R&D and Productivity: An Assessment of Robustness

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Abstract

We model domestic productivity for a sample of 16 OECD countries focusing on the issues of *omitted variables*, *cross-country heterogeneity* and *endogeneity*. Theoretical models put forward a range of determinants of productivity. We propose a dynamic heterogeneous panel model which encompasses ten of these determinants and allows for the cross-country heterogeneity. Our specification nests homogeneous panel models as special cases. Sources of knowledge and human capital appear as the universal drivers of productivity. Other arguments show country-specific effects. The productivity relationship is heterogeneous across OECD countries hence the country-specific factors may play an important role in policy design.

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

Key Words: Sources of Knowledge; Dynamic Heterogeneity; MFP; Methods of Moments.

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Introduction

Innovations drive long-run productivity and economic growth in both classes of growth models - exogenous and endogenous. [1] Given the central role of research and development (R&D), a voluminous empirical literature has examined the relationship between R&D and productivity. Micro studies, which typically focus on the manufacturing sector and analyze firm and industry level cross-sectional data (Mansfield, 1988; Griliches and Mairesse, 1990; Hall and Mairesse, 1995; Wang Tsai, 2003; to name but a few) report statistically significant R&D elasticity of about 0.10 to 0.20 (Griliches, 1988). Studies that take a cost function approach (Nadiri, 1980; Nadiri and Pucha, 1990) also report positive and statistically significant returns to R&D. Macro studies, which utilize aggregate data, are either multi-country cross-sectional or panel studies (Lichtenberg, 1992; Coe and Helpman, 1995; Park, 1995; Keller, 1998). Time series studies are extremely scarce (Luintel and Khan, 2004). Macro studies also report: (i) a significant positive effect of domestic R&D on productivity and (ii) a positive and significant international knowledge spillover. [2] In view of the accumulating evidence, a consensus in the literature is that R&D contributes to productivity and knowledge spillovers are positive.[3]

Interestingly, empirical studies on R&D and productivity primarily focus on knowledge stocks as the driver of productivity. Yet, competing theoretical models put forward a range of productivity determinants, viz., human capital, public infrastructure, access to export markets (learning-by-doing), imports, foreign direct investments (FDI), information and communication technology (ICT) etc. To date, empirical literature has only gone as far as augmenting the knowledge-productivity relationship by stocks of human capital and trade variables (e.g., Engelbrecht, 1997; Griffith et. al., 2004c). No study has jointly examined the role of the sources of knowledge and various other determinants of productivity. This exclusion of relevant covariates – mis-specification – is potentially costly because it results into (i) biased parameter estimates, and (ii) unreliable statistical inference. The bias is a positive function of the extent of correlation between the excluded and the included regressors and the correlation matrix indeed shows a very high degree of correlation between them. [4] Inference is compromised because excluding relevant covariates invariably inflates the precision (reduces the standard errors) of the parameters of a mis-specified (short) regression. [5] The potential bias and the sceptical inference cast doubt on the reported significance of knowledge stocks in the literature because, as stated above, the extant empirical studies exclude several of the productivity determinants postulated by the theory. Addressing this issue is vital not least because it establishes the potency of knowledge stocks amongst the drivers of productivity. Our first aim is to advance the empirical literature in this direction. We estimate an empirical model of domestic productivity which, in addition to the three forms – domestic business (S^b) and public (S^p) sector and foreign (S^f) – of knowledge stocks, allows for a range of other determinants of productivity. In effect, we examine the robustness of knowledge stocks vis-à-vis the other determinants of productivity.

Second, countries exhibit important differences in the levels and growth rates of domestic productivity – this is true for OECD countries as well. In fact, the efficacy of some of the productivity determinants is hard to generalize. For example, ‘learning-by-doing’ is likely to augment the productivity of a technological laggard but the same is unlikely to hold true for a technological leader. Similar arguments apply in relation to technology ‘outsourcing’ which requires domestic capacity to absorb foreign technology.

The existing empirical literature mostly estimates the fixed effects models that allow for the country-specific fixed and country-invariant time effects but imply that the parameters and adjustment dynamics of productivity relationships are homogeneous across the sample countries. We call them ‘homogeneous panel models’. [6] OECD countries differ markedly in their business and public knowledge stocks, human capital bases and infrastructure. Their annual R&D expenditures also differ greatly. The scales of inward and outward FDI are different and so are the magnitudes of high tech exports and imports. In view of these differences, the assumption of homogeneous productivity relationships across OECD countries implied by the fixed effects models appears quite strong. Instead, productivity relationships across OECD countries may be heterogeneous and show country-specific partial elasticities vis-à-vis their determinants. A rigorous scrutiny of this issue is important because: (i) in panel regressions if one ignores parameter heterogeneity then this engenders bias and inconsistency (Pesaran et. al., 2000) which may compound the problems of omitted variables, and (ii) if parameters of productivity relationships are indeed heterogeneous across countries then their knowledge may help design the country-specific productivity policies better. Our second aim is precisely to model this cross-country heterogeneity of productivity relationships across the sample countries through a sufficiently general dynamic heterogeneous panel model.

We reveal that the cross-country differences in R&D intensity cannot capture the vast differences in innovative activities across countries. Instead, the levels of innovative activities appear more plausible to capture the cross-country heterogeneity in knowledge-productivity relationship, which we utilize.

We apply the system GMM (Generalized Method of Moments) estimator because it addresses the key estimation issues of endogeneity, weak instruments and measurement errors. Although the system GMM is our preferred estimator, we adopt a structured empirical strategy. First, we report the results from the customary fixed effects models that employ OLS (Ordinary Least Squares) and IV (Instrumental Variables) estimators. We then move on to a dynamic heterogeneous panel model – which accounts for cross-country heterogeneity in parameters - and to the GMM estimators. Our empirical approach reveals the robustness of our results vis-à-vis different specifications and estimators; and it allows us to compare our results with those in the literature.

The rest of the paper is organized as follows. We discuss theory and empirical specification in section 2; data in section 3; issues of heterogeneity in section 4, econometric issues in section 5, and empirical results in section 6. Section 7 summarizes and concludes.

2. Theory and Empirical Specification

We focus on three issues, viz., omitted variables, cross-country heterogeneity and endogeneity in modeling productivity. Our specification draws from the competing theoretical models of productivity. It includes most of the major theoretical determinants of productivity and explicitly allows for the cross-country heterogeneity in parameters. In order to motivate our specification, a brief discussion of the theoretical and empirical literature is in order.

Theoretically, all three sources of knowledge exert positive effects on domestic productivity (see among others, Lichtenberg, 1993; Coe and Helpman, 1995; Keller, 1998; Nadiri and Mamuneas, 1994; Guellec and Van Pottelsberghe, 2004). Thus, the theoretical *priors* are that all three sources of knowledge enter as covariates and appear significantly positive. [7]

Infrastructure usually enters directly as factors of production in the private sector production function (Arrow and Kurz, 1970; Grossman and Lucas, 1974). In these models, the ‘quality’ and the ‘size’ of the public infrastructure augment productivity and growth through cost reductions and/or improved specializations (see Gramlich, 1994 for a review). The evidence is far from conclusive, however. Aschauer (1989 and 1990), Munnell (1990), Berndt and Hansson (1992) and Nadiri and Mamuneas (1994), among others, report positive effects of infrastructure on productivity and economic growth, whereas Tatom (1991), Holtz-Eakin (1994), Gracia-Mila and McGuire (1992) and Evans and Karras (1994) find it has a negligible or even negative role. Despite empirical irregularity, we hypothesize a positive effect of infrastructure on productivity on theoretical grounds.

