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THE INTERNATIONAL DYNAMICS OF R&D AND INNOVATION IN THE LONG RUN AND IN THE SHORT RUN*

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In this article we estimate the dynamic relationship between employment in R&D and generation of knowledge as measured by patent applications across OECD countries. In several recently developed models, known as 'idea-based' models of growth, the 'idea-generating' process is the engine of productivity growth. Moreover, in real business cycle models technological shocks are an important source of fluctuations. Our empirical strategy is able to test whether knowledge spillovers are strong enough to generate sustained endogenous growth and to estimate the quantitative impact of international knowledge on technological innovation of a country in the short and in the long run.

The scientific and technological knowledge creation process is extremely important from an economic perspective. In the long run it underlies the phenomenon of technological growth. In the short and medium run, fluctuations in the process of knowledge creation underlie periods of either fast productivity growth or technological slowdowns. These fluctuations may, together with other shocks, trigger economic cycles of the kind analysed by the Real Business Cycle literature, e.g. Prescott (1986); Kydland and Prescott (1982); Christiano and Eichenbaum (1992). From an empirical point of view Jones (2002, p. 92) notices that the secular increase in patented innovations per year (and of scientists and engineers) in the US since 1880 corresponded to a secular growth in labour productivity. Specifically he points out that the 1970s experienced a decline in innovation rates per year (as measured by patent applications) while the 1990s exhibited a significant acceleration in innovations per year. In both cases labour productivity followed a similar pattern. A related interesting empirical observation is that labour productivity in EU countries, after catching up with the US labour productivity at a sustained rate during the 1970s and 1980s (Gordon, 2004; Van Ark *et al.*, 2003), slowed and lost ground beginning with the 1990s and in particular after 1995. Examining the rates of innovation in the US and in Germany as measured by the number of patents per year (Figures 1 and 2), we see how those indicators suggest a possible role of innovation in explaining the productivity patterns. Germany experienced sustained growth of innovation rates until the late 1980s, followed by a decline in the early 1990s, which it had not still fully recovered by the end of the decade. To the contrary, the US had stagnating or declining innovation rates up until the early 1980s, followed by a surge of innovative activity, especially in 1995. These facts suggest that innovation rates, with a possible time lag, might explain productivity accelerations and slowdowns and might also explain the narrowing or widening of productivity gaps.

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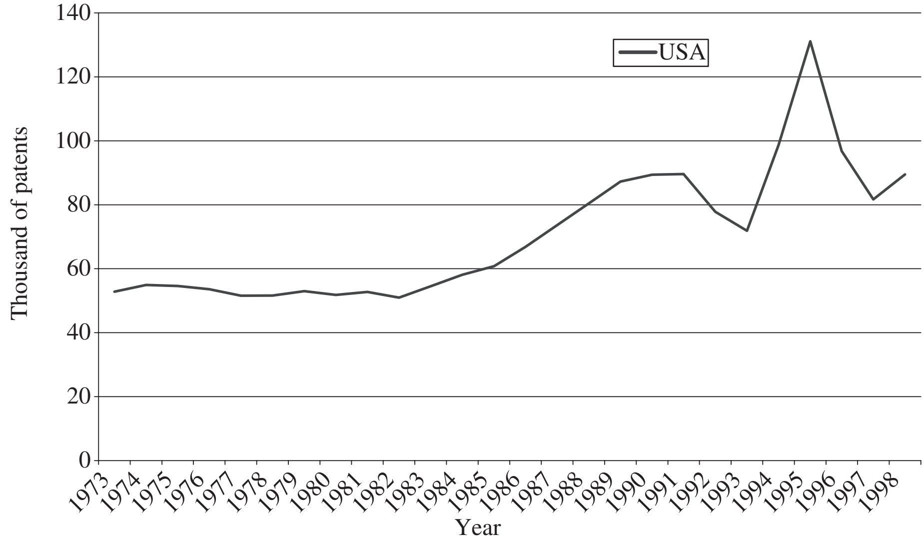


Fig. 1. *Patents per Year, USA*

Fig. 2. *Patents per Year, Germany*

In spite of its importance, the process of innovation is still not very well known and understood. Only in recent decades have economists made progress in analysing it from a theoretical and empirical point of view. Models based on endogenous technological innovation have been developed to explain productivity growth in the aggregate economy. At the same time better and more comprehensive data on research and development (R&D) across countries and on patents and their characteristics have become available. Patenting has been studied as a window on the process of technological change; see, for an overview, the book by Jaffe and Trajtenberg (2002). This article develops an empirical dynamic analysis of the knowledge-generating sector in order to characterise the long and short-run behaviour of innovation and its determinants across countries. Innovation is treated as the output of a process that uses R&D resources and existing ideas as inputs.

In this work we take a macro approach in that we aggregate the idea-generating activities across sectors at the country level. We focus on the idea-generating sector (R&D sector) for three reasons. First, very little is known on the origin, timing and delays of technological shocks. Our goal is to begin opening the black box of Total Factor Productivity (TFP) by understanding the underlying innovation process and its dynamics.[1] While ultimately the behaviour of TFP is crucial, the novelty of this article is that it focuses on innovation itself. The second reason for focusing on the knowledge-generating sector is that it determines the long run dynamic behaviour of the so called 'idea-based' models of growth. In particular the distinction between *endogenous* and *semi-endogenous* growth models can be tested analysing the dynamics of the knowledge-generating sector. A key distinction between the first generation of 'idea-based' models of growth – the *endogenous* growth models exemplified in Romer (1990) or Aghion and Howitt (1992) – and the second generation of models – the *semi-endogenous* growth models such as Jones (1995), Kortum (1997) and Segerstrom (1998) – is based on the effect of the 'scale' of a country's R&D sector on its creation of technological knowledge. If the *level* of R&D resources in an economy is positively related to the *growth rate* of its technological knowledge, then such an economy exhibits *strong scale effects*. Such evidence would be in favour of the endogenous growth models. On the other hand, if the *level* of total R&D resources is positively related to the *level* of its technological knowledge then we would be in the presence of *weak scale effects*. Such a relation would be corroborating evidence in favour of the semi-endogenous models of growth. Importantly, this property depends *only* on the effect of R&D on the creation of technological knowledge and can be tested by looking at the long-run dynamic behaviour of R&D and accumulated knowledge.[2] The third reason for focusing on the knowledge-generating sector is that international knowledge spillovers are likely to be the strongest and most pervasive in this sector. Scientists communicate across countries, ideas are diffused promptly and technological innovations cross borders.

Our article is a step towards a new way of identifying and studying aggregate technological progress. The problems of identifying technological progress with measured changes of total factor productivity are well known. Changes in efficiency in the use of factors, reallocation of factors across sectors, changes in unmeasured capacity utilisation may all pollute that relationship. Hence, it is important to complement the TFP approach and consider alternative measures of technological progress for the

[1] The existing empirical studies on R&D and growth such as Coe and Helpman (1995), Keller (1998), Kao *et al.* (1999), Funk (2000) and Edmond (2001) are mostly focused on the reduced-form relationship between R&D and TFP.

[2] In a previous test to distinguish between endogenous and semi-endogenous models of growth Jones (1995), relied on time-series data for a small number of countries. We consider observations on R&D and innovation in a panel of countries, increasing the power of the test, and we need to account for international diffusion of knowledge.

aggregate economy. Patented innovation is one of the most promising and measurable indices. The first part of our article explores the long run relationship between R&D resources and knowledge creation. Once we have identified this long-run relation, we estimate the short-run dynamics of the innovation process by means of an Error Correction Mechanism panel VAR (VECM). The impulse responses of this model allow us to evaluate the effect of R&D resources on knowledge creation in a country and abroad, in both the short and long run. To the best of our knowledge this has not been done in the literature yet.[3] The rest of the article is organised as follows. Section 1 presents a simple 'idea-based' model of growth. Within the context of these models we can test, using the dynamic properties of the knowledge generating sector, whether the data support a model of endogenous or of semi-endogenous growth. We describe the idea-generating function and how we construct variables to measure R&D resources, new ideas, existing knowledge and their relationship. Section 2 describes the data covering a panel of fifteen countries over the period 1973–99. We show and test some of the basic time-series properties of the data before pursuing our estimation strategy. Section 3 studies the long-run behaviour of R&D and innovation, testing the stationarity of knowledge growth rates and then estimating the panel cointegration between R&D employment, domestic knowledge and international knowledge. Section 4 analyses the short-run behaviour of the R&D sector by showing some representative impulse response functions. Section 5 concludes the article.

1. Idea-based Growth Models and the R&D Sector

1.1. *A Simple Framework*

The mechanism through which resources devoted to R&D are transformed into new knowledge is the centrepiece of several recent models of growth. These models are referred to as 'idea-based' models of growth.[4] Both the first generation of 'idea-based' models, such as Romer (1990); Aghion and Howitt (1992); Grossman and Helpman (1991) and the second generation (Jones, 1995, Kortum 1997 and Segerstrom 1998) build on the analysis of the R&D sector as the engine of long-run productivity growth. For a given amount of resources allocated to R&D, the parameters of the knowledge-producing function are the only ones responsible for the long-run growth of knowledge, which in turn, determines productivity growth. At the same time, the transitional fluctuations of the R&D sector together with those of the production sector are responsible for cyclical fluctuations of labour productivity due to the adjustments of the capital stock and knowledge stock per worker around their long-run trajectories. Using a simple framework, similar to Jones (2004) to illustrate this point let us consider an economy for which the production of output per worker, y_t, is given by:

[3] A partial and interesting exception is Shea (1999). Emphasising the role of R&D spending and patenting as sources of technological shocks, that article estimated the effects of those shocks on short-run fluctuations for US sectors. The study did not find a large effect of technological shocks on short-run productivity fluctuations. However, the study did not apply the modern techniques for estimating cointegration and the Error Correction Mechanism panel VAR.

