OECD Science, Technology and Industry Working Papers
2005/10

An Empirical Contribution to Knowledge Production and Economic Growth

Kul B. Luintel,

Mosahid Khan

https://dx.doi.org/10.1787/861778011460

OECD

Unclassified **DSTI/DOC(2005)10**

Organisation de Coopération et de Développement Economiques
Organisation for Economic Co-operation and Development

14-Dec-2005

English text only

DIRECTORATE FOR SCIENCE, TECHNOLOGY AND INDUSTRY

DSTI/DOC(2005)10
Unclassified

AN EMPIRICAL CONTRIBUTION TO KNOWLEDGE PRODUCTION AND ECONOMIC GROWTH

STI WORKING PAPER 2005/10
Statistical Analysis of Science, Technology and Industry

Kul B. Luintel and Mosahid Khan

English text only

JT00196006

Document complet disponible sur OLIS dans son format d'origine
Complete document available on OLIS in its original format

STI Working Paper Series

The Working Paper series of the OECD Directorate for Science, Technology and Industry is designed to make available to a wider readership selected studies prepared by staff in the Directorate or by outside consultants working on OECD projects. The papers included in the series cover a broad range of issues, of both a technical and policy-analytical nature, in the areas of work of the DSTI. The Working Papers are generally available only in their original language – English or French – with a summary in the other.

Comments on the papers are invited, and should be sent to the Directorate for Science, Technology and Industry, OECD, 2 rue André-Pascal, 75775 Paris Cedex 16, France.

The opinions expressed in these papers are the sole responsibility of the author(s) and do not necessarily reflect those of the OECD or of the governments of its member countries.

http://www.oecd.org/sti/working-papers

Copyright OECD, 2005
Applications for permission to reproduce or translate all or part of this material should be made to: OECD Publications, 2 rue André-Pascal, 75775 Paris, Cedex 16, France.

AN EMPIRICAL CONTRIBUTION TO KNOWLEDGE PRODUCTION AND ECONOMIC GROWTH

Kul B. Luintel, University of Wales, Swansea (k.b.luintel@swan.ac.uk)
and
Mosahid Khan, OECD (mosahid.khan@oecd.org)*

Abstract

We examine the dynamics of knowledge production for a panel of 19 OECD countries. A new and unique data set is used to proxy the domestic flows of "new-to-the-world" knowledge and ideas. We rigorously address the cross-country heterogeneity in the production of knowledge and the endogeneous nature of this process. The parameters of the knowledge production function point to large cross-country differences. Domestic and foreign stocks of knowledge and ideas have a net positive effect on the production (flows) of new ideas. Countries with a low domestic knowledge base appear to improve their TFP considerably through the accumulation of knowledge. This effect is very modest for countries that already have a sizeable domestic knowledge base. We find ample evidence of duplicate R&D but no support for endogenous growth. Given the heterogeneous nature of knowledge production across OECD countries, R&D policy will need to be adapted to the specific nature of each country; a one-size-fits-all approach will not be effective.

JEL classification: F12; F2: O3; O4; C15

Key words: knowledge stocks; dynamic heterogeneity; TFP; methods of moments.

* We thank Hélène Dernis for patent data and Dirk Pilat and seminar participants at Brunel University and the University of Wales, Swansea, for their comments and suggestions. Kul B. Luintel gratefully acknowledges the support of the OECD Directorate for Science, Technology and Industry (DSTI). The views expressed are those of authors and do not implicate any institutions. The usual disclaimer applies.

PRODUCTION DE CONNAISSANCES ET CROISSANCE ÉCONOMIQUE : UNE CONTRIBUTION EMPIRIQUE

Kul B.Luintel, University of Wales, Swansea (k.b.luintel@swan.ac.uk)
et
Mosahid Khan, OCDE (mosahid.khan@oecd.org)*

Résumé

Cet article examine la dynamique de la production de connaissances dans un échantillon de 19 pays de l'OCDE, au moyen d'un ensemble nouveau et original de données servant à représenter les flux intérieurs de connaissances et données « nouvelles pour le monde entier ». L'hétérogénéité entre pays de la production de connaissances et le caractère endogène du processus sont examinés à la loupe. Les paramètres de la fonction de production de connaissances font ressortir de grandes différences entre les pays. Les stocks intérieurs et étrangers de connaissances et d'idées ont un effet positif net sur la production (les flux) de nouvelles idées. Les pays dotés d'une base de connaissances nationale modeste semblent améliorer considérablement leur PTF par l'accumulation de connaissances. Cet effet est très limité pour les pays qui disposent déjà d'une base de connaissances nationale d'une certaine importance. Les auteurs observent de nombreux éléments montrant une duplication de la R-D, mais aucun signe de croissance endogène. Etant donné le caractère hétérogène de la production de connaissances parmi les pays de l'OCDE, la politique de R-D devra être adaptée aux spécificités de chaque pays ; Il n'existe de formule unique applicable à tous.

JEL classification: F12; F2: O3; O4; C15

Mots clés : *knowledge stocks*; *dynamic heterogeneity*; *TFP*; *methods of moments*.

---

* Les auteurs remercient Hélène Dernis pour les données sur les brevets et Dirk Pilat et les participants au séminaire de la Brunel University et de l'University of Wales à Swansea pour leurs commentaires et suggestions. Kul B. Luintel tient à exprimer sa reconnaissance pour le soutien apporté par l'OCDE (Direction de la Science, de la Technologie et de l'Industrie). Les opinions exprimées sont celles des auteurs et n'engagent en aucune façon quelque institution que ce soit.

AN EMPIRICAL CONTRIBUTION TO KNOWLEDGE PRODUCTION AND ECONOMIC GROWTH

The production of knowledge is at the heart of R&D (research and development) based models of endogenous growth (*e.g.* Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). In these models, new knowledge raises productivity and stimulates sustained capital formation. Continued technological progress - enabled by a constant allocation of resources to the ideas-producing sector - and sustained capital accumulation, together, bring about long-run growth. Growth rates are typically predicted to be proportional to the level of R&D. The technology is assumed to progress endogenously; self-motivated, rational, profit-maximising agents who respond to market incentives undertake R&D in search of innovation. Government policies designed to encourage R&D investment influence the long-run rate of economic growth. These models contrast sharply with the neoclassical growth model, proposed by Solow (1956), which assumes that technological change and hence long-run growth are exogenously determined.

Romer's (1990) seminal work on "endogenous technical change" states that the production (flow) of new ideas ($\dot{A}$) depends on the amount of human capital (H_A) devoted to the ideas-producing sector and on the stock of knowledge (A) available in that sector. One of the underlying features of this model is that the R&D sector exhibits increasing returns to scale: a doubling of H_A and A more than doubles $\dot{A}$.[1] Romer assumes a proportional relationship between $\dot{A}$ and its determinants (H_A and A). However, proportionality between $\dot{A}$ and A is sufficient for endogenous growth to occur.[2]

The predictions of knowledge-driven growth models have spurred a new wave of interest in these models. Jones (1995a, 1995b) examined the "scale effect" predicted by these models. His model finds that while growth rates across OECD countries show little or no persistence, their determinants (investments in physical capital, R&D, etc.) are highly persistent and exhibit strong exponential growth. This discrepancy of persistence between growth rates and their key determinants goes against the predicted "scale effect" and prompts Jones to conclude that R&D-based growth models are "counterfactual". In another study Coe and Helpman (1995), analysing panel data for 21 OECD countries and Israel over the period 1971-1990, report that domestic (S^d) and foreign (S^f) R&D capital stocks affect domestic total factor productivity (TFP) positively and that S^d has a bigger effect than S^f on large countries whereas the opposite holds for smaller ones. Their findings are supportive of the R&D-based growth models, according to which the knowledge stock augments productivity and international knowledge spillovers are positive. However, Luintel and Khan (2004) investigate 10 OECD countries and find that R&D spillovers are extremely heterogeneous across countries and that knowledge appears to flow from the knowledge leader to the follower.

Porter and Stern (2000) test for the parametric restrictions of Romer's (1990) knowledge production function. They use international patent data (patents granted by the United States Patent & Trademark Office to the inventors of other OECD countries) to measure the domestic flows of new-to-the-world knowledge ($\dot{A}^d_{i,t}$) and the stocks of domestic ($A^d_{i,t}$) and rest-of-the-world's ($A^f_{i,t}$) knowledge. They analyse 17 OECD countries for the period 1973-1993. Their key findings are: *(i)* while $\dot{A}^d_{i,t}$ and $A^d_{i,t}$ are proportionally related, the returns to idea researchers ($H_{Ai,t}$) are less than proportional, *(ii)* $A^f_{i,t}$ exerts a negative effect on $\dot{A}^{d}_{i,t}$, *i.e.* the stock of foreign knowledge considerably reduces a country's ability to produce new-to-the-world technologies (the raising-the-bar effect); and *(iii)* $A^{d}_{i,t}$ exerts a small positive and significant effect on $TFP_{i,t}$ but the effect of $A^{f}_{i,t}$ on TFP_{it} is insignificant. This last finding contrasts sharply with the positive knowledge spillovers reported by Coe and Helpman (1995) and others.[3]

I. Motivation

The aim of this paper is to contribute to the empirical literature on the knowledge production function by addressing three key issues: *(i)* data and measurements of new-to-the-world knowledge (new ideas); *(ii)* the cross-country heterogeneity of knowledge production; and *(iii)* endogeneity, *i.e.* the estimation problem posed by simultaneity between knowledge production and its determinants. Knowledge and ideas are intangible and difficult to measure. Patent data are widely used to proxy them. Griliches (1990) calls patents "a good index of inventive activity"; Eaton and Kortum (1996) approve of patent data as a widely accepted measure of innovation. However, patents are a rather "noisy" measure of innovations because: *(i)* they cannot discriminate between the quality of innovations, and *(ii)* not all innovations are patented.[4] Patents differ markedly in their technical and economic importance. Among the thousands of patents awarded each year, only a few may embody valuable knowledge and ideas. How to capture the critical mass of patents that measures the net accrual of economically valuable knowledge to society is a critical issue. Jaffe and Trajtenberg (2002) propose the use of patent citations and/or citation-weighted patent data. Keller (2004), however, warns that citations are often added by the patent examiner rather than the applicant.

