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HETEROGENEOUS IDEAS PRODUCTION AND ENDOGENOUS GROWTH: AN EMPIRICAL INVESTIGATION

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Abstract

We examine the dynamics of ideas production and knowledge-productivity relationship in a panel of 19 OECD countries. A new data set of triadic patents is used. We rigorously address the issues of cross-country heterogeneity and endogeneity. Domestic and foreign ideas stocks exert positive but heterogeneous effects on ideas production. We find evidence of duplicate R&D but little support for endogenous growth. Countries with low domestic ideas bases could considerably improve productivity through ideas accumulation; however, this effect is modest for countries with sizeable ideas bases. An implication is that country-specific R&D policy appears potentially more effective than the one-size-fits-all approach.

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

Key Words: Knowledge Stocks; Dynamic Heterogeneity; TFP; Methods of Moments.

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HETEROGENEOUS IDEAS PRODUCTION AND ENDOGENOUS GROWTH: AN EMPIRICAL INVESTIGATION

1. INTRODUCTION

The production of knowledge (new ideas) and its central role in driving productivity are the key building blocks of R&D based new growth models. Romer's (1990) seminal work on "endogenous technical change" posits a proportional relationship between the domestic flow of new ideas ($\dot{A}$) and the stocks of knowledge (A) and human capital (H_A) employed in the ideas-producing sector. In these models, new ideas raise productivity and stimulate sustained capital formation that enables long-run growth. [1]

Empirical studies have examined different aspects of idea-based growth models albeit with mixed results. [2] However some key issues remain and those that regularly feature in the literature are of: (i) data and measurement; (ii) cross-country heterogeneity; and (iii) endogeneity. The measurement issue concerns how best to proxy ideas. Patent data and particularly those from the US Patent & Trademark Office (USPTO) are extensively used to measure knowledge in empirical work. Yet, the trouble is that the USPTO dataset is extremely noisy; it suffers from significant home bias hence a poor proxy for innovations (on this issue, among others, see Jaffe and Trajtenberg, 2002; Harhoff *et al*. 2003). The widely used NBER citations dataset (Hall *et al*., 2001) only includes references to US patents; it excludes references to patents published elsewhere (see Webb et. al., 2005). Health warnings are also issued vis-à-vis the EPO (European Patent Office) and the JPO (Japanese Patent Office) datasets. The EPO is criticized for its "minimalist" approach to patenting whereby applicants may only refer to a minimum relevant state of the art and not embrace all. The JPO dataset, on the other hand, is not readily accessible due to the language barrier and they too suffer from a considerable degree of home bias (Michel and Bettels, 2001). Furthermore, different national patenting offices

require different threshold of inventiveness to qualify for a patent. Consequently, a patent in a given subject may be granted in one country but not in another. Such incongruities in patenting rules across countries pose a formidable problem in conducting any comparative and/or multi-country study on the subject. Hence, the issue of finding a better proxy of innovations that measures knowledge (stocks and flows) more accurately and homogeneously across countries.

The second issue concerns the potential cross-country heterogeneity in ideas production and the knowledge-productivity relationship. The extant empirical literature, mostly based on fixed-effects models, assumes that the slope coefficients, adjustment dynamics, and error variances are homogeneous in these relationships across the sample of countries. These assumptions are unlikely to hold because countries differ in their stages of development, domestic technology stocks, capacity to absorb foreign technology, and the level and intensity of R&D they perform. Keller (2004, p. 760) highlights that there is a need to address cross-country heterogeneity in technology diffusion. The empirical literature confirms a positive cross-country knowledge spillover. However, it is conceivable that when countries accumulate more and more of their own domestic knowledge stock, the benefits from foreign knowledge spillovers may decrease — the stand-in effect because the domestic know-how may replace the foreign know-how. Likewise, when countries innovate and accumulate more and more of knowledge stock it may prove harder to generate new ideas — the fishing-out effect. Similar arguments may apply vis-à-vis the productivity of human capital employed in the R&D sector. These issues are of considerable importance in shaping the R&D policies at both national and regional levels. Therefore, there is a need for a rigorous analysis of cross-country heterogeneity in ideas production and knowledge-productivity relationship.

Finally, doubts exist on whether the extant empirical literature on this topic adequately addresses the problem of endogeneity. In an influential survey of international technology diffusion, Keller (2004, p. 761) states: “endogeneity has

been recognized in the literature, but it is rarely fully addressed" and he goes on to say, "more research is clearly needed".

This paper attempts to bridge the gaps discussed above and further contribute to the empirical literature in this field. We propose and use a new dataset — the triadic patent families — to resolve the measurement issue. This dataset, recently assembled by the OECD, consists of high value patents based on priority dates and its construction largely eliminates the problems of home bias and double counting. The triadic patents also provide a comparable measure of knowledge across countries. We argue that this dataset is potentially a more reliable measure (proxy) of knowledge than any other dataset analyzed previously. We elaborate on this dataset in section II.

We address the issue of cross-country heterogeneity both for the ideas production function and for the domestic productivity. The existing standard empirical specifications for these relationships in a panel setting are the fixed-effect static and/or the first-order-autoregressive panel data models. Unfortunately, these models do not account for the cross-country heterogeneity in parameters and adjustment dynamics. However, such heterogeneity is conceivable because countries differ in their research intensity, the levels of domestic knowledge stocks they possess and the population of scientists and engineers they engage in their R&D sector. We present and estimate dynamic heterogeneous panel models that explicitly capture cross-country heterogeneity in these relationships. The heterogeneity in ideas production is modeled as a linear function of country-specific mean levels of researchers engaged in the ideas-producing sector ($\overline{H}_{A,i}$) and the mean level of domestic knowledge stock ($\overline{A}_i^d$). We also separately model for the potential role of research intensity across countries. The heterogeneity in the knowledge-productivity relationship is specified as a linear function of country-specific mean stock of domestic knowledge.

Much of the literature in international knowledge diffusion constructs foreign knowledge stock ($A_{i,t}^{f}$) by using bilateral total import ratios as weights (e.g., Coe and Helpman, 1995). However, Xu and Wang (1999) show that capital goods imports, due to their high tech contents, are better conduit of technology transfer than the total imports. We compute foreign knowledge stocks utilizing bilateral capital goods import ratios (henceforth import ratios) as weights and denote them as $A_{i,t}^{fm}$. In addition, we compute a better measure of $A_{i,t}^{f}$ by using the ratios of bilateral R&D collaboration coefficients between country "i" and country "j_s" (j_s = 1, 2…,N-1) as weights and denote them as A^{fc} . These weights are country-specific 18X20 matrixes of bilateral R&D cooperation coefficients (see Appendix for details). A^{fc} 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.

We address endogeneity through the system GMM (Generalized Methods of Moments) estimator as it tackles the key estimation issues of endogeneity, weak instruments and measurement errors. [3] The existing empirical studies on R&D field mostly use the OLS (Ordinary Least Squares) and / or the Two-Stage Least Squares estimators.

Our results are quite revealing. We find that ideas production is extremely heterogeneous across the OECD countries; the slope coefficients and the adjustment dynamics are diverse. The flow of new-to-the world ideas tends to be higher in countries that engage more scientists and engineers in the ideas-producing sector. However, when countries accumulate more and more of their own domestic knowledge stock the flow of new ideas tends to reduce — the fishing-out effect. Likewise, the positive foreign knowledge spillovers tend to dwindle with increasing accumulation of knowledge domestically — the standing-in effect. Furthermore, there is evidence of standing-on-shoulders effects and that of the duplicative R&D. We

also find a net positive cross-border externality (i.e., $0 \prec \partial \dot{A}^{d}_{i,t} \big/ \partial A^{f}_{i,t} \prec 1$) for domestic ideas production across all the sample countries. On productivity, domestic knowledge stock affects domestic total factor productivity (TFP) significantly positively across all the sample countries. The low knowledge base (stock) countries show large TFP effect of domestic knowledge stock but this effect systematically dissipates for countries with higher and higher knowledge bases. Thus, low knowledge base countries can boost their TFP through knowledge accumulation. The effect of foreign knowledge stock on TFP appears insignificant. The qualitative nature of our findings is robust to various sub-samples and estimators.

The rest of the paper is organized as follows. Section II discusses the triadic patent family; section III presents data and descriptive statistics; section IV covers the issues of heterogeneity; sections V and VI outline specification and econometric issues; section VII presents empirical results and section VIII summarizes and concludes.

2. TRIADIC PATENTS

Ideas are intangible and difficult to measure. Ideas also differ in their "universality" and "size": some ideas are widely adopted while others are not (Eaton et al., 1998). Patent data are widely used to proxy new ideas. 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 the quality of innovations, and (ii) not all innovations are patented. [4] How to capture the critical mass of patents that measures the net accrual of economically valuable knowledge to the 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 it is the patent examiner rather than the applicant who often adds citations. Besides, there are issues in the citation data; they too are noisy (Harhoff et

al., 2003). Researchers have attempted to infer the value of patents through the renewal behavior of patent-holders (Schankerman and Pakes,1986; Lanjouw, 1998). The argument is that since it is expensive to renew patent protection, only valuable patents are renewed. The trouble however is that the value distribution of the most valuable patents (those that are renewed to full statutory term) is unobservable consequently this approach is also contaminated by distributional assumptions.

The triadic patent families data used in this paper go some way to resolving the issues of data and measurement. The OECD defines it as a set of patents at the EPO, JPO and the USPTO that share one or more priorities. Triadic patents are thus global in nature and are potentially better than any other patent dataset used previously. Some distinguishing features of this dataset are as follows.

First, the triadic patent data are based on priority dates and are superior in this respect to the datasets based on grant dates such as those from USPTO, EPO and JPO analyzed in 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) emphasize this point. Second, the OECD has consolidated the triadic patent family data 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). Third, the diversity of patenting rules across countries generates different propensities to patent and causes home biases in the data. Indeed, country share data in Table 1 shows excessive home bias in USPTO. The United States has a 52.8% share in USPTO as opposed to a share of 33.9% in triadic patents. Home biases are less likely in triadic patent families because the same rules and regulations apply to all. In this respect, triadic patents provide a comparable measure of innovations across countries. Fourth, triadic patents are likely to embody high quality innovations because they are global patents and are likely to be of universal

applicability. Unless the inventor is certain (with a high degree of probability) that the invention will receive universal adoptability, s/he is unlikely to file for triadic patents (i.e., filing for USPTO, EPO and JPO patents simultaneously). This is because triadic patents entail high costs to the patentor; approximately, it costs between three to five times a patent taken at any national and/or regional level. [5] Given the high patenting costs, we argue that only valuable ideas that merit patenting at the global level will enter the triadic family. Eaton and Kortum [1999] also argue: "only the best and hence most valuable inventions are patented in many countries". Overall, the triadic patent data analyzed in this paper proxy the most valuable innovations across countries and potentially shed new light on the relationships under investigation. [6]

3. DATA

Our sample consists of 19 OECD countries (see Table 1). Data frequency is annual for a period of 20 years (1981-2000). Our sample represents 98 percent of the world's total triadic patent families. We have a balanced panel of 380 observations.

