Measuring Convergence and Divergence of Output across Countries *

Michele Battisti†

Gianfranco di Vaio‡

Joseph Zeira§

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Abstract

This paper introduces a new way to measure convergence and divergence of output across countries. This new method reconciles the conflicting results of the two existing methods of measuring convergence, β-convergence and σ-convergence. The new method examines whether countries follow the global frontier fully or partially, and it also uses new available data on total factor productivity across countries. The empirical analysis shows that β-convergence should be interpreted as convergence of output per worker to productivity in each country and that for many countries this productivity does not follow fully the global frontier, but diverges away from it.

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

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† University of Palermo, CeLEG–LUISS and RCEA, E-mail: mbattisti@unipa.it.

‡ Cassa Depositi e Prestiti, CeLEG–LUISS and RCEA, E-mail: gdivaio@luiss.it.

§ The Hebrew University of Jerusalem, LUISS, CEPR and RCEA, E-mail: joseph.zeira@mail.huji.ac.il.

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1. Introduction

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

This paper offers a new way to measure convergence and divergence across countries, which reconciles these conflicting results. It is done by introducing two new ideas. The first one is use of new data. According to the canonical growth regression model, as described in the authoritative survey by Durlauf, Johnson and Temple (2005), hereafter DJT, the ratio between output per worker and productivity should converge to a long-run value, at a rate of convergence denoted by b.[1] However, until recently productivity data were not available for most countries, so standard growth regressions estimated the rate of convergence b by adding variables that are supposed to explain economic growth, like education, political stability and more, to control for the missing data. Instead, we use the new PWT 8.0 data set that includes, in addition to output, also data on labor, capital and the labor share, so it enables us to calculate productivity for many countries. As a result we can estimate the rate of convergence b without using any control variables and we show that output per worker indeed converges to productivity.

[1] In productivity we mean labor augmented total factor productivity, which is defined precisely below.

The second innovation in this paper is to change the assumption on the dynamics of productivity in the standard growth model. Instead of growing at a constant rate, we assume that productivity follows the global frontier, either partially or fully. More specifically, we assume that in the long-run a country adopts in each period only d of the new technologies, where d is country specific and can be equal to or lower than 1. If d is equal to 1, the country follows the global frontier fully in the long-run, but if d is lower than 1, it diverges away from the frontier. In the short-run, productivity converges at a rate c to its long-run productivity path.

This extended growth model yields a dynamic process with two rates of convergence, b and c, and one rate of divergence, d. By using the US as the global frontier, we estimate for each country these three parameters and reach three main empirical results. First, the coefficient b is similar across countries and is close to 2 percent, which is the rate of β-convergence found in many growth regressions.[2] Second, c is also similar across countries and is close to 9 percent. Third, the coefficients d differ across countries and for many countries they are significantly lower than 1. These results lead to the following conclusion. The fact that the rate of growth depends negatively on initial output, which is implied by β-convergence, does not mean that countries converge to one another, but only that output per worker converges to the country's productivity. Since productivities tend to diverge from the frontier, they also diverge across countries and so do levels of output per worker across countries. Hence, these conclusions reconcile the findings of β-convergence and σ-convergence.

As explained above, we estimate the growth regression model without using control variables, which usually represent theories of economic growth, like human capital, geography, institutions, etc.[3] However, to examine how such variables affect our extended model, we run a regression of the estimated country coefficient d on a set of such explanatory variables. The results of this test differ significantly from those of a parallel standard growth regression. We therefore claim that while standard growth regressions measure the combined short and long-run effects of such variables, our method can identify the separate effects of such variables on long-run growth.

[2] See DJT (2005) and Barro (2012).
[3] We are aware of the criticism of using such control variables as explanations of economic growth. See DJT, Durlauf, Kurtelos and Tan (2008) and elsewhere.

This paper belongs to the empirical literature on convergence and divergence in economic growth, which consists of two main lines of research. The first and most famous is 'growth regressions,' which began with Barro (1991), Mankiw, Romer and Weil (1992), Barro and Sala-i-Martin (1992) and has developed over the years into a huge literature.[4] DJT contains an excellent summary of this literature until 2005. The main result of this line of research is β-convergence. 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, rather than to the frontier." But what if the steady states themselves are moving over time? Barro (2012) offers a more ambitious interpretation of β-convergence: "convergence rate parameters are important to pin down because they provide guidance on how fast countries like China or India are likely to catch up to richer countries. The convergence rate may also reveal how fast a poor African country could develop." A second important critique focuses on the choice of control variables, which seems to be quite arbitrary, and as a result the number of such variables used in growth regressions has become very large over time and has already passed 150.

The second line of literature on convergence and divergence analyzes how the distribution of output per worker, or per capita, changes over time. These tests usually find divergence over time. Early studies in this line of research are Bernard and Durlauf (1995, 1996), Quah (1996) and Pritchett (1997), who titled his paper "Divergence, Big Time."[5] These studies therefore stand in 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, recently there is renewed interest in this topic. The survey on economic growth by Jones (2015) devotes much attention to it. To that we can add two recent papers by Rodrik (2011, 2013), one on the potential for global

[4] Earlier papers that influenced growth regressions are Baumol (1986) and Kormendi and Meguire (1985).
[5] 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).

convergence and one on convergence of industries across countries. Barro (2012) is another recent essay on convergence. 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 tries to find solutions to the various critiques on the various lines in this literature. It reconciles the results of β-convergence and σ-divergence within the neoclassical model of growth. It estimates the dynamic system without use of explanatory variables and it estimates the coefficient of divergence d for each country and not just divergence of the distribution as a whole.

Of the many theories of economic growth, this paper is mostly related to that on technology adoption. Since countries do not invent most of their technologies, but adopt them from the frontier, these theories try to explain why some countries might adopt only part of the available technologies. Examples for such theories are Krugman (1979), Parente and Prescott (1994), Zeira (1998), Eaton and Kortum (1999) and Acemoglu, Aghion and Zilibotti (2006). Recently this view gained empirical support from new data on the use of technologies across countries, in Comin and Hobijn (2010) and Comin and Mestieri (2013).[6] This paper provides additional empirical support for partial adoption of technologies, as it shows that many countries follow the global frontier only partially. Partial adoption of technologies is also documented in Phillips and Sul (2007, 2009), who use a similar formulation of the dynamics of productivity, but apply it differently. Another recent paper that bears some similarity to our model is Gourinchas and Jeanne (2013), who study capital flows in developing countries. They also assume that productivity adjusts gradually to its long-run path, but they assume that this long-run path follows the global frontier fully, namely they assume that $d = 1$.

The paper is organized as follows. Section 2 presents the extended growth regression model. Section 3 describes the data. Section 4 presents the tests of convergence of output to productivity. Section 5 estimates how productivity and output follow the global frontier. Section 6 extends the estimation of the rates of divergence to a larger set of countries over a longer period of time. Section 7 estimates the effects of some explanatory variables on long-run growth. Section 8 summarizes, while the Appendix presents some theoretical additions.

[6] Dowrick and Rogers (2002) also show that technical change differs significantly across countries.

2. Extending the Growth Model

To explain our contributions and how we depart from growth regressions, we use the canonical representation of the neoclassical country growth model, as described in DJT. Assume first that production in country *j* in period *t* is described by:

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

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 standard CRS production function.[7] Define 'output per worker' in country *j* at time *t* as $y(j,t) = Y(j,t)/L(j,t)$ and similar to DJT define 'efficiency output per worker' to be $y^E(i,t) = y(j,t)/A(j,t)$, the ratio between output per worker and LATFP.