Our first contribution is to suggest a way to resolve this issue. We propose and use a new and unique data set - the triadic patent families data - to measure the flows of new-to-the-world knowledge and ideas. At the OECD, this data set is defined as a set of patents at the European Patent Office (EPO), the Japanese Patent Office (JPO) and the US Patent & Trademark Office (USPTO) that share one or more priorities. These patents are thus global in nature.[5]

Two features in particular distinguish this data set from those comprised of patents at regional and/or national levels alone: *(i)* triadic patent families embody highly research-intensive innovations; and *(ii)* they entail high costs to the patentors. The fact that only about 18% of the patents taken at the EPO and USPTO enter the triadic family suggests that these patents may indeed embody highly research-intensive innovations. Moreover, it took, on average, 80 researchers to produce one triadic patent during 1981-2000; less than half that number are needed for each EPO or USPTO patent. Patenting is a costly affair. A triadic family patent costs between two to six times more than a patent taken at any national and/or regional level.[6] Given the high patenting costs, we argue that only valuable ideas that merit a patent at the global level will enter the triadic family. Eaton and Kortum (1999) also argue that "only the best and hence most valuable inventions are patented in many countries". Hence, the unique data set analysed in this paper may proxy the most valuable innovations across countries and reduce "measurement noise" considerably. Our sample spans 20 years (1981-2000) and covers 19 OECD countries. This data set represents 98% of the world's total triadic patent families.

This data set has other attractive features. The OECD has consolidated it to eliminate double counting of the same invention at different patent offices (*i.e.* regrouping all the interrelated priorities in EPO, JPO and USPTO patent documents). Further, the data are based on priority dates and are superior in this respect to the data sets based on grant dates analysed by previous studies (on this issue, see Trajtenberg, 2002 and OECD, 2004, among others). Since new ideas are patented in the early phase of innovation, data based on priority dates preclude researchers from making "strong" assumptions about the time lag involved in the diffusion of ideas. Porter and Stern (2000) emphasise this point. This data set also minimises potential home biases. The diversity of patenting rules across countries generates different propensities to patent and leads to home biases in the data. Such biases are less likely in triadic patent families because the same rules and regulations apply to all. Thus, they provide a comparable measure of innovations across countries.

Second, we construct an arguably better measure of $A_{i,t}^{f}$. The foreign knowledge stock for country "i" is the weighted sum of the rest of the sample countries' domestic knowledge stocks, with the bilateral R&D co-operation coefficients between country "i" and country "js" (js = 1,2…,N-1) used as weights. These weights are country-specific 18X20 matrixes of bilateral R&D co-operation coefficients (see Appendix for details). Our measure of the relevant A^{f} for each sample country reflects: *(i)* the extent of its successful R&D collaboration with the rest of the world; and *(ii)* the notion that ideas proliferate across countries through R&D collaboration.[7] A further advantage is that our measure of $A_{i,t}^{f}$ allows us to identify the parameters of international knowledge spillovers.[8]

Third, we explicitly model the potential cross-country heterogeneity in the knowledge production function. The existing empirical literature based on fixed-effects models only allows for a limited degree of cross-country heterogeneity in knowledge production. The fixed-effects specification assumes that all the slope coefficients, adjustment dynamics, and error variances are the same across countries. A disquieting outcome of these assumptions is that knowledge production appears to be equivalent across countries, whether the country is a leader (*e.g.* the United States) or laggard (*e.g.* New Zealand or Italy). Yet, the assumptions of cross-country homogeneity in slope parameters, adjustment dynamics and error variance are unlikely to hold, because countries differ in their stages of development, domestic technology stocks, capacity to absorb foreign technology, and level and intensity of the R&D they perform. In short, the shape of the knowledge production function is likely to differ across countries. Keller (2004, p. 760) highlights the need to address cross-country heterogeneity in technology diffusion. We bridge this gap by estimating a knowledge production function that allows for cross-country variations in slope coefficients and adjustment dynamics. The potential cross-country divergence in the parameters of knowledge production is modeled as a linear function of country-specific levels of R&D activity. We explain why we prefer levels of R&D activity to R&D intensity measures in section III.

Fourth, we address endogeneity - the estimation problem posed by the simultaneous determination of knowledge production and its determinants. Unless simultaneity is addressed, the estimated parameters become biased and inconsistent. The existing empirical studies on this topic are largely confined to OLS and / or IV estimators.[9] We implement a range of estimators, including the generalised method of moments (GMM) developed for dynamic panel data models. The GMM uses a different number of internal instruments in each time period to address endogeneity. In recent years, GMM has become a well-established methodology in the empirical growth literature. We use the system GMM as our preferred estimator, as it tackles the key estimation issues of endogeneity, weak instruments and measurement errors. We take a structured empirical approach, beginning with the customary static fixed-effect OLS and IV estimators and gradually progressing toward our preferred estimator. This allows us to assess the robustness of our results to various estimators and, at the same time, compare our results with those in the literature. Finally, we estimate a dynamically heterogeneous relationship for TFP and assess its link to stocks of knowledge.

To recapitulate, this is, to our knowledge, the first study that models cross-country heterogeneity in knowledge production using a unique data set of triadic patent families. The cross-country heterogeneity in slope parameters and adjustment dynamics is explicitly modeled as a function of country-specific levels of R&D activity. Our data set provides a comparable measure of innovation across countries. It potentially proxies the most valuable innovations and it is the least likely to be contaminated by home biases and double counting. Patents are enumerated on the basis of priority dates. The issue of endogeneity is rigorously addressed. A better measure of $A_{i,t}^f$ is proposed which, among other things, helps identify the parameters of international knowledge spillovers. The link between TFP and the stocks of ideas is assessed through a dynamic heterogeneous panel model.

To preview our results, we find that the production of new-to-the-world knowledge is extremely heterogeneous across the OECD countries; the slope coefficients and the adjustment dynamics are diverse. These findings are robust to a range of dynamic heterogeneous panel estimators, namely, the OLS, IV and GMM single equation and system estimators. Thus, this study unveils important cross-country differences in the production of knowledge that have thus far remained unexplored. The elasticity of $\dot{A}_{i,t}^d$ with respect to $A_{i,t}^d$ is less than unity for all but one country (Switzerland). Thus, we find standing-on-shoulders effects (*i.e.* current researchers benefit from previously accumulated knowledge) of differing magnitude across countries. Likewise, we find a net positive cross-border externality (*i.e.* $0 \prec \partial \dot{A}_{i,t}^d \big/ \partial A_{i,t}^f \prec 1$) of varying degrees for all the sample countries. Thus, knowledge spillovers are positive but their magnitude varies across countries. This is in sharp contrast to the findings of Porter and Stern (2000) who report a substantial raising-the-bar effect. The elasticity of $\dot{A}_{i,t}^d$ with respect to $H_{Ai,t}$ is positive but less than unity for all but one country (Switzerland). This suggests duplicative R&D - stepping-on-toes effect; extensive variations in cross-country parameters are evident here too.[10] We find a negative point elasticity for the Swiss H_A, which reflects a prolonged decline in the marginal product of Swiss researchers (see Figure 2).

The effect of A^d on TFP is direct and significantly positive; however, the effect of A^f on TFP is indirect: it operates via the accumulation of domestic knowledge stocks only. An interesting pattern concerns the relationship between TFP and A^d. We find a relatively high point elasticity of TFP with respect to A^d for countries with a low knowledge base ($\overline{A}^d$) but this dissipates systematically for countries with a larger knowledge base. Countries with a very low knowledge (stock) base, may thus noticeably improve their TFP through knowledge accumulation.

The rest of the paper is organised as follows. Section II discusses data; section III covers issues of heterogeneity; section IV outlines specification and econometric issues; section V presents empirical results and section VI summarises and concludes.

II. Data

Our sample consists of 19 OECD countries (see Table 1). We use annual data for a period of 20 years (1981-2000), which leads to a balanced panel of 380 observations. The data series required for the core analysis are $\dot{A}^d{}_{i,t}$, $H_{Ai,t}$, $A_{i,t}^d$, $A_{i,t}^f$ and $TFP_{i,t}$. As noted, we proxy the domestic flows of new-to-the-world knowledge by using a unique data set of triadic patent families that provides an analogous measure of innovations across the countries. The $A_{i,t}^d$ for each country is derived from the respective $\dot{A}^d{}_{i,t}$, and is based on the perpetual inventory method. The relevant $A_{i,t}^f$ for each sample country is computed as the weighted sum of the rest of the world's stocks of domestic knowledge, where the time-varying weight reflects the extent of successful international R&D collaboration for each country being considered. The details of the relevant data series, their sources and construction, are provided in the Appendix.

Table 1. **Descriptive statistics (1981-2000)**

	Triadic patents		EPO patents		USPTO patents		R&D expenditure		R&D expenditure as a percentage of GDP		Researchers, 1000s		Researchers as % of total employment		Triadic patents per 1000 researchers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AU	183	64	464	175	584	189	5 151	1 779	1.3	0.2	46	15	0.58	1.3	4.0	0.8
AT	184	54	671	220	410	96	2 631	830	1.4	0.2	12	5	0.30	1.1	16.4	4.1
BE	253	105	677	318	469	180	3 655	787	1.7	0.1	20	6	0.53	1.3	12.4	2.7
CA	308	121	709	387	2 272	893	10 483	2 847	1.6	0.2	70	18	0.53	1.1	4.3	0.7
DK	138	67	407	220	309	130	2 006	694	1.6	0.4	13	4	0.47	1.4	10.5	2.0
FIN	198	137	544	409	467	230	2 199	955	2.1	0.6	16	8	0.73	3.9	11.0	4.9
FR	1 732	356	4 784	1 301	3 219	646	27 881	4 247	2.2	0.1	128	27	0.56	1.1	13.6	1.5
DE	4 254	1 040	12 487	4 380	8 481	1 900	39 748	5 980	2.5	0.2	197	48	0.59	0.6	21.9	3.4
IRL	24	12	82	57	77	43	609	335	1.0	0.2	5	2	0.37	1.1	5.0	1.2
IT	568	154	2 198	885	1 340	307	13 034	2 139	1.1	0.1	69	7	0.31	0.3	8.1	2.0
JP	8 057	2 731	10 981	4 449	24 238	7 873	76 396	16 517	2.8	0.2	562	93	0.87	1.1	14.0	3.3
NL	645	146	1 664	657	1028	221	6 460	1 118	2.0	0.1	30	7	0.44	0.5	21.8	2.8
NZ	20	10	62	36	81	38	688	107	1.0	0.1	6	2	0.52	0.9	3.4	1.1
NO	60	25	187	95	166	62	1 748	409	1.6	0.2	13	4	0.62	1.5	4.4	1.0
SP	65	30	316	218	183	82	4 566	1 738	0.7	0.2	39	17	0.29	1.0	1.6	0.3
SE	533	209	1 246	507	1 082	387	5 796	1 556	3.0	0.5	28	8	0.66	2.0	18.5	2.8
CH	737	92	1 745	386	1 280	106	4 771	714	2.6	0.2	18	4	0.49	0.8	41.9	7.2
UK	1 397	234	3 758	871	3 040	500	23 843	1 854	2.1	0.2	138	12	0.50	0.3	10.1	1.3
US	10 280	2 920	17 397	6 422	60 125	20 718	186 963	37 232	2.6	0.1	970	177	0.76	0.6	10.4	1.4
Mean	1 560	448	3 178	1 157	5 729	1 821	22 033	4 307	1.8	0.2	125	24	0.53	1.2	12.3	2.3

In this and subsequent tables the country mnemonics are: Australia (AU), Austria (AT), Belgium (BE), Canada (CA), Denmark (DK), Finland (FIN), France (FR), Germany (DE), Ireland (IRL), Italy (IT), Japan (JP), Netherlands (NL), New Zealand (NZ), Norway (NO), Spain (SP), Sweden (SE), Switzerland (CH), United Kingdom (UK), United States (US). EPO patents: number of patent applications filed at the European Patent Office; USPTO patents: number of patents granted by the US Patent and Trademark Office; R&D expenditure: gross domestic expenditure on research and development, million constant 2000 PPP dollars. Data source: OECD, Patent and Main Science and Technology Indicators Databases.