Theoretically, the stock of human capital exerts positive effect on productivity and economic growth. This is embedded in both the exogenous and endogenous growth models (see, among others, Lucas, 1988 and 1993; Mankiw et. al., 1992; Romer, 1990a, b; Benhabib and Spiegel, 1994; Engelbrecht, 1997; Glomm and Ravikumar, 1992; Barro and Sala-i-Martin, 2003; Bassanini and Scarpetta, 2002). [8]

The theory of ‘learning-by-exporting’ postulates that export market access improves domestic productivity (Bernard and Jensen, 1999; Clerides et al., 1998; Eaton and Kortum, 2001 and 2002). In these models, domestic firms improve their specialization and productivity while meeting the high product quality imposed by foreign customers. However, this effect may be more prominent amongst the technological laggards. In order to capture this ‘learning-by-exporting’ effect, we use the ratio of high tech exports to total exports.

Imports are conduits of technology diffusion (Grossman and Helpman, 1991; Coe and Helpman, 1995; Keller, 1998 and 2004; van Pottelsberghe and Lichtenberg, 2001). Countries engaged in imports benefit from international knowledge spillovers. In particular, technological laggards are seen to benefit more than technological leaders. Recent literature on this issue emphasizes the importance of trade in differentiated capital goods. We use the ratio of high tech imports to total imports to capture this effect.

Theoretically, FDI produces technological externalities and elevates the degree of product market competition, both of which boost productivity and growth. FDI has two facets – foreign firms invest in the domestic economy (inward FDI), and domestic firms invest abroad (outward FDI). Both forms of FDI foster technology diffusion and competition (see among others, Lipsey, 2002). Hence, we expect positive effects of FDI flows on domestic productivity, *a priori.* The empirical evidence is not clear-cut, however. Xu (2000), Keller and Yeaple (2003), Griffith et al., (2004a, b) report positive and large FDI effects whereas Aitken and Harrison (1999) and Blonigen and Slaughter (2001), among others, find either negligible or even negative effects of FDI on productivity. Finally, we capture the business cycle effect on domestic productivity through annual change in the rate of employment. Much of the literature predicts a pro-cyclical effect of business cycle on productivity.

Pulling together all the foregoing theoretical arguments, a typical fixed-effect dynamic (autoregressive) equation for domestic productivity is (all variables are in natural logarithms):

$$P^m_{i,t} = \alpha_i + \gamma_t + \lambda P^m_{i,t-1} + \beta_1 S^b_{i,t-1} + \beta_2 S^p_{i,t-1} + \beta_3 S^f_{i,t-1} + \beta_4 Z_{i,t-1}$$
$$+ \beta_5 H_{i,t-1} + \beta_6 X^h_{i,t-1} + \beta_7 M^h_{i,t-1} + \beta_8 F^0_{i,t-1} + \beta_9 F^I_{i,t-1} + \beta_{10} \Delta U_t + e_{i,t} \qquad (1)$$

(i= 1,…,N; t=1,…, τ_i ; and $\Sigma \tau_i = T$) .

where "i" and "t" indicate the cross-sectional and time series dimensions; α_i captures the time-invariant fixed effects (e.g., differences in the initial productivity levels across countries) and γ_t captures the individual-invariant time effects (e.g., productivity shocks that are common to all countries). In equation (1), $P^m_{i.t}$ is multifactor productivity; $S^b_{i,t-1}$, $S^p_{i,t-1}$ and $S^f_{i,t-1}$ denote the three sources of knowledge viz., the lagged business sector, public sector and foreign knowledge stocks. The lagged stock of public infrastructure is denoted by $Z_{i,t-1}$; $H_{i,t-1}$ represents for the lagged stock of human capital; $X^h_{i,t-1}$ and $M^h_{i,t-1}$ denote the lagged proportion of high tech exports and imports in total exports and imports, respectively. $F^0_{i,t-1}$ and $F^I_{i,t-1}$ represent the stocks of outward and inward foreign direct investment (FDI), both lagged; and ΔU_t (rate of change of employment) captures the effects of the business cycle on productivity.[9] Theoretical *priors* suggest that all parameters $\beta_1,...,\beta_{10}$ resume positive sign except β_6 for the technological leaders.

Specification (1) is the standard fixed-effect model, which we refer to as the 'homogeneous panel model'. One difference from the existing literature is that specification (1) augments the basic productivity-knowledge relationship by most of the determinants of productivity postulated by economic theories.[10] It captures the unobservable fixed effects but assumes homogeneity of slope parameters and adjustment dynamics across all the sample countries in the panel. We have argued above that this assumption may be untenable given the heterogeneity in productivity levels (or growth rates) and their determinants across the sample countries. In this context, the best empirical strategy would be to conduct country-by-country econometric analyses of equation (1). Unfortunately, we only have 23 data points for each country and it is evident from equation (1) that there are 10 theoretical determinants of domestic productivity excluding the lagged dependent variable. This precludes us from conducting country-by-country time series analyses. We specify a dynamic heterogeneous panel model that directly captures the cross-country heterogeneity in productivity parameters and nests the 'homogeneous panel model' as a special case. Our specification is:

$$P_{i,t}^{m} = \alpha_i + \gamma_t + \lambda_1 P_{i,t-1}^{m} + \lambda_2(\bar{S}_i^{b} * P_{i,t-1}^{m}) + \lambda_3(\bar{S}_i^{p} * P_{i,t-1}^{m}) + \lambda_4(\bar{H}_i * P_{i,t-1}^{m}) + \lambda_5(\bar{Z}_i * P_{i,t-1}^{m}) + \beta_k^{'} W_{k,i,t}$$
$$+ \delta_k^{'}(\bar{S}_i^{b} * W_{k,i,t}) + \theta_k^{'}(\bar{S}_i^{p} * W_{k,i,t}) + \varphi_k^{'}(\bar{H}_i * W_{k,i,t}) + \phi_k^{'}(\bar{Z}_i * W_{k,i,t}) + \psi \Delta U_{i.t} + e_{i,t} \qquad (2)$$

where $W_{k,i,t} = [S_{i,t-1}^{b}, S_{i,t-1}^{p}, H_{i,t-1}, S_{i,t-1}^{f}, Z_{i,t-1}, X_{i,t-1}^{h}, M_{i,t-1}^{h}, F_{i,t-1}^{o}, F_{i,t-1}^{I}]'$; $\bar{V}_i = T_i^{-1}\sum_{t=1}^{T_i} V_{i,t}$;

$V_{i,t} \in (S_{i,t}^{b}, S_{i,t}^{p}, H_{i,t}, Z_{i,t})$; and (k = 1,…,9).

Specification (2) allows for the country-specific slope parameters ($\beta_k + \Omega$) – where $\Omega \in (\delta_k, \theta_k, \varphi_k, \phi_k)$ – and adjustment dynamics (λ_j) for each country in the panel.

Since all potential determinants of productivity - S^b, S^p, S^f, H, Z, F^I, F^O, X^h and M^h - differ across the sample countries (see section 4), intuitively they can all be considered when modeling cross-country heterogeneity in productivity parameters. However, we assume that diversity in only four key variables - S^b, S^P, H and Z that together shape the domestic knowledge absorptive capacity of each country - adequately captures the cross-country heterogeneity in productivity parameters. Our focus on four key variables also circumvents the over parameterization of the empirical model. Country-specific productivity parameters are assumed to depend linearly on the country-specific mean stocks of $S_{i,t}^{b}$, $S_{i,t}^{p}$, $Z_{i,t}$, and $H_{i,t}$. [11] The cross-country productivity parameters differ because the extent of the productivity determinants ($\bar{S}_i^b$, $\bar{S}_i^p$, $\bar{Z}_i$, and $\bar{H}_i$) differ across countries. [12] From (2) the country-specific parameter vector (ϑ_i) can be obtained by: [13]

$$\vartheta_i = \zeta_1 + (\zeta_2 * \bar{S}_i^b) + (\zeta_3 * \bar{S}_i^p) + (\zeta_4 * \bar{H}) + (\zeta_5 * \bar{Z}_i) \qquad (3)$$

where $\zeta_\ell = [\lambda_j, \beta_k, \delta_k, \theta_k, \varphi_k, \phi_k]'$; ($\ell = 1, 2, .., 5$). The standard errors of country-specific parameters, $\sigma(\vartheta_i)$, are given by:

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

where $\bar{U}_{i,t} = (1, \bar{S}_{i,t}^b, \bar{S}_{i,t}^p, \bar{H}_{i,t}, \bar{Z}_{i,t})$ and $\sum$ is the variance co-variance matrix of ζ_ℓ.