Note that in the long-run marginal productivity of capital should be constant, either because it is equal to the subjective discount rate plus the rate of depreciation in a closed economy model, or because it should be equal to the global interest rate plus the rate of depreciation in an open economy model. Due to CRS, the marginal productivity can be constant only if the ratio between the capital-labor ratio and productivity $K(j,t)/[L(j,t)A(j,t)]$ is constant. Note that the efficiency output per worker is equal to:

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

Hence, 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 $y^E(j,\infty)$.

The basic 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 it converges gradually. There are two possible mechanisms that can explain gradual adjustment of capital. One is derived from the Solow model, where capital accumulation is bounded by savings, since the economy is closed. As a result capital is adjusted gradually.[8] An alternative explanation is adjustment costs to investment, and this

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

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

mechanism works well also in open economies, where investment can exceed savings. This mechanism is demonstrated in Appendix 2 in this paper.[9] The gradual convergence of efficiency output per worker is described by the following log-linear dynamic equation:[10]

$$\ln y^E(j,t) = b(j)\ln y^E(j,\infty) + [1-b(j)]\ln y^E(j,t-1). \tag{2}$$

The parameter $b(j)$ measures the rate of convergence of efficiency output per worker to its long-run value. Most growth regressions assume that this parameter is equal across countries.[11] The open economy adjustment costs model in Appendix 2 implies that the size of $b(j)$ should be around 2%.

In addition to equation (2) the standard growth model includes two more assumptions. First, labor grows at a constant rate $n(j)$:

$$L(j,t) = L(j,0)\exp[n(j)t], \tag{3}$$

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

$$A(j,t) = A(j,0)\exp[g(j)t]. \tag{4}$$

The rates of growth $g(j)$ and $n(j)$ can differ across countries, but g is usually assumed to be equal across countries.[12]

From equations (2), (3) and (4) we can derive the following presentation of the average growth rate of country j over T periods:

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

This is the classical cross-section growth regression.[13] 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 unobservable, such regressions control for them by adding variables like educational attainment, political stability, rate of saving, geographical characteristics, quality of institutions, religion, and many more. These

[9] We think that when we compare economic growth across many countries, the open economy model is better suited to describe each country's growth.
[10] Equation (2) is the same as equation (1) in DJT, except for approximating 1 – exp(-b) by b.
[11] A non-parametric study that differs with this assumption is Henderson (2010).
[12] See DJT.
[13] It is equivalent to equation (8) in DJT.

additional variables are sometimes called 'explanatory variables,' since they can be viewed as explaining differences in growth rates across countries. Actually, there has been quite a proliferation of such explanatory variables in the literature and their total number has already exceeded 150. The arbitrary choice of these control variables is one of the main weaknesses of this literature. Another problem is that the regression of (5) estimates the effects of such explanatory variables on $g(j)+[1-(1-b)^T]T^{-1}\ln A(j,0)$ without differentiating between their long-run effect on the rate $g(j)$ and the short-run effect on the level $A(j,0)$.

Our main point of departure from the standard growth model is to replace assumption (4) by a more realistic model of productivity dynamics, where LATFP is following the global frontier. Assume first that there is a global productivity frontier, denoted by *F*, which can also be viewed as the global technology frontier. It grows steadily over time:

(6) $$\ln F(t) = \ln F(t-1) + g + v(t),$$

where *g* is the average rate of growth of the frontier and $v(t)$ is a white noise. Assume that in the long-run a country can follow this frontier either fully or partially. It means that a country follows over time only *d*(*j*) of the additions to the frontier, where this coefficient is country specific and might be smaller than 1. If $d(j)=1$ the country follows the frontier fully, but if $d(j)<1$ the country follows the frontier only partially. As explained in the introduction, this assumption is based on the literature on imperfect technology adoption. We assume that the coefficient *d*(*j*) is constant over time.[14] We therefore assume that the long-run productivity path of country *j*, which is denoted $LRA(j,t)$, satisfies:

(7) $$\ln LRA(j,t) = a(j) + d(j)\ln F(t).$$

Productivity of country $j, A(j,t)$, converges gradually to this long-run productivity path:

(8) $$\ln A(j,t) - \mathrm{E}_{t\text{-}1}\ln LRA(j,t) = [1-c(j)][\ln A(j,t-1) - \ln LRA(j,t-1)].$$

[14] We discuss below the possibility of one-time changes in *d*.

The expectation operator is used at $t - 1$, because when productivity $A(j,t)$ is determined the global frontier is yet unknown. This convergence is similar to the convergence of output in equation (2), but with a different coefficient, as $c(j)$ can a-priori differ from the rate of convergence of output, $b(j)$. The assumption of gradual adjustment of productivity can be justified by costs to adoption of technologies, as in Parente and Prescott (1994).

Combining equations (6), (7) and (8) together we get:

$$\begin{aligned} &\ln A(j,t) - d(j)\ln F(t-1) - d(j)g - a(j) = \\ &= [1-c(j)][\ln A(j,t-1) - d(j)\ln F(t-1) - a(j)]. \end{aligned} \tag{9}$$

Hence, the overall picture that the extended model paints is more nuanced than the standard picture of growth regressions. For each country output converges to the country's productivity, as implied by equation (2), but productivity might diverge from the frontier, as implied by (9), if the country coefficient $d(j)$ of the country is smaller than 1. Hence, countries experience both β-convergence and divergence at the same time, if they differ in their coefficient d. Thus, the extended model has three main coefficients. One is $b(j)$, which we call 'rate of convergence of output.' The second is $c(j)$, which measures the rate of convergence of productivity to the country's long-run productivity path, and we call 'rate of convergence of productivity.' The third coefficient, $d(j)$, measures by how much productivity follows the global frontier in the long-run, and we call it the 'rate of divergence.' Our next goal is to estimate these three coefficients for each country.

3. Data for Productivity and the Global Frontier

Standard growth regressions use data on output per capita or output per worker but not on productivity and hence they need to use various explanatory variables to control for this missing data, as explained above. We overcome this problem in two ways. First, we calculate for each country its productivity, LATFP, which is enabled by the new Penn World Table 8.0. Second, we use a variable that represents the global productivity frontier. The use of these two variables enables us to estimate the coefficients of the model without, or almost without, use of control variables.[15] In this section we describe the data, while the estimations and their results are presented in the following sections.

3.1 Country Data

We use the new data of the Penn World Table, PWT 8.0, as described in Feenstra, Inklaar and Timmer (2013). 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).[16] 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 for the labor share we use the series 'labsh.'[17] 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 whole period. This is available for only 29 countries. In most of our estimations we focus on a set of 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 in the estimation.

For one of the tests below, which does not require data on productivity, but only of output, we use not only data from PWT 8.0, but also from another data set, with a wider set of countries over a longer period of time. These are data from the Maddison project, conducted at the Groningen Growth and Development Center (GGDC, 2011). This project has data on output per capita for 139 countries over the years 1950-2010, in PPP adjusted Geary-Khamis 1990 US$.