Table 1 presents some summary statistics of our dataset. The sample-wide average annual flow of triadic patent families is 1 560 per country with a standard deviation of 448. The equivalent figures for the EPO and USPTO are 3 178 and 5 729 with respective standard deviations of 1 157 and 1 821. Thus, of the total innovations patented at the USPTO and the EPO, only a fraction (about 18%) enter the triadic patent family. This suggests that the latter may indeed contain patents with a high innovative value that are of global importance.[11] Further, an average of 80 researchers produce one triadic patent; the equivalent numbers are 39 and 22 for EPO and USPTO patents, respectively. This reinforces our conjecture that the knowledge embedded in the triadic patent families is more research-intensive than that included only in country and/or regional level patents. There are 38 triadic patents per million population, compared to 216 per million population for the EPO and USPTO, taken together. The average number of researchers per country is 125 000, or 0.53% of the average total employment for the sample of OECD countries.

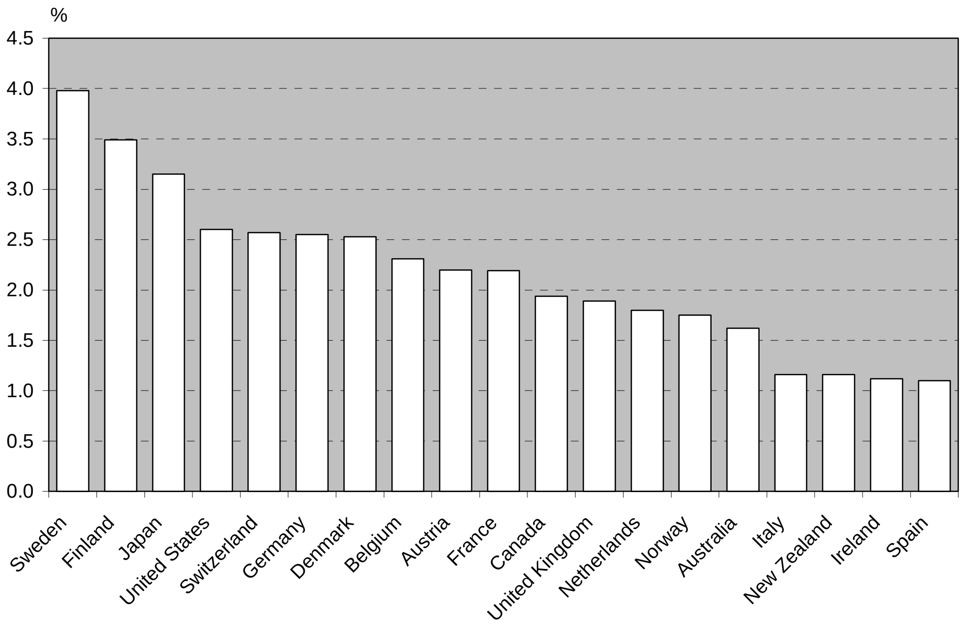
III. Heterogeneity in R&D and knowledge production

The data in Table 1 reveal important cross-country differences in knowledge production and the level and intensity of R&D activity. Clearly, Sweden, Japan, the United States, Switzerland and Germany have the highest R&D intensity (the ratio of R&D expenditure to GDP); they spend between 2.5% and 3.0% of their GDP on R&D. On the other hand, countries like Spain, New Zealand, Ireland, Italy, Austria and Australia are at the bottom end; their R&D expenditure is around 1.0% of GDP. The remaining sample countries spend, on average, 1.8% of their GDP on R&D activity. The proportion of researchers in total employment (research intensity) also differs across countries. Finland, Japan, Norway, Sweden and the United States have a very high research intensity (from 0.62% to 0.87% of persons employed are researchers), whereas Spain, Italy, Ireland and Austria are at the low end (from 0.20% to 0.37% of persons employed are researchers); for the rest of the sample countries this is between 0.44% and 0.59%.

Although these intensity measures are a good indicator of heterogeneity, they nevertheless fail to capture the true degree of disparity in the levels of R&D activity across the sample countries. This is because OECD economies are vastly dissimilar in size. To put this in perspective, the United States and Switzerland each spend 2.6% of their GDP on R&D; however, the level of R&D activity each generates vary: US R&D expenditure amounted to USD 186.96 billion per annum over the 20-year period considered, whereas the equivalent Swiss sum was only USD 4.77 billion. Sweden spent on average 3% of GDP (the world's highest R&D intensity), which amounts to USD 5.80 billion; however, this is less than half the amount spent by Italy, whose R&D intensity is just 1.1%.

In Figures 1 and 2, we report the cross-country R&D intensity as well as each country's shares in total OECD R&D expenditure for the year 2003. Figure 1 shows that the intensity measures for the United States, Switzerland, Germany and Denmark are almost identical. However, Figure 2 reveals the tremendous differences in their R&D activities despite their virtually identical R&D intensities.

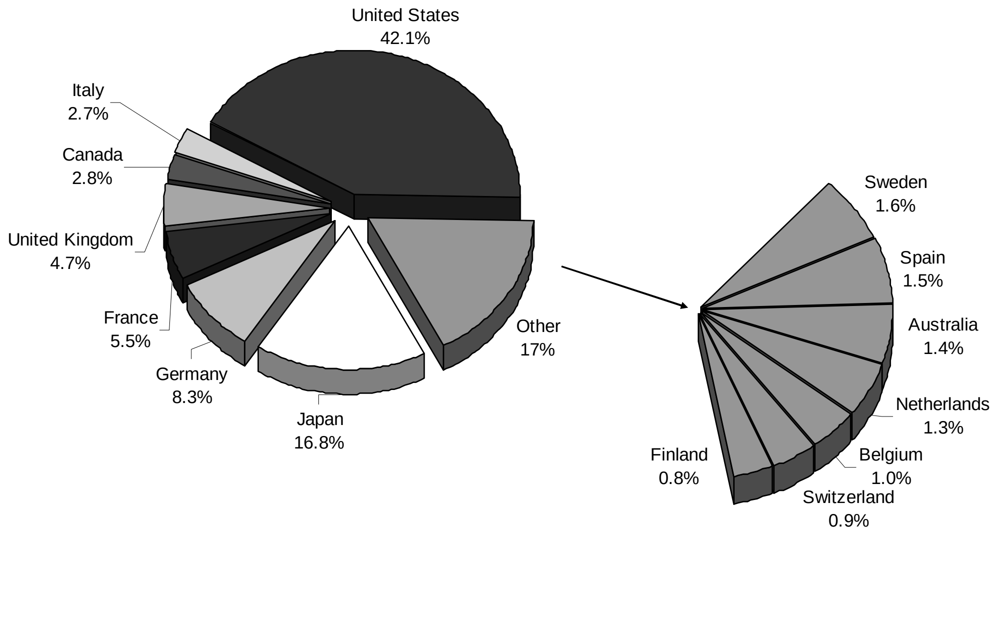
Figure 1. **R&D Intensity (R&D expenditure[1] as a percentage of GDP), 2003 or the latest available year**



1. Gross Domestic Expenditure on Research and Development.

Source: OECD *Science, Technology and Industry Scoreboard*, 2005.

Figure 2. **Share of total R&D expenditure,[1] 2003 or the latest available year**



1. Gross Domestic Expenditure on Research and Development.

Source: OECD Science, Technology and Industry Scoreboard, 2005.

Vast cross-country differences also exist in the number of full-time scientists and engineers engaged in the R&D sector. The United States has by far the largest pool of researchers (970 000) followed by Japan (562 000), Germany (197 000) and the United Kingdom (138 000). Indicators of research intensity fail to capture these vast cross-country differences in the number of full-time scientists and engineers. For example, in terms of research intensity, Norway (0.62%) is ahead of Germany (0.59%), yet the number of full-time researchers employed in Germany is more than 15 times the number in Norway. Switzerland (0.49%) and the United Kingdom (0.51%) appear very similar in research intensity; however, the number of full-time UK researchers is more than seven times that of Switzerland. Table 1 clearly shows these discrepancies. The all-important message is that country-specific mean levels of R&D activity capture the cross-country diversity of innovative activities better than measures of R&D intensity.

Important cross-country differences are also evident in the productivity of knowledge production (measured as the flow of triadic patent families per 1 000 researchers). Over the sample period, Switzerland (41.9), Germany (21.9), the Netherlands (21.8) and Sweden (18.5) top the list. Spain (1.6), New Zealand (3.4), Australia (4.0), Canada (4.3), Norway (4.4), and Ireland (5.0) are at the bottom, as they produced no more than five triadic patents a year per 1 000 researchers. The productivity of the remaining countries is, on average, 8 to 16 new triadic patents per 1 000 researchers.