Table I presents some summary statistics of relevant data series. The sample-wide average annual flow of triadic patent families is 1,560 per country. The equivalent figures for the EPO and USPTO are 3,178 and 5,729. Of the total innovations patented at the USPTO and the EPO, only a fraction (about 18 percent) enters the triadic patent families. This suggests that the latter may indeed contain high innovative value of global importance.[7]

A high degree of home bias is evident in USPTO - the US share is 52.8%. The second major share in USPTO is that of Japan (21.3%). As expected, the US share dominates across all three patent categories; nonetheless, the country shares in triadic family appear less skewed than in USPTO. Triadic and EPO appear close in terms of country share distributions but triadic patents are registered across all three patent offices whereas the same is not true for all the patents in EPO. In terms of patent intensity, on average, 80 ideas researchers appear to produce one triadic

patent; the equivalent numbers are 39 and 22 for the EPO and USPTO patents, respectively. All these reinforce our argument that the ideas embedded in the triadic patent families are more research-intensive than those registered in the country and/or regional level patent offices only; hence supporting our choice of this dataset for the present analyses.

In the last two columns, we report some descriptive statistics of two set of weights – the bilateral import ratios and the ratios of bilateral R&D collaboration – used in computing the foreign knowledge stocks for each of our sample countries. Reported ratios are the sample mean values. R&D collaboration ratios are the proportion of bilateral triadic patents in the total triadic patents of the country (for details see Appendix). It is evident that the mean values of both of these ratios (weights) are quite small in their magnitudes except for the United States. The bilateral US R&D collaboration leads to the largest number of triadic patents amongst all the sample countries. Germany (0.049), the United Kingdom (0.035) and France (0.021) follow the United States (0.102) in successful bilateral R&D collaborations resulting in triadic patents. Ireland and New Zealand appear to be the least successful. Again, the United States shows the highest mean bilateral import ratio whereas Ireland and New Zealand show the lowest.

The magnitudes of (bilateral mean) R&D collaboration ratios are higher than the respective import ratios for most countries in the sample. The collaboration ratios also show high variability (measured by their respective standard deviations) compared to import ratios for most (11 out of 19) countries. We plot in Figure 1 the foreign knowledge stocks generated through these weights for six (representative) countries of our sample in order to reveal how they impinge on our computations. These plots clearly show that the $A_{i,t}^{fc}$ have more variation than $A_{i,t}^{fm}$. This reflects the higher variability of bilateral R&D collaboration ratios. We use both measures of foreign knowledge stocks in the estimation. Other required data series for the core

analysis are the level of human capital employed in the R&D sector ($H_{Ai,t}$), domestic knowledge stock ($A^d_{i,t}$) and domestic total factor productivity ($TFP_{i,t}$). Their construction details and sources are given in the Appendix.

4. HETEROGENEITY IN R&D AND IDEAS PRODUCTION

Table 1 also reveals important cross-country differences in ideas production and the level and intensity of R&D activities. Clearly, Sweden, Japan, the United States, Switzerland and Germany are at the top end of R&D intensity (the ratio of R&D expenditure to GDP); they spend between 2.5 and 3.1 percent of their GDP on innovative activities. On the other hand, countries such as Spain, New Zealand, Ireland, Italy, Austria and Australia appear at the bottom ends, as their R&D expenditure is around 1.0 percent of GDP. The remaining sample countries spend, on average, 1.8 percent of their GDP on R&D activities. The proportion of ideas researchers in total employment (research intensity) also differs across countries. Finland, Japan, Norway, Sweden and the United States appear to have high research intensity (from 0.63 to 0.88 percent), whereas Spain, Italy, Ireland and Austria have low research intensity (from 0.29 to 0.38 percent); the rest of the sample countries are between 0.44 and 0.59 percent.

Although these intensity measures are widely used indicators of cross-country differences in R&D activities, they still fail to reveal the full extent of disparity in the levels of R&D activity across the sample countries. This is because the OECD economies are vastly dissimilar in size. To put this in perspective, the United States and Switzerland each spend 2.6 percent of their GDP on R&D; however, the level of R&D activity each generates is immensely different. The US R&D expenditure amounts to 186.96 billion dollars per annum (sample average) whereas the equivalent Swiss sum is only 4.77 billion dollars. Sweden spends 3.1 percent of GDP (the world's highest R&D intensity), which amounts to 5.80 billion dollars; however,

this is less than a-half the amount spent by Italy whose R&D intensity is just 1.1 percent.

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 ideas researchers (970,000) followed by Japan (562,000), Germany (197,000) and the United Kingdom (138,000). Again, the use of research intensity not only fails to capture these vast cross-country differences in the number of full-time scientists and engineers; at times, it can convey the wrong message. For example, in terms of research intensity, Norway (0.63 percent) is ahead of Germany (0.59 percent), yet the number of full-time ideas researchers employed in Germany is more than fifteen times the number in Norway. Switzerland (0.47 percent) and the United Kingdom (0.50 percent) appear very similar in research intensity; however, the number of full-time UK ideas researchers is more than seven times that of Switzerland. Table I 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 the measures of R&D intensity.

Important cross-country differences are also evident in ideas productivity (the flow of triadic patent families per 1,000 ideas researcher). Over the sample period, Switzerland (40.8), Germany (21.6), the Netherlands (21.7) and Sweden (19.0) top the list. Spain (1.7), New Zealand (3.5), Australia (4.0), Canada (4.4), Norway (4.6), and Ireland (5.1) are at the bottom. The productivity of the remaining sample countries is, on average, 8 to 16 new ideas per 1,000 ideas researchers.

Figure II about here

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

Figure III about here

In figure III, we plot ideas productivity at the country level. In view of their time profile, we classify sample countries into four groups and plot them in panels A through D. In panel A, we plot the productivity of Swiss ideas researchers only. [8] The average product of Swiss researchers is still the highest in the world, but it has been in continuous decline since 1987. This decline in Swiss ideas productivity is not unique to our data set. Porter and Stern (2000), using USPTO data, report very similar patterns. Given this downward trend in Swiss ideas productivity, one would expect a negative marginal product ($\partial \dot{A}^d / \partial H_A$) for the Swiss ideas researchers.

The ideas 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 the productivity gap is in favor of France. 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 productivity. Japan and Sweden show opposite time profiles for ideas productivity. Sweden's productivity level has always been higher than that of Japan, except for a brief period from 1988 to 1991. Germany and the Netherlands exhibit very similar productivity patterns.

Finally, panel D plots the countries with low ideas productivity: Australia, Ireland, Canada, Italy, New Zealand, Norway, and Spain. All these countries exhibit stable but low productivity of five or fewer triadic patents a year except Italy. Italy's productivity is also well below 10 patents per 1,000 researchers for the most part of the sample. Overall, Figure I indicates declining OECD-wide ideas productivity, while

figure II reveals important cross-country heterogeneity in the time profile of ideas productivity.

5. SPECIFICATION

Our empirical specification allows for the potentially separate effects of domestic and foreign ideas stocks in the domestic production of new-to-the-world ideas. This approach is sensible, given the existence of barriers to international trade and R&D collaboration.[9] We begin by specifying a dynamic (autoregressive) ideas production function, which is typical in the literature (all variables in natural logarithms):

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

(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 $A^f_{i,t-1}$, respectively. Conceptually, $A^d_{i,t}$ has two opposing effects: it may facilitate the production of new ideas—the standing-on-shoulders effect—or it may make the discovery of new ideas more difficult. The latter is because ideas that are easy to discover are invented first making subsequent discoveries 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 ideas is independent of the ideas domestically discovered and accumulated in the past. Likewise, ψ nets out two

opposing effects of $A_{i,t}^{f}$: the stock of foreign ideas may complement the domestic production of new ideas—positive international externality—or foreign inventions may raise the global innovation bar—the raising-the-bar effect. A positive ψ implies that positive international externalities dominate the raising-the-bar effect and vice versa.

Specification (1) is standard in the literature. However, it only allows for unobservable individual and time effects. All other parameters are assumed homogeneous across all the countries in the panel, which as argued above are unlikely to hold. We model cross-country heterogeneity in ideas production directly by estimating the following model:

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

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. [10] It allows the slope parameters (β_j, ϕ_j and Ψ_j) and the adjustment dynamics (λ_j; j= 2,3) of the ideas 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 ideas-producing sector ($\bar{H}_{A,i}$) and the stock of domestically invented and accumulated ideas in the past ($\bar{A}_i^{d}$). From a theoretical perspective, the relevant measure of human capital in the ideas production function is the level of scientists and engineers engaged in the R&D sector rather than the intensity measure. Hence, our choice of $\bar{H}_{A,i}$ and $\bar{A}_i^{d}$ in equation (2) is consistent with the theoretical literature. Moreover, as shown in section IV, intensity measures fail to capture the profound cross-country differences in R&D activities. Yet, given the

prominence of research intensity (R = ratio of scientists and engineers employed in the R&D sector to total employment) in policy circles, we replace $\bar{H}_{A,i}$ by $\bar{R}_i$ (mean research intensity) in model (2) and present an additional set of results. We also report results pertaining to two measures of foreign knowledge stocks – $A_{i,t}^{fc}$ and $A_{i,t}^{fm}$.