3.2 Calculation of LATFP

The new PWT 8.0 also includes calculated TFP, but we calculate productivity ourselves, for two reasons. First, PWT 8.0 calculates productivity net of human capital, while we want to examine the overall effect of productivity on output and therefore it should also include human capital. Second, we follow the standard growth regression model by assuming that total factor productivity is labor augmenting, which requires a slightly different method of calculation than the standard Solow Growth Accounting. This

[15] More precisely, in one of the estimations of *b* we use one variable for control, which is not a standard explanatory variable. But *b* is also estimated in another method without using any control variable.
[16] This series is chained, so it is also PPP adjusted.
[17] 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.

method is described in detail in Appendix 1. It is shown there that the rate of growth of LATFP should be calculated by the following formula:

$$\text{(10)} \qquad \begin{aligned} \frac{A(j,t)-A(j,t-1)}{A(j,t-1)} = \frac{1}{s_L(j,t-1)}\left[\frac{Y(j,t)-Y(j,t-1)}{Y(j,t-1)} - \frac{K(j,t)-K(j,t-1)}{K(j,t-1)}\right]+ \\ + \frac{K(j,t)-K(j,t-1)}{K(j,t-1)} - \frac{L(j,t)-L(j,t-1)}{L(j,t-1)}. \end{aligned}$$

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 by how much productivity rises over time, and not its absolute level, hence it is sufficient to use the rate of growth of LATFP in (10). For some of the analysis, the regressions of the efficiency output per worker, $y^E(j,t) = y(j,t)/A(j,t)$, we also need an estimate of 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 in (10).

3.3 The Global Frontier

For the global frontier variable we use US LATFP. The United States is considered to be a leader of the global economy for a long period of time and its output per capita and per worker have grown quite steadily over more than a hundred and forty years. Figure 1 presents a comparison of US GDP per worker in the blue curve to US LATFP in the red curve, in the years 1950-2011. Both variables are in natural logarithms and productivity is adjusted so that the two curves coincide at 1950. Note that the two curves fit each other quite well as expected, and they also have a fairly stable slope, which fits well the assumption in equation (6) on the global frontier.

[Insert Figure 1 here]

To further examine the use of the US as the global frontier, we test whether US productivity satisfies equation (6) by running a regression of its growth rate on a 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. When we use the Maddison data set for estimating divergence of output per capita, as explained above, we use US GDP per capita from this data set as the global frontier, to keep the data consistent. We also check that this variable satisfies (6) and find that in a regression of the growth rate of US GDP per capita on a constant 1 in 1950-2010 the coefficient is equal exactly to the mean growth rate in that period, 1.95 percent. We also run unit root tests and find that the first differences are stationary.

3.4 Smoothing Output and Productivity Series

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

$$(11) \qquad \ln y_5(i,t) = \frac{1}{5}\left[\ln y(i,t) + \ln y(i,t-1) + \ln y(i,t-2) + \ln y(i,t-3) + \ln y(i,t-4)\right].$$

A similar calculation is done for productivity of all countries.

4. Estimation of the Rate of Convergence of Output *b*

This section begins the empirical analysis of the paper with estimating *b*(*j*), the rate of convergence of output per worker to productivity, for each country *j*. This coefficient is estimated, like other coefficients below, in at least two different methods to check robustness of the results. We first derive the dynamic equations that should be estimated and then present the results of the estimations and discuss them.

4.1. The Dynamic Equations

To estimate the rate of convergence of output per worker to productivity we do not need the extended growth regression model, which focuses on the dynamics of productivity itself, so we limit ourselves to the dynamic implications of equation (2) alone. Hence, the only innovation in this part of the paper is using the data on productivity directly. By writing efficiency output y^E explicitly as the ratio of output per worker to productivity, we get from equation (2) the following dynamic equation:

$$(12) \qquad \begin{aligned} &\ln y(j,t) - \ln A(j,t) - \ln y^E(j,\infty) = \\ &= [1-b(j)]\left[\ln y(j,t-1) - \ln A(j,t-1) - \ln y^E(j,\infty)\right]. \end{aligned}$$

Equation (12) implies that output per worker, in logarithm, converges to a long-run growth path, which is described by: $\ln A(j,t) + \ln y^E(j,\infty)$. Empirically, equation (12) states that the logarithm of output per worker in each country should be cointegrated with $\ln A(j,t)$, where the coefficient of cointegration is 1. The error correction coefficient is *b*(*j*) and the long-run distance between logarithm of output per worker and cointegrated logarithm of productivity is $\ln y^E(j,\infty)$. Therefore, an empirical test of equation (10) should be a cointegration test of $\ln y(j,t)$ on $\ln A(j,t)$. Such a test is required also because output per worker and productivity are non-stationary.

Another way to write equation (2) is the following equation that describes the dynamics of efficiency output per worker:

(13) $$\ln y^E(j,t) - \ln y^E(j,t-1) = b(j)\ln y^E(j,\infty) - b(j)\ln y^E(j,t-1).$$

Note that 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, which is the ratio of output per worker and productivity, which we can calculate. Hence, another empirical test of convergence of output can be estimation of (13) by use of standard methods of growth regressions. This estimation should yield an alternative measurement of the rate of convergence *b*.

4.2 Panel Cointegration of Output per Worker over Productivity

We first estimate the dynamic equation (12). We run 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 present results for a smaller set of 28 countries over the years 1950-2008. The results are presented in Table 1. The first column presents 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 Asia (EA) countries in column (3), Central and South America (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 period 1950-2008. The two panel cointegrations exclude Turkey, which is an outlier.[18]

[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, which is higher. This also explains the higher overall average. In the data set from 1950-2008 the rate of convergence of output is equal to 1.6 percent. These findings are very similar to the rate of convergence of 2 percent found originally by Barro (1991) and Barro and Sala-i-Martin (1992). This result fits what Barro (2012) calls "the iron law of convergence." Note that it also fits the prediction of the open economy model in Appendix 2. Importantly, the rate of convergence of output b is estimated separately for each country, but its values are quite close.

4.3 A Growth Regression of Efficiency Output per Worker

We next turn to estimate equation (13), which describes the convergence of efficiency output per worker to its long run level $y^E(j,\infty)$. Before the estimation we examine this convergence diagrammatically in Figure 2, which shows the graphs of natural logarithms of efficiency output per worker for each of the OECD countries in the years 1970-2008 and in Figure 3, which shows such graphs for averages of global regions.

[Insert Figure 2 here]

[Insert Figure 3 here]

[18] 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.

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. The only strong outlier is Turkey, where y^E rises significantly over time. We also conducted a panel unit root test (the Levin-Lin-Chu test) for the full panel of efficiency output per worker with 80 countries (Turkey excluded) and the unit root hypothesis is strongly rejected with an adjusted t* of -5.55 and probability 0.0000. Figures 2 and 3 imply that efficiency output per worker tends to converge overtime, but might converge to different levels, namely $y^E(j,\infty)$ 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 and we test it in the following analysis.

[Insert Table 2 here]

Table 2 presents the results of the estimation of the growth regression (13) with respect to efficiency output per worker. To reduce the effect of cyclicality we run 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. The rate of convergence *b* is calculated from the coefficient estimated by this regression. Each column describes a different regression. Column (1) is the simplest growth regression (pooled) and it measures convergence at a rate of 1.9 percent. 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.[19] In regression (3) we use instead a panel estimation with fixed effects, which are supposed to control for the different values of $y^E(j,\infty)$. This regression also shows convergence of efficiency output per worker as expected, but the measured rate of convergence is higher, around 8 percent. Note that using fixed effect increases the rate of convergence in all growth regressions, as observed by Abreu, de Groot and Forax (2005). Actually, Barro (2012) claims that this is due to biased estimation. In regression (4) we run a Pesaran-Smith panel estimation which measures the rates of convergence separately for each country. The results of this estimation are similar to the estimation with fixed effects.

