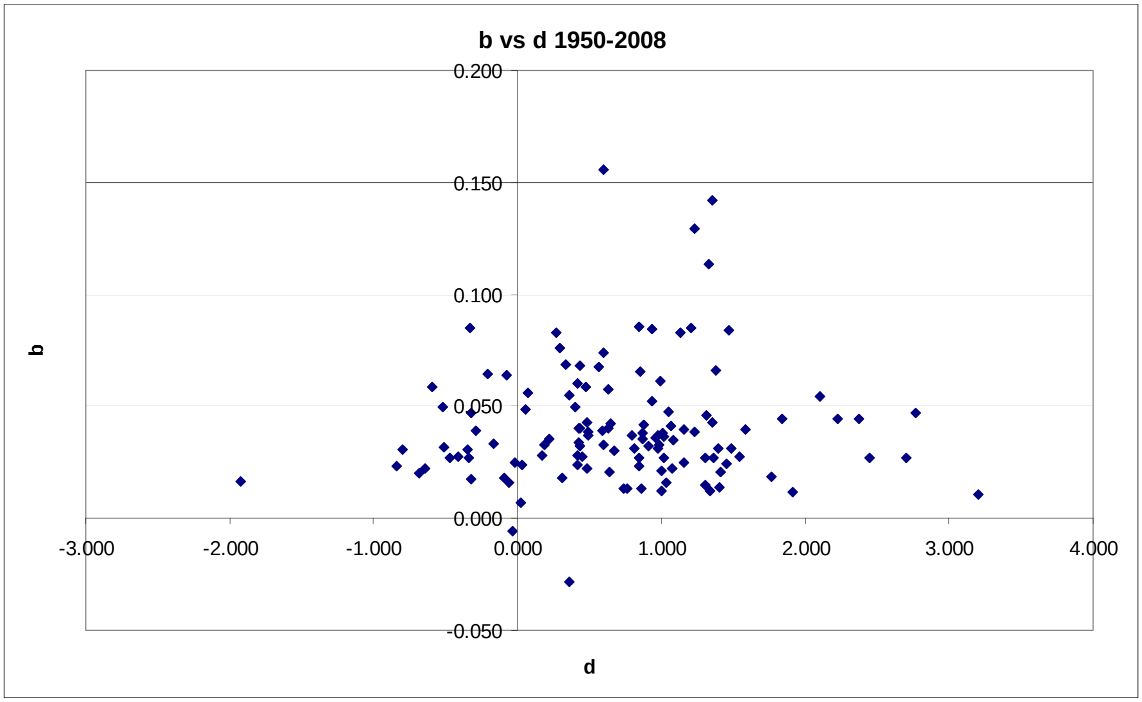

Figure 3: A Scatter Diagram of *b* vs. *d* 1950-2008

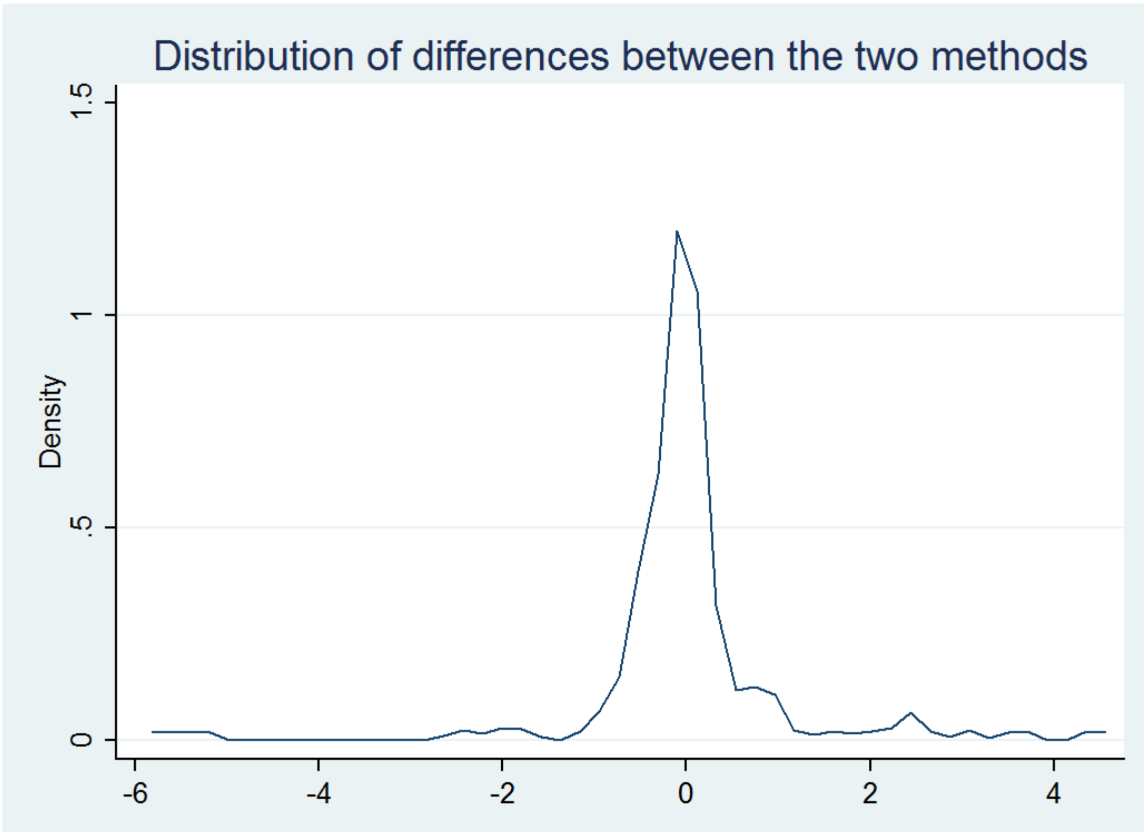

Figure 4 : Distribution of Gap Between *d* in The Two Estimations

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

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 5: Estimation of b and d with y^H

	TROPICS	COAST	ETHNIC	Y_50	ED-PRIM	ED-SEC	ED-TERT	OPEN	G/Y
TROPICS	1.0000								
COAST	-0.1881	1.0000							
ETHNIC	0.5773	-0.5786	1.0000						
Y_50	-0.5544	0.3288	-0.4300	1.0000					
ED-PRIM	-0.5032	0.4626	-0.5134	0.7120	1.0000				
ED-SEC	-0.5731	0.3691	-0.5108	0.7197	0.7282	1.0000			
ED-TERT	-0.5356	0.3764	-0.4722	0.6862	0.7441	0.8499	1.0000		
OPEN	-0.4495	0.3268	-0.4097	0.4916	0.5260	0.7122	0.5513	1.0000	
G/Y	0.4486	-0.3290	0.3791	-0.6298	-0.5368	-0.5720	-0.5425	-0.4781	1.0000
ICRG	-0.5501	0.3094	-0.3966	0.6317	0.6378	0.7366	0.6141	0.7185	-0.4338

Table 6: Correlations between the Explanatory Variables

Dependent Variable: AVG			
Explanatory Variable	(1) Whole sample	(2) Without SEA	(3) Without SEA and OECD
TROPIC	-0.008*** (0.002)	-0.008*** (0.003)	-0.008*** (0.003)
COAST	0.00007** (0.00002)	0.000 (0.000)	0.000 (0.000)
Y_50	-0.010*** (0.002)	-0.08*** (0.002)	-0.006*** (0.002)
ETHNIC	-0.004 (0.005)	-0.004 (0.005)	-0.003 (0.007)
ED_PRIM	0.002** (0.001)	0.002** (0.001)	0.002** (0.001)
OPEN	0.014*** (0.002)	0.011*** (0.003)	0.014** (0.006)
G/Y	-0.068*** (0.019)	-0.066*** (0.022)	-0.053** (0.026)
CONST.	0.091*** (0.012)	0.076*** (0.014)	0.063*** (0.018)
R^2	0.66	0.61	0.48