Specification (2) nests both static 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:

$$\delta_i = \delta_1 + (\delta_2 * \bar{H}_{Ai}) + (\delta_3 * \bar{A}_i^d) \qquad (3)$$

where $\delta = [\lambda_j, \beta_j, \phi_j, \psi_j]'$. The standard errors of country-specific parameters, $\sigma(\delta_i)$, are given by:

$$\sigma(\delta_i) = [\bar{U}_i' \sum \bar{U}_i]^{0.5} \qquad (4)$$

Where $\bar{U}_{i,t} = (1, \bar{H}_{i,t}, \bar{A}_{i,t}^d)$ and $\sum$ *is the variance co-variance matrix of* δ_i *.*

The main theoretical premises of our analyses are knowledge-based growth models. We therefore focus on knowledge stocks as the key drivers of productivity. We specify a TFP relationship similar in spirit to equation (2). Formally:

$$TFP_{i,t} = \mu_i + \eta_t + \xi_1 TFP_{i,t-1} + \xi_2 (TFP_{i,t-1} * \bar{A}_i^d) + \varphi_1 A_{i,t-1}^d + \theta_1 A_{i,t-1}^f + \varphi_2 (A^d{}_{i,t-1} * \bar{A}_i^d) + \theta_2 (A_{i,t-1}^f * \bar{A}_i^d) + e_{i,t} \qquad (5)$$

where μ_i and η_t capture the usual fixed and time effects. The domestic productivity is proxied by the total factor productivity (TFP). Domestic and foreign knowledge stocks both affect domestic TFP with a lag. The country-specific slope (φ_j and θ_j)

and adjustment (ξ_j) parameters, for j=2, are modeled as a linear function of $\overline{A}_i^d$. Thus, the extent to which $A_{i,t-1}^d$ and $A_{i,t-1}^f$ affect $TFP_{i,t}$ depends on the stock of knowledge available domestically. We acknowledge that economic theory postulates several determinants of domestic productivity, viz., human capital, public infrastructure, access to export markets (learning-by-doing), imports, foreign direct investments (FDI) etc. Still, studies of knowledge-based growth models focus on knowledge and the sources of knowledge while modeling productivity (e.g., Coe and Helpman, 1995; Jones, 1995a; Porter and Stern, 2000). Equation (5) precisely captures the spirit of ideas-based growth models in TFP modeling which is fitting to our purposes at hand. [11] In empirical implementations, we allow for human capital as an additional factor of productivity determinant. Computations of country-specific parameters and their respective standard errors are as shown in equations (3) and (4).

6. ECONOMETRIC ISSUES

Any prospective estimator for specification (2) needs to address: (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 ideas) 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 ideas. Among the available dynamic panel data estimators, the system GMM estimator appears best suited for our purpose. In particular, it controls for all the estimation issues listed in (i)-(iii) above. For a short illustration of this approach, we rewrite equation (2) by suppressing the interaction terms for simplicity but without loss of generality, as:

$$y_{i,t} = \alpha_i + \gamma_t + \lambda y_{i.t-1} + X_{it}\varphi + e_{i,t} \qquad (6)$$

where y_{it} denotes $\dot{A}^{d}_{it}$; vector X = ($H_{Ai,t}$, $A^{d}_{i,t}$, $A^{f}_{i,t}$); and $\varphi = [\beta_{ij}, \phi_{ij}, \psi_{ij}]'$; (j=1).

If $E(e_{it} e_{is})$ = 0 holds for s≠t across all "i", then it yields the following moment conditions (see, Arellano and Bond, 1991):

$E(y_{i,t-s}\ \Delta e_{it})=0$ for $s \geq 2$; t= 3,…, T. (7)

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

$E(X_{i,t-s}\ \Delta e_{i,t})=0$ for $s \geq 2$; t= 3,…, T. (8)

The single equation GMM estimator usually specifies a dynamic panel data model in the first differences and exploits the above moment conditions. 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 small, the single equation estimator suffers from the problem of weak instruments resulting in large finite sample biases and poor precision of the estimated parameters [see, among others, Ahn and Schmidt 1995, Staiger and Stock 1997]. Arellano and Bover [1995] and Blundell and Bond [1998] propose the system GMM estimator which dramatically reduces these biases and imprecision. The system GMM estimator estimates the relationship 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. The latters' validity is based on the following moment conditions:

$E[(\alpha_{i,t} + e_{i,t})\ \Delta y_{i,t-s}] = 0$ for s=1 (9)

$$E[(\alpha_{i,t} + e_{i,t})\ \Delta X_{i,t-s}] = 0 \quad \text{for } s = 1 \qquad (10)$$

Bond et al. [2001] show that the system GMM estimator performs better than a range of other method-of-moment type estimators. 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 to establish the validity of instruments.[12] A second order serial correlation test is carried out to establish whether the error term is well behaved.

7. EMPIRICAL RESULTS

Table 2 reports the system GMM estimates of the dynamic heterogeneous panel model specified in equation (2). All GMM results pertain to the first step estimation. The regressors $\dot{A}^{d}{}_{t-1}$, $H_{Ai,t}$ and $A^{d}_{i,t}$ are GMM-instrumented setting $s \geq 3$; all mean-interacted regressors are treated exogenously. Column A of the table contains results from the empirical model that utilizes A^{fc}_{it} measure of foreign knowledge stocks. It is evident that none of the level variables — $H_{Ai,t}$, A^{d}_{it} and A^{f}_{it} — appears significant on its own; instead, only interacted regressors (with $\bar{H}_{A,i}$ and $\bar{A}^{d}_{i}$) appear highly significant. These results reject the homogeneity of slope coefficients and adjustment dynamics across all the countries in the panel. The parameters of the ideas production function are country-specific and they systematically depend on the levels of domestic knowledge accumulated in the past and the number of scientists employed in the R&D sector by each country.

The signs of interaction coefficients suggest that, on average, the flow of new-to-the world ideas tends to be higher when countries engage more and more scientists and engineers in the ideas-producing sector. In contrast, when the level of domestic ideas stock increases, the flow of new ideas appears to decline — evidence of the fishing-out effect. Another finding is that when countries accumulate

more and more of their own domestic ideas stock, the benefits from foreign ideas spillover appear to decrease — the stand-in effect. All these estimates are statistically highly significant.

In column B, we report results when the empirical model employs A_{it}^{fm} measure of foreign knowledge stocks in the estimation. Results are close to those of column A. This similarity confirms that R&D collaboration and import trade are both significant vehicles of cross-boarder knowledge diffusion.

Results based on research intensity appear in columns C and D. Under this specification, research intensity variable replaces the level of human capital (i.e., scientists and engineers employed in the R&D sector) in the model. Column C uses $A^{fc}{}_{i,t}$ measure of foreign knowledge stock whereas column D uses the A_{it}^{fm}. The use of research intensity in estimations does not change the earlier findings of the (i) fishing-out effect and (ii) stand-in effect; however, it does provide two further insights. First, ceteris paribus, the higher the research intensity the higher the extent of international knowledge diffusion; this is consistent with the domestic absorptive capacity argument. The other insight is the evidence of diminishing returns in research intensity because $\partial \dot{A}_{i,t}^{d} \big/ \partial (R_{i,t} * \bar{R}_i) \prec 0$. This contrasts with the increasing returns found earlier vis-à-vis the level of human capital in the R&D sector (i.e., $\partial \dot{A}_{i,t}^{d} \big/ \partial H_{Ai,t} * \bar{H}_i \succ 0$). Given that, from theoretical perspective, the accurate variable in the empirical model is the level of human capital rather than research intensity, we attach more importance to the level-based results.[13]

All estimated models pass diagnostic checks. A test for second-order residual serial correlation is clearly insignificant which indicates that residuals are well behaved. Under GMM, the serial correlation test is performed on the first differenced residuals. The evidence of a negative and significant first order serial correlation coupled with an insignificant second order serial correlation establish that the

residuals in levels are not serially correlated. Our serial correlation tests confirm this. Sargan tests confirm the joint validity of the both sets of instruments (lagged level and lagged difference) employed. [14] The country and time effects continue to be significant. The qualitative nature of these findings is robust to various sensitivity tests. We assessed their sensitivity to big and small countries in the panel by dropping USA, Germany, New Zealand, Switzerland, Spain and Austria, in turn, and re-estimating the models. The reported results remain qualitatively the same. [15]

Table 3 reports the country-specific parameters computed from the results of table 2 following the method shown in equation (3), along with their cross-sectional averages. The standard errors of country-specific parameters are computed as shown in equation (4). The first panel of the table contains results pertaining to the A^{fc} measure of foreign knowledge stocks. The impact parameters of A^d and A^{fc} are all positive and highly significant (at 1% or better) implying that they both exert positive effect on the production of new-to-the-world ideas across all the countries in the sample. There is extensive cross-country variation in the magnitude of these parameters however. The impact elasticity of $\dot{A}^d$ with respect to A^d, (ϕ), ranges from a minimum of 0.080 (United States) to a maximum of 0.234 (Ireland); this is a difference of 2.93 times. The cross-sectional average is 0.161. Likewise, the impact elasticity of A^{fc}, (ψ), ranges from a minimum of 0.091 (United States) to a maximum of 0.267 (Ireland) and the cross-sectional average is 0.183. Ireland shows the highest impact elasticity of $\dot{A}^d$ with respect to both A^d and A^f whereas the United States shows the lowest. Statistically, no country supports (accepts) the parametric restriction of first-degree homogeneity (ϕ=1) proposed by Romer (1990).

The cross-country impact effects of H_A, (β), are even more varied. They range from a minimum of -0.029 (Switzerland) to a maximum of 0.592 (Spain). Except for Switzerland, all country specific parameters of H_A are positively signed

and highly significant. The negative marginal product (-0.020) for Swiss ideas researchers is rather befitting to the decline in ideas productivity evident in Swiss data (Figure II, panel A) but this decline appears statistically insignificant.

A large cross-country variation is also apparent in the adjustment dynamics (λs). New Zealand shows the lowest adjustment parameter (0.108) and Switzerland the highest (0.873). All adjustment coefficients are statistically significant. The other countries with a high adjustment coefficient are Germany (0.791), the Netherlands (0.691), Japan (0.654) and the United States and France (0.638).

These differences in cross-country adjustment dynamics — the λ coefficients — generate long-run effects of H_A, A^d and A^f on $\dot{A}^d$ that are entirely different from their impact effects. [16] The United States depicts the highest long-run point elasticity of $\dot{A}^d$ with respect to H_A (1.402) followed by Japan (1.281) and Germany (1.227). For the rest of sample countries the long-run elasticity of $\dot{A}^d$ with respect to H_A is less than unity. For Switzerland, it is of the magnitude of -0.230 but statistically insignificant. The magnitudes of the long-run elasticity prompt us to suggest that the US community of researchers is probably the most innovative. Austria (0.246), Ireland (0.300), New Zealand (0.334) and Belgium (0.395) typically demonstrate low ideas productivity in the long-run.

