A New Measure of Divergence[*]

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Abstract

This paper introduces a new measure of divergence or convergence of output across countries. It measures divergence for each country separately, by measuring how technology, or productivity, or output per worker in each country follows the global frontier. We use the US as the global frontier. We find that during the years 1970-2008 most countries did not follow the global frontier fully. This implies that these countries diverged from the countries at the frontier. We then examine how following the global frontier is related to various explanatory variables, in order to better understand long-run growth.

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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 it has received conflicting answers. Worse than that, there is no single agreed method to measure divergence or 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 shows that the standard error of the distribution of income across countries 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 the empirics of economic growth by Jones (2015). This paper presents a new way to measure divergence, which avoids many of the problems involved with previous measures. Our main assumption is that each country tries to follow the global technology frontier, some do it fully and some only partially. We then present a way to measure by how much a country follows the frontier. If it follows fully, the country is converging to the frontier. If not, it diverges away from the frontier. The degree of following the frontier is our measure of divergence.

We begin with the standard growth model in the authoritative survey on growth empirics by Durlauf, Johnson and Temple (2005), hereafter DJT. In this model, total factor productivity is labor augmenting and output per worker is assumed to converge to this productivity at a rate b. We add to this benchmark model a new assumption. We decompose the changes in productivity to accumulation of human capital and to technical change and assume that a country's technical change adopts in each period a share d of the new technologies in the frontier, and d can be either 1 or smaller than 1. If it is 1, the country adopts all new technologies and follows the frontier fully, while if d is lower than 1, the country follows the frontier partially. Hence, productivity might diverge from the global frontier if d is lower than 1. Since output per worker converges to productivity, a country with d lower than 1 diverges away from the countries that follow the global frontier.

The paper then estimates empirically the coefficients b and d for each country. We do it by using two new variables, which were not used in many empirical growth studies. The first is total factor productivity, whose calculation for a large set of countries has become available with the new PWT 8.0, which contains data on output, labor, capital and the labor share. This enables us to calculate labor augmented total factor productivity, which we denoted LATFP, for 80 countries over the years 1970-2010. We then measure the rate of convergence of output per worker to this productivity. The second new variable we use is the global frontier, and we choose to represent it by US economic growth. We estimate *d* and *b* mainly by cointegration regression, since we estimate correlations between non-stationary variables, like output per worker, productivity and the global frontier.

The main empirical result of the paper is that for many countries *d* is lower than 1. This implies that many countries adopt only part of the new technologies in each period. Another result is that output per worker indeed converges in most countries to productivity, and the rate of convergence *b* is around 2 percent, which is also the rate of β-convergence found in many growth regressions.[1] These two results mean that the output per worker of many countries, with *d* lower than 1, diverge away from the countries at the frontier. Hence, divergence is indeed the main pattern in economic growth over the years we test, 1970-2008. These results also reconcile the seemingly conflicting findings of β-convergence and σ-convergence. The reason is that the results of growth regressions should not be interpreted as convergence across countries, but rather as convergence of output to productivity in each country, while 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 for this dynamic estimation the explanatory variables, which are used in growth regressions and which usually represent theories of economic growth, like human capital, geography, institutions, etc. However, we examine how such variables affect our estimated country coefficient *d*. This is done mainly in order to get a better identification of the long-run effects of such variables on economic growth. The results are indeed illuminative. The rate of divergence *d* is negatively affected by tropical climate, by initial output in 1970 and by the rate of fertility. Other explanatory variables, like schooling, fiscal policy, openness to trade and quality of institutions do not have significant effects.

This paper belongs mainly to the empirical literature on convergence and divergence in economic growth, which can be divided to two main lines of research. The first is 'growth regressions,' which was founded by Barro (1991), Mankiw, Romer and Weil (1992), Barro and Sala-i-Martin (1992), though inspired by earlier work by Baumol (1986) and Kormendi and Meguire (1985). This

[1] See DJT (2005) and Barro (2012).

line of research has developed over the years into a huge literature. DJT is an excellent summary of this literature until 2005. The main result of this research is β-convergence, which means that the rate of growth of output per worker in a country is negatively related to its initial level of output per worker, if some additional variables are controlled for. 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 on growth regressions focuses on the ad-hoc choice of control variables, and as a result the number of such variables has become very large over time and has already exceeded 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."[2] These studies are 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 more recent papers like Rodrik (2011, 2013), one on the potential for global convergence and one on convergence of industries, an essay on convergence by Barro (2012) and Madsen and Timol (2011). 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 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. It also measures the degree of divergence and not just the dichotomy of divergence vs. convergence.

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

[2] 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).

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 economic growth over time.