[4] See Jones (2004) for a survey.

$$y_t = (BA_t^\sigma)k_t^\alpha, \tag{1}$$

BA_t^σ is total factor productivity (TFP). It depends on a factor B that captures efficiency in production and is determined mainly by institutions, geography and the legal structure of a country. These characteristics are slow to change and thus are assumed to be constant. TFP also depends (with an elasticity $\sigma > 0$) on technological knowledge represented by the stock of total available scientific and technological ideas A_t.[5] k_t is physical capital per worker and $\alpha < 1$ is the elasticity of output with respect to physical capital, so that k_t^α satisfies the usual assumptions of decreasing marginal returns to capital and the Inada conditions. Taking derivatives of the logged variables with respect to time on both sides of (1) and denoting by g_x, the growth rate of variable x, we can write the growth rate of output per worker in period t as:

$$g_{yt} = \sigma g_{At} + \alpha g_{kt}. \tag{2}$$

At any given time the growth rate of output per worker (g_{yt}) is a linear combination of the growth rate of the stock of ideas (g_{At}) and the growth rate of capital per worker (g_{kt}). Moreover, in the long run, due to decreasing returns of physical capital, any growth model characterised by an aggregate production function as in (1) converges to a balanced growth path (BGP) in which $g_y^* = g_k^*$ (the asterisks denote BGP values).[6] Hence the growth rate of output per worker in BGP is given by:

$$g_y^* = \frac{\sigma}{1-\alpha} g_A^*. \tag{3}$$

For macroeconomists, the dynamics of A_t are an extremely interesting and important empirical object They are a key determinant (according to 2 and 3) of the fluctuations and growth of income per capita.

1.2. *The Knowledge Generating (R&D) Sector*

For its crucial role in determining the growth rate of productivity, the knowledge-generating sector is the focus of this article. New ideas are produced by people working in R&D who use their creativity and the existing non-obsolete stock of knowledge. In the aggregate, the uncertainty in the rate of arrival of ideas can be reduced to a random noise so that new ideas, existing knowledge, and R&D resources can be represented by a stable relationship (up to a random error term) which we view as a production function of new ideas. Omitting the error term (that we will re-introduce in the empirical section) the function can be expressed as:

$$I_{i,t} = F\left(R\&D_{i,t}, A_{i,t}, A_{ROWi,t}\right). \tag{4}$$

$I_{i,t}$ (for 'Ideas') is the measure of new knowledge generated in country i during year t. We assume that resources devoted to research during year t affect the generation of

[5] See Weil (2005), chapter 10, for a similar decomposition of total factor productivity.

[6] This result can easily be derived in a model with exogenous saving rate, as in Solow (1956), or in a model with optimising agents, as in Ramsey (1928). See Barro and Sala i Martin (2004), Chapter 1 and 2, for details.

ideas during that year.[7] $R\&D_{i,t}$ is the employment in the private R&D sector for country i during year t. $A_{i,t}$ is the stock of usable domestic knowledge measured as accumulated past ideas that were generated in country i up to year $t-1$ and available at the beginning of year t. Similarly $A_{ROWi,t}$ is the stock of international knowledge measured as accumulated past ideas generated by countries in the rest of the world (ROW) up to year $t-1$ and hence available at the beginning of year t. The quantitative impact of existing knowledge ($A_{i,t}$,$A_{ROWi,t}$) on the generation of new ideas can be positive, negative or zero due to the existence of two opposite effects. As illustrated by Caballero and Jaffe (1993) or Jones (2002), existing ideas could widen the basis of usable knowledge to generate further innovation and may therefore have a positive impact (such an effect is known as 'standing on shoulders'). This effect could be so strong as to increase the rate of innovation as more knowledge becomes available. Alternatively, as ideas are discovered it may become harder to find new ones so that the effect of existing knowledge on innovation may be negative (this effect is referred to as 'fishing-out'). Our approach allows us to use the data to test whether the impact of existing knowledge on innovation is positive and large enough to generate accelerating innovation, positive but incompatible with accelerating innovation, or negative. Finally, in a world where knowledge is exchanged across countries, each country benefits from ideas discovered by the rest of the world. Several studies (Branstetter, 2001; Jaffe *et al.*, 1993; Peri, 2005) show that the international diffusion of ideas while important is less than perfect and, in particular, less efficient than their diffusion within a country. For this reason we include knowledge created outside of a country $A_{ROWi,t}$ as a separate input so that we are able to estimate the (external) impact of this factor on the generation of new ideas.

1.3. *Construction of Variables and Measurement Issues*

In this Section we describe in detail how to make (4) operational for the empirical analysis by constructing variables using the available data. Our main identifying assumption is that the number of new ideas produced in country i during year t, $I_{i,t}$, is proportional to the number of inventions for which an international patent application is filed during year t by an inventor residing in that country. Following an established tradition we utilise patent statistics to proxy the creation of innovative ideas. According to the standards of patentability defined by the US patent office, a patentable idea should be original, non-obvious and exploitable for economic profit. Many applied economists have drawn from the large pool of patent data, and used it to measure new ideas.[8] Similarly, theoretical economists (Romer, 1990; Grossman and Helpman, 1991) have equated one idea to one patent in their models. In practice, however, there are two main sources of 'noise' which prevent a perfect correspondence between patents and ideas. The first is that the propensity to patent a new idea may vary across countries. This is easily accounted for by introducing a country fixed effect. The second is that patents may have dissimilar 'contents of ideas', with some patents containing many

[7] Early empirical studies, such as Hall *et al.* (1986) show the strong effect of R&D on innovation within the same year. Past R&D is captured, in this specification, by the accumulated stock of idea $A_{i,t}$ and $A_{ROWi,t}$.

[8] See Griliches (1990) for a survey.

relevant ideas while others contain less relevant ideas.[9] Since in our case, each unit of observation (country-year) includes the sum of a large number of patents, differences in the content of ideas for individual patents are likely to be averaged out. Moreover, we include a correction for the importance of a patent by weighting each of them by the number of citations received during the first 3 years. This correction does not change the results much relative to the use of a simple patent count.

Our choices of selecting only international patents (filed in the US) and of adopting the residence of the inventor as country of origin of the idea, have several advantages that make our dataset particularly appealing. First, by selecting patents taken in the US we are likely to select only the most important (and potentially profitable) innovations originating from each country. Since the US is the most important world market, any relevant innovation will be patented there. If an innovation is marginal it may not be worth the cost to patent in the US. Such a choice, would tend to select 'high-quality' ideas, which should be the most relevant in examining the effects on productivity. These ideas are also the ones that are most likely to benefit from international diffusion of knowledge. Second, the US patent data allow us to locate the residence of the inventor and use it as the idea's country of origin. Aggregate statistics from the World Industrial Property Office (WIPO) identify only the location of the headquarters of the applying company. The literature agrees that the inventor's residence is a better way of identifying where the R&D was performed and the idea developed.[10] Third, the NBER patents and citations data report the citations between patents and allows us to construct a measure of the importance of a patent (based on the received citations in a period of three years) that in turn can be used to weight each of them in a more accurate measure of innovation.

We can summarise the relationship between patents and ideas, allowing for country-specific propensity to patent, as: $Pat_{i,t} = \varkappa_i I_{it}$ where $Pat_{i,t}$ is the number of patent applications filed with the US patent office by inventors living in country i during year t and $\varkappa_i$ is the country-specific propensity to patent. The choice of the application year to capture the generation of an idea is appropriate because the process of obtaining a patent is slow. While an application is filed very early after the discovery took place, the patent may be granted several years later; see Jaffe and Trajtenberg (2002, Chapter 13).

In order to study the relationship defined by (4) we assume that the mapping $F(.,.,.)$ can be approximated by a log-linear function as follows:

$$\ln(Pat_{i,t}) = \ln(\varkappa_i) + \lambda \ln(R\&D_{i,t}) + \phi \ln(A_{i,t}) + \xi \ln(A_{ROWi,t}). \tag{5}$$

Equation (5) states that the log number of patent applications originating in country i during year t is a function of a country fixed effect ($\ln(\varkappa_i)$), the log level of R&D (personnel employed in R&D in full time equivalents) of country i during year t ($R\&D_{i,t}$), the stock of knowledge generated in country i ($A_{i,t}$), as well as in the rest of the world ($A_{ROWi,t}$) at time $t-1$ and available at the beginning of year t.[11] The coefficient λ

[9] See, for instance, Jaffe and Trajtenberg (2002), Chapter 2.

[10] See Jaffe *et al.* (1993) and Jaffe and Trajtenberg (2002) for an accurate discussions of this issue.

