A New Way to Measure Divergence of Output across Countries[*]

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Abstract

This paper introduces a new way to measure divergence of output across countries. It measures how productivity, technology or output per worker in each country follow the global frontier. We find that during the years 1970-2008 most countries followed the global frontier only partially, so they diverged from it. We use the tools of 'development accounting' to measure by how much countries follow the global technology frontier and find that the rates of following it are even lower. Finally, we show that the result of β-convergence in growth regressions, should be interpreted as convergence of output in each country to its own productivity path, but does not imply convergence across countries.

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

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1. Introduction

Do income levels across countries converge or diverge over time? This question haunts empirical research on economic growth in the last three decades and receives conflicting answers. Worse than that, there is no single agreed method to measure divergence of convergence. One method, growth regressions, examines dependence of growth on initial conditions and finds negative dependence if we control for some explanatory variables, like education, political stability, etc. This result is called β-convergence. A second method directly examines the dynamics of the distribution of income across countries and finds divergence. For example, the σ-convergence test examines the standard error of the distribution of income across countries and finds that it increases over time, which is interpreted as divergence. This dichotomy between different tests and different results plagues the literature to this day, as can be seen in a recent survey on economic growth by Jones (2015).

This paper offers a new way to measure divergence across countries, which avoids much of the problems involved with previous tests. Our main assumption is that each country tries to follow the global frontier, but it might do so only partially. More specifically, we assume that in the long-run a country adopts in each period only d of the new technologies, where d is country specific and is between 0 and 1. If d is equal to 1, the country follows the global frontier fully, but if d is lower than 1, it diverges away from the frontier. Hence, if we can estimate empirically the coefficient d for each country, we can tell whether a country is converging to the frontier or diverging away from it. Since finding d requires estimating a correlation between two non-stationary variables, a country's productivity and the global frontier, our main tool of analysis is cointegration regression.

In order to compare our tests with previous ones, we embed our assumption on technology adoption within a standard growth model, as described in the authoritative survey by Durlauf, Johnson and Temple (2005), hereafter DJT. According to that model, output per worker in each country converges to the country's productivity at a rate b. In productivity we mean labor augmented total factor productivity, LATFP. We then assume that in the long run this productivity itself follows the global frontier at a rate d. More precisely, using the tools of 'development accounting' we decompose the changes in productivity to accumulation of human capital and to the residual, which is interpreted as the country's technical change. We then assume that this technology path follows the global frontier by a rate *d*, which can be 1 or less.

The paper then estimates the coefficients *b* and *d* for each country. We use direct measures of LATFP, derived from the new PWT 8.0, which includes data on output, labor, capital and the labor share, so it enables us to calculate productivity for many countries. The results are very interesting. First, for many countries *d* is lower than 1, namely many countries do not follow the global frontier fully and diverge away from the countries in the frontier, which are the developed countries. Second, technology follows the frontier by even less then productivity, due to high rates of accumulation of human capital. Third, output per worker indeed converges in most countries to productivity, and the rate of convergence is around 2 percent, which is the rate of β-convergence in many growth regressions.[1] These results have a number of implications. First, they show that divergence is indeed the main pattern in economic growth over the years we test, 1970-2008. Second, they imply that the results of growth regressions should not be interpreted as convergence across countries, but rather as convergence between output and productivity within each country. Third, these results reconcile the seemingly conflicting findings of β-convergence and σ-convergence. While output per worker in each country converges to the country's productivity, productivity itself tends to diverge for many countries.

As explained above, we estimate the dynamic coefficients of growth for each country, using data on output, labor, capital, labor share and education only. We do not need the explanatory variables used in growth regressions, which usually represent theories of economic growth, like human capital, geography, institutions, etc. However, we examine how such variables affect our estimated country coefficients *d* and claim that it identifies the long-run effect of such variables on economic growth, while standard growth regressions estimate the combined short and long-run effects of such variables. Since the results of the two tests for the same data differ significantly, it strengthens our claim that our method can identify the separate effects of such variables on long-run growth.

This paper belongs to the empirical literature on convergence and divergence in economic growth, which consists of two main lines of research. The first and most famous is 'growth regressions,' which began with Barro (1991), Mankiw, Romer and Weil (1992), Barro and Sala-i-Martin (1992) and has developed over the years into a huge literature.[2] DJT contains an excellent summary of this literature until 2005. The main result of this research is β-convergence, which means

[1] See DJT (2005) and Barro (2012).
[2] Earlier papers that influenced growth regressions are Baumol (1986) and Kormendi and Meguire (1985).

that the growth of output per worker in a country is negatively related to its initial level of output per worker. Over the years this literature has been criticized on various grounds. First, the economic meaning of β-convergence is not fully clear. Jones (2015) writes that it implies that "countries around the world are converging, but to their own steady states." But what if the steady states themselves are moving over time? A second important critique focuses on the choice of control variables, which seems to be quite arbitrary, and as a result the number of such variables used in growth regressions has become very large over time and has already passed 150.

The second line of literature on convergence and divergence analyzes how the distribution of output per worker, or per capita, changes over time. These tests usually find divergence over time. Early studies in this line of research are Bernard and Durlauf (1995, 1996), Quah (1996) and Pritchett (1997), who titled his paper "Divergence, Big Time."[3] These studies stand in some contrast with the result of β-convergence. One possible criticism on this line of research is that it focuses on the overall distribution and not on the dynamics of individual countries.

The literature on convergence and divergence is so wide and rich that one might wonder what else can be added to it. And still, there is renewed interest in this topic recently. The survey by Jones (2015) on economic growth devotes much attention to it. To that we can add two recent papers by Rodrik (2011, 2013), one on the potential for global convergence and one on convergence of industries across countries, and another essay on convergence by Barro (2012). This new wave of articles shows not only renewed interest in this issue, but also how torn the literature is between different methods and different results. This paper offers a new method that avoids the various critiques on these literatures. It reconciles the results of β-convergence and σ-divergence within the neoclassical model of growth. It estimates the dynamic system without use of explanatory variables and it estimates the coefficient of divergence *d* for each country and not just divergence of the distribution as a whole.

Another literature this paper relates to is that of 'development accounting,' which began with Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), and is summarized in Caselli (2005). This line of research uses data on schooling across countries and studies on the effect of schooling on wages in order to estimate the aggregate levels of human capital. Most of these studies apply human capital estimates to examine differences in output across countries, while this paper uses it to analyze

[3] See also Pesaran (2007a), Philips and Sul (2007, 2009), 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).

economic growth over time. More precisely, we use this method to subtract accumulation of human capital from the rise of productivity over time, to get an estimate to technical change in a country.

Among the many theories of economic growth, this paper is mostly related to that on technology adoption. Since countries do not invent most of their technologies, but adopt them from the frontier, these theories try to explain why some countries adopt only part of the available technologies. Such theories are Krugman (1979), Parente and Prescott (1994), Zeira (1998), Eaton and Kortum (1999) and Acemoglu, Aghion and Zilibotti (2006). Recent empirical support to these theories appears in Dowrick and Rogers (2002), Comin and Hobijn (2010) and Comin and Mestieri (2013). This paper provides additional empirical support for partial adoption of technologies, as it shows that many countries follow the global frontier only partially. Phillips and Sul (2007, 2009) use a similar formulation to ours of the dynamics of productivity, but apply it differently. Another recent paper that bears some similarity to our paper is Gourinchas and Jeanne (2013), who also assume that productivity adjusts gradually to its long-run path, but they assume that this long-run path follows the global frontier fully, namely they assume that $d = 1$.

The paper is organized as follows. Section 2 presents the extended growth model and Section 3 discusses its empirical implications. Section 4 presents the data. Section 5 estimates the convergence of output to productivity. Section 6 examines how country technology follows the global frontier. Section 7 estimates how productivity in each country follows the global frontier and Section 8 examines how output per worker follows it. Section 9 estimates the effects of some explanatory variables on long-run growth. Section 10 summarizes, while the Appendix presents some theoretical additions and robustness checks.

2. The Extended Growth Model

2.1 The Standard Growth Model

In order to clarify our method we begin with the canonical presentation of the neoclassical growth model of a single country, as described in DJT. Assume first that production in country j in period t is described by:

(1) $$Y(j,t) = G\left[K(j,t), A(j,t)L(j,t)\right],$$

where $Y(j,t)$ is output, $L(j,t)$ is labor, $K(j,t)$ is the amount of capital and $A(j,t)$ is labor augmenting total factor productivity, hereafter LATFP or just productivity. The function G is a CRS production function.[4] The DJT model also assumes that labor grows at a fixed rate $n(j)$:

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

and productivity grows at a constant rate $g(j)$:

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

The rates of growth $g(j)$ and $n(j)$ can differ across countries, but g is usually assumed to be equal across countries.[5]

Define 'output per worker' in country j at time t as $y(j,t) = Y(j,t)/L(j,t)$. Similar to DJT define 'efficiency output per worker' to be the ratio between output per worker and LATFP. Since G has constant returns to scale we get:

(4) $$y^E(j,t) = \frac{y(j,t)}{A(j,t)} = \frac{Y(j,t)}{L(j,t)A(j,t)} = G\left[\frac{K(j,t)}{L(j,t)A(j,t)},1\right].$$

In the long-run, the marginal productivity of capital should be constant, in the closed economy because it is equal to the subjective discount rate plus the depreciation rate, or in an open economy because it is equal to the global interest rate plus the depreciation rate. The marginal productivity of capital is:

$$MPK(j,t) = G_K\left[K(j,t), A(j,t)L(j,t)\right] = G_K\left[\frac{K(j,t)}{A(j,t)L(j,t)},1\right].$$

Hence, in the long-run, the ratio between the capital-labor ratio and productivity $K(j,t)/[L(j,t)A(j,t)]$ should be constant as well. From equation (4) it follows that in the long-run the efficiency output per worker should be constant as well and as in DJT, we denote this long-run efficiency output per worker by $y^E(j,\infty)$.

A standard assumption in the growth literature is that the efficiency output per worker converges to its long-run value, $y^E(j,\infty)$ through capital adjustment, and that this convergence is gradual. There are two possible mechanisms that can explain why capital adjustment should be gradual. One applies to a closed economy, where capital accumulation is bounded by savings.[6] An

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[4] DJT assume a specific production function, Cobb-Douglas. We use a more general specification.

[5] See DJT.

[6] The Solow model of a closed economy was used by Mankiw, Romer and Weil (1992) and later by many others. Barro and Sala-i-Martin (1992) used the Ramsey-Cass model, also for a closed economy.

alternative explanation is adjustment costs to investment, and this mechanism works well also in open economies, where investment can exceed savings. This mechanism is explained in Appendix 2 in this paper.[7] The gradual convergence of efficiency output per worker is described by the following log-linear dynamic equation:[8]

(5) $$\ln y^E(j,t) = b(j)\ln y^E(j,\infty) + [1-b(j)]\ln y^E(j,t-1).$$

The parameter $b(j)$ measures the rate of convergence of efficiency output per worker to its long-run value. Most empirical studies assume that this parameter is equal across countries.[9] In this paper we call it the rate of convergence of output. The open economy adjustment costs model in Appendix 2 implies that the size of $b(j)$ should be around 2%.