Figure 3. **Total OECD-wide knowledge productivity (triadic patent families per 1 000 researchers)**

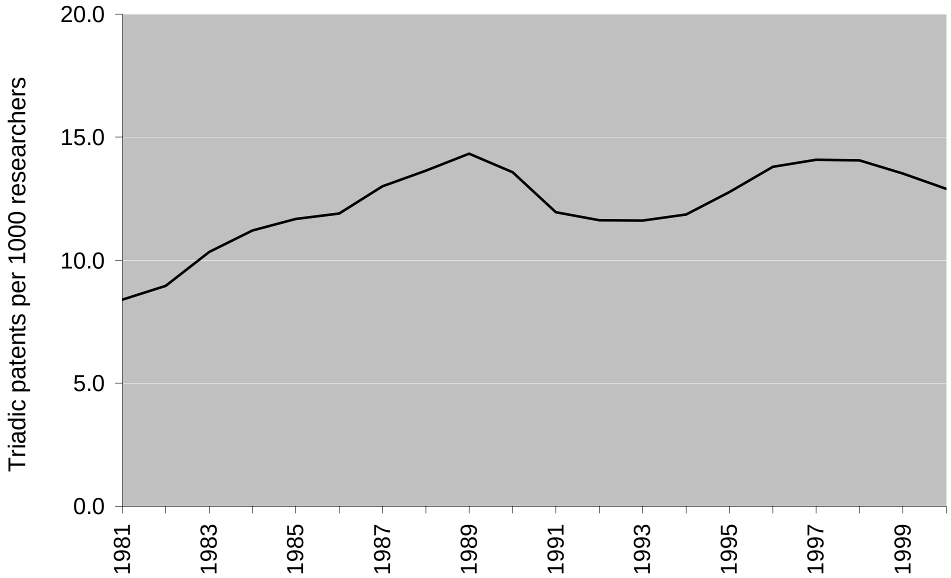
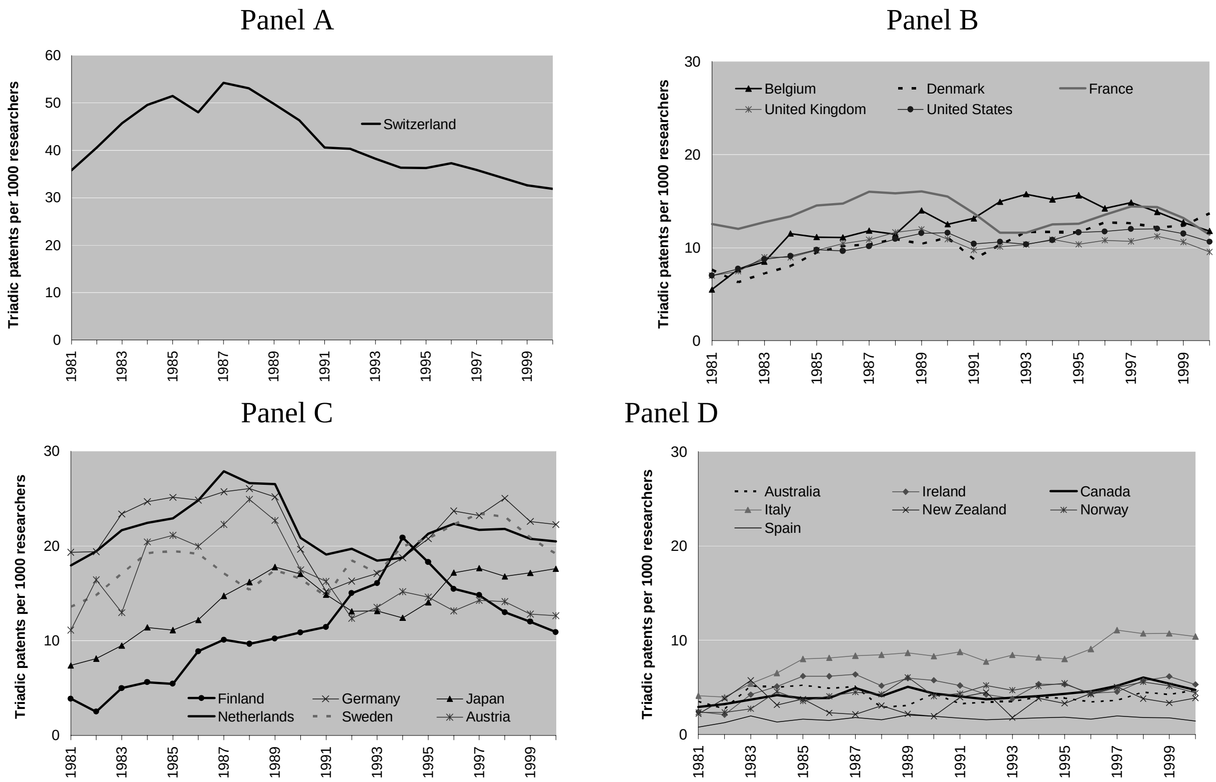


Figure 3 plots the productivity of knowledge production aggregated across all sample countries. It is evident that OECD-wide productivity in knowledge production rose until 1989, followed by a deep slide during 1990-1994. Although the productivity of knowledge production showed some signs of recovery beginning in 1995, the recovery was mild and short-lived and a new decline set in from 1998. Overall, OECD-wide productivity in knowledge production shows a secular decline since 1989.

Figure 4. **Country-by-country knowledge productivity (triadic patent families per 1 000 researchers)**



In Figure 4, we plot the productivity of knowledge creation at the country level. Based on their time profile, we classify the sample countries into four groups and plot them in panels A through D. In panel A, we plot the productivity of Swiss researchers only.[12] The average productivity of Swiss researchers is still the highest in the world, but it has been in continuous decline since 1987. This decline in Swiss research productivity is not unique to our data set. Porter and Stern (2000), using data from the USPTO only, report a similar pattern. Given this downward trend in Swiss research productivity, one would expect a negative marginal product ($\partial \dot{A}^d / \partial H_A$) for Swiss researchers. As will become evident below, one of the strengths of our empirical approach is that it captures precisely this type of cross-country heterogeneity with the parameters of the knowledge production function. We are able to capture this decline in Swiss productivity in a panel setting.

The research productivity of Belgium, Denmark, France, the United Kingdom, and the United States is plotted in panel B. For the most part, these countries exhibit a relatively stable productivity level of 10 to 14 triadic patents a year per 1 000 researchers. France and the United Kingdom show a very similar time profile but France has higher productivity than the United Kingdom. The United States shows a positive trend in productivity for most of the sample period except for mild declines in the early and late 1990s.

Plots for Austria, Finland, Germany, Japan, the Netherlands, and Sweden are shown in panel C. Compared to those in panel B, this set of countries exhibits generally higher but more volatile research productivity. Japan and Sweden show opposite time profiles for productivity; Sweden's research productivity has always been higher than that of Japan, except for a brief period from 1988 to 1991. Germany and the Netherlands exhibit very similar research productivity patterns.

Finally, panel D plots the countries with low research productivity: Australia, Ireland, Canada, Italy, New Zealand, Norway, and Spain. Except for Italy, almost all exhibit stable but low productivity of five or fewer triadic patents a year per 1 000 researchers. For the most part, Italy's productivity is also well below 10 patents per 1 000 researchers. Overall, Figure 1 indicates declining OECD-wide knowledge productivity, while Figure 2 reveals important cross-country heterogeneity in the time profile of knowledge productivity.

IV. Specification and econometric issues

Romer (1990) defines "ideas" as a non-rivalrous but partially excludable global commodity. This partial excludability distinguishes ideas (or knowledge) from "pure" public goods. Romer does not discuss domestic and foreign knowledge stocks separately. In fact, in his model, the flows of new ideas are proportional to the global stock of knowledge. However, our specification follows in the tradition of Coe and Helpman (1995) and Porter and Stern (2000). We allow for separate effects of domestic and foreign knowledge stocks in the domestic production of new-to-the-world knowledge. This approach is sensible, given the existence of barriers to international trade that may affect international knowledge flows and the degree of international R&D collaboration. In view of these considerations, a typical dynamic (autoregressive) knowledge production function popular in the literature (all variables are expressed in natural logarithms), is:

$$(1) \quad \dot{A}^{d}_{i,t} = \alpha_i + \gamma_t + \lambda \dot{A}^{d}_{i,t-1} + \beta H_{Ai,t} + \phi A^{d}_{i,t} + \psi A^{f}_{i,t} + e_{i,t}$$

(i= 1,…,N; and t=1,…,T).

where "i" and "t" denote the cross-sectional and time series dimensions; α_i captures the time-invariant unobserved country-specific fixed effects (*e.g.* differences in the initial level of innovative efficiency) and γ_t captures the unobservable individual-invariant time effects (*e.g.* technological shocks that are common to all countries). The autoregressive parameter, λ, measures the speed of adjustment while β, ϕ and ψ measure the contemporaneous elasticity of $\dot{A}^{d}_{i,t}$ with respect to $H_{Ai,t}, A^{d}_{i,t}$ and $A^{f}_{i,t}$, respectively. Conceptually, $A^{d}_{i,t}$ has two opposing effects: it may facilitate the production of new knowledge - the standing-on-shoulders effect - or it may make the discovery of new ideas more difficult because the knowledge that is easy to discover comes first and makes the subsequent discovery of new knowledge difficult - the fishing-out effect. The parameter ϕ nets out these two opposing effects. If ϕ>0, then the standing-on-shoulders effect dominates the fishing-out effect and vice versa. If, however, ϕ=0 then the production of new knowledge is independent of the knowledge domestically discovered and accumulated in the past. Likewise, ψ nets out two opposing effects of $A^{f}_{i,t}$: the stock of foreign knowledge may complement the domestic production of new knowledge – *i.e.* a positive international externality – or foreign inventions may raise the global innovation bar, making the domestic discovery of new knowledge more difficult - the raising-the-bar effect. A positive ψ implies that positive international externalities dominate the raising-the-bar effect and vice versa. If ψ=0 then the domestic production of new-to-the-world knowledge is independent of the rest of the world's stock of knowledge.

Specification (1) is standard in the literature. Unfortunately, it only allows for unobservable individual and time effects. All other parameters are assumed homogeneous across all the countries in the panel. However, as explained above, this assumption is quite strong and unlikely to hold. Hence, we model cross-country heterogeneity in knowledge production directly by estimating the following model:

$$(2)\quad \dot{A}^{d}{}_{i,t} = \alpha_i + \gamma_t + \lambda_1 \dot{A}^{d}{}_{i,t-1} + \lambda_2(\dot{A}^{d}{}_{i,t-1} * \bar{H}_{Ai}) + \lambda_3(\dot{A}^{d}{}_{i,t-1} * \bar{A}_i^{d}) + \beta_1 H_{Ai,t}$$
$$+ \phi_1 A_{i,t}^{d} + \psi_1 A_{i,t}^{f} + \beta_2(H_{Ai,t} * \bar{H}_{A,i}) + \beta_3(H_{Ai,t} * \bar{A}_i^{d}) + \phi_2(A^{d}{}_{i,t} * \bar{H}_{Ai})$$
$$+ \phi_3(A^{d}{}_{i,t} * \bar{A}_i^{d}) + \psi_2(A_{it}^{f} * \bar{H}_{Ai}) + \psi_3(A_{i,t}^{f} * \bar{A}_i^{d}) + e_{i,t}$$

where $\bar{H}_{Ai} = T_i^{-1}\sum_{t=1}^{T_i} H_{Ai,t}$ and $\bar{A}_i^{d} = T_i^{-1}\sum_{t=1}^{T_i} A_{it}$. Equation (2) is a dynamic heterogeneous model in a panel framework.[13] It allows the slope parameters (β_j, ϕ_j and Ψ_j) and the adjustment dynamics (λ_j; j= 2,3) of the knowledge production function to differ across countries. Heterogeneity in parameters and adjustment dynamics are assumed to be a linear function of country-specific mean levels of researchers engaged in the knowledge-producing sector ($\bar{H}_{A,i}$) and the stock of domestically invented and accumulated knowledge in the past ($\bar{A}_i^{d}$).[14] The use of R&D intensity is also intuitively appealing; however, as shown in section III, it fails to capture profound cross-country differences in R&D activity. We therefore decided not to use the intensity measures. Specification (2) nests both static models and some variants of dynamic models. If $\lambda_j=\beta_j=\phi_j=\psi_j=0$ holds for j=2,3; then the relationship is static. If $\lambda_2=\lambda_3=0 \cup \beta_j=\phi_j=\psi_j \neq 0$, then the relationship is heterogeneous in slope parameters but homogeneous in adjustment dynamics (autoregressive parameters); if however $\lambda_2=\lambda_3\neq 0 \cup \beta_j=\phi_j=\psi_j \neq 0$, then the relationship is heterogeneous in both slope parameters and adjustment dynamics. From (2) the vector of the country-specific parameters is computed as:

(3) $\delta_i = \delta_1 + (\delta_2 * \bar{H}_{Ai}) + (\delta_3 * \bar{A}_i^{d})$; where $\delta = [\lambda_j, \beta_j, \phi_j, \psi_j]'$.