The long-run elasticity of $\dot{A}^d$ with respect to A^d is the highest for Switzerland (1.099) and the lowest for the United States (0.220). The same holds for the A^{fc}. Switzerland shows the highest long-run international knowledge spillover effect (1.253) vis-à-vis the domestic production of ideas and United States the lowest (0.251). For the remaining countries, the magnitude of the long-run parameters of A^d and A^{fc} are clearly less than a half each. The low point elasticity for the United States' A^d may reflect its huge domestic stock of ideas and hence a low marginal

return. Likewise, its small long-run elasticity of $\dot{A}^d$ with respect to A^{fc} may reflect its innovative edge in the world of ideas, thus leaving little scope for ideas diffusion from the rest of the world.

The second panel of Table 3 reports results of the empirical model that employs import ratio weighted foreign knowledge stocks. Overall, the country-specific parameters are close and qualitatively similar across these two measures of foreign knowledge stocks. The impact effect of H_A for Switzerland appears positive but the magnitude is small and continues to be statistically insignificant. However, one difference is that the impact effects of knowledge diffusion appear bigger vis-à-vis the A^{fc} compared to that of A^{fm} for most countries. In other words, the use of bilateral R&D collaboration weights improves the prominence of international knowledge diffusion in domestic ideas production.

Table 4 reports the country-specific parameters computed from columns C and D of table 2 where the empirical model replaces the level of human capital in the R&D sector by research intensity. As before, results of the first panel are from the model that utilizes A^{fc} and those in the second panel uses A^{fm}. We have noted that, from a theoretical perspective, the correct measure in modeling ideas production is the level of human capital in the R&D sector rather than research intensity. Indeed, the use of research intensity produces some uncomfortable results. First, the marginal product of Swiss researchers now turns significantly positive (0.289) and both the impact and the long-run elasticities appear higher than that of the United States. With the level of human capital, we found a negative but insignificant marginal product for the Swiss ideas researchers (Table 3: Panel I). Although imprecisely estimated, the negative sign of the coefficient is consistent with the downward productivity trend found in Swiss data. Thus, the positive and significant point elasticity found with the research intensity data is at odds with the reality (the actual data pattern). Second, based on the magnitude of long–run parameters, we

concluded that the United States might have the best pool of ideas researchers across the sample countries. The use of research intensity reverses this result. Surprisingly, Italy turns out to be on the top vis-à-vis the long-run returns to ideas researchers. According to the intensity-based results, US ideas researchers even lag behind those of France, Italy, Spain and the Netherlands (let alone those of the United Kingdom and Germany). This is contrary to the beliefs as well as the earlier findings (Table 3). Finally, when the level of human capital is used, three countries (Germany, Japan and the United States) show the long-run elasticity of above unity vis-à-vis the level of human capital. In contrast, with research intensity, all sample countries have long-run elasticity of well below unity. The parameters of domestic and foreign knowledge stocks are qualitatively similar to those obtained from the model that uses the level of human capital in the R&D sector. Results of panel II, which uses import weighted foreign knowledge stock, are qualitatively similar to those of panel I.

In table 5, we report results for the TFP specified in equation (5). The upper panel reports the results of dynamic heterogeneous panel models for both measures of foreign knowledge stocks (A^{fc} and A^{fm}). The lower panel reports the respective country-specific parameters. Under both specifications, only interacted domestic knowledge stock, ($A^{d}_{i,t-1} * \bar{A}_i$), and the lagged dependent variable appear significant; foreign knowledge stocks appear insignificant. The knowledge-productivity relationship is heterogeneous cross-countries depending on country's domestic knowledge stock ($\bar{A}_i$). The signs of these parameters indicate that the higher the domestic knowledge stock the lower its productivity effects. However, results on TFP dynamics are mixed. The TFP dynamics appears heterogeneous vis-à-vis the collaboration weighted foreign knowledge stocks only.[17]

The country-specific TFP parameters are reported in the lower panel of the table. The first two columns of country-specific parameters pertain to the empirical

model that uses A^{fc}. The estimated point elasticities ($\partial TFP_{i,t} \big/ \partial A^{d}_{i,t-1} = \varphi_i$) differ widely across countries. The impact elasticity varies from a minimum of 0.004 (United States) to a maximum of 0.013 (Ireland). The long-run elasticity ranges between a minimum of 0.018 (United States) to a maximum of 0.406 (Ireland). [18]

Our results reveal an interesting pattern regarding the effect of domestic knowledge stock on TFP. The magnitude of the TFP effect (φ_i) appears high for countries with low knowledge base ($\overline{A}^{d}_{i}$); however, the TFP effect systematically falls for countries with higher and higher knowledge base. Ireland and New Zealand, the two countries with the smallest size of A^{d} in the sample, show the highest impact (long-run) elasticity of 0.013 (0.406) and 0.012 (0.353), respectively. They are followed by countries like Norway, Spain, Denmark and Finland, which are the other countries with low ideas bases. On the other hand, the United States, Germany and Japan — the largest three in terms of the domestic knowledge stocks — exhibit very small point elasticity of TFP with respect to their domestic knowledge stocks. The respective impact (long-run) elasticities — calculated from the model that utilizes A^{fc} — are 0.004 (0.018), 0.005 (0.025) and 0.005(0.024) for the United States, Germany and Japan. Thus, countries with a small knowledge base (stock) may notably improve their TFP through knowledge accumulation. Finally, the effect of domestic knowledge stock on TFP is direct whereas the foreign knowledge stock affects TFP only indirectly via the accumulation of domestic knowledge. The magnitudes of the effect of knowledge stock on TFP, for most countries, appear much smaller than predicted by R&D-based growth models. In the last two columns country-specific parameters obtained from the model that uses import-weighted foreign knowledge stocks are presented. The domestic knowledge stock continues to appear positive but parameters appear significant at 10% only. There is no evidence of heterogeneous dynamics of TFP adjustment. Overall, the use of A^{fm} does not change the qualitative nature of the effect of domestic knowledge stock on TFP but

the cross-country parameters obtained from the empirical model that uses A^{fc} appear more pronounced.[19]

Results of dynamic heterogeneous panel models (equations (2) and (5)) discussed above shed new light on the issues of cross-country heterogeneity in ideas production and knowledge-productivity relationship. Now, a pertinent question is does triadic patent data shed any new light. We find that it does. For example, Porter and Stern (2000) model ideas production function and knowledge-TFP relationship using USPTO data. Our work differs from theirs in three distinct respects. First, we use triadic patent family data, which as argued above is a better proxy of knowledge. Second, we estimate dynamic heterogeneous panel models that explicitly account for the cross-country heterogeneity in parameters and adjustment dynamics whereas they estimate the standard fixed effects static and/or autoregressive models. Finally, we apply the system GMM estimator while they use the OLS and instrumental variable estimators.

To reveal if our dataset shed new light, we estimate fixed-effect static and first-order-autoregressive panel data models through the OLS and the instrumental variable estimators ensuring methodological similarities to Porter and Stern (2000). We find that our results differ from theirs in quite a few respects. First, they report impact elasticity of unity between $\dot{A}^d_{i,t}$ and $A^d_{i,t}$ irrespective of the inclusion (exclusion) of $A^f_{i,t}$ in (from) the estimating equation. In contrast, we do not find a proportional relationship between $\dot{A}^d_{i,t}$ and $A^d_{i,t}$; the magnitudes of our impact elasticity are less than a quarter (0.25). Second, they report a substantial raising-the-bar effect (i.e., , $\partial \dot{A}^d_{i,t} \big/ A^f_{i,t} = -1$), whereas we find quite the opposite (i.e., $\partial \dot{A}^d_{i,t} \big/ A^f_{i,t} > 0$). Similar to them, we also find insignificant effect of foreign knowledge stock on domestic TFP but with one key difference. We find that the foreign knowledge stock affects TFP positively but indirectly through the accumulation of domestic knowledge stocks. This

is because foreign knowledge stock positively contributes to domestic knowledge accumulation ($\partial \dot{A}^{d}_{i,t} \big/ \partial A^{f}_{i,t-1} \succ 0$) which subsequently drives domestic productivity ($\partial TFP_{i,t} \big/ \partial A^{d}_{i,t-1} \succ 0$). However, this link is missing in their results because they find foreign knowledge stock significantly reducing domestic production of ideas ($\partial \dot{A}^{d}_{i,t} \big/ \partial A^{f}_{i,t} \prec 0$) and $A^{f}_{i,t-1}$ does not affect domestic productivity either ($\partial TFP_{i,t} \big/ \partial A^{f}_{i,t} = 0$). Thus, the triadic patent family data provide some distinct results vis-à-vis the existing literature.

8. SUMMARY, CONCLUSION AND IMPLICATIONS

We estimate the key parameters of the ideas production function and knowledge-productivity relationship for a panel of 19 OECD countries by allowing for cross-country heterogeneity. 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 an effective R&D policy.

This paper contributes to the existing literature in at least three important respects. First, it explicitly models cross-country heterogeneity in the parameters of ideas production function and knowledge-TFP relationship through dynamic heterogeneous panel models. The heterogeneity is modeled as a function of country-specific mean stocks of domestic ideas and full-time researchers employed in the R&D sector. We show why stock measures capture the cross-country diversity in innovative activities better than alternative measures of R&D intensity.

Second, a new data set—the triadic patent family data— is used to measure the domestic flows of innovations. These patents are research-intensive and entail high patenting costs; hence are expected to proxy valuable innovations more accurately. They are also analogous measures of innovations across countries. Further, they are less likely to be tainted by home biases and double counting and

are enumerated on priority dates. In short, we analyze a good quality data set of high-value patents. We also compute a new measure of foreign knowledge stock by employing the bilateral R&D collaboration as weights. This measure is used alongside the capital goods imports weighted foreign knowledge stocks. Finally, we follow system GMM estimator, which addresses endogeneity rigorously.

We find that the parameters of the ideas 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 ideas, however, the impact elasticity is well below unity for all countries. This implies that the contemporary ideas 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 but less than unity for all countries except Switzerland. This suggests a sizeable but heterogeneous duplicative R&D — the stepping-on-toes effect. We are able to pick up the decline in Swiss ideas productivity evidenced in her data through our preferred empirical model (that uses R&D collaboration weighted foreign knowledge stocks) but find that the fall in Swiss productivity is statistically insignificant.

