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A Romerian contribution to the empirics of economic growth

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Abstract

Mankiw, Romer, and Weil (1992) made the Solovian set up widely used to test the determinants of economic growth and the speed of convergence. In accordance with the nature of the Solow framework, almost all empirical growth studies considered technological progress constant and identical across countries and over time, and hence underemphasized its role. In this study, in order to overcome this weakness, we propose that the Mankiw, Romer, and Weil (1992) set-up should be replaced by the Solovianized Romer (1990) framework, thus allowing the role of technology to be considered in the empirical analysis. In particular, within this framework, the growth rate of technology varies across economies and over time. We estimate the convergence equation derived from Solovianized Romer model for 31 OECD countries for the period 1980–2008 by applying the system GMM approach. The empirical findings of the model support the conditional convergence hypothesis, but reveal a lower convergence rate than that predicted by the existing literature. As a policy implication, we argue that, investment in R&D and human capital are important determinants of convergence, and in cases where economies are unable to allocate sufficient resources to R&D, policy makers should ease the diffusion of technology (e.g., via FDI or trade) in order to retain a high convergence rate.
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1. Introduction

Empirical studies on economic growth have expanded rapidly since the early 1990s. In 1990, only one publication appeared in SSCI-indexed economics journals with key words "empirical" and "economic growth" in topic search. By 1995, this had risen to 49. After this, the number increased over successive five year periods to 71, 131, and 225 and, by January 2012, a total of 2223 articles in this area had been published in SSCI-indexed economics journals. The rapid development of the new economic growth theory, the availability of richer databases, and improvements in econometric techniques, which provide a higher degree of precision and greater confidence in the analysis and findings, have all contributed to the rapid expansion of the empirical studies in that direction.

The neoclassical growth theory (i.e., Solow framework), under the assumptions of constant returns to scale and diminishing marginal returns to capital, reveals that the investment rate is the major determinant of economic growth in the transitional period, and that technological progress, which is regarded exogenous to the system, is the determinant of the long run growth. Two (interrelated) empirical research strands have emerged from this theory. The first strand aimed to determine the sources of international differences in income per capita. Even though the findings were not fully conclusive, a wide range of studies have demonstrated that investment in physical and human capital, innovation and R&D, as well as macroeconomic policies, trade openness, the institutional framework, geography, demographic trends, political and socio-cultural factors are all likely to have important impacts on the process of economic growth.[1]

The second strand investigated whether low-income economies grow faster than the high-income ones, in line with the neoclassical growth theory, which conjectures that countries having identical characteristics but lower initial physical capital will grow at a higher rate due to diminishing marginal returns premise. This argument has quickly become dubbed 'Convergence Analysis'. Early works in this direction were Baumol (1986), Abramovitz (1986) and De Long (1988). Research in this area dramatically increased, however, after Mankiw, Romer, and Weil (1992), which rapidly emerged as the fundamental empirical framework to test for convergence, as their suggested equation was very well-fitted for empirical research.[2] MRW (1992) estimates an augmented Solow model, which includes human capital stock in addition to physical capital stock. Their model reveals that convergence in income per capita is determined by population growth, and the accumulation of physical and human capital. Within this set up, they find strong evidence for (conditional) convergence: countries with similar technologies and rates of physical and human capital accumulation converge in income per capita. Given the Solovian set up, and the fact that technology is exogenous, a simplification adopted by MRW (1992) was to assume no variation in technological growth across countries.[3] Following MRW (1992), most empirical studies concerned with the convergence issue or on sources of international differences in income per capita, not only treated technology as an exogenous component, but in addition, regarded it

[1] See, for example, Sala-i-Martin (1997) and Levine and Renelt (1992).
[2] Henceforth, MRW (1992).
[3] In particular, it was taken as 0.02. In contrast, there are many TFP studies such as Fagerberg (1994), Young (1994) and Young (1995), showing country-specific TFP growth. Howitt (2000) documents that technology differences are significant across countries.

only a component in the constant term in econometric sense.[4] The implicit assumption behind this misconception was perhaps instantaneous and costless diffusion of technological progress. Many convergence studies, including Islam (1995), Caselli, Esquivel, and Lefort (1996), Murthy and Chien (1997), and Nonneman and Vanhoudt (1996) estimated the convergence rate in the range 0.02–0.10. These studies used equations in which convergence takes place through the adjustment of the capital output ratio, rather than changes in technology or its determinants. We believe, as a result of this stance, a large body of empirical studies on conditional convergence has overemphasized the role of capital accumulation, while underestimating the role of technological change.[5]

We argue that one major reason for the convergence literature underemphasizing the varying role of technological change across countries and over time is the over-simplicity of the Solovian framework. As mentioned above, variables such as investment/GDP and population growth rate are capable of explaining economic growth *only* in the transitional period. Conversely, technological change plays a continual determining role at every stage of economic growth, transitional or long run, a fact which is overlooked in the convergence literature.[6] It is also possible that derivation of the convergence equation in the neighborhood of the steady state has contributed to this underestimation. In this respect, the convergence literature needs an augmented framework that allows differentiation of economies on the sources of economic growth in general, and on technological change in particular.[7]

Another result of the over simplicity of the Solovian framework has been the superficial extension of the convergence equation by adding a variety of variables, ranging from fiscal variables to trade variables, and from monetary and political variables to institutional and social factors. Levine and Renelt (1992) identify at least 50 such variables. Most empirical studies selected only a small number of explanatory variables from the superficial 'pool of variables' in attempting to explain economic growth through establishing a statistically significant relationship. In almost most instances, there was no explicit theory at all.[8]

This paper aims to contribute to resolving the aforementioned weaknesses of empirical economic growth literature. In particular, we aim to show the contribution of technology to convergence and economic growth under exogenous technological change and by developing a framework which is open to extension in several directions for future study. To this end, we propose an easily-testable framework, which incorporates the two major strands of theoretical growth literature, namely, the neoclassical growth model of Solow (1956) and the endogenous

[4] Panel data studies initiated by Islam (1995) and Caselli et al. (1996) overcome the overall weakness of convergence literature to a certain extent by allowing for individual country effects to capture the technology differences across countries.