Econometric issues

Any prospective estimator for specification (2) needs to address the following three issues: *(i)* the likely endogeneity due to the joint determination of some of the right- and left-hand-side variables (*e.g.* the stock and the flow of new knowledge) and/or the presence of lagged dependent variables; *(ii)* inertia - quite common in annual data - which may cause bias and imprecision in the estimated parameters; and *(iii)* measurement errors that may be linked to the proxies of new knowledge.

Among the available dynamic panel data estimators, the system GMM estimator appears best suited for our purpose. The GMM estimators use a different number of internal instruments for each period to address endogeneity. The system GMM, in particular, allows us to control for all the estimation issues listed in *(i)*-*(iii)* above. The initial development of the GMM estimator is due to Holtz-Eakin *et al.* (1988) and to Arellano and Bond (1991). For a short illustration of this approach, we rewrite equation (2) by suppressing the interaction terms for simplicity but without loss of generality, as:

(4) $y_{i,t} = \alpha_i + \gamma_t + \lambda y_{i.t-1} + X_{it}\varphi + e_{i,t}$

where y_{it} denotes $\dot{A}^{d}{}_{it}$; vector X = ($H_{Ai,t}$, $A_{i,t}^{d}$, $A_{i,t}^{f}$); and $\varphi = [\beta_{ij}, \phi_{ij}, \psi_{ij}]'$; (j=1). If $E(e_{it}e_{is})$ = 0 holds for $s\neq t$ across all "i", then it yields the following moment conditions:

(5) $E(y_{i,t-s}\,\Delta e_{it})=0$ for $s\geq 2$; t= 3,…, T.

Likewise, if X_{it} are weakly exogenous then the following additional moment conditions are also valid:

(6) $E(X_{i,t-s}\,\Delta e_{i,t})=0$ for $s\geq 2$; t= 3,…, T.

The single equation GMM estimator usually specifies a dynamic panel data model in the first differences and exploits the above moment conditions.[15] Hence, the lagged (two periods or more) levels of endogenous and weakly exogenous variables of the model become suitable instruments for addressing endogeneity. The single equation GMM estimator provides consistent parameter estimates.

However, when data are persistent (issue *ii* above) and the time-series dimension is moderately short, the single equation estimator suffers from the problem of weak instruments. In other words, the lagged levels (internal instruments) and the regressors (subsequent first differences or other suitable transformations) show weak correlation. As a result, the estimated parameters suffer from large finite sample biases and poor precision. Ahn and Schmidt (1995) and Staiger and Stock (1997), among others, illustrate this point. Fortunately, Arellano and Bover (1995) and Blundell and Bond (1998) propose the system GMM estimator which dramatically reduces the biases and imprecision associated with the single equation estimator. The system GMM estimator estimates a system of equations in the first differences (or other suitable transformations) and levels by stacking the data. It combines the standard set of (T-s) transformed equations with an additional set of (T-s) equations in levels (note $s \geq 2$). The first set of transformed equations continues to use the suitably lagged levels as instruments. The level equations, on the other hand, use the suitably lagged first differences as instruments. Their validity is based on the following moment conditions:[16]

(7) $E[(\alpha_{i,t} + e_{i,t})\, \Delta y_{i,t-s}] = 0$ for $s=1$

(8) $E[(\alpha_{i,t} + e_{i,t})\, \Delta X_{i,t-s}] = 0$ for $s = 1$

Bond et al. (2001) show that the system GMM estimator performs better than a range of other method-of-moment type estimators. In our empirical work, we focus on the system GMM estimator as our preferred approach. The consistency of GMM estimators hinges crucially on whether the lagged values of the explanatory variables are indeed a valid set of instruments and whether e_{it} is serially uncorrelated. We perform Sargan's instruments validity test (applicable to single equation GMM) and the Difference-Sargan test (applicable to system GMM) to establish the validity of instruments. A second order serial correlation test is carried out to establish whether the error term is well behaved.

V. Empirical results

We first report the results obtained from the fixed-effect static and first-order-autoregressive panel data models in Table 2. The OLS and IV estimators are applied. These approaches are extensively used in the panel literature but, as discussed above, they fail to capture cross-country heterogeneity. Nevertheless, they serve two important purposes: *(i)* they allow us to assess the robustness of our results *vis-à-vis* different specifications and estimators; and *(ii)* we can compare our results with those in the literature.

The fixed effect estimates show that the stocks of both domestic and foreign knowledge facilitate the production of new-to-the-world knowledge domestically. The OLS point estimates (elasticities) are 0.604 and 0.266 for $A^d_{i,t}$ and $A^f_{i,t}$, respectively; they are statistically significant but well below unity. The point elasticity of H_A is also significantly positive but below unity (0.402). The IV estimates are qualitatively similar. In most cases, the fixed and time effects both appear significant, suggesting that the country- and time-specific shocks differ significantly across the sample countries. However, the static models show significant first-order residual serial correlation. The last column of the table reports the results from the first-order autoregressive model. In this column, the first-order serial correlation disappears; nonetheless, results remain qualitatively the same, because the long-run solutions of parameters appear very close to those obtained from the static models.

Table 2. **The fixed effects panel estimates**

Specification: $\dot{A}^{d}_{i,t} = \alpha_i + \gamma_t + \lambda \dot{A}^{d}_{i,t-1} + \beta H_{Ai,t} + \phi A^{d}_{i,t} + \psi A^{f}_{i,t} + e_{i,t}$			
	OLS-Static	IV- Static	OLS-AR(1)
Constant	-0.017 (0.984)	0.342 (0.731)	
$\dot{A}^{d}_{i,t-1}$	-	-	0.377 (0.000)
$H_{Ai,t}$	0.402 (0.001)	0.328 (0.028)	0.233 (0.016)
$A^{d}_{i,t}$	0.604 (0.000)	0.581 (0.000)	0.318 (0.004)
$A^{f}_{i,t}$	0.266 (0.000)	0.361 (0.000)	0.216 (0.000)
α_i	(0.000)	(0.127)	(0.000)
γ_t	(0.001)	(0.000)	(0.000)
R^2	0.994	n.a.	0.995
σ	0.151	0.149	0.140
AR(1)	(0.003)	(0.002)	(0.136)
AR(2)	(0.290)	(0.351)	(0.641)
Observations	380	361	361

Note: AR(1) and AR(2) are Lagrange-multiplier (LM) tests of serial autocorrelations of order 1 and 2, under the null of no autocorrelation; α_i and γ_t are fixed and time effects, respectively. σ is the regression standard error. Numbers (.) are p-values. The reported results remain qualitatively the same when a GLS estimator is used. The IV estimates are obtained by using A^{d}_{t-1}, $H_{Ai,t-1}$ and $A^{f}_{i,t-1}$ as instruments. Following Porter and Stern (2000), we also experimented with "coarser controls". Real 1978 GDP is used to proxy the base line per capita productivity measure, a trend variable [0 to 19] and a year dummy 1981=1 are also used. The trend variable has a small negative but significant coefficient, however, the reported results remain almost identical.

The results of Table 2 are methodologically similar to the work of Porter and Stern (2000). The latter also estimate the parameters of the knowledge production function. Our results differ from theirs in two respects. First, we do not find a proportional relationship between $\dot{A}^{d}_{i,t}$ and $A^{d}_{i,t}$. They report unit elasticity of $\dot{A}^{d}_{i,t}$ with respect to $A^{d}_{i,t}$ irrespective of the inclusion (exclusion) of $A^{f}_{i,t}$ in (from) the estimating equation. Second, they report a substantial raising-the-bar effect of A^{f} (*i.e.* $\partial \dot{A}^{d}_{i,t} \big/ A^{f}_{i,t} = -1$), whereas we find quite the opposite (*i.e.* $\partial \dot{A}^{d}_{i,t} \big/ A^{f}_{i,t} > 0$). However, a common difficulty associated with these results is that they emanate from models that neglect the cross-country heterogeneity in knowledge production. This raises concerns because the reliability of these results critically hinges on the degree to which the assumptions of cross-country homogeneity in parameters and adjustment dynamics hold. Pesaran *et al.* (2000) formally illustrate this point.

Table 3 reports the results obtained from our dynamic heterogeneous panel model specified in equation (2). For the sake of robustness, we report results based on three different estimators, namely, the dynamic heterogeneous OLS, the single-equation GMM, and the system GMM. The results reject the homogeneity of slope coefficients and adjustment dynamics across all sample countries. In sharp contrast to the fixed-effect estimates of Table 2, none of the level variables ($H_{Ai,t}$, A^{d}_{it} and A^{f}_{it}) appears significant on its own; instead, regressors interacted with $\overline{H}_{A,i}$ and $\overline{A}^{d}_{i}$ dominate and appear highly significant. All coefficients associated with $\dot{A}^{d}_{i,t-1}$, $H_{Ai,t}$, $A^{d}_{i,t}$ and $A^{f}_{i,t}$ show significant cross-country variations.

Therefore, it is evident that the parameters of the knowledge production function are country-specific and systematically depend on the scale of innovative activities performed by each country.