3. Data

We analyze 16 OECD countries (see table 1). We collect data on multifactor productivity (P^m), domestic business (S^b) and public (S^p) sector knowledge stocks, foreign knowledge stock (S^f), stocks of human capital (H) and governments' infrastructure related physical capital (Z), stocks of inward (F^I) and outward (F^O) foreign direct investments, ratios of high tech exports to total exports (X^h) and high tech imports to total imports (M^h), and a control variable for the business cycle (U).

The relevant S^f for each sample country is computed as the weighted sum of the rest of the sample countries' S^b. We use time-varying bilateral R&D collaboration weights to compute S^f. Data frequency is annual for a period of 23 years (1980-2002). We have a balanced panel of 368 observations. Further details of all the data series, their sources and construction are given in the appendix.

Figure 1 about here

Figure 1 plots data on P^m. All plots are normalized at 2000=1 for ease of cross-country comparisons. In econometric analyses, we use un-indexed data. US productivity shows a modest upward trend throughout the sample period. UK productivity slows down during 1987-1991 but improves somewhat since 1992. German productivity shows a noticeable rise throughout the 1980s but stagnates from early 1990s. Plots for Canada, Greece, Denmark, and the Netherlands appear flat throughout. Australian productivity shows long swings, although the trend is clearly positive since the 1990s. French productivity was on the rise until 1990 but declined thereafter. Spanish productivity shows a strong positive trend in the early 1980s, stagnates during 1985-1995, and is in decline since 1997. Irish productivity shows a rapid rate of growth from its low base. The Finnish productivity trend is similar to the Irish case but the Finnish rate of growth is slower. Belgian and Italian productivity exhibit similar patterns of slow growth. Japanese productivity grew quite rapidly throughout the 1980s, but has been similar to the other major industrialized countries since 1990. Finally, despite a high R&D intensity, Swedish productivity does not appear noticeably different from that of the other countries in the sample. Overall, the plots indicate a modest upward trend in the multifactor productivity of our sample countries – Spain seems to be an exception however.

Figure 2 about here

Figure 2 plots S^b. They appear smooth and positively trended for most countries. The only two exceptions are Italy and the Netherlands whose plots of S^b appear rather flat since 1990. Plots of S^b also indicate cross-country variations in accumulation rates: Australia, Denmark, Ireland and Greece have accumulated S^b rapidly whereas mature economies like UK, USA, Germany and France have accumulated it relatively slowly. Other countries lie in-between.

Figure 3 about here

Figure 3 plots S^p. They are also smooth and positively trended across all the sample countries. However, plots of S^p appear much flatter than those of S^b for the UK, Ireland and Japan whereas the opposite holds for Greece, Spain and Finland. Overall, S^p appears somewhat flatter in the late 1990s and into the 21st century than it was in the 1980s, which may reflect a gradual decline in public R&D expenditure.

Figure 4 about here

Figure 4 plots S^f. Greece, Finland, Ireland and Spain show rather volatile foreign R&D stocks. This may reflect fluctuations in their weights rather than fluctuations in the domestic R&D stocks of other sample countries. For the rest of the countries, plots of S^f are trending upwards. In view of the weights used, this indicates increasing bilateral R&D collaborations between the sample countries.

4. Heterogeneity

Table 1 presents some summary statistics of our dataset. They show significant heterogeneity in the growth rates of productivity and their determinants across the sample OECD countries. The average annual growth rate of P^m ranges between a minimum of 0.2 percent (Canada) to a maximum of 3.3 percent (Ireland); the sample mean is 1.1 percent. The productivity of USA and UK grew by around 1% during the sample period, whilst Japan, Germany and France experienced somewhat higher growth rates of 1.4 % or above. The sample mean of business sector R&D intensity (business sector R&D expenditure to GDP ratio) is 1.6 percent but it ranges from a minimum of 0.1 percent (Greece) to a maximum of 2.2 percent (Sweden). Likewise, the intensity of public sector R&D ranges from a minimum of 0.3 percent (Greece) to a maximum of 0.9 percent (the Netherlands); the sample mean is 0.7 percent. Thus, business sector and public sector R&D intensity differ respectively by a factor of 22 and 3 across the sample countries. The stock of human capital is lowest in Spain (7.6 average years of schooling) and highest in the USA and Germany (12.8 average years of schooling in each). The USA, the richest country in knowledge stocks and at the forefront of innovations, shares the smallest stock of S^f. Canada, Greece and Ireland appear to share large stocks of S^f. The intensity of public infrastructure (government's infrastructure related gross fixed capital formation to GDP ratio) ranges from a minimum of 1.4 percent (the UK) to a maximum of 7.3 percent (Japan). [14] The cross-country intensity of high tech exports and imports differs respectively by a factor of 11.0 [from Greece (3%) to Ireland (33.5%)] and 2.2 [from Greece (9.8%) to Australia (20.6%)]. Likewise, the intensity of inward FDI (inflows of FDI to gross fixed capital formation) ranges from 0.3% (Japan) to 28.4 % (Ireland). The intensity of outward FDI ranges from a minimum of 0.4% (Greece) to a maximum of 18.4% (the Netherlands and Belgium).

A common belief is that cross-country diversity in R&D intensity should adequately explain the cross-country heterogeneity in productivity levels. However, a close look at Table 1 casts doubt on such ability of intensity measures. Several countries in the sample have comparable (in some cases identical) intensity measures, yet exhibit enormous diversity in their stocks of knowledge and in other determinants of productivity. This is due to the acutely dissimilar size of OECD economies. For example, the USA and Japan have the same business sector R&D intensity of 1.9% but USA's S^b is more than 2.5 times that of Japan. As a result, the US per capita S^b (i.e., S^b per head of labour force) is 1.4 times that of Japan. Denmark and the Netherlands have very similar business sector R&D intensity yet the Netherlands' S^b is almost three times that of Denmark. The Dutch labor force enjoys 29% higher S^b per head compared to their

Danish counterparts. [15] Finland and France have identical (1.4%) business sector R&D intensities but the French S^b is much larger (eleven times) than the Finnish S^b. The French per capita S^b is 42% higher than Finnish per capita S^b.

Likewise, the intensity of public sector R&D also falls short of capturing the vast differences in S^p across the sample countries. For example, the UK and Germany have the same (0.7%) public sector R&D intensity but the German S^P is much larger than that of the UK; consequently, the German labor force enjoys 15% higher public knowledge stock per capita than their UK counterparts. Australia, France, Finland and Japan show identical public R&D intensity of 0.8% but their stocks of S^P and per capita S^P vary notably. French per capita S^P is 46% higher than that of Finland; 30% higher than that of Australia; and 25% higher than that of Japan. A similar picture emerges vis-à-vis public infrastructure but the extent is somewhat less than in the cases of S^b and S^P. Thus, the intensity measures only reflect cross-country diversity between a few disparate nations – e.g., between countries like Greece or Spain versus USA or Germany. They reveal little for several of the major sample countries – for example, between the USA and Germany or between Denmark and the Netherlands even though these countries differ substantially in their stocks of knowledge and public infrastructure. Thus, intensity measures appear unsuitable for capturing the cross-country heterogeneity in productivity parameters. This leaves us with two choices: country-specific mean levels of $S_{i,t}^b$ ($\bar{S}_i^b$), $S_{i,t}^p$ ($\bar{S}_i^p$), $Z_{i,t}$ ($\bar{Z}_i$), and $H_{i,t}$ ($\bar{H}_i$) or their respective per capita (per head of labor) measures.