2.2 The Extended Model

Our main point of departure from the standard growth model is to replace assumption (3) by a more realistic model of productivity dynamics. We first note that human capital should enter the production function as labor augmenting as well, so we can write:

(6) $$A(j,t) = h(j,t)B(j,t).$$

Here, $h(j,t)$ is average human capital in country j in period t and $B(j,t)$ is the state of technology in country j in period t.

We next describe the dynamics of technology adoption of a country. First, assume that the global technology frontier, denoted by F, grows steadily over time:

(7) $$\ln F(t) = \ln F(t-1) + g + v(t).$$

The constant g is the average rate of growth of the frontier and $v(t)$ is a white noise. Assume next that in the long-run a country can follow this frontier either fully or partially. Formally, a country follows over time only $d(j)$ of the additions to the frontier, where this coefficient is country specific, between 0 and 1 and constant over time. If $d(j)=1$ the country follows the frontier fully, but if $d(j)<1$ the country follows the frontier only partially and therefore diverges from it. This is why we call d the rate of divergence. Hence, the long-run technology path of country j, denoted $LRB(j,t)$, should satisfy:

(8) $$\ln LRB(j,t) = \ln B(j) + d(j)\ln F(t).$$

[7] Actually, the open economy model is better suited for describing a comparison of economic growth across countries.
[8] Equation (5) is the same as equation (1) in DJT, except for approximating 1 – exp(-*b*) by *b*.
[9] A non-parametric study that differs with this assumption is Henderson (2010).

We next assume that this long-run technology path is not instantaneously reached. Hence, the technology of country *j*, $B(j,t)$, converges gradually to its long-run technology path:

$$\ln B(j,t) - \ln LRB(j,t) = [1 - c(j)][\ln B(j,t-1) - \ln LRB(j,t-1)]. \tag{9}$$

This convergence is similar to the convergence of output in equation (5), but with a different coefficient, *c*(*j*), which we call the rate of convergence of technology. Gradual adjustment of technology can be justified by costs to adoption of technologies, as in Parente and Prescott (1994).

With respect to the dynamics of human capital we also assume that its accumulation is gradual in each country, due to the need to build and expand systems of education. Since human capital in the long run is bounded, for example by 20 years of schooling if not by less, the adjustment of human capital is described by the standard dynamics of convergence to a constant:

$$\ln h(j,t) - \ln h(j) = [1 - e(j)][\ln h(j,t-1) - \ln h(j)]. \tag{10}$$

Here, $h(j)$ is the long run level of human capital and $e(j)$ is the rate of convergence of human capital. If we can measure output per worker *y*, productivity *A*, human capital *h*, and technology *B* for each country and the global frontier *F*, then we can estimate the dynamic parameters of the model, which are *b*(*j*), *d*(*j*), *c*(*j*), and *e*(*j*). In the next section we explain how.

3. Empirical Implications of the Model

In this section we discuss the empirical implications of the model, which enable us to estimate its various parameters. We examine first how output per worker in each country follows the productivity of the country. Then we examine how a country's technology follows the global technology frontier and finally how a country's productivity follows the global frontier.

3.1 Convergence of Output per Worker to Productivity

Equation (5) describes the dynamics of the efficiency output per worker. From it we derive the following dynamic equation, which describes how output per worker follows productivity:

$$\begin{aligned} &\ln y(j,t) - \ln A(j,t) - \ln y^E(j,\infty) = \\ &= [1 - b(j)][\ln y(j,t-1) - \ln A(j,t-1) - \ln y^E(j,\infty)]. \end{aligned} \tag{11}$$

Equation (11) means that output per worker, in logarithm, converges to the path of productivity, described by: $\ln A(j,t) + \ln y^E(j,\infty)$. Empirically, equation (11) states that the logarithm of output per worker in each country should be cointegrated with $\ln A(j,t)$, and the coefficient of cointegration should be equal to 1, the error correction coefficient to *b*(*j*) and the long-run distance between logarithms of output per worker and productivity should $\ln y^E(j,\infty)$. As explained in Section 4 we can calculate the LATFP for a large set of countries from the new WPT 8.0. Therefore, we can run a cointegration test of $\ln y(j,t)$ over $\ln A(j,t)$ and so measure the rate of output convergence *b*(*j*).

3.2 How Country Technology Follows the Global Technology

From (8) and (9) we derive the following dynamics of technology according to the extended model:

$$(12) \qquad \ln B(j,t) - d(j)\ln F(t) - \ln B(j) = [1-c(j)][\ln B(j,t-1) - d(j)\ln F(t-1) - \ln B(j)].$$

Equation (12) shows that technology converges gradually to the following long-run path: $d(j)\ln F(t) + \ln B(j)$. Empirically it implies that the logarithm of technology should be cointegrated with the logarithm of the global technology frontier, where the coefficient of cointegration is the rate of divergence *d*(*j*) and the error correction coefficient is the rate of convergence of technology *c*(*j*). Hence, a cointegration test of $\ln B(j,t)$ on $\ln F(t)$ should measure these two coefficients for each country.[10]

3.3 The Dynamics of Human Capital

The estimation of the rate of convergence of human capital can be derived directly from equation (10), by differencing it over time, to get rid of the constant ln *h*(*j*). We get:

$$(13) \qquad \ln h(j,t) - \ln h(j,t-1) = [1-e(j)][\ln h(j,t-1) - \ln h(j,t-2)].$$

Hence, testing the rate of change of human capital over the lagged rate of change will enables us to estimate the coefficient *e*(*j*) for each country.

3.4 How Productivity Follows the Global Frontier

As shown below in the paper, our measure of technology of each country yields some problems in estimating the coefficient of divergence *d* across countries and they happen to be too low. One way to overcome this problem is to move to an examination of the dynamics of productivity *A* instead of technology *B*. Combining together equations (10) and (12) and using (6) we get:

$$(14) \qquad \begin{aligned} \ln A(j,t) - d(j)\ln F(t) - a(j) &= [1-c(j)][\ln A(j,t-1) - d(j)\ln F(t-1) - a(j)] + \\ &+ [c(j) - e(j)][\ln h(j,t-1) - \ln h(j)], \end{aligned}$$

Where the coefficient *a* is defined by: $a(j) = \ln B(j) + \ln h(j)$. The last element on the right hand side of (14), $[c(j) - e(j)][\ln h(j,t-1) - \ln h(j)]$, is rather small and it converges to 0 with time. As a result

[10] The cointegration test can also measure *B*(*j*), but we do not use it in this paper.

it should not have a significant effect on our cointegration results. Hence we make an approximation assumption from here on that it is equal to 0. Then, equation (14) becomes:

$$\ln A(j,t) - d(j)\ln F(t) - a(j) = [1 - c(j)][\ln A(j,t-1) - d(j)\ln F(t-1) - a(j)]. \tag{15}$$

Equation (15) implies that a cointegration test of productivity *A* over the global frontier *F* should yield an estimate for *d* as the coefficient of cointegration and an estimate for *c* as the error correction coefficient. In Appendix 4 we present additional tests for (15) by using differences over time.

3.5 How Output per Worker Follows the Global Frontier

Note that while output per worker should follow productivity fully, productivity itself might not follow the global frontier fully. This means that output per worker might not follow the global frontier fully as well, if the country coefficient *d*(*j*) is smaller than 1. To see it formally, note that from iterating equations (11) and (15) over a long period of time we get the following dynamic relationship:

$$\begin{aligned} \ln y(j,t) - d(j)\ln F(t) &= \{1 - [1 - b(j)]^t\}\ln y^E(j,\infty) + \{1 - [1 - c(j)]^t\}a(j) + \\ &+ [1 - b(j)]^t[\ln y(j,0) - \ln A(j,0)] + [1 - c(j)]^t[\ln A(j,0) - d(j)\ln F(0)]. \end{aligned} \tag{16}$$

Equation (16) implies that the difference between $\ln y(j,t)$ and $d(j)\ln F(t)$ should converge in the long run to $\ln y^E(j,\infty) + a(j)$. This implies that output per worker $\ln y(j,t)$ and the global frontier $\ln F(t)$ should be cointegrated and the coefficient of cointegration should be $d(j)$, the same rate of divergence that measures how technology follows the frontier. Hence, a cointegration test of output per worker over the global frontier, as implied by equation (16), can be an additional test of the findings of (15). Note that estimating (16) does not enable us to identify the rates of convergence of output and technology, *b* and *c*, since the error correction coefficient of (16) is some average of these two.[11] But the estimation of (16) should still be valuable for our paper, since it measures *d* for each country. Note that in the same way that testing the cointegration of output per worker over the frontier enables us an additional estimation of *d* to (16), testing the cointegration of ln*y* – ln*h* with the global frontier gives us an additional estimation to (12). Hence, we perform this test as well.

Our main interest in this paper is in estimating the rate of divergence *d*. If it is equal to 1 across countries, then all countries follow the global frontier and there is no divergence. But if *d* is below 1 for many countries, these countries are diverging from the countries at the frontier. In other words, the lower *d* is and the larger its variability, the greater the divergence across countries. But the picture we

[11] In Appendix 3 we show that this combination of *b* and *c* might be one of the reasons for the different results for the rate of convergence in the standard growth regression literature.

get from the values of *d* is of course much finer than just examining the overall distribution. It points at the countries that follow the frontier fully against those that are left more and more behind.

4. Data: Productivity, Technology and the Global Frontier

This paper introduces three new variables to the measurement of divergence of output across countries. These are the labor augmented productivity, LATFP, a measure of technical change, and a measure of the global frontier. In this section we explain how we derive these data. Our main source of data is the new Penn World Table, PWT 8.0, as described in Feenstra, Inklaar and Timmer (2013).

4.1 Labor Augmented Total Factor Productivity

The PWT 8.0 includes data on output, employment, capital and the share of labor for a large panel of countries. For output levels we use the series ‘rgdpna,’ namely real GDP of national accounts at 2005 US dollars (millions).[12] This is the series recommended by PWT 8.0 for comparing output over time, which is the type of tests we run in this paper. For the labor input we use the series ‘emp’ in millions of workers. For capital stocks we use the series ‘rkna’ that is real capital stock at 2005 millions of US dollars and it fits the output series. For the labor share we use the series ‘labsh.’[13] As shown below, these data enable us to calculate output per worker and also LATFP. There are 167 countries in the data set and its time span is 1950-2011, but not all countries have full data for the entire period. This is available for only 29 countries. In most of our estimations we focus on 81 countries, for which these data are available since 1970. For these countries we run tests for the period 1970-2008, since we prefer not to include the years of the recent global crisis. For tests that use only data on output per worker, like equation (17), we use a larger set of 100 countries over the period 1970-2008.

The new PWT 8.0 also includes calculated TFP, but we calculate it independently since we need labor augmented TFP to fit our model. Calculating such productivity requires a slightly different method than the standard Solow Growth Accounting. This method is described in detail in Appendix 1, which shows that the rate of change of LATFP should be calculated by:

[12] This series is chained, so it is also PPP adjusted.