Table 3. **The dynamic heterogeneous panel estimates**

$$\dot{A}^{d}{}_{i,t} = \alpha_i + \gamma_t + \lambda_1 \dot{A}^{d}{}_{i,t-1} + \lambda_2(\dot{A}^{d}{}_{i,t-1} * \bar{H}_{A,i}) + \lambda_3(\dot{A}^{d}{}_{i,t-1} * \bar{A}_i^{d}) + \beta_1 H_{Ai,t} + \phi_1 A^d_{i,t} + \psi_1 A^f_{i,t} + \beta_2(H_{Ai,t} * \bar{H}_{Ai}) + \beta_3(H_{i,t} * \bar{A}_i^{d}) + \phi_2(A^{d}{}_{i,t} * \bar{H}_{Ai}) + \phi_3(A^{d}{}_{i,t} * \bar{A}_i^{d}) + \psi_2(A^f_{it} * \bar{H}_{Ai}) + \psi_3(A^f_{i,t} * \bar{A}_i^{d}) + e_{i,t}$$

	OLS	GMM single equation	GMM system
Constant	-1.202 (0.005)	-1.079 (0.011)	-1.396 (0.004)
$\dot{A}^{d}{}_{t-1}$	1.472 (0.000)	1.551 (0.000)	1.308 (0.000)
$(\dot{A}^{d}{}_{i,t-1} * \bar{H}_i)$	-0.178 (0.003)	-0.190 (0.001)	-0.155 (0.002)
$(\dot{A}^{d}{}_{i,t-1} * \bar{A}_i^{d})$	0.235 (0.000)	0.251 (0.000)	0.204 (0.000)
$H_{Ai,t}$	-	-	-
$A^d_{i,t}$	-	-	-
$A^f_{i,t}$	-	-	-
$(H_{Ai,t} * \bar{H}_{Ai})$	0.139 (0.003)	0.145 (0.003)	0.138 (0.026)
$(H_{Ai,t} * \bar{A}_i^{d})$	-0.093 (0.002)	-0.098 (0.001)	-0.088 (0.035)
$(A^{d}{}_{i,t} * \bar{H}_i)$	-	-	-
$A^{d}{}_{i,t} * \bar{A}^{d}{}_i$	-0.043 (0.002)	-0.043 (0.001)	-0.042 (0.004)
$(A^{f}{}_{i,t} * \bar{H}_i)$	-	-	-
$(A^{f}{}_{i,t} * \bar{A}^{d}{}_i)$	-0.022 (0.000)	-0.023 (0.000)	-0.024 (0.000)
α_i	(0.000)	(0.000)	(0.000)
γ_t	(0.000)	(0.000)	(0.000)
σ	0.136	0.136	0.137
AR(1)	(0.361)	(0.378)	(0.611)
AR(2)	(0.619)	(0.608)	(0.678)
Sargan χ^2 [r]	-	241.2[458]	282.1[509]
Diff. Sargan χ^2 [r]	-	-	40.9 [51]
Observations	361	361	361

Note: For OLS, AR(1) and AR(2) are the first and second order LM tests of residual serial correlation. Under GMM, these tests are implemented on the first differenced residuals because of the transformations involved. α_i and γ_t are the fixed and time effects. Numbers (.) are p-values. Sargan tests are χ^2 distributed with 'r' degree of freedom under the null of valid instruments. $\dot{A}^{d}{}_{t-1}$, $H_{Ai,t}$ and $A^d_{i,t}$ are GMM-instrumented setting $s \geq 3$; All GMM results pertain to the first step. $A^f_{i,t}$ and the mean-interacted regressors are treated exogenously. Reported results are robust even when the latter are instrumented by their lagged values. Results are also robust to "coarser variables" (see footnote to Table 2), only the trend variable appears with a significantly negative coefficient ranging from -0.048 to -0.081 across specifications.

The signs of these coefficients suggest that, on average, the flow of new-to-the world knowledge is likely to be higher in countries that engage more scientists and engineers in the knowledge-producing sector. In contrast, however, when the domestic knowledge stock is large, the flow of new knowledge exhibits a low return. Interestingly, our results also reveal that when countries accumulate more and more of their own domestic stock of knowledge, the spillover benefits from foreign knowledge are reduced. The qualitative nature of these findings is robust to all three estimators. All estimated models pass diagnostic checks. A test for second-order residual serial correlation is clearly insignificant which indicates that residuals are well behaved.[17] Sargan tests confirm the validity of the instruments in both GMM models. The fixed and time effects continue to be significant.

Table 4 reports the country-specific parameters computed from the results in Table 3, following the method shown in equation (3), along with their cross-sectional averages. Although our results are robust to different estimators, we focus on the parameter estimates obtained from the system GMM owing to its superiority over other estimators (see section IV).[18] These parameters show positive effects of A^d and A^f on $\dot{A}^d$ for all countries; however, there is extensive cross-country variation. The point elasticity of $\dot{A}^d$ with respect to A^d ranges from a minimum of 0.390 (Spain) to a maximum of 1.069 (Switzerland); this is a ratio of 2.74. The cross-sectional average is 0.553. Likewise, the coefficients of A^f range from a minimum of 0.220 (Spain) to a maximum of 0.603 (Switzerland); this again represents a cross-country difference of more than 2.5. The cross-sectional average is 0.312. Switzerland shows the highest sensitivity of $\dot{A}^d$ with respect to A^d and A^f and Spain shows the lowest.

The estimated point elasticity of $\dot{A}^d$ with respect to H_A exhibits an even wider cross-country variation (*i.e.* the estimated point elasticities differ widely between nations). It ranges from a minimum of -0.272 (Switzerland) to a maximum of 0.807 (United States). A striking result is that we identify a negative marginal product (-0.272) for Swiss researchers. At first instance, this may appear puzzling; however, it reflects the prolonged decline in Swiss knowledge productivity (see Figure 4, panel A). While Swiss researchers are still the best in terms of their average product level, their productivity has been in continuous decline since 1987. Our result captures this secular decline - a finding not revealed by other panel studies, as they neglect cross-country heterogeneity.

The highest point elasticity of $\dot{A}^d$ with respect to H_A for the United States suggests that the US community of researchers is probably the most innovative. The low point elasticity of the United States' flows of new knowledge vis-à-vis its A^d may reflect its huge stock of domestic knowledge and hence a low marginal return to A^d. Likewise, its low point elasticity of $\dot{A}^d$ with respect to A^f may reflect its innovative edge in the world of knowledge, thus leaving little scope for the overflow of new knowledge from the rest of the world. Austria, Belgium, Denmark, Finland, Ireland, the Netherlands, New Zealand and Sweden typically demonstrate low knowledge productivity. Huge cross-country variations are also apparent in the adjustment dynamics (λs). Spain shows the lowest adjustment parameter (0.086) and Switzerland the highest (0.778). Other countries with a high adjustment coefficient are Germany (0.748), the United States (0.656), Japan (0.661), and France (0.629).[19]

Table 4. **Country-specific parameters obtained from the estimates of Table 3**

	Knowledge production function												TFP*	
	OLS				GMM single equation				GMM system approach				GMM system	
	λ	β	φ	ψ	λ	β	φ	ψ	λ	β	φ	ψ	ξ	φ
AU	0.321	0.357	0.459	0.238	0.318	0.380	0.461	0.246	0.312	0.297	0.442	0.249	0.930	0.246
AT	0.574	0.113	0.729	0.378	0.588	0.135	0.761	0.406	0.533	0.023	0.648	0.366	0.930	0.243
BE	0.532	0.219	0.642	0.333	0.544	0.246	0.664	0.355	0.496	0.131	0.581	0.328	0.924	0.218
CA	0.341	0.401	0.446	0.232	0.340	0.427	0.449	0.240	0.329	0.341	0.427	0.241	0.921	0.205
DK	0.448	0.187	0.599	0.311	0.453	0.208	0.611	0.326	0.423	0.111	0.559	0.316	0.940	0.304
FIN	0.400	0.230	0.554	0.287	0.402	0.251	0.561	0.300	0.382	0.159	0.524	0.296	0.941	0.309
FR	0.687	0.541	0.674	0.350	0.711	0.625	0.735	0.392	0.629	0.387	0.554	0.313	0.878	0.095
DE	0.825	0.820	0.983	0.510	0.858	1.078	1.222	0.653	0.748	0.487	0.666	0.376	0.858	0.067
IRL	0.207	0.165	0.514	0.267	0.195	0.178	0.511	0.273	0.215	0.104	0.506	0.286	0.980	1.102
IT	0.492	0.405	0.524	0.272	0.502	0.441	0.538	0.287	0.461	0.321	0.480	0.271	0.906	0.156
JP	0.725	0.931	0.566	0.294	0.752	1.089	0.631	0.337	0.661	0.697	0.446	0.252	0.849	0.057
NL	0.709	0.210	0.873	0.453	0.733	0.256	0.960	0.513	0.649	0.088	0.706	0.399	0.900	0.141
NZ	0.182	0.189	0.496	0.257	0.169	0.203	0.492	0.263	0.194	0.131	0.490	0.277	0.978	1.037
NO	0.245	0.250	0.485	0.251	0.236	0.267	0.483	0.258	0.248	0.192	0.474	0.267	0.958	0.480
SP	0.060	0.353	0.389	0.202	0.038	0.368	0.384	0.205	0.086	0.315	0.390	0.220	0.958	0.483
SE	0.646	0.230	0.758	0.393	0.666	0.268	0.810	0.432	0.595	0.121	0.645	0.364	0.908	0.159
CH	0.857	-0.219	1.700	0.882	0.891	-0.267	2.259	1.206	0.778	-0.272	1.069	0.603	0.895	0.127
UK	0.633	0.537	0.593	0.307	0.652	0.604	0.631	0.337	0.582	0.408	0.507	0.286	0.882	0.101
US	0.721	1.055	0.496	0.257	0.747	1.229	0.553	0.295	0.656	0.807	0.393	0.222	0.841	0.048
Mean	0.506	0.367	0.657	0.341	0.516	0.420	0.722	0.386	0.473	0.255	0.553	0.312	0.915	0.294
SD	0.232	0.305	0.294	0.153	0.249	0.369	0.422	0.226	0.201	0.245	0.155	0.088	0.041	0.301

Note: λs are solutions for the country-specific long-run coefficients of the lagged dependent variables. β, φ and Ψ are the country-specific long-run elasticities of $\dot{A}^{d}_{i,t}$ with respect to $H_{Ai,t}$, $A^d_{i,t}$, $A^f_{i,t}$. * The estimated TFP relationship, equation (9) in the text, is:

$$TFP_{i,t} = 0.574 + 0.769\,TFP_{i,t-1} - 0.022(TFP_{i,t-1} * \bar{A}^d_i) - 0.008\,(A^d_{i,t-1} * \bar{A}^d_i) + 0.001(A^f_{i,t} * \bar{A}^d_i) + 0.002\,A^f_{i,t}$$

[0.053] [0.000] [0.064] [0.000] [0.280] [0.828]

This specification passes the second order residual serial correlation and instrument validity tests. [.] are p-values. Lagged dependent variables and $A^d_{i,t}$ are GMM instruments setting $s \geq 3$. φ_s are country-specific long-run elasticities of $TFP_{i,t}$ with respect to $A^d_{i,t}$. ξ_s are estimates of country-specific long-run persistence of TFP.