Knowledge stocks however are non-rivalous and only partially excludable. Therefore, what matters for $S_{i,t}^b$ and $S_{i,t}^p$ is their volume; high stocks of knowledge would ensure increased access for all. The per capita measure does not make much sense vis-à-vis knowledge stocks because any one can access and utilize any piece of knowledge (e.g., a computing package, a formula or a mechanism) in its totality so long as s/he pays the license fee or some similar cost. The stock of infrastructure is a public good subject to congestion and similar arguments apply. Obviously, $H_{i,t}$ is rivalous; however, we only have data on its stock - measured as the average number of schooling years of the 25-64 age group. In view of the economic nature of $S^b_{i,t}$, $S^p_{i,t}$ and $Z_{i,t}$ and the data availability of $H_{i,t}$ we prefer to use their country-specific mean levels to capture the cross-country heterogeneity in productivity parameters. However, in order to assess the robustness of our results, we also estimate the model using per capita measures of $S^b_{i,t}$, $S^p_{i,t}$ and $Z_{i,t}$.

5. Econometric Approach

Any prospective estimator of equation (2) must address the issues of (i) potential endogeneity - because productivity and some of its determinants may be jointly determined; (ii) inertia - which may cause bias and imprecision in the estimated parameters; and (iii) possible measurement errors. Amongst the available panel estimators, the system GMM estimator (Arellano and Bover, 1995 and Blundell and Bond, 1998) appears best suited to tackle these estimation issues. For a brief illustration of GMM, we rewrite equation (2) by suppressing the interaction terms for simplicity as:

$$y_{i,t} = \alpha_i + \gamma_t + \lambda y_{i,t-1} + W_{k,i,t}\beta_k^{'} + v_{i,t} \qquad (5)$$

where y_{it} denotes $P^m_{i,t}$; $W_{k,i,t}$ and $\beta_k{}'$ are as defined above. If $E(v_{it}v_{is}) = 0$ holds for s≠t across all "i", then the following moment conditions are valid:

$$E(y_{i,t-s}\,\Delta v_{it})=0 \quad \text{for } s\geq 2; \quad t= 3,\ldots, T. \qquad (6)$$

Furthermore, if a subset of $W_{k,i,t}$, say $Q_{i,t}$, is weakly exogenous then the following additional moment conditions also hold:

$E(Q_{i,t-s}\Delta v_{i,t}) = 0$ for s≥2; t= 3,…, T. (7)

The single equation (or the difference) GMM estimator utilizes the above moment conditions and uses lagged (two periods or more) levels of endogenous and weakly exogenous model variables as instruments (see Holtz-Eakin, Newey and Rosen, 1988; Arellano and Bond, 1991). [16] The GMM estimator provides consistent parameter estimates. However, when data are persistent – which is a common occurrence in macroeconomic series - and the time-series dimension is short, the single equation GMM estimator suffers from the problem of weak instruments. The instruments (in levels) tend to be weakly correlated with the regressors (in differences). Consequently, the estimates suffer from large finite sample biases and poor precision (see, among others, Ahn and Schmidt, 1995; Staiger and Stock, 1997). The system GMM estimator considerably reduces these biases and imprecision.

The system GMM estimator estimates equations in first differences and levels by pooling together. The first difference specification uses the suitably lagged level variables as instruments whereas the level equations use suitably lagged first differences. The latter are valid instruments if the following moment conditions hold:

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

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

The consistency of GMM estimators requires a valid set of instruments and a non-auto-correlated residual series. The validity of the instruments in single equation and system GMM is tested respectively by Sargan’s instruments validity test and the difference-Sargan test. We test for residual serial correlation through a second-order LM (Lagrange Multiplier) test.

6. Empirical Results

As a precursor, we report the results obtained from the fixed-effect static and the first-order-autoregressive panel models in table 2. Although they are not our preferred specifications – because they do not capture the cross-country heterogeneity – nevertheless they allow us to compare our results with those in the literature.

The static fixed effects OLS estimates (column 2) show that S^b, S^f, H and M^h augment productivity in sample countries - their coefficients are positive and statistically significant at 10% or better. The coefficient of S^p is negative but insignificant. Thus, public sector knowledge stocks do not to appear to augment productivity. Likewise, X^h, F^I and F^O also appear statistically insignificant. The stock of public infrastructure appears negatively signed and significant – public infrastructure appears to weaken productivity. The ΔU_t resumes a positive and statistically significant coefficient, which is consistent with the expected pro-cyclical effect of business cycle on productivity. The fixed and time effects both appear significant, suggesting that the country- and time-specific shocks differ significantly across the sample countries. The point estimates obtained from the IV estimator (column 3) are qualitatively similar to those of OLS except that S^f and ΔU_t become statistically insignificant. Thus, fewer determinants of productivity appear statistically significant under the IV estimator. However, these static models suffer from the problem of residual serial correlation – the second order residual serial correlation tests are significant.

In column 4, we report the OLS based results of the first-order autoregressive model. Although the problem of residual serial correlation disappears, the results are disappointing. The lagged dependent variable is highly significant which flushes out the residual serial correlations but only two regressors (S^b and X^h) appear positive and statistically significant. S^p resumes a negative and statistically significant coefficient implying that the stock of public knowledge worsens productivity. The stock of infrastructure is also negatively signed and marginally significant at 11 percent. Inward FDI is negative and significant whereas outward FDI is negative but insignificant. ΔU_t is positive but insignificant. The IV results (column 5) are even more disappointing; besides the lagged dependent variable, only one determinant of productivity - S^b - remains positive and significant; S^p and ΔU_t appear negative and significant; all other determinants are insignificant.

Overall, these results are uncomfortable because (i) they are in disagreement with the existing empirical literature that reports positive and statistically significant effects of the sources of knowledge on domestic productivity, and (ii) they are inconsistent with different theoretical models of productivity because most of the proposed theoretical determinants appear insignificant and/or wrongly signed. Nevertheless, they illustrate that the positive and statistically significant effect of the sources of knowledge reported by earlier fixed-effects models may not be robust once the other potential determinants of productivity are accounted for in the empirical model. Indeed, when we estimate model (1) using only three sources of knowledge as regressors, the results are broadly consistent with the literature - S^b and S^f are positive and significant whereas S^p is insignificant. [17] Thus, the results of table 2 cannot be ascribed to our (extended) data set alone. We put forward two potential explanations for reconciliation.

First, the existing empirical studies exclude several of the potential determinants of productivity (discussed above) from the specification. This mis-specification results into (i) unreliable significance tests, and (ii) biased parameter estimates. When the actual regression excludes the relevant variables, the standard errors of its parameters become unequivocally smaller than when it includes those relevant variables. Consequently, the parameters of a mis-specified short regression appear precisely estimated but this may cease to be the case when all the relevant variables are included (see footnote 4). This may explain why most regressors are insignificant in our fully specified model (Specification (1)).

Second, the fixed effect models are only credible so long as the assumptions of cross-country homogeneity in parameters and adjustment dynamics hold. Ignoring parameter heterogeneity is another source of mis-specification, which also engenders bias and inconsistency in the estimates (Pesaran et. al., 2000). Thus, neglected heterogeneity may further compound the omitted variables problem. Hence, the twin arguments of omitted variables and cross-country heterogeneity are important.

Table 3 reports the results obtained from our dynamic heterogeneous panel model (Specification 2). Although our preferred estimator is the system GMM, we nevertheless report results based on three different estimators, namely, the dynamic heterogeneous OLS (DHOLS), the single-equation GMM, and the system GMM. All three estimators reject the homogeneity of slope coefficients across all the sample countries. Two estimators - DHOLS and the system GMM - reject the homogeneity of adjustment dynamics as well. Most level regressors remain insignificant but the mean interacted regressors are statistically highly significant. Thus, allowing for the cross-country parameter heterogeneity in the empirical model produces fundamentally different results.

