Convergence and Divergence in Growth Regressions*

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Abstract

This paper introduces two new innovations to growth regressions. First, it adds the global frontier as a dynamic variable, assuming that countries follow it, some fully and others partially. Second, it uses data on productivity, now available from PWT. With these two additions we reach four new results. First, although output per worker in each country converges to a long-run productivity path, for many countries this path diverges away from the global frontier. Hence, this paper reconciles the findings of β-convergence of growth regressions with findings of divergence in other studies. Second, we conduct all dynamic estimations without using any control variables. Third, the paper improves the estimation of the rate of convergence and shows that it is close to the famous 2 percent measured by Barro. Fourth, our method enables us to separate the long-run effect on growth of explanatory variables from their overall effect, which cannot be done in standard growth regressions.

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1. Introduction

A major tool in the empirical research on economic growth is growth regressions, which follow the seminal contribution of Barro (1991). Over the years growth regressions have been criticized on various grounds. First, growth regressions find 'conditional convergence,' namely output per capita of each country converges to its own steady state. That implies that the distribution of output per capita across countries should converge to some long-run distribution. But studies that examine directly this distribution find that it diverges over time.[1] Second, growth regressions use a large set of control variables to estimate convergence, and the choice of such variables seems to be arbitrary. Third, the measured rates of convergence in standard growth regressions differ across studies. Fourth, the control variables used in growth regressions are also viewed as explanatory variables for economic growth, but their estimated effects do not differentiate between short and long-run effects. This paper tries to overcome these critiques by extending growth regressions in two ways. First, we use data on labor augmented productivity, in addition to data on output. Second, we estimate the effect of the global frontier on economic growth, following an extended model of growth regressions. These two extensions enable us to reconcile the conflicting findings on convergence and divergence, to estimate the rate of convergence without using control variables, to ass an explanation why standard growth regressions come up with different rates of convergence, and to differentiate between short and long run effects of explanatory variables.

The best way to understand our contributions is in the context of the canonical growth regression model from the authoritative survey of this literature, Durlauf, Johnson and Temple (2005) (hereafter DJT). According to this model the ratio between output per worker and labor augmented productivity, called 'efficiency output per worker,' should converge to some long-run value. The speed of convergence is denoted *b*, which is usually assumed to be equal across countries. Standard growth regressions estimate this coefficient by using data on output per worker or per capita and additional variables as

[1] Some of these studies test for what is called σ-convergence, and reject it, while growth regressions test for what is usually called β-convergence. See Abreu, de Groot and Forax (2005).

controls. In this paper we use the new PWT 8 data set, which includes data on labor, capital and labor share in addition to output. This enables us to calculate productivity within the same data set, and with it we estimate the coefficient of convergence *b* without using any control variables.

Next we change one assumption in the basic DJT model, on how productivity itself changes over time. Instead of assuming that productivity grows at a constant rate, we assume that each country's productivity follows the global productivity frontier, or the global technology frontier, but may follow it partially and not fully. More specifically, in the long-run a country adopts in each period only *d* of the new technologies, where *d* is a country specific parameter lower or equal to 1. If *d* is equal to 1, the country's productivity follows the global frontier fully, but if *d* is less than 1, the productivity long-run path diverges away from the frontier.[2] In the short-run, productivity converges at a rate *c* to this long-run productivity path.

With this assumption the convergence model yields a dynamic process with two rates of convergence and one rate of divergence. The coefficient *b* measures convergence of output per worker to productivity, *c* measures convergence of productivity to its long-run path, and *d* measures by how much long-run productivity follows the global frontier. Using this model and using US productivity as the global frontier, we estimate for each country these three parameters, *b*, *c* and *d*. These estimations do not use any control variables that are added in previous growth regression. We don't need such control variables because we use alternative variables, namely productivity and the global frontier, but their choice is not arbitrary but rather natural.

The estimation of the three parameters leads to very interesting results. First, we replicate the result of β-convergence, which is actually convergence of output to productivity. We even measure a rate of convergence *b* close to 2 percent, the number found by Barro (1991). Second, the estimated coefficients *d* of following the global frontier differ significantly across countries and for many countries are much lower than 1. Hence, despite the measured convergence, there is significant divergence across countries. Output converges to the country's productivity path, but this path itself might diverge away from the frontier and from the countries that are close to it. Thus, this paper

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

reconciles convergence in growth regressions with the findings of global divergence.[3] A third result is that the rate of convergence of productivity to its long-run path c is higher than b, at around 9 percent. This finding can help in explaining why many growth regressions differ in their estimated rate of convergence, since what they actually measure is a weighted average of b and c, which differ significantly. We show for example that the estimated rate of convergence differs with the time length of averaging of growth rates from 5 years to 25 years.

