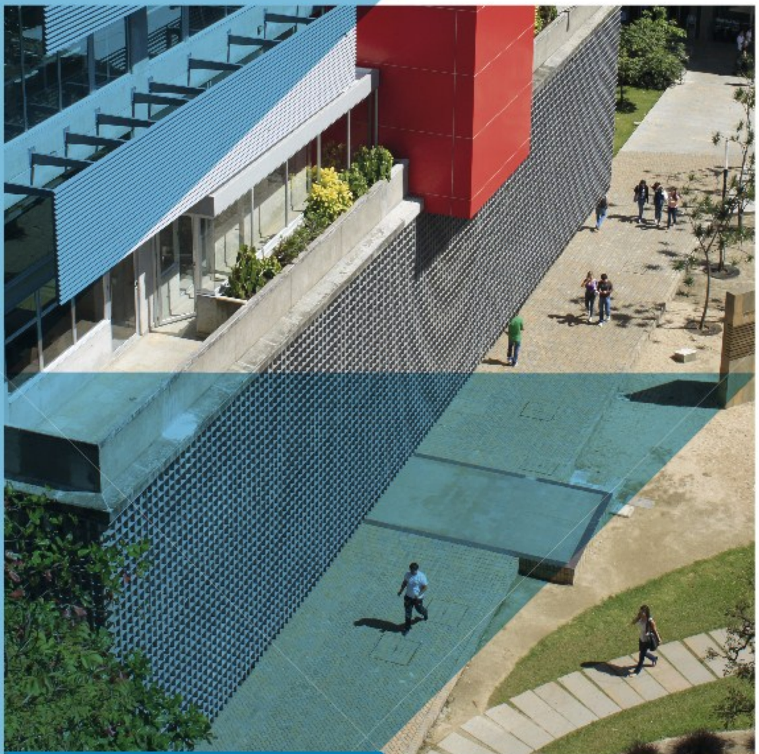

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Explaining economic growth in developed economies after 1980

Carlos Andrés BALLESTEROS* Carlos Esteban POSADA†

Abstract

We use the Aghion and Howitt (2009) theoretical model of endogenous economic growth to explain the declining economic growth in developed economies in the 1981-2009 period. Aghion and Howitt's theoretical framework combines Solownian and Schumpeterian elements in a single scenario, so that labor-augmenting technological progress and capital accumulation per efficiency unit of labor are both caused not only by exogenous changes in the investment rate but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process. Empirical results reveal that both output per worker growth rates and capital stock per efficiency unit of labor growth rates have a common panel unit root. Since the panel cointegration tests and estimates reveal a statistical significant negative long-run relationship between output per worker growth rate and capital stock per efficiency unit of labor, the interpretation of the econometric results analyzed from the Aghion and Howitt's theoretical perspective is that labor-augmenting technological progress declines endogenously over time mainly because of an exogenous deterioration of the environmental conditions for the transformation of investment rate and R&D expenditures in technological progress.

JEL classification: O11, O31, O33, O41, O47, O57.

Keywords: Economic growth, Solownian and Schumpeterian models of growth, investment rate, R&D expenditures, capital stock per efficient unit of labor.

1. Introduction

Economists have noted a progressive and generalized decrease in annual growth rates of output per worker in the advanced economies since the 1980s. Although developed economies have experienced serious difficulties in recovering their previous growth numbers since the 2008 crisis, recent literature has emphasized that these challenges are not only a cyclical issue related to the recent deep recession, but also a result of a progressive deterioration of long-run fundamentals of economic growth. Figure 1 shows this through Penn World Tables version 8.1 data (Feenstra, Inklaar and Timmer, 2015) which display the time trajectories of annual output per hour worked growth rates between 1981 and 2009 for five advanced economies. A clearly negative trend can be noted in economic growth rates, which is stronger in the years 2008 and 2009.

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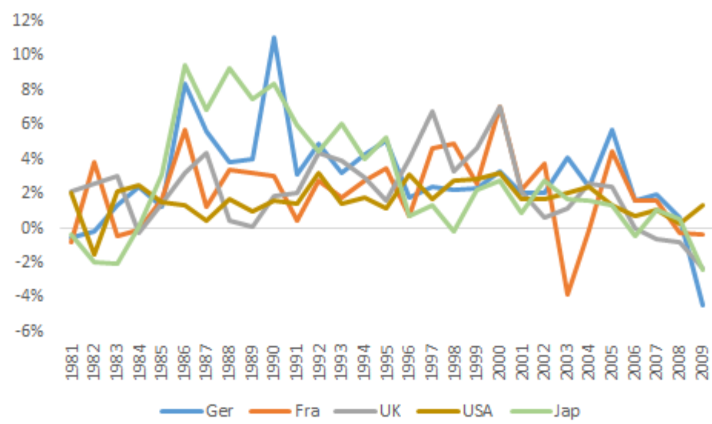
Figure 1: Per worker GPD growth rates (annual)



Source: Penn World Tables version 8.1 and authors' calculations.

An IMF report (2015) documents that advanced economies have experienced a secular decline in GDP growth and average labor productivity growth since the 1970s and argues that these decreasing trends were magnified by the 2008 crisis. Specifically, it shows that trend growth in output per hour worked declined from about 3 percent in 1970 to less than 1.5 percent in 2007. The recent literature has named this long-run slowdown in product per worker growth in advanced economies as "secular stagnation" (Summers, 2014; Gordon, 2015), which in part has been related to a long-run slowdown in Total Factor Productivity (TFP) growth.

We use the Aghion and Howitt (2009) theoretical model of endogenous economic growth and panel cointegration methods to explain the declining economic growth in developed economies in the period 1981-2009. Aghion and Howitt's theoretical framework combines Solownian and Schumpeterian elements in a single scenario, so that labor-augmenting technological progress, which is the only factor that explains economic growth in the long-run, and capital accumulation per efficiency unit of labor are both caused not only by exogenous changes in the investment rate, but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process.

Results from panel unit root tests revealed that output per worker growth rates and capital stock per efficiency unit of labor growth rates both have a common unit root, which allowed us to test for panel cointegration. Since the panel cointegration tests and estimates revealed a statistically significant negative long-run relationship between output per worker growth rate and capital stock per efficiency unit of labor, the theoretical model suggests that declining investment rates contributes to the slowdown in economic growth, but they are not the main explanation for the declining per worker growth. The main interpretation of the econometric results analyzed from Aghion and Howitt's theoretical perspective is that labor-augmenting technological progress is endogenously falling over time, which is mainly motivated by an exogenous deterioration of the environmental conditions for the transformation of investment and R&D expenditures in new technology. This result means that marginal productivity of capital stock for making innovations has decreased. Although investment rates and efficiency of R&D expenses both explain the decelerating growth rates, a theoretical interpretation of econometric results suggests that the latter exogenous force predominates over the former.

Declining investment rates and decreasing efficiency of R&D investments to account for low growth rates are consistent with various findings in the literature. For instance, Desroches and Francis (2006) and Eichengreen (2015) argue that the slowdown in productivity growth has been related to a decrease in real interest rates since the 1980s, which can be explained by an excess of desired savings over desired investments (Fisher, 2006; IMF, 2014; Eichengreen, 2015). Furthermore, Eichengreen (2015) points out that low real interest rates and slow economic growth could be associated with a dearth of attractive investment opportunities. For instance, Gordon (2012) argues that returns on innovation processes have slowed since the 1970s.

The structure of the paper is as follows. Section 2 describes the theoretical model of Aghion and Howitt (2009), which seeks to explain the decelerating output per worker growth rates. Section 3 sets out data sources and the econometric strategy, followed by Section 4, where results are documented and summarized. Finally, Section 5 presents the interpretation of econometric results based on the Aghion and Howitt endogenous growth model and the conclusions drawn.

2. Theoretical framework

In this section we set out the Aghion and Howitt endogenous growth hybrid model as our theoretical reference framework[1]. Firstly, we explain why this model is suitable for studying the slowdown in the output per worker growth rates in developed economies. Later on, we show the assumptions and workings of the model for determining the optimal endogenous long-run economic growth and capital stock per efficiency unit of labor. These elements will be useful for understanding the empirical strategy and the results from the econometric estimates.

2.1. Endogenous growth model approach

As highlighted by Aghion and Howitt, the accounting discussion around the role of capital and TFP growth on output per worker growth has been sustained by Young (1995) and Hsieh (2002). Estimating TFP growth as a Solow residual, Young finds that Singapore, Hong-Kong, Taiwan and Korea reached most of their remarkable income growth rates through capital accumulation and greater efficiency in allocating productive resources, rather than through technological progress. However, Hsieh argues that capital stock is usually overestimated, and further, he used the "dual method"[2] for estimating TFP growth, to find that total factor technological progress played a more important role in generating per worker income growth.

Nevertheless, even when capital stock growth accounts for between 30% and 70% of output per worker growth, all long-run economic growth is entirely caused by technological progress, which is consistent with the Solow growth model. As Aghion and Howitt explain, an accounting relationship is not the same thing as a causal relationship. In this regard, consider the following labor-augmenting technology production function with constant returns to scale:

$$Y = A^{1-\alpha} L^{1-\alpha} K^{\alpha}$$

Where Y is the agregate level of output, K is aggregate capital stock, L is labor input and A is the labor-augmenting technology, which captures the productivity of capital.

In the equation above, $B = A^{1-\alpha}$ is the Total Factor Productivity (TFP) parameter. Dividing the last equation by L, output per worker becomes:

$$\frac{Y}{L} = y = B\left(\frac{K}{L}\right)^{\alpha} = Bk^{\alpha}$$

[1] Aghion and Howitt (2009), Chapter 5.
[2] See Aghion and Howitt (2009) for a more detailed description of the "dual method".

Expressing the last equation in terms of growth rates of the variables, output per worker growth rate takes this form:

$$\frac{\dot{y}}{y} = g = \frac{\dot{B}}{B} + \alpha\frac{\dot{k}}{k} \tag{1}$$

This equation says that economic growth is the sum of the rate of TFP growth and the "capital deepening" process ($\alpha\frac{\dot{k}}{k}$). Equation (1) implies that:

$$\frac{\dot{B}}{B} = (1-\alpha)\frac{\dot{A}}{A}$$

Following the Solow growth model, output per worker growth rate is equal to the labor-augmenting technological process:

$$\frac{\dot{A}}{A} = \frac{\dot{y}}{y} \tag{2}$$

And this implies that TFP growth is $(1-\alpha)\%$ of long-run output per worker growth:

$$\frac{\dot{B}}{B} = (1-\alpha)\frac{\dot{y}}{y} \tag{3}$$

Equation (2) says that labor-augmenting technological progress is entirely the cause of long-run economic growth, and equation (3) says that TFP growth is a fraction $(1-\alpha)$ of per worker growth.