In sharp contrast to the results of the fixed-effects models (table 2), all but two of the theoretical determinants of productivity specified in equation (1) are significant – the exceptions being F^0 and ΔU. This raises doubt on the fixed-effects models that neglect cross-country heterogeneity while modeling productivity relationships. All estimated point elasticities of S^b, S^p, S^f, H, Z, F^I, X^h and M^h show significant cross-country variations that systematically depend on the mean levels of S^b, S^p, Z and H of the respective countries.

The reported GMM results pertain to the first-step estimators. The P-values of the parameters are computed using the robust standard errors. Our estimated models pass all relevant diagnostics. The second order residual serial correlation tests are insignificant ensuring the consistency of GMM estimators. The Sargan and difference-Sargan tests confirm the validity of instruments used under both (single and system) GMM estimators. It is interesting to note that the time-invariant fixed effects (α_i) and individual-invariant time effects (γ_t) both continue to remain significant in spite of accounting for the cross-country parameter heterogeneity. This implies that the sample of OECD countries differs not only in their initial productivity levels (endowments) but that they are also exposed to different productivity shocks.

Our results reveal that the higher the stock of S^b the bigger tends to be the international knowledge spillovers and the productivity gains from M^h. This is consistent with the view that knowledge spillovers require absorptive capacity, which may take the form of a sufficient accumulation of S^b. However, higher stocks of S^b tend to lessen the effects of S^p and X^h. This implies that S^b and S^p are not complimentary in augmenting productivity; and countries with sizable S^b may not make productivity gains from high tech exports.

We find two opposing effects of S^p; a high stock of S^p tends to lessen the productivity effect of S^b (yet again evidence of non-complimentarity) but it appears to complement the productivity effect of Z. A rather intriguing result is that the productivity effect of S^p increases with its size – there is no evidence of diminishing returns on the productivity effect of S^p. The higher the human capital base the greater tends to be its effect on productivity – no evidence of diminishing returns in the productivity effects of human capital either. However, a higher level of H seems to lessen the productivity effect of F^I. In contrast, the larger the stock of public infrastructure the smaller tends to be its productivity effect - evidence of diminishing returns in its productivity effects. Finally, Z appears to complement the productivity effects of S^b and X^h whereas it lessens the productivity effect of M^h. Technology outsourcing (F^O) and the variable that captures business cycle effects (ΔU) are statistically insignificant in explaining P^m.

Table 4 reports the country-specific parameters along with their significance levels based on the system GMM estimates of table 3, computed as shown in equations (3) and (4). Since the estimated country specific parameters are broadly similar across all three estimators, we focus on the parameters obtained from the system GMM as this estimator is superior to other estimators (see section V). [18]

The country-specific points estimates of $\partial P^m / \partial S^b$, $\partial P^m / \partial S^p$ and $\partial P^m / \partial S^f$ are positive and statistically significant for all sample countries except for one case - S^p for Belgium is positive but insignificant. Importantly, however, these parameters exhibit considerable cross-country heterogeneity. The point elasticity of $\partial P^m / \partial S^b$ range from a minimum of 0.015 (UK) to a maximum of 0.038 (Ireland); for $\partial P^m / \partial S^p$ they range from a minimum of 0.017 (Belgium) to a maximum of 0.049 (Australia). Likewise, the point elasticity of $\partial P^m / \partial S^f$ shows a difference of more than two folds (contrast the point elasticities for the USA and Greece). Thus, S^b, S^p and S^f exert positive and statistically significant effects of varying magnitudes on the productivity of sample countries. This is in sharp contrast to the results of 'homogeneous panel models' reported in table 2. The point elasticities of S^b and S^p on domestic productivity appear very similar in their magnitudes; however, the coefficients of S^f are smaller than those of S^b and S^p.

We find a positive and statistically significant effect of human capital on domestic productivity for eleven countries; insignificant for four countries (Belgium, Greece, Ireland and Italy); and negative for Spain. The negative coefficient for Spain is puzzling and hard to explain. Again, the cross-country parameter heterogeneity is apparent. The eleven countries with positive and significant partial elasticities ($\partial P^m / \partial H \succ 0$) have magnitudes varying from 0.101 (France) to 0.269 (the United States). Germany, the USA, Canada and Australia show large effects of human capital on domestic productivity.

Five countries in the sample (Belgium, Finland, Greece, Ireland and Spain) show small negative but statistically significant effects of the stock of public physical infrastructure on their domestic productivity. For the remaining countries, this effect is statistically insignificant. Thus, the stock of public infrastructure does not appear to augment the domestic productivity of any sample country. This finding is consistent with some of the literature cited above (e. g., Tatom, 1991; Holtz-Eakin, 1994; Evans and Karras, 1994).

The effect of inward FDI on domestic productivity is rather mixed. Of the 16 sample countries, six countries (France, Italy, Japan, Spain, the UK and the USA) show positive and significant effects; four countries (Denmark, Finland, Greece and Ireland) show negative and significant effects; and for the rest (Australia, Belgium, Canada, Germany, the Netherlands and Sweden) the effect is statistically insignificant. The magnitudes of the estimated parameters are small; nevertheless they differ across countries. Results indicate that countries with sizable knowledge stocks and human capital bases benefit from inward FDI in terms of their productivity enhancements. Interestingly, technology outsourcing – outward FDI – appears insignificant.

Six countries (Australia, Finland, Greece, Ireland, Italy and Spain) show a positive and significant effect of high tech exports on their domestic productivity. However, for two major industrialized countries (the UK and the USA) its effects are negative and significant. The remaining eight countries show an insignificant effect of high tech exports on domestic productivity. Overall, it appears that the technologically advanced countries do not achieve productivity gains through learning-by-exporting, while relatively less advanced OECD countries (e.g., Greece, Spain, Italy etc.) do.

The partial semi-elasticity of M^h, ($\partial P^m / \partial M^h$), is positive for two countries (Sweden and the UK), negative and significant for three countries (Ireland, Greece and Spain) and statistically insignificant for the rest. Although insignificant, the sign of the point estimates ($\partial P^m / \partial M^h$) are positive for most of the industrialized countries. Interestingly, however, less advanced OECD countries like Greece, Ireland and Spain appear to have an adverse impact of high tech imports on their productivity. Finally, results also reveal a mild degree of cross-country variation in adjustment dynamics (λs).

Our results pass a number of robustness checks. The results are robust to three estimators, DHOLS, the single-equation and the system GMM estimators. The only exception is that F^I does not appear significant under the single-equation GMM estimator. We replaced the country specific mean levels of S^b, S^p and Z by their per capita mean values to capture the cross-country heterogeneity. The results remain broadly similar. Likewise, results are robust to alternate depreciation rates of 12 and 20 percent to knowledge stocks. We also estimate the model by dropping USA, Germany, Greece and Spain from the panel, in turn. The reported results remain qualitatively the same.

7. Conclusion and implications

We model domestic productivity in a panel of 16 OECD countries by focusing on the issues of (i) omitted variables, (ii) heterogeneity and (iii) endogeneity. These issues are important because they impinge on the bias, precision and the consistency of estimated parameters. The competing theoretical models propose a range of determinants of domestic productivity. Our empirical model incorporates ten of them and explicitly allows for the cross-country heterogeneity in productivity parameters. The econometric approach we follow addresses the estimation issues of endogeneity, persistence and measurement errors.

Results are revealing. When we follow the customary fixed-effects approaches, we find that the majority of the theoretical determinants of productivity appear insignificant in our general model; few that are significant appear wrongly signed; the only variable that appears significant and confirms to the theoretical priors is business sector knowledge stock. However, when we estimate a short regression including only three sources of knowledge we find results consistent to those in the literature. Thus, the insignificance of the majority of theoretical determinants of productivity as well as the inconsistent parameter signs associated with some of the regressors echo the implications of omitted variables discussed above.

Interestingly, the dynamic heterogeneous panel model which allows for the cross-country parameter heterogeneity shows almost all (eight out of ten) theoretical determinants of productivity to be significant. Results reject both the homogeneity of slope coefficients and adjustment dynamics across all the OECD sample countries. Therefore, the issue of cross-country heterogeneity appears crucial to unravel the determinants of productivity.