Finally, we examine the relationship between total factor productivity (TFP) and stocks of knowledge. The latter are the key drivers of TFP in ideas (or knowledge)-based growth models. Our behavioural specification, which is similar in spirit to equation (2), allows for possible cross-country heterogeneity in the responses of TFP to A^d and A^f. Formally:

$$(9) \qquad TFP_{i,t} = \mu_i + \eta_t + \xi_1 TFP_{i,t-1} + \xi_2 (TFP_{i,t-1} * \bar{A}_i^d) + \varphi_1 A_{i,t}^d + \theta_1 A_{i,t}^f + \varphi_2 (A^d{}_{i,t} * \bar{A}_i^d) + \theta_2 (A_{i,t}^f * \bar{A}_i^d) + e_{i,t}$$

where μ_i and η_t capture the usual fixed and time effects. The country-specific slope parameters (φ_j and θ_j) and adjustment dynamics (ξ_j), for j = 2, are modeled as a linear function of $\bar{A}_i^d$. Thus, the extent to which $A_{i,t}^d$ and $A_{i,t}^f$ affect $TFP_{i,t}$ depends on the stock of knowledge available domestically. The last two columns of Table 4 report the TFP results obtained from the system GMM estimator. They reveal a number of important insights. First, $A_{i,t}^f$ (either level or interacted) does not appear statistically significant at any conventional level of significance (*i.e.* 10% or better); therefore, its parameters are not reported (however, see footnotes to Table 4). Thus, international spillovers of knowledge do not appear to drive the level of TFP. Porter and Stern (2000) also report the effects of $A_{i,t}^f$ on $TFP_{i,t}$ to be insignificant. However, there is one key difference between their results and ours. We find that A^f affects TFP positively through the accumulation of domestic knowledge stocks because $\partial \dot{A}_{i,t}^d \big/ \partial A_{i,t}^f \succ 0$ and $\partial TFP_{i,t} \big/ \partial A_{i,t}^d \succ 0$. This link is missing in their results.

They report that $\partial \dot{A}_{i,t}^d \big/ \partial A_{i,t}^f \prec 0$ and $\partial TFP_{i,t} \big/ \partial A_{i,t}^f = 0$. Thus, we find that A^f positively contributes to the production of new knowledge via the accumulation of A^d.

Second, A^d exerts significantly positive effects on TFP, but the estimated point elasticity differs widely across countries; it varies from a minimum of 0.048 (United States) to a maximum of 1.102 (Ireland). In fact, our results reveal an interesting pattern: the magnitude of the TFP effect ($\partial TFP_{i,t} \big/ \partial A_{i,t}^d$) falls when one moves from a country with a low knowledge base ($\bar{A}^d$) to one with a high one. Ireland and New Zealand, the two countries with the smallest size of A^d in the sample show the largest point elasticity ($\partial TFP \big/ \partial A^d$) of above unity. They are followed by Norway and Spain (with point elasticities of 0.480 and 0.483, respectively), the two other countries with a very low level of A^d. On the other hand, the United States, Germany, and Japan, the largest three in terms of their domestic stock of knowledge, exhibit very small point elasticities of TFP with respect to A^d. Thus, countries with a very small knowledge base (stock) may significantly improve their TFP through knowledge accumulation. Finally, although the stocks of domestic and foreign knowledge affect TFP positively, the magnitude of their effect, for most countries, appears much smaller than predicted by R&D-based growth models.[20]

VI. Summary, conclusion and implications

We estimate the key parameters of the knowledge production function for a panel of 19 OECD countries. This is of both theoretical and practical importance. At the theoretical level, knowledge of these parameters allows us to evaluate whether economic growth occurs endogenously, as predicted by endogenous growth models. At the practical level, they can help devise a more effective R&D policy.

This paper contributes to the existing literature in at least three important respects. First, it is, to our knowledge, the first study to explicitly model cross-country heterogeneity in knowledge production. This heterogeneity is modeled as a function of country-specific mean levels of stocks of domestic knowledge and of full-time researchers employed in the knowledge-producing sector. We show why these measures capture the cross-country diversity in innovative activities better than some alternative measures of R&D intensity.

Second, a new and unique data set - the triadic patent families data - is used to measure the domestic flows of new-to-the-world knowledge. These patents are research-intensive and entail high patenting costs; they can therefore be expected to proxy valuable innovations more accurately. Given their global nature, they also form an analogous measure of innovations across countries. Further, they are less likely to be tainted by home biases and double counting and are enumerated on the basis of priority dates. In short, we analyse a good quality data set of high-value patents. We also compute a better measure of the stock of foreign knowledge, which allows us to identify the parameters of spillovers of foreign knowledge. Finally, we follow a comprehensive and well-structured empirical strategy. Our specification directly captures the potential cross-country heterogeneity of knowledge production and our preferred estimator addresses endogeneity rigorously.

We find that the parameters of the knowledge production function are extremely heterogeneous across countries; both slope coefficients and adjustment dynamics are different. The A^d exerts a net positive effect on the domestic production of new-to-the-world knowledge; however, the point elasticity is below unity for all countries except Switzerland. Thus, contemporary knowledge researchers stand on the shoulders of earlier inventors. Likewise, A^f also exerts a net positive effect on $\dot{A}^d$; positive externalities dominate the raising–the-bar effect. Again, parameters vary across countries and point estimates are well below unity. The point elasticity of $\dot{A}^d$ with respect to H_A is significantly positive for all countries except Switzerland. We are able to pick up the prolonged decline in Swiss knowledge productivity; the point elasticity is -0.272. Earlier panel studies (*e.g.* Porter and Stern, 2000) also reported the decline in Swiss productivity (see figure 4, panel A) but were unable to identify the negative marginal product of Swiss researchers which the graph shows quite clearly. This is because they did not address cross-country heterogeneity, hence the difference in the results. For the remaining countries, the coefficient of H_A is positive but less than unity, suggesting sizeable but heterogeneous duplicative R&D - the stepping-on-toes effect.

On the role of inputs to knowledge, we find that, on average, the flow of new-to-the world knowledge is likely to be higher in countries that engage more scientists and engineers in the knowledge-producing sector. However, when the level of the stock of domestic knowledge is high, the return to A^d is low, and the benefits from spillovers of foreign knowledge appear to diminish when countries accumulate a larger and larger stock of knowledge domestically. The qualitative nature of these findings is robust to all the three estimators used.

The results show a direct and positive effect of the stock of domestic knowledge on TFP; however, the effect of the stock of foreign knowledge is indirect and appears only via the increased accumulation of new domestic knowledge. Our results reveal an interesting pattern: the magnitude of the TFP effect ($\partial TFP / \partial A^d$) declines sequentially for countries with a larger and larger domestic knowledge base ($\overline{A}^d$). Countries like Ireland and New Zealand, with a small knowledge base, demonstrate a very high elasticity of TFP with respect to their respective A^d, whereas countries that have acquired a sizeable domestic knowledge base (*e.g.* Germany, Japan, Switzerland, the United Kingdom, the United States) exhibit a very small point elasticity.

The main implications of our findings are as follows. First, knowledge production is extremely heterogeneous across OECD countries and so is the relationship between knowledge stocks and TFP. Our results indicate that it is important to account for country-specific factors when designing R&D and innovation policy; a one-size-fits-all approach is unlikely to be effective. Clearly, countries that rank at the bottom of the list in terms of world-class knowledge acquisition (*e.g.* Ireland, New Zealand, Norway, Spain) may potentially make important gains in productivity by adopting an R&D policy that augments their knowledge accumulation. However, in countries that already have an important R&D sector (*e.g.* the United States, Germany, Japan, the United Kingdom, Switzerland), the contribution of knowledge stocks to TFP appears very modest. As is evident, our results do not support the well-known parametric restriction of first-degree homogeneity proposed by Romer (1990). Our results appear more in line with the analysis of Jones (1995b) who shows, among other things, that long-run economic growth ceases to be endogenous if $0 \prec \partial \dot{A}^d / \partial A \prec 1$; and this is what we find as well. Finally, for most advanced countries, the magnitude of the TFP effect ($\partial TFP / \partial A^d$), appears far too low from the perspective of R&D-based growth models.

NOTES

1 . In fact, in Romer (1990) the production function also exhibits increasing returns to scale. This is primarily due to the non-rivalrous nature of knowledge. A doubling of capital, labour and the stock of knowledge would more than double the level of output.

2. Jones (1995b) relaxes Romer's (1990) proportionality assumption by allowing the relationship between $\dot{A}$ and A to be less than proportional. The implication is that the long-run growth rate becomes a function of exogenously determined population growth rates.

3. It should be noted, however, that the work initiated by Coe and Helpman (1995) models the relationship between TFP and domestic and foreign R&D stocks, whereas Porter and Stern (2000) examine the relationship of $\dot{A}^d$ with A^d and A^f .

4. For example, the formula for Coca-Cola is a closely guarded secret that has never been patented (Jones, 2002).

5. For further details on triadic patent families, see Dernis and Khan (2004).

6. The EPO, JPO and USPTO levy separate fees. According to the European Commission (2002), the cost of obtaining a patent at USPTO, JPO, and EPO is around EUR 10 330, EUR 16 450, and EUR 49 900, respectively. We base our assertion on these cost estimates; however, other estimates abound (see, for example, Jonathan Eaton and Samuel Kortum, 1996 and 1999).

7. Coe and Helpman (1995) use import shares, whereas van Pottelsberghe and Lichtenberg (2001) use foreign direct investment as channels of international knowledge diffusion. We use bilateral R&D collaboration coefficients, which are more pertinent when modeling the effects of the diffusion of knowledge on the production of knowledge.

8. Porter and Stern (2000) generate the foreign knowledge stock (A^f) as the straight sum of the rest of the sample countries' domestic knowledge stock (A^d). Hence, $A^d + A^f$ is identical for all the sample countries. This precludes identifying the parameters of international knowledge spillovers. Our measure of A^f does not suffer from this deficiency and allows us to identify the spillover parameters.

9. Keller (2004, p. 761), in his influential survey of international technology diffusion remarks that "endogeneity has been recognized in the literature, but it is rarely fully addressed". He goes on to say that "more research is clearly needed". This study helps to bridge this gap.

10. When the elasticity of knowledge production with respect to researchers is less than unity, then that is seen as evidence of some degree of research duplication. The idea is that several researchers (or several groups of researchers) may be working on the same issue separately but only one researcher (or one group of researchers) may succeed by producing new knowledge.