As explained above, we estimate the growth regression model with data on output, productivity and the global frontier, without adding the usual control variables that account for geography, education, institutions, ethnic diversity, fiscal policy and more. Usually, these variables are not only used as controls, but also to test what affects economic growth. But such tests cannot tell whether the effect is short or long-run. Our extended model enables us to overcome this problem by testing how explanatory variables affect the country coefficient of divergence d. A comparison of these results to a standard growth regression that uses these same variables shows significant difference. Hence, we can identify the long-run effect from the overall effect for each variable.

This paper is mainly related to the literature of growth regressions, which began with Barro (1991), Mankiw, Romer and Weil (1992), Barro and Sala-i-Martin (1992) and developed over the years into a huge literature.[4] An excellent summary of growth regressions and their critiques appears in DJT. As shown above, this paper offers ways to overcome some of the main critiques of this literature. This paper is also related to the literature on technology adoption, as it shares the view that most countries do not invent most of their technologies, but adopt them from others. A country might also adopt only part of the global technologies and there is a growing literature that tries to explain such partial adoption, beginning with Krugman (1979).[5] Recently this view also gained empirical support from data collected and analyzed by Comin and others.[6] This paper

[3] Some of the first studies that have found global divergence are Bernard and Durlauf (1995, 1996), and Quah (1996). 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).
[4] Earlier papers that influenced growth regressions are Baumol (1986) and Kormendi and Meguire (1985).
[5] See also Parente and Prescott (1994), Zeira (1998), Eaton and Kortum (1999), and Acemoglu, Aghion and Zilibotti (2006).
[6] Examples are Comin and Hobijn (2010) and Comin and Mestieri (2013).

provides additional empirical support for partial adoption of technologies, as it shows that many countries follow the global frontier only partially. A similar formulation is also made by Phillips and Sul (2007, 2009), but they use it mainly as a critique of growth regressions, while this paper instead embeds it within the growth regression model in order to improve it. Another closely related research is Dowrick and Rogers (2002), who also show that rates of technical change differ significantly across countries, but their paper differs from ours in method.

Note, that our extended growth regression model could become relevant 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 otherwise changes in the global frontier would not have been sufficient for such estimation. Also, the use of unified data on both output and productivity has become possible only recently with the new PWT 8.0.

The paper is organized as follows. Section 2 presents the extended growth regression model. Section 3 presents dynamic and empirical implications of the extended model. Section 4 describes the estimation and data. Section 5 presents the tests of convergence of output to productivity. Section 6 estimates how productivity and output follow the global frontier. Section 7 extends the estimation of the rates of divergence to a larger set of countries over a longer period of time. Section 8 estimates the effects of some explanatory variables on the long-run rate of growth. Section 9 summarizes, while the Appendix presents some theoretical additions.

2. The Growth Regression Model and Its Extension

To explain our contributions, we use the canonical representation of the growth regression model, as described in DJT. Assume first that production in country j in period t is described by:

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

where $Y(j,t)$ is output, $L(j,t)$ is labor, $K(j,t)$ is the amount of capital and $A(j,t)$ is productivity, which is assumed to be labor augmenting, as in DJT.[7] The function G is a

[7] We use the term productivity instead of total factor productivity as it is labor augmenting and not neutral.

standard CRS production function.[8] 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 productivity.

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 equals 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:

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

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 regression 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.[9] As a result capital is adjusted gradually. An alternative explanation is that there are adjustment costs to investment, and this mechanism works well also in open economies, where investment can exceed savings. The gradual convergence of efficiency output per worker is described by the following log-linearized dynamic equation:[10]

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

The parameter *b*(*j*) measures the rate of convergence of efficiency output per worker to its long-run value. Most growth regressions assume that it is equal across countries.[11] In Appendix 2 we describe an open economy theoretical model of economic growth, which implies that *b*(*j*) should be around 2%.

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[8] DJT assume a specific production function, Cobb-Douglas. We use a more general specification.
[9] The Solow model was used by Mankiw, Romer and Weil (1992) and later by many others, as described in DJT. Barro and Sala-i-Martin (1992) used the Ramsey-Cass model, also of a closed economy.
[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).

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

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

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

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

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

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

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

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, the regressions control for them by adding variables like educational attainment, political stability, rate of saving, geographical characteristics, quality of institutions, ethnic diversity, religion, and many more. These additional variables are sometimes called 'explanatory variables,' since they can be viewed as explaining differences in growth rates across countries. Actually, there has been quite a proliferation of such explanatory variables in the literature and their total number has already passed 150. The arbitrary choice of these control variables is one of the main weaknesses of this literature. Another problem is that the regression (5) estimates the effects of such explanatory variable on $g(j) + [1-(1-b)^T]T^{-1}A(j,0)$ without differentiating between the long-run rate of effect on the rate of growth $g(j)$ and the short-run effect on the level $A(j,0)$.