We find evidence of increasing returns to scale on the productivity effects of human capital and public knowledge stocks. The magnitude of their elasticity increases with their stock. The business sector knowledge stock, S^b, does not show increasing returns but it complements foreign knowledge stock and high tech imports in augmenting productivity. Results show that S^b and S^p are not complementary. The higher the level of infrastructure, the smaller its productivity effects – evidence of a diminishing return to infrastructure investment.

All three sources of knowledge (S^b, S^p and S^f) exert significantly positive effects on domestic productivity across the sample countries with only one exception - S^p appears insignificant for Belgium. Human capital also shows significantly positive effects on the productivity of the majority of sample countries (11 out of the 16 countries). Public infrastructure does not appear to augment domestic productivity – its effects are insignificant for 11 countries and significantly negative for the remaining five. Inward FDI, high tech exports and imports show mixed results. The technology outsourcing (outward FDI) appears insignificant; however, its productivity effects may be evident at a more dis-aggregated (micro) level.

Overall, the three sources of knowledge and human capital appear as the key drivers of productivity. Their parameters conform to theoretical *priors* and they are statistically significant across the large majority of sample countries. Therefore, one can generalize these findings. One difference however is that the effect of human capital is much larger than that of knowledge stocks especially for the advanced countries. The other determinants – Z , F^I , X^h , M^h – show mixed results. They are statistically significant in several cases but the signs of their parameters do not always conform to theoretical *priors*. Thus, they are important at the country level but their effect is not sufficiently general. [19] The technological laggards appear to benefit more from 'learning-by-doing' than the technologically advanced. With few exceptions, countries with sizable knowledge stock and human capital base seem to make productivity gains from inward FDI. These are plausible findings. Given these insights, productivity policy across OECD countries may benefit if it accounts for the country-specific factors. Importantly, we have shown that some factors (F^I , X^h and M^h) exert opposing productivity effects across countries. But why? The very nature and the sophistication of each country's production technology may explain this phenomenon. A rigorous analysis of this issue – relating the sophistication of production processes to its drivers of productivity – would be an interesting avenue for future research.

Table 1: Descriptive statistics (1980-2002 mean value)

	MFP [1]	Business R&D [2, 3]		Public R&D [2, 4]		Foreign R&D [2]	Human Capital [5]	Public Infrastructure [2, 6]		High-technology [2, 7]		Outward FDI [2, 8]	Inward FDI [2, 9]	LF [10]
	Growth rate	Expenditure [Intensity]	Stocks	Expenditure [Intensity]	Stocks	Stocks	Stocks	Expend-iture [Intensity]	Stocks	Exports [Intensity]	Imports [Intensity]	Stocks [Intensity]	Stocks [Intensity]	
AU	1.1	2.3 [0.6]	10.6	2.9 [0.8]	16.2	58.7	12.1	8.7 [2.4]	78.6	2.6 [4.4]	11.9 [20.6]	48.5 [6.3]	86.3 [7.9]	8.4
BE	0.7	2.7 [1.2]	14.8	1.0 [0.5]	5.6	92.2	10.1	4.9 [2.2]	94.8	13.3 [8.5]	14.8 [10.0]	66.9 [18.4]	88.1 [21.7]	4.2
CA	0.2	5.9 [0.9]	29.2	4.8 [0.7]	26.2	145.2	12.6	15.7 [2.4]	139.7	17.0 [8.5]	29.7 [16.7]	133.7 [10.9]	149.1 [5.6]	14.1
DK	0.7	1.3 [1.0]	6.1	0.8 [0.7]	4.5	48.9	11.1	2.2 [1.7]	30.4	4.5 [12.3]	4.3 [12.6]	18.4 [12.0]	18.5 [10.9]	2.8
FIN	1.9	1.5 [1.4]	6.9	0.8 [0.8]	4.3	26.2	10.6	3.5 [3.3]	38.6	4.2 [11.7]	4.1 [15.7]	15.9 [11.1]	8.2 [5.6]	2.5
FR	1.5	17.3 [1.4]	97.4	10.8 [0.8]	62.4	24.8	10.3	39.9 [3.1]	394.1	41.6 [16.5]	39.8 [15.4]	174.5 [9.9]	124.4 [6.0]	24.9
DE	1.4	28.4 [1.7]	165.3	12.3 [0.7]	70.9	18.7	12.8	37.7 [2.3]	490.3	62.1 [14.3]	60.4 [15.9]	213.1[6.6]	165.6 [5.7]	35.6
EL	0.7	0.2 [0.1]	0.8	0.4 [0.3]	2.2	128.1	9.1	4.6 [3.1]	37.9	0.4 [3.0]	3.5 [9.8]	7.0 [0.4]	19.0 [1.0]	4.1
IRL	3.3	0.4 [0.7]	1.9	0.2 [0.4]	1.2	132.2	9.5	2.5 [3.9]	26.7	15.7 [33.5]	9.2 [26.4]	18.6 [3.0]	67.0 [28.4]	1.5
IT	0.8	7.2 [0.6]	41.5	6.1 [0.5]	32.5	17.3	8.6	36.9 [3.0]	382.4	21.8 [9.5]	30.2 [13.1]	96.5 [3.8]	70.0 [2.3]	22.8
JP	1.4	53.5 [1.9]	281.7	21.2 [0.8]	126.8	11.1	11.0	203.2 [7.3]	2229.4	77.9 [28.0]	29.3 [13.1]	191.6 [1.0]	19.5 [0.3]	63.5
NL	0.9	3.6 [1.1]	20.5	2.9 [0.9]	17.0	35.2	11.1	10.7 [3.2]	112.7	25.9 [16.1]	27.1 [17.9]	161.9 [18.4]	112.1 [18.4]	7.3
SP	0.8	2.5 [0.4]	12.2	2.3 [0.4]	11.3	50.4	7.6	22.9 [3.6]	176.2	7.4 [7.3]	17.7 [13.6]	61.7 [8.1]	96.0 [8.3]	14.9
SE	0.6	4.4 [2.2]	21.9	1.8 [0.9]	9.9	30.6	11.3	5.7 [2.9]	58.6	10.1 [16.5]	8.4 [16.4]	50.8 [16.0]	28.8 [13.4]	4.4
UK	1.1	16.1 [1.3]	98.5	7.9 [0.7]	48.7	57.7	11.3	17.8[1.5]	179.0	57.1 [23.4]	56.8 [20.0]	380.5 [14.8]	235.3 [9.7]	28.2
US	1.0	138.5 [1.9]	759.3	45.7 [0.6]	260.7	7.3	12.8	236.6[3.2]	2105.6	151.9 [29.2]	147.4 [18.9]	684.5 [4.3]	560.7 [4.0]	126.1
Mean	1.1	17.9 [1.6]	98.0	7.6 [0.7]	43.8	55.3	10.7	40.8[3.6]	410.9	32.1 [15.2]	30.9 [16.0]	145.3 [5.7]	115.5 [4.8]	22.8

1. Multi-factor productivity. 2. Billions of constant 2000 PPP US dollars. 3. Intensity (business-sector R&D expenditure as % of GDP). 4. Intensity (public-sector R&D expenditure as a % of GDP). 5. Stock of human capital is proxy by the average number of years of schooling of the population from 25 to 64 years of age. 6. Public infrastructure is proxied by the stock of public physical capital stock (intensity expressed as % of GDP). 7. Intensity (high-technology exports (imports) as a % of total exports (imports)). 8. Intensity (outflow of foreign direct investment as a % of gross fixed capital formation). 9. Intensity (inflow of foreign direct investment as a % of gross fixed capital formation). 10. Total labour force in millions.

Country mnemonics: Australia (AU), Belgium (BE) Canada (CA), Denmark (DK), Finland (FIN), France (FR), Germany (DE), Greece (EL), Ireland (IRL), Italy (IT), Japan (JP), Netherlands (NL), Spain (SP), Sweden (SE), United Kingdom (UK) and United States (US).