Finally we examine the use of smoothed data by adding two regressions with raw unsmoothed data. Note that equation (12) holds also if data are smoothed and this holds also for the other cointegration equations we use below. Since (13) is not a cointegration equation we add these tests to see if the results are affected by smoothing. Regression (5) is the pooled regression with the variable gA and regression (6) is a fixed effects panel. The results are quite similar to the smoothed ones, so we deduce that the use of smoothed data does not affect the results by much.[20]

We can therefore summarize this section with three main conclusions. First, output per worker converges in the long-run to labor augmented total factor productivity for the large majority of countries. Second, the rate of this convergence is in most regressions around the famous 'iron law' of 2 percent, which also fits our theoretical open economy model in Appendix 2. Third, this estimation does not require any additional explanatory variable.[21]

5. Estimation of the Coefficients *c* and *d*

In this section we analyze how productivity, LATFP, follows the global frontier. Hence, in this section we estimate the rate of divergence of each country, $d(j)$, and the rate of

[19] The coefficient of gL is positive, but significant only at 5%, while the coefficient of gA is much more significant.
[20] We also tried to use annual rate of growth instead of 5 years average of rates of growth. A regression of the rate of growth over last year's efficiency output yields similar but weaker results. In such a regression b is 1.2 percent but it is significant only at 10%.
[21] We have added the explanatory variable 'years of schooling' as a control for regression (2) in Table 2, since such a variable is used in almost all growth regressions. It came up insignificant. Hence, we not only do not need control variables, but adding them does not affect the results.

convergence of productivity to its long-run path, *c*(*j*). These coefficients are estimated in three different methods to check robustness of the results. We first derive the dynamic equations that should be estimated and then present the results of the estimations and discuss them.

5.1. The Dynamics of Productivity and Output

We next use equations (6) and (9) to derive the following dynamics of productivity according to the extended model:

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

Equation (14) shows that productivity converges to a long-run path, which is described by: $d(j)\ln F(t) + a(j)$. Empirically it implies that the logarithm of productivity should be cointegrated with the logarithm of the global frontier, where the coefficient of cointegration is the rate of divergence *d*(*j*) and the error correction coefficient is the rate of convergence of productivity *c*(*j*). Hence, a cointegration test of $\ln A(j,t)$ on $\ln F(t)$ should measure these two coefficients for each country.[22]

Another method to estimate the dynamic equation (9) is by differencing it over *T* periods of time, which yields the following dynamic condition:

$$\begin{aligned}(15)\qquad &\ln A(t+T) - \ln A(t) = [1-c(j)][\ln A(t+T-1) - \ln A(t-1)] + \\ &+ c(j)d(j)[\ln F(t+T-1) - \ln F(t-1)].\end{aligned}$$

Hence, the average rate of growth of productivity depends 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 (15) can supply us with coefficients from which we can calculate *c* and *d* and that is an alternative estimation of these parameters.

We next describe an additional approach to the estimation of the rate of divergence *d*. From combining the dynamic conditions (12) and (14) and from iterating them over a long period of time we get:

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

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

Equation (16) implies that the difference between $\ln y(j,t)$ and $d(j)\ln F(t)$ should converge in the long run to $\ln y^E(j,\infty) + a(j)$. This implies that output per worker $\ln y(j,t)$ and the global frontier $\ln F(t)$ should be cointegrated and the coefficient of cointegration should be $d(j)$, the same coefficient that measures how productivity follows the frontier. Hence, a cointegration test of output per worker over the global frontier, as implied by equation (16), can be an additional test of the findings of (14) and (15). Note that estimation of (16) does not enable us to identify the rates of convergence, *b* and *c*, since the error correction coefficient of (16) is some average of these two rates, but it does measure *d* for each country.

5.2. Panel Cointegration of Productivity over US Productivity

We estimate the dynamic equation (14) by a panel cointegration test of each country's productivity over the global frontier, namely US productivity, using the data from PWT 8.0 for 81 countries over the period 1970-2008. This test enables us to estimate the divergence coefficient *d* of each country and the rate of convergence of productivity *c*. Table 3 presents the results, where the first column contains the results for the full sample, columns (2)-(6) present the results for the global regions defined above, and column (7) presents the results for the smaller set of countries with data over the years 1950-2008. Note that the US is not in the regression as it is used on the right hand side as the global frontier. In this estimation we also exclude Turkey as in Table 1, and also some oil producing countries, since they experienced declining productivity over a long period of time. The excluded oil countries are Bahrain, Iran, Kuwait, Nigeria, Oman, Qatar, Saudi-Arabia, and Venezuela.

[Insert Table 3 here]

The main result that emerges from Table 3 is that the value of *d* across many countries is significantly lower than 1. The average is 0.5, and in some regions it is actually lower than that. 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 despite the β-convergence found in growth regressions and in Section 4 in this paper, there is actually divergence of countries from the frontier and as a result from one another as well. This means that β-convergence should only be interpreted as convergence of output to productivity, while long-run productivity itself usually diverges away from the frontier. The estimated average of *d* does not change much when we smooth productivity over 10 years instead of 5 years. Furthermore, in an unbalanced cointegration test, which enables us to include many more countries, we find that the average coefficient of cointegration *d* is still significantly lower than 1.[23]

Table 3 also implies that *d* follows a regional pattern to some extent. In Central and South America and in South Saharan Africa it is even close to zero. Namely, these countries do not catch up 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' through much of the period. Since this process might involve a gradual rise of the coefficient *a* in such countries, the regression might bias the estimation of *d* upwards. We therefore treat the high values of *d* in this region with some caution in some of the tests below. Note that the 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 (14), especially if the coefficient *a* is changing during this period. 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 3 is that the value of *c*, which measures the rate of convergence of productivity to its long-run path, is around 9%. This result is robust across regions. It is actually much higher than the rate of convergence of output to productivity, *b*. 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

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

percent. Thus, our approach supplies one explanation to the variation in estimated rates of β-convergence, as shown by Abreu, De Groot and Florax (2005).

5.3. Estimating the Difference Equation

In order to examine these results in an alternative method we next estimate the difference equation (15). We test the dynamic relationship between the average growth rate of productivity over its lagged average growth rate and over the lagged average growth rate of the global frontier, namely US productivity, by use of a Pesaran-Smith panel regression. From the coefficients of these regressions we can calculate the values of *c* and *d* for each country. We then compare the results of these tests to the cointegration results in Table 4. The regression is run over the same set of countries, but in addition to the oil-producing countries we also exclude Trinidad-Tobago, which is an outlier.

[Insert Table 4 here]

The estimation of differences over the period 1970-2008 yields the same basic results as the cointegration analysis, but the coefficients are slightly different. The average *d* is around 0.8, above the 0.5 of the cointegration analysis, but it is still significantly lower than 1. Hence, 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 as the countries in the data of 1950-2008 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.

5.4 Panel Cointegration of Output per Worker on US Productivity

We next present a test of equation (16) by estimating a panel cointegration of output per worker over the global frontier, which is the productivity of US. 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. Hence, this test should be viewed mainly as a measurement of *d*. The results of these panel regressions are presented in Table 5, which is constructed in a similar way to Table 3.