Our main point of departure from the standard growth regression model is replacing assumption (4) by a more realistic model of productivity dynamics. Assume

[12] See DJT.
[13] This is equation (8) in DJT.

first that productivity of each country j converges gradually to some long-run productivity path, denoted by: $LRA(j,t)$. Convergence to this path is described by:

$$\ln A(j,t) - \mathrm{E}_{t\text{-}1} \ln LRA(j,t) = \left[1 - c(j)\right]\left[\ln A(j,t-1) - \ln LRA(j,t-1)\right]. \tag{6}$$

We use the expectation operator at t – 1, because that is when productivity $A(j,t)$ is determined. This convergence is similar to the convergence of output in equation (2), but with a different coefficient. The assumption of gradual adjustment of productivity can be explained by costs to adoption of technologies, as in Parente and Prescott (1994). The coefficient of convergence to the long-run productivity path is $c(j)$, which is assumed a-priori to differ from the rate of convergence of output, $b(j)$.

We next specify the long-run productivity path. Assume that each country tries to follow the global productivity frontier, which is denoted by F. This frontier, which can also be viewed as the global technology frontier, grows steadily over time:

$$\ln F(t) = \ln F(t-1) + g + v(t), \tag{7}$$

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. We do not supply here a theoretical explanation to this assumption, but it is justified empirically below, when $d(j)$ is estimated for each country and it is shown that for many countries it is strictly below 1. We therefore assume that the long-run productivity path of country j satisfies:

$$\ln LRA(j,t) = a(j) + d(j) \ln F(t). \tag{8}$$

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

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

The overall picture that the extended model paints is therefore 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 coefficient d of the country is smaller than 1. Hence, countries experience both convergence and divergence at the same time, if they differ in their coefficient d. To sum, the extended model identifies three coefficients. One is $b(j)$, which measures convergence of output to own productivity, and 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.'

3. Dynamic Implications of the Extended Model

In this section we show how the two main dynamic equations of the model, equation (2) of convergence of output to productivity, and equation (9), of following the global frontier, are used to estimate for each country its three parameters, *b*, *c* and *d*.

3.1 Convergence of Output to Productivity

We first discuss the dynamic condition (2), namely the convergence of output to productivity. By writing efficiency output as a ratio of output per worker to productivity we get from condition (2) the following dynamic condition:

$$\begin{aligned} &\ln y(j,t) - \ln A(j,t) - \ln y^E(j,\infty) = \\ &= [1-b(j)]\left[\ln y(j,t-1) - \ln A(j,t-1) - \ln y^E(j,\infty)\right] \end{aligned} \tag{10}$$

Equation (10) 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 (10) states that the logarithm of output per worker in each country is 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 output per worker and cointegrated 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:

$$\ln y^E(j,t) - \ln y^E(j,t-1) = b(j)\ln y^E(j,\infty) - b(j)\ln y^E(j,t-1). \tag{11}$$

Note that this equation is very similar to the 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 (11) by use of standard methods of growth regressions. This estimation should yield an alternative measurement of the rate of convergence *b*.

3.2. How Productivity Follows the Global Frontier

We next use equations (7) and (9) to derive the following dynamics of productivity according to the extended model:

$$\begin{aligned}(12)\qquad & \ln A(j,t) - d(j)\ln F(t) - a(j) = \\ & = [1-c(j)]\left[\ln A(j,t-1) - d(j)\ln F(t-1) - a(j)\right] - d(j)v(t).\end{aligned}$$

Equation (12) implies that productivity converges to a long-run path, which is described by: $d(j)\ln F(t) + a(j)$. Empirically this equation implies that productivity should be cointegrated with 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 productivity $\ln A(j,t)$ on the global frontier $\ln F(t)$ should measure these two coefficients.[14]

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

$$\begin{aligned}(13)\qquad & \ln A(t+T) - \ln A(t) = [1-c(j)][\ln A(t+T-1) - \ln A(t-1)] + \\ & + c(j)d(j)[\ln F(t+T-1) - \ln F(t-1)].\end{aligned}$$

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 measure 1 minus $c(j)$, while the coefficient of the lagged rate of growth of the frontier measures the multiple $c(j)d(j)$. Thus, the estimation of equation (13) can supply us with coefficients from which we can calculate c and d and that is an alternative estimation of these parameters.