[5] However, Easterly and Levine (2001) show clearly that "the "residual" (total factor productivity, TFP) rather than factor accumulation accounts for most of the income and growth differences across countries".

[6] As the complete solution of Fundamental Equation of Growth of Solow is possible, the role of technology during the transitional period can easily be observed.

[7] Another issue is the endogeneity of technological change. In this paper, however, we take technological change to be exogenous to derive an equation comparable with established econometric practice.

[8] Durlauf, Kourtellos, and Tan (2008), investigating the strength of empirical evidence for various growth theories when there is model uncertainty, describes this extemporaneousness as follows: "individual papers typically employ regressions that include modest subsets of the body of regressors that have been proposed in the literature as a whole. Others employ a 'kitchen sink' approach to evaluate the relative evidentiary support of competing growth theories. In such an exercise, a large number of variables are included in a regression and those variables that prove to be significant are then declared to be the important determinants of growth while the others are dismissed as unimportant" (Durlauf et al., 2008:329).

technological change model of Romer (1990).[9] The exogenous allocation of consumption-saving tradeoff, borrowed from the first strand, is incorporated into the second strand in order to make the resulted solution fit for empirical research, as in the case with MRW (1992). We suggest naming the framework 'Solovianized Romer model'.[10] The model has the potential to overcome two important weaknesses of the convergence literature. First, it develops a theory-backed convergence equation, in which the rate of technological change varies across economies, reflecting its dependence on the characteristics of R&D sector.[11] Second, as it is a three-sector model, it allows extensions in several directions, and enables the use of theory to test the contribution of a particular variable in growth process. In addition, the study introduces human capital to the model à la Romer (1990), which is more elegant, compared to MRW (1992) tradition. We consider the treatment of human capital as a simple duplicate of physical capital, à la MRW (1992), as being over-mechanical, as it undervalues the unique role played by human capital. We argue that this is a further improvement over MRW (1992).

The paper presents a theoretical framework, which to a large extent reproduces the convergence equation of MRW (1992) with a theoretical support which allows technological progress to be treated asymmetrically across economies and over time.[12] The convergence equation derived necessarily implies that technological change is different across economies and depends on the characteristics of the R&D sector in general, an approach which, to the best of our knowledge, has only rarely been considered in the literature. We believe that this is an important step toward understanding the genuine convergence mechanism, as many developing countries provide a minimal contribution to technological progress, and these economies generally have a low R&D intensity. This study addresses the apparent lack of rigorous econometric work aimed at assessing the impact of different technological intensities on economic growth and convergence. More than this, the point in the theoretical framework at which Solow (1956) meets Romer (1990) brings into forefront in a more elegant way the role of human capital (in the final-good and R&D sectors) in convergence, since it is no longer treated solely as a mechanic duplicate of physical capital, as has been the case since MRW (1992).

[9] There is a concrete reason why we have chosen the Romer (1990) framework. The first-generation endogenous growth models emphasized R&D activities as major force behind economic growth (cf., Aghion & Howitt, 1992; Grossman & Helpman, 1991; Romer, 1990). Since the scale-effect prediction of R&D-based endogenous growth models were not supported by the data (cf., Jones, 1995), this led to the emergence of second generation endogenous growth or semi-endogenous growth models, which assumes that the rate of technological progress in any individual country depends on its research intensity, that is, the proportion of the labor force employed in the R&D sector and the proportion of income devoted to R&D sector. Some studies in that direction are Ha and Howitt (2007), Howitt (2000), Zachariadis (2004), Madsen (2008) and Ulku (2007). In particular, Ulku (2007) notes that two effective measures of R&D intensity are the share of researchers in the labor force and the share of R&D expenditures in GDP. The current paper makes use of these two variables to explain convergence in the empirical part of the study.

[10] The primitive idea of this framework may also be found in Whelan (2012).

[11] There are many studies, such as Nonneman and Vanhoudt (1996), Murthy and Chien (1997) and Keller and Poutvaara (2005), in which the stock of knowledge (or its change) is introduced to the model directly (and exogenously) through the production function. In contrast, in this study, the know-how is introduced to the model through a dynamic general equilibrium model.

[12] We are aware of the fact that our model has several limitations and simplifications that make it less than perfect. Nonetheless, our aim in this paper is not solely to develop a good-looking theoretical model but a structure to support empirical work. The model derives an MRW-like convergence equation at the cost of assuming exogenous allocation of human capital between final good and R&D sectors. In the working paper version of this paper, we discuss three extensions. We will refrain from discussing these in this paper, as they do not add radically different insight. Interested readers may refer to Bayraktar-Sağlam and Yetkiner (2012).

The empirical part of the paper estimates the Solovianized Romer model for 31 OECD countries across the period 1980–2008 by employing system GMM approach. We have run the basic theoretical model by adopting three different econometric techniques, OLS, Within Group and system GMM. The dependent variable for all regressions is the log differences in GDP per working person. The identifying nature of our empirical equation is that technological progress, which is proxied by the share of R&D workers in the labor force, together with population growth rate, is considered an explanatory variable in addition to other standard explanatory variables (that is, the logarithm of the initial GDP, the logarithm of the investment to GDP ratio, and the logarithm of the human capital). To check the robustness of the results, the share of R&D expenditure in GDP is also used as a proxy for the technological progress. Our findings can be summarized as follows:

1. All runs imply a convergence rate lower than suggested by the literature in general.
2. The investment rate has a positive and statistically significant contribution to convergence in all runs.
3. Human capital has a positive and frequently significant impact on economic growth in all runs.
4. The effective depreciation rate has the expected sign, although may not be statistically significant in all runs.

Our initial findings suggest that (i) the framework is suitable for use in empirical growth studies, (ii) has the potential to explain convergence behavior by also considering technological change. We are aware of the fact that our results can only be considered preliminary, and that further test of the framework is needed. In this respect, this paper should only be considered as a first step in the process of developing a more realistic test of convergence hypothesis. The organization of the paper is as follows. Section 2 presents a theoretical framework, which develops growth and convergence equations for empirical use. Section 3 is reserved for the empirical research. We show that the convergence rate is lower than what is suggested by the conventional literature. Section 4 concludes the paper.