[11] To understand how patents (measured as a flow) are produced using R&D (also a flow of resources) and knowledge (measured as a stock), it is useful to think of a standard aggregate production function. GDP at the aggregate level (measured as a yearly flow) is produced using labour inputs (a flow of worked hours) and capital stock. Knowledge plays the role of a stock variable in (5) and we would like to measure its services but we can only measure its total amount.

captures the impact of R&D resources on patenting, while ϕ and ξ capture, respectively, the effects of domestically-generated and internationally-generated knowledge on patenting. The stock variable $A_{i,t}$ captures the accumulated, non-obsolete knowledge originating from country i. We assume that the stock of knowledge is continually increased by the addition of new ideas and, at the same time, it is continually decreased by a constant depreciation (obsolescence) rate δ that captures the fact that new ideas may displace (or improve on) old ideas.[12] Therefore, using the correspondence between patents and ideas and omitting the country fixed factors (that could be factored out and bundled with the country fixed effects $\varkappa_i$) the variable $A_{i,t}$ is defined by the following recursive formula:

$$A_{i,t+1} = Pat_{i,t} + (1-\delta)A_{i,t}. \tag{6}$$

Assuming that the accumulation of knowledge in the past has been compatible with a balanced growth path, we construct the initial value A_{it_0}, (following the perpetual inventory method)[13] as:

$$A_{it_0} = \sum_{t=0}^{\infty} \frac{Pat_{it_0}}{(1+\bar{g}_i)^{t+1}}(1-\delta)^t = \frac{Pat_{i,t_0}}{(\bar{g}_i+\delta)} \tag{7}$$

where $\bar{g}_i$, is the growth rate of patenting in country i in the five years between t_0 and t_0+5, and δ is equal to 0.1. The value obtained from (7) is, at best, a rough estimate of the initial stock of knowledge in country i. However, we use $t_0 = 1963$ as the first year in which patent data are available while we begin our analysis of cross-country innovation in 1973. This allows us to reduce the effect of any mistake due to an imprecise estimate of the initial stock of knowledge. The impact of $A_{i,1963}$ on $A_{i,1973}$ is rather small. Most of the existing literature on knowledge spillovers (Coe and Helpman, 1995; Funk, 2000) used the stock of accumulated past R&D, rather than patents, to measure the international stock of knowledge. There are several reasons, however, for prefering the choice of accumulated patents in our context. First, R&D resources (such as scientists and labs) are excludable resources while the ideas generated with them are public. The external effect on innovation comes from knowledge generated abroad (rather than directly from R&D) and accumulated patents measure it more accurately. Second, as data on patents are available beginning in 1963, but data on R&D only since 1973, using the perpetual inventory method and (7) to initialise the stock would imply higher imprecision when using accumulated R&D rather than accumulated patents. Third, R&D resources take some time-one year according to (5)- to become available as domestic and international knowledge so that only $A_{i,t+1}$ and $A_{ROWi,t+1}$ contain ideas generated using $R\&D_{i,t}$.The timing of R&D may be leading its impact on innovation by one or more periods. Constructing the lagged stock of knowledge would imply that we lose further initial observations for each country. Ultimately, as R&D in a country is the most important determinant of patenting, the two measures (stock of R&D and stock of

[12] We choose a depreciation rate to be within the range estimated using data on patent-citations (Caballero and Jaffe, 1993) and close to what is chosen as depreciation for the R&D stock (Keller, 2002). Such rate is set to $\delta = 0.1$. We conduct robustness checks for the case of $\delta = 0.15$, and $\delta = 0.08$ and we do not find any significant variation in the results.

[13] See Young (1995, footnote 16 pp. 652).

patents) are highly correlated in the long run. Studies limited to the long-run analysis (Coe and Helpman, 1995; Funk, 2000) could use either measure to obtain similar results (see Section 3). In the short-run analysis, however, the use of stock of patents is preferable.

Finally we construct $A_{ROWi,t}$ as the simple sum of the stock of ideas generated in countries other than i by year $t-1$, and available at the beginning of year t. Namely, $A_{ROWi,t} = \sum_{j \neq i} A_{j,t}$. The choice of a simple sum is driven by three considerations. First, Keller (1998) showed that an unweighted sum of external R&D works just as well as a trade-weighted sum when measuring the external effect of research. Second, Edmond (2001) has shown that the specification with unweighted sum is more robust to different specifications and estimation methods than the weighted one. Finally Peri (2005) finds that international flows of ideas are much less localised than trade flows and most of the attrition takes place within a country. Weighting the contribution of foreign ideas by trade shares would incorrectly reduce their impact, thus taking their unweighted sum would be the preferred method.

1.4. *Long-run Implications of Strong and Weak Scale Effects*

We divide both sides of (6) by $A_{i,t}$ and take natural logs. Substituting for $Pat_{i,t}$ its expression from (5), and for $A_{ROWi,t}$ its definition given above, we obtain the following relation, which is the basis of our econometric analysis of the long-run:

$$\ln(g_{Ai,t} + \delta) - \ln(\varkappa_i) = (\phi - 1)\ln(A_{i,t}) + \lambda \ln(R\&D_{i,t}) + \xi \ln(\sum_{j \neq i} A_{j,t}) \tag{8}$$

where $g_{Ai,t} = (A_{i,t+1} - A_{i,t})/A_{i,t}$ is the growth rate of the stock of ideas generated in country i in year t. This equation holds in each period and can be used to study the dynamics of the knowledge stock which, according to (2) and (3), has a direct bearing on the dynamics of output per worker. If the stock of ideas converges to a stochastic balanced growth path then the term $\ln(g_{Ai,t} + \delta) - \ln(\varkappa_i)$ on the left-hand side of (8) converges to a country-specific stationary stochastic process. In this case (8) implies a stationary long-run relation between the variables $\ln(A_{i,t})$, $\ln(R\&D_{i,t})$ and $\ln(A_{ROWi,t})$ on the right-hand side. In particular, if each of the three variables is non-stationary, convergence to a stochastic balanced growth path implies that there must be a cointegration relation among them, (i.e. a linear combination that is stationary). The cointegration vector, standardising by the coefficient of $\ln(A_{i,t})$, would be $(-1,\mu,\gamma)$ where $\mu = \lambda/(1-\phi)$ and $\gamma = \xi/(1-\phi)$. It can be estimated using the following regression

$$\ln(A_{i,t}) = \mu \ln(R\&D_{i,t}) + \gamma \ln(\sum_{j \neq i} A_{j,t}) + s_{i,t}, \tag{9}$$

where we have collected all the stationary variables (deterministic and stochastic) in the term $s_{i,t}$. From the estimates of this cointegration vector we are also able to establish whether ξ is larger than, smaller than, or equal to 0 (as its sign will be the same as the sign of γ). Alternatively, if the stock of ideas does not converge to a balanced growth path so that $g_{Ai,t}$ is not stationary in the long run but increases with the levels of

$\ln(R\&D_{i,t})$, $\ln(A_{i,t})$ and $\ln(A_{ROWi,t})$ then no cointegration exists between those variables and the system would experience stocks of ideas diverging across countries in explosive growth paths over time.

The tests of stationarity of $g_{Ai,t}$ and of cointegration between the variables $\ln(R\&D_{i,t})$, $\ln(A_{i,t})$ and $\ln(A_{ROWi,t})$ allow us to discriminate between the two alternative idea-based models of growth (endogenous vs. semi-endogenous). If $g_{Ai,t}$ is stationary then, in the long run, the *levels* of R&D resources and world knowledge determine (are cointegrated with) the *level* of knowledge of a country and therefore the *level* of its productivity. This is a typical property of the semi-endogenous models of growth such as Jones (1995) and Segerstrom (1998). Within this case, a positive sign of the coefficient γ, would be evidence of a net 'standing on shoulders' effect, while a negative sign of γ would imply that the 'fishing-out' effect prevails. Alternatively, if $g_{Ai,t}$ is non-stationary then *levels* of R&D resources and stocks of knowledge – on the right hand side of (8) – determine the *growth rate* of knowledge of a country ($g_{Ai,t}$) and, as a consequence, the *growth rate* of its productivity. This is a typical property of the endogenous models of growth such as Romer (1990), Aghion and Howitt (1992) and Grossman and Helpman (1991). In this case R&D would have a strong scale effect, implying that its *level* affects the *growth rate* of the stock of ideas. Once we have tested the long run dynamic properties of (9) we can use (5) to identify and estimate the effect of R&D and innovation shocks on creation of ideas in the short-run.

2. Data: Description and Time-Series Properties

2.1. *Data Description*

Our empirical analysis is performed on data from 15 OECD Countries during the period 1973-99. These 15 countries (listed in Table 1), taken together, account for about 90% of the world R&D and for 97–98% of the total US granted patents. R&D resources are measured by personnel in the R&D sector in full-time equivalents. The data on R&D are from the ANBERD, OECD-STAN data set. The patent data, grouped by country of residence of the first inventor and by year of application, are obtained by aggregating individual patents from the NBER Patent and Citations Data set described in detail in the book by Jaffe and Trajtenberg (2002), and publicly available at http://www.nber.org/patents. The dataset includes over 3 million patents granted by the US patent office between the years 1963 and 1999. $Pat_{i,t}$ is the total number of patent applications by residents of country i during year t, and we weight each patent by the factor $(1 + \mu_3)$ where μ_3 is the average number of yearly citations received by the patent during the first three years after it has been granted. This accounts for the importance of the innovation embedded in the patent. As argued in several articles[14] citations are, on average, an indicator of the importance of a patent and of its market value. For robustness purposes we also conduct our analysis using absolute patent counts obtaining similar results.