[13] We are aware that this data set is new and might suffer from some ‘childhood’ problems, but these are offset by having a unified data set for both output and productivity. See also Johnson, Larson and Papagiorgiou (2013) and Karabargounis and Nieman (2014).

$$\frac{A(j,t)-A(j,t-1)}{A(j,t-1)} = \frac{1}{s_L(j,t-1)}\left[\frac{Y(j,t)-Y(j,t-1)}{Y(j,t-1)} - \frac{K(j,t)-K(j,t-1)}{K(j,t-1)}\right] + \\ + \frac{K(j,t)-K(j,t-1)}{K(j,t-1)} - \frac{L(j,t)-L(j,t-1)}{L(j,t-1)}. \tag{17}$$

Note that the rate of growth of LATFP is actually equal to the rate of growth of standard TFP divided by the share of labor s_L.

For most of the dynamic analysis below it is sufficient to know only the rate of growth of productivity LATFP, and not its absolute level. For the calculation of the efficiency output per worker, $y^E(j,t) = y(j,t)/A(j,t)$, we also need the level of LATFP. This is done by calculating productivity in the year 2005, the year from which the data are chained, and by assuming a Cobb-Douglas production function, $Y = K^{\alpha}(AL)^{1-\alpha}$, where $1 - \alpha$ is the labor share of that year. From the year 2005 LATFP is chained to all other years by use of its annual growth rates, which are derived by (17).

4.2. Level of Technology

To calculate the state of technology B in a country we use the following version of equation (6):

$$\ln B(j,t) = \ln A(j,t) - \ln h(j,t).$$

Hence, we need to subtract a measure of human capital from our measure of labor augmented total factor productivity. Of course, a country's productivity is affected not only by human capital and technology, but also by other factors, like geography, institutions, etc. But these factors are usually stable over time, while the changes over time in productivity can be assigned mainly to accumulation of human capital and to technical change. To measure the level of human capital in each country, we use the schooling data from Barro and Lee (2013). We turn the variable 'average years of schooling' into human capital using the methodology of 'development accounting,' as described in Caselli (2005). This method uses average results of many labor studies that show that each of the first 4 years of schooling increases human capital by 0.134, each of the next 4 years increases it by 0.101, and each additional year increases human capital by 0.068. Since the Barro and Lee data are in intervals of 5 years, we fill in the sequences of human capital by interpolation between each two observations. This seems to be justified as the data on education are moving over time quite smoothly.

4.3 The Global Frontier

We choose the US to represent the global frontier. The United States is leading the global economy for a long period of time and its per worker has grown quite steadily over more than a hundred and forty years.[14] Furthermore, the US is clearly the leader in global technical change and in innovations, where more than half of the global patents are invented by it. Therefore, for the variable F in our empirical analysis we use either by US productivity, $A(\mathrm{US}, t)$, or US technology, $B(\mathrm{US}, t)$. Whenever our dependent variable is technical change, we use the US technology as the global frontier and then the coefficients d estimate the rate of following the technology frontier. If the dependent variable is productivity, we use US productivity as F, and then the estimated d represents the rate of following the global productivity frontier. In both cases countries with d smaller than 1 experience divergence from the frontier and from the countries at the frontier.

Figure 1 presents the two measures of the frontier together with the US GDP per worker over the years 1950-2010, all in natural logarithms. The blue curve is US output per worker, the red curve is US labor augmented productivity and the green curve is US technology. All three were adjusted to coincide in 1950 in order to have a better view of their changes over time. Figure 1 shows that output per worker and LATFP in the US indeed follow one another very closely over time, as implied by equation (11). The two curves also have a fairly stable slope, which fits well the assumption (7). The technology curve has a somewhat lower slope than the productivity curve, but their slopes seem to become more equal over time, as human capital gets closer to its long-run level. To further examine the use of the US productivity as the global frontier, we tested whether it satisfies equation (7) by a regression of its growth rate on the constant 1 for the period 1970-2008. We find that the coefficient is equal exactly to the mean growth rate in this period, 1.68 percent.

[Insert Figure 1 here]

4.4 Smoothing Output and Productivity Series

In most of our tests we use 5 years moving averages of output per worker, productivity and technology to reduce cyclical high-frequency autocorrelations. This is done also for the US measures of the global frontier. We therefore calculate for each year the following geometric average:

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

In some of the robustness checks in Appendix 4 we show that the main results of the paper hold for raw unsmoothed data as well.

[14] Except in the years 1929-1945, which are not in our period of analysis.

5. Convergence of Output per Worker to Productivity

We begin the empirical analysis by examination of convergence of output per worker to productivity and estimating $b(j)$, the country rate of convergence of output to productivity, for each country j. We estimate the dynamic equation (11) by running a panel cointegration test of output per worker on LATFP. The panel is balanced and covers 80 countries over the period 1970-2008. We also run this test for a smaller set of 28 countries over the years 1950-2008. The two panel cointegrations exclude Turkey, which is an outlier.[15] Table 1 presents the results of these panel cointegrations. The first column shows the average of the regression results for the whole sample of 1970-2008. The following columns present averages for different regions, which are OECD countries in column (2), East Asian (EA) countries in column (3), Central and South American (CSA) countries in column (4), Sub-Sahara African (SSA) countries in column (5), and Middle East and North Africa (MENA) with 3 other countries (Malta, Cyprus and Bulgaria) in column (6). Finally, column (7) presents the results of the regression for the smaller sample of 28 countries over the longer period 1950-2008.

[Insert Table 1 here]

The results of Table 1 fit our model quite well. The average coefficient of cointegration is 0.94, which is very close to 1, as expected by the model, and 1 lies within the 95% confidence interval. This is also the case with respect to the countries with data from 1950. This coefficient is close to 1 in most regions, except for East Asia, where it is higher and in South Saharan Africa, where it is lower. The estimated average rate of convergence of output is 3.1 percent, and its 95% confidence interval is between 2 to 4 percent. In the various regions this rate of convergence is between 1.5 percent and 3 percent, except for MENA, where it is higher. In the data set from 1950-2008 the rate of convergence of output is equal to 1.6 percent. The size of the rate of convergence of output to productivity therefore also fits the prediction of the open economy model in Appendix 2.

Importantly, the rates of convergence of output b and of the cointegration coefficients are estimated separately for each country, but their values are quite close. The following figures give an idea on the concentration of the results across countries. The value of the coefficient of cointegration

[15] Output per worker in Turkey increased significantly, while its productivity did not grow by much, so its cointegration coefficient is extremely high. This is also reflected in Figure 2 below.

is between 0.5 and 1.5 for 41 countries out of 80 in the estimation over 1970-2008. In the estimation of the smaller sample over 1950-2008, the coefficient of cointegration is between 0.7 and 1.3 for 21 countries out of 28. The results with respect to *b* are also concentrated around 2 percent. In the estimation of the larger sample *b* is between 1 and 4 percent for 39 countries out of 80. Concentration of *b* is even higher in the estimation over the smaller sample, where *b* is between 1 and 4 percent for 15 countries out of 28 and between 1.5 and 2.5 percent for 12 countries. These results therefore support the assumption made in many empirical studies, that *b* is similar for all countries.

The cointegration results are also supported by Figure 2, which draws the graphs of the natural logarithms of efficiency output per worker, $\ln y^E$, for each of the OECD countries in the years 1970-2008. As figure 2 shows, for most OECD countries efficiency output per worker has been quite stable over time and it exhibits convergence to some level, as implied by equation (5). The only strong outlier is Turkey, where y^E rises significantly over time. Appendix 4 presents formal tests of the convergence of efficiency output per worker to its long-run value for each country.

[Insert Figure 2 here]

This section therefore finds that output per worker converges in the long-run to the dynamic path of LATFP, labor augmented total factor productivity, as implied by assumption (5) in the standard growth model. This might not be a surprising result in itself, but this paper supports it empirically in a novel way. While growth regressions estimate the rate of convergence *b* by using various explanatory variables for control, this paper estimates this convergence directly, by using data on productivity and without use of any explanatory variable. The fact that the size of the coefficient we estimate is very similar to the rate of convergence of 2 percent found originally by Barro (1991), only strengthens our claim that this is the same coefficient, namely, that this is what Barro (2012) calls "the iron law of convergence." This finding supports our claim that the finding of β-convergence in growth regressions is not about convergence of countries to one another, but only of output in each country to its own productivity path. This claim is implied by the model in DJT, and is empirically verified here.

6. How Country Technologies Follow the Global Technology Frontier

In this section we begin to test the extended model. We first estimate by how much technology *B* of each country follows the global technological frontier. We run a cointegration test of technology on the technology of the US, as implied by equation (12). This test should estimate the rate of divergence of each country, $d(j)$, and the rate of convergence of short-run productivity to its long-run path, $c(j)$. This test is new and innovative and has some fascinating results, but it also has a significant problem. The period of our test, 1970-2008, has been a period of rapid expansion of public education in most countries in the world and especially in the poor ones, as is clear from Barro and Lee (2013). Hence our measure of accumulation of human capital might be too high, because in many developing countries the expansion of education does not fully materialize itself in the labor market for many reasons, like lack of jobs, lack of matching physical capital etc. Hence, the rise in human capital might be upward biased, and as a result the rate of technical change might be downward biased. This might lead to a downward bias of the estimated coefficient d for many countries.

[Insert Table 2 here]

Table 2 presents the results from the panel cointegration test of equation (12). The number of countries in this estimation is not 80 as in Table 1, but 77, since we do not include the US in the regression and we also do not have data on education to three countries in the sample. The results of the estimation with respect to the rate of divergence d, are quite disappointing, as anticipated. The average d over all countries is insignificant. We only see that it is significantly lower than 1. The average of d within the OECD countries is significant, but quite low at 0.3. This might be a result of rapid expansion of education in the OECD countries in this period, while the US has done that mainly before 1970, which reduces significantly the coefficient d. The average d in Central and South America is also significant, but negative and close to -.5, which is quite improbable. In contrast to the parameter d, the error correction coefficient is highly significant and it is quite equal across all countries. Hence, the value of c, which measures the rate of convergence of technology to its long-run path, is around 9 percent. This rate of technology convergence is actually much higher than the rate of convergence of output to productivity, b.[16] Table 2 also contains the results of the panel cointegration without 5 oil producing countries, Bahrain, Iran, Kuwait, Nigeria, and Venezuela and the results are quite similar.

[16] This finding reinforces a point made in Appendix 3, that the estimated rate of convergence in standard growth regressions is a weighted average of 2 and 9 percent. Thus, our approach supplies one explanation to the variation in estimated rates of β-convergence, as found by Abreu, De Groot and Florax (2005).

We next test the convergence of human capital to its long-run levels, as implied by equation (13). Table 3 presents the results of this estimation for a larger set of 93 countries, since we are not constrained here by data on productivity, but only by data from Barro and Lee (2013). Table 3 is structured in a similar way to Table 2, but its results are much stronger. The dependent variable is the rate of change of human capital, and the independent variables are the lagged rate of change and a constant. The coefficient of lagged rate of growth is around 0.85, which implies that the rate of convergence of human capital is around 15 percent on average. The constant, which should have been 0 according to (13), is positive at 0.002, but it is very small. The most important result of Table 3 is that it supports our approximation assumption, which leads to equation (15), since *e* and *c* are quite close to one another. This further justifies turning to the estimation of (15) in the next section.