As Aghion and Howitt explain, the term $\alpha\frac{\dot{k}}{k}$ is the economic growth rate that would have been observed if the capital-labor ratio had grown at its observed rate, but there had been no technological progress. However, it is hard to observe a significant increase in capital-labor ratio with a constant state of technological progress because in general one can see that an increase in capital stock is accompanied by improvements in the quality of the new capital goods, but this quality adjustment is imperfectly observable. As the growth model implies that technological progress is required for preventing diminishing returns from increasing the capital-labor ratio, techological progress is the principal cause of both components of per worker growth, i. e. capital deepening and TFP growth rates.

The Solow growth model considers that investment rate, depreciation rate and population growth rate are exogenous factors that affect long-run output per worker. However, since long-run growth is exogenously explained by technological progress, then there are no elements that endogenously explain technological progress and its interactions with capital accumulation. Therefore, this model does not capture the fact that increases in capital stock are probably accompanied by an improvement in the included quality standards. As a starting solution, the interaction between higher quality of intermediate goods and economic growth is modeled by the Schumpeterian growth model (Aghion and Howitt, 1992), making technological progress endogenous through the existence of private R&D expenditures and a probability of success in the innovation process, where if the innovation process succeeds, then positive long-run per worker income growth will take place. Since the Solow model is consistent with growth accounting results but keeps the idea that all long-run growth is caused by technological progress, it seems reasonable that a mixture between Neoclassical (Solownian) and Schumpeterian elements may be appropriate for endogenously explaining long-run economic growth.

2.2. The model

The Aghion and Howitt (2009) model, aka hybrid model, combines Solownian and Schumpeterian elements in a single scenario so that labor-augmented technological progress, which is the only factor that explains economic growth in the long-run and capital accumulation are both caused not only by exogenous changes in the investment rate, but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process.

Compared to the Solow model, Aghion and Howitt's (2009) show that the hybrid model offers an improved explanation of the growth accounting results for advanced economies so that Total Factor Productivity (TFP) growth and capital deepening shares are now caused endogenously by the investment rate and innovation trajectories, which in turn account for long-run per worker income growth.

The model considers three kinds of goods: i) a final good, ii) labor, and iii) a continuum of specialized intermediate goods. The final good is storable in the form of capital stock, and it is assumed that intermediate goods are produced employing capital stock. There are L workers, each of them inelastically supplying one unit of skilled work. The final good is produced in a perfectly competitive market, with an aggregate constant returns to scale production funtion:

$$Y_t = L^{1-\alpha} \int_0^1 A_{it}^{1-\alpha} x_{it}^{\alpha} di; \quad 0 < \alpha < 1 \tag{4}$$

Where A_{it} is the number of efficiency units of labor and the productivity of the intermediate input in sector i, x_{it} is the flow of the intermediate input from sector i, and L is the aggregate labor input. For simplicity, it is assumed that $L = 1$.

Intermediate inputs are produced by monopolist entrepeneurs through the production function:

$$x_{it} = K_{it} \tag{5}$$

Where K_{it} is the capital stock used as a production factor in generating intermediate products. Given that final goods are produced under perfect competition but intermediate products are generated under monopolistic competition, it is assumed that the price of intermediate inputs equals the marginal productivity of intermediate inputs:

$$p_{it} = \frac{\partial Y_t}{\partial x_{it}} = \alpha A_{it}^{1-\alpha} x_{it}^{\alpha-1}$$

The equation above represents the demand funtion of intermediate input for final good firms and depicts the inverse demand function dealt by the monopolist. So the cost of producing x_{it} for the local monopolist is:

$$r_t x_{it} = r_t K_{it}$$

Then the local monopolist's profits are:

$$\Pi_{it} = p_{it} x_{it} - r_t x_{it} = \alpha A_{it}^{1-\alpha} x_{it}^{\alpha} - r_t x_{it} \tag{6}$$

Where r_t is the rental rate of capital stock. The local monopolist chooses x_{it} to maximize its profits, such that:

$$\frac{\partial \Pi_{it}}{\partial x_{it}} = \alpha^2 A_{it}^{1-\alpha} x_{it}^{\alpha-1} - r_t = 0 \quad \rightarrow \quad x_{it} = A_{it} \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} \tag{7}$$

The rental rate of capital is determined by the supply and demand for capital stock. In particular, capital supply is historically predetermined, whereas aggregate demand for capital can be expressed as:

$$\int_0^1 K_{it} = \int_0^1 x_{it}$$

The equilibrium condition above can be rewritten as the endogenous aggregate capital stock:

$$K_t = \int_0^1 \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} A_{it} di = \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} A_t \tag{8}$$

Where $\int_0^1 A_{it} di$ is the aggregate capital productivity parameter. Let $\tilde{k} = \frac{K}{AL} = \frac{K}{A}$ be the capital stock per efficient work unit, so equation (8) can be written in the form:

$$\tilde{k} = \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} \quad \rightarrow \quad r_t = \alpha^2 \tilde{k}_t^{\alpha-1} \tag{9}$$

Equation (9) says that the rental rate of capital is negatively related to the capital stock per efficient work unit. From equations (7) and (8) it can be inferred that:

$$x_{it} = A_{it} \left(\frac{K_t}{A_t} \right) = A_{it} \tilde{k} \tag{10}$$

Substituting equations (9) and (10) in (6), local monopolist profits function becomes:

$$\Pi_{it} = \alpha A_{it} \tilde{k}_t^{\alpha} - (\alpha^2 \tilde{k}_t^{\alpha-1}) A_{it} \tilde{k} = \alpha(1-\alpha) \tilde{k}_t^{\alpha} A_{it}$$

$$\rightarrow \quad \Pi_{it} = \tilde{\pi}(\tilde{k}_t) A_{it}; \qquad \tilde{\pi}(\tilde{k}_t) = \alpha(1-\alpha)\tilde{k}_t^{\alpha} \tag{11}$$

Equation (11) shows that monopolist i profit function is increasing in $\tilde{k}_t$, and the reason is that a greater level of capital stock per efficiency unit of labor reduces costs of production per unit, r_t. Substituting equation (10) in (4), aggregate production function is re-expressed as:

$$Y_t = \int_0^1 A_{it}^{1-\alpha} A_{it}^{\alpha} \tilde{k}_t^{\alpha} = A_t \tilde{k}_t^{\alpha} \tag{12}$$

2.3. Innovation and economic growth

It is assumed that in each period t an entrepeneur of sector i spends resources on R&D activities with a certain probability of innovating successfully. If the entrepeneur is successful, then it becomes the next period local monopolist because the innovation will create an improved, more productive version of the intermediate product, and no other entrepeneur can produce it. If the entrepreneur fails, no innovation process will be available so intermediate input will not improve in quality. In this case, the monopoly will pass to another entrepeneur chosen at random who is able to produce old intermediate products. Specifically the probability of success in R&D expenditures is expressed as:

$$\mu_t = \phi(\eta_t)$$

Where $\eta_t = \frac{R_{it}}{A_{it}^*}$ is the productivity-adjusted level research, R_{it} are expenditures in research activities, and A_{it}^* is the productivity of the intermediate product. If the entrepeneur succeeds, then $A_{it}^* = \gamma A_{it-1}$ $(\gamma > 1)$ will be the productivity of the new improved intermediate product. However, if the entrepeneur fails then $A_{it}^* = A_{it} = A_{it-1}$ and the intermediate input used in t will be the same as in $t-1$. The assumption of A_{it}^* being inversely related to the probability of success, μ_t, is because it is more difficult to innovate as technological progress increases over time. Therefore, what matters in augmenting the probability of success is the productivity-adjusted level of research, $\eta_t = \frac{R_{it}}{A_{it}^*}$. The probability of success μ_t follows a Cobb-Douglas form:

$$\mu_t = \lambda \eta_t^{\sigma}; \quad \lambda > 0; \quad 0 < \sigma < 1$$

Where λ is the effiency of research. Hence the profits function if the entrepeneur succeeds is:

$$\phi\left(\frac{R_{it}}{A_t^*}\right)\Pi_{it}^* - R_{it}$$

The entrepeneur will choose R_{it} so that it maximizes its profits:

$$\frac{\partial\left[\phi\left(\frac{R_{it}}{A_t^*}\right)\Pi_{it}^* - R_{it}\right]}{\partial R_{it}} = \phi^{\prime}\left(\frac{R_{it}}{A_t^*}\right)\Pi_{it}^*\left(\frac{1}{A_t^*}\right) - 1 = 0$$

$$\rightarrow \quad \phi^{\prime}\left(\frac{R_{it}}{A_t^*}\right)\Pi_{it}^*\left(\frac{1}{A_t^*}\right) = 1$$

Based on equation (11) it can be assumed that:

$$\frac{\Pi_{it}^*}{A_{it}^*} = \frac{\Pi_{it}}{A_{it}} = \tilde{\pi}(\tilde{k}_t)$$

In this case the entrepreneur's first order condition becomes:

$$\phi^{\prime}(\eta_t)\tilde{\pi}(\tilde{k}_t) = 1 \tag{13}$$

Equation (13) is called the research arbitrage condition. This optimality condition says that the marginal benefits of spending in R&D (left hand side) must be equal to its marginal cost (right hand side). So an increase in the capital stock per efficient work unit will diminish per unit costs, r_t, and then profits will rise. Given that $\phi^{\prime}(\eta_t)$ is decreasing in η_t, satisfying the arbitrage condition implies that η_t must be boosted in order to maximize profits. This means that augmenting $\tilde{k}_t$ makes it more profitable to increase expenditures in technology-adjusted research, which in turn raises the probability of success in the innovation process. This can be seen by solving equation (13) for η_t and μ_t:

$$\eta_t = \left[\sigma\lambda\tilde{\pi}(\tilde{k}_t)\right]^{\frac{1}{1-\sigma}}$$

$$\mu_t = \lambda\left[\sigma\lambda\tilde{\pi}(\tilde{k}_t)\right]^{\frac{\sigma}{1-\sigma}}$$

As in the Schumpeterian model, the productivity growth rate g_t is the frequency of innovations μ_t times the factor $(\gamma - 1)$:

$$g_t = (\gamma - 1)\lambda\left[\sigma\lambda\tilde{\pi}(\tilde{k}_t)\right]^{\frac{\sigma}{1-\sigma}} \tag{14}$$

Which means that:

$$g_t = \tilde{g}(\tilde{k}_t); \quad \tilde{g}' > 0$$

2.4. Capital accumulation and economic growth: the steady state

As usual in the Solow growth model, a neoclassical labor-augmenting technology production function is supposed, adjusted by efficient units of work:

$$\tilde{y}_t = \tilde{k}_t^{\alpha}$$

Where $\tilde{y}_t$ is output per efficiency unit of labor. A stedy state condition in the Solow model is that savings are equal to the depreciation of the capital stock, so that:

$$\dot{\tilde{k}}_t = 0 \quad \leftrightarrow \quad s\tilde{y} = (\delta + g + n)\tilde{k}$$