Of the many theories of economic growth, this paper is mostly related to those 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 include 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 also presents additional empirical support for partial adoption of technologies from the frontier. Phillips and Sul (2007, 2009) use a similar formulation 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 the 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 productivities follow the global frontier and Section 8 examines how output per worker follows it. Section 9 estimates the effects of some explanatory variables on our measure of divergence. 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 highlight our specific contribution, 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.[3] 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.[4]

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. This holds in a closed economy because marginal productivity of capital should be equal to the subjective discount rate plus the depreciation rate, and in an open economy because should be 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. 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

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

gradual. One applies to a closed economy, where capital accumulation is bounded by savings.[5] An 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.[6] The gradual convergence of efficiency output per worker is described by the following log-linear dynamic equation:[7]

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

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.[8] 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%. The error term u is assumed to be independent over time and across countries.

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 productivity should be split into human capital and technology in the following way:

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

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:

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

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

[5] 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.

[6] Actually, the open economy model is better suited for a comparison of economic growth across countries.

[7] Equation (5) is the same as equation (1) in DJT, except for approximating 1 – exp(-*b*) by *b*.

[8] A non-parametric study that differs with this assumption is Henderson (2010).

of divergence. Formally, the long-run technology path of country *j*, which is denoted $LRB(j,t)$, should satisfy:

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

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. More precisely, we assume that the ratio of *B* to *LRB* converges to 1:

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

This convergence is similar to the convergence of efficiency output per worker 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:

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

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 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 then 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:

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

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 should be equal to $b(j)$ and the long-run distance between logarithms of output per worker and productivity should be $\ln y^E(j,\infty)$. 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 measure the coefficient $b(j)$. In Appendix 4 we present additional tests for measuring b by estimating directly the divergence of efficiency output per worker y^E.

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:

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

Equation (12) shows that technology converges gradually to the following long-run path: $d(j)\ln F(t) + a(j)$. 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.[9]

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:

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

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, the country measure of technology has some problems in estimating the coefficient of divergence d across countries. We suspect that one of the reasons is the use of data on

[9] The cointegration test can also measure $a(j)$, but we do not use it in this paper.

human capital. In many less developed countries people with education do not find jobs that fit their education and as a result their formal schooling level does not necessarily reflect their actual human capital. One way to overcome this problem is to examine the dynamics of productivity *A* instead of technology *B*. Combining together equations (10) and (12) and using (6) we get:

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

where the coefficient *m* is defined by: $m(j) = a(j) + \ln h(j)$. 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 over time. Furthermore, our estimations show that *e* is quite close to *c*, which makes this term even smaller. As a result 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:

$$(15)\qquad \ln A(j,t) - d(j)\ln F(t) - m(j) = [1-c(j)][\ln A(j,t-1) - d(j)\ln F(t-1) - m(j)].$$

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.

<u>3.5 How Output per Worker Follows the Global Frontier</u>

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:

$$\begin{aligned}(16)\qquad \ln y(j,t) - d(j)\ln F(t) = \{1-[1-b(j)]^t\}\ln y^E(j,\infty) + \{1-[1-c(j)]^t\}m(j) + \\ + [1-b(j)]^t[\ln y(j,0) - \ln A(j,0)] + [1-c(j)]^t[\ln A(j,0) - d(j)\ln F(0)] + \\ + \sum_{\tau=1}^{t}[1-b(j)]^{t-\tau}u(j,\tau).\end{aligned}$$

Equation (16) implies that the difference between $\ln y(j,t)$ and $d(j)\ln F(t)$ should converge in the long run to $\ln y^E(j,\infty) + m(j)$. 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 to (15) of the coefficient *d*. 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.[10] But equation (16) adds an estimation of *d*, which is our main interest in this paper, since the lower *d* is and the larger its variability, the greater is divergence across countries. Furthermore, estimating *d* 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).[11] 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.'[12] 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:

[10] In Appendix 3 we discuss how adding *c* to the model can affect the results of standard growth regressions.
[11] This series is chained, so it is also PPP adjusted.
[12] 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).

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

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.[13] 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.

[13] 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.[14] 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

[14] 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.[15] 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.

[15] 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 accurate 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.[16]

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

[16] 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 LATFP. 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.[17] The results of this panel cointegration regression are presented in Table 5, which is built similarly to Table 4.

[17] 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. Our finding of convergence among OECD countries fits well the recent results of Madsen and Timol (2011).

[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

Our analysis shows that many countries do not adopt all new technologies and do not follow the global frontier fully. This naturally raises the question why? What are the reasons that some countries are lagging behind so much and so persistently? There is of course a large literature that tries to cope with this question, but we can offer here a very preliminary empirical examination of this question. Since we have a new measure of divergence, *d*, which is continuous, we can try and see, using a regression analysis, how it is related to various variables that are assumed or believed to affect economic growth, like education, public policies, geography, quality of institutions and more. It is important to stress, that unlike standard growth regressions, our estimations of the dynamic coefficients growth do not use any explanatory variables. What we can do is examine whether such explanatory variables can affect the parameters that we have estimated above, and mainly $d(j)$, which differs so much across countries. It is also important to stress that this estimation of *d* over a set of explanatory variables focuses on the long-run growth effect of these variables, without the short-run level effect. Appendix 5 shows that standard growth regressions do not separate the long-run from the short run effect of such variables.