On the role of inputs to ideas production, we find that, on average, the flow of innovations is likely to be higher in countries that engage more scientists and engineers in this sector. However, we could only capture this effect when we use the theoretically consistent measure of human capital — the level of scientists and engineers engaged in the R&D sector — in the empirical model. We find that the use of research intensity in the empirical model shows diminishing return on ideas researchers. We also find that when the level of domestic ideas stock is high, the return on it tends to be low. Likewise, the benefits from foreign knowledge diffusion

appear to diminish when countries accumulate larger and larger stock of ideas domestically. The qualitative nature of these findings is robust to sample size and estimators.

The results show a direct and positive effect of domestic ideas stock on TFP; however, the effect of foreign ideas stock is indirect and appears only via the increased accumulation of new domestic ideas. Our results reveal that the magnitude of the TFP effect ($\partial TFP / \partial A^d$) declines sequentially for countries with a larger and larger domestic ideas base ($\overline{A}^d$). Countries with a small ideas base, demonstrate high elasticity of TFP with respect to their A^d, whereas countries that have acquired a sizeable domestic knowledge base exhibit small point elasticity. Thus, 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.

The main implications of our findings are as follows. Ideas production is extremely heterogeneous across OECD countries and so is the relationship between knowledge stocks and TFP. Therefore, it may be fruitful to account for the country-specific factors while designing R&D policy; the one-size-fits-all approach may not be the best way forward.

Table 1: Descriptive Statistics (mean 1981-2000)

	Number of Patents			Share in World Total			Patent Intensity			R&D [Expenditure and Intensity]		Researchers [in 1,000s and Intensity]		R&D Collaboration Weights		Capital Goods Imports Weights	
	Triadic	EPO	USPTO	Triadic	EPO	USPTO	Triadic	EPO	USPTO	Exp.	Int.	'000'	Int.	Mean	SD	Mean	SD
AU	183	464	584	0.6	0.7	0.5	4.0	10.1	12.7	5151	1.4	46	0.59	0.005	0.008	0.003	0.005
AT	184	671	410	0.6	1.1	0.4	15.6	56.9	34.8	2631	1.5	12	0.31	0.003	0.003	0.003	0.003
BE	253	677	469	0.8	1.1	0.4	12.8	34.3	23.7	3655	1.7	20	0.52	0.006	0.006	0.007	0.009
CA	308	709	2272	1.0	1.1	2.0	4.4	10.2	32.6	10483	1.6	70	0.53	0.005	0.004	0.002	0.003
DK	138	407	309	0.5	0.7	0.3	11.0	32.5	24.7	2006	1.6	13	0.48	0.004	0.005	0.003	0.004
FIN	198	544	467	0.7	0.9	0.4	12.0	33.0	28.3	2199	2.1	16	0.72	0.003	0.003	0.002	0.003
FR	1732	4784	3219	5.7	7.7	2.8	13.5	37.4	25.2	27881	2.2	128	0.57	0.021	0.018	0.015	0.016
DE	4254	12487	8481	14.0	20.2	7.4	21.6	63.5	43.1	39748	2.5	197	0.59	0.049	0.044	0.027	0.025
IRL	24	82	77	0.1	0.1	0.1	5.1	17.2	16.3	609	1.0	5	0.38	0.001	0.001	0.001	0.001
IT	568	2198	1340	1.9	3.5	1.2	8.2	31.9	19.4	13034	1.1	69	0.31	0.006	0.004	0.010	0.008
JP	8057	10981	24238	26.6	17.7	21.3	14.3	19.6	43.2	76396	2.8	562	0.88	0.011	0.006	0.005	0.004
NL	645	1664	1028	2.1	2.7	0.9	21.7	55.8	34.5	6460	2.0	30	0.45	0.013	0.014	0.008	0.012
NZ	20	62	81	0.1	0.1	0.1	3.5	10.9	14.3	688	1.1	6	0.45	0.001	0.001	0.001	0.001
NO	60	187	166	0.2	0.3	0.1	4.6	14.2	12.5	1748	1.6	13	0.63	0.002	0.003	0.003	0.005
SP	65	316	183	0.2	0.5	0.2	1.7	8.1	4.7	4566	0.7	39	0.29	0.002	0.001	0.004	0.003
SE	533	1246	1082	1.8	2.0	0.9	19.0	44.4	38.6	5796	3.1	28	0.66	0.014	0.018	0.006	0.007
CH	737	1745	1280	2.4	2.8	1.1	40.8	96.6	70.9	4771	2.6	18	0.47	0.012	0.010	0.004	0.004
UK	1397	3758	3040	4.6	6.1	2.7	10.1	27.3	22.1	23843	2.1	138	0.50	0.035	0.039	0.020	0.024
US	10280	17397	60125	33.9	28.1	52.8	10.6	17.9	62.0	186963	2.6	970	0.81	0.102	0.071	0.024	0.032
Mean	1560	3178	5729	5.1	5.1	5.0	12.4	32.7	29.7	22033	1.9	125	0.53	0.016	0.014	0.008	0.009

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). Triadic = a set of patents at the EPO (European Patent Office), JPO (Japan Patent Office) and the USPTO (US Patent and Trademark Office) that share one or more priorities. Patent Intensity = Patents per 1000 researchers. R&D Exp. = R&D expenditure in million of constant 2000 PPP dollars. R&D Int. = R&D expenditure as % of GDP. Researchers Int. = Researchers as % of total employment. SD = Standard deviation. R&D collaboration weights and Imports weights are defined in the Appendix. Source: OECD Patent, R&D and International Trade by Commodities Statistics databases.

Table 2: Dynamic Heterogeneous Panel Estimates (System GMM)

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

	Specification: I (Human capital in levels)		Specification: II (Human capital expressed as research intensity)	
	A	B	C	D
Constant	-1.999 (0.000)[a]	-1.357 (0.006)[a]	-2.119 (0.000)[a]	-0.608 (0.203)
$\dot{A}^d{}_{t-1}$	1.514 (0.000)[a]	1.482 (0.000)[a]	1.150 (0.000)[a]	1.046 (0.000)[a]
$\dot{A}^d{}_{i,t-1} * \bar{H}_i$	-0.227 (0.000)[a]	-0.232 (0.000)[a]	#	#
$\dot{A}^d{}_{i,t-1} * \bar{A}_i^d$	0.274 (0.000)[a]	0.259 (0.000)[a]	0.085 (0.000)[a]	0.028 (0.040)[b]
$\dot{A}^d{}_{i,t-1} * \bar{R}_i$	#	#	0.236 (0.004)[a]	0.514 (0.000)[a]
$H_{Ai,t} * \bar{H}_{Ai}$	0.233 (0.000)[a]	0.207 (0.001)[a]	#	#
$H_{Ai,t} * \bar{A}_i^d$	-0.160 (0.000)[a]	-0.148 (0.000)[a]	#	#
$A^d{}_{i,t} * \bar{A}^d{}_i$	-0.025 (0.000)[a]	-0.028 (0.000)[a]	-0.021 (0.001)[a]	-0.017 (0.015)[b]
$A_i^{fc} * \bar{A}_i$	-0.028 (0.000)[a]	#	-0.036 (0.000)[a]	#
$A_i^{fm} * \bar{A}_i$	#	-0.024 (0.000)[a]	#	-0.039 (0.000)[a]
$R_i * \bar{R}_i$	#	#	-0.380 (0.000)[a]	-0.347 (0.000)[a]
$A_{it}^{fc} * \bar{R}_i$	#	#	0.084 (0.011)[b]	#
α_i	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
γ_t	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
σ	0.141	0.145	0.138	0.141
AR{1}	(0.006)[a]	(0.016)[b]	(0.005)[a]	(0.012)[b]
AR{2}	(0.326)	(0.321)	(0.320)	(0.263)
Sargan χ^2	(0.151)	(0.816)	(0.908)	(0.612)

GMM results pertain to the first step estimates. Numbers (.) are p-values under the null. In estimation, specification I uses the level of human capital employed in the R&D sector. Columns A and B respectively utilize bilateral R&D collaboration weighted ($A_{i,t}^{fc}$) and bilateral import ratio weighted ($A_{i,t}^{fm}$) foreign ideas stocks. Specification II uses research intensity instead of the level of human capital employed in the R&D sector; Columns C and D respectively use ($A_{i,t}^{fc}$) and ($A_{i,t}^{fm}$). # indicates that the regressor is not applicable to the specification in question. AR{1} and AR{2} are the first and the second order LM tests of residual serial correlation. Under GMM, these tests are implemented on the first differenced residuals because of the transformations involved, therefore, AR{1} is expected to be significant and AR{2} insignificant (see text). α_i and γ_t are the fixed and time effects. Sargan test tests the null that both sets of instruments (lagged level and lagged first differences) are valid. $\dot{A}^d{}_{t-1}$, $H_{Ai,t}$ and $A_{i,t}^d$ are GMM-instrumented setting $s \geq 3$. Foreign knowledge stocks and the mean-interacted regressors are exogenously treated. Superscripts a, b and c indicate significance at 1%, 5% and 10% respectively.