Table 1 shows the average values of the variables of interest, by country, for the whole period 1973–99. The first column shows the average full-time equivalent units

[14] See for instance Jaffe and Trajtenberg (2002, Chapter 2) and Hall *et al.* (2005).

Table 1

Summary Statistics for R&D, Patents and the Constructed Stocks of Knowledge

Country	Average R&D personnel, full-time Equivalents	Average number of patent applications per year	Average value of ln(A), stock of domestically generated knowledge	Average value of $\ln(A_{ROW})$, stock of international knowledge
Australia	63,390	551	8.18	13.66
Canada	103,418	2,245	9.64	13.65
Germany	401,850	8,738	11.11	13.59
Denmark	21,871	253	7.49	13.66
Spain	53,537	148	6.85	13.67
Finland	25,369	326	7.39	13.67
France	271,446	3,559	10.16	13.64
Great Britain	289,102	3,491	10.33	13.63
Ireland	6,774	57	5.69	13.67
Italy	120,927	1,339	9.13	13.66
Japan	764,375	23,215	11.66	13.50
The Netherlands	65,264	1,094	9.01	13.66
Norway	18,510	140	6.90	13.67
Sweden	49,587	1,073	9.06	13.66
USA	1,687,929	70,600	13.23	12.59

Notes. The averages are taken for each country over the years 1973–1999. The variables ln(A) and $\ln(A_{ROW})$ are constructed as described in the main text, by accumulating patents using the perpetual inventory method.

of personnel in R&D, the second shows the average number of patent applications per year, the third and fourth report the average values of the constructed stocks of domestic knowledge $\ln(A_{i,t})$ and rest-of-the-world knowledge $\ln(A_{ROWi,t})$. Large variations in total R&D resources and total patenting exist across these countries. The US is the technological leader by a large margin employing an average of almost 1.7 million full-time equivalent persons in its R&D sector and filing more than 70,000 patent applications every year. Japan, Germany and the UK are distant second, third and fourth in terms of R&D and patents. Ireland is the smallest innovator in our sample, filing an average of merely 57 patent applications each year. The averages over the whole time-period mask the interesting time-evolution of the variables in each country. Before performing formal tests on the time-series properties of these variables, we illustrate their behaviour for the subset of G7 countries in Figures 3–5. Figure 3 shows the behaviour of the variable $\ln(R\&D_{i,t})$ for the G7 economies over the 1973–99 period. In spite of different average growth rates (from 0% in the UK to 6% per year for Canada) the Figure confirms a common upward trend (except for the UK) as well as high persistence of year to year movements. Also, some countries exhibit noticeable differences over different periods. Japan, for instance, increased its R&D employment up until 1990, and then later experienced very slow growth or possible stagnation. Similarly, Italy experienced growth in R&D resources only up until the early 1990s. The countries with the fastest growing R&D employment in our sample were Spain and Finland (neither country among the G7) with annual rates of growth of 10 and 11% respectively. Figure 4 illustrates the time behaviour of log patent applications per year for the G7 countries in the 1993–9 period. This variable, which measures new knowledge generated in the seven countries, also shows a

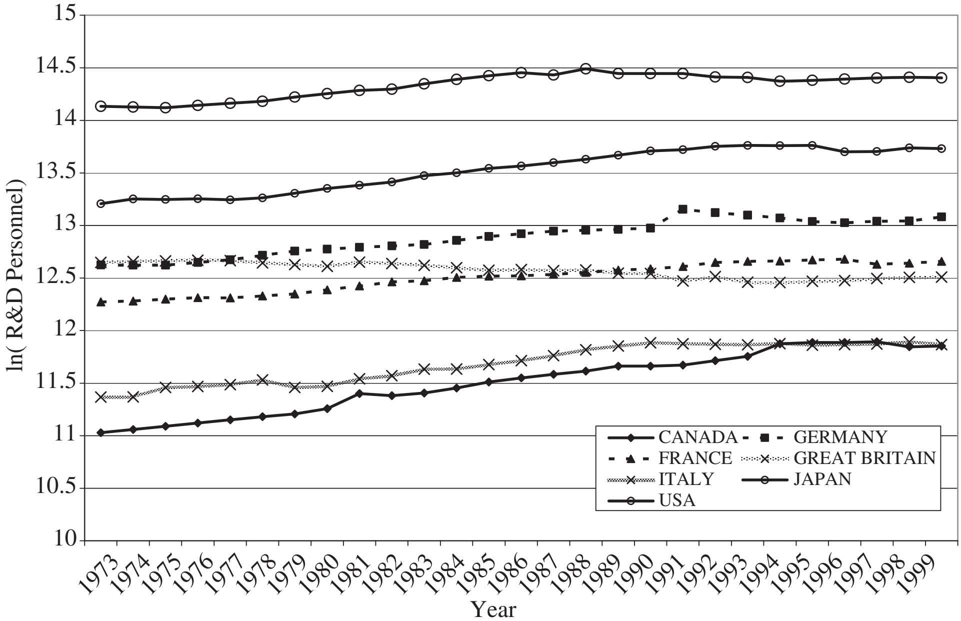


Fig. 3. *R&D Personnel in the G7 Countries,* ln(R&D)

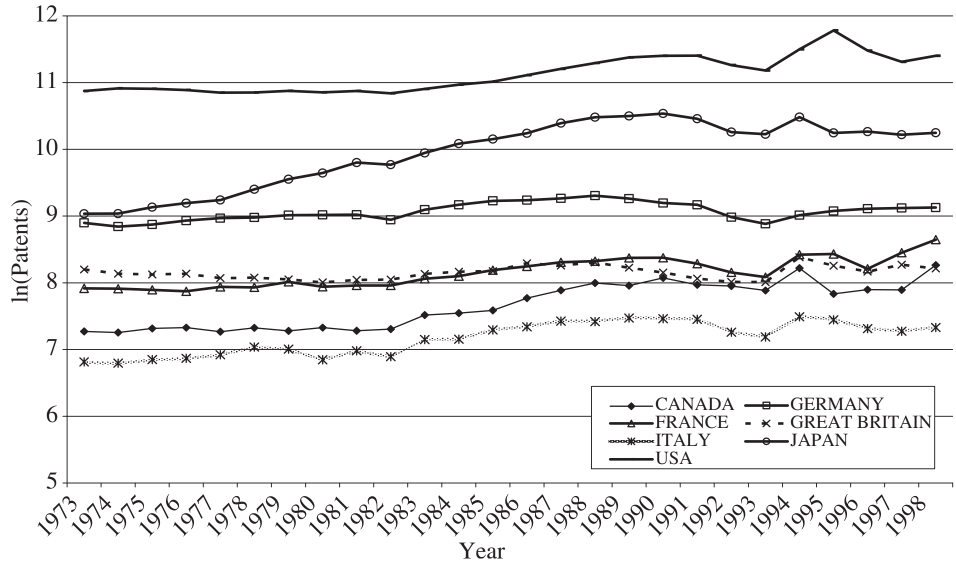


Fig. 4. *Annual Patent Applications in the G7 Countries,* ln(Pat)

general upward trend. Some fluctuations especially during the 1990s are also visible. Finally, Figure 5 shows the behaviour of the constructed variable $\ln(A_{i,t})$ for each one of the G7 countries during the same period. The variables are trending up and Japan

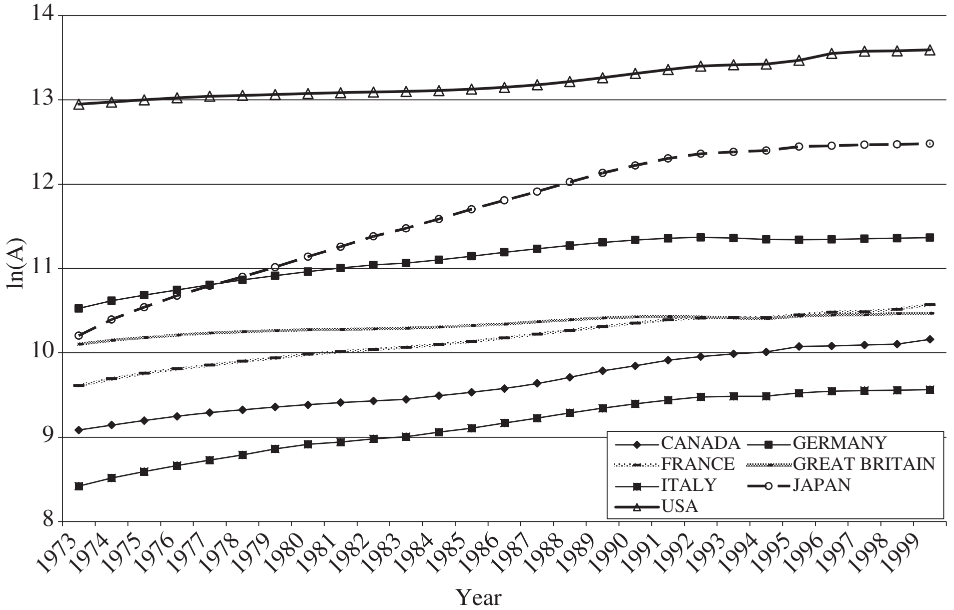


Fig. 5. *Stock of Knowledge Generated in the G7 Countries as Measured by Accumulated Patents,* ln*(A)*

exhibits a particularly fast-growing stock of domestic knowledge. The persistent and common upward movements in the variables $\ln(R\&D_{i,t})$ and $\ln(A_{i,t})$ suggest that they could be non-stationary and cointegrated over time. We move, therefore, to perform formal tests of non-stationarity and cointegration of the variables of interest.