[Insert Table 3 here]

The disappointing results of Table 2 lead us to test in the next section how productivity of each country, $A(j,t)$, converges or diverges from the global frontier. The benefit of using productivity instead of technology is the problem mentioned above, that technology seems to be downward biased. The data on productivity are closer to the raw data than the measure of technology and can therefore serve us better in estimating the divergence coefficient *d*. We can therefore say that estimation of (15) is less direct in estimating the model, but is a more direct measurement of divergence.

7. How Country Productivities Follow the Global Frontier

In this section we examine how productivity, LATFP, follows the global frontier, LATFP of the US, to estimate again the rate of divergence of each country, *d*(*j*), and the rate of convergence of productivity to its long-run path, *c*(*j*). We run a panel cointegration of productivity on the global frontier, according to equation (15). In Appendix 4 we also examine the difference estimation as a robustness check. Table 4 presents the results of the panel cointegration. The first column shows the average for the full sample, columns (2)-(6) present the results for the global regions defined above. Column (7) presents the results for the whole sample without eight oil countries, since they experienced declining productivity over a long period of time. These are Bahrain, Iran, Kuwait, Nigeria, Oman, Qatar, Saudi-Arabia, and Venezuela. The US is also excluded from the regression, since it is used on the right hand side as the global frontier, and Turkey is excluded as well, as done in Table 1.

[Insert Table 4 here]

The main result that emerges from Table 4 is that the value of *d* across many countries is significantly lower than 1. The average is 0.3, but if we exclude the oil producing countries the average is higher at 0.5, which is still much lower than 1. In some regions it is even lower. This finding implies that our initial hypothesis, that many countries might follow the global frontier partially and not fully, is indeed supported strongly by the data. It means that while β-convergence should be interpreted as convergence of output to productivity, the productivity itself diverges away from the frontier for many countries. The estimated average of *d* does not change much when we smooth productivity over 10 years instead of 5 years and also if we add more countries in an unbalanced cointegration test, the average *d* remains significantly lower than 1.[17]

Table 4 also implies that *d* follows a regional pattern to some extent. The average *d* in the OECD countries is equal to 0.67, namely it is high but still lower than 1. Interestingly, the set of countries with data on productivity from 1950 is quite identical to the OECD countries. The average value of *d* for these countries over the longer period 1950-2008 is 0.77. It shows that *d* declined somewhat after 1970, but not by much. In Central and South America and in South Saharan Africa *d* is even close to zero. This means that these countries do not follow most of the growth of the global frontier year by year. Interestingly, the value of *d* for East Asia is above 1. This is caused by the famous Asian Tigers: Hong Kong, Korea, Singapore, Taiwan and recently China. These countries went through rapid 'catch up' over much of the period. Since this process might involve a gradual rise of the coefficient *a* from equation (15) in such countries, it might bias the estimation of *d* upwards. We therefore treat the high values of *d* in this region with some caution.

Note that our estimations do not constrain the coefficient *d* to be between 0 and 1 as the extended model in Section 2 implies. The main reason is to avoid possible misspecification in the estimation of (16). 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. The second main result of Table 4 is that the value of *c*, which measures the rate of convergence of productivity to its long-run path, is around 9 percent. This result is robust across regions and this rate of convergence of productivity to

[17] These tests are not reported in Table 3 and are available upon request.

its long run path is the same as the rate of convergence of technology to its long run path, the 9 percent reported in Table 2. This also reinforces our approximation assumption, which leads to (15).

The results on the coefficient of divergence *d*, that happens to be significantly lower than 1 for many countries, are clearly the major result of the paper. They show that there is significant divergence of output across countries. Figure 4 provides additional support to our claim that the coefficient *d* is indeed indicative of divergence. This figure plots a scatter of countries with *d* on the horizontal axis and the average rate of growth of output per worker over the period 1970-2008 on the vertical axis. As Figure 4 shows, the two variables are positively correlated. This means that countries with high *d* tend to grow faster than countries with low *d*. This supplies an additional motivation to our focusing on this parameter and its importance for understanding the growth dynamics of countries over time.

[Insert Figure 4 here]

8. How Output per Worker Follows the Global Frontier

In Section 7 we measure the size of the coefficient of divergence *d* for each country and find that for many countries it is significantly lower than 1. In this section we present an additional estimation of these coefficients by using output per worker instead of productivity. We therefore test equation (16) by estimating a panel cointegration of output per worker over the global frontier, the productivity of US in this case. Note that this cointegration test should provide estimates of the coefficient *d*, but it does not measure separately *b* and *c*, but only a weighted average of the two. This is not a significant drawback, since *c* is already estimated and found to be significant at 9% in both measures of productivity and of technology, in Tables 2 and 4. Hence, the test of (16) focuses on the measurement of *d*. This test is added for two main reasons. First, we think that the estimation of *d* by equation (16) is more accurate than the estimation of equation (15), since output per worker is a more directly measured variable than productivity. Second, this estimation enables us to add countries with data on output per worker, which do not have data on productivity. Actually, there are 100 countries with such data and we include 99 countries in the estimation, as US is the explanatory variable.[18] The results of this panel cointegration regression are presented in Table 5, which is built similarly to Table 4.

[18] We do not exclude Turkey in this estimation, as the problematic variable for Turkey appears to be its calculated LATFP, its productivity, rather than its output per worker.

[Insert Table 5 here]

In general the results of Table 5 tell a similar story of divergence as in Table 4, but the estimated values of *d* are higher. This coefficient is around 0.63 on average in the large sample of countries, but it is still significantly lower than 1. Except for the OECD countries and for the East Asian countries, this coefficient is significantly lower than 1 in all other regions. The error correction coefficient, which should be an average of *b* and *c*, is indeed 6.6 percent, which is between 2 and 9 percent. Hence this estimation further supports the main results of the paper. If we remove the oil producing countries, which have experienced negative growth throughout most of the period, the results are still similar, where the average *d* is now 0.68, still lower than 1. The rate of divergence across the OECD countries is equal to 1, which is very reasonable and we also get significant results for Central and South America. We therefore view this estimation of *d* as an improvement over testing productivity, due to the reasons given above and due to the results. Hence, we see these results as the best estimation for the coefficient of divergence *d* and will use it below in Section 9.

[Insert Table 5 here]

Finally, we use the data on output per worker to return to the original estimation of equation (12) of following the technological frontier and to overcome the disappointing results of Table 2. We divide output per worker by human capital in order to get a measure of technical change. We therefore run a cointegration test of $\ln y(j,t) - \ln h(j,t)$ over the global technical frontier, $\ln B(\mathrm{US},t)$. The number of countries in this test is 92 and not 99, due to lack of schooling data for some countries. Table 6 presents the results of this estimation and they seem to be much better than the results of Table 2, with respect to the rates of divergence. The average *d* is significant and equal to 0.6 and the results are significant also for the OECD and EA. The error correction coefficients are around 7 percent, which is also between 2 and 9 percent, similar to Table 5. The estimated values of *d* in this regression are lower than in Table 5, but not by much. Figure 5 presents a scatter plot of countries, with the technological *d* in the vertical axis and the *d* from estimation of (16) in the horizontal axis. Indeed, most countries are below the diagonal, but not by much.

[Insert Figure 6 here]

9. Effects of Explanatory Variables on Global Divergence

Unlike standard growth regressions, our estimations of the dynamic coefficients of country economic growth do not use any explanatory variables, like educational attainment, political stability, rate of saving, geographical characteristics, quality of institutions, religion, and many more that are viewed as explaining differences in growth rates across countries. The fact that this paper does not use such variables can be viewed positively, since much of the critique on growth regressions focuses on the ad-hoc choice of such variables. But we also miss something by not using explanatory variables, since we cannot say much on which variables affect economic growth and how. In this section we try to fix it and we actually show that our method might even improve the estimation of the effects of various explanatory variables, by splitting these effects to long and short run effects. Before we turn to our estimation, we explain why standard growth regressions do not differentiate between the long and the short run effects. The standard growth regression is derived from the model by calculating the average growth rate of country *j* over *T* periods. Using equations (1), (2), (3), and (5), yields:

$$\begin{aligned} \frac{\ln y(j,T)-\ln y(j,0)}{T} &= g(j)+\frac{1-[1-b(j)]^T}{T}\ln A(j,0)+ \\ &+\frac{1-[1-b(j)]^T}{T}\ln y^E(j,\infty)-\frac{1-[1-b(j)]^T}{T}\ln y(j,0). \end{aligned} \tag{20}$$

This is the classical cross-section growth regression.[19] Estimation of this average growth rate over the initial output per worker $\ln y(i,0)$ should yield the rate of convergence $b(j)$. Since $g(j)$, $A(j,0)$ and $y^E(j,\infty)$ are usually unobservable, such regressions control for them by adding explanatory variables. But these variables are not viewed merely as controls, but also as a test to the effect of the variable on growth. Note, that according to equation (20), this regression estimates the effects of such explanatory variables on the sum $g(j)+[1-(1-b)^T]T^{-1}\ln A(j,0)$, without differentiating between their effect on the long-run rate of growth $g(j)$ and the short-run level of productivity $A(j,0)$.

In this paper we do not use such explanatory variables in the estimation of the dynamic parameters, but it is possible that these dynamic parameters themselves might depend on such variables. In other words, country specific explanatory variables might have an effect on the parameters $b(j)$, $c(j)$ and $d(j)$. Since $b(j)$ and $c(j)$ are quite equal across countries, while $d(j)$ differs significantly across them, we

[19] It is equivalent to equation (8) in DJT.

suspect that *d* is the main parameter that should depend on some of the explanatory variables. Furthermore, since *d* is the long run divergence parameter, it should capture only the long run effect of any explanatory variable, without the short run effect. To test this hypothesis we run cross-country regressions of *d* over a set of common explanatory variables and find that it is indeed correlated with some variables. It is important to stress that the goal of this estimation is not to find the ultimate explanation for divergence across countries.[20] We use this test only for comparison with a standard growth regression over the same sample and with the same explanatory variables, in order to show that the two tests yield different results. Namely, the goal of this section is only to highlight the ability of our method to isolate the long-run effect of explanatory variables from their overall effect.

In order to achieve this goal we pick a standard set of explanatory variables, which are used in many growth regressions:

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_70 is the natural logarithm of the GDP per capita in the country at 1970.
4. ETHNIC is a measure for ethnic fractionalization in a country.
5. EDU is average years of schooling of people above age 25 over the period 1970-2010 (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).[21]
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 over the years 1960-1970, taken from Feenstra, Inklaar, and Timmer (2013).

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 represents human

[20] We are aware of the criticism of using such variables as explanations of economic growth. See DJT, Durlauf, Kurtelos and Tan (2008) and elsewhere.
[21] 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.