11. This ratio will fall further if data from the JPO is also considered.

12. A separate plot for Swiss productivity is required because of: *(i)* the high scale required in the vertical axis; and *(ii)* the prolonged decline in Swiss productivity.

13. For the development and implementation of this approach, see Pesaran *et al.* (2000). Specification (2) is not motivated by time-varying parameters. Instead, the assumption is that the slope coefficients in each country are fixed over time but vary across countries linearly with $\bar{H}_A$ and $\bar{S}^d$. This is a reasonable assumption to maintain while investigating the role of the levels of R&D activity in the production of new knowledge across countries. Moreover, it is shown that a dynamic heterogeneous panel specification tends to be robust to non-linearity.

14. We use the country-specific mean level of domestic knowledge stocks instead of the mean levels of R&D expenditure because the former is a more accurate measure of innovative capacity.

15. The specification of the model in first differences is aimed to get rid of the fixed effects. However, other transformations, such as mean and/or orthogonal deviations, also flush out fixed effects. The GMM estimators are valid to any of these transformations (Arellano and Bond, 1991). Clearly, our formulation (2) uses mean deviations.

16. The typical time-varying matrix of instruments (Z) for the first difference GMM estimator takes the form:

$$Z_i = \begin{bmatrix} y_{i1}\ x_{i1}x_{i2}...0.....0.......0........0......0 \\ 0 \quad 0 \quad 0\, y_{i1}\ y_{i2}x_{i1}x_{i2}x_{i3}.......0......0 \\ . \quad . \quad .. \quad . \quad . \quad .. \quad . \quad .. \quad . \quad . \quad . \\ 0......................y_{i1}...y_{iT-2}x_{i1}...x_{iT-1} \end{bmatrix}$$

The time-varying instrument matrix for the system estimator is:

$$\begin{bmatrix} Z_i & 0............0 \\ 0 & \Delta y_{i2}\Delta x_{i2}....0 \\ & .... \\ 0 & \Delta y_{i,T-1}\Delta\, x_{i,T-1} \end{bmatrix}$$

where *Zi* is as above. See Arellano and Bover (1995) for details.

17. Under GMM, the serial correlation test is performed on the first differenced residuals. The evidence of negative and significant first order serial correlation coupled with insignificant second order serial correlation establishes that the residuals in levels are not serially correlated. We find evidence of negative but insignificant first order serial correlation and insignificant second order serial correlation. This does not necessarily mean that the residuals are serially correlated, instead such an outcome is possible when data are persistent.

18. The GMM is criticised on the grounds that it uses too many instruments and that may result in over-fitting biases. Our results appear immune from this criticism because *(i)* the alternative OLS and IV estimators provide similar results, and *(ii)* the numbers of time periods (T) and individuals (N) are very similar in the panel.

19. The coefficient on the lagged dependent variable is an indicator of the speed of adjustment towards a steady state. A high coefficient implies a fast rate of adjustment.

20. We also used the OECD multi-factor productivity data which covers 15 OECD countries; however, the weak relationship between TFP and knowledge stocks remains.

BIBLIOGRAPHY

Aghion, Philippe and Peter Howitt (1992), "A Model of Growth through Creative Destruction", *Econometrica*, March, 60(2), pp. 323-351.

Ahn, C. Seun and Peter Schmidt (1995), "Efficient Estimation of Models for Dynamic Panel Data", *Journal of Econometrics*, July, 68(1), pp. 5-27.

Arellano, Manuel and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies*, April, 58(2), pp. 277-297.

Arellano, Manuel and Olympia Bover (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models", *Journal of Econometrics*, July, 68(1), pp. 29-51.

Blundell, Richard and Stephen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", *Journal of Econometrics*, November, 87(1), pp. 115-143.

Bond, Stephen R., Anke Hoeffler and Jonathan Temple (2001), "GMM Estimation of Empirical Growth Models", Centre for Economic Policy Research (London, England) *Discussion Paper* No. 3048, November.

Coe, David T. and Elhanan Helpman (1995), "International R&D Spillovers", *European Economic Review*, May, 39(5), pp. 859-887.

Dernis, Hélène and Mosahid Khan (2004), "Triadic Patent Families Methodology", OECD Science, Technology and Industry Department (Paris, France) *Working Paper* No. 2004/2, March.

Eaton, Jonathan and Samuel Kortum (1996), "Trade in Ideas: Patenting and Productivity in the OECD", *Journal of International Economics*, May, 40(3-4), pp. 251-278.

Eaton, Jonathan, Eva Gutierrez and Samuel Kortum (1998), "European Technology Policy", *Economic Policy*, October, pp. 404-438.

Eaton, Jonathan and Samuel Kortum (1999), "International Technology Diffusion: Theory and Measurement", *International Economic Review*, August, 40(3), pp. 537-570.

European Commission (2000), "Proposal for a Council Regulation on the Community Patent", COM(200) 412 final, Brussels, August, http://europa.eu.int/comm/internal_market/en/indprop/patent/412en.pdf

Griliches, Zvi (1990), "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature*, December, 28(4), pp. 1661-1707.

Grossman, Gene M. and Elhanan Helpman (1991), *Innovation and Growth in the Global Economy*, Cambridge, MA, and London: MIT Press.

Holtz-Eakin, Douglas, Newey, Whitney and Harvey S. Rosen (1988), "Estimating Vector Autoregressions with Panel Data", *Econometrica*, November, 56(6), pp. 1371-1395.

Jaffe, Adam and Manuel Trajtenberg (2002), *Patents, Citations & Innovations: A Window on the Knowledge Economy*, Cambridge, Massachusetts and London, England: The MIT Press.

Jones, Charles I. (1995a), "Time Series Tests of Endogenous Growth Models", *Quarterly Journal of Economics*, May, 110(2), pp. 495-525.

Jones, Charles I. (1995b), "R&D-Based Models of Economic Growth", *Journal of Political Economy*, August, 103(4), pp. 759-784.

Jones, Charles I. (2002), "Introduction to Economic Growth", second edition, W.W. Norton and Company, New York and London.

Keller, Wolfgang (2004), "International Technology Diffusion", *Journal of Economic Literature*, September, 42(3), pp. 752-782.

Luintel, Kul B. and Mosahid Khan (2004), "Are International R&D Spillovers Costly for the US?", *Review of Economics and Statistics*, November, 86(4), pp. 896-910.

OECD (2004), "Compendium of Patent Statistics 2004", OECD, Paris.

Pesaran M. Hashem, Nadeem U. Haque and Sunil Sharma (2000), "Neglected Heterogeneity and Dynamics in Cross Country Savings", in J. Krishnakumar and E. Ronchetti (eds.), *Panel Data Econometrics – Future Directions*, Elsevier Science, Chapter 3, pp. 53-82.

Porter, Michael and Scott Stern (2000), "Measuring the 'Ideas' Production Function: Evidence from International Patent Output", National Bureau of Economic Research (Cambridge, MA) *Working Paper* No. 7891, September.

Romer, Paul M. (1990), "Endogenous Technological Change", *Journal of Political Economy*, October, 98(5), pp. S71-S102.

Staiger, Douglas and James H. Stock (1997), "Instrumental Variables Regression with Weak Instruments", *Econometrica*, May, 65(3), pp. 557-586.

Solow, Robert M. (1956), "A Contribution to the Theory of Economic Growth", *Quarterly Journal of Economics*, February, 70(1), pp. 65-94.

Trajtenberg, Manuel (2002), "A Penny for your Quotes: Patent Citations and the Value of Innovations", in Adam Jaffe and Manuel Trajtenberg (eds.), *Patents, Citations & Innovations: A Window on the Knowledge Economy*, Cambridge, Massachusetts and London, England: The MIT Press, pp. 25-49.

Van Pottelsberghe de la Potterie, Bruno and Frank Lichtenberg (2001), "Does Foreign Direct Investment Transfer Technology across Borders?", *Review of Economics and Statistics*, August, 83(3), pp. 490-497.

APPENDIX: VARIABLES DEFINITION AND DATA SOURCES

Definitions

1. The triadic patent families are defined at the OECD as a set of patents taken at the EPO, JPO and the USPTO that share one or more priorities. Data on triadic patent families are available from 1977 for some countries, but a consistent data series for all the countries analysed in this paper is available only from 1981. The domestic knowledge stock ($A^d_{i,t}$) for each country is computed from the respective flows of triadic patents ($\dot{A}^d_{i,t}$) following the perpetual inventory method. A depreciation rate of 15% and the growth of $\dot{A}^d_{i,t}$ (average growth rate during the sample period) are used to generate the initial patent stock for the year 1981. The relevant foreign knowledge stocks ($A^f_{i,t}$) for each sample country are computed as the weighted sum of the rest of the world's domestic knowledge stocks, $\left(\sum_{j=1}^{N-1} w_{ij,t} A^d_{j,t}; i \neq j \right)$, where $t = 1, 2, .., T_i$. The time-varying weight ($w_{ij,t}$) is the bilateral R&D co-operation coefficient between countries i and j which is calculated as the ratio of joint triadic patent applications due to R&D collaboration between the two countries to their respective total triadic patent applications. Thus, we compute 18X20 matrixes of bilateral R&D co-operation coefficients for each sample country. To avoid sharp yearly fluctuations, we compute $w_{ij,t}$ utilising the four-year moving average of its numerator and denominator. The $w_{ij,t}$ effectively measures successful R&D collaboration that results in a joint triadic family of patents between nations. The distinction between domestic and foreign patents is based on the standard practice followed at the OECD (by residence of inventor) when developing patent indicators.

2. Total factor productivity (TFP) is computed as: log TFP = log GDP – γ log K – (1- γ) log L; where K and L are capital stock and labour, respectively. Following much of the literature, we set the value of the γ coefficient to 0.3. Gross domestic product (GDP) for each country is measured at 1995 PPP (purchasing power parity) dollars. Although OECD's Productivity database contains data on capital services, it does not cover all the sample countries analysed here. Therefore, for the sake of consistency, K is computed on the basis of data on non-residential fixed capital formation using the perpetual inventory method. Nominal non-residential fixed capital formation (I) is converted into real 1995 PPP dollars (IR) by using the non-residential fixed capital formation deflator (IP) and the 1995 PPP dollar exchange rate. A depreciation rate of 8% and the sample-period average growth rate of IR are used to generate the initial capital stock. Labor force employed in the non-knowledge-producing sector (L) is defined as the total employment level (E) minus the total number of full-time equivalent researchers (H_A).

Data sources

3. Data for H_A is derived from OECD' Main Science and Technology Indicators database. Patent data are obtained from OECD's patent database. Data on E, GDP, I, IP and PPP equivalent exchange rates are obtained from OECD's ADB database. Multifactor productivity data are obtained from OECD's productivity database.