2.2. *Test of Unit Root of R&D and Stocks of Knowledge*

Visual inspection of Figures 4 and 5 as well as previous literature (e.g. Jones, 1995) suggest that the variables $\ln(A_{i,t})$ and $\ln(R\&D_{i,t})$ might be non-stationary. In a short time series of yearly data (26 observations), it is hard to discern non-stationarity so we have to rely on panel unit roots tests that exploit both the cross-section and the time series dimension of the data. Specifically, we want to test for non-stationarity against the alternative of trend stationarity, allowing for a different intercept for each country. We employ the test proposed by Im *et al.* (2003) as it allows each panel member to have different autoregressive parameters and short time dynamics under the alternative hypothesis of trend stationarity. The test is based on the average of the adjusted Dickey-Fuller (ADF) statistics calculated independently for each member of the panel, with one lag to adjust for auto-correlation. The test statistics, adjusted using the tables in Im *et al.* (2003) is distributed as a standard normal under the null hypothesis of a unit root with large negative values leading to the rejection of a unit root in favour of stationarity. Table 2, Columns 1–3, report the Im *et al.* (2003) test statistics for the variables $\ln(A_{i,t})$, $\ln(A_{ROWi,t})$ and $\ln(R\&D_{i,t})$. In no case can we reject the null of non-stationarity at standard levels of significance. Furthermore, no country exhibits ADF statistics relative

Table 2

Tests of Unit Roots for R&D and Stocks of Knowledge

Test	Im, *et al.* (2003)			Pesaran (2003)		
Variable:	ln(A)	ln(A_{ROW})	ln(R&D)	ln(A)	ln(A_{ROW})	ln(R&D)
Australia	−2.709	−0.768	−0.338	−0.294	−0.200	−4.060
Canada	−0.096	−0.792	−1.370	0.816	−0.108	−1.661
Germany	−1.531	−0.590	−1.314	−0.199	−1.098	−2.604
Denmark	−0.527	−0.780	0.015	−1.787	−0.268	−1.572
Spain	−0.309	−0.781	−0.252	0.502	−0.214	−2.004
Finland	−2.480	−0.778	0.760	−0.871	−0.151	−0.502
France	−0.873	−0.777	−1.577	−1.915	−0.761	−0.379
UK	−1.355	−0.773	−0.711	0.009	−1.084	−2.101
Ireland	−1.512	−0.779	0.481	−2.775	−0.182	0.441
Italy	−1.983	−0.755	−1.919	−1.760	−0.188	−2.083
Japan	−1.403	−0.125	−1.098	1.902	6.396	−0.349
Nether.	−1.858	−0.767	0.813	0.408	−0.242	−2.268
Norway	−1.711	−0.778	−1.035	−3.942	−0.258	−1.885
Sweden	−0.897	−0.773	−0.611	−2.115	−0.629	−1.580
USA	0.293	−1.546	−1.655	−0.332	1.856	−0.521
Average ADF	−1.269	−0.770	−0.654	n.a.	n.a.	n.a.
Test Statistic	4.117	6.404	6.939	n.a.	n.a.	n.a.
Average CADF	n.a.	n.a.	n.a.	−0.823	0.191	−1.550

Notes. The test statistics are distributed as N(0, 1) under the null hypothesis of non-stationarity.
The statistics in the first three columns are constructed using small sample adjustment factors from Im *et al.* (2003). Test statistics in column three to six follow the method described in Pesaran (2003).
In no case can we reject the null hypothesis of non-stationarity (against the alternative of stationarity) at the 10%, 5%, 1% significance levels.

to $\ln(R\&D_{i,t})$, $\ln(A_{i,t})$ and $\ln(A_{ROWi,t})$ that are larger (in absolute value) than the threshold for rejecting the unit-root hypothesis.

The test proposed by Im *et al.* (2003), however, is not robust to the presence of cross-sectional dependence. Therefore we also perform the test proposed by Pesaran (2003) and we report it, for each variable and country, in Columns 4–6 in Table 2. Such unit root test based on the simple averages of the individual cross sectionally augmented ADF statistics, denoted by CADF in Table 2, is robust to cross sectional dependence. Even in this case the test never rejects the null of non-stationarity for any of the three variables. We can conclude that shocks to R&D and to the domestic or international stock of knowledge are very persistent and that these variables can be represented by non-stationary processes.

2.3. *Stationarity of Growth Rates: Test of Strong Scale Effects*

Next, we test for a unit root in the first time-differences of the variable $\ln(A_{i,t})$, $g_{Ai,t}$. In this case the alternative hypothesis is stationarity without a trend, since any time trend in levels is removed by differencing. We use the same tests that we used in Section 2.2 above. A rejection of the null of non-stationarity would be evidence in favour of convergence of the stock of knowledge to a balanced growth path. Table 3 reports the unit-root tests (Im *et al.*, 2003; Pesaran, 2003) applied to the variable $g_{Ai,t}$ as well as to the growth rates of $R\&D_{i,t}$ ($\Delta\ln(R\&D_{i,t})$) and to the growth of international stock of knowledge $A_{ROWi,t}$ ($\Delta\ln(A_{ROWi,t})$). The test statistic is negative and large in each case.

Table 3

Tests of Unit Roots for the Growth Rates of R&D and Stocks of Knowledge

Test	Im *et al.* (2003)			Pesaran (2003)		
Variable	Δln A)	Δln (A_{ROW})	Δln(R&D)	Δln A)	Δln (A_{ROW})	Δln(R&D)
Australia	−2.647	−3.623	−2.824	−5.016	−2.522	−2.640
Canada	−2.008	−3.651	−3.222	−2.744	−4.257	−4.586
Germany	−2.284	−3.595	−3.411	−1.213	−2.634	−4.864
Denmark	−3.783	−3.625	−3.723	−6.824	−3.449	−4.482
Spain	−2.702	−3.627	−3.050	−5.227	−2.714	−4.191
Finland	−2.611	−3.628	−1.150	−3.643	−2.714	−2.376
France	−3.032	−3.608	−2.702	−1.020	−4.422	−3.684
UK	−2.777	−3.611	−2.933	−1.240	−4.325	−6.359
Ireland	−2.042	−3.624	−2.626	−6.637	−2.538	−3.527
Italy	−2.354	−3.642	−2.986	−2.367	−3.167	−5.318
Japan	−1.860	−4.128	−2.191	−1.607	0.635	−3.367
Nether.	−2.016	−3.626	−4.440	−1.427	−2.514	−5.452
Norway	−2.910	−3.624	−3.563	−3.646	−3.035	−3.790
Sweden	−3.119	−3.579	−3.677	−2.528	−6.524	−2.614
USA	−3.425	−1.433	−1.968	−3.368	−1.281	−5.729
Average ADF	−2,638	−3,508	−2,964	n.a.	n.a.	n.a.
Test Statistic	−2,160***	−6,152***	−3,657***	n.a.	n.a.	n.a.
Average CADF	n.a.	n.a.	n.a.	−3.234***	−3.044***	−4.198***

Notes. The test statistics are distributed as N(0, 1) under the null hypothesis of non-stationarity.
The statistics in the first three columns are constructed using small sample adjustment factors from Im *et al.* (2003). Test statistics in column three to six follow the method described in Pesaran (2003).
The symbol *** denote rejection of the null hypothesis of non-stationariety (against the alternative of stationarity) at the 1% significance levels.

For each one of these growth rates we are able to reject the null hypothesis of non-stationarity at the 1% significance level. Hence, this test provides a clear rejection of the existence of a strong scale effect in the production of knowledge. As $g_{Ai,t}$ is stationary, the variable $\ln(A_{i,t})$ converges to a stochastic balanced growth path. This implies that there is a long-run relationship between the variables $\ln(A_{i,t})$, $\ln(A_{ROWi,t})$ and $\ln(R\&D_{i,t})$, (which are all integrated processes of order one, $I(1)$) so that their linear combination expressed by (8) is stationary. In the long run the three variables move together so that the level of $R\&D_{i,t}$ of a country and the international stock of knowledge $A_{ROWi,t}$ determine the stock of knowledge created in country i, $\ln(A_{i,t})$. The remainder of our analysis proceeds on the assumption, supported by the tests performed above, that all log level variables follow non-stationary, $I(1)$, processes while all log differenced variables follow stationary, $I(0)$, processes.

3. The long run Dynamics: Estimating the Cointegration Relation

Thus far the results point to the existence of a cointegration relation between the variables $\ln(A_{i,t})$,$\ln(A_{ROWi,t})$ and $\ln(R\&D_{i,t})$. We estimate this relationship by dynamic ordinary least squares (DOLS) using the whole panel of 15 countries and 26 years. We impose homogeneity of the cointegration vector across countries but allow for country-specific effects and time trends as well as a common time effect. As in Phillips and Moon (1999), Kao (1999) and Pedroni (1999), the errors are assumed to be independent across countries. As in the single-equation environment, this estimator sacrifices asymptotic efficiency because it does not take into account the cross-equation dependence in the equilibrium errors.