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). Before turning to estimation, we have examined the correlations between these explanatory variables. Thus, being in the tropics is strongly negatively correlated with most other variables, like education and institutions. We also find that the quality of institutions is strongly correlated with openness and education. This is probably the reason why some 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 7 and 8. Table 7 presents the results of standard growth regressions, where the dependent variable is the average rate of growth over the years 1970-2008. These growth regressions serve for comparison with Table 8 that presents the regressions with d as the dependent variable. Table 8 therefore shows how the explanatory variables affect d, namely the long-run rate of growth of a country. 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, but data availability of the explanatory variables reduces the number of countries in this regression to 79. In the next regression we omit the East Asian countries, and in the third we omit both the EA countries and the OECD countries. The reasons for these omissions are as follows. First, there is probably a bias in the estimation of d among the EA countries, as discussed in Section 7, and it is too high above 1. Since these countries are in a period of changing their parameters, including d, it is preferred not to include them when testing for a statistical regularity between explanatory variables and these coefficients. The reason for excluding the OECD countries in the estimation of the effects on d is very different. 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, these countries become insensitive to 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 6 and 7 omit not only the EA countries, but the OECD countries as well. Note, that these omissions are important to improve the estimation of the explanatory variable on *d*, but are not required for the growth regressions. Such omissions are reported also in Table 7 only for the sake of comparison.

[Insert Table 7 here]

Table 7 presents the results of the standard growth regression. There are 4 variables that are significant throughout, in addition to the constant. These variables are TROPIC, which reduces growth, initial output Y_70, which has a negative effect on economic growth as expected, ethnic fractionalization, which reduces growth, and education, which has a positive effect on growth. These results are similar to many other growth regressions. Note that the results of the growth regressions over the different samples are quite similar, as explained above. Hence we choose the growth regression (1) over the whole sample as the most relevant and reliable one. Thus, it adds to the significant explanatory variables also proximity to coast, which increases growth, and openness, which also increases growth. Hence, the standard growth regression over this sample of countries and over this period identifies TROPIC, COAST, Y_70, ETHNIC, EDU, and OPEN as the main explanatory variables that affect economic growth.

[Insert Table 8 here]

Table 8 presents the effects of the same explanatory variables on the long-run coefficient *d*. The main difference between this table and Table 6 is that the dependent variable *d* is itself an estimated coefficient. To take care of it, we calculate in Table 8 bootstrapped standard errors instead of regular standard errors. Of the six variables found significant in the most relevant growth regression, only four remain in the long-run analysis in Table 8. One variable with a negative significant effect is TROPIC. Its effect is increasing as we narrow the set of countries in the test. In the most relevant group, without East Asia and the OECD, the effect of TROPIC is around 0.8. Namely being in the Tropics can reduce *d* by almost 0.8 relative to the developed countries. Hence, this variable alone can account for much of the divergence of Africa and Latin America. The second variable that affects *d* positively although less significantly is COAST. Initial output has a negative effect on *d*, but the size is diminishing as we reduce the sample. This effect means that poor countries, other things equal, tend to diverge less from the frontier. Ethnic fractionalization also has a significant effect on *d*, although this effect becomes less significant when we exclude East Asia and the OECD countries. The big difference between Table 8 and Table 7 is that education and openness lose their effect when we narrow the sample to the more relevant countries. Hence, although these variables show a positive effect in a standard growth regression, our analysis shows that they do not have an effect in the long-run. The result on education is quite surprising.[22] One possible interpretation can be that education affects only the level of output but not its long-run rate of growth. The results of Tables 7 and 8 mean that the effect of some variables on *d* is very different than the overall effect on output and growth. This demonstrates that the dynamic estimation suggested in this paper enables us to differentiate between short and long-run effects of various explanatory variables on economic growth.

9. Conclusions

The main contribution this paper is to offer a method of how to model and how to measure the dynamics of economic growth across countries. The paper also shows that the extended model is indeed supported by the data. Our method is an improvement relative to previous methods of studying international growth dynamics. It does not use explanatory variables as controls like growth regressions, and it narrows the interpretation of β-convergence. It shows that there is significant divergence of growth across countries, but unlike studies on the overall distribution of output across countries, it can identify which country is diverging and which is not. This method also enables us to separate the effects of various explanatory variables on long-run growth from their overall effect on output and growth.

The methodological contribution of the paper requires some qualification. It should not be interpreted as a critique on previous studies, like growth regressions.[23] The main reason is that application of our method has become feasible only recently due to data availability. First, initial growth regressions had only 25 years of data, while we use 60 years of data. This makes the estimation of *d* possible, since earlier variability of the global frontier was not sufficiently large for such estimation. Also, the use of a unified data set, which has both output and productivity, has become

[22] For similar results on the effect of education on growth see Delgado, Henderson, and Parmeter (2014).
[23] Such critiques are summarized in DJT, in Durlauf (2009) and in many other papers.

possible only very recently with the new PWT. We therefore view this paper as a suggestion on how to move ahead, rather than a critique on past research.

Second, this paper can also be related to some claims that analyzing differences in levels of output across countries is more important than analyzing differences in rates of growth. Such claims followed a number of studies on ‘development accounting.’ It is true that if rates of growth are similar in the long-run across countries, then the main important differences are in levels, but if long-run rates of growth differ significantly across countries over a long period of time, as shown by our study, then the distribution of output levels changes continuously. In other words, countries are poor because they have followed the frontier only partially for a long time. This view is also reflected in the recent survey by Jones (2015).

Finally, this paper contains not only a methodological contribution, but also an empirical investigation of convergence and divergence of output across countries. Its main result is that many countries are not fully catching up with the frontier and thus there is significant divergence. This result should also be qualified. Our results hold for the period 1970-2008. It is possible that the coming years will experience greater convergence if some countries in East Asia, Africa and Latin America will continue to catch up with the frontier, or if other countries might join them. Hence such studies should be repeated once in a while in order to track changes in the growth performance of countries. Future research should also try to improve our estimations, by using improved data, and better methods of estimation. Future research can also extend the second stage regressions of Section 9 to more explanatory variables and to control better for endogeneity problems. But we hope that the results we have already reached with this new method to measure divergence, will tempt researchers to use it even more.

Appendix:

1. Growth Accounting if Productivity is Labor Augmenting

Assume that productivity is labor augmenting, as in the growth regression model (1) in the paper and in DJT.

$$Y(t) = F[K(t), A(t)L(t)].$$

The differential of the change in output between period $t - 1$ and t is described by the following equation, where the derivatives are taken in period $t - 1$:

$$Y(t) - Y(t-1) = F_K(t-1)[K(t) - K(t-1)] +$$
$$+ F_L(t-1)A(t-1)[L(t) - L(t-1)] + F_L L(t-1)[A(t) - A(t-1)].$$

Divide by output at time $t - 1$ and get:

$$\frac{Y(t) - Y(t-1)}{Y(t-1)} = \frac{F_K(t-1)K(t-1)}{Y(t-1)} \frac{K(t) - K(t-1)}{K(t-1)} +$$
$$+ \frac{F_L(t-1)A(t-1)L(t)}{Y(t-1)} \frac{L(t) - L(t-1)}{L(t-1)} + \frac{F_L(t-1)A(t-1)L(t-1)}{Y(t-1)} \frac{A(t) - A(t-1)}{A(t-1)}.$$

Since $F_K(t-1) = MPK(t-1)$ and $F_L(t-1)A(t-1) = MPL(t-1)$ we can rewrite this equation with the shares of capital and labor in output, s_K and s_L respectively, and get:

$$\frac{Y(t) - Y(t-1)}{Y(t-1)} = [1 - s_L(t-1)] \frac{K(t) - K(t-1)}{K(t)} +$$
$$+ s_L(t-1) \frac{L(t) - L(t-1)}{L(t)} + s_L(t-1) \frac{A(t) - A(t-1)}{A(t)}.$$

We can derive the rate of growth of productivity from this equation:

(A.1)
$$\frac{A(t) - A(t-1)}{A(t-1)} = \frac{1}{s_L(t-1)} \left[\frac{Y(t) - Y(t-1)}{Y(t-1)} - \frac{K(t) - K(t-1)}{K(t-1)} \right] +$$
$$+ \frac{K(t) - K(t-1)}{K(t-1)} - \frac{L(t) - L(t-1)}{L(t-1)}.$$

The rate of growth of this labor augmenting productivity is very similar to the rate of growth of productivity which is multiplicative in the production function as in 'Solow's Growth Accounting.' It can be shown that it is equal to (A.1) multiplied by $s_L(t-1)$. Namely, the rate of growth of productivity that is labor augmenting should be around 1.5 higher than the rate of growth of the standard TFP.

2. 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:

(A.2) $$Y(t) = K(t)^{\alpha}\left[A(t)L(t)\right]^{1-\alpha},$$

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

where *g* and *n* are positive numbers.[24] Each person supplies 1 unit of labor per period, so $L = N$. Investment has adjustment costs, which are assumed to be quadratic and of CRS:

(A.4) $$a(t) = \frac{1}{2z}\frac{[K(t+1)-K(t)]^2}{K(t)}.$$

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, the market value of capital *V*(*t*) satisfies:

(A.5) $$V(t) = q(t)K(t+1),$$

where *q*(*t*) is the economy wide value of one unit of capital. Denote the wage rate in period *t* by *w*(*t*). Profit maximization by firms leads to the following two first order conditions. Equilibrium wage is:

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

The rate of capital accumulation is:

(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, the returns on capital and on lending are equal, so that:

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

[24] Note that this open economy model fits the canonical growth regression model of DJT but it can be applied also to the extended model.

In order to describe the dynamics of the economy 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:

$$Q(t)(1+r) = \exp[x(t+1)] + Q(t+1) - (r+\delta) + \frac{z}{2}Q(t+1)^2. \tag{A.10}$$

The dynamics of x are derived from (A.3) and (A.7):

$$x(t+1) = x(t) + (1-\alpha)\{g + n - \ln[1 + zQ(t)]\}. \tag{A.11}$$

The equilibrium solution to this dynamic system, (A.10) and (A.11), is a saddle path, which is described by a function: $Q(t) = Q[x(t)]$, where Q is monotonic increasing. Using a linear approximation we get that the steady state of the system is described by:

$$Q^* = \frac{g+n}{z}, \tag{A.12}$$

And:

$$x^* = \ln(r+\delta) + \ln\left[1 + \frac{g+n}{z}\frac{r-(g+n)/2}{r+\delta}\right]. \tag{A.13}$$

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

$$\ln y^E(t) = -\frac{\alpha}{1-\alpha}[x(t) - \ln\alpha]. \tag{A.14}$$

Hence, efficiency output per worker converges to a steady state $\ln y^E(\infty)$ along the saddle path, which can be calculated from (A.12) and (A.13) and is equal to:

$$\ln y^E(\infty) = \frac{\alpha}{1-\alpha}\left\{\ln\alpha - \ln(r+\delta) - \ln\left[1 + \frac{g+n}{z}\frac{r-(g+n)/2}{r+\delta}\right]\right\} \cong \cong \frac{\alpha}{1-\alpha}\left[\ln\alpha - \ln(r+\delta)\right]. \tag{A.15}$$

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.