F PROB.	0.0000	0.0000	0.0000
OBS.	88	76	56

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

Table 7: 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	-0.282 (0.159)	-0.333** (0.152)	-0.416*** (0.165)
COAST	0.003 (0.002)	0.000 (0.002)	0.001 (0.002)
Y_50	-0.517*** (0.100)	-0.315*** (0.117)	-0.284** (0.137)
ETHNIC	-0.203 (0.266)	-0.360 (0.247)	-0.496 (0.345)
ED_PRIM	0.109** (0.053)	0.093* (0.053)	0.086 (0.060)
OPEN	0.776*** (.143)	0.448*** (0.163)	0.960*** (0.356)
G/Y	-3.592*** (1.306)	-2.866** (1.207)	-2.401 (1.437)
CONST.	4.432*** (0.746)	3.140*** (0.847)	2.953*** (1.025)
R^2	0.55	0.48	0.47
F PROB.	0.0000	0.0000	0.0000
OBS.	88	76	56

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

Table 8: Effect of Explanatory Variables on *d*

Dependent Variable: ***e***			
Explanatory Variable	(1) Whole sample	(2) Without SEA	(3) Without SEA and OECD
TROPIC	-0.108 (0.118)	-0.138** (0.069)	-0.136 (0.170)
COAST	-0.001 (0.001)	-0.002* (0.001)	-0.001 (0.001)
Y_50	-0.015 (0.052)	0.018 (0.063)	-0.014 (0.086)
ETHNIC	0.005 (0.105)	-0.068 (0.098)	-0.126 (0.126)
ED_PRIM	-0.013 (0.023)	-0.014 (0.024)	-0.027 (0.026)
OPEN	-0.063 (0.062)	-0.138** (0.069)	0.097 (0.072)
G/Y	-1.522*** (0.456)	-0.908 (0.663)	-1.061 (0.813)
CONST.	0.765* (0.434)	0.556 (0.531)	0.818 (0.697)
R^2	0.17	0.18	0.19
F PROB.	0.0082	0.0220	0.0032
OBS.	87	75	55

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

Table 9: Effect of Explanatory Variables on *e*

	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 A1: Averaging over Different Periods of Time