3.3. Divergence of Output per Worker

In this sub-section we describe an additional approach to the estimation of the rate of divergence d. From combining the dynamic conditions (10) and (12) and from iterating them over a long period of time we get:

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

$$\ln y(j,t) - d(j)\ln F(t) = \{1-[1-b(j)]^t\}\ln y^E(j,\infty) + \{1-[1-c(j)]^t\}a(j) +$$

$$(14) \qquad + [1-b(j)]^t[\ln y(j,0) - \ln A(j,0)] + [1-c(j)]^t[\ln A(j,0) - d(j)\ln F(0)] -$$

$$- d(j)\sum_{\tau=0}^{t-1}[1-c(j)]^\tau v(t-\tau).$$

Equation (14) 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 over the global frontier, as implied by equation (14), can be an additional test of the findings of (12) and (13). Note that estimation of (14) does not enable us to identify the rates of convergence, *b* and *c*, since the error correction coefficient is some average of these two rates.

Equation (14) further demonstrates how despite the convergence of each country to its long-run growth path, this path itself can diverge from the frontier, if $d(j) < 1$ for that country. As a result, such a country diverges also from the countries that follow the frontier fully. This is how we reconcile the convergence found in growth regressions with the results of alternative empirical studies that examined the dynamics of the distribution of output per worker or per capita across countries and found divergence.[15]

3.4. Varying Rates of Convergence in Growth Regressions

We next return to the standard growth regression model, as presented by equation (5), but instead of assuming that productivity follows (4), we use our extended model, as summarized by (14). In this extended model the average growth rate over *T* periods is:

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

$$(15) \qquad + \frac{1-[1-c(j)]^T}{T}[a(j) + d(j)\ln F(0)] + d(j)g + d(j)\sum_{t=0}^{T-1}\frac{1-[1-c(j)]^t v(T-t)}{T} -$$

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

If our extended model is the right one, then equation (15) 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

[15] See Durlauf and Bernard and others.

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 $R < 1$, then the estimated coefficient of $\ln y(j,0)$ in (15) is actually equal to:

$$COEFF = \frac{-1 + (1-R)(1-b)^T + R(1-c)^T}{T}. \tag{16}$$

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.

Indeed our measurements below show 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 mainly 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.[16] Hence, our model can offer an additional explanation to the results of this meta-analysis.

4. Estimation of the Extended Model

In this section we explain how we estimate the dynamic equations derived in Section 3. These estimations enable us to measure the dynamic coefficients of the extended model, namely b, c and d for each country. Each of these coefficients is estimated in more than one method, for robustness. More importantly, these coefficients are estimated without the use of control variables, as in standard growth regressions. This is made possible by using instead two alternative variables in the estimation, namely productivity and the global frontier. Finally, following the dynamic estimations, we also test the effect of some explanatory variables on the country estimated coefficient d. This enables us to identify the long-run effect of these variables. A comparison of our results with those of a standard growth regression reveals significant differences.

4.1 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

[16] 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.

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).[17] 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.'[18] As shown below these data enable us to calculate output per worker and labor augmented productivity. There are 167 countries in the data set and the time span is 1950-2011, but not all countries have the 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 series are available since 1970. For these countries we run tests on the period 1970-2008, since we prefer to leave the years of the recent global crisis outside the estimation.

Note that the dynamic equation (14) does not require data on productivity, but only of output per worker or output per capita. Hence, we also estimate this equation by use of a wider set of countries over a longer period of time. For that we use data from the Maddison project, conducted at the Groningen Growth and Development Center (GGDC, 2011), which has data on output per capita for 139 countries over the years 1950-2010, in PPP adjusted Geary-Khamis 1990 US$.

4.2 Calculation of Productivity

The new PWT 8.0 also includes calculated TFP, but we calculate productivity ourselves, for two reasons. First, PWT 8.0 uses development accounting, namely it calculates productivity without human capital, while we want to examine the effect of productivity on output, and therefore it should also include human capital. Second, we follow DJT by assuming that productivity is labor augmenting, which requires a slightly different method of calculating productivity growth rates than the standard Solow Growth Accounting. This method is described in detail in Appendix 1. It is shown there that the rate of growth of labor augmenting productivity should be calculated by:

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

[18] 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.

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

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

The rates of growth of productivity give us enough data for the cointegration estimations of equations (10) and (12) and for the differences estimation of equation (13), as the level of productivity has no effect on these equations. For the estimation of the growth regression in equation (11) we need to calculate the level of productivity as well. We do it by calculating productivity in the year 2005, the year from which the data are chained, using a Cobb-Douglas production function, $Y = K^{\alpha}(AL)^{1-\alpha}$, and assuming that $1 - \alpha$ is the labor share of that year. From the year 2005 productivity is chained to all other years by use of its annual growth rates calculated by (17).