From (A.11) and (A.14) we derive the dynamics of efficiency output per worker:

$$\ln y^E(t+1) = \ln y^E(t) + \alpha z Q\left[\ln\alpha - \frac{1-\alpha}{\alpha}\ln y^E(t)\right] - \alpha(g+n). \tag{A.16}$$

Hence, the coefficient of convergence of y^E in the neighborhood of the steady state is equal to:

(A.17) $$b = (1-\alpha) z Q'(x^*).$$

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.18) $$(1-\alpha) z (1+g+n)[Q'(x^*)]^2 + \left[r - g - n + (1-\alpha) z e^{x^*}\right] Q'(x^*) - e^{x^*} = 0.$$

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

Hence:

(A.20) $$b = (1-\alpha) MPK^* \frac{\partial[\ln K(t+1) - \ln K(t)]}{\partial MPK(t)} \cong (1-\alpha)(r+\delta) \frac{\partial[\ln K(t+1) - \ln K(t)]}{\partial MPK(t)}.$$

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 0.3 and 0.5. According to standard assumptions $r+\delta$ is around 0.1 and $1-\alpha = 0.65$. Hence, the rate of self convergence *b* should be somewhere between 1.7% and 3.2%. Therefore, the open economy model yields a rate of convergence that fits the data well, unlike the closed economy models used in many other growth regressions, as shown by DJT.

3. Varying Rates of Convergence in Growth Regressions

In this appendix we examine how the results of the standard growth regressions are affected if we assume that the data behaves according to our extended model, namely equations (6), (7), (8), (9) and (10) instead of (3). We show that it leads to misspecification of the estimation of the rate of convergence *b*. In the extended model the average growth rate over *T* periods is:

(A.21) $$\begin{aligned} \frac{\ln y(j,T) - \ln y(j,0)}{T} &= \frac{1-[1-b(j)]^T}{T} \ln y^E(j,\infty) + \\ &+ \frac{1-[1-c(j)]^T}{T}\left[a(j) + d(j)\ln F(0)\right] + d(j)g + d(j)\sum_{t=0}^{T-1} \frac{1-[1-c(j)]^t v(T-t)}{T} - \\ &- \frac{1-[1-b(j)]^T}{T} \ln y(j,0) + \frac{[1-c(j)]^T - [1-b(j)]^T}{T} \ln A(j,0). \end{aligned}$$

If our extended model is the right one, then equation (A.21) implies that the regression coefficient of initial output $\ln y(j,0)$ reflects not only *b*, but also *c*, through the coefficient of productivity *A*, since productivity is correlated with output per worker across countries. If we denote the coefficient of

$\ln A(j,0)$ on $\ln y(j,0)$ in a cross-country regression in period 0 by *R*, and assume that $R < 1$, then the estimated coefficient of $\ln y(j,0)$ in (A.21) is actually equal to:

$$\text{(A.22)} \qquad COEFF = \frac{-1+(1-R)(1-b)^T + R(1-c)^T}{T}.$$

If $c > b$, the calculated rate of convergence from this coefficient is a weighted average of *b* and *c*, which is closer to *c* if *T* is low and closer to *b* if *T* is high.

Note that our paper shows that *b* is around 2 percent, while *c* is around 9 percent. In a meta-analysis of more than 600 growth regressions Abreu, de Groot and Florax (2005) show that the estimated rates of convergence in growth regressions differ quite a lot across studies and tend to be between 1.5 percent and 8.5 percent. They also find that averaging growth rates over longer periods, namely increasing *T*, reduces the measured rate of convergence in growth regressions.[25] Hence, our model can offer an additional explanation to the results of this meta-analysis.

4. Robustness Checks

4.1 A Growth Regression of Efficiency Output per Worker

Studying the convergence of output per worker to productivity is equivalent to studying convergence of efficiency output per worker to a constant, as implied by equation (5). We next test this convergence directly. We use the data on output per worker and on LATFP to calculate the efficiency output per worker, y^E. This enables us to estimate equation (5) in two additional ways. First, we estimate the following version of (5):

$$\text{(A.23)} \qquad \ln y^E(j,t) - \ln y^E(j,t-1) = b(j)\ln y^E(j,\infty) - b(j)\ln y^E(j,t-1).$$

This equation is very similar to a standard growth regression, but instead of the dynamics of output per worker, it describes the dynamics of efficiency output per worker. The main problem with this estimation is that the constant might differ across countries. One way to overcome this problem is to take differences of equation (5) and estimate the following:

$$\text{(A.24)} \qquad \ln y^E(j,t) - \ln y^E(j,t-1) = [1-b(j)]\left[\ln y^E(j,t-1) - \ln y^E(j,t-2)\right].$$

Table A.1 presents the results of the estimation of these equations. Columns (1) to (3) estimate equation (A.23), while columns (4) to (6) estimate equation (A.24). The first column presents an estimation of a pooled growth regression of equation (A.23). To reduce the effect of cyclicality we run

[25] Each year reduces the rate of convergence by 0.1 percentage points, so that moving from 5 years averages to 25 years can reduce the rate of convergence by 2 percentage points.

a regression of the average rate of growth of efficiency output per worker over the last 5 years on the level of efficiency output per worker at the beginning of these 5 years. We assume in this estimation that *b* is equal across countries, as is justified in the paper. The rate of convergence *b* is calculated from the coefficient of this regression. Column (1) measures convergence at a rate of 1.9 percent. As explained above, $y^E(j,\infty)$ might differ across countries. According to equation (A.15) in Appendix 2, $y^E(j,\infty)$ should depend on the interest rate, the rate of depreciation of capital, the average rate of growth of LATFP and the average rate of growth of labor. Since small open economies face the same global real interest rate and the same rate of depreciation, the remaining variables that should affect $y^E(j,\infty)$ are the average rate of growth of productivity, which we denote by gA(j) and the average rate of growth of the labor force, gL(j). Their effect should be negative. In regression (2) we add the country average rate of growth over the period 1970-2008, gA(j). Indeed the coefficient of gA is negative as expected and highly significant, and regression (2) raises the R^2 from 0.09 in regression (1) to 0.31. Interestingly, the rate of convergence remains similar, 2.0 percent. We also added the rate of growth of labor to the regression, but it did not change the R^2 at all and also the rate of convergence remained 2.0 percent, so we do not report this regression in the table.[26] Column (3) present the regression in (2), but this time with unsmoothed data, to check the effect of this assumption. Note that cointegration tests should not be affected by smoothing, while the test of (A.23) might be. The results of this regression are similar to those of regression (2), except that the coefficient *b* is significant only at 10 percent.

[Insert Table A.1 here]

Regression (4) in Table A.1 presents an Arellano-Bond test of (A.24), regression (5) presents a Blundell-Bond estimation of this equation while (6) presents a standard fixed effects test of this equation. The coefficients of the lagged difference of $\ln y^E$ are all significant and they yield estimates of b that are equal to 3.2 percent, 0.9 percent and 3.8 percent respectively. These results are within the range of results we get in Table 1 in the paper with the cointegration analysis and thus give it additional support.

4.2. Estimating the Difference Equation

[26] The coefficient of gL is positive, but significant only at 5%, while the coefficient of gA is much more significant.

For robustness we can also estimate the dynamic equation (15) by differencing it over *T* periods of time, which yields the following dynamic condition:

$$\text{(A.25)}\qquad \begin{aligned}\ln A(t+T) - \ln A(t) = [1-c(j)][\ln A(t+T-1) - \ln A(t-1)] + \\ + c(j)d(j)[\ln F(t+T-1) - \ln F(t-1)].\end{aligned}$$

Hence, this empirical implication of the extended model is that the average rate of growth of productivity should depend on its own lagged value and on the lagged rate of growth of the frontier. When estimating this relationship, the coefficient of lagged productivity growth should be 1 minus $c(j)$, while the coefficient of the lagged rate of growth of the frontier is the multiple $c(j)d(j)$. Thus, the estimation of equation (A.25) can supply us with coefficients from which we can calculate c and d and that is an alternative estimation of these parameters.

Table A.2 presents the results of these tests and compares them with the results of the cointegration tests in Table 4. In the difference test we regress the average growth rate of productivity over its lagged average growth rate and over the lagged average growth rate of US productivity, by use of a Pesaran-Smith panel regression. In the regression we exclude the oil-producing countries and also Trinidad-Tobago, which is an outlier.

[Insert Table A.2 here]

The estimation of differences over the period 1970-2008 yields the same basic results as the cointegration analysis, but the coefficients are different in size. The average d is around 0.8, above the 0.5 of the cointegration analysis, but it is still significantly lower than 1, so many countries lag persistently behind the global frontier. The average d in the difference regression for 1950-2008 is close to 1, but that is not surprising, since these countries are the more developed countries, which are expected to follow the frontier fully. With respect to the rate of convergence of productivity c, the difference regressions come up with a higher estimate, around 15 percent. But importantly this coefficient is significantly higher than b, the rate of convergence of output.

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Figures and Tables

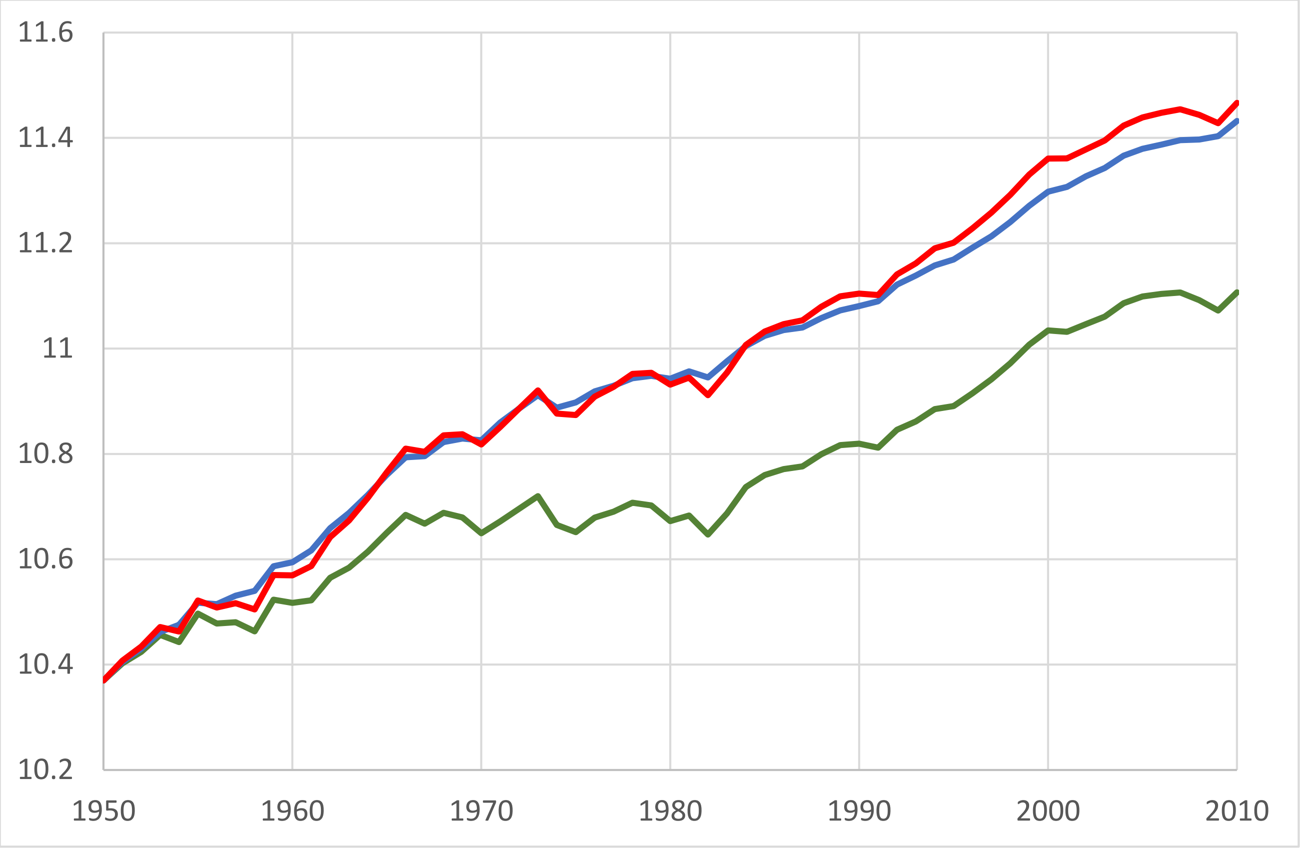

Figure 1: Natural Logarithm of US GDP per worker, LATFP and Technology in 1950-2010