In practical terms, the estimation of the equation by DOLS involves adding leads and lags of the first differences of the $I(1)$ regressors in (9). Thus, all nuisance parameters, which represent short-run dynamics are $I(0)$ and by construction, uncorrelated with the error term.[15]

In order to estimate the cointegration relation between R&D and the stock of ideas we re-write expression (9) adding two lags of the differenced variables as follows:[16]

$$\ln(A_{it}) = c_i + \lambda_i t + \mu \log(R\&D_{i,t}) + \sum_{j=1}^{2} \mu_i \Delta \ln(R\&D_{i,t-j}) + \gamma \log(A_{ROWi,t}) + \sum_{j=1}^{2} \gamma_i \Delta \ln(A_{ROWi,t-j}) + \epsilon_{i,t}. \tag{10}$$

Table 4 reports the estimates of μ in the first row, labelled $\ln(R\&D)$, and γ in the second row, labelled $\ln(A_{ROW})$. Those parameters capture the long-run elasticity of knowledge generated in a country to R&D employment and to knowledge created in the rest of the world. The variance-covariance matrix of the coefficients is consistently

Table 4

Estimates of the Long-run Cointegration Relation

Dependent variable: ln(*A*)	I: Basic	II: Allowing heterogeneous time trends	III: Using un-weighted patents to construct *A*	IV: Allowing year Effects	V: Omitting the US	VI: Splitting the Non-G7 (a)	Sample-G7(b)
ln(*R&D*)	0.786***	0.304***	0.317***	0.746***	0.401***	0.030	0.699***
	(12.075)	(4.671)	(6.46)	(11.162)	(5.98)	(0.379)	(6.498)
$\ln(A_{ROW})$	0.557***	0.168**	0.385***	0.276***	0.366***	0.749***	−0.300***
	(9.319)	(1.719)	(6.525)	(3.004)	(3.388)	(4.989)	(−2.280)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trends	No	Yes	Yes	No	Yes	Yes	Yes
Time fixed effects	No	No	No	Yes	No	No	No
Observations	390	390	390	390	364	208	182

Note. Panel Data using 15 countries for the period 1972–99.
Method of Estimation: Dynamic Ordinary Least Squares (DOLS)
Variance-covariance matrix of the coefficients is estimated using the dynamic panel variance estimator proposed by Mark *et al.* (2003).
t- statistics in parenthesis. *, **, *** = significant at the 10, 5 and 1% level.
Dependent variable: log of *A*, the stock of accumulated patents invented by residents of the country. The patents considered are those registered at the US patent office. Each patent is weighted by the average number of yearly citations during the first three years (except in specification III). The construction of *A* is described in detail in the main text.

[15] Further details and a more technical description of the unit root tests and of the estimation of the cointegrating relations are reported in the working paper version of this article, Bottazzi and Peri (2005).

[16] The lag length can be determined by Campbell and Perron (1991) top-down t-test approach.

estimated by applying the dynamic panel variance estimator proposed by Mark *et al.* (2003).[17] As different countries may exhibit permanent differences in their innovation generating (or patenting) process we allow for country-specific fixed effects, c_i, in each specification. We include a country specific time-trend in most of the specifications (Specifications II, III, V and VI) to control for time-effects. Finally specification IV includes a common time fixed effect as a way of capturing common movements over time.

Column I of Table 4 reports the estimates when we only control for country fixed effects. Both coefficients, μ and γ, are estimated precisely. A 1% increase of a country's R&D employment is associated with a 0.79% increase in the domestically generated stock of scientific and technological knowledge (the standard error is 0.06%). At the same time a 1% increase of the international stock of knowledge is associated, in the long run, with a 0.56% increase in domestically generated knowledge (with a standard error of 0.06%). These point estimates are reasonable when compared to findings of previous studies. For instance Branstetter (2001) uses firm-level data and finds an elasticity of innovation to R&D equal to 0.72. Pakes and Griliches (1980) found a value of 0.61. Peri (2005), using data on sub-national regions, found values between 0.6 and 0.8. At the same time, the existing estimates of the elasticity of domestic innovation to international accessible knowledge are between 50% and 80% of the elasticities to domestic R&D (Griliches, 1992). These estimates are qualitatively consistent with the macroeconomic finding of a positive long run relation between R&D and Total Factor Productivity (e.g. Coe and Helpman, 1995; Kao *et al.*, 1999).[18]

Introducing a country-specific time trend (Specifications II, III and V) reduces the point-estimates of the two elasticities. However, both coefficients remain positive and very significant. The elasticity of R&D employment is close to 0.30 in specification II, and the effect of international knowledge reduced to 0.168. Specification III shows that using the absolute number of patents (rather than the count weighted by the average number of citations within 3 years) as a measure of innovation does not change the results. The impact of international knowledge on domestic knowledge increases somewhat (to 0.385), while the impact of R&D on domestic knowledge is unchanged. Specification IV introduces year fixed effects in place of country specific trends. This is a more demanding specification as it requires that the effects of international knowledge on domestic knowledge be identified only by variations specific to each country while most of the variation of the stock $\ln(A_{ROW})$ takes place over years. The estimates reveal that the effect of international knowledge remains very strong and significantly positive at 0.276. The effect of R&D on innovation is 0.74, close to the estimate in the basic specification. Altogether, the consistently positive and significant estimates of the coefficient γ reported in Table 4 are strong evidence in favour of the existence of a 'standing on shoulders' effect that implies a positive effect of knowledge on innovation. However, such an effect is not as strong as to generate endogenous growth (non-stationary $g_{Ai,t}$).

[17] To control for potential serial correlation in $\epsilon_{i,t}$ we have computed the Newey-West estimates of the long-run variance.

[18] If we use the sum of the contemporaneous flow of *R&D* resources in the rest of the world as measure of international knowledge the coefficient on this variable equals 0.76 (s.e. 0.077). However, the coefficient on own *R&D* spending would be estimated more imprecisely due to stronger collinearity.

Specifications V and VI examines the relative impact of international knowledge on innovation in countries at the technological frontier *vis-à-vis* other countries. Due to concentration of R&D activity, the US, which is the largest innovator, generates more than half of the world innovations. The seven largest economies combined (G7 countries) perform the large part of R&D and produce the vast majority of innovation in the OECD group. We can think that the ideas generated in countries at the technological frontier are of higher quality and have more visibility than those generated in other countries. This would imply that the impact of international knowledge on innovation of a country will be asymmetric. While the technological leaders benefit mostly from their own R&D, the technological followers depend heavily on the international flow of knowledge to 'feed' their innovative activity. Coe and Helpman (1995) and Peri (2005) show that the stock of knowledge generated among the technological leaders has a particularly strong effect on productivity growth and innovation of the followers, but not *vice-versa*. In specification V we simply consider the US as the world technological leader and omit it from the sample. An early paper by Eaton and Kortum (1996) estimated that the US is the only country in the world in which more than half of the technological progress stems from domestically generated ideas, rather than from international knowledge. By estimating the cointegration relation among technological followers (non-US) we expect to find that the relevance of international knowledge for innovation is larger than for the whole sample (including the US). The estimates confirm that this is true. The effect of international knowledge in specification V is almost twice as large as the estimate in the corresponding specification II (that includes the US). Similarly, specification VI splits the sample between G7 countries and non-G7 countries and estimates the cointegration relation separately for each sample. We construct the stock of international knowledge for each country (within or outside the G7) adding knowledge generated in the 'complementary' country group only. That is, in specification VI(a) the coefficient on the variable $\ln(A_{ROWi,t})$ estimates the importance of ideas generated in the G7 on knowledge created in non-G7 countries, while the coefficient on the same variable in specification VI(b) represents the importance of knowledge generated in non-G7 on knowledge created in G7 countries. Consistent with previous findings, the stock of international knowledge is relevant in the domestic creation of knowledge for technological followers, with an elasticity close to 0.75 (recall that the average elasticity of innovation to international knowledge was 0.168, while for non-US was 0.366). We also find that for non-G7 countries the effect of own R&D does not seem particularly significant. In contrast, G7 countries rely mostly upon their own R&D to generate knowledge while international knowledge has no positive impact (in fact we estimate a somewhat puzzling negative effect).

Finally, as a test of cointegration between $\ln(A_{i,t})$, $\ln(A_{ROWi,t})$ and $\ln(R\&D_{i,t})$, (a further test of weak scale effect) we check whether the estimated residuals from regression (10) are stationary. We perform a whole battery of cointegration tests based on different statistics, two of them developed in Pedroni (1995) and seven described in Pedroni (1999). The tests and their results are described in detail and reported in Bottazzi and Peri (2005, Table 5, p.39) Seven of the nine tests performed reject the null hypothesis of no cointegration at the 1% significance level. The two statistics that fail to reject the no cointegration hypothesis are the group-rho statistic and the variance test statistic. As shown in Pedroni (2004), the group-rho statistic is undersized in small panel and is the most conservative test. The panel-variance statistics tend to have the best power when the panel is large, which is not our case. Taken together the tests strongly supports cointegration. We also test the validity of our assumption that only one cointegration relation exist between the three variables $\ln(A_{i,t})$, $\ln(A_{ROWi,t})$ and $\ln(R\&D_{i,t})$. To do this one has to adjust the procedure based on the likelihood ratio inference for VAR models, developed in Johansen (1988, 1991, 1995), to heterogeneous panel data. In particular, we apply the LR-bar test statistics proposed by Larsson *et al.* (2001). We leave the details of the procedure to Bottazzi and Peri (2005, Table 6, p. 40). It suffices to say that the most commonly selected rank, for each country, is one, implying that this test supports the assumption of only one cointegration relation in the panel.