2. The model

Following Romer (1990), we assume that the production technology has an additively separable characteristic[13]:

$$Y = H_Y^{1-\alpha} \int_0^{A(t)} X_i^{\alpha} di, \quad 0 < \alpha < 1 \tag{1}$$

where Y is final good (GDP), H_Y is the amount of human capital used in final good production, $1-\alpha$ is the production elasticity of that human capital, X_i are intermediate goods (varieties), and

[13] As the Romer (1990) model is widely known we will be as compact as possible in its presentation. We purposefully refrained from defining unskilled labor as the third argument in the production function to keep derivations simple. This simplification will result in having a long-run growth equation in which some coefficients are unitary and a convergence equation with identical coefficients for human capital share and previous period income. We show in Annex A of Bayraktar-Sağlam and Yetkiner (2012) that they should not be taken literally, as it is due to our simplified approach.

$A(t)$ is the number of intermediate goods at time t. We assume that human capital is allocated between the final-good and R&D sectors, that is,

$$H_Y = \theta_Y \cdot \overline{H} \quad \text{and} \quad H_{\text{R\&D}} = \theta_{\text{R\&D}} \cdot \overline{H} \tag{2}$$

where H_Y ($H_{\text{R\&D}}$) is amount of human capital employed by the final-good (R&D) sector, θ_Y ($\theta_{\text{R\&D}}$) is the respective share of human capital, and $\overline{H}$ is the stock of human capital, which is constant. Note that $\theta_Y + \theta_{\text{R\&D}} = 1$ at all times. In original Romer model, the allocation of human capital between final good sector and R&D sector is endogenous. Below, given our aim to derive an empirically usable convergence equation, we will assume that the tradeoff is exogenous to the model. Hence, θ_Y and $\theta_{\text{R\&D}}$ are constant.[14]

Final good sector

We assume that there is perfect competition in the final-good sector and we take final output to be the numéraire. Hence, the profit equation is

$$\Pi_Y = \overline{H} \cdot \left[\theta_Y^{1-\alpha} \int_0^{A(t)} x_i^{\alpha} di - w_Y \cdot \theta_Y - \int_0^{A(t)} p_i \cdot x_i di \right] \tag{3}$$

where x_i are intermediate goods per human capital, w_Y is the real wage rate for the skilled labor in final good sector, and p_i is the user cost of intermediate-good i. The level of demand for each intermediate and human capital employed at final-good production follows directly from the first order profit maximization conditions:

$$\frac{\partial \Pi_Y}{\partial H_Y} = (1-\alpha) \cdot \theta_Y^{-\alpha} \cdot \int_0^{A(t)} x_i^{\alpha} di - w_Y = 0 \tag{4a}$$

$$\frac{\partial \Pi_Y}{\partial X_i} = \alpha \cdot \theta_Y^{1-\alpha} \cdot x_i^{\alpha-1} - p_i = 0, \quad \forall i \tag{4b}$$

Eqs. (4a) and (4b) are inverse demand functions for human capital employed at final-good production and individual intermediate i.

Intermediate-good sector

We assume that the intermediate-good producing sectors only use 'raw' capital in order to produce an intermediate good: $K_i = X_i$ (or $k_i = x_i$ in per human capita terms), where K_i measures the total amount of raw capital going into intermediate good of type i. Raw capital can be rented at the real rate of interest r plus depreciation δ, $r' \equiv r + \delta$, where r' is the rental rate of capital. We assume that each intermediate-good producer has monopoly power right over the production and sale of the good X_i, as the patent (the blueprint) of the product belongs to it. Hence, the seller of the intermediate good faces a downward-sloping demand curve (cf., Eq. (4b)). Therefore, the profit that the ith monopolist has to maximize is $\Pi_i = \overline{H} \cdot [p_i \cdot x_i - r' \cdot x_i]$. The profit maximizing price for the intermediate good i is obtained as $p_i = p = r'/\alpha$, which underlines the fact that price is identical across intermediates. Substitution of price information in Eq. (4b) reveals that $x_i = x = \theta_Y(\alpha^2/r')^{1/(1-\alpha)}$, the quantity of each intermediate are identical across varieties. Identical prices and quantities across intermediates naturally imply that profits are identical across intermediates,

[14] The nature of this assumption is not uncommon in the literature. So-called semi-endogenous growth models, e.g., Jones (1995), has the same nature, in which, economic growth is function of exogenous population growth rate. Interested readers may refer to Annex B in Bayraktar-Sağlam and Yetkiner (2012) to see how results do change when labor allocation is endogenous.

$\pi_i = \pi \equiv \Pi_i/\overline{H} = (1-\alpha)\cdot\alpha\cdot\theta_Y^{1-\alpha}\cdot x^{\alpha}$. Given that price, quantity, and profit are identical across intermediates, it must be true that $k = \int_0^{A(t)} x_i di = x\cdot A$. Using this information in (1) yields

$$y = \theta_Y^{1-\alpha}\cdot x^{\alpha}\cdot A \quad \text{or} \quad y = \theta_Y^{1-\alpha}\cdot k^{\alpha}\cdot A^{1-\alpha} \tag{5}$$

Note from above derivations that $x = x(r)$ for a constant θ_Y. We will below show that real interest rate is constant at steady state and hence y and k grow at the rate of A.

R&D sector

À la Romer (1990), we will define the knowledge production function as $\dot{A} = a_{\mathrm{R\&D}}\cdot H_{\mathrm{R\&D}}\cdot A$. Given (2), the growth rate of knowledge accumulation, $\hat{A} = a_{\mathrm{R\&D}}\cdot\theta_{\mathrm{R\&D}}\cdot\overline{H} \equiv g$, is exogenous, as in MRW (1992).[15] The difference is that we now know the components of it. Given the standard perfectly competitive R&D sector assumption and the knowledge production function, the value of the latest patent may easily be determined as $V_{\mathrm{R\&D},A}(t) = \overline{H}\cdot\pi(t)/r(t)$, which is an arbitrage rule stating that the return out of investing an amount equal to the value of patent in the 'financial market' at time t, $r(t)\cdot V_{\mathrm{R\&D},A}(t)$, must be equal to profit $\overline{H}\cdot\pi(t)$ derived from the latest patent at time t. The arbitrage rule is valid as long as per capita profit is constant, which is true at steady state. Finally, using the arbitrage rule in the equilibrium process condition in R&D sector, $V_{\mathrm{R\&D},A}\cdot a_{\mathrm{R\&D}}\cdot A = w_{\mathrm{R\&D}}$, gives $\overline{H}\cdot\pi(t)/r(t)\cdot a_{\mathrm{R\&D}}\cdot A = w_{\mathrm{R\&D}}$, where $w_{\mathrm{R\&D}}$ is the real wage rate in the R&D sector.