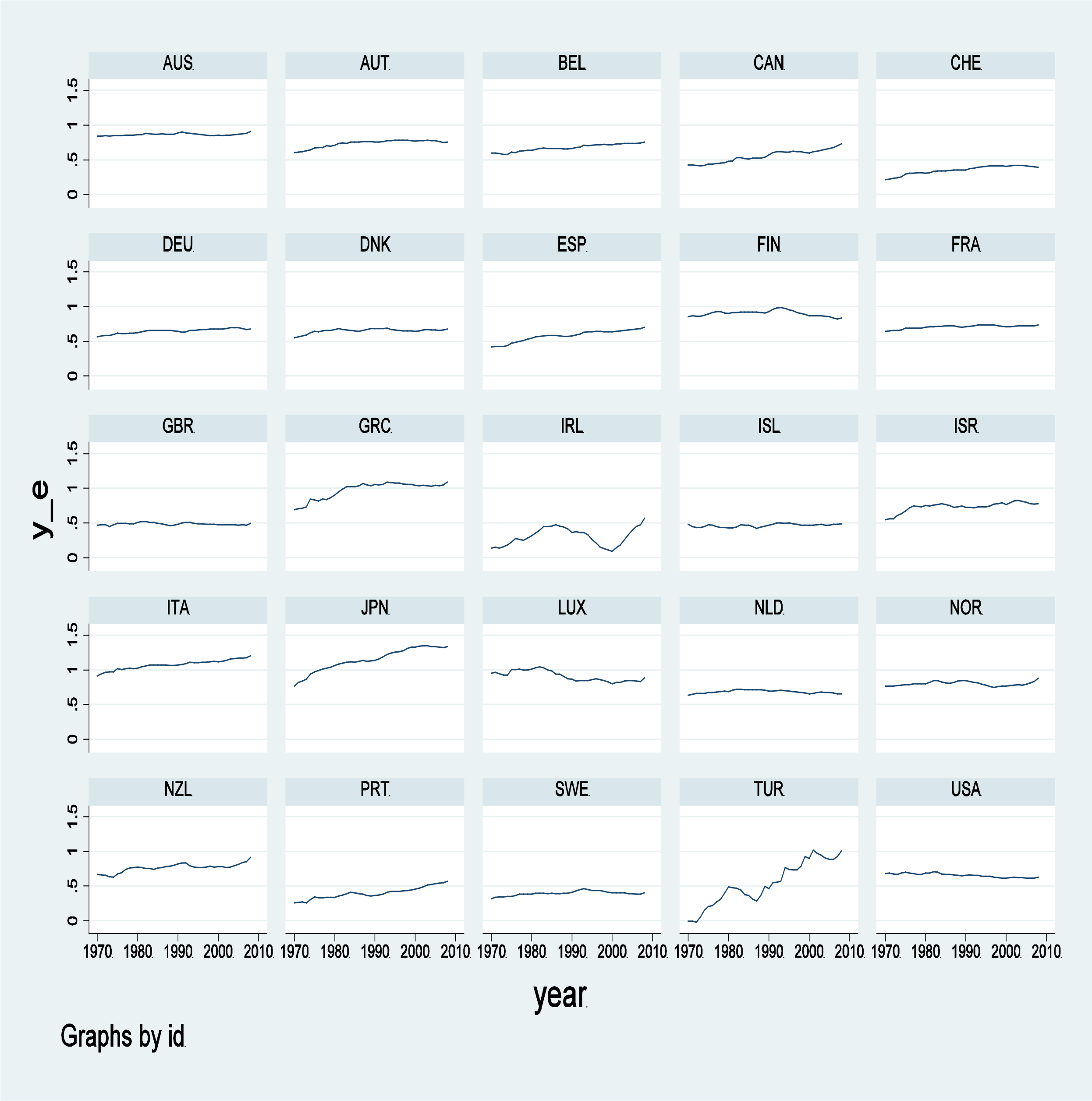

Figure 2: Efficiency Output per Worker in OECD Countries in 1970-2008

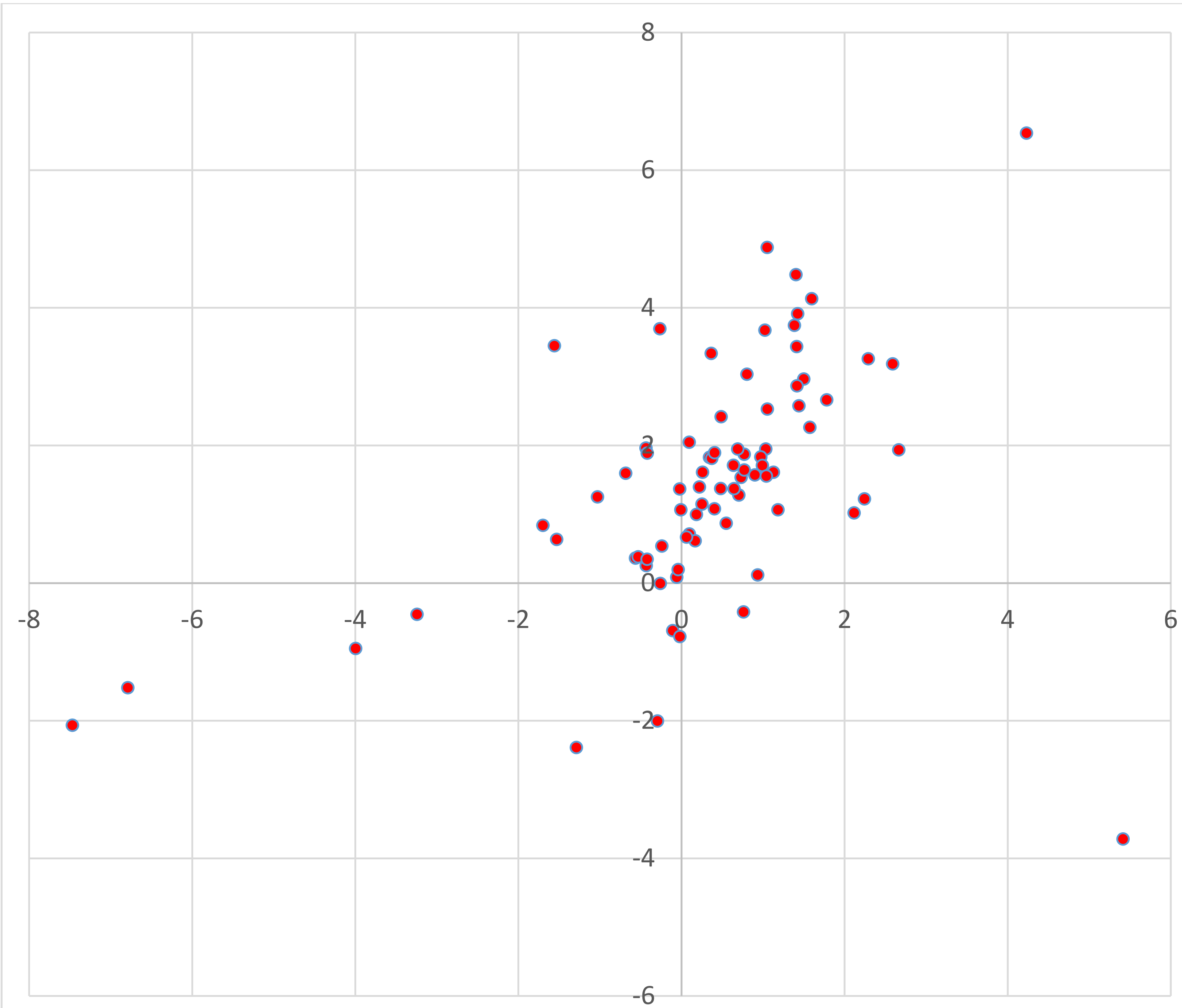

Figure 4: A Scatter Diagram of Growth in 1970-2008 over *d*

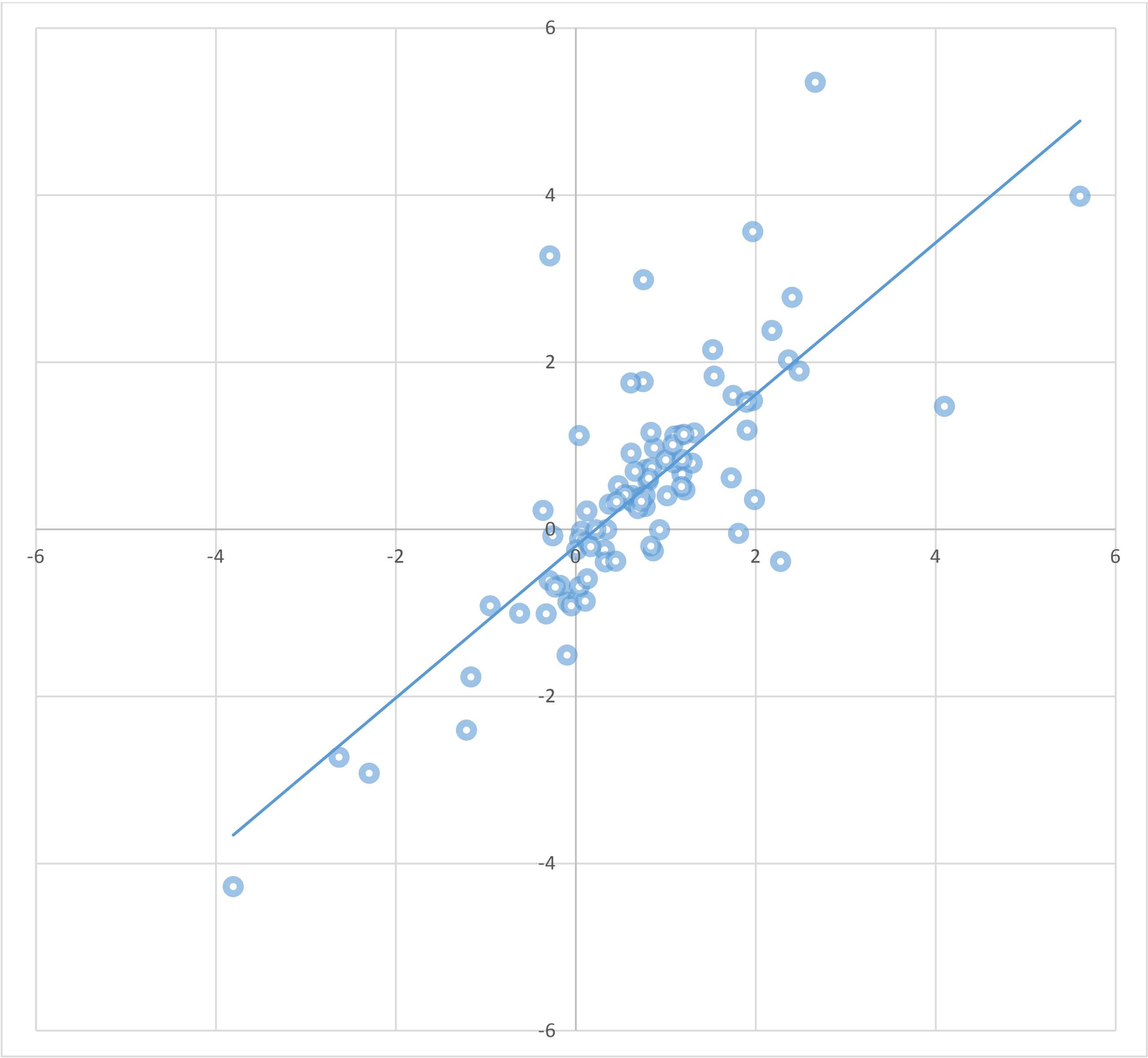

Figure 5: A Scatter Diagram of Technological *d* over Productivity *d*

Coefficient	**1970-2008** (1)	**OECD** (2)	**EA** (3)	**CSA** (4)	**SSA** (5)	**MENA & Others** (6)	**1950-2008** (7)
Co-integration	0.943*** (0.18)	0.927*** (0.22)	1.987*** (0.92)	0.611** (0.33)	0.477*** (0.14)	1.018* (0.584)	1.171*** (0.29)
b	0.031*** (0.005)	0.023*** (0.005)	0.0094 (0.014)	0.031*** (0.006)	0.016*** (0.016)	0.079*** (0.02)	0.016*** (0.005)
No. of Countries	80	29	10	16	12	13	28

1. Standard errors in parenthesis.
2. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 1: Cointegration Estimation of Rate of Convergence *b*

Coefficient	**1970-2008 (1)**	**OECD (2)**	**EA (3)**	**CSA (4)**	**SSA (5)**	**MENA & Others (6)**	**1970-2008 No Oil (7)**
d	-0.215 (0.58)	0.298*** (0.10)	0.662 (0.60)	-0.454** (0.22)	-0.624 (0.40)	-1.387 (3.79)	-0.120 (0.17)
c	0.087*** (0.003)	0.093*** (0.009)	0.118*** (0.023)	0.094*** (0.015)	0.065*** (0.017)	0.061*** (0.013)	0.092*** (0.007)
Test $d = 1$	χ^2=4.32 P=0.04	χ^2=45.71 P=0.000	χ^2=0.31 P=0.58	χ^2=42.05 P=0.000	χ^2=16.23 P=0.000	χ^2=0.40 P=0.53	χ^2=44.97 P=0.000
No. of Countries	77	28	10	18	10	12	72

1. Standard errors in parenthesis.
2. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 2: Cointegration Test of Technology over Global Technology Frontier

Coefficient	**1970-2008 (1)**	**OECD (2)**	**EA (3)**	**CSA (4)**	**SSA (5)**	**MENA & Others (6)**	**1970-2008 No Oil (7)**
$1 - e$	0.842*** (0.009)	0.826*** (0.018)	0.835*** (0.018)	0.831*** (0.022)	0.855*** (0.025)	0.867*** (0.016)	0.840*** (0.010)
Constant	0.002*** (0.0001)	0.001*** (0.0002)	0.002*** (0.0002)	0.002*** (0.0002)	0.001*** (0.0003)	0.001*** (0.0003)	0.002*** (0.0001)
Test: $1 - e = 1$	χ^2=312.74 P=0.000	χ^2=97.00 P=0.000	χ^2=84.74 P=0.000	χ^2=59.61 P=0.000	χ^2=33.92 P=0.000	χ^2=72.82 P=0,000	χ^2=302.41 P=0.000
No. of Countries	93	28	14	18	17	16	88

1. Standard errors in parenthesis.
2. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 3: Estimation of Rate of Adjustment of Human Capital

Coeff.	**1970-2008** (1)	**OECD** (2)	**EA** (3)	**CSA** (4)	**SSA** (5)	**MENA & Others** (6)	**1970-2008 No Oil** (7)
d	0.325* (0.20)	0.670*** (0.13)	1.392*** (0.48)	-0.009 (0.16)	-0.022 (0.43)	0.405 (0.55)	0.495*** (0.13)
c	0.084*** (0.006)	0.095*** (0.01)	0.093*** (0.02)	0.102*** (0.01)	0.050*** (0.02)	0.094*** (0.02)	0.089*** (0.006)
Test $d = 1$	χ^2=11.26 P=0.000	χ^2=6.9 P=0.008	χ^2=0.68 P=0.41	χ^2=42.0 P=0.0000	χ^2=5.61 P=0.02	χ^2=1.17 P=0.28	χ^2=14.7 P=0.0001
No. of Countries	79	28	10	15	11	7	71

1. Standard errors in parenthesis.
2. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 4: Cointegration Test of LATFP to Global Frontier

Coefficient	**1970-2008** **(1)**	**OECD** **(2)**	**EA** **(3)**	**CSA** **(4)**	**SSA** **(5)**	**MENA & Others** **(6)**	**1970-2008 No Oil** **(7)**
d	0.631*** (0.22)	1.019*** (0.20)	1.861*** (0.23)	0.293*** (0.10)	0.359 (0.60)	-0.261 (0.861)	0.683*** (0.23)
EC	0.066*** (0.005)	0.068*** (0.01)	0.051*** (0.01)	0.090*** (0.007)	0.061*** (0.01)	0.062*** (0.01)	0.066*** (0.005)
Test of $d = 1$	χ^2=2.91 P=0.09	χ^2=0.01 P=0.93	χ^2=13.6 P=0.00	χ^2=48.5 P=0.00	χ^2=1.15 P=0.28	χ^2=2.14 P=0.14	χ^2=1.94 P=0.16
No. of Countries	99	28	14	19	22	17	92

1. Standard errors in parenthesis.
2. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 5: Cointegration Test of Output per Worker over the Global Frontier