[Insert Table 5 here]

The results of Table 5 are quite similar to those of Table 3. The coefficient *d*, which is around 0.6 in the large sample of countries, is quite close to the results of the cointegration of productivity over the global frontier. Except for the OECD countries and for the East Asian countries, this coefficient is significantly lower than 1. The error correction coefficient, which should be an average of *b* and *c*, is indeed 6.5 percent, which is between 2 and 9 percent. Hence this estimation further supports the main results of the paper. Since the small sample of countries, with data from 1950-2008, is quite identical to the developed OECD countries, it is not surprising that the *d* in this sample is close to 1.

6. Divergence of Output in a Larger Set of Countries

In this section we expand the estimation of the dynamic equation (16) that describes the divergence of output per worker from the global frontier. Since this equation does not include productivity, we can expand the estimation to a larger set of countries over a longer time period by using instead of PWT 8.0 an alternative source of data. The Maddison data set does not include data on productivity, or on labor, but it includes data on output per capita for 140 countries over the years 1950-2010. We therefore use this data to estimate a panel cointegration test of equation (16). Since we cannot calculate productivity with this data set we change slightly the variable that represents the global frontier to US GDP per capita from the same data set. We still use smoothed data over 5 year averages. The results for the whole sample are presented in Table 6. Its main result is that most countries are diverging from the global frontier, the coefficient *d* is equal on average to 0.69, it is significantly lower than 1 and it is significantly heterogeneous across countries. Actually, the average *d* in Table 6 is quite close to the average *d* in the large sample of countries in Table 5.

[Insert Table 6 here]

We also test the ADF of cointegration for the various countries and the results are very supportive. Only for 5 countries the probability of not being cointegrated was higher than 10% and only for 9 countries the probability of not being cointegrated was higher than 7%. Most of these countries suffered from intense conflicts and severe interruptions of economic activity.[24] We therefore treat these countries as outliers from here on. An additional group of countries that deserves attention are the oil-producing countries, which experienced declining output since the 1970s.[25] Such countries might bias *d* downward.[26] Table 6 also presents the results of the panel cointegration without the outliers and without the oil-producing countries. Removing them indeed increases *d* slightly, but it is still significantly lower than 1. We have also estimated the country specific parameters *d* by differences in addition to estimation by cointegration and the results of the two estimations have been very close. We have also estimated the *d* coefficients for sub-periods 1950-1980 and 1980-2008, to test for stability of d, and found that it has been quite stable over the two sub-periods.[27]

[Insert Table 7 here]

Table 7 presents the results by regions and shows that *d* follows a regional pattern to some extent. The regions are the same as above, except that MENA does not include any additional countries, and we add a separate region for Eastern Europe, EER. Table 7 paints a clear picture of divergence from the frontier. While the OECD countries and the East European countries follow the frontier fully with *d* very close to 1, and while in East Asia *d* is higher than 1, the rest of the world lags behind the frontier. Not surprisingly the most miserable region is South Saharan Africa, but Central and South American countries are lagging behind as well, and so is MENA. As explained in Section 5, the

[24] The countries not cointegrated with probability above 10% are Bangladesh, Indonesia, Kenya, Laos and Vietnam. The countries with probability between 10% and 7% are Ghana, Cambodia, Nepal and Senegal.
[25] Mankiw, Romer and Weil (1992) have eliminated these countries from their analysis.
[26] We define countries as oil producers if their oil rents exceed 30% of GDP in 1975-2000. The countries are Bahrain, Republic of Congo, Equatorial Guinea, Gabon, Ghana, Kuwait, Libya, Nigeria, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.
[27] These two results on differences and sub-periods are available from the authors upon request.

high d of East Asia should be attributed to the 'Asian Tigers' and is probably a result of a change in parameters during the period.

7. Effects of Explanatory Variables on Global Divergence

In this paper we estimate the convergence and divergence of output across countries without using explanatory variables as controls. But these country specific explanatory variables might have an effect on the parameters $b(j)$, $c(j)$ and $d(j)$. Since $b(j)$ and $c(j)$ are quite equal across countries, but $d(j)$ differs significantly across them, we suspect that d is the main parameter that should depend on some of the explanatory variables. To test this hypothesis we run cross-country regressions of d over a set of common explanatory variables and find that it is indeed affected by some variables. Note that the goal of this estimation is not to find the ultimate explanation for divergence across countries. We use this test only in comparison with a standard growth regression over the same sample and with the same explanatory variables, in order to show that the two tests yield different results. Namely, the goal of this section is only to highlight the ability of our method to isolate the long-run effect of explanatory variables from their overall effect.

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

1. TROPIC is the share of land in a country that is tropical (Gallup *et al.*, 2010).
2. COAST is the share of land in a country that is within 100 km from a coast or from a navigable river (Gallup *et al.*, 2010).
3. Y_50 is the natural logarithm of the GDP per capita in the country at 1950.
4. ETHNIC is a measure for ethnic fractionalization in a country.
5. EDU is average years of schooling of people above age 15 over the period 1950-2010 (Barro and Lee, 2013).
6. OPEN is a measure of openness of a country. It is a measure of trade policy over the years 1965-1990, which has been introduced by Sachs and Warner (1995).[28]

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

7. ICRG is average measure of quality of institutions during the period 1982-1997 according to the International Country Risk Guide (Knack and Keefer, 1995).
8. G/Y is the share of public expenditures in GDP, averaged over the years 1950-1960, taken from Feenstra, Inklaar, and Timmer (2013).

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

[Insert Table 8 here]

Before we turn to the direct estimation, we present the matrix of correlations between these variables in Table 8. This table can already give us some preliminary insights into the relationship between these variables and economic performance. For example, being in the tropics is strongly negatively correlated with most other variables, like education and institutions. It is also clear that the quality of institutions is strongly correlated with openness and with initial output. This is probably the reason that some of these variables come out insignificant in the regressions. As a result, we omit in the following analysis the variable ICRG.

The regressions are presented in Tables 9 and 10. Table 9 presents the results of standard growth regressions, where the dependent variable is the average rate of growth over the years 1950-2008, which we denote by AVG. These growth regressions serve for comparison with Table 10 that presents the regressions with *d* as the dependent variable. Table 10 therefore shows how the explanatory variables affect the rate of divergence from the frontier, namely how they affect the long-run rate of growth of a country. All the regressions in the two tables include constants and are OLS in a cross-section of countries. In each table we present three separate regressions. One is with all the countries for which the data is available without outliers. Data availability of the explanatory variables reduces the number of countries in this regression to 90. In the next regression we omit the East Asian countries, and in the third we omit both the EA countries and the OECD countries. The reasons for these omissions are as follows. First, there is probably a bias in the estimation of *d* among the EA countries, as discussed in Section 5, and it is too high above 1. This is mainly because these are countries that change their pattern of growth during the period covered by the data. Since they change their *d* and probably also change their coefficient *a*, it is preferred not to include these countries when testing for a statistical regularity between explanatory variables and these coefficients. The reason for excluding the OECD countries in the estimation of the effects on *d* is very different. In these countries *d* is around 1, which is a corner solution, since in the long-run countries cannot adopt technologies at a higher rate than the frontier. Being at such a corner, these countries become insensitive to explanatory variables. The OECD countries may have more or less education, larger or smaller government, better or worse institutions, but they all have *d* around 1, since it is a corner solution. Thus, including the OECD countries in the estimation reduces its ability to identify relationships between *d* and the explanatory variables. Hence, the third regressions in Tables 9 and 10 omit not only the SEA countries, but the OECD countries as well.