Table 3: Country-Specific Parameters Obtained from the Estimates of Table 2 (Specification I)

	Panel I: Country-specific parameters obtained from the results of column A of Table 2.				Panel II: Country-specific parameters obtained from the results of column B of Table 2.			
	λ	β	ϕ	ψ	λ	β	ϕ	ψ
AU	0.230 [a] [0.048]	0.436 [a] [0.075]	0.179 [a] [0.049]	0.204 [a] [0.020]	0.322 [a] [0.047]	0.431 [a] [0.080]	0.203 [a] [0.049]	0.176 [a] [0.049]
AT	0.552 [a] [0.048]	0.110 [0.070]	0.178 [a] [0.048]	0.203 [a] [0.020]	0.651 [a] [0.054]	0.141 [b] [0.069]	0.202 [a] [0.049]	0.176 [a] [0.048]
BE	0.493 [a] [0.039]	0.200 [a] [0.056]	0.172 [a] [0.047]	0.196 [a] [0.019]	0.586 [a] [0.044]	0.219 [a] [0.058]	0.195 [a] [0.047]	0.170 [a] [0.047]
CA	0.245 [a] [0.054]	0.471 [a] [0.082]	0.169 [a] [0.046]	0.192 [a] [0.019]	0.330 [a] [0.053]	0.459 [a] [0.087]	0.191 [a] [0.046]	0.166 [a] [0.046]
DK	0.403 [a] [0.039]	0.205 [a] [0.063]	0.190 [a] [0.052]	0.217 [a] [0.021]	0.509 [a] [0.043]	0.228 [a] [0.065]	0.215 [a] [0.052]	0.187 [a] [0.051]
FIN	0.343 [a] [0.036]	0.263 [a] [0.060]	0.191 [a] [0.052]	0.217 [a] [0.022]	0.448 [a] [0.039]	0.280 [a] [0.063]	0.216 [a] [0.052]	0.188 [a] [0.052]
FR	0.638 [a] [0.050]	0.304 [a] [0.052]	0.121 [a] [0.033]	0.138 [a] [0.014]	0.690 [a] [0.054]	0.299 [a] [0.056]	0.137 [a] [0.033]	0.119 [a] [0.033]
DE	0.791 [a] [0.058]	0.257 [a] [0.044]	0.099 [a] [0.027]	0.112 [a] [0.011]	0.827 [a] [0.064]	0.252 [a] [0.047]	0.112 [a] [0.027]	0.097 [a] [0.027]
IRL	0.141 [a] [0.048]	0.258 [a] [0.077]	0.234 [a] [0.064]	0.267 [a] [0.026]	0.279 [a] [0.048]	0.285 [a] [0.079]	0.265 [a] [0.064]	0.230 [a] [0.063]
IT	0.422 [a] [0.044]	0.370 [a] [0.063]	0.153 [a] [0.042]	0.174 [a] [0.017]	0.496 [a] [0.046]	0.365 [a] [0.068]	0.173 [a] [0.042]	0.150 [a] [0.041]
JP	0.654 [a] [0.075]	0.443 [a] [0.092]	0.089 [a] [0.024]	0.102 [a] [0.010]	0.679 [a] [0.075]	0.415 [a] [0.093]	0.101 [a] [0.025]	0.088 [a] [0.024]
NL	0.691 [a] [0.049]	0.127 [b] [0.052]	0.146 [a] [0.040]	0.166 [a] [0.016]	0.765 [a] [0.057]	0.148 [b] [0.052]	0.165 [a] [0.040]	0.144 [a] [0.040]
NZ	0.108 [b] [0.047]	0.298 [a] [0.074]	0.233 [a] [0.063]	0.265 [a] [0.026]	0.244 [a] [0.046]	0.321 [a] [0.077]	0.264 [a] [0.064]	0.229 [a] [0.063]
NO	0.165 [a] [0.042]	0.351 [a] [0.067]	0.210 [a] [0.057]	0.239 [a] [0.024]	0.283 [a] [0.042]	0.362 [a] [0.072]	0.238 [a] [0.058]	0.207 [a] [0.057]
SP	0.134 [c] [0.072]	0.592 [a] [0.104]	0.210 [a] [0.057]	0.240 [a] [0.024]	0.041 [0.070]	0.577 [a] [0.109]	0.238 [a] [0.058]	0.207 [a] [0.057]
SE	0.619 [a] [0.044]	0.162 [a] [0.051]	0.154 [a] [0.042]	0.175 [a] [0.017]	0.699 [a] [0.051]	0.181 [a] [0.052]	0.174 [a] [0.042]	0.151 [a] [0.042]
CH	0.873 [a] [0.071]	-0.029 [0.079]	0.140 [a] [0.038]	0.159 [a] [0.016]	0.947 [a] [0.080]	0.007 [0.075]	0.158 [a] [0.038]	0.138 [a] [0.038]
UK	0.572 [a] [0.051]	0.351 [a] [0.061]	0.125 [a] [0.034]	0.142 [a] [0.014]	0.626 [a] [0.054]	0.342 [a] [0.065]	0.142 [a] [0.034]	0.123 [a] [0.034]
US	0.638 [a] [0.086]	0.507 [a] [0.112]	0.080 [a] [0.022]	0.091 [a] [0.009]	0.655 [a] [0.085]	0.470 [a] [0.112]	0.090 [a] [0.022]	0.078 [a] [0.022]
Mean	0.458	0.292	0.161	0.183	0.530	0.304	0.183	0.159
S.D.	0.238	0.143	0.045	0.051	0.232	0.136	0.052	0.045

Note: λ are solutions for the country-specific coefficients of the lagged dependent variables. [.] contains the standard errors. Superscripts a, b and c indicate significance at 1%, 5% and 10%, respectively. β, ϕ and ψ are the country-specific impact elasticity of $\dot{A}^{d}{}_{i,t}$ with respect to $H_{Ai,t}$, $A^{d}_{i,t}$ and $A^{f}_{i,t-1}$. Two measures of foreign knowledge stocks ($A^{f}_{i,t}$) are used in the estimation. Panel I uses the bilateral R&D collaboration weighted foreign knowledge stock ($A^{fc}_{i,t}$) whereas panel II uses bilateral import weighted one ($A^{fm}_{i,t}$). Impact elasticity needs to be divided by (1-λ) to obtain the long-run elasticity.

Table 4: Country-Specific Parameters Obtained from the Estimates of Table 2 (Specification II)

	Panel I: Country-specific parameters obtained from the results of column C of Table 2.				Panel II: Country-specific parameters obtained from the results of column D of Table 2.			
	λ	β	ϕ	ψ	λ	β	ϕ	ψ
AU	0.378 [a] [0.038]	0.245 [a] [0.038]	0.156 [a] [0.047]	0.210 [a] [0.019]	0.513 [a] [0.038]	0.224 [a] [0.040]	0.123 [b] [0.050]	0.282 [a] [0.043]
AT	0.253 [a] [0.043]	0.451 [a] [0.071]	0.155 [a] [0.047]	0.164 [a] [0.023]	0.235 [a] [0.041]	0.412 [a] [0.074]	0.122 [b] [0.050]	0.281 [a] [0.042]
BE	0.365 [a] [0.034]	0.303 [a] [0.047]	0.150 [a] [0.045]	0.188 [a] [0.018]	0.442 [a] [0.037]	0.277 [a] [0.050]	0.118 [b] [0.048]	0.272 [a] [0.041]
CA	0.391 [a] [0.035]	0.281 [a] [0.044]	0.147 [a] [0.044]	0.187 [a] [0.017]	0.476 [a] [0.037]	0.256 [a] [0.046]	0.116 [b] [0.047]	0.266 [a] [0.040]
DK	0.287 [a] [0.035]	0.330 [a] [0.052]	0.165 [a] [0.050]	0.208 [a] [0.020]	0.386 [a] [0.037]	0.301 [a] [0.054]	0.130 [b] [0.053]	0.299 [a] [0.045]
FIN	0.362 [a] [0.047]	0.205 [a] [0.032]	0.166 [a] [0.050]	0.236 [a] [0.022]	0.554 [a] [0.041]	0.187 [a] [0.034]	0.131 [b] [0.054]	0.301 [a] [0.045]
FR	0.568 [a] [0.044]	0.262 [a] [0.041]	0.105 [a] [0.032]	0.121 [a] [0.014]	0.555 [a] [0.048]	0.240 [a] [0.043]	0.083 [b] [0.034]	0.191 [a] [0.029]
DE	0.673 [a] [0.051]	0.218 [a] [0.034]	0.086 [a] [0.026]	0.098 [a] [0.011]	0.639 [a] [0.055]	0.200 [a] [0.036]	0.068 [b] [0.028]	0.155 [a] [0.023]
IRL	0.063 [0.045]	0.447 [a] [0.070]	0.203 [a] [0.062]	0.247 [a] [0.025]	0.178 [a] [0.045]	0.408 [a] [0.073]	0.160 [b] [0.066]	0.369 [a] [0.056]
IT	0.331 [a] [0.054]	0.469 [a] [0.073]	0.133 [a] [0.040]	0.122 [a] [0.024]	0.240 [a] [0.047]	0.428 [a] [0.077]	0.105 [b] [0.043]	0.241 [a] [0.036
JP	0.809 [a] [0.059]	0.052 [a] [0.008]	0.077 [a] [0.023]	0.120 [a] [0.012]	0.876 [a] [0.060]	0.047 [a] [0.008]	0.061 [b] [0.025]	0.141 [a] [0.021]
NL	0.446 [a] [0.039]	0.321 [a] [0.050]	0.127 [a] [0.038]	0.145 [a] [0.016]	0.448 [a] [0.042]	0.293 [a] [0.052]	0.100 [b] [0.041]	0.230 [a] [0.035]
NZ	0.077 [c] [0.044]	0.430 [a] [0.067]	0.202 [a] [0.061]	0.249 [a] [0.024]	0.202 [a] [0.044]	0.393 [a] [0.070]	0.159 [b] [0.065]	0.367 [a] [0.055]
NO	0.298 [a] [0.055]	0.201 [a] [0.031]	0.182 [a] [0.055]	0.266 [a] [0.025]	0.537 [a] [0.046]	0.184 [a] [0.033]	0.144 [b] [0.059]	0.331 [a] [0.050]
SP	0.073 [0.054]	0.563 [a] [0.088]	0.183 [a] [0.055]	0.186 [a] [0.028]	0.048 [0.046]	0.514 [a] [0.092]	0.144 [b] [0.059]	0.331 [a] [0.050]
SE	0.502 [a] [0.041]	0.186 [a] [0.029]	0.134 [a] [0.040]	0.186 [a] [0.017]	0.621 [a] [0.041]	0.170 [a] [0.030]	0.105 [b] [0.043]	0.242 [a] [0.037]
CH	0.487 [a] [0.039]	0.289 [a] [0.045]	0.121 [a] [0.037]	0.142 [a] [0.015]	0.497 [a] [0.043]	0.264 [a] [0.047]	0.096 [b] [0.039]	0.220 [a] [0.033]
UK	0.550 [a] [0.043]	0.270 [a] [0.042]	0.109 [a] [0.033]	0.125 [a] [0.014]	0.540 [a] [0.047]	0.247 [a] [0.044]	0.086 [b] [0.035]	0.197 [a] [0.030]
US	0.807 [a] [0.058]	0.108 [a] [0.017]	0.069 [a] [0.021]	0.094 [a] [0.008]	0.810 [a] [0.062]	0.099 [a] [0.018]	0.054 [b] [0.022]	0.125 [a] [0.019]
Mean	0.406	0.296	0.140	0.173	0.463	0.271	0.111	0.255
S.D.	0.218	0.130	0.039	0.053	0.212	0.119	0.031	0.072

Note: λ are solutions for the country-specific coefficients of the lagged dependent variables. [.] contains the standard errors. Superscripts a, b and c indicate significance at 1%, 5% and 10%, respectively. β, ϕ and ψ are the country-specific impact elasticities of $\dot{A}^{d}_{i,t}$ with respect to $H_{Ai,t}$, $A^{d}_{i,t}$ and $A^{f}_{i,t}$. Two measures of foreign knowledge stocks ($A^{f}_{i,t}$) are used in the estimation. Panel I uses the bilateral R&D collaboration weighted foreign knowledge stock ($A^{fc}_{i,t}$) whereas panel II uses bilateral import weighted one ($A^{fm}_{i,t}$). Impact elasticity needs to be divided by (1-λ) to obtain the long-run elasticity.