Consumption-saving tradeoff

We assume that the consumption-saving tradeoff is exogenous, á la Solow (1956). This assumption allows us to simplify Romer (1990) considerably, without losing the main deriving forces of the role of technological progress on economic growth. We assume that capital accumulation is led by:

$$\dot{K} = s\cdot Y - \delta\cdot K \tag{6}$$

where K is capital, s is the exogenous saving (investment) rate, Y is output and δ is depreciation rate of capital.

Long-run equilibrium

Let us now determine the steady state value of unknowns of the model. To this end, first, by using the capital accumulation function in (6), we can show that

$$\hat{\tilde{k}} = s\cdot\theta_Y^{1-\alpha}\cdot\tilde{k}^{\alpha-1} - (\delta+g) \tag{7}$$

where a tilde on top of a variable defines per efficient human capita, e.g., $\tilde{k} = K/(A\cdot\overline{H})$, which does not grow at the steady state. Hence, the steady state value of capital per efficient human capita is $\tilde{k}_{ss} = \theta_Y\cdot(s/(\delta+g))^{1/(1-\alpha)}$, where subscript ss indicates steady state. By construction, this may be interpreted as the supply of capital per efficient human capita in the model. We need to define also demand for capital. Recall that we had already indicated that $k = x\cdot A$, which implies $\tilde{k} = x$. Hence, at steady state, $(s/(\delta+g))^{1/(1-\alpha)}\cdot\theta_Y = \theta_Y\cdot(\alpha^2/r'_{ss})^{1/(1-\alpha)} \Rightarrow r'_{ss} = \alpha^2(\delta+g)/s$. Note that r'_{ss} responds negatively to an increase in the saving rate and positively to the exogenous growth rate, which are intuitive. The rest of the model can be solved through substitution. In particular, one should be able to get $\tilde{y}_{ss} = \theta_Y\cdot(s/(\delta+g))^{\alpha/(1-\alpha)}$. Finally, it is straightforward to show that $\hat{y}_{ss} = \hat{k}_{ss} = \hat{A} \equiv g$, for $y = Y/\overline{H}$ and $k = K/\overline{H}$. The growth rate of GDP increases if (i) the productivity of R&D sector and (ii) the size or the share of human capital increases. It can

[15] A hat on top of a variable indicates the growth rate.

be clearly shown that the real rate of interest, the price of intermediate-good, the quantity of each intermediate-good and the profit for each intermediate are all constant at the steady state. There are two approaches to use the Solovianized Romer framework for empirical research. Below, we show them.

2.1. Determinants of steady state growth

Through taking natural log of $\tilde{y}_{ss} = \theta_Y \cdot (s/\delta + g)^{\alpha/(1-\alpha)}$, and after simple algebraic transformation, we can show that

$$\ln \quad y_{ss} = a + g \cdot t + \ln[\theta_Y] + \frac{\alpha}{1-\alpha}\ln[s] - \frac{\alpha}{1-\alpha}\ln[\delta + g] + \varepsilon \tag{8}$$

where $Ln[A(0)] = a + \varepsilon$ and $g = a_{\text{R\&D}} \cdot \theta_{\text{R\&D}} \cdot \overline{H}$. Eq. (8) may be considered as a base for studying long-run determinants of economic growth, á la MRW (1992).[16] The main contribution of Eq. (8) is that the exogenous growth rate is decomposed into its components. In addition, there are two additional added values in (8). First, human capital is incorporated into the model through a general equilibrium modeling approach. Second, the three-sector structure of Romer framework has obvious advantages over the one-sector Solow framework in terms of flexibility for extending the framework in several research directions. All in all, we believe (8) is richer than the Solow version for empirical research.

2.2. Convergence

Let us first express (7) in terms of $\tilde{y}$, as it is better to directly work with GDP per efficient human capita for derivation of convergence equation. To this end, through log differentiating the production function, and after simple arithmetic operations, we may re-express (7) in terms of $\tilde{y}$:

$$\frac{dLn(\tilde{y})}{dt} = \alpha[s \cdot \theta_Y^{(1-\alpha)/\alpha} \cdot e^{((\alpha-1)/\alpha)Ln(\tilde{y})} - (\delta + g)] \equiv \phi(Ln(\tilde{y})) \tag{9}$$

The differential equation in (9) is not linear. Through log-linearization, we find that

$$\frac{dLn(\tilde{y})}{dt} \approx -(1-\alpha)(\delta + g)[Ln(\tilde{y}) - Ln(\tilde{y}_{ss})] \tag{10}$$

Let us now define $\nu = (1-\alpha)(\delta + g)$. Just to understand the meaning of (10), suppose that $Ln(\tilde{y}) < Ln(\tilde{y}_{ss})$ that is, income is approaching its steady state from below. As $Ln(\tilde{y}) - Ln(\tilde{y}_{ss})$ is negative, $-\nu \cdot [Ln(\tilde{y}) - Ln(\tilde{y}_{ss})]$ would be positive. The higher the difference between $Ln(\tilde{y})$ and $Ln(\tilde{y}_{ss})$, the higher would be $-\nu \cdot [Ln(\tilde{y}) - Ln(\tilde{y}_{ss})]$. Then, an economy further away from its steady state would have a higher growth rate. That is, the speed that an economy converges to its own steady state is $d(\hat{\tilde{y}})/dLn(\tilde{y}) \approx -\nu$. Notably, assuming an identical rate of technological progress causes a downward bias in the convergence rate for those that have higher rates of technological progress and upward bias for those having lower rates of technological progress. The solution of

[16] Recall that in the standard Solow set-up, the steady state value of output per efficient capita is obtained as $\tilde{y}_{ss} = (s/(\delta + g))^{\alpha/(1-\alpha)}$ for $Y = K^\alpha (A \cdot \overline{H})^{1-\alpha}$ and $A = A(0) \cdot e^{g \cdot t}$. Hence, the determinants of economic growth are found as $\ln y_{ss} = a + g \cdot t + (\alpha/(1-\alpha))\ln[s] - (\alpha/(1-\alpha))\ln[\delta + g] + \varepsilon$, where $Ln[A(0)] = a + \varepsilon$. Notably, the determinants of g and $A(0)$ are undefined in that case.