[Insert Table 9 here]

Table 9 presents the results of the standard growth regression. There are 6 variables that are significant throughout, in addition to the constant. These variables are TROPIC, which reduces growth, proximity to coast, which increases growth, initial output Y_50, which has a negative effect on economic growth as expected, education, which has a positive effect on growth, openness, also with a positive effect on growth and the share of government in GDP, which has a negative effect on economic growth. These results are similar to many other growth regressions. Putting aside Y_50, which measures β-convergence, there are five explanatory variables that affect economic growth.

[Insert Table 10 here]

Table 10 presents the effects of the same explanatory variables on the long-run coefficient *d*. The main difference between this table and Table 9 is that here the dependent variable *d* is itself an estimated coefficient. To take care of it, we calculate bootstrapped standard error instead of regular standard errors in Table 10. Of the six variables found significant in the growth regressions only two remain in the long-run analysis in Table 10. One variable with a negative significant effect is TROPIC. Its effect is increasing as we narrow the set of countries in the test. In the most relevant group, without East Asia and OECD, the effect of TROPIC is around half. Namely being in the Tropics can reduce *d* by almost 0.5 relative to the developed countries. Hence, this variable alone can account for much of the divergence of Africa and Latin America. The second variable that affects *d* positively and significantly is OPEN. Hence, it has a significant positive effect on growth both in the short and in the long-run. The effect of the other variables that are significant in the growth regressions is losing its significance in Table 10. Initial output becomes less and less significant as we narrow the sample. Education and the share of government in output become insignificant once we begin to narrow the set of countries. The result on education is quite surprising.[29] One possible interpretation can be that education affects only the level of output but not its long-run rate of growth. Thus, Tables 9 and 10 yield very different results, which meanse that the effect of various variables on *d* is very different than the overall effect on output and growth. This demonstrates that the dynamic estimation suggested in this paper enables us to differentiate between short and long-run effects of various explanatory variables on economic growth.

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

8. Conclusions

This paper reconciles the conflicting results of growth regressions and of distribution dynamics on the issue of whether income across countries tends to converge or to diverge over time. But we think that the paper does more than that. Its main contribution is to offer a method of how to model and how to measure the dynamics of economic growth across countries. The paper also shows that the extended model is indeed supported by the data. Our method is an improvement relative to previous methods of studying international growth dynamics. It does not use explanatory variables as controls like growth regressions, and it narrows the interpretation of β-convergence. It also enables us to separate the effects of various explanatory variables on long-run growth from their overall effect on output and growth. Our method also presents an improvement relative to studies of the dynamics of the distribution of income over time, as it studies the dynamics of each country separately and not only of the distribution as a whole.

The methodological contribution of the paper requires some qualifications. First, it should not be interpreted as a critique on previous studies, like growth regressions.[30] The main reason is that application of our method has become feasible only recently due to data availability. Initial growth regressions had only 25 years of data, while we use 60 years of data. This makes the estimation of d possible, since earlier variability of the global frontier was not sufficiently large for such estimation. Also, the use of a unified data set, which has both output and productivity, has become possible only very recently with the new PWT. We therefore view this paper as a suggestion on how to move ahead, rather than a critique on past research.

Second, this paper can also be related to some claims that analyzing differences in levels of output across countries is more important than analyzing differences in rates of growth. Such claims followed a number of studies on 'development accounting,' which are surveyed in Caselli (2005). It is true that if rates of growth are similar in the long-run across countries, then the main important differences are in levels, but if long-run rates of growth differ significantly across countries, as shown by our study, then the distribution of output levels changes continuously. In other words, countries are poor because they

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

have followed the frontier only partially for a long time. This view is reflected also in the survey by Jones (2015), who views differences across countries as resulting from differences in following the frontier.

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 most countries are not fully catching up with the frontier and thus there is significant divergence. This result should also be qualified, as it holds for the period 1970-2008 for the productivity data and for 1950-2008 for the output data. 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 non-parametric estimation, rolling regressions, or other methods. Future research can also extend the second stage regressions of Section 7 to more explanatory variables and to control better for endogeneity problems.

Appendix:

1. Growth Accounting of Labor Augmenting Productivity

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

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

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

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

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

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

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

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

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

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

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

2. Convergence in a Small Open Economy

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

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

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

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

where g and n are positive numbers.[31] 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:

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

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

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 self convergence b should be somewhere between 1.7% and 3.2%. Therefore, the open economy model yields a rate of convergence that fits the data well, unlike the closed economy models used in many other growth regressions, as shown by DJT.

3. Varying Rates of Convergence in Growth Regressions

In this appendix we examine how the results of the standard growth regressions are affected if we assume that the data behaves according to our extended model, namely equations (6), (7), and (8) instead of (4). 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:

$$\frac{\ln y(j,T)-\ln y(j,0)}{T}=\frac{1-[1-b(j)]^T}{T}\ln y^E(j,\infty)+$$

$$\text{(A.21)}\quad +\frac{1-[1-c(j)]^T}{T}\left[a(j)+d(j)\ln F(0)\right]+d(j)g+d(j)\sum_{t=0}^{T-1}\frac{1-[1-c(j)]^t v(T-t)}{T}-$$

$$-\frac{1-[1-b(j)]^T}{T}\ln y(j,0)+\frac{[1-c(j)]^T-[1-b(j)]^T}{T}\ln A(j,0).$$

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.[32] Hence, our model can offer an additional explanation to the results of this meta-analysis.

[32] 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.