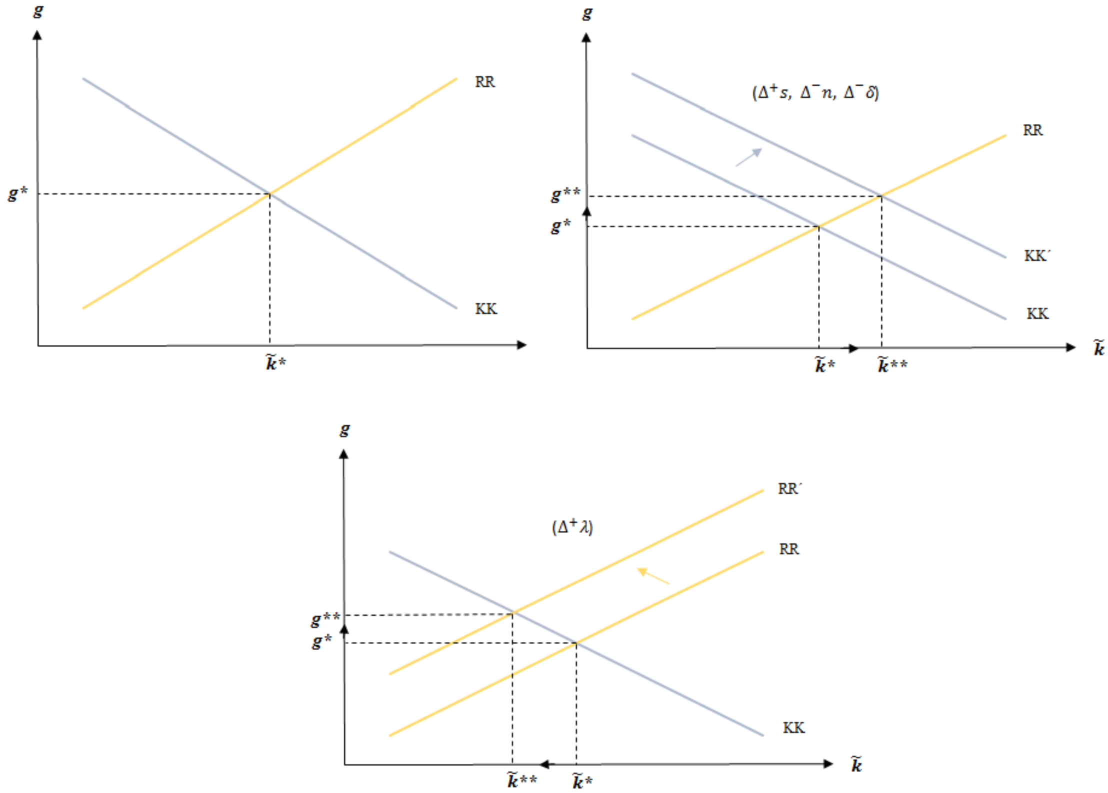
Where $\dot{\tilde{k}}_t$ is the derivative of capital stock per efficiency unit of labor with respect to time, s is the saving (investment) rate, δ is the depreciation rate and n is the population/labor growth rate. Substituting $\tilde{y} = \tilde{k}^{\alpha}$ in the equation above and solving for $\tilde{k}$:

$$\tilde{k} = \left(\frac{s}{\delta + g + n}\right)^{\frac{1}{1-\alpha}} \tag{15}$$

As in the Solow model, in the steady state capital stock per efficiency unit of labor is negatively related to output per worker growth. Furthermore, since in steady state $\dot{\tilde{k}}_t = \dot{\tilde{y}}_t = 0$, the per worker income growth will be equal to the labor-augmenting technological progress, such that: $\frac{\dot{y}}{y} = \frac{\dot{A}}{A} = g$.

Therefore, the reduced form of the model around the steady state is represented by equations (14) and (15), which are called respectively the "research" and "Solownian" equations. As shown by Aghion and Howitt (2009), these two equations can be drawn respectively in a two dimensional plane as the "RR" and "KK" curves, just as in figure 2. As mentioned above, the research equation implies

Figure 2: Long-run equilibrium patterns in the Aghion-Howitt model



Source: Aghion and Howitt (2009).

that economic growth is increasing in $\tilde{k}$ because when capital per efficiency unit of labor rises then incentives to innovate increase, which in turn boosts productivity and economic growth. In contrast, the Solownian curve says that long-run economic growth is a decreasing function of $\tilde{k}$ because of the assumption of drecreasing marginal returns from capital stock per efficiency unit of labor, implied by the Solow model. As in the neoclassical framework, the steady state equilibrium between g and $\tilde{k}$ is dinamically stable[3].

As a result, changing key parameters in both equations allows for making steady state comparative static exercises. In particular, an increase in efficiency of research λ will shift the RR curve up. As a result, long-run economic growth will rise and capital stock per efficiency unit of labor will decline. This result means that if the efficiency of research improves, then the frequency of innovations increases, enabling greater long-run per worker income growth, which results in a lower capital stock per efficiency unit of labor given the workings of the decreasing marginal returns implied by the neoclassical equation. By contrast, an investment rate hike pushes curve derived from equation (15) upwards and to the right, which generates both an increase in long-run economic growth and capital stock per efficiency units of labor. The reason is that a greater level of $\tilde{k}$ makes it more profitable to increase the research efforts by monopolists, which in turn raises the frequency of innovations, and therefore economic growth.

[3]See Aghion and Howitt (2009) Chapter 5 annex for details.

3. Data and empirical strategy

Reduced form equations for g and $\tilde{k}$ makes that long-run movements of these two variables endogenously depend on exogenous changes in λ, s, δ and n. In order to estimate these relations and to give an explanation of the persistent low per worker growth rates in advanced economies, we start by showing and analyzing the data. Later on, details of the econometric strategy will be explained.

3.1. Data

Data for obtaining the processes $\left\{g, \tilde{k}, s, \delta, n\right\}$ were collected from the 8.1. Penn World Tables. Our dataset covers the 1981-2009 time period and we considered 18 developed economies[4]. We use output-side real GDP (rgdpo) as our measure of the real aggregate GDP variable. To calculate real GDP per worker, aggregate real output is divided by a measure of total hours worked by employed population. This measure is calculated as the average annual hours worked by an engaged person (avh), multiplied by the number of persons engaged in employment (emp):

$$(per\ worker\ real\ gdp)_t = y_t = \frac{rgdpo_t}{(avh_t)(emp_t)}$$

This measure of output per worker is suitable from a neoclassical point of view because it can be understood as the real output produced per hour worked. Moreover, capital stock per efficiency unit of labor is calculated as the real value of capital stock (ck) divided by our measure of labor, $(avh_t)(emp_t)$, which is multiplied by a measure of labor-augmenting technological progress, which in turn is obtained as a Solow residual. Assuming a constant returns to scale production technology, we have:

$$\tilde{k}_t = \frac{ck_t}{A_t(avh_t)(emp_t)}$$

Where $A_t = \left\{\frac{rgdpo_t}{(ck_t)^{1-\theta_t}[(avh_t)(emp_t)]^{\theta_t}}\right\}^{\frac{1}{\theta_t}}$ being θ_t the time-varying labor share in real aggregate output (labsh).

Measures for investment, depreciation and population growth rates are obtained from the Penn World Tables. Specifically, for the saving rate we chose the investment (gross capital formation) shares in real GDP (csh_i), and for depreciation and population growth rates we respectively took "average depreciation rate of the capital stock (delta)" and "population (pop)".

3.2. Empirical strategy

As the reduced form of our theoretical framework consists of a stable long-run equilibrium relationship between output per worker growth g and capital stock per efficiency unit of labor $\tilde{k}$, we want to empirically estimate how this equilibrium endogenously changes when certain exogenous variables are shocked. In particular, the Aghion and Howitt model above implies that positive exogenous shocks to investment rates (or negative shocks to depreciation and population growth rates) yield a long-run increase in both g and $\tilde{k}$. In contrast, we have seen that an exogenous rise in the efficiency of R&D investments rises the frequency of innovations, which results in higher g accompanied by a decrease in $\tilde{k}$.

[4]The countries in the sample are: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Japan, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, United Kingdom and the United States.

From an econometric point of view, it is hard to estimate how the long-run equilibrium between g and $\tilde{k}$ changes when one exogenous variable changes separately. Therefore, we propose estimating "continuos" endogenous changes in steady-state equilibrium $\left\{g^*, \tilde{k}^*\right\}$ by employing panel cointegration techniques. In particular, we want to estimate this relation through testing for panel cointegration in the endogenous variables g_{it} and $\tilde{k}_{it}$[5] and by estimating the corresponding cointegrating vector. Given the predictions made by the theoretical model when there are shocks to the exogenous variables, one could expect that if the long-term relation between g and $\tilde{k}$ is positive and stable, then exogenous changes in investment, depreciation and population growth rates would predominate over exogenous changes in the efficiency of R&D expenditures through time. In graphic terms, this can be seen as succesive shifts of the Solownian (KK) curve along the Schumpeterian (RR) curve. Nevertheless, if the latter relationship is negative and stable, exogenous shocks to efficiency of R&D expenses would predominate over exogenous changes in investment, depreciation and population growth rates. Analogously, this could be seen as continuous shifts of the Schumpeterian (RR) curve along the Solownian (KK) curve. Since the predominance of Solownian exogenous movements over Schumpeterian exogenous shocks, or the reverse, determines the long-term relationship between per worker growth and capital accumulation per efficient work unit, this link is entirely an empirical issue, and as such, there are reasons for expecting either a positive or a negative sign of the long-run coefficient that relates g_{it} and $\tilde{k}_{it}$.

With regard to the existence and (if possible) estimates of panel cointegration between g and $\tilde{k}$, we start by reviewing the panel unit root tests, panel cointegration tests and panel cointegration estimation methods that we will use in the econometric exercise.

3.2.1. Panel unit root tests

Following Baum (2006) and Baltagi (2013), consider a panel data autoregresive model of the form:

$$y_{it} = \rho_i y_{it-1} + D_{it}^{\prime}\theta_i + \varepsilon_{it} \tag{16}$$

Where i=1,...,N; t=1,..., T; ε_{it} is the white noise error term and D_{it} is a term which captures deterministic components. In this case, if $D_{it}^{\prime} = 0$ then there will not be any deterministic component in (16); however if $D_{it}^{\prime} = 1$ then it will control for panel-specific fixed effects; and if $D_{it}^{\prime} = (1, t)$ the equation will have panel-specific constants and time trends. Analogously to the single time series case, most panel unit root tests consist of testing the null hypothesis of $H_0 : \rho_i = 1$ against the alternative of $H_1 : \rho_i < 1$. Equation (16) can be rewriten as:

$$\triangle y_{it} = \varphi_i y_{it-1} + D_{it}^{\prime}\theta_i + \varepsilon_{it} \tag{17}$$

Where $\varphi_i = \rho_i - 1$. In this way, the panel unit root tests will have $H_0 : \varphi_i = 0$ against the alternative of $H_1 : \varphi_i < 0$. As in the familiar case of single time series, the null hypothesis is that y_{it} is a non-stationary process, while rejecting it will imply that y_{it} is stationary.