We therefore present in this section regressions of the parameter *d* on a number of explanatory variables. The dependent variable is *d*, as calculated in the best measure in Section 8, which is the *d* found in cointegration of output per worker on the global frontier. The explanatory variables are quite standard and 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. FERTILITY is the average rate of lifetime fertility of women in a country at the year 1980.
7. OPEN is a measure of openness of a country. It is the ratio between the sum of exports and imports to GDP at the year 1970.

8. G/Y is the share of public expenditures in GDP, averaged over the years 1960-1970, taken from Feenstra, Inklaar, and Timmer (2013). This variable is tested with its square to examine the possibility of a non-monotonic effect.
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).

Variables 1 and 2 reflect the geographical explanation to growth. Variables 3 and 4 reflect the history of the country, namely its initial conditions, both economic and social. Variable 5 represents human capital and variable 6 is represents demographic trends. Demography can affect growth in many ways, some of them through acquisition of human capital. Variables 7 and 8 reflect public policy, while variable 9 reflects the effect of institutions on long run growth. 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. Public policies are also related to technology adoption, especially policies that affect international trade, as stressed by Grossman and Helpman (1991).

The regressions are presented in Tables 7a and 7b, where the explanatory variables are added gradually. All the regressions include constants and are OLS in a cross-section of countries. There are two regional issue that are taken care in the regressions. The first is by controlling for the East Asian countries. The reason is that 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 catching up with the frontier, they are changing their parameters, including d. Hence, we decided to control for them when testing for a statistical regularity between explanatory variables and these coefficients. Interestingly, Durlauf, Kourtellos and Tan (2008) also control for regions. We tried to control for other regions but they were insignificant except for East Asia. In the regressions in Tables 7a and 7b we do not report the control for East Asia, but it came highly significant in all regressions. In addition to that we present two regressions for each set of variables, one with all the countries with available data and one excluding the OECD countries. The reason for that is the following. In the OECD 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 higher or lower fertility, larger or smaller government, 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. Indeed, the regressions without the OECD countries yield similar results to the more inclusive regressions, but they come out much more significant.[18]

[Insert Tables 7a and 7b here]

Tables 7a and 7b show that adding variables one after the other indeed increases the explanatory power of the regressions, as the R^2 increases along the way, except for the last regression, where adding ICRG increases the R^2 of the regression for the whole sample, but reduces it for the regression without the OECD countries. Of the large set of explanatory variables only three have strong and significant effects through most regressions. The first is the variable TROPIC that has a strong negative and very significant effect on *d* in all the regressions. The coefficient is around -0.7 and that means that in countries that are fully in tropical climate, it is very hard to follow the frontier. The second variable that has a significant (negative) effect on *d* is initial output per worker in 1970. In Table 7a its effect is not yet significant, but after adding the variable OPEN it becomes consistently significant with every additional variable. Hence, countries that are poorer at the beginning of the period tend to catch up technologically more than countries that are richer. The third variable that appears to be consistently significant in all regressions it is included in, is the rate of fertility. It has a significant negative effect of the size around -0.3. Note that in 1980 the rate of fertility fluctuated between 1.5 and 8, so a country with fertility rate of 5 would have a d lower by 1 from a country with a rate of fertility 1.5, other things equal. Since, these three variables, being in the tropics, initial output and the rate of fertility, seem to be the only variables with a significant clear negative effect on *d*, we conclude that they are the main variables that affect long-run growth. Of these two variables two are clearly exogenous, namely climate and initial output, while the rate of fertility is more endogenous. But recent history shows that the rate of fertility is affected by public policies to a large extent, as the example of China shows.

[18] All regressions omit Ethiopia, which is an outlier with a very high value of *d*.

Examination of the explanatory variables that do not have a significant effect on *d* is not less interesting than the examination of the variables that have a significant effect. The most surprising result is that years of schooling (EDU) do not have a significant effect on *d*. This holds in all regressions except for regression 4 in Table 7b, where the effect is mildly significant and has a negative sign, which is counter to all expectations. This result is surprising both because we expect education to support technology adoption, as mentioned above, and also because all growth regressions find that education has a positive effect on growth.[19] We do not have a full explanation to this finding, but we think that it is related to differences between long and short-run effects. This finding points to one observation already made in the paper, namely that education is a bounded variable and thus cannot have a long-run effect, only a short-run effect. Hence, this is an additional support to our claim that *d* captures long-run economic growth and is independent of short-run level effects. Openness to trade has a significant effect only in some regressions and seems to be overall insignificant. To that we might add that this variable is very endogenous. The variable ICRG, which measures quality of institutions also has no effect on the country parameter *d*. Another interesting result is that fiscal policy comes out insignificant. Although initial growth regressions, like Barro and Sala-i-Martin (1992) found that public expenditures had a negative effect on growth, later studies have found that the effect is not significant. We also reach a similar conclusion. We test for the possibility that fiscal policy might have a non-monotonic effect on growth and find some support for that, but a regression on G/Y alone yields similar insignificant results.