Table 1
Basic statistics.

Variables	Mean	Std. Dev.	Min	Max
Real GDP per capita	21,291	8858	5326	62,731
Share of investment in GDP	22.8	3.8	37	17
Secondary enrollment rates	45.6	13.9	8.2	88
The share of				
R&D personnel in the labor force	4.9	2.68	0.44	15
R&D expenditure in GDP	1.56	0.83	0.2	3.9
The population growth rate	0.65	0.68	−0.4	6

the linearized differential equation in (10) yields:

$$Ln\left(\frac{Y(t_2)}{\overline{H}}\right) - Ln\left(\frac{Y(t_1)}{\overline{H}}\right) = (1 - e^{-\nu\cdot\tau})\left(\frac{\alpha}{1-\alpha}\right)\cdot Ln(s)$$
$$-(1 - e^{-\nu\cdot\tau})\left(\frac{\alpha}{1-\alpha}\right)\cdot Ln(\delta + g) - (1 - e^{-\nu\cdot\tau})\cdot Ln\left(\frac{Y(t_1)}{\overline{H}}\right) + (1 - e^{-\nu\cdot\tau})\cdot Ln(\theta_Y)$$
$$+(1 - e^{-\nu\cdot\tau})\cdot Ln(A(0)) + g(t_2 - t_1 e^{-\nu\cdot\tau}) \qquad (11)$$

where $\tau = t_2 - t_1$. The LHS of (11) is the growth rate of income per human capita relative to initial level. Determinants of this change take place on the RHS. There is at least two-fold improvement relative to MRW (1992). First, contrary to many previous studies, we do not have to consider g the same and constant across economies, which was previously the common assumption. Second, we are able to incorporate human capital into the model in a more elegant way in the convergence equation. Another value added over the existing literature is that the three-sector nature of the model allows further extensions in several directions by using the competitive equilibrium approach.

3. Data, methodology and findings

3.1. Data

The empirical analysis is based on the OECD database, World Development Indicators database and Barro-Lee Education database. Due to missing R&D data, the sample we study is limited to OECD countries and period 1980–2008. Data on real GDP per capita, the share of R&D personnel in the labor force, the share of R&D expenditure in GDP, and the growth rate of population are from OECD database. The data on saving rate, which is proxied by the share of investment in GDP, comes from World Development Indicators database. The data for human capital, which is proxied by secondary-enrollment rates, are from the Barro-Lee Education dataset (2010 version). The sample statistics are shown in Table 1.

3.2. Empirical methodology and findings

In this section, we estimate a version of (11), which allows us to compare our results with MRW (1992). In estimations, we no longer assume constant and identical technology growth, g, across economies. We proxy the growth rate of technology of (11) by the R&D intensity of the countries, measured either by the share of income devoted to R&D or by the share of R&D labor in total labor force. The equation is estimated for 31 OECD countries over the period 1980–2008.[17] According to standard practice in the empirical growth literature, the data is transformed into five-year averages over the period 1980–2008 in order to eliminate the cyclical component. The estimated model has the following form:

$$\ln y_{it} - \ln y_{it-1} = \beta_1 \ln y_{it-1} + \beta_2 \ln s_{it} + \beta_3 \ln h_{it} + \beta_4 \ln[n_{it} + g_{it} + \delta] + \mu_i + \phi_t + \varepsilon_{it} \tag{12}$$

In (12) $\beta_1 = -(1 - e^{-\nu \cdot \tau})$ is the coefficient of initial level of income per capita. Notably, this coefficient is expected to be negative, which is consistent with the convergence idea. Coefficients $\beta_2 = (1 - e^{-\nu \cdot \tau})(\alpha/(1-\alpha))$ and $\beta_3 = (1 - e^{-\nu \cdot \tau})$ show the contribution of investment rate and human capital on convergence, which are expected to be positive. $\beta_4 = -(1 - e^{-\nu \cdot \tau})(\alpha/(1-\alpha))$ measures the joint effect of population growth rate and rate of technological progress augmented by depreciation on convergence. Finally, $\mu_i = (1 - e^{-\nu \cdot \tau}) \cdot Ln(A(0))$ measures country fixed effects and $\phi_t = g(t_2 - t_1 e^{-\nu \cdot \tau})$ measures time fixed effects. The dependent variable is the change in the logarithm of growth in real GDP per head of population aged 15–64 years expressed in 2000 purchasing power parities. The lagged dependent variable is the logarithm of lagged growth in real GDP per head of population aged 15–64 years expressed in 2000 purchasing power parities. The logarithm of s_{it} and h_{it} stand for physical and human capital investment rates, respectively. The logarithm of $n_{it} + g_{it} + \delta$ is the effective depreciation rate. The depreciation rate δ is assumed to be 0.03, as in MRW (1992). Deviating from MRW (1992), the effective depreciation rate includes two components, the population growth rate and the technology growth rate, both of which change across countries and over time. g_{it} is proxied either by the share of R&D expenditure in GDP or by the share of R&D labor in total labor force. Country specific and time specific effects are represented by μ_i and ϕ_t, respectively, and $\beta_1, \ldots, \beta_4$ are parameters to be estimated.

To estimate the parameters of a dynamic panel like Eq. (12) we utilize OLS, Within Group and system GMM estimation methods. However, OLS and Within Group estimators provide biased and inconsistent estimates in a dynamic panel framework (Hsiao, 1986; Nickell, 1981). In line with Bond, Hoeffler, and Temple (2001) and Hoeffler (2002), estimates obtained from OLS estimator can be regarded as an upper bound, whereas estimates obtained from Within Group estimator regarded as a lower bound. Due to the existence of biased estimates from OLS and Within Group estimators, in order to estimate the parameters of the above equation, we adopt the system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). There are four reasons for selecting the system GMM. Firstly, it provides consistent and efficient parameter estimates, even in the presence of measurement error and endogenous regressors. Second, it is highly recommended for empirical growth models (Bond et al., 2001). Third, it particularly suits the short time dimension panel data sets. A final benefit of this system is its greater efficiency, compared to the difference GMM, in dynamic panel data, as lagged levels in the latter can be weak instruments for subsequent changes (Blundell and Bond, 1998, 2000; Blundell, Bond, and Windmeijer, 2000).