Table 5 (Upper Panel): Knowledge-Productivity Relationship

$$TFP_{i,t} = \mu_i + \eta_t + \xi_1 TFP_{i,t-1} + \xi_2 (TFP_{i,t-1} * \overline{A}_i^d) + \varphi_1 A^d_{i,t-1} + \theta_1 A^f_{i,t-1} + \varphi_2 (A^d_{i,t-1} * \overline{A}_i^d) + \theta_2 (A^f_{i,t-1} * \overline{A}_i^d) + e_{i,t}$$

Constant	$TFP_{i,t-1}$	$(TFP_{i,t-1} * \overline{A}_i^d)$	$A^d_{i,t-1}$	$A^{fc}_{i,t-1}$	$A^{fm}_{i,t-1}$	$(A^d_{i,t-1} * \overline{A}_i^d)$	$(A^{fc}_{i,t-1} * \overline{A}_i^d)$	$(A^{fm}_{i,t-1} * \overline{A}_i^d)$
0.783 (0.000)	0.677 [a] (0.000)	-0.031 [a] ((0.001)	-	0.005 (0.353)	#	-0.0013 [a] (0.001)	0.001 (0.170)	#
0.078 (0.421)	0.986 [a] (0.000)	-0.0001 (0.742)	-	#	-0.001 (0.833)	-0.0005 [c] (0.076)	#	0.001 (0.211)

Results are from the first step System GMM estimator. $TFP_{i,t-1}$ and $A^d_{i,t-1}$ are GMM instrumented setting $s \geq 3$. (.) are p-values; superscripts a, b and c indicate significance at 1%, 5% and 10%, respectively.. The foreign knowledge stocks and the interacted regressors are treated weakly exogenous. # indicates that the regressor is not applicable to the specification in question. Country and time effects both appear significant (at 1% or better) and are included in estimations. The LM tests confirm the significance (insignificance) of the first (second) order residual serial correlations. Sargan test does not reject the null of instrument validity. The regression standard errors (σ_s) are 0.016 and 0.017 for the empirical models reported in the first and the second rows respectively.

Table 5 (Lower Panel): Country-Specific Parameters Obtained from the results of Table 5

	Model that uses $A^{fc}_{i,t-1}$		Model that uses $A^{fm}_{i,t-1}$	
	ξ	φ	ξ	φ
AU	0.900 [a] [0.015]	0.010 [a] [0.003]	0.986 [a] [0.012]	0.003 [c] [0.002]
AT	0.899 [a] [0.015]	0.010 [a] [0.003]	0.986 [a] [0.012]	0.003 [c] [0.002]
BE	0.891 [a] [0.017]	0.009 [a] [0.003]	0.986 [a] [0.012]	0.003 [c] [0.002]
CA	0.887 [a] [0.018]	0.009 [a] [0.003]	0.986 [a] [0.012]	0.003 [c] [0.002]
DK	0.913 [a] [0.013]	0.010 [a] [0.003]	0.986 [a] [0.012]	0.004 [c] [0.002]
FIN	0.914 [a] [0.013]	0.010 [a] [0.003]	0.986 [a] [0.012]	0.004 [c] [0.002]
FR	0.827 [a] [0.033]	0.006 [a] [0.002]	0.986 [a] [0.012]	0.002 [c] [0.001]
DE	0.800 [a] [0.041]	0.005 [a] [0.002]	0.986 [a] [0.012]	0.002 [c] [0.001]
IRL	0.968 [a] [0.018]	0.013 [a] [0.004]	0.986 [a] [0.012]	0.004 [c] [0.002]
IT	0.867 [a] [0.022]	0.008 [a] [0.002]	0.986 [a] [0.012]	0.003 [c] [0.002]
JP	0.788 [a] [0.045]	0.005 [a] [0.001]	0.986 [a] [0.012]	0.002 [c] [0.001]
NL	0.858 [a] [0.025]	0.008 [a] [0.002]	0.986 [a] [0.012]	0.003 [c] [0.002]
NZ	0.966 [a] [0.018]	0.012 [a] [0.004]	0.986 [a] [0.012]	0.004 [c] [0.002]
NO	0.938 [a] [0.013]	0.011 [a] [0.003]	0.986 [a] [0.012]	0.004 [c] [0.002]
SP	0.938 [a] [0.013]	0.011 [a] [0.003]	0.986 [a] [0.012]	0.004 [c] [0.002]
SE	0.868 [a] [0.022]	0.008 [a] [0.002]	0.986 [a] [0.012]	0.003 [c] [0.002]
CH	0.851 [a] [0.027]	0.007 [a] [0.002]	0.986 [a] [0.012]	0.003 [c] [0.001]
UK	0.832 [a] [0.032]	0.007 [a] [0.002]	0.986 [a] [0.012]	0.002 [c] [0.001]
US	0.776 [a] [0.048]	0.004 [a] [0.001]	0.986 [a] [0.012]	0.001 [c] [0.001]
Mean	0.878	0.009	0.986	0.003
S.D.	0.056	0.002	0.000	0.001

ξ_s are solutions for the country-specific coefficients of the lagged dependent variables. φ_s are impact elasticity of A^d_{it} on $\dot{A}^d_{it}$. Impact elasticity should be divided by ($(1-\xi)$ for the long-run elasticity. [.] are the standard errors. Superscripts a, b and c indicate significance at 1%, 5% and 10%, respectively.

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APPENDIX: VARIABLE DEFINITIONS AND DATA SOURCES

Definitions

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 1978, but a consistent data series for all the countries analyzed in this paper is only available from 1981. The domestic ideas 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 percent and the growth rate of $\dot{A}^d_{i,t}$ (sample average growth rate) are used to generate the initial (base year =1978) patent stock. Reported econometric results are robust to alternative depreciation rates of 12 and 20 percent. The classification of domestic and foreign patents follows standard practice at the OECD (by residence of inventor). Two measures of foreign knowledge stocks are computed. The first measure is computed as the weighted sum of the rest of the world's domestic ideas stock, $\left(A^{fc}_{it} = \sum_{j=1}^{N-1} w_{ij,t} A^d_{j,t}; i \neq j \right)$, where $t = 1, 2, .., T_i$. The time-varying weight ($w_{ij,t}$) is the bilateral R&D cooperation coefficient between countries i and j defined as the ratio of joint triadic patent applications due to joint-invention between the two countries to their respective total triadic patent applications. These weights are the authors' own calculations utilizing data from the OECD. We compute 18X20 matrixes of bilateral R&D cooperation coefficients for each sample country. Thus, $A^{fc}_{i,t}$ is the bilateral R&D collaboration weighted foreign knowledge stock. To avoid sharp yearly fluctuations, we compute $w_{ij,t}$ utilizing the four-year moving average of its numerator and denominator. The $w_{ij,t}$ effectively measures successful R&D collaboration that results in joint triadic family of patents between nations. The second measure of foreign knowledge stock uses bilateral capital goods import ratios as weights. Coe and

Helpman (1995) use bilateral total import ratios as weights. However, Xu and Wang (1999) show that bilateral capital goods import ratios better capture the knowledge spillovers embodied in trade flows because they embody higher technology content than total imports. Hence, for robustness checks, we compute foreign knowledge stocks based on bilateral capital goods import weight: $m_{ij} = M_{ij}^{C} / \sum_{j \neq i} Y_j$, where M_{ij}^{C} is country i's imports of capital goods from country j and Y_j is country J's GDP. 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 labor, respectively. Following much of the literature, we set the value of the γ coefficient to 0.3. For robustness, we also use the Multi Factor Productivity (MFP) data from the OECD, which is available for only 16 countries of our sample. Gross domestic product (GDP) for each country is measured at 1995 PPP (purchasing power parity) dollars. A consistent series of total physical capital stock (K) for the whole sample period is lacking (see Luintel and Khan, 2004). Therefore, K is computed from the non-residential fixed capital formation using the perpetual inventory method. The 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 percent and the sample-period average growth rate of IR are used to generate the initial capital stock. Labor force employed in the non-ideas-producing sector (L) is defined as the total employment level (E) minus the total number of full-time equivalent researchers (H_A).

Data sources

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

Figure I

R&D collaboration and capital goods imports weighted foreign knowledge stocks: 1981-2000