Finally, we would like to report results of a similar test on the OECD countries only, which is not fully presented here.[20] In a regression of *d* over the whole set of explanatory variables among 26 OECD countries we find the following results. First, TROPIC and FERTILITY are no longer significant. There are two variables, which have a significant effect on *d*. The first is initial output, which is significant at 99 percent, and the second is years of schooling, which is positive and significant at 97 percent. The quality of institutions is significant at 88 percent, which is not actually significant. The obvious reason why TROPIC and FERTILITY do not have an effect on OECD countries is that these countries are out of the tropics and they all have low fertility rates, relative to third world countries. The surprising result is that education has a significant effect within the OECD countries. One possible explanation to that could be that the differences in education between OECD countries

[19] For similar results on the effect of education on growth see Delgado, Henderson, and Parmeter (2014).
[20] The results are available upon request from the authors.

are more persistent than between these countries and developing countries, which have increased education significantly in recent decades. Thus, education might have a stronger effect on catching up with technology within OECD countries, than in other countries. It is worth noting that two recent papers that find a strong effect of human capital on growth and on technology adoption, Ciccone and Papaioannou (2009) and Madsen (2014) focus mainly on developed countries and thus they do not contradict our main result in Tables 7a and 7b, that human capital has an insignificant effect on long-run following of the frontier in countries outside the OECD.

10. 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. 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.[21] 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, from which we can calculate both output per worker and productivity, has become available 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 follow a number of studies of 'development accounting.' It is true that if rates of growth are similar in the long-run across countries, then the main important differences across countries are in levels. But if

[21] Such critiques are summarized in DJT, in Durlauf (2009) and in many other papers.

long-run rates of growth differ significantly across countries over a long period of time, as shown by this paper, 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 better data, and better methods of estimation. Future research can also extend the regressions of Section 9 to more explanatory variables and to control better for endogeneity problems.

Appendix:

1. Growth Accounting if Total Factor 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 $t - 1$:

$$\begin{aligned} Y(t) - Y(t-1) &= F_K(t-1)[K(t) - K(t-1)] + \\ &+ F_L(t-1)A(t-1)[L(t) - L(t-1)] + F_L(t-1)L(t-1)[A(t) - A(t-1)]. \end{aligned}$$

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

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

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:

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

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

$$\begin{aligned} \frac{A(t) - A(t-1)}{A(t-1)} &= \frac{1}{s_L(t-1)} \left[\frac{Y(t) - Y(t-1)}{Y(t-1)} - \frac{K(t) - K(t-1)}{K(t-1)} \right] + \\ &+ \frac{K(t) - K(t-1)}{K(t-1)} - \frac{L(t) - L(t-1)}{L(t-1)}. \end{aligned} \qquad \text{(A.1)}$$

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 with Adjustment Costs

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

[22] 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:

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

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

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

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:

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

And:

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

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

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

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

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

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.

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

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

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

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

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

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 output 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.[23] 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

[23] 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.[24] 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

[24] 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.

5. Long-Run and Short-Run Effects of Explanatory Variables in Growth Regressions

In this appendix we claim that standard growth regressions do not differentiate between the long and the short run effects of explanatory variables on economic growth. 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:

$$\text{(A.26)} \qquad \begin{aligned} \frac{\ln y(j,T) - \ln y(j,0)}{T} &= g(j) + \frac{1-[1-b(j)]^T}{T}\ln A(j,0) + \\ &+ \frac{1-[1-b(j)]^T}{T}\ln y^E(j,\infty) - \frac{1-[1-b(j)]^T}{T}\ln y(j,0). \end{aligned}$$

This is the classical cross-section growth regression.[25] 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 $A(j,0)$.