4. The Short-run Impulse Response Function

4.1. *The Error Correction Mechanism Panel VAR*

While departures from the cointegration relation (9) cannot last in the long run, the innovation process is subject to shocks in the short-run. There could be shocks to the amount of resources allocated to research or to the productivity of researchers in generating new ideas. In order to analyse the propagation and impulse response to such shocks in the short-run, we adopt an error correction representation of our dynamic relationship between $\ln(R\&D_{i,t})$ and $\ln(A_{i,t})$. In particular, we consider that the change of each variable depends on prior changes of the other variables (a VAR in differences) but we include a term that captures the deviation from the estimated long run relationship. This disequilibrium term ensures that we account properly for the convergence to the estimated long-run stochastic balanced growth path when tracking the short-run dynamics. We represent the dynamic behaviour of $\Delta\ln(A_{i,t})$ and $\Delta\ln(R\&D_{i,t})$ as follows:

$$\Delta\ln(A_{i,t}) = d_1\hat{\epsilon}_{it-1} + \sum_{z=1}^{2}\eta_{1z}\Delta\ln(R\&D_{i,t-z}) + \sum_{z=1}^{2}\eta_{2z}\Delta\ln(A_{i,t-z}) + \sum_{z=1}^{2}\eta_{3z}\Delta\ln(A_{ROWi,t-z}) + e_{Ait} \tag{11}$$

$$\Delta\ln(R\&D_{i,t}) = d_2\hat{\epsilon}_{it-1} + \sum_{z=1}^{2}\upsilon_{1z}\Delta\ln(R\&D_{i,t-z}) + \sum_{z=1}^{2}\upsilon_{2z}\Delta\ln(A_{i,t-z}) + \sum_{z=1}^{2}\upsilon_{3z}\Delta\ln(A_{ROWi,t-z}) + e_{RDit}. \tag{12}$$

Equations (11) and (12) are sufficient to characterise the dynamics of the idea-generating system in any country, as the international stock of knowledge, $A_{ROWi,t}$, is simply given by the sum of $A_{j,t}$ for all countries other than i. The term $\hat{\epsilon}_{i,t}$ is the disequilibrium term and is equal to $\ln(A_{it}) - \hat{c}_i - \widehat{\lambda}_i t - \hat{\mu}\ln(R\&D_{it}) - \hat{\gamma}\ln(A_{ROWi,t})$. We construct it using the cointegration relation estimated in the previous Section. It represents the deviation from the equilibrium relationship. The coefficients d_1 and d_2 measure how the disequilibrium generates adjustments in order to preserve the long run equilibrium. The Granger representation theorem implies that at least one of the d_i coefficients must be non-zero if a long-run relationship between the variables is to hold. The estimates of d_1 and d_2 in our system are equal to -0.070 (s.e 0.020) and 0.022 (s.e.0.08) respectively. The first coefficient estimate is negative and significant guaranteeing that the system does actually converge to its stochastic long-run relation. The second coefficient is positive but not statistically significant, implying that in the long run the variable R&D is weakly exogenous. Rather than presenting the estimates of the other dynamic coefficients, we show and discuss the impulse responses (IR) of knowledge and R&D resources to e_{Ait} and e_{RDit} respectively. These responses provide a description of the short and medium-run effects of shocks.

4.2. *Impulse Response and Discussion*

Given our flexible specification that allows for country specific effects and spillover effects through the term $A_{ROWi,t}$, the impulse response of country i to an innovation of one of the two equations in country j is different for each i and j. We impose, however, that the sets of coefficients η_{1z},η_{2z},η_{3z} and υ_{1z},υ_{2z},υ_{3z} are equal across countries. The VECM identification is Choleski-type with $\Delta\ln(A_{i,t})$ ordered first and $\Delta\ln(R\&D_{it})$ ordered last. In order to illustrate the effects of shocks to the R&D sector originating in different countries we report only the two most extreme cases.[19] Considering the shocks e_{Ajt} and e_{RDjt} originating in the US (the largest country in the sample) and in Ireland (the smallest country in the sample), we report the impulse response of $\ln(R\&D_{i,t})$, and $\ln(A_{i,t})$ for the domestic economy and for the representative foreign country (Figure 6).[20] Panels 1 to 4 present the complete set of estimated impulse response functions (along with the 99% confidence intervals) for each variable in the originating country and the representative foreign country.[21] Panel 1 tracks the 23 year response in the US and in the representative foreign country to a shock to US innovation, $e_{A,USt}$. Panel 2 does the same for a shock to US R&D employment, $e_{RD,US,t}$. Panel 3 tracks the effect of a shock to Ireland's innovation, $e_{A,IEt}$, and Panel 4 shows the effect of a shock to Ireland's R&D employment, $e_{RD,IE,t}$. The remainder of this Section describes each panel, in turn.

Parts 1.1 and 1.2 of Panel 1 represent the dynamic response to a 1% (0.13) unexpected increase in US innovation at the beginning of the period. Both the US and country r stocks of knowledge increase significantly during the first ten to thirteen years after the shock, and then revert to a smaller yet still positive effect, exhibited by an overall hump-shape. The impact of the US shock on the stock of knowledge of the representative foreign country (r) reaches + 0.02 at the end of the period considered, which corresponds to an increase of 0.17-0.30% of the average stock of its knowledge. This effect is due to two components. First, higher US knowledge increases the stock of world knowledge and this benefits innovation in all countries. Second, in the medium-long run, higher world knowledge drives higher investment in R&D resources of both the US (1.3) and in the representative

[19] Impulse response functions for single countries to the same shocks are available from the authors.

[20] The representative country is obtained by averaging the impulse responses in all countries other than the one where the shock originates.

[21] The confidence intervals are calculated using the Monte Carlo method and the updating algorithm due to Jain and Chlamtac (1985) provided by Eviews 5.1. The algorithm provides a reasonable estimate of the tails of the underlying distribution when the number of repetitions is not too small.

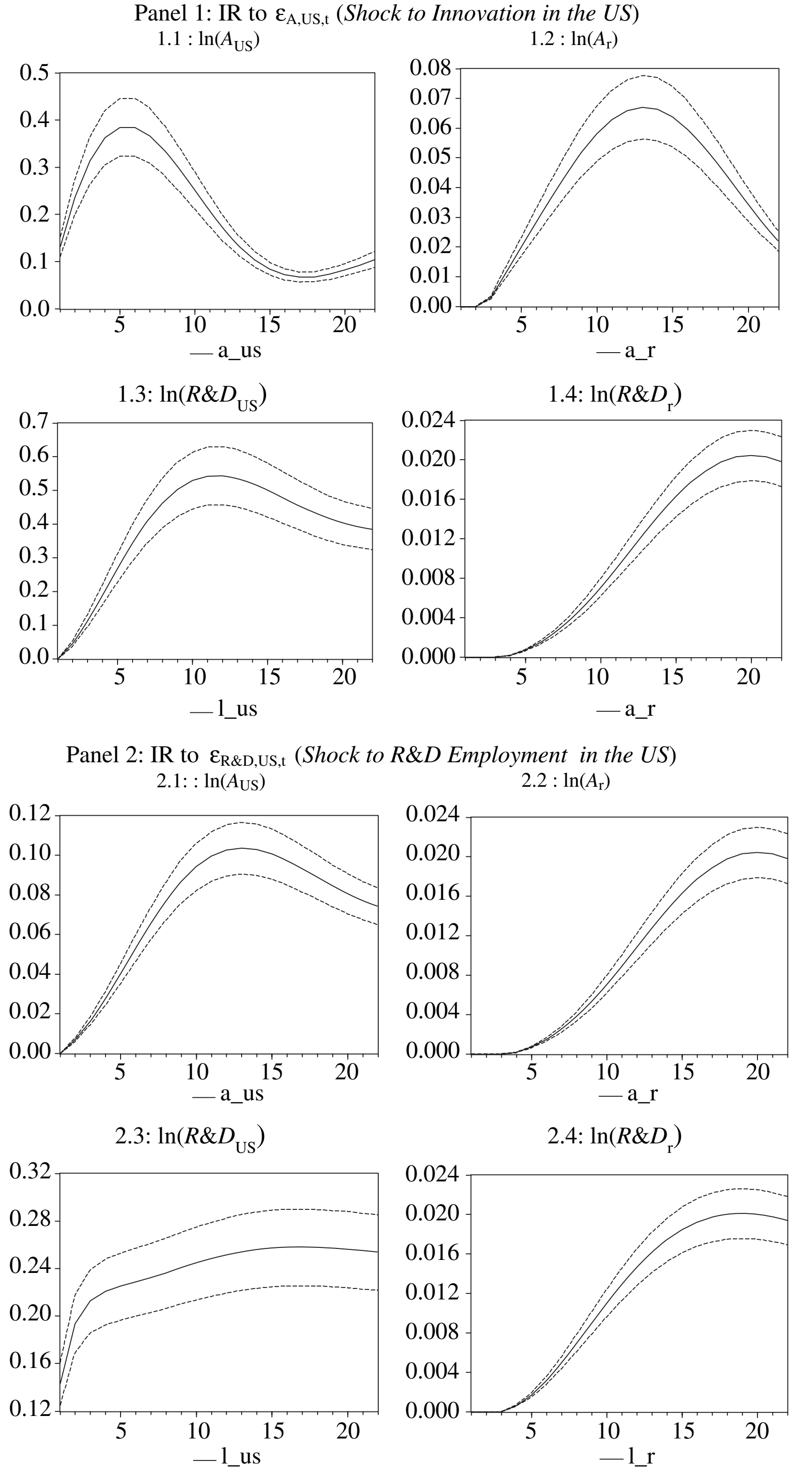
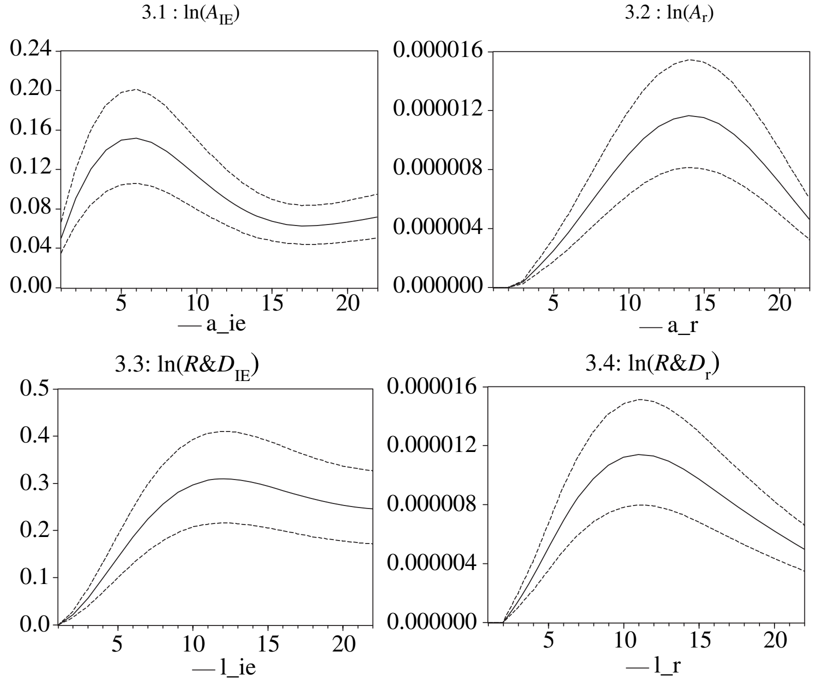