On the other hand, the panel unit root test developed by Hadri (2000) is a generalization of the Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test used in time series, so the null hypothesis is that all panels y_{it} are stationary against the alternative that some panels are stationary.

We employ five panel unit root tests, which can be divided in three kinds of tests. The first kind are the tests developed by Levin, Li and Chu (LLC, 2002) and Breitung (2000), which restrict the autoregresive parameter in (17) to be the same for all panels, so that $\varphi_i = \varphi$. Another kind of test that we consider are those that permit the autoregresive parameter to be panel-specific, such

[5] In our specific sample N and T dimensions are defined by i=1,..., 18 and t=1,..., 29.

as the Im, Pesaran and Shin (2003) and Fisher-Type tests. Finally, the third kind of test is that developed by Hadri (2000), which builds a residual-based LM test from an autoregresive panel process similar to (16). Common features shared by these tests are: i) the fact that all the test statistics are asymptotically distributed N(0, 1), ii) their asymptotic convergence properties make them behave relatively well under T>N[6], and iii) they assume cross-sectional independence.

Specifically, the LLC test specifies an equation which is very similar to (17), with the difference that the test restricts the autoregresive term to be common across the panels and the test controls for serial correlation in the error term by considering lags to the dependent variable, as in the augmented Dickey-Fuller test. So the model proposed by LLC is:

$$\triangle y_{it} = \varphi y_{it-1} + D_{it}^{'} \theta_i + \sum_{k=1}^{p} \alpha_{ik} \triangle y_{it-k} + \mu_{it} \tag{18}$$

For the Breitung test, it is assumed that the variable of interest forllows an AR (1) process, so that:

$$y_{it} = D_{it}^{'} \theta_i + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \varepsilon_{it} \tag{19}$$

The test procedure makes the serial correlation vanish in the error terms, and it has two possible outcomes, depending on the assumption about the correlation across panels of the terms ε_{it}. In particular, if ε_{it} is uncorrelated across the N units then using the non-robust version of the test is appropriate. By contrast, if there exists cross-section correlation of ε_{it} therefore the test allows for using a robust version so that this cross-correlation is controlled. As in equation (19) the null hypothesis is that y_{it} as a whole has a unit root, then $H_0 : \gamma_1 + \gamma_2 = 1$ against the alternative of y_{it} being a stationary process $H_1 : \gamma_1 + \gamma_2 < 1$.

Moreover, the Im, Pesaran and Shin (2003) test (IPS) is very similar to the LLC test, in the sense that IPS follows the same autoregresive structure of the model, with the difference that the autoregresive coefficient is panel-specific. First, consider the case in which there is no serial correlation along the T dimension, so that y_{it} follows a process of the form:

$$\triangle y_{it} = \varphi_i y_{it-1} + D_{it}^{'} \theta_i + \mu_{it} \tag{20}$$

Where φ_i is the panel-specific autoregresive coefficient. They assume that μ_{it} is serially uncorrelated in both dimensions N and T and that is the reason why there are no lags of the dependent variable on the left hand side, but it allows for different variances across the panels. For hypothesis testing, φ_i is estimated for each i and then panel-specific t-statistics are computed, so that they are averaged to obtain a single t-statistic. The null hypothesis is that $H_0 : \varphi_i = 0$ for all i (all panels have unit roots) agains the alternative $H_0 : \varphi_i < 0$, which implies that some panels are stationary. The test builds various test statistics, such as $\bar{t}$ which is the average of all panel-specific t-statistics t_i; $\bar{\tilde{t}}$ which is the average of similar t-statistics as $\bar{t}$ but with the difference that $\tilde{t}_i$ is constructed by a different error variance estimator of (20); and Z_t and $Z_{\tilde{t}}$ are respectively standardized versions of $\bar{t}$ and $\bar{\tilde{t}}$, although Z_t does not have an asymptotic normal distribution, which makes it not commongly appropriate for hypothesis testing (Baum, 2006).

However, when there is serial correlation in μ_{it}, information-criterion based selected lags are added to equation (20) to remove autocorrelation. In this case the IPS test considers the following model:

$$\triangle y_{it} = \varphi_i y_{it-1} + D_{it}^{'} \theta_i + \sum_{k=1}^{p} \alpha_{ik} \triangle y_{it-k} + \mu_{it} \tag{21}$$

[6]See Baltagui (2013) for a detailed discussion of the asymptotic properties of the panel unit root tests.

In this situation a different built test statistic is generated, labeled $W_{\bar{t}}$, which is appropriate when $T \rightarrow \infty$ followed by $N \rightarrow \infty$, meaning that relatively large dimensions are required for N and T.

Fisher-Type tests perform units root tests for each panel, and then make transformations to the p-values according to the four methos developed by Choi (2001). The panel-specific unit root test chosen must be either the Augmented Dickey-Fuller or Phillips-Perron tests. Each one of these transformation methods has its own test statistic and p-values, which are labeled inverse chi-squared (P), inverse-normal (Z), inverse-logit (L) and modified inverse chi-squared (Pm). The null-hypothesis is that all panels have unit roots against the alternative that at least one panel is stationary. Using this test is appropriate when $T \rightarrow \infty$ and N could be either finite or infinite.

Finally, we use the panel unit root test developed by Hadri (2000), which is considered to be a residual-based LM test. Unlike the last four tests, in the Hadri panel unit root test the null hypothesis is that all panels are stationary, but the alternative is that at least one panel has a unit root, analogous to the time series KPSS test. Consider the following process for y_{it} with (optional) time trend:

$$y_{it} = z_{it} + \alpha_i t + \varepsilon_{it} \tag{22}$$

Where $z_{it} = z_{it-1} + u_{it}$ is a random walk process, and ε_{it} and u_{it} are mutually independent normal variables that are independent and identically distributed across i and t. Using back substitution of equation (22):

$$y_{it} = z_{i0} + \alpha_i t + \sum_{s=1}^{t} u_{is} + \varepsilon_{it} = z_{i0} + \alpha_i t + v_{it} \tag{23}$$

Where $v_{it} = \sum_{S=1}^{t} u_{is} + \varepsilon_{it}$. Then the null hypothesis is $H_0 : \lambda = \frac{\sigma_u^2}{\sigma_\varepsilon^2}$ against the alternative $H_0 : \lambda > 0$. If the null hypothesis is not rejected, then $v_{it} = \varepsilon_{it}$ and the variable y_{it} is stationary in all panels. The test calculations has the option of making a version of the test which is robust to heteroskedasticity across panels, and also has the option of building the test to be robust to serial correlation and heteroskedasticity.

3.2.2. Panel cointegration tests

Following Baltagi (2013), consider a panel regression of y_{it} against x_{it} of the form:

$$y_{it} = \alpha_i + x_{it}^{\prime}\beta + e_{it} \tag{24}$$

Where y_{it} and x_{it} are non-stationary variables and α_i controls for non-observed heterogeneity in each panel. As in the Engel and Granger (1987) methodology for time series, Pedroni (1999, 2004) and Kao (1999) contruct residual-based tests which consist of evaluating whether the term e_{it} is a stationary process in a panel data framework, such that the absolute value of the autoregresive coefficient in $e_{it} = \rho e_{it-1} + v_{it}$ (if there is no serial correlation) or in $e_{it} = \rho e_{it-1} + \sum_{s=1}^{p_i} \theta_{is} \triangle e_{it-s} + v_{it}$ (if there is serial correlation) takes a value less than unity.

In particular, Pedroni (1999, 2004) developed eleven statistics for testing panel cointegration, and each test statistic differs in size and power, depending on the N and T dimensions[7]. The first eight test statistics tests for cointegration when ρ is restricted to be the same across panels (within dimension) and the remaining three tests allow ρ to differ across panels (between dimension), and therefore there is a specific ρ_i for each cross-section. For hypothesis testing, the null hypothesis of

[7] See Baltagi (2013) for details involved in the calculations of Pedroni´s test statistics.

no-cointegration is $H_0 : \rho_i = 1$, while the alternative hypothesis under the within-dimension case ($\rho_i = \rho$) is $H_a : \rho < 1$ and under the between-dimension case the alternative becomes $H_a : \rho_i < 1$ for all i. Finally, all test statistics converge approximately to a standard normal distribution N(0, 1).

Moreover, the structure of Kao's (1999) panel cointegration test is similar to Pedroni's test. Remarkable differences are that the Kao test assumes no time trends (but heterogeneous constant terms) and constrains the residual equation to have a common autoregresive parameter accompanying the residual lagged term. Specifically, assume that the residuals in (24) can follow one of the following processes:

$$e_{it} = \rho e_{it-1} + v_{it} \tag{25}$$

$$e_{it} = \rho e_{it-1} + \sum_{s=1}^{p_i} \theta_{is} \triangle e_{it-s} + v_{it} \tag{26}$$

When estimating the model, one can assume that there is no serial correlation in error terms (as indicated in equation (25)), in which case Kao developed the test based on Dickey-Fuller (DF) regressions. Further, when the existence of serial correlation is assumed (as indicated in equation (26)), then the test works based on Augmented Dickey-Fuller regressions (ADF). Similarly to Pedroni test, in Kao the null hypothesis of panel cointegration is $H_0 : \rho = 1$ against the alternative $H_a : \rho < 1$. All Kao test statistics are asymptotically distributed N(0, 1).

Unlike the above tests based on the Engle-Granger methodology, the Fisher-type test combines panel-specific Johansen tests for building a whole-panel combined test, which was developed by Maddala and Wu (1999). Therefore, trace and maximum-eigenvalue test statistics are used for panel cointegration testing. Analogously to the time series case, the null hypothesis for both test statistics is that there is no cointegration relationships, against the alternative that there is at most one long-run relation between variables. If null hypothesis is rejected, then alternative is accepted, and the next step is testing the null of having one cointegrating relation against the alternative of having at most two cointegrating relations, and so on.

We also use a more recent panel cointegration test developed by Westerlund (2007). As Persyn and Westerlund (2008) argues, despite of the power gains derived of panel cointegration techniques because of considering the N and T dimensions, many studies do not reject the null hypothesis of no-cointegration, even when a long-run relationship is strongly suggested by economic theory. This testing failure has been interpreted as a loss of power of residual-based cointegration tests, because these procedures requires that coefficients accompanying independent variables in the cointegrating equation to be equal to the short-run coefficients when variables are in differences. Westerlund (2007) developed a panel cointegration test based on assessing whether the error-correction term in a panel error correction model is statistically iqual to zero, in which case it is inferred that there is no cointegration. In particular, Westerlund built four tests for testing the null of no-cointegration: two tests evaluate the alternative of having cointegration in the panel as a whole, while the remaining two tests analyze the case in which at least one panel is cointegrated. To see this, we follow Persyn and Westerlund (2007) in considering the error-correction form process:

$$\triangle y_{it} = \delta_i^{'} d_t + \alpha_i (y_{it-1} - \beta_i^{'} x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \triangle y_{it-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \triangle x_{it-j} + e_{it} \tag{27}$$

Where y_{it} and x_{it} are non-stationary variables, e_{it} is independent across both i and t, and d_t contains the deterministic components, which will determine if there will be either no constants terms ($d_t = 0$), or if there will be only a constant ($d_t = 1$), or if there will be a constant with a time trend ($d_t = (1, t)^{'}$).