System GMM procedure consists of a joint estimation of the equation in first-differences and in levels. The instruments used for the equations in first-differences are the lagged levels of the regressors, and for the equations in levels, the lagged first-differences of the explanatory variables.

[17] The data set is a slightly unbalanced panel with 186 observations where the data is missing for some countries for some periods. The list of countries is in Annex A.

Table 2
Estimation of the Solovianized Romer Model (the share of labor devoted to R&D).

Dependent variable: log differences in GDP per working person						
	OLS	OLS	Within group	Within group	System GMM	System GMM
Constant	0.206	0.183	2.468***	2.222***	0.261	0.408
	(0.465)	(0.277)	(0.393)	(0.412)	(2.063)	(1.811)
$Ln(y_{it-1})$	−0.062***	−0.060***	−0.298***	−0.2927***	−0.121***	−0.208***
	(0.025)	(0.027)	(0.030)	(0.032)	(0.163)	(0.138)
$Ln(s_{it})$	0.119*	0.111**	0.204***	0.203***	0.419**	0.453**
	(0.043)	(0.043)	(0.064)	(0.064)	(0.187)	(0.184)
$Ln(h_{it})$		0.026***		0.044*		0.136*
		(0.015)		(0.023)		(0.074)
$Ln(n_{it}+g_{it}+\delta)$	0.045**	0.044**	−0.001	0.005	−0.012	−0.075
	(0.017)	(0.017)	(0.036)	(0.037)	(0.089)	(0.088)
R^2	0.97	0.97	0.98	0.98		
Implied v	0.012	0.012	0.070	0.069	0.025	0.046
Number of observations	150	150	150	150	150	150
Number of groups			30	30	30	30
Number of instruments					22	21
Hansen test p value					0.22	0.28
Difference Hansen p value					0.10	0.14
M2					0.089	0.102

Note: Time dummies are included in all regressions. Heteroskedasticity-consistent standard errors are in parentheses. The test statistics for second order correlation is given by M2 and p values in brackets.
* The coefficient is significant at 10%.
** The coefficient is significant at 5%.
*** The coefficient is significant at 1%.
The $Ln(y_{i,t-1})$ is treated as predetermined variable and $Ln(s_{i,t})$, $Ln(h_{i,t})$ and $Ln(n_{i,t}+g_{i,t}+\delta)$ are treated as endogenous regressors.

The consistency of the system GMM estimator depends on the two conditions: First, there should be no serial correlation in the error term, and second, the instruments should not be correlated with the error term. There are two key diagnostics to check for these problems. The Arellano-Bond test for serial correlations examines the first and second order correlations of the first differenced residuals, while the conventional Hansen test of over-identifying restrictions checks the correct specification and the validity of the instruments. In addition, the number of cross section units should be larger than the number of instruments.[18]

Table 2 presents the empirical results when g is proxied by the share of labor devoted to R&D.[19] First, OLS levels regression was run. The lagged dependent variable and the investment rate are significant and have the expected sign. The negative coefficient on the lagged dependent variable is interpreted as showing the existence of conditional convergence. The implied speed of convergence, v, is around 1.2 percent per annum. The effective depreciation rate, $n_{it}+g_{it}+\delta$, is positive and significant where g is proxied by the share of labor devoted to R&D. The second column of the OLS, in which the role of human capital accumulation is added to the model in

[18] We have use the command of collapse available in Stata (v. 10) as mentioned in Roodman (2009).
[19] Roodman (2009) "xtabond2" command was used in Stata (v. 10) for the system GMM estimations. Windmeijer (2005) is implemented for the small sample correction.

the form of secondary enrollment rates, has a positive and significant effect on economic growth. Next, Within Group estimators are used, and results are presented in the third and fourth columns of Table 2. Since the coefficient of the lagged dependent variable is lower than that of the estimates with OLS, the implied speed of convergence is higher than the rate obtained by the OLS, that is, 7% per annum. The fourth column shows the Within Group estimates after the human capital variable is added. The human capital term is positive and significant. The effective depreciation coefficient is positive but insignificant. In conclusion, OLS and Within Group estimators reveal that there is conditional convergence, and the rate in OLS estimation is lower relative to Within Group estimation. The role of both human capital and physical capital accumulation on economic growth is positive and significant according to the OLS and Within Group estimators.

The last two columns of Table 2 show the system GMM estimates, which is our preferred estimator. The coefficients on lagged dependent variable have the expected negative sign and are highly significant, which is evidence of conditional convergence. Contrary to OLS and within effect estimations, the inclusion of human capital raises the convergence rate significantly under system GMM estimates. In particular, the convergence rate rises from 2.5% to 4.6% per year. It is notable that the coefficient of the lagged dependent variable in system GMM estimations falls between the upper and lower bounds suggested by OLS and Within Group. That is, the system GMM estimator is shown to be unbiased. The coefficients on the physical and human capital accumulation have the expected sign (positive) and are significant. The coefficient of the effective depreciation rate, the sum of population and technology growth augmented by the constant depreciation rate, however, is insignificant, though has the expected sign (negative). According to the specification tests reported in Table 2, the instruments are valid for the estimation of system GMM, which is clear from both the Hansen test and the difference Hansen test. The p values relating to the first and second order serial correlations, given by M2, reject the existence of the serial correlation. In this respect, the overall performance of all models is good in terms of valid instrument selection and of expected signs and of the significance level of coefficients.

To check the level of sensitivity of the results, Table 3 provides estimation of the Solovianized Romer model by proxying g with the share of R&D expenditure in GDP. The coefficient of the lagged dependent variable is negative and significant for all regressions. Notably, the rank of the convergence rate suggested by the three estimation methods in Table 3 are similar to the rank of convergence rates suggested by Table 2. That is, OLS yields the lowest and Within Group the highest convergence rate. According to the system GMM estimates, coefficients of the physical capital accumulation and human capital are positive and significant. The effective depreciation rate has a negative and significant impact on economic growth.