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Figures and Tables

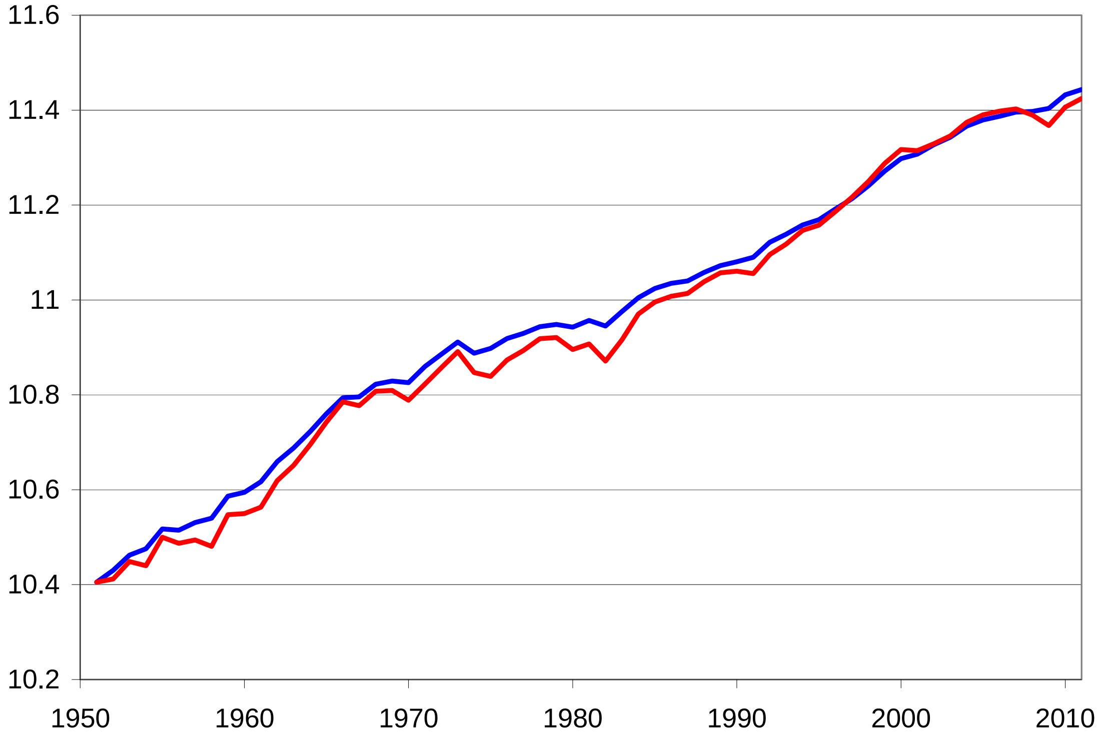

Figure 1: Natural Logarithm of US GDP per worker and US TFP in 1950-2010

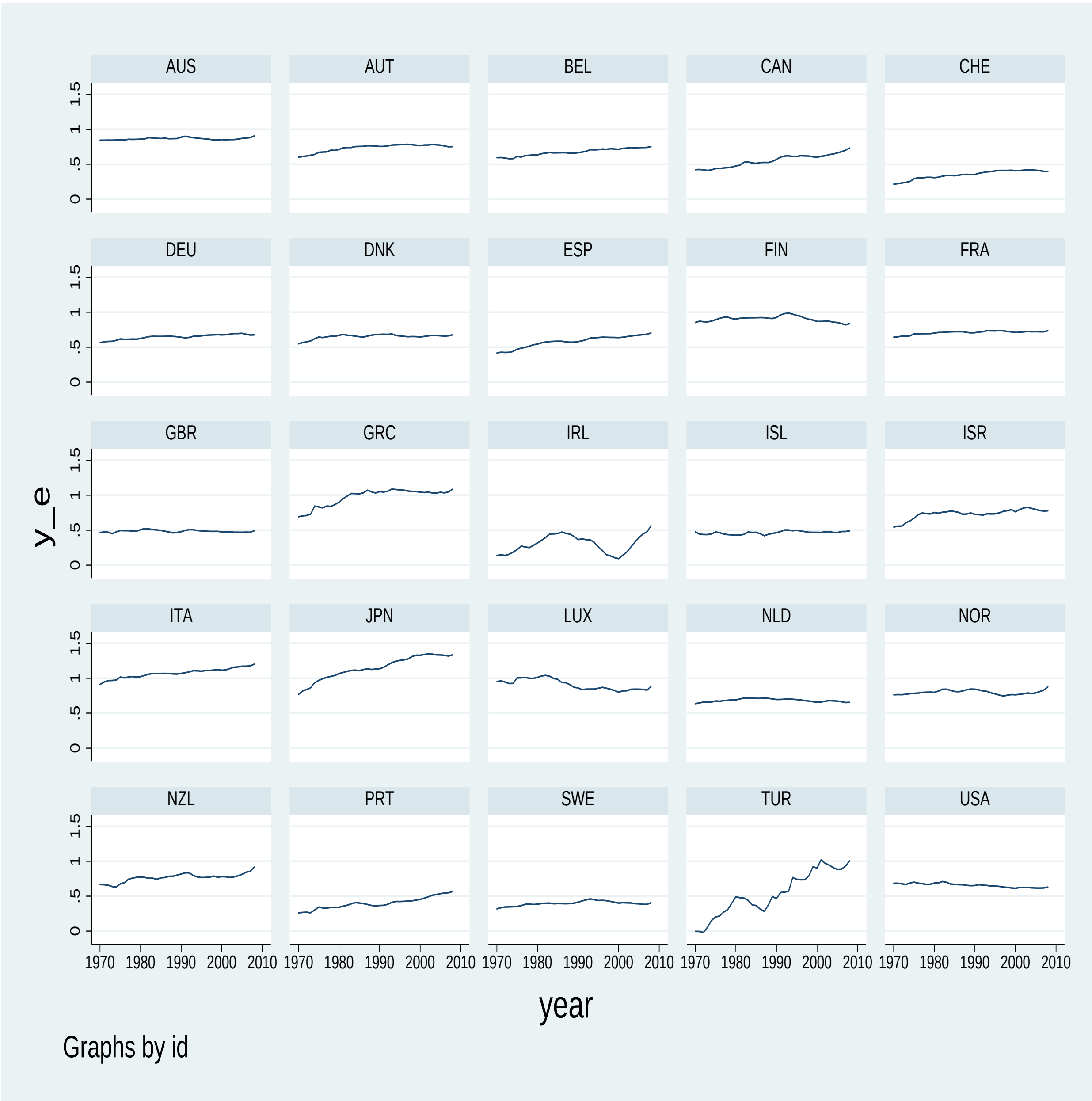

Figure 2: Efficiency Output per Worker in OECD Countries in 1970-2008

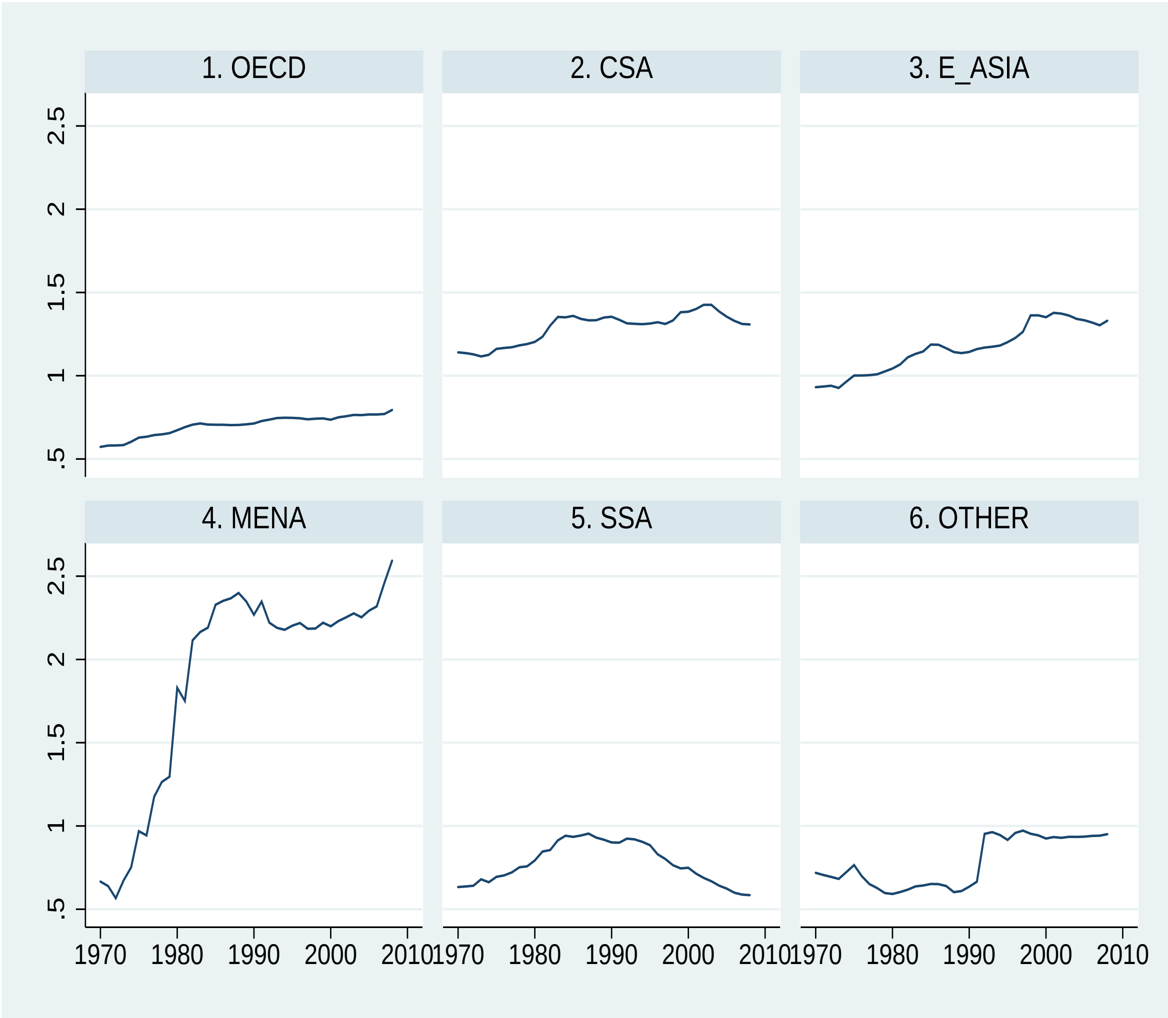

Figure 3: Efficiency Output per Worker in Global Regions in 1970-2008

Coeff.	**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	**(1) Pooled Smoothed**	**(2) Pooled Smoothed**	**(3) FE Smoothed**	**(4) PS Smoothed**	**(5) Pooled Raw**	**(6) FE Raw**
of Initial y^E	0.018*** (0.004)	0.019** (0.011)	0.068*** (0.002)	0.068*** (0.006)	0.021* (0.012)	0.089*** (0.003)
Calculated *b*	0.019	0.020	0.080	0.080	0.022	0.111
Constant	0.030*** (0.005)	0.035*** (0.013)	0.080*** (0.002)	0.066*** (0.007)	0.037*** (0.015)	0.102*** (0.003)
gA		-0.870*** (0.13)			-0.902*** (0.21)	
R^2	0.09	0.31	within 0.42		0.28	within 0.53
No. of Observations	2754	2754	2754	2754	2750	2750
No. of Countries	81	81	81	81	81	81

1. Robust standard errors in parenthesis.
2. In regressions (2) and (5) standard errors are clustered around countries.
3. Panel regressions (4) is Pesaran-Smith.
4. Significance levels are denoted: * of 10%, ** of 5%, *** of 1%.

Table 2: Growth Regression of Efficiency Output per Worker

Coeff.	1970-2008 (1)	OECD (2)	EA (3)	CSA (4)	SSA (5)	MENA & Others (6)	1950-2008 (7)
d	0.495*** (0.13)	0.670*** (0.13)	1.392*** (0.48)	-0.009 (0.16)	-0.022 (0.43)	0.405 (0.55)	0.770*** (0.10)
c	0.089*** (0.006)	0.095*** (0.01)	0.093*** (0.02)	0.102*** (0.01)	0.050*** (0.02)	0.094*** (0.02)	0.036*** (0.006)
Test $d = 1$	χ^2=14.7 P=0.0001	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=4.94 P=0.02
No. of Countries	71	28	10	15	11	7	27

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

Table 3: Cointegration Test of TFP to Global Frontier

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 4: Difference Regressions of Productivity and Comparison with Cointegration

Coeff.	1970-2008 (1)	OECD (2)	EA (3)	CSA (4)	SSA (5)	MENA & Others (6)	1950-2008 (7)
d	0.603*** (0.23)	0.955*** (0.20)	1.914*** (0.31)	0.239*** (0.09)	-0.026 (0.21)	-0.909 (2.03)	1.015*** (0.13)
EC	0.067*** (0.006)	0.068*** (0.05)	0.046*** (0.01)	0.086*** (0.01)	0.064*** (0.01)	0.059*** (0.02)	0.029*** (0.005)
Test of $d = 1$	χ^2=2.99 P=0.084	χ^2=0.05 P=0.823	χ^2=8.81 P=0.003	χ^2=64.9 P=0	χ^2=22.9 P=0	χ^2=9.53 P=0.002	χ^2=0.01 P=0.91
No. of Countries	71	28	10	15	11	7	28

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