In those cases in which there is cross-sectional dependence of the error terms, cointegration tests will be robust through considering mean bootstrap methods. As in the Granger Representation theorem, if $\alpha_i < 0$ and statistically significant, then there is error correction when a certain shock occurs, and hence there will be cointegration between y_{it} and x_{it}; on the contrary, if $\alpha_i = 0$ then there is no error correction and therefore there is no cointegration. In this sense, the null hypothesis is that $H_0 : \alpha_i = 0$ against two sets of alternatives. The first set permits α_i to differ across panels and consists in $H_a^1 : \alpha_i < 0$ for at least one i (Group-mean test). On the other hand, the remaining two tests (panel tests) constrains α_i to be the same across panels, which implies $H_a^2 : \alpha_i = \alpha < 0$ for all i. Weterlund (2007) and Persyn and Westerlund (2008) show that all four test statistics are asymptotically normally distributed the extend to which $T \to \infty$ and then $N \to \infty$ sequencially, which in practical terms means that using the test is suitable when T is larger than N. For practical purposes, the two Group-mean statistics are denoted by G_τ and G_α, and the two Panel-test statistics are denoted by P_τ and P_α[8]. In dealing cross-section dependence in the error-correction residual terms, the cointegration panel test statistics are generalized by using bootstrap methods, which can be found in Westerlund (2007). For robustness of our panel cointegration results, we also use the Westerlund bootstrap approach as an alternative way of testing for panel cointegration.

3.2.3. Panel cointegration estimation

Assume that the long-run relationship between two variables y_{it} and x_{it} can be represented by the following cointegrating equation:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + \epsilon_{it} \tag{28}$$

Where α_i are panel-specific intercepts capturing fixed-effects, β is a cross-section common vector of long-run coefficients, y_{it} and x_{it} are non-stationary, and u_{it} are stationary disturbance terms, implying that variables in equation (28) are cointegrated. The autoregresive distributive lag (ARDL) process of order (p, q) for y_{it} can be expressed as:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=1}^{q} \delta_{ij} x_{i,t-j} + \mu_i + \epsilon_{it} \tag{29}$$

Where λ_{it} and δ_{ij} are scalars and μ_i is the group-specific effect. Converting equation (29) into its error correction form, we have:

$$\triangle y_{it} = \varphi_i \left(y_{it} - \alpha_i - x_{it}^{'}\beta \right) + \sum_{j=1}^{p} \lambda_{ij}^{*} y_{i,t-j} + \sum_{j=1}^{q} \delta_{ij}^{*} x_{i,t-j} + \epsilon_{it} \tag{30}$$

Where $\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$ $(j = 1, \ldots, p-1)$ and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$ $(j = 1, \ldots, q-1)$. In equations (28), (29) and (30) time trends and other kinds of deterministic regressors could be specified. As mentioned in the previous sections, φ_i is the error-correcting term which must be negative and statistically significant for having cointegrated variables.

We will consider eight alternative methods for estimating the long-run relationship between our panel time series g_{it} and $\tilde{k}_{it}$. Following Blackburne and Frank (2007), first we use three methods for estimating long-run coefficients in heterogeneous panels: i) a traditional dynamic fixed-effects (DFE) estimator, ii) a mean-group (MG) estimator (Pesaran and Smith, 1995), and a pool-mean-group

[8] See Westerlund (2007) and Persyn and Westerlund (2008) for details in constructing Group-mean and panel-test statistics.

(PMG) estimator (Pesaran, Shin and Smith, 1997, 1999). This kind of estimator assumes cross-sectional independency and is correctly used when the panel has both large T and N dimensions, although they have usually been used in a context of $T > N$. In particular, the DFE estimator carries out the estimates of parameters over the pooled sample and restricts the long-run coefficients to be equal through i, although intercepts can differ across groups. Further, the MG approach estimates values for each cross-section intercept, slope coefficient and error variance, and then makes simple averages of them. After considering the last two opposite properties of DFE and MG estimators, the PMG estimator is an intermediate one, in the sense that it permits that intercepts, short-run coefficients and error-variances to vary across groups, but long-run coefficients are constrained to be equal across panels. Since equation (30) is highly non-linear, Pesaran, Shin and Smith (1999) estimate the set of parameters $\{\varphi, \beta, \alpha, \sigma\}$ by the maximum-likelihood approach.

Assesing which estimator is better than the another is an important issue. As Blackburne and Frank (2007) discuss, since the PMG estimator restricts a single long-run coefficient across panels, it gives efficient and consistent estimators when pooling the panels is a true constraint. However, if the pooling restriction is not true, then PMG estimates will be inconsistent, which would make the MG estimator better because it will be consistent in either case. For testing the common-slope restriction, we use the Hausman procedure for testing the difference in both estimators. In this context, the null hypothesis is that the PMG estimator is efficient (in which case this is the preferred approach) against the alternative that the PMG estimator is not consistent, which makes the MG estimator better. Furthermore, DFE estimators can suffer from endogeneity between the error terms and the lagged dependent variable (Baltagi, Griffin, and Xiong, 2000), which makes it necessary to test whether the FE estimator overcomes the MG estimator. To do so, we again use the Hausman test for testing the difference in the two estimators, where the DFE estimator is efficient under the null-hypothesis. If the null is not rejected, then simultaneous equation bias is minimal and the DFE estimator would become preferred over the MG estimator (Blackburne and Frank, 2007).

Further, Pesaran (2006) and Westerlund (2007) warned about the possibility of cross-section correlation across panel members, so that the existence of cross-dependence would make long-run coefficients inconsistent. To deal with this, we also estimate cross-dependence robust MG and PMG estimators proposed by Pesaran (2006) and Eberhardt and Teal (2010). In particular, Pesaran (2006) developed the Common Correlated Effects Mean Group (CCEMG) and Common Correlated Effects Mean Pooled (CCEP) estimators as the cross-dependence robust versions of MG and PMG estimators, respectively. Additionally, we use the Augmented Mean Group (AMG) estimator developed by Eberhardt and Teal (2010) for an alternative cross-dependence robust version of the MG estimator. However, in spite of CCEMG, CCEP and AMG estimators allowing for cross-section dependence, Eberhardt (2011) argues that using the PMG estimator makes a lot of sense when similar countries are considered. Since we have 18 OECD countries, the PMG estimator is still a good way in estimating our long-run coefficient of interest.

In addition to the maximum-likelihood estimation approach, the Ordinary Least Squares (OLS) approach has also been explored in panel cointegration estimation. However, despite the consistency of OLS estimates in a cointegration single time series approach, Kao and Chiang (2000) show that OLS estimates of long-run coefficients in a panel cointegration framework are inconsistent. Following Baltagi (2013), Phillips and Moon (1999) and Pedroni (1999) proposed a Fully Modified Ordinary Least Squares (FMOLS) estimator and Kao and Chiang (2000) proposed a Dynamic OLS (DOLS) estimator, both approaches dealing with panel cointegration estimation under the assumption of cross-section independence. Kao and Chiang suggested that FMOLS and DOLS estimators are suitable for estimating panel cointegration and demonstrated that both estimators are asymptotically distributed normal. As mentioned in Baltagi (2013), Kao and Chiang studied the finite-sample properties of OLS-type estimators in panel cointegration, and found that although FMOLS little improves the performance of OLS estimates, DOLS seems to behave much better than OLS and FMOLS. Therefore, as an alternative for estimating our cointegrating relation of interest, we also use the FMOLS and DOLS estimators.

4. Results

The aim of this study is to understand why per worker income growth in various developed economies has been stagnated over the past 30 years. Based on the reduced form of the Aghion and Howitt theoretical model, we test for the possibility of a long-run relationship between per worker GDP growth, g_{it}, and the capital stock per efficiency unit of labor, $\tilde{k}_{it}$, through panel cointegration techniques. In particular, we test for the existence of unit roots in the panel, then we perform the panel cointegration tests, and finally we show the panel cointegration estimates. Then, in section 5 we will interpret the empirical evidence based on the implications of the Aghion and Howitt theoretical model.

4.1. Panel unit root tests

Table 1: Panel unit root tests

Test	Variable	Deterministics	Type-statistic	Statistic-value (1981-2007)	p-value (1981-2007)	Statistic-value (1981-2009)	p-value (1981-2009)
LLC	g_{it}	no-cons	adjusted-t	-5.8084	0.0000	-4.0782	0.0000
	$\Delta\tilde{k}_{it}$	no-cons		-9.7139	0.0000	-9.4850	0.0000
	g_{it}	cons		-6.5402	0.0000	-4.6075	0.0000
	$\Delta\tilde{k}_{it}$	cons		1.6253	0.9480	0.0584	0.5233
	g_{it}	cons-trend		1.6293	0.9484	3.1405	0.9992
	$\Delta\tilde{k}_{it}$	cons-trend		2.4647	0.9931	4.7704	1.0000
Breitung	g_{it}	cons-trend	t-statistic	1.6485	0.9504	-0.0241	0.4904
	$\Delta\tilde{k}_{it}$	cons-trend		-0.3664	0.3570	2.0450	0.9796
IPS	g_{it}	cons	w-statistic	-8.5084	0.0000	-7.0682	0.0000
	$\Delta\tilde{k}_{it}$	cons		-6.4515	0.0000	-5.6210	0.0000
	g_{it}	cons-trend		-4.3585	0.0000	-2.4591	0.0070
	$\Delta\tilde{k}_{it}$	cons-trend		-2.8764	0.0020	-3.9522	0.0000
Fisher-ADF	g_{it}	no-cons	F Chi-square	70.6717	0.0005	58.3111	0.0107
			Choi Z	-3.2916	0.0005	-2.6219	0.0044
	$\Delta\tilde{k}_{it}$	no-cons	F Chi-square	165.072	0.0000	168.307	0.0000
			Choi Z	-9.3737	0.0000	-9.5743	0.0000
	g_{it}	cons	F Chi-square	149.734	0.0000	145.056	0.0000
			Choi Z	-8.1791	0.0000	-6.7861	0.0000
	$\Delta\tilde{k}_{it}$	cons	F Chi-square	105.850	0.0000	94.6238	0.0000
			Choi Z	-6.5084	0.0000	-5.6159	0.0000
	g_{it}	cons-trend	F Chi-square	86.3926	0.0000	75.9691	0.0001
			Choi Z	-3.8582	0.0001	-1.6892	0.0456
	$\Delta\tilde{k}_{it}$	cons-trend	F Chi-square	56.1146	0.0175	74.5440	0.0002
			Choi Z	-2.2817	0.0113	-3.5673	0.0002
Hadri	g_{it}	cons	Z-statistic	1.4353	0.0756	1.6971	0.0448
			H Z-statistic	0.4396	0.3301	1.0481	0.1473
	$\Delta\tilde{k}_{it}$	cons	Z-statistic	1.5788	0.0572	2.3328	0.0098
			H Z-statistic	2.3982	0.0082	3.6396	0.0001
	g_{it}	cons-trend	Z-statistic	4.2448	0.0000	4.9984	0.0000
			H Z-statistic	4.9170	0.0000	6.5066	0.0000
	$\Delta\tilde{k}_{it}$	cons-trend	Z-statistic	6.3922	0.0000	6.2642	0.0000
			H Z-statistic	5.3817	0.0000	5.8415	0.0000

Source: Authors' calculations.