4.3 The Global Frontier

For the global frontier variable we use the US labor augmenting productivity. 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 labor augmented productivity in the red curve, in the years 1950-2011, both in natural logarithms and where productivity is adjusted so that the two curves coincide at 1950. Note that the two curves fit each another quite well as expected, and they also have a fairly stable slope, which fits well the assumption in equation (7) 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 (7) by running a regression of its growth rate on a constant 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 equation (14) for a large set of countries, 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 (7) and indeed in a regression of the growth rate of this variable on a constant during 1950-2010 we find that the constant 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.

4.4 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:

$$\ln y_5(i,t) = \frac{1}{5}\left[\ln y(i,t) + \ln y(i,t-1) + \ln y(i,t-2) + \ln y(i,t-3) + \ln y(i,t-4)\right]. \tag{18}$$

A similar calculation is done for productivity of all countries. Note that equations (10) and (12) remain intact after smoothing and hence the estimated coefficients of b, c, and d should not be affected by it.[19] In some regressions we use raw instead of smoothed data and show that the result are not affected significantly.

5. Measuring the Rate of Convergence of Output

5.1 Panel Cointegration of Output per Worker over Productivity

We begin by estimating the dynamic equation (10). We run a panel cointegration test of output per worker on productivity. 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, the OECD countries in column (2), East Asia in column (3), Central and South America (CSA) in column (4), the Sub-Saharan African countries (SSA) in column (5), and the Middle East and North Africa (MENA) with 3 other countries (Malta, Cyprus and Bulgaria) in column (6). Finally, column (7) presents the results of

[19] Due to cyclical autocorrelation it is better to average over a long period of time, but that reduces the number of observations. We find that 5 years averages are a good balance between the two concerns, but we also tried averaging over 10 years and the results were quite similar.

the regressions for the smaller sample of 28 countries over a longer period of 1950-2008. The two panel cointegrations exclude Turkey, which is an outlier.[20]

[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 could also explain the higher average. In the data set from 1950-2008 the rate of convergence of output is equal to 1.6 percent. These findings are very close to the 'mythical' 2 percent found originally by Barro (1991) and Barro and Sala-i-Martin (1992).[21] Note that the rate of convergence of output b is estimated separately for each country, but its values are quite close.

5.2 A Growth Regression of Efficiency Output per Worker

We next turn to estimate equation (11), which describes the convergence of the 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 the OECD countries in the years 1970-2008.

[Insert Figure 2 here]

As figure 2 shows, for most OECD countries efficiency output has been quite stable over time and 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

[20] Output per worker in Turkey increased significantly, while its productivity did not grow much, so its cointegration coefficient is extremely high. This is also reflected in Figure 2 below.
[21] Since they averaged growth rates over a long period their measure of the rate of convergence should have been close to our b, as explained in Section 3.4.

(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. Figure 2 implies that efficiency output per worker tends to converge overtime, but might converge to different levels, namely $y^E(j,\infty)$ might differ across countries.

[Insert Table 2 here]

Table 2 presents the results of the estimation of the growth regression (11) with respect to efficiency output per worker. Each column describes a different regression. Column (1) is the simplest growth regression (pooled) and it measures convergence at a rate of 1.7 percent. Remembering that the long-run values of efficiency output differ across countries we next try to account for it. We consider the possibility that it depends on the long-run rate of growth of productivity, since if productivity grows faster, output should lag behind when trying to follow it. Hence in regression (2) we add a country average rate of growth over the period 1970-2008, which is denoted by gA and we assume that it should have a negative effect on y^E. Indeed regression (2) has a much higher R^2, the same rate of output convergence, and the coefficient of gA is negative and significant, as expected. In regression (3) we use instead of this variable 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 7 percent. Note that using fixed effect increases the rate of convergence in all growth regressions, as observed by Abreu, de Groot and Forax (2005). 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 data, regression (5) is pooled with gA and regression (6) is a fixed effects panel. The results are quite similar, so we deduce that the use of smoothed data does not affect the results by much.

We can therefore summarize this section with three main conclusions. First, output per worker converges in the long-run to labor augmented productivity for the large majority of countries. Second, the rate of this convergence is in most regressions around the ‘mythical’ 2 percent, which also fit our theoretical open economy model in Appendix 2. Third, this estimation does not require any additional control variable.[22]

6. Measuring the Dynamics of Productivity

6.1. Panel Cointegration of Productivity over US Productivity

We estimate the dynamic equation (12) by a panel cointegration test of each country’s productivity over the global frontier, namely US productivity, for the same data from PWT 8.0 of 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 from 1950. 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 excluded 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. This means that despite the usual convergence found in growth regressions, and also found in Section 5 in this paper, there is actually divergence of countries from the frontier and as a result from one another as well. The convergence is only of output to productivity, but long-run productivity usually diverges from the

[22] We have added the famous variable ‘years of schooling’ as a control variable to regression (2) in Table 2, as 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.