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

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Figures and Tables

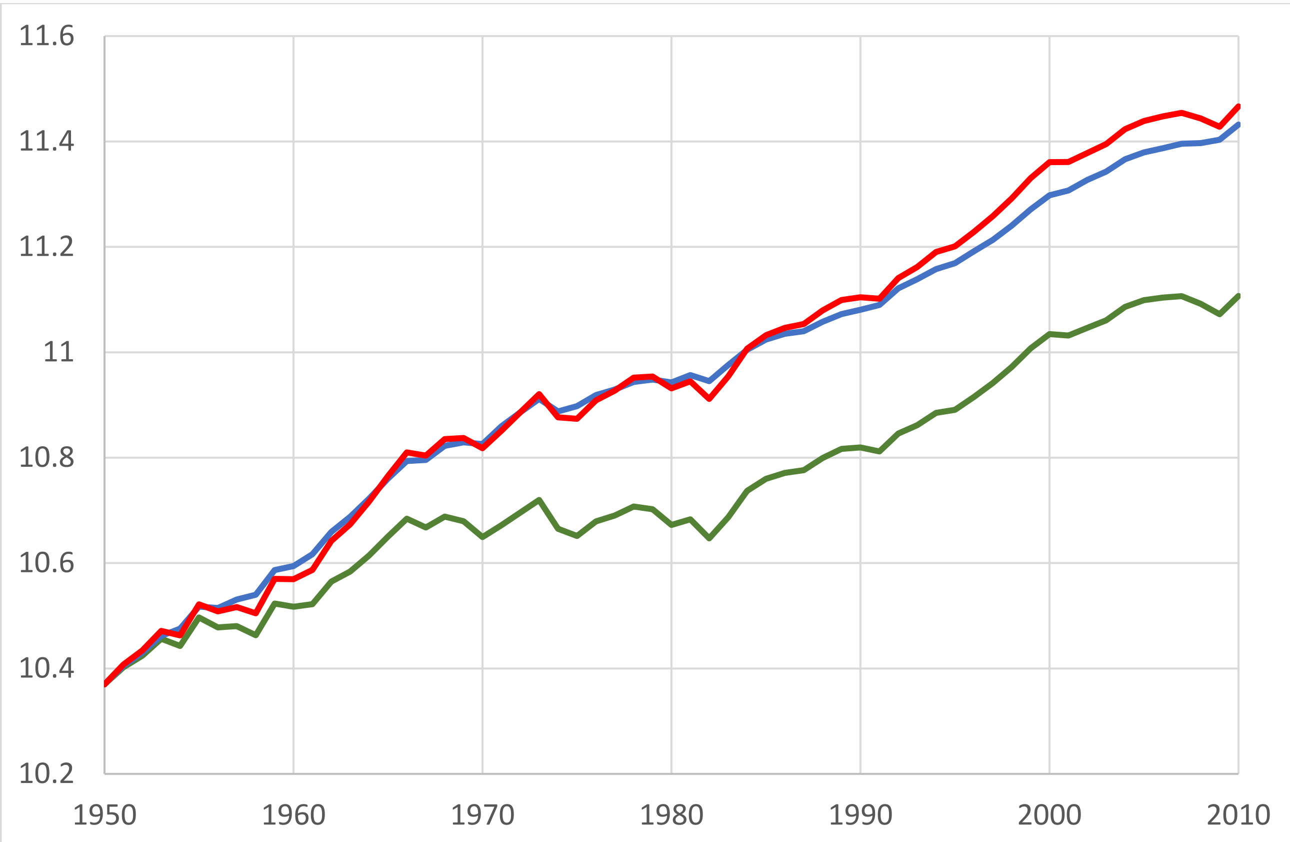

Figure 1: Natural Logarithm of US GDP per worker, LATFP and Technology in 1950-2010