Panel unit root tests results are presented in Table 1[9]. Since cointegration requires endogenous variables to be equally integrated, capital stock per efficiency unit of labor (in natural logarithms)

[9] It can be noted in the empirical analysis that results are shown for both periods 1981-2007 and 1981-2009. This cut in the time availability is done for checking the robustness of our results. Considering the possibility that our empirical conclusions may be sensitive to the 2008 crisis, we show throughout the emprirical analysis that our results are maintained over this cut in the sample.

is differenciated to become integrated of order one, because it showed to be integrated of order two in levels. This fact implies that our capital stock per efficiency unit of labor measure in the empirical exercise will be $\triangle\tilde{k}_{it}$, which is henceforth denoted as the capital stock per efficient unit of labor growth rate. Table 1 shows that the LLC, Breitung and Hadri tests validate the presence of a common unit root in the processes g_{it} and $\triangle\tilde{k}_{it}$, especially when constants (individual effects) and (individual linear) trends are included; whereas IPS and Fisher-type ADF tests reject their null that each panel i has its own unit root.

In particular, LLC and Breitung tests have the null hypothesis that panels contain unit roots against the alternative that all panels are stationary. If the null is not rejected, then the panels, viewed as a whole single set, have a unit root. It can be seen in table 1 that LLC and Breitung tests do not reject the null of unit root for g_{it} and $\triangle\tilde{k}_{it}$ when individual effects and individual linear trends are included, which means that there exist homogeneous unit roots in both variables once not-observed heterogeneous factors have been controlled for. Further, the Hadri test assesses the null that all panels are stationary against the alternative that at least one panel has a unit root. For g_{it} the Hadri null hypothesis is not rejected when only individual effects are included but not linear trends, and the null is evaluated under the heteroskedastic robust Z-statistic. However, the Hadri tests reject the null of stationarity for variable $\triangle\tilde{k}_{it}$ even when only constants are considered and the null is evaluated under the heteroskedastic robust Z-statistic. Once individual effects and specific linear trends are included together, the Hadri test rejects the null of stationarity for both g_{it} and $\triangle\tilde{k}_{it}$. These results carried out by LLC, Breitung and Hadri tests support the existence of a common unit root in our variables of interest.

Meanwhile, when non-stationarity is evaluated under the IPS and Fisher-ADF tests, then the null that all individual panels have a unit root is rejected in all possible cases, which strengthens the existence of a common unit root over all panel units, rather than an individual unit root for each cross-sectional panel. Therefore, even when IPS and Fisher-ADF tests reject the possibility that each panel has a unit root, LLC, Breitung and Hadri tests conclude that g_{it} and $\triangle\tilde{k}_{it}$ have unit roots when they are seen as a whole process, which allows us to go on with the panel cointegration testing exercise.

4.2. Panel cointegration tests

We employ four different panel cointegration tests for g_{it} and $\triangle\tilde{k}_{it}$. Firstly, we test for panel cointegration using the residual-based Pedroni test, which considers the possibility of no-cointegration as the null hypothesis. Table 2 shows the Pedroni test results including individual constants and linear trend terms to control for fixed-effects across panel units. It can be observed that the null hypothesis of no-cointegration is strongly rejected for most of the test statistics, and it is true for both time periods, which implies that g_{it} and $\triangle\tilde{k}_{it}$ are cointegrated.

The last panel cointgeration result is verified using the residual-based Kao test and the Fisher-type combined-Johansen test developed by Maddala and Wu (1999). Tables 3 and 4, respectively, show the results of these tests. As in the Pedroni test, Kao and Fisher-type tests strongly reject the null hypothesis of no-cointgeration between g_{it} and $\triangle\tilde{k}_{it}$ for both time periods, which again support the claim that the output per worker growth rate and the capital per efficiency unit of labor growth rate are panel cointgerated.

Finally, we use the error-correction-based Westerlund test for panel cointegration. Table 5 shows the results, where again the null hypothesis of no-cointegration is strongly rejected for both time periods. No matter which deterministic assumptions are considered, the cointegrating relationship between g_{it} and $\triangle\tilde{k}_{it}$ is again supported. However, Westerlund (2007) warns about the possibility of cross-sectional dependence across the error terms in the error-correction equations. This likely cross-dependency is not considered by the standard Westerlund test, which could alter the cointegration

Table 2: Pedroni panel cointegration test

Panel cointegration test (Pedroni)	**Statistic and p-value (1981-2007)**	**Statistic and p-value (1981-2009)**
Constant		
Panel v	-0.0821 (0.5328)	2.4504 (0.0071)
Panel rho	-10.705 (0.0000)	-8.4558 (0.0000)
Panel-pp	-11.584 (0.0000)	-10.856 (0.0000)
Panel-ADF	-10.401 (0.0000)	-11.936 (0.0000)
Weighted Panel v	-0.7819 (0.7829)	-0.3283 (0.6287)
Weighted Panel rho	-11.265 (0.0000)	-8.6208 (0.0000)
Weighted panel-pp	-12.272 (0.0000)	-10.904 (0.0000)
Weighted panel ADF	-11.459 (0.0000)	-11.039 (0.0000)
Group rho	-8.4430 (0.0000)	-7.2614 (0.0000)
Group pp	-13.065 (0.0000)	-12.649 (0.0000)
Group ADF	-9.245 (0.0000)	-11.936 (0.0000)
Constant and trend		
Panel v	-3.6934 (0.9999)	-1.6917 (0.9546)
Panel rho	-6.3555 (0.0000)	-4.7709 (0.0000)
Panel-pp	-12.617 (0.0000)	-12.185 (0.0000)
Panel-ADF	-11.476 (0.0000)	-12.5922 (0.0000)
Weighted Panel v	-4.2907 (1.0000)	-4.0068 (1.0000)
Weighted Panel rho	-6.7942 (0.0000)	-4.3338 (0.0000)
Weighted panel-pp	-13.242 (0.0000)	-11.111 (0.0000)
Weighted panel ADF	-12.556 (0.0000)	-10.545 (0.0000)
Group rho	-4.6012 (0.0000)	-3.4702 (0.0000)
Group pp	-14.155 (0.0000)	-13.234 (0.0000)
Group ADF	-10.413 (0.0000)	-12.092 (0.0000)
Observations	486	522

Source: Authors' calculations.

test results suggested by Table 5, once the cross-dependence is taken into account. Westerlund (2007) proposed a bootstrapped method for building his panel cointgeration test, where the resulting test is robust to the presence of cross-sectional correlation. Results of the Westerlund panel cointegration test robust to cross-sectional dependence are shown in Table 6. It can be noted that once the cross-dependence is considered, the panel cointegration results are strongly maintained.

From the above four panel cointegration tests, we can say that results are successful in concluding that g_{it} and $\triangle\tilde{k}_{it}$ are cointgerated, even when cross-sectional dependence across error terms of the error-correction equations is present. Therefore, results support these two variables having a long-run relationship, as our theoretical framework argues. In this direction, the next step is estimating the sign and the statistical properties of this long-term link.

Table 3: Kao panel cointegration test

Panel cointegration test (Kao)	**Statistic and p-value (1981-2007)**	**Statistic and p-value (1981-2009)**
ADF	2.4747 (0.0067)	3.0821 (0.0010)
Observations	486	522

Source: Authors' calculations.

Table 4: Combined Fisher-ADF panel cointegration test

Panel cointegration test (Combined Johansen)	Fisher trace and p-value (1981-2007)	Fisher max-eigen and p-value (1981-2007)	Fisher trace and p-value (1981-2007)	Fisher max-eigen and p-value (1981-2007)
Constant				
None	88.58 (0.0000)	99.11 (0.0000)	95.42 (0.0000)	102.2 (0.0000)
At most 1	25.31 (0.9085)	25.31 (0.9085)	26.94 (0.8627)	26.94 (0.8627)
Constant-trend				
None	90.21 (0.0000)	96.23 (0.0000)	96.24 (0.0000)	95.45 (0.0000)
At most 1	24.66 (0.9234)	24.66 (0.9234)	31.19 (0.6966)	31.19 (0.6966)
Observations	486		522	

Source: Authors' calculations.

Table 5: Westerlund panel cointegration test

Westerlund test	Value (1981-2007)	Z-value (1981-2007)	p-value (1981-2007)	Value (1981-2009)	Z-value (1981-2009)	p-value (1981-2009)
no-constant						
G_τ	-1.253	-1.127	0.130	-1.565	-2.399	0.008
G_a	-3.336	0.435	0.668	-4.910	-1.034	0.151
P_τ	-6.711	-3.894	0.000	-7.235	-4.343	0.000
P_a	-6.711	-3.894	0.000	-5.355	-6.343	0.000
constant						
G_τ	-3.442	-7.861	0.000	-3.332	-7.340	0.000
G_a	-12.425	-4.117	0.000	-14.855	-6.011	0.000
P_τ	-13.976	-7.880	0.000	-13.976	-7.880	0.000
P_a	-14.513	-9.827	0.000	-16.454	-11.682	0.000
constant-trend						
G_τ	-3.730	-7.121	0.000	-3.703	-6.977	0.000
G_a	-15.412	-2.122	0.017	-17.666	-3.528	0.000
P_τ	-16.053	-8.108	0.000	-15.406	-7.368	0.000
P_a	-17.435	-5.883	0.000	-19.791	-7.514	0.000

Source: Authors' calculations.