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 has not ended yet, the regression captures these countries as having higher d than 1. 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 (12), especially if the coefficient a is changing during the period, which might bias d. We therefore follow Eberhardt and Teal (2013), who claim that unconstrained heterogeneous estimation is preferred, since it reduces bias of average estimates, where the noise created by misspecification at the country-level is filtered out.

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 also robust across regions. It is therefore much higher than the rate of convergence of output to productivity b. This finding reinforces the point made in sub-section 3.4, that the estimated rate of convergence in standard growth regressions is a weighted average of 2 and 9 percent and as a result it can be anywhere between these two values. Thus, our approach supplies some explanations to the findings of the meta-analysis by Abreu, De Groot and Florax (2005).

6.2. Estimating the Difference Equation

In order to examine these results in an additional method we next estimate the difference equation (13). 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

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

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 with data since 1950 are the more developed countries, which are expected to follow the frontier more fully. With respect to the rate of convergence of productivity *c*, both difference regressions come up with a higher estimate, around 15 percent. But most importantly this coefficient is significantly higher than *b*, the rate of convergence of output.

6.3 Panel Cointegration of Output per Worker on the Global Frontier

Next we present a test of equation (14), namely a panel cointegration estimation 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 an assessment of the 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 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 around 6.5 percent, 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, is quite identical to the OECD countries, it is not surprising that the *d* in this sample is close to 1.

7. Divergence of Output in a Larger Set of Countries

In this section we expand the estimation of the dynamic condition (14) that describes the divergence of output per worker from the global frontier. Since this equation does not include productivity, we can expand the estimation from Table 5 to a larger set of countries over a longer time period by using instead of PWT 8.0 another data set. The Maddison data set does not include data on productivity, or on labor, but it includes data on output per capita for 140 countries for the years 1950-2010. We therefore use this data to estimate a panel cointegration test of equation (14). Since we cannot calculate productivity with this data set we change slightly the variable that represents the global frontier to US GDP per capita. 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

[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.

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.

[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 quite behind as well and so is MENA. As explained in Section 6, the 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.

8. Effects of Explanatory Variables on Global Divergence

In this paper we estimate the convergence and divergence of output across countries without using any control variable. But these country specific explanatory variables might have an effect on the parameters $b(j)$, $c(j)$ and $d(j)$. As we have seen that $b(j)$ and $c(j)$ are quite equal across countries, but $d(j)$ differs significantly across them, we suspect that *d* 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 in comparison

[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.

with a standard growth regression over the same sample and with the same explanatory variables in order to show that the two sets of regressions 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 the 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).[27]
7. ICRG is average measure of quality of institutions during the period 1982-1997 according to the International Country Risk Guide (Knack and Keefer, 1995).
8. G/Y is the share of public expenditures in GDP, averaged in the years 1950-1960, taken from Feenstra, Inklaar, and Timmer (2013).

Note that variables 1-2 reflect the geographical explanation to growth. Variables 3-4 reflect the history of the country, namely its initial conditions, both economic and social. Variable 5 is human capital and variables 6-8 reflect institutional explanations to economic growth. As mentioned above, these variables were chosen not only because they are used in many growth regressions, but also because they are potentially related to following the global technology frontier, which lies at the heart of this paper. As explained by Sachs (2001), geography is a barrier to technology transfer, since technology might be region-specific, especially in agriculture or health. This is also

[27] 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.

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 the 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 the 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 following. First, there is a bias in the estimation of d among the EA countries and it is too high above 1. This is mainly because most of the rapid growth in these countries happens toward the end of the period, and thus the cointegration procedure tends to interpret the convergence in these countries as a higher trend. Another reason for considering omission of these countries is that they are clearly countries that change their pattern of growth during the period covered by the data. Since they change their d and probably also change their coefficient a, it is preferred not to include these countries when testing for a statistical regularity between explanatory variables and these coefficients. 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 the explanatory variables. The OECD countries may have more or less education, larger or smaller government, better or worse institutions, but they all have d around 1, since it is a corner solution. Thus, including the OECD countries in the estimation reduces its ability to identify relationships between d and the explanatory variables. Hence, the third regressions in Tables 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 resemble results of many other studies. Ethnic fractionalization appears to be insignificant.

[Insert Table 10 here]

Table 10 presents the effects of the same explanatory variables on the long-run coefficient d. Of the six variables found significant in the growth regressions only two keep this in the long-run. 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 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 prove 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.[28] One possible interpretation is that education affects only the level of output but not its long-run rate of growth.

Another difference between Tables 9 and 10 is with respect to ethnic fractionalization. Although it does not affect growth in the standard growth regression, it has a negative significant effect on *d*, namely on long-run growth. Thus, Tables 9 and 10 demonstrate 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 and their effects are indeed different.