3.2.1. Discussion and policy implications

In Table 4, we present the implied convergence rate found in some benchmark studies and in our estimations. We also replicate the basic MRW (1992) model by employing the data set used in this paper (the last row). Bearing in mind that these studies use different data ranges and country groups, all the implied convergence rates, including the replica of MRW (1992), are always lower for our estimations. We conjecture that removing the identical and constant technology growth assumption of MRW (1992) from the model would result in a much lower rate of convergence because the heterogeneous rate of technological progress increases the variance of the data set and lowers the implied convergence rate. These results show the importance of investment in R&D and human capital in the achievement of higher convergence rates.

There are two main ways of realizing an identical and constant rate of technological progress across countries and over time, in accordance with our framework. First, resources allocated to

Table 3
Estimation of the Solovianized Romer Model (the share of income devoted to R&D).

Dependent variable: log differences in GDP per working person

	OLS	OLS	Within group	Within group	System GMM	System GMM
Constant	−0.089	−0.084	2.169***	2.015***	0.069	0.242
	(0.292)	(0.402)	(0.427)	(0.417)	(4.103)	(2.415)
$Ln(y_{it-1})$	−0.023***	−0.032***	−0.2784***	−0.2749***	−0.179**	−0.165***
	(0.024)	(0.027)	(0.031)	(0.032)	(0.380)	(0.233)
$Ln(s_{it})$	0.133**	0.123**	0.245***	0.243***	0.647***	0.374**
	(0.047)	(0.046)	(0.066)	(0.067)	(0.229)	(0.136)
$Ln(h_{it})$		0.030*		0.031		0.121*
		(0.017)		(0023)		(0.062)
$Ln(n_{it}+g_{it}+\delta)$	0.005	0.007	−0.043	−0.040	−0.201**	−0.136**
	(0.016)	(0.016)	(0.036)	(0.037)	(0.079)	(0.063)
R^2	0.97	0.97	0.94	0.94		
Implied ν	0.004	0.006	0.065	0.064	0.039	0.036
Number of observations	150	150	150	150	150	150
Number of groups			30	30	30	30
Number of instruments					15	25
Hansen test p value					0.30	0.14
Difference Hansen p value					0.14	0.25
M2					0.088	0.077

Note: Time dummies are included in all regressions. Heteroskedasticity-consistent standard errors are in parentheses. The test statistics for second order correlation is given by M2 and p values in brackets.
* The coefficient is significant at 10%.
** The coefficient is significant at 5%.
*** The coefficient is significant at 1%.
The $Ln(y_{i,t-1})$ is treated as predetermined variable and $Ln(s_{i,t})$, $Ln(h_{i,t})$ and $Ln(n_{i,t}+g_{i,t}+\delta)$ are treated as endogenous regressors.

Table 4
Implied convergence rates by selected studies.

	Method	Data	w/t human capital	w/human capital
MRW (1992)	OLS, Cross-sectional	22 OECD countries, 1960–85	0.0173	0.0203
Islam (1995)	OLS, Cross-sectional	22 OECD countries, 1960–85	0.0158	0.0187
	OLS, Pooled		0.0161	0.0162
	LSDV		0.1067	0.0913
Caselli et al. (1996)	System GMM	97 countries, 1960–85	0.128	0.0790
This paper	OLS, Pooled	31 OECD countries, 1980–2008	0.0128 (0.0047)[a]	0.0124 (0.0065)[a]
	Within Group		0.0708 (0.0653)[a]	0.0693 (0.0643)[a]
	System GMM		0.0258 (0.0394)[a]	0.0466 (0.0361)[a]
Adapted MRW (1992)	Cross-sectional	31 OECD countries, 1980–2008	0.0007	0.0011

[a] The implied convergence rates presented in parenthesis are due to Table 3.

R&D (e.g., the share of R&D expenditure over GDP or the share of human capital in R&D) must be very similar. Second, technological diffusion should be instantaneous and costless. If either of these conditions is not satisfied, it would be unrealistic to assume a constant and identical rate of technological progress. Our analyses show that the convergence rate declines substantially when the rate of technological progress is heterogeneous. This result has one very important policy implication: if sufficient resources cannot be allocated to R&D, policy makers should implement the second condition, which is, facilitating a rapid and costless diffusion of technology. This is necessary to enable countries, such as Turkey, which, for various reasons, are unable to allocate sufficient resources to R&D to catch up with other OECD member countries, such as Germany or U.S., allocating abundant resources to R&D. FDI and international trade appear to be two very effective mechanisms for this purpose.[20] In addition, our results suggest that a joint policy on R&D and human capital may accelerate the convergence rate.

4. Concluding remarks

Following MRW (1992), the greater part of the convergence literature has assumed that all countries face a common and constant technology growth rate. This assumption, however, is inconsistent with empirical regularity, as resources allocated to R&D are very different across countries and over time, and technological diffusion is not necessarily instantaneous and costless. Unless one of these conditions is satisfied, however, it would be unrealistic to assume a constant and identical rate of technological progress. The empirical convergence literature has nevertheless continued to insist on such an assumption in the name of convenience. Hence, the challenge is to develop a theory-backed convergence equation which avoids the unrealistic assumption of constant and identical technological growth. To this end, we combined the two strands of the growth literature, namely the neoclassical and the endogenous growth setups, in order to develop a convergence equation that falsifies a constant and identical technological change across economies and over time. In the empirical part of our study, we estimated a dynamic convergence equation, in which the rate of technological progress varies across countries and over time. We find that (i) the convergence rate is significant but lower than suggested by the majority of previous studies, (ii) the investment rate has a positive and statistically significant contribution to convergence, (iii) human capital has positive and significant impact on economic growth. The paper underlines the importance of investment in R&D and human capital; In order to achieve higher convergence rates, the proportion of both income and human capital devoted to R&D should be increased. In cases where economies are unable to allocate sufficient resources to R&D, it is important to compensate for this deficiency by facilitating the diffusion of technology via various mechanisms, such as FDI or international trade, which are often less costly than allocating resources to R&D. Otherwise, as demonstrated, the convergence rate would actually be considerably lower than that which is conjectured by the literature under the assumption of constant and unchanging level of technological innovation, even for a group of countries rather homogenous in other dimensions (e.g., OECD countries). Hence, the conjecture that lower income countries will rapidly catch up with higher income countries may be less likely than is currently taken for granted, and instead

[20] For example, Borensztein, De Gregorio, and Lee (1998), Bengoa and Sanchez-Robles (2005) and Alguecal, Cuadros, and Orts (2011) state that FDI is one of the channels whereby technology may be diffused from advanced to laggard countries, allowing the latter to grow at higher rates. Similarly, Herrerias and Orts (2013) state that import of capital goods are a way to improve both the efficiency of capital accumulation and the efficiency of domestic production processes due to the technological progress embodied in these imported goods.

the process may be much more lengthy and arduous. Further research in this direction has a great deal of potential to reveal the true convergence process.