Table 6: Cross-dependence robust Westerlund panel cointegration test

Westerlund robust test	Value (1981-2007)	Z-value (1981-2007)	p-value (1981-2007)	Robust p-value (1981-2007)	Value (1981-2009)	Z-value (1981-2009)	p-value (1981-2009)	Robust p-value (1981-2007)
no-constant								
G_τ	-1.457	-1.960	0.025	0.033	-1.624	-2.643	0.004	0.015
G_a	-4.181	-0.353	0.362	0.138	-5.138	-1.246	0.106	0.045
P_τ	-6.713	-3.895	0.000	0.008	-7.580	-4.638	0.000	0.000
P_a	-4.186	-4.631	0.000	0.003	-4.946	-5.744	0.000	0.005
constant								
G_τ	-3.076	-6.132	0.000	0.000	-3.233	-6-875	0.000	0.000
G_a	-13.255	-4.764	0.000	0.000	-14.682	-5.876	0.000	0.000
P_τ	-13.377	-7.278	0.000	0.000	-14.942	-8.851	0.000	0.000
P_a	-13.005	-8.386	0.000	0.000	-14.884	-10.182	0.000	0.000
constant-trend								
G_τ	-3.468	-5.752	0.000	0.000	-3.478	-5.802	0.000	0.000
G_a	-15.815	-2.373	0.009	0.000	-16.318	-2.687	0.004	0.000
P_τ	-16.053	-8.108	0.000	0.000	-16.446	-8.557	0.000	0.000
P_a	-17.435	-5.883	0.000	0.000	-17.380	-5.845	0.000	0.000

Source: Authors' calculations.

4.3. Panel cointegration estimation

Once we know that g_{it} and $\triangle\tilde{k}_{it}$ are cointegrated, we want to estimate the long-run coefficients that relate these two variables. We use five methods in estimating the long-run coefficients of interest. Firstly, we use a maximum-likelihood estimation approach that includes a Pooled-Mean-Group (PMG) estimator, a Mean-Group (MG) estimator, and a Dynamic Fixed-Effects (DFE) estimator[10]. Second, we focus on an OLS estimation approach, where estimation results of panel DOLS and FMOLS estimators will be shown.

In particular, Table 7 shows the estimation results of PMG, MG and DFE estimators, for both the 1981-2007 and 1981-2009 time periods. Specifically, it can be noted that the sign of the cointegration coefficients is always negative and statistically significant at the 1% level. An implication of the theoretical model is that a negative cointegrated relation between g_{it} and $\triangle\tilde{k}_{it}$ would imply that in the long-run the Schumpeterian curve shifts have predominated over the shifts of the Solownian curve. Further in Section 5, we will interpret this results based on the implications of Aghion and Howitt theoretical model.

Table 7 shows that the MG estimator is the greatest in absolute value, followed by the PMG estimator. As mentioned in Section 3.2.3, Blackburne and Frank (2007) discuss the PMG estimator as an intermediate between the MG and DFE estimators, in the sense that it permits intercepts, short-run coefficients and error-variances to vary across groups, but long-run coefficients are constrained to be equal across panels. Since the PMG estimator restricts a single long-run coefficient across panels, it gives efficient and consistent estimators when pooling the panels is a true constraint. However, if the pooling restriction is not true, then PMG estimates will be inconsistent, which would make the MG estimator better. Altough the panel cointegration tests rejected the null of no-cointegration both at the within (panel-specific) and between (group-common) dimensions, testing the common-slope restriction is mostly motivated by the panel unit root results, which indicated that there exists a common unit root in both g_{it} and $\triangle\tilde{k}_{it}$ once individual effects are controlled for (LLC, Fisher-ADF and Hadri) instead of a situation in which each panel has a unit root. For testing whether the common-slope is true, we use the Hausman procedure for testing the difference in both estimators. In this context, the null hypothesis is that the PMG estimator is efficient (in which case this is the preferred approach) against the alternative that the PMG estimator is not consistent, which makes the MG estimator better. Furthermore, since the DFE estimator only permits intercepts to vary over the panel units (considering common short-run coefficients, common error variances and common long-run coefficients), we also test the null that the DFE estimator overcomes the MG estimator.

Hausman test results are shown in Table 8. It can be noted that PMG estimates are preferred over the MG estimates (null is not rejected), but MG estimates are preferred over DFE estimates (rejection of the null hypothesis at 10% significance level). This results makes the PMG estimates preferred over MG and DFE estimates, which is consistent with the panel unit root tests results. All these findings together mean that the restriction of a common long-run coefficient is true, and that the PMG estimator is a good approach in estimating our long-run relationship of interest.

Table 9 shows the CCEP, CCEMG and AMG estimates. Since the Hausman test results suggest that the PMG estimation is a good approach, then its cross-dependence robust version (CCEP estimator) is also a suitable way of estimating our long-run relationship of interest. It can be noted that PMG and CCEP estimates are size-similar and statistically significant at the 1% level, although the CCEP estimated long-run coefficient are slightly smaller for both sample periods.

We also estimate the long-run coefficient between g_{it} and $\triangle\tilde{k}_{it}$ through the OLS estimation approach. Given that OLS estimates suffer from endogeneity between the error term and the lagged dependent variable, we instead carry out the estimates by FMOLS and DOLS. However, Kao and Chiang studied the finite-sample properties of OLS-type estimators in panel cointegration, and found that although

[10] See section 3.2 for a more detailed description of the estimation methods.

Table 7: PMG, MG and DFE panel cointegration estimates

Estimator	Coefficient and p-value (1981-2007)	Coefficient and p-value (1981-2009)
PMG	-0.0720 (0.000)	-0.0978 (0.000)
MG	-0.1218 (0.001)	-0.1693 (0.003)
DFE	-0.0605 (0.009)	-0.0898 (0.000)
Obs.	468	504

Source: Authors' calculations.

Table 8: Hausman tests for differences between PMG, MG and DFE estimates

Hausman Test	Statistic (p-value) (1981-2007)	Statistic (p-value) (1981-2009)
MG vs PMG	2.28 (0.131)	2.00 (0.157)
MG vs DFE	5.00 (0.025)	3.04 (0.081)

Source: Authors' calculations.

FMOLS offer little improvement to the performance of OLS estimates, DOLS seem to behave much better than OLS and FMOLS (Baltagi, 2013). Estimates of the long-run coefficient by FMOLS and DOLS are shown in Table 10. There are three ways of estimating by FMOLS and DOLS, so that i) the whole coefficient may be either an average of cross-section standard FMOLS and DOLS estimates (Group-mean), or ii) it may be the result of weighting the data by the panel-specific long-run error-variances and then estimating the pooled sample by FMOLS and DOLS (Pool-weighted), or iii) it may be the result of performing standard FMOLS and DOLS over the pooled sample, once deterministic components have been dropped from g_{it} and $\triangle\tilde{k}_{it}$. It can be observed that all long-run coefficients in table 10 are negative and statistically significant, almost all at 1% significance level.

Given that the common-slope assumption is true (by the Hausman test and panel unit root tests) and that Kao and Chiang (2000) argue that DOLS tend to behave better than FMOLS, it seems reasonable to maintain that pooled and pool-weighted DOLS estimates are the preferred estimates in Table 10, as these estimation methods considerably control for heterogeneity across panels maintaining the common-slope restriction. It can be noted that these estimates have the highest goodness of fit numbers (R^2) in Table 10, and the coefficient values are close to the PMG and CCEP ones.

Finally, if we take the PMG and CCEP estimators as our preferred estimates then, controlling for fixed effects and cross-dependence, a long-run equilibrium increase of $\triangle\tilde{k}_{it}$ by 1 percentage point would have made g_{it} decrease between 0.0626 and 0.0720 percentage points if the sample goes until 2007, but between 0.0725 and 0.0978 percentage points if the sample goes until 2009.

Table 9: CCEP, CCEMG and AMG panel cointegration estimates

Estimator	Coefficient and p-value (1981-2007)	Coefficient and p-value (1981-2009)
CCEP	-0.0626 (0.000)	-0.0725 (0.001)
CCEMG	-0.1515 (0.000)	-0.1539 (0.000)
AMG	-0.1026 (0.000)	-0.0967 (0.000)
Obs.	486	522

Source: Authors' calculations.

Table 10: DOLS and FMOLS panel cointegration estimates

DOLS and FMOLS	DOLS (1981-2007) Coefficient (p-value) (Obs.) (R^2)	DOLS (1981-2009) Coefficient (p-value) (Obs.) (R^2)	FMOLS (1981-2007) Coefficient (p-value) (Obs.) (R^2)	FMOLS (1981-2009) Coefficient (p-value) (Obs.) (R^2)
Group-mean				
Constant	-0.1343 (0.0000) (451) (0.2918)	-0.1601 (0.0000) (478) (0.2460)	-0.0976 (0.0000) (468) (0.1922)	-0.1344 (0.0000) (504) (0.1672)
Constant-trend	-0.0708 (0.0203) (454) (0.2565)	-0.1124 (0.0002) (477) (0.1812)	-0.0829 (0.0001) (468) (0.2146)	-0.1164 (0.0000) (504) (0.1936)
Pool-weighted				
Constant	-0.1178 (0.0000) (451) (0.3378)	-0.1496 (0.0000) (478) (0.2877)	-0.1249 (0.0039) (468) (0.1857)	-0.2010 (0.0000) (504) (0.1153)
Constant-trend	-0.1162 (0.0000) (454) (0.3786)	-0.1536 (0.0000) (477) (0.3318)	-0.1297 (0.0073) (468) (0.2315)	-0.2249 (0.0000) (504) (0.1499)
Pooled				
Constant	-0.1045 (0.0002) (451) (0.3382)	-0.1267 (0.0000) (478) (0.2891)	-0.0816 (0.0000) (468) (0.2001)	-0.1091 (0.0000) (504) (0.1840)
Constant-trend	-0.0790 (0.0064) (454) (0.3812)	-0.1257 (0.0000) (477) (0.3334)	-0.0885 (0.0000) (468) (0.2436)	-0.1175 (0.0000) (504) (0.2332)

Source: Authors' calculations.

4.4. Econometric evidence

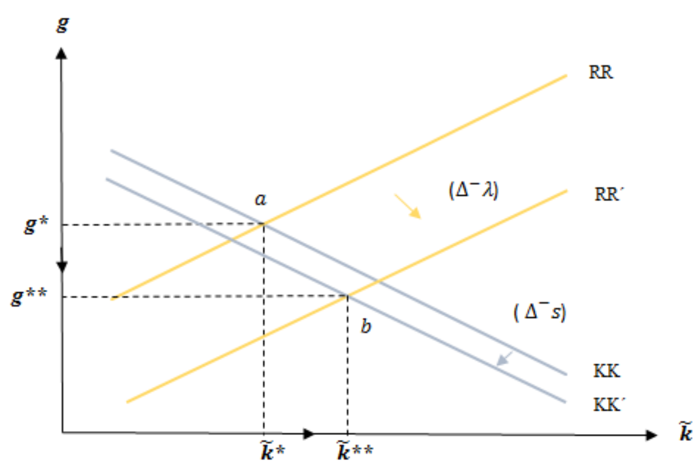
Summarizing the econometric results, the most important findings are the following:

- Even when IPS and Fisher-ADF tests reject the possibility that each panel has a unit root, LLC, Breitung and Hadri tests support the existence of a common unit root in g_{it} and $\triangle\tilde{k}_{it}$, which means that they have a unit root when they are seen as a whole process.
- g_{it} and $\triangle\tilde{k}_{it}$ are cointgerated, even when there is cross-sectional dependence across error terms in error-correction equations.
- If we take the PMG and CCEP estimators as our preferred ones, then, controlling for fixed effects and cross-dependence, a long-run equilibrium increase of $\triangle\tilde{k}_{it}$ of 1 percentage point, would have made g_{it} decrease between 0.0626 and 0.0720 percentage points if the sample goes until 2007, but between 0.0725 and 0.0978 percentage points if the sample goes until 2009.