9. Conclusions

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

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

In a world where the global technology expands continuously and countries can choose whether to adopt a new technology or not, the growth path of each country reflects, among other things, how much it follows the global technology frontier. This is why this paper claims that growth regressions should include the global technology frontier. And indeed, this paper finds that most countries run more slowly than the frontier. Hence, this paper supplies support to the claim that global divergence continues.

Another contribution of this paper is the use of data on productivity in measuring the dynamics of convergence and divergence. This and the use of the global frontier, enable us to estimate the dynamic parameters of each country without controlling for explanatory variables. Our approach can also help in separating the effects of explanatory variables on growth into long-run and short-run effects. Our regressions demonstrate that this difference is significant.

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

Appendix:

1. Growth Accounting of Labor Augmented 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:

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

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

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

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:

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

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

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.[29] Each person supplies 1 unit of labor per period. 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:

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

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

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

From (A.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 model used by Barro and Sala-i-Martin (1992).

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Figures and Tables

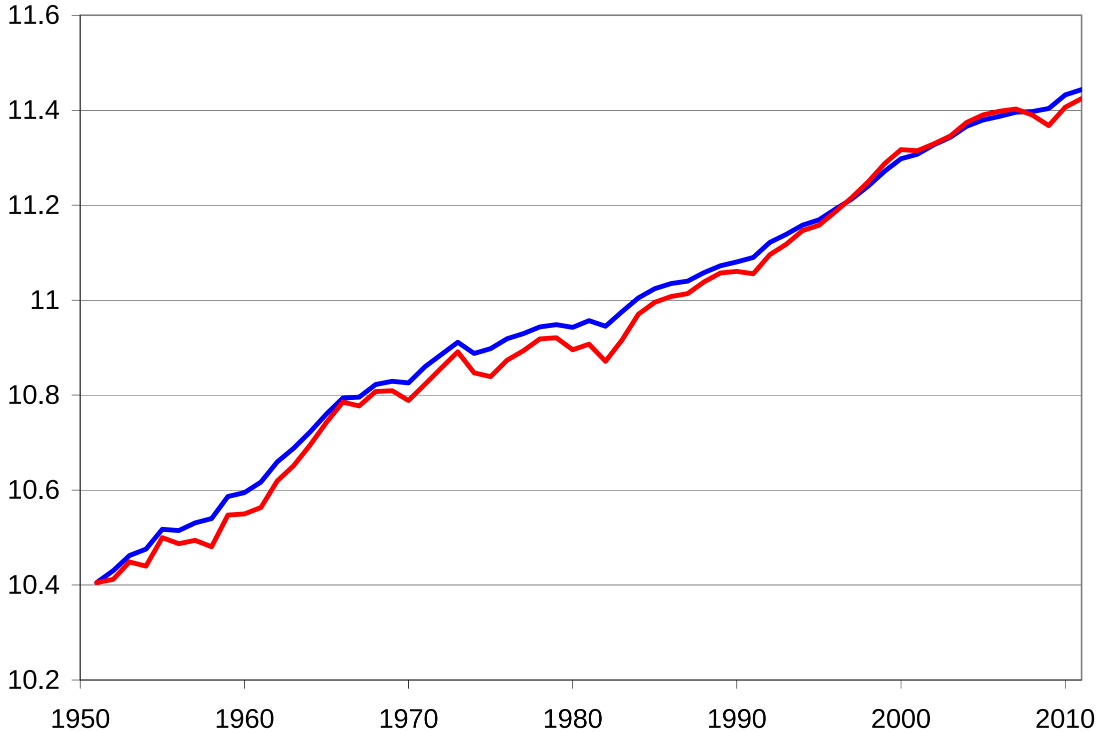

Figure 1: Natural Logarithm of US GDP per worker and US TFP in 1950-2010

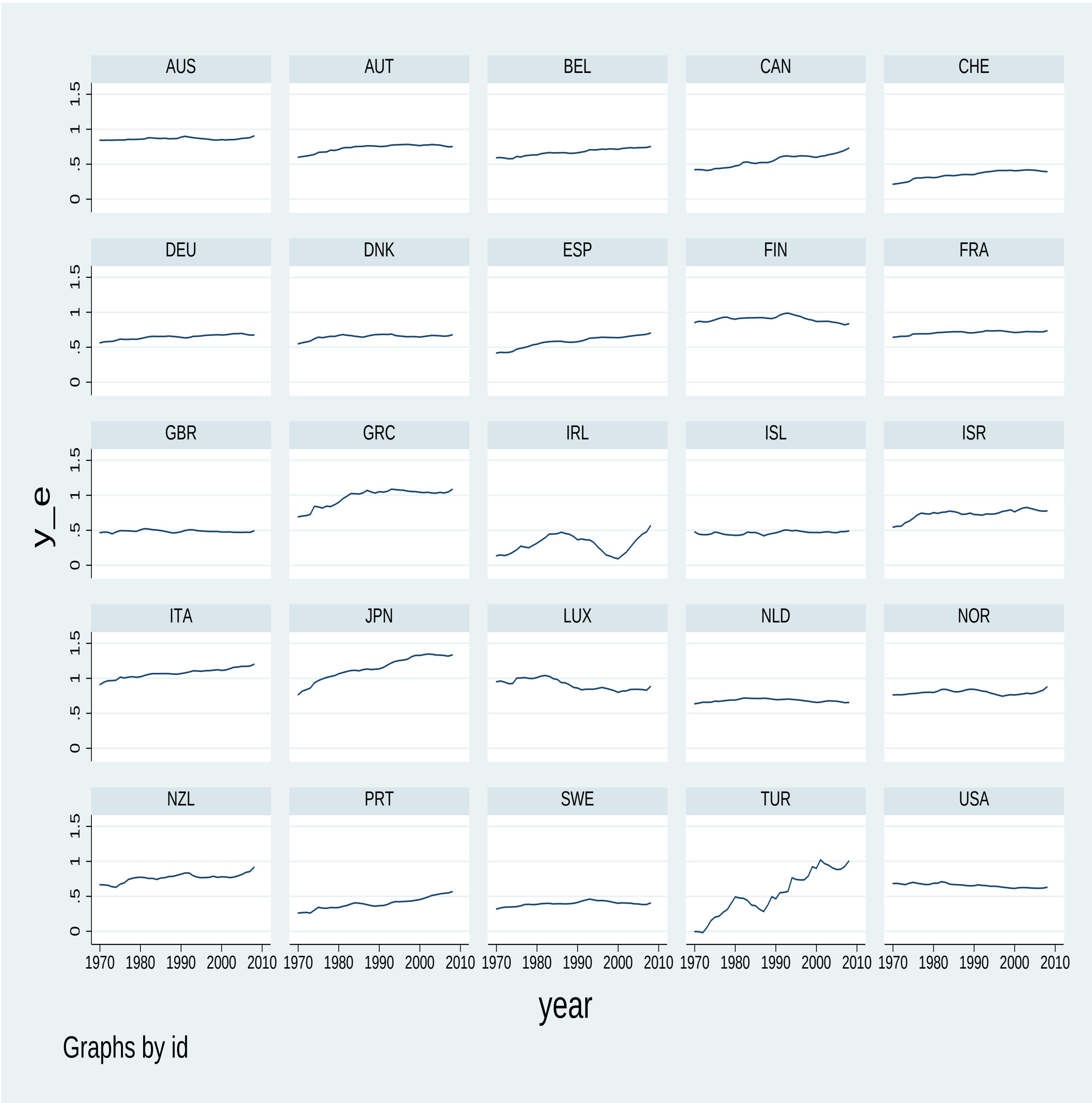

Figure 2: Efficiency Output per Worker in OECD Countries in 1970-2008

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**	**(7) FE Raw**
of Initial y^E	0.016*** (0.003)	0.0167* (0.009)	0.061*** (0.001)	0.062*** (0.005)	0.017*** (0.003)	0.072*** (0.001)
Calculated b	0.017	0.017	0.070	0.072	0.017	0.085
Constant	0.025*** (0.004)	0.030*** (0.01)	0.070*** (0.001)	0.060*** (0.006)	0.030** (0.012)	0.083*** (0.002)
gA		-0.702*** (0.15)			-0.728*** (0.17)	
R^2	0.11	0.31	within 0.48		0.25	within 0.47
No. of Observations	2754	2754	2754	2748	2748	2748
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** (0.152)	-0.389*** (0.133)	-0.459*** (0.144)
COAST	0.004** (0.002)	0.002 (0.002)	0.003 (0.002)
Y_50	-0.468*** (0.127)	-0.240** (0.122)	-0.225* (0.137)
ETHNIC	-0.432* (0.282)	-0.417** (0.218)	-0.574** (0.304)
EDU	0.088** (0.039)	0.053 (0.038)	0.048 (0.043)
OPEN	0.591*** (.150)	0.319** (0.150)	0.875*** (0.291)
G/Y	-1.290** (0.578)	-0.483 (0.513)	-0.927 (.680)
CONST.	4.051*** (0.946)	2.517*** (0.835)	2.580*** (0.966)
R^2	0.45	0.44	0.48
F PROB.	0.0000	0.0000	0.0000
OBS.	90	77	57

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

Table 10: Effect of Explanatory Variables on *d*