Table 2: The fixed effects panel estimates				
	OLS static	IV static	OLS AR(1)	IV AR(1)
Constant	3.855 (0.000)	3.805 (0.000)	0.553 (0.000)	0.639(0.000)
$P^m_{i,t-1}$	-	-	0.917 (0.000)	0.893 (0.000)
$S^b_{i,t-1}$	0.105 (0.040)	0.100 (0.043)	0.019 (0.001)	0.022 (0.006)
$S^p_{i,t-1}$	-0.042 (0.534)	-0.043 (0.536)	-0.018 (0.036)	-0.028 (0.023)
$S^f_{i,t-2}$	0.024 (0.095)	0.022 (0.163)	0.001 (0.846)	-0.004 (0.268)
$Z_{i,t-1}$	-0.102 (0.016)	-0.099 (0.023)	-0.012 (0.113)	-0.011 (0.201)
$H_{i,t-1}$	0.378 (0.073)	0.399 (0.101)	0.021 (0.565)	0.049 (0.230)
$X^h_{i,t-1}$	0.264 (0.240)	0.244 (0.414)	0.117 (0.068)	0.123 (0.193)
$M^h_{i,t-1}$	0.832 (0.001)	0.981 (0.003)	-0.0001 (0.992)	0.058 (0.598)
$F^O_{i,t-1}$	-0.006 (0.760)	-0.002 (0.921)	-0.001 (0.620)	-0.001 (0.838)
$F^I_{i,t-1}$	-0.002 (0.916)	-0.005 (0.820)	-0.009 (0.002)	-0.006 (0.319)
ΔU_t	0.482 (0.027)	0.341 (0.542)	0.053 (0.656)	-0.577 (0.002)
α_i	(0.000)	(0.000)	(0.000)	(0.000)
γ_t	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.874	-	0.984	-
σ	0.037	0.037	0.014	0.015
AR [2]	(0.004)	(0.003)	(0.779)	(0.199)
Obs	333	332	333	332

Variable definitions are: P^m = multifactor productivity; S^b = business, S^p = public and S^f = foreign knowledge stock; H = human capital; Z = stock of infrastructure; F^I = inward and F^O = outward FDIs; X^h and M^h are the ratios of high tech exports and imports their respective totals, and U = 1- unemployment rate. AR [2] is the second order Lagrange Multiplier [LM] test of residual serial correlation 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 for the null that the coefficient in question is zero. For IV estimates S^f is treated as weakly exogeneous. All other regressors, except for ΔU_t, are instrumented by their second order lags. ΔU_t is instrumented by ΔU_{t-1}.

Table 3: Results of Dynamic Heterogeneous Panel model (Equation: 3) [#]			
	OLS	**GMM single equation**	**GMM system**
$P^{m}_{i,t-1}$	1.324 (0.000)	0.826 (0.000)	1.116 (0.000)
$P^{m}_{i,t-1} * \overline{H}_i$	-0.216 (0.013)	-	-0.117 (0.080)
$S^{b}_{i,t-1} * \overline{S}^{p}_{i}$	-0.023 (0.001)	-0.029 (0.000)	-0.012 (0.071)
$S^{b}_{i,t-1} * \overline{Z}_i$	0.021 (0.000)	0.026 (0.000)	0.012 (0.033)
$S^{p}_{i,t-1}$	-	-0.195 (0.000)	-
$S^{p}_{i,t-1} * \overline{S}^{b}_{i}$	-	-0.028 (0.000)	-0.018 (0.004)
$S^{p}_{i,t-1} * \overline{S}^{p}_{i}$	0.005 (0.000)	0.052 (0.000)	0.022 (0.001)
$S^{f}_{i,t-1} * \overline{S}^{b}_{i}$	0.003 (0.001)	0.001 (0.060)	0.001 (0.115)
$S^{f}_{i,t-1} * \overline{H}_i$	-0.010 (0.002)	-	-
$H_{i,t-1}$	-1.799 (0.000)	-1.324 (0.000)	-1.704 (0.000)
$H_{i,t-1} * \overline{H}_i$	0.812 (0.000)	0.621 (0.000)	0.775 (0.000)
$Z_{i,t-1}$	0.191 (0.000)	-	-
$Z_{i,t-1} * \overline{S}^{p}_{i}$	0.035 (0.000)	0.023 (0.000)	0.023 (0.023)
$Z_{i,t-1} * \overline{Z}_i$	-0.046 (0.000)	-0.020 (0.000)	-0.019 (0.013)
$F^{I}_{i,t-1}$	-0.050 (0.000)	-	-
$F^{I}_{i,t-1} * \overline{S}^{b}_{i}$	-0.010 (0.000)	-	-
$F^{I}_{i,t-1} * \overline{S}^{p}_{i}$	0.016 (0.000)	-	0.006 (0.000)
$F^{I}_{i,t-1} * \overline{H}_i$	-	-	-0.024 (0.000)
$X^{h}_{i,t-1} * \overline{S}^{b}_{i}$	-0.197 (0.000)	-0.177 (0.000)	-0.215 (0.000)
$X^{h}_{i,t-1} * \overline{Z}_i$	0.175 (0.000)	0.156 (0.000)	0.188 (0.000)
$M^{h}_{i,t-1}$	-	0.541 (0.001)	0.460 (0.068)
$M^{h}_{i,t-1} * \overline{S}^{b}_{i}$	0.148 (0.000)	0.157 (0.001)	0.175 (0.000)
$M^{h}_{i,t-1} * \overline{Z}_i$	-0.126 (0.000)	-0.175 (0.000)	-0.184 (0.000)
ΔU_t	0.151 (0.159)	0.106 (0.303)	0.100 (0.377)
α_I	(0.000)	(0.000)	(0.000)
γ_t	(0.000)	(0.000)	(0.000)
σ	0.013	0.129	0.013
AR (2)	(0.149)	(0.244)	(0.321)
Sargan χ^2 [r]	-	226.2 [1135]	-
Diff. Sargan χ^2 [r]	-	-	53.9[115]
Observations	352	352	352

Refer to footnote 20 for the notes to this table.

Table 4: Country specific parameters based on the estimates of table 3									
GMM system estimation									
	λ	S^b	S^p	S^f	H	Z	F^I	X^h	M^h
AU	0.825 [a]	0.019 [a]	0.049 [a]	0.009 [a]	0.226 [a]	0.008	-0.002	0.007 [b]	-0.005
BE	0.846 [a]	0.034 [a]	0.017	0.010 [a]	0.085	-0.020 [b]	-0.004	0.008	0.003
CA	0.820 [a]	0.020 [a]	0.040 [a]	0.010 [b]	0.259 [a]	0.009	0.000	0.002	0.012
DK	0.834 [a]	0.023 [a]	0.030 [a]	0.009 [a]	0.162 [b]	-0.003	-0.007 [b]	0.011	0.009
FIN	0.840 [a]	0.027 [a]	0.026 [a]	0.009 [a]	0.121 [b]	-0.010 [c]	-0.007 [b]	0.014 [c]	0.006
FR	0.843 [a]	0.022 [a]	0.036 [a]	0.011 [b]	0.101 [c]	0.009	0.010 [b]	-0.007	0.015
DE	0.818 [a]	0.023 [a]	0.029 [b]	0.012 [a]	0.270 [a]	0.007	0.006	-0.016	0.024
EL	0.858 [a]	0.035 [a]	0.050 [a]	0.006 [b]	0.005	-0.026 [b]	-0.008 [b]	0.018 [a]	-0.034 [a]
IRL	0.853 [a]	0.038 [a]	0.024 [a]	0.007 [b]	0.040	-0.032 [b]	-0.012 [a]	0.121 [a]	-0.037 [b]
IT	0.865 [a]	0.030 [a]	0.037 [a]	0.011 [a]	-0.044	-0.006	0.011 [b]	0.012 [c]	-0.006
JP	0.836 [a]	0.034 [a]	0.033 [b]	0.012 [b]	0.153 [b]	-0.008	0.013 [b]	0.018	-0.006
NL	0.835 [a]	0.023 [a]	0.036 [a]	0.010 [a]	0.159 [b]	0.003	0.001	0.009	0.010
SP	0.879 [a]	0.033 [a]	0.036 [a]	0.009 [b]	-0.134 [b]	-0.015 [b]	0.007 [c]	0.018 [a]	-0.016 [a]
SE	0.833 [a]	0.022 [a]	0.023 [b]	0.010 [a]	0.173 [a]	0.003	-0.003	-0.012	0.029 [c]
UK	0.832 [a]	0.015 [c]	0.031 [b]	0.011 [b]	0.175 [a]	0.019	0.007 [c]	-0.046 [b]	0.050 [b]
US	0.818 [a]	0.025 [a]	0.031 [b]	0.014 [a]	0.269 [a]	0.010	0.014 [b]	-0.050 [c]	0.029
Mean	0.840	0.027	0.033	0.010	0.126	-0.003	0.002	0.007	0.005
SD	0.017	0.007	0.009	0.002	0.115	0.014	0.008	0.037	0.023