From the above findings, we can conclude that g_{it} and $\triangle\tilde{k}_{it}$ have common unit roots, they are cointegrated, and are negatively related in the long-run.

5. Discussion and conclusions

Figure 3: Shifts in Schumpeterian (RR) and Solownian (KK) curves



The econometric exercise consisted in estimating a long-run relationship between per worker growth rates and capital stock per efficiency unit of labor growth rates, which drove us to an estimation of a panel cointegrating equation between g_{it} and $\triangle\tilde{k}_{it}$, once we concluded that these variables were non-stationary. We decided to include only endogenous variables and excluded from the cointegrating relation variables such as λ, s, n and δ because the theoretical model of Aghion and Howitt consider these latter variables as exogenous. Therefore, since g_{it} and $\triangle\tilde{k}_{it}$ proved each to have a common unit root, the sign of the cointegration between these two variables allows us to infer the extent to which each exogenous variable is affecting the long-run equilibrium $\left\{g_{it}, \triangle\tilde{k}_{it}\right\}$, according to the Aghion and Howitt model.

The fact that g_{it} and $\triangle\tilde{k}_{it}$ have common unit roots and are cointegrated indicates that their relationship is stable through time, but also that they are cotinuously responding to permanent exogenous shocks. As is predicted by the theoretical model, exogenous movements in λ would make g_{it} and $\triangle\tilde{k}_{it}$ to relate negatively in the long run, whereas exogenous shocks to s, n and δ would make g_{it} and $\triangle\tilde{k}_{it}$ to relate positively in the long-term. Therefore, the sign of the net equilibrium relationship between g_{it} and $\triangle\tilde{k}_{it}$ through time will determine which exogenous shocks predominate over the long-term movements in the $\left\{g_{it}, \triangle\tilde{k}_{it}\right\}$ equilibrium. Given that the panel cointegration estimates indicate that this relationship is negative and statistically significant through several methods, it can be inferred from the theoretical model that efficiency of R&D investments effects on the $\left\{g_{it}, \triangle\tilde{k}_{it}\right\}$ equilibrium predominate over the Solownian exogenous factors, such as s, n and δ. In graphical terms, according to Figure 2 this means that the RR curve has been shifting in greater magnitudes than the KK curve has shifted over time.

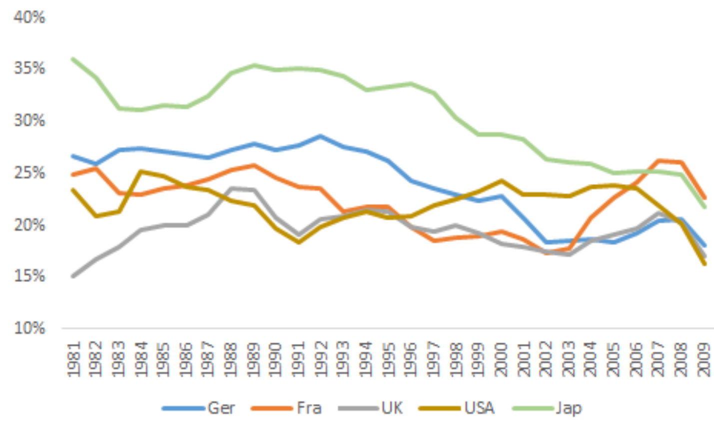
Figures 4, 5 and 6 show respectively Penn World Tables data of the investment rates, population growth rates and capital stock depreciation rates for five big countries included in the sample. They show that investment rates have a clearly negative trend through time, not all population growth rates are decreasing, and depreciation rates seem to be roughly stable. Keeping in mind the theoretical effects of these exogenous variables on the long-run equilibrium of g_{it} and $\triangle\tilde{k}_{it}$, the up-right shift of the KK curve derived from a whole-brief decrease in population growth rates is more than compensated by a down-left shift of the KK curve derived from a clearly declining path in investment rates. Therefore, we interpret the joint movements in s, n and δ as a contraction of the KK curve led by a declining path in investment rates.

However, since the panel cointegration results revealed a negative long-run relationship between g_{it} and $\triangle\tilde{k}_{it}$, the inwards Solownian curve shift due to the falling investment rates, has contributed to the slowdown in output per worker growth rates but our empirical results and our data imply that declining investment rates are not the principal explanation for declining per worker growth. Figure 7 shows that capital stock per efficiency unit of labor shows a rising trend during our sample period. Since the theoretical model predicts that a contraction of the KK curve (motivated by a decrease in investment rates) results in lower output per worker growth accompanied by less capital per efficiency unit of labor, investment rates are not the key explanation for the slowdown in output per worker growth. In contrast, as we have seen that product per worker growth is declining and capital per efficiency unit of labor grows over time, the implication of theoretical model of Aghion and Howitt is that this endogenous situation is mainly explained by an exogenous decrease in the efficiency of R&D investments. In this respect, Figure 3 shows the new equilibrium from situation a to situation b, in which the economy is in its steady-state equilibrium (a) and then it shifts to a situation (b) characterized by lower long-run output per worker growth with a greater capital stock per efficiency unit of labor.

How to understand a situation in which investment rates falls and capital per efficiency unit of labor grows? The reason implied by the theoretical model is that labor-augmenting tecnological progress is endogenously falling over time, which is motivated mostly by an exogenous deterioration of the environmental conditions for the transformation of capital investment in new technology. This result means that marginal productivity of capital stock for making innovations has decreased, which lowers returns on R&D spending. Declining investment rates and decreasing efficiency of R&D investments explaining low growth rates are consistent with various findings in the literature. For instance, Desroches and Francis (2006) and Eichengreen (2015) argue that the slowdown in productivity growth has been related to a decrease in real interest rates since the 1980s, which can be explained by an excess of desired savings over desired investments (Fisher, 2006; IMF, 2014; Eichengreen, 2015). Furthermore, Eichengreen (2015) points out that low real interest rates and the slow economic growth could be associated with a dearth in attractive investment opportunities. For instance, Gordon (2012) argues that returns on innovation processes have slowed since the 1970s.

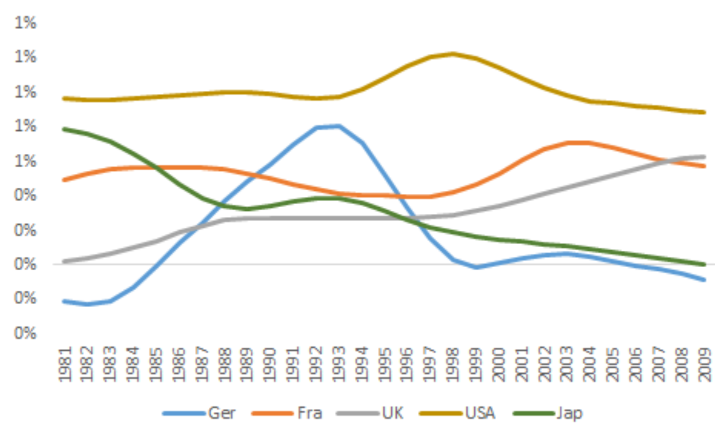
Since we conclude that a decrease in the efficiency of R&D expenditures is the key explanation for

Figure 4: Investment rates



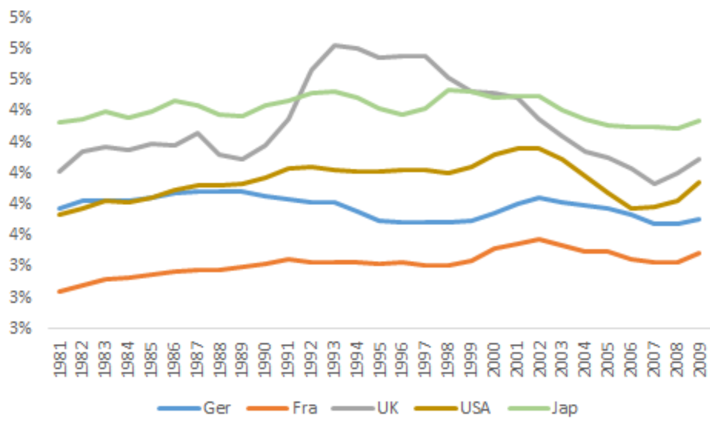
Source: Penn World Tables version 8.1.

Figure 5: Population growth rates



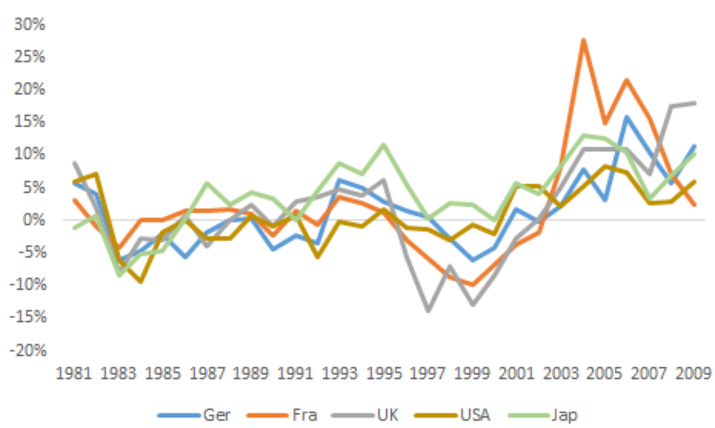
Source: Penn World Tables version 8.1 and authors' calculations.

Figure 6: Depreciation rates



Source: Penn World Tables version 8.1.

Figure 7: Capital stock per efficiency unit of labor growth rates



Source: Penn World Tables version 8.1 and authors' calculations.

declining output per worker growth rates, one implication is that economic policies must be focused in generating a suitable environment for investment and R&D expenditures to be transformed into new technology. Monetary and fiscal policy stimuli have recently demonstrated (in Japan, USA, and several European countries) their serious difficulties in recovering previous product per worker growth numbers. Improving conditions under which investment and R&D expenditures generate new technology would be a factor for a stronger productivity growth which would complement monetary and fiscal stimuli. In particular, the IMF (2015) found that the key reason for the negative trend in TFP growth in advanced economies has been the existence of policy rigidities that are hurdles to an efficient allocation of capital and labor inputs between and within sectors (Hopenhayn and Rogerson, 1993; Lagos, 2006; Foster, Haltiwanger, and Syverson, 2008; IMF, 2015). Focusing economic policy on a reduction in such rigidities could probably lead to a suitable environment for investment and R&D expenditures to be transformed in new and better technologies.

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