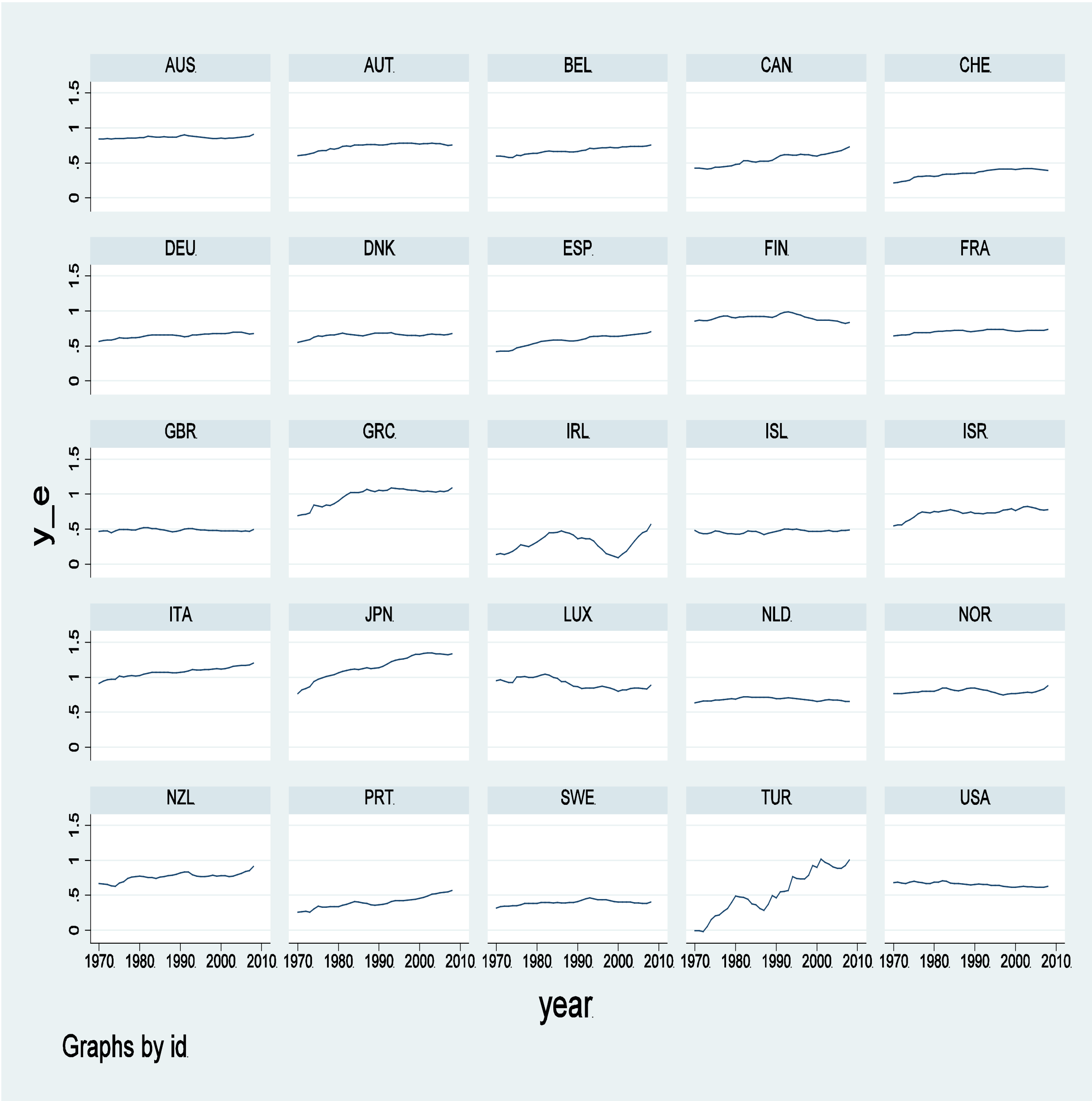

Figure 2: Efficiency Output per Worker in OECD Countries in 1970-2008

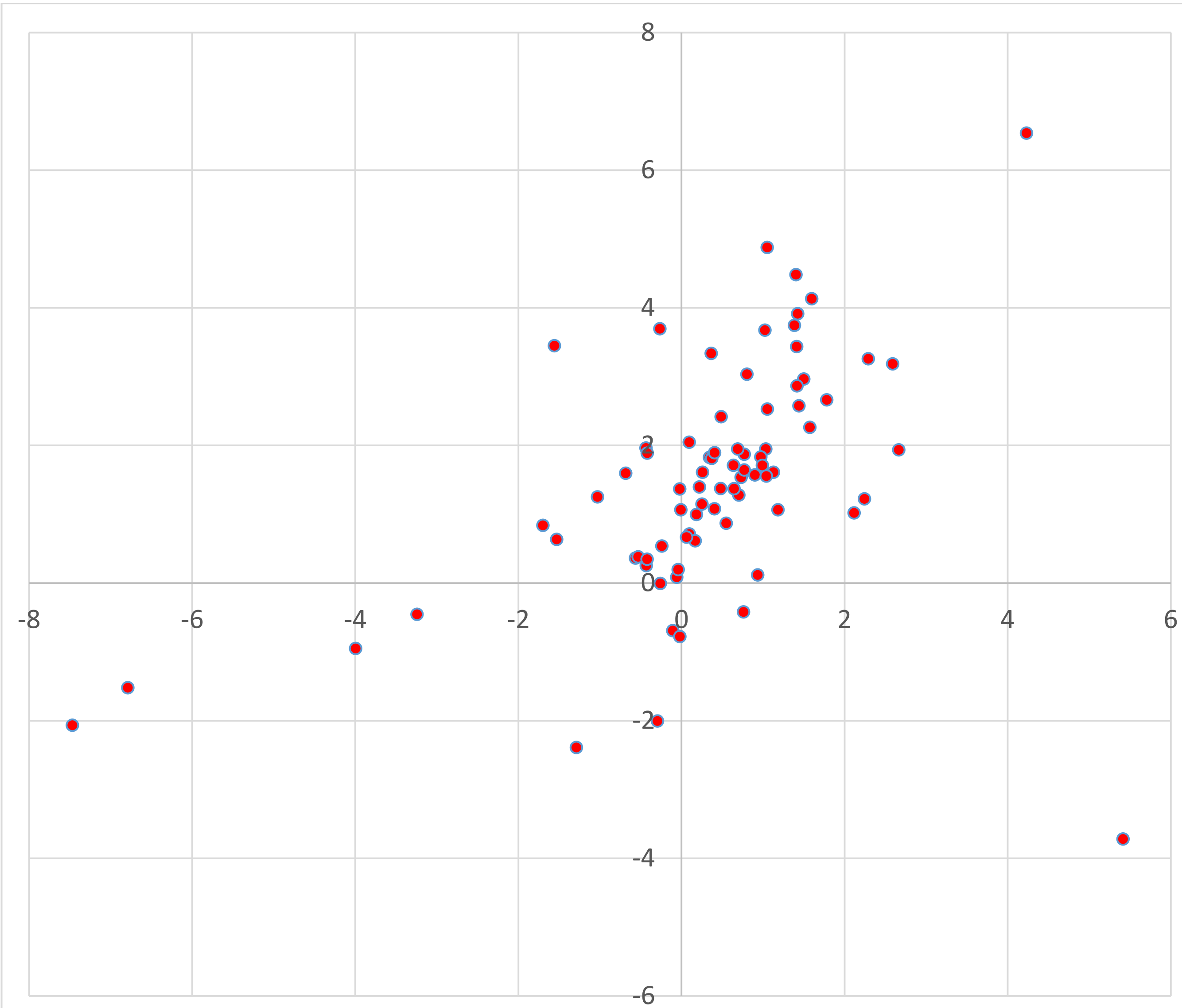

Figure 4: A Scatter Diagram of Growth in 1970-2008 over *d*

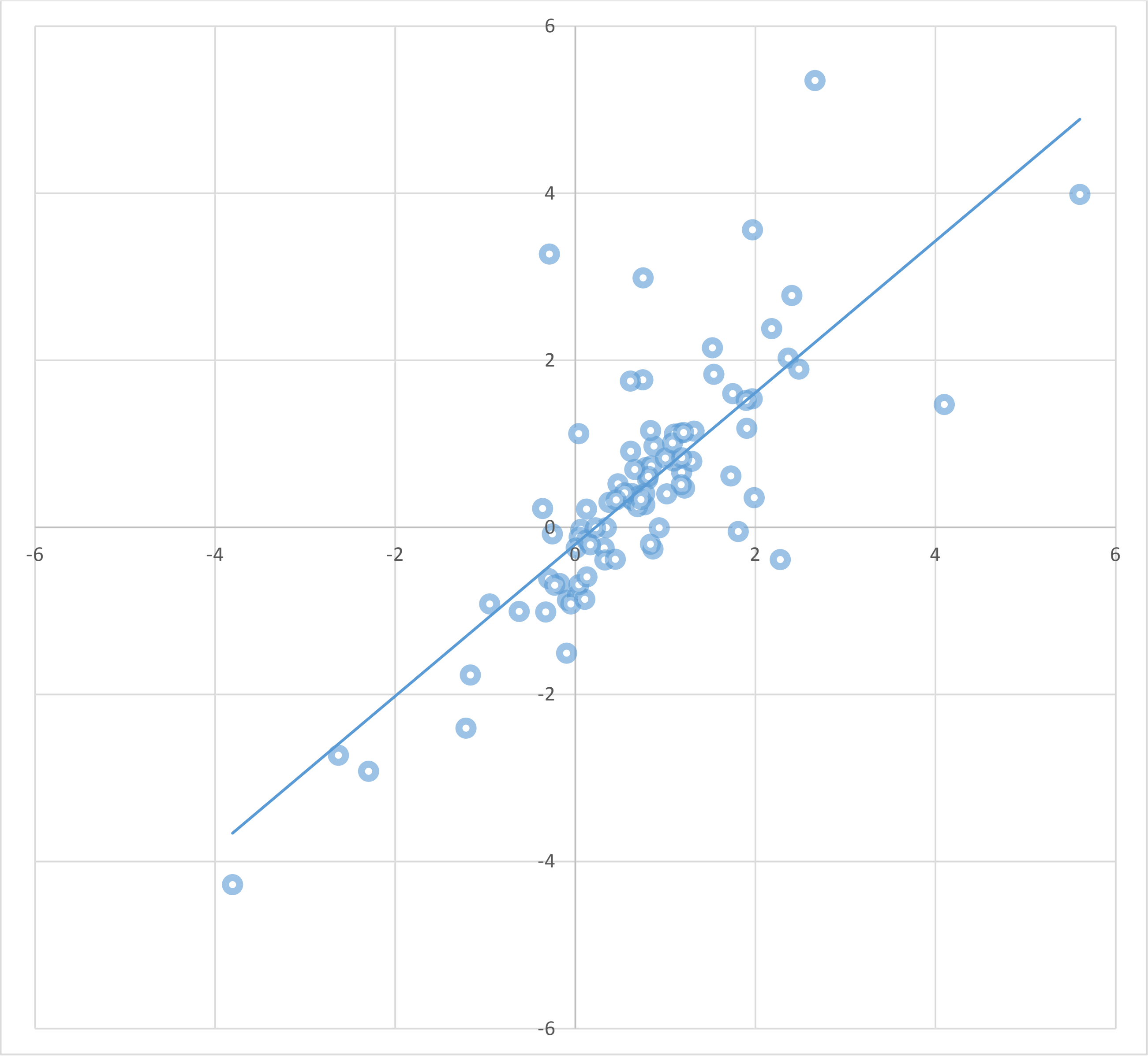

Figure 5: A Scatter Diagram of Technological *d* over Productivity *d*

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: *d*						
Explanatory Variable	**(1) Whole sample**	**(2) Without OECD**	**(3) Whole Sample**	**(4) Without OECD**	**(5) Whole sample**	**(6) Without OECD**
TROPIC	-0.813*** (0.230)	-0.730*** (0.291)	-0.791*** (0.250)	-0.784*** (0.325)	-0.819*** (0.270)	-0.915*** (0.299)
COAST	0.005 (0.003)	0.005 (0.004)	0.005 (0.004)	0.007 (0.005)	0.005 (0.004)	0.007 (0.005)
Y_70			-0.238 (0.165)	-0.177 (0.163)	-0.327 (0.243)	-0.166 (0.184)
ETHNIC			-0.868 (0.691)	-0.343 (0.817)	-0.346 (0.622)	0.251 (0.658)
EDU					-0.034 (0.108)	-0.209 (0.132)
FERTILITY					-0.168 (0.119)	-0.377*** (0.135)
OPEN						
G/Y						
$(G/Y)^2$						
ICRG						