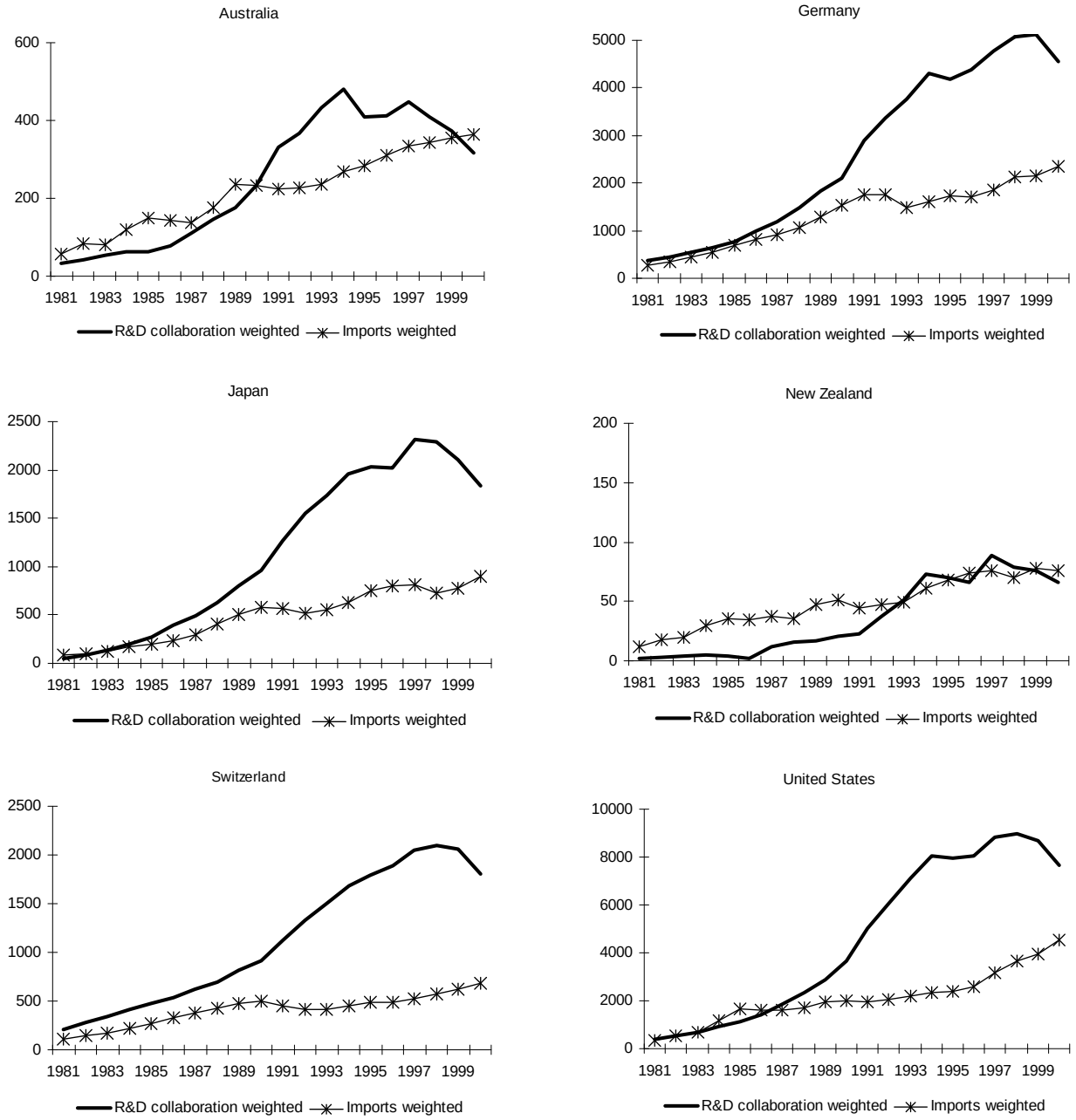


Figure II

Total OECD-Wide Ideas Productivity (Triadic Patent Families Per 1,000 Researchers)

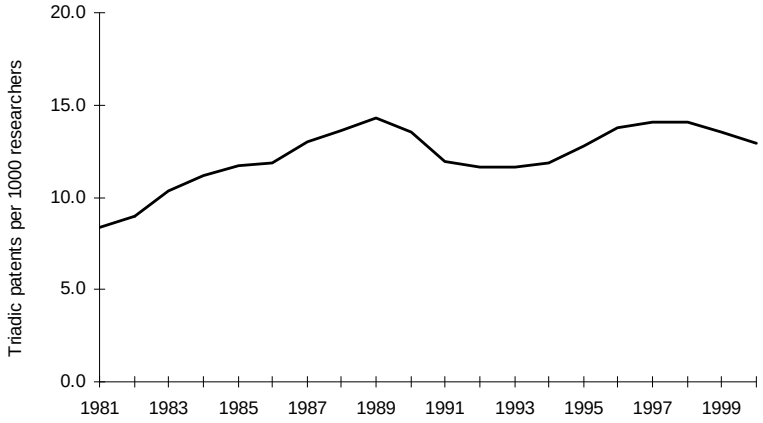
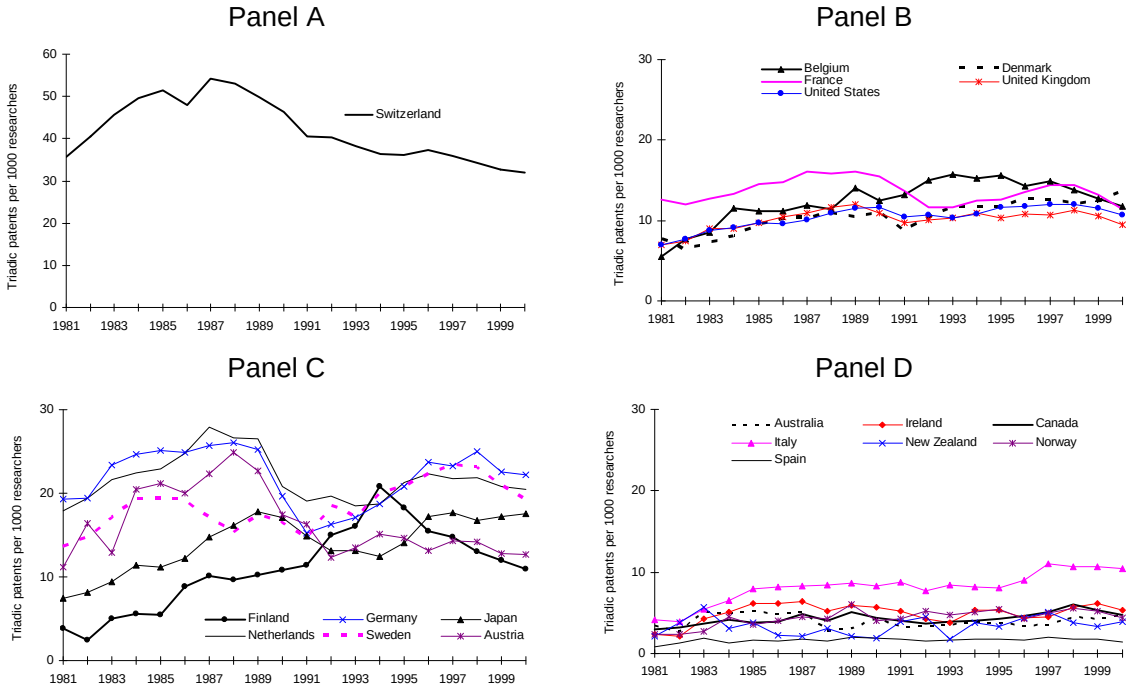


Figure III

Country-By-Country Ideas Productivity (Triadic Patent Families Per 1,000 Researchers)



Lead footnote: We thank Hélène Dernis, Elena Bernaldo and Colin Webb for data. Dirk Pilat at the OECD and seminar participants at Brunel, Cardiff and Swansea Universities and WIPO also deserve our thanks for valuable comments and suggestions. The views expressed are those of authors and do not implicate any institutions. The usual disclaimer applies.

[1] For example, see Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992).

[2] For example, Jones (1995a, 1995b) empirically assesses the "scale effect" of these models and concludes that R&D-based growth models are "counterfactual". Porter and Stern (2000) test for the parametric restrictions proposed by Romer's (1990) model using USPTO data (patents granted by the United States Patent & Trademark Office) in a sample of 17 OECD countries and find that these restrictions are only partially supported.

[3] In fact, we take a structured empirical approach beginning with the customary static fixed-effect OLS and INSTV (Instrumental Variables) estimators and gradually progressing toward the system GMM (Generalized Method of Moments) estimator. For the sake of brevity, we do not report the full-set of results of fixed effects models. We summarize the main findings in a footnote in the empirical sections (see footnote 15).

[4] For example, the formula for Coca-Cola is a closely guarded secret that has never been patented (Jones, 2002, pp. 92).

[5] 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 10,330 Euro, 16,450 Euro, and 49,900 Euro, respectively. We base our assertion on these cost estimates; however, other estimates abound [see, for example, Eaton and Kortum 1996 and 1999].

[6] For further details on triadic patent families, see Dernis and Khan [2004]. Michel and Bettels (2001) argue that triadic patents are the most suited dataset for international comparisons and multi-country studies.

[7] This ratio will come down further if data from the JPO is also considered.

[8] A separate plot for Swiss productivity is necessitated by: (i) the high scale required in the vertical axis; and (ii) the prolonged decline in Swiss productivity.

[9] Coe and Helpman (1995) and Porter and Stern (2000) take similar approach in their specifications.

[10] Specification (2) is shown to be robust to non-linearity (see Pesaran et al., 2000). This specification 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 ideas across countries.

[11] Elsewhere (Khan and Luintel, 2006), we model domestic productivity in a more rigorous way by accounting for at least ten of its theoretically proposed determinants. Thus, we address the problems of omitted variables and endogeneity in TFP modeling. Knowledge stocks continue to appear significantly positive in explaining productivity.

[12] Sargan's instruments validity test can be applied in two steps: (i) Sargan test (applicable to single equation GMM which tests the validity of lagged level variables used as instruments) and (ii) Difference-Sargan test (applicable to system GMM which tests the validity of instruments that appear in lagged differences only). We report their joint test under the null that both set of instruments are valid, which is more relevant to the system GMM.

[13] An explanation of this discrepancy may be that the intensity effect captures some self-limiting agglomeration effect due to, for example, congestion when countries shift more and more of their work force to the ideas producing sector. We are thankful to Patrick Minford and one of the anonymous referees for this insight.

[14] Andrews (1999) proposes the selection of correct moment conditions through the GMM analogues of the well-known BIC (Bayesian), AIC (Akaike), and HQIC (Hannan-Quinn) moment selection criterion (MSC). However, these criteria are only reliable if different moment selections that produce close MSC values do not yield visibly different parameter estimates. In our case this reliability criterion is violated, therefore, we do not peruse for this approach.

[15] Results are robust to other specifications and estimators as well. We estimated the standard fixed-effects static and first-order-autoregressive panel data models using both the OLS and the instrumental variable estimators. Although, these methods do not account for the cross-country heterogeneity nonetheless the stocks of domestic and foreign knowledge continue to appear significantly positive in the production of new-to-the-world ideas domestically.

[16] The long-run effect is calculated by dividing the impact parameter by $(1-\lambda)$.

[17] We also estimated fixed-effects (homogeneous) models for TFP and find that $A^{d}_{i,t-1}$ explains domestic TFP significantly but the effect of $A^{f}_{i,t-1}$ is insignificant. These results are consistent with the findings of Porter and Stern (2000).

[18] Barro and Lee (2000) provide five yearly periodic data on educational attainment for several countries of the world. We interpolated to get annual series for our sample countries and used them as a proxy of human capital in the TFP estimation. The qualitatively nature of the reported results do not change. Surprisingly, human capital appears either insignificant or negatively signed. Barro and Lee advised us strongly

against interpolation, on the grounds of unreliability, which may explain this unexpected outcome.

[19] We also used the OECD multi-factor productivity data, which covers 16 countries of our sample. The results remain qualitatively similar.