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

Coefficient	Whole Sample	Without Oil & Outliers
d	0.688*** (0.093)	0.708** (0.072)
Error Correction	0.0389*** (0.002)	0.0405*** (0.002)
Test for $d = 1$	χ^2=11.28 P=0.00	χ^2=16.63 P=0.00
Hausman Test for Heterogeneity	χ^2=2.80 P=0.094	χ^2=9.23 P=0.002
Countries	139	124
1. Standard errors in parenthesis. 2. Hausman null hypothesis: difference in coefficient not systematic.		

Table 6: Panel Cointegration of Maddison Data in 1950-2008

Coefficient	OECD	EA	CSA	SSA	MENA	EER
d	1.096*** (0.09)	1.33*** (0.049)	0.600*** (0.104)	0.242** (0.11)	0.526*** (0.22)	0.98*** (0.15)
Error Correction	0.034*** (0.005)	0.025*** (0.006)	0.049*** (0.004)	0.042*** (0.004)	0.047*** (0.006)	0.027*** (0.005)
Test for $d = 1$	χ^2=1.26 P=0.263	χ^2=0.46 P=0.498	χ^2=14.9 P=0.000	χ^2=47.1 P=0.000	χ^2=4.51 P=0.034	χ^2=0.02 P=0.89
Countries	28	20	21	47	18	5

Table 7: Maddison Results by Regions 1950-2008

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

Table 8: Correlations between the Explanatory Variables

Dependent Variable: Growth over 1950-2008			
Explanatory Variable	(1) Whole sample	(2) Without EA	(3) Without EA and OECD
TROPIC	-0.704*** (0.235)	-0.938*** (0.242)	-0.906*** (0.281)
COAST	0.008*** (0.003)	0.007*** (0.003)	0.007** (0.004)
Y_50	-0.857*** (0.178)	-0.648*** (0.194)	-0.529*** (0.222)
ETHNIC	-0.766* (0.452)	-0.569 (0.422)	-0.530 (0.574)
EDU	0.149*** (0.059)	0.123** (0.060)	0.156** (0.076)
OPEN	1.109*** (0.231)	0.754*** (0.234)	1.190*** (0.471)
G/Y	-2.558*** (0.898)	-1.707** (0.859)	-1.883** (0.986)
CONST.	8.012*** (1.267)	6.527*** (1.343)	5.509*** (1.566)
R^2	0.61	0.60	0.52
F PROB.	0.0000	0.0000	0.0000
OBS.	90	77	57

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

Table 9: Effect of Explanatory Variables on growth rate 1950-2010

Dependent Variable: *d*			
Explanatory Variable	(1) Whole sample	(2) Without EA	(3) Without EA and OECD
TROPIC	-0.287** (0.158)	-0.389*** (0.129)	-0.459*** (0.167)
COAST	0.004** (0.0017)	0.002 (0.002)	0.003 (0.002)
Y_50	-0.468*** (0.153)	-0.240** (0.118)	-0.225 (0.150)
ETHNIC	-0.432 (0.302)	-0.417* (0.249)	-0.574* (0.373)
EDU	0.088** (0.049)	0.053 (0.037)	0.048 (0.040)
OPEN	0.591*** (.155)	0.319*** (0.119)	0.875*** (0.342)
G/Y	-1.290** (0.611)	-0.483 (0.525)	-0.927 (.883)
CONST.	4.051*** (1.012)	2.517*** (0.835)	2.580*** (1.118)
R^2	0.45	0.44	0.48
F PROB.	0.0000	0.0000	0.0000
OBS.	90	77	57

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

Table 10: Effect of Explanatory Variables on *d*