Coefficient	**1970-2008 (1)**	**OECD (2)**	**EA (3)**	**CSA (4)**	**SSA (5)**	**MENA & Others (6)**	**1970-2008 No Oil (7)**
d	0.610*** (0.24)	0.662*** (0.17)	1.182*** (0.23)	-0.028 (0.19)	-0.429 (0.41)	1.873 (1.186)	0.427*** (0.14)
EC	0.075*** (0.007)	0.091*** (0.02)	0.049*** (0.01)	0.092*** (0.001)	0.072*** (0.015)	0.057*** (0.01)	0.076*** (0.007)
Test of $d = 1$	χ^2=2.65 P=0.10	χ^2=4.02 P=0.04	χ^2=0.65 P=0.42	χ^2=30.48 P=0.00	χ^2=11.90 P=0.001	χ^2=0.54 P=0.46	χ^2=17.11 P=0.000
No. of Countries	92	28	14	18	17	16	87

3. Standard errors in parenthesis.
4. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 6: Cointegration Test of Output per Worker minus Human Capital over the Global Frontier

Dependent Variable: Growth over 1970-2008			
Explanatory Variable	**(1) Whole sample**	**(2) Without EA**	**(3) Without EA and OECD**
TROPIC	-0.013^{***} (0.004)	-0.014^{***} (0.002)	-0.014^{***} (0.004)
COAST	0.001^{***} (0.000)	0.002^{*} (0.001)	0.008 (0.007)
Y_70	-0.013^{***} (0.002)	-0.009^{***} (0.002)	-0.009^{***} (0.002)
ETHNIC	-0.014^{**} (0.006)	-0.017^{***} (0.006)	-0.16^{*} (0.009)
EDU	0.003^{***} (0.001)	0.002^{***} (0.001)	0.002^{**} (0.001)
OPEN	0.009^{**} (0.003)	0.0001 (0.003)	0.003 (0.007)
G/Y	-0.006 (0.025)	-0.002 (0.024)	0.006 (0.031)
CONST.	0.132^{***} (0.021)	0.101^{***} (0.021)	0.095^{***} (0.022)
R^2	0.57	0.56	0.48
F PROB.	0.0000	0.0000	0.0000
OBS.	79	66	57

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

Table 7: Effects of Explanatory Variables on Growth Rates

Dependent Variable: *d*			
Explanatory Variable	**(1) Whole sample**	**(2) Without EA**	**(3) Without EA and OECD**
TROPIC	-0.758** (0.258)	-0.761*** (0.247)	-0.807** (0.295)
COAST	0.035** (0.014)	0.183 (0.196)	0.755* (0.414)
Y_50	-0.924*** (0.193)	-0.666*** (0.274)	-0.453*** (0.149)
ETHNIC	-1.362 (0.479)	-1.533*** (0.531)	-1.287* (0.752)
EDU	0.185*** (0.054)	0.137** (0.057)	0.022 (0.082)
OPEN	0.431* (0.250)	-0.024 (0.215)	0.530 (0.717)
G/Y	-2.107 (2.444)	-1.881 (2.529)	-1.374 (3.376)
CONST.	9.208*** (1.890)	7.126*** (2.355)	5.293*** (1.766)
R^2	0.46	0.41	0.34
F PROB.	0.0000	0.0000	0.0000
OBS.	79	66	40

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: Difference of lny^E over Time						
Coefficient	**(1) Pooled Smoothed**	**(2) Pooled Smoothed**	**(3) Pooled Raw**	**(4) Arellano Bond**	**(5) Blundell Bond**	**(6) Fixed Effects**
Initial lny^E	0.018*** (0.004)	0.019** (0.011)	0.021* (0.012)			
Lagged difference of lny^E				0.968*** (0.003)	0.962*** (0.002)	0.962*** (0.006)
Calculated *b*	0.019	0.020	0.022	0.032	0.009	0.038
Constant	0.030*** (0.005)	0.035*** (0.013)	0.037*** (0.015)	0.0002 (0.0001)	-0.0001 (0.0001)	0.0002 (0.0002)
gA		-0.870*** (0.13)	-0.902*** (0.21)			
R^2	0.09	0.31	0.28			
No. of Observations	2754	2754	2750			
No. of Countries	81	81	81	80	80	80

1. Robust standard errors in parenthesis in regressions (1) to (3).
2. In regressions (2) and (3) standard errors are clustered around countries.
3. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table A.1: Growth Regressions of Efficiency Output per Worker

Coefficient	1970-2008 Differences (1)	1970-2008 Cointegration (2)	1950-2008 Differences (3)	1950-2008 Cointegration (4)
Lagged gA	0.833*** (0.01)		0.849*** 0.01	
Lagged gF	0.136*** (0.02)		0.157*** (0.01)	
Calculated *d*	0.803	0.495	1.163	0.770
Calculated *c*	0.167	0.089	0.151	0.036
No. of Countries	70	71	28	27

1. Robust standard errors are in parenthesis.
2. Regressions (1) and (2) are Pesaran-Smith panel regressions.
3. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table A.2: Difference Regressions of Productivity and Comparison with Cointegration