CONST.	0.641*** (0.218)	0.552** (0.262)	3.225** (1.710)	2.303 (1.597)	4.767** (2.257)	4.994*** (1.846)
R^2	0.3095	0.3802	0.3549	0.4005	0.4193	0.5530
OBS.	90	64	90	64	84	58
1. Robust standard errors in parentheses. 2. Significance levels of 99%, 95% and 90% are denoted by ***, **, and * respectively.						

Table 7a: Effects of Explanatory Variables on *d*

Dependent Variable: ***d***						
Explanatory Variable	**(1) Whole Sample**	**(2) Without OECD**	**(3) Whole sample**	**(4) Without OECD**	**(5) Whole sample**	**(6) Without OECD**
TROPIC	-0.710*** (0.207)	-684*** (0.240)	-0.682*** (0.216)	-0.643*** (0.217)	-0.671*** (0.249)	-0.816*** (0.300)
COAST	0.005 (0.004)	0.006* (0.004)	0.005 (0.005)	0.006* (0.003)	0.001 (0.003)	0.006 (0.005)
Y_70	-0.456** (0.207)	-419*** (0.133)	-0.440** (0.234)	-0383*** (0.148)	-0.767*** (0.261)	-0.520*** (0.163)
ETHNIC	-0.614 (0.533)	-0.100 (0.549)	-0.637 (0.526)	-0.117 (0.534)	-0.752 (0.491)	-0.070 (0.571)
EDU	-0.001 (0.087)	-0.153* (0.096)	-0.014 (0.097)	-0.175** (0.094)	0.091 (0.108)	-0.116 (0.131)