Fig. 6. *Impulse Responses*

Panel 3: IR to $\varepsilon_{A,IE,t}$ (*Shock to Innovation in Ireland*)



Panel 4: IR to $\varepsilon_{R\&D,IE,t}$ (*Shock to R&D Employment in Ireland*)

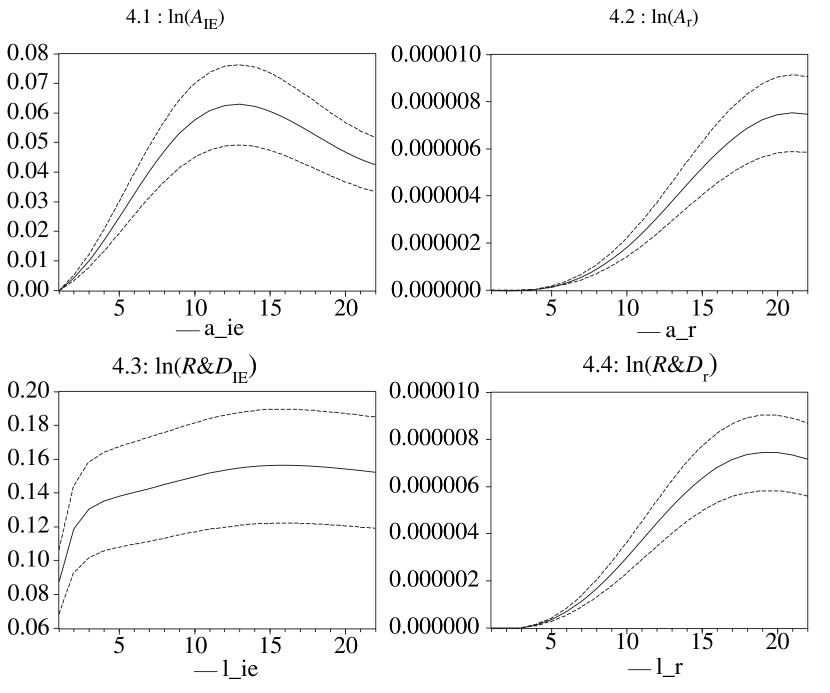


Fig. 6. *Continued*

country (1.4), which in turn contributes to innovation. The effect of this shock on US innovation (1.1) and on US R&D employment (1.3) is large and builds up in the short-run, reaching a peak after 5–10 years and declining afterwards. After 20 years the impact on the US stock of knowledge is roughly equal to 0.13, which is a value close to the initial shock. Interestingly, these impulse responses reveal that both US and foreign R&D employment react positively to an innovation shock in the US, and that such a reaction takes some time to reach its peak (5–10 years). This implies that the strongest effect of a positive shock to innovation is felt in the US and in the international scientific community with a significant delay.

Panel 2 reports the dynamic effects of a shock to US R&D employment on its stock of knowledge and subsequent R&D employment, as well as on those of the representative country *r*. As expected, it takes some periods for the R&D shock (represented in Part 2.3 as the initial jump of the variable) to build its full effect on the stock of knowledge generated in the US (2.1). Moreover, the positive feedback of R&D employment to increases in knowledge (illustrated in Panel 1) is simultaneously at work so that R&D employment further increases after the initial positive shock. After 23 years, the increase in $\ln(A_{US,t})$ reaches a level equal to 0.6% (+0.08) of the average stock of US knowledge. The increase in $\ln(R\&D_{US})$ resources stabilises earlier (after 10–12 years) at +0.25, which represents a 1.9% increase over the average stock of knowledge in the sample. Consistent with the behaviour shown in Panel 1, the impact of $e_{RD,US,t}$ on the stock of knowledge of the representative foreign country is positive (an average increase of 0.18–0.35%) and is somewhat delayed (as shown in 2.3). Finally, the R&D of the representative country responds positively and with a delay to the increased US R&D employment (2.4). Overall, the strongest effect of an increase in R&D employment on innovation takes place with a five to ten year lag. In the long run, an increase in the stock of world knowledge is consistent (due to the cointegration relation) with higher R&D and higher stock of national knowledge for all countries.

Panels 3–4 show the impulse response of knowledge and R&D resources to shocks taking place in Ireland, the smallest country in our sample (in terms of both number of patents and R&D employment). The general shape and timing of these impulse responses are similar to those of Panels 1 and 2. However, there is a notable difference. Given that the US is the major contributor to world knowledge, while Ireland is a marginal one, shocks to the Irish R&D sector have quantitatively minuscule effects on the innovation sector of the representative foreign country *r*. The impulse response of Irish knowledge and $R\&D$ to its own shocks $(e_{A,IEt}, e_{RD,IE,t})$, reported in Panels 3 and 4, are similar to the own responses found for US variables. The response of $\ln(A_{it})$ to $e_{A,IEt}$ (3.1) is hump shaped with maximum effect after five years: the initial 1% increase in the stock of Irish knowledge is almost unchanged after twenty years. The increase in R&D resources after the shock (portrayed in 3.3) is smaller (in absolute value) for the simple reason that the spillover effect generated by other countries' increased stock of knowledge and R&D (reported respectively in 3.2 and 3.4) is now much smaller (notice the scale). Similar patterns emerge when we look at a response to the shock $e_{R\&D,IEt}$ (4.1 and 4.3). Impulse responses for Ireland show a steady increase and by the twentieth year they have reached a plateau. To the contrary, the responses of other countries to these shocks are very small and, even in the long run, amount to less than a hundredth of a percentage point of the initial shock (as seen in 4.2 and 4.4). Altogether, the external effect of a small country such as Ireland on the dynamics of another country's innovation and R&D is negligible both in the short and in the long run.

5. Conclusions

Positive shocks to the innovative activity of a country are the source of booms in the short-run and of sustained productivity growth in the long run. Analysing them in a coherent framework that tracks their consequences at different time horizons is a worthwhile empirical task. Recent economic analysis has largely neglected such research. This article takes a first step in filling this gap by analysing one phase of the innovation process: namely, the interaction of R&D resources and technological knowledge in the generation of new ideas. We apply some recent methods to estimate the long run cointegration relationship between these variables. Moreover, we use an error correction mechanism to estimate short and medium run responses. We find that, in the long run, internationally generated knowledge is an important contributor to the innovation of a country. The stock of knowledge of a country responds to international knowledge with elasticity between 0.2 and 0.5. We then estimate the impulse dynamic response to an innovation shock in the short and medium run. A large country, such as the US, would have a non-negligible impact on other countries' knowledge creation even in the short-run. A 1% positive shock to the log of R&D in US increases the knowledge creation in other countries by an average of 0.35% within ten years. The same shock generates a maximum 6% effect on the US stock of knowledge after five to ten years and then declines slightly.

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