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Annex A. List of OECD countries

Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

References

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *Journal of Economic History*, *46*(2), 385–406.

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351.

Alguecal, M., Cuadros, A., & Orts, V. (2011). Inward FDI and growth: The role of macroeconomic and institutional environment. *Journal of Policy Modelling*, *33*, 481–496.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51.

Barro, R. J., & Lee, J. W. (2010). *A New Data Set of Educational Attainment in the World, 1950–2010. NBER Working Paper 15902*.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *American Economic Review*, *76*(5), 1072–1085.

Bayraktar-Sağlam, B., & Yetkiner, I. H. (2012). *A Romerian Contribution to the Empirics of Economic Growth. IUE Working Paper Series, No. 2012-02*.

Bengoa, M., & Sanchez-Robles, B. (2005). Policy shocks as a source of endogenous growth. *Journal of Policy Modelling*, *27*, 249–261.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*, 115–143.

Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews*, *19*(3), 321–340.

Blundell, R., Bond, S., & Windmeijer, F. (2000). Estimation in dynamic panel data models: Improving on the performance of the standard GMM estimator. In B. Baltagi (Ed.), *Nonstationary panels, panel cointegration and dynamic panels*. New York: Elsevier Science.

Bond, S., Hoeffler, A., & Temple, J. (2001). *GMM Estimation of Empirical Growth Models. CEPR Discussion Paper No. 3048*.

Borensztein, E., De Gregorio, J., & Lee, J. W. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, *45*, 115–135.

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth*, *1*, 363–389.

De Long, B. (1988). Productivity growth, convergence, and welfare. *American Economic Review*, *78*(5), 1138–1154.

Durlauf, S. N., Kourtellos, A., & Tan, C. M. (2008). Are any growth theories robust? *Economic Journal*, *118*, 329–346.

Easterly, W., & Levine, R. (2001). What have we learned from a decade of empirical research on growth? It's not factor accumulation: Stylized facts and growth models. *The World Bank Economic Review*, *15*(2), 177–219.

Fagerberg, J. (1994). Technology and international differences in growth rates. *Journal of Economic Literature*, *32*(3), 1147–1175.

Grossman, G., & Helpman, E. (1991). *Innovation and growth in the global economy*. Cambridge, MA: MIT Press.

Ha, J., & Howitt, P. (2007). Accounting for trends in productivity and R&D: A Schumpeterian critique of semi-endogenous growth theory. *Journal of Money, Credit and Banking*, *39*(4), 733–774.

Herrerias, M. J., & Orts, V. (2013). Capital goods imports and long-run growth: Is the Chinese experience relevant to developing countries? *Journal of Policy Modelling*, *35*, 781–797.

Hoeffler, A. E. (2002). The augmented Solow model and the African growth debate. *Oxford Bulletin of Economics and Statistics*, *64*(2), 135–158.

Howitt, P. (2000). Endogenous growth and cross-country income differences. *American Economic Review*, *90*(4), 829–846.

Hsiao, C. (1986). *Analysis of panel data, econometric society monographs No. 11*. New York: Cambridge University Press.

Islam, N. (1995). Growth empirics: A panel data approach. *Quarterly Journal of Economics*, *110*, 1127–1170.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, *103*, 759–784.

Keller, K. R. I., & Poutvaara, P. (2005). Growth in OECD countries and elsewhere: How much do education and R&D explain. *Economics Bulletin*, *15*, 1–11.

Levine, R., & Renelt, D. (1992). A sensitivity analysis of cross-country growth regressions. *American Economic Review*, *82*(4), 942–963.

Madsen, J. B. (2008). Semi-endogenous versus Schumpeterian growth models: Testing the knowledge production function using international data. *Journal of Economic Growth*, *13*(1), 1–26.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, *107*, 407–437.

Murthy, N. R. V., & Chien, I. S. (1997). The empirics of economic growth for OECD countries: Some new findings. *Economics Letters*, *55*, 425–429.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*, 1399–1416.

Nonneman, W., & Vanhoudt, P. (1996). A further augmentation of the Solow model and the empirics of economic growth for OECD countries. *Quarterly Journal of Economics*, *111*, 943–953.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102.

Roodman, D. (2009). *How to do Xtabond2: An Introduction to 'Difference' and 'System' GMM in Stata. Center for Global Development Working Paper No. 103*.

Sala-i-Martin, X. (1997). I just ran two million regressions. *American Economic Review, Papers and Proceedings*, *87*(2), 178–183.

Solow, R. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*, 65–94.

Ulku, H. (2007). R&D, innovation and growth: Evidence from four manufacturing sectors in OECD. *Oxford Economic Papers*, *59*(3), 513–535.

Whelan, K. (2012). *Macro 2 Notes*. Retrieved from http://www.karlwhelan.com/Teaching/Macro2/Notes3.pdf

Windmeijer, F. (2005). A finite sample correction for the variance of linear two-step GMM estimators. *Journal of Econometrics*, *126*, 25–51.

Young, A. (1994). Lessons from the East Asian NICs: A contrarian view. *European Economic Review*, *38*, 964–973.

Young, A. (1995). The tyranny of numbers: Confronting the statistical realities of the East Asian growth experience. *Quarterly Journal of Economics*, *110*, 641–680.

Zachariadis, M. (2004). R&D-induced growth in the OECD. *Review of Development Economics*, *8*, 423–439.