FERTILITY	-0.194* (0.116)	-0.393*** (0.128)	-0.217* (0.123)	-0.427*** (0.123)	-0.303*** (0.110)	-0.464*** (0.136)
OPEN	1.594 (1.397)	2.711*** (1.039)	1.630 (1.372)	2.765*** (0.973)	-0.021 (1.540)	2.149 (1.912)
G/Y			-1.191 (2.683)	-1.185 (3.108)	2.545 (6.826)	5.926 (7.766)
$(G/Y)^2$			3.429 (3.493)	4.389 (4.235)	-7.294 (12.636)	-8.433 (13.577)
ICRG					-0086* (0.052)	-0.017 (0.105)
CONST.	6.049*** (1.975)	7.174*** (1.680)	6.152*** (2.248)	7.140*** (1.880)	9.333*** (2.866)	7.735*** (2.153)
R^2	0.4572	0.6523	0.4622	0.6671	0.5040	0.6529
OBS.	84	58	84	58	75	49

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

Table 7b: Effects of Explanatory Variables on *d*

Dependent Variable: Difference of $\ln y^E$ over Time						
Coefficient	**(1) Pooled Smoothed**	**(2) Pooled Smoothed**	**(3) Pooled Raw**	**(4) Arellano Bond**	**(5) Blundell Bond**	**(6) Fixed Effects**
Initial $\ln y^E$	0.018*** (0.004)	0.019** (0.011)	0.021* (0.012)			
Lagged difference of $\ln y^E$				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