λs are solutions for the country-specific coefficients of the lagged dependent variables. Impact elasticities of all regressors are listed in their respective columns. Impact elasticity should be divided by 1-λ for the long-run elasticity. For example, the long run point elasticity of S^b (i.e., $\partial P^m / \partial S^b$) is 0.137 for the US. Superscripts a, b, and c indicate significance at 1%, 5% and 10%, respectively. The variances of country specific parameters are calculated as shown in equation (4) in the text.

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Data Appendix

The relevant data series used are as follows. Multi-factor productivity (P^m); research and development expenditures of business (E_b^{RD}), higher education (E_{he}^{RD}), and government (E_{gov}^{RD}) sectors; stock of human capital (H); high technology exports (X^h) and import (M^h); bilateral joint patent application (PAT_{cop}) at the European Patent Office (EPO); gross domestic product (Y); business-sector value added (Y_b); government's fixed capital formation excluding the public R&D and military expenditures (I_{gov}); total employment (L); business-sector employment (L_b); labor force (LF); government expenditure (E_{gov}); unemployment rate (U); purchasing power parity exchange rate 2000 (PPP); gross domestic product deflator (Y^P); government investment deflator (I_{gov}^p); and stocks of inward (F^I) and outward (F^O) foreign direct investments.

Data on P^m are obtained from OECD's Productivity database. For Germany this series is available only from 1991 onwards. We extrapolated the pre-1991 data for Germany from the TFP series of Timmer, Ypma and Van Ark (2003). The source for E_b^{RD}, E_{he}^{RD}, E_{gov}^{RD} and Y_b is OECD's R&D database. PAT_{cop} is authors' own calculation using the EPO patent data obtained from OECD's Patent database. The relevant series to construct X^h and M^h are derived from OECD's STAN Indicators database. OECD's definition of high tech industries includes Aircraft and spacecraft; Pharmaceuticals; Office, accounting and computing machinery; Radio, TV and communications equipment; Medical, precision and optical instruments (see annex A, OECD, 2005). We have followed their definitions while constructing the ratios of high tech exports and imports.

Data on Y, I_{gov}, L, L_b, LF, E_{gov}, U, PPP, I^p_{gov} and Y^P are obtained from OECD's ADB database. Series on F^I and F^O are obtained from OECD (International Direct Investment Statistics Year Book) and UNCTAD (World Investment Reports).

Following the literature (e.g., Coe and Helpman, 1995; Luintel and Khan, 2004), business sector R&D capital stock (S^b) is calculated from E_b^{RD} using the perpetual inventory method. The nominal E_b^{RD} is converted into constant 2000 PPP US dollars by using the GDP deflator and PPP exchange rate (2000=100). The initial business-sector R&D capital stock (S_0^b) is calculated as:

$$S_0^b = \frac{E_{b,0}^{RD}}{g+\delta} \qquad \text{(A1)}$$

where δ is the depreciation rate, assumed to be 15.0 percent, g is the average annual growth rate of E_b^{RD} over the sample, and $E_{b,0}^{RD}$ is the initial value of E_b^{RD} in the sample. We have also used alternate depreciation rates of 12 and 15 percent for sensitivity checks. The total public sector R&D expenditure (E_p^{RD}) is the sum of higher education and government sectors R&D expenditure ($E_{he}^{RD}+E_{gov}^{RD}$). The public sector domestic R&D capital stock (S^p) is computed following the method shown in equation (A1); E_p^{RD} is expressed in constant 2000 PPP US dollars. The foreign R&D capital stock (S^f) for each sample country is calculated as the weighted sum of the rest of the sample countries' S^b :

$$S_i^f = \sum_{j=1}^{N-1} w_{ij,t} S_{j,t}^b ; i \neq j \qquad \text{(A2)}$$

where, t = 1, 2,……, T_i, and *i, j* = 1, 2,..,15. The bilateral time varying weight ($w_{ij,t}$) between country i and country j, are the ratios of joint patent applications made by two countries at the EPO to their respective total patent applications at the EPO. We use three-year moving averages of both the numerator and denominator to avoid sharp yearly fluctuations. Patent data refers to patent applications at the EPO. Thus, we compute 15X23 matrixes of bilateral patent cooperation coefficient for each sample country. The stock of human capital (H) is proxied by the average number of years of schooling of the population from 25 to 64 years of age. Bassanini and Scarpetta (2002) kindly provided data on H.

Stock of public infrastructure investment is proxied by the stock of public physical capital. This is computed from I_{gov} series using the perpetual inventory method as shown in equation (A1). The nominal I_{gov} is converted into constant 2000 PPP US dollars by using the government investment deflator and the 2000 PPP exchange rate. A depreciation rate of 8 percent (see Luintel and Khan, 1999 and 2004) and the sample-period average growth rate of real I_{gov} are used to generate the initial stock of public capital. We would have liked to cover more than 16 OECD countries, but data constraint on P^m proved prohibitive.

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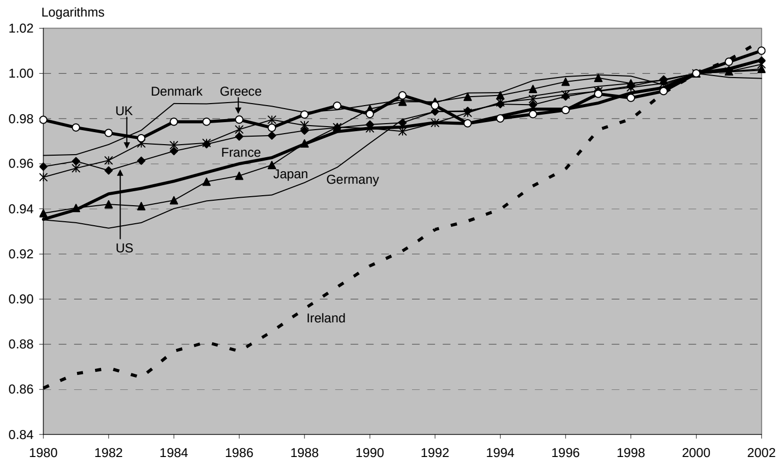
Data for P^m are obtained from the OECD productivity database. Data on S^b and S^p for each sample country are constructed from the flow of real R&D expenditures incurred respectively by the business and public (higher education and government) sectors. We use the perpetual inventory method to construct the stock measures (see Coe and Helpman 1995, among others). The relevant S^f for each sample country is computed as the weighted sum of the rest of the sample countries' S^b. We use bilateral time-varying weights: they are ratios of joint patent applications made by two countries at the EPO to their respective total patent applications at the EPO (European Patent Office).

We compute 15X23 matrixes of bilateral patent application ratios for each sample country. To control for the sharp yearly fluctuations, we use three-year moving averages of both the numerator and the denominator while computing these weights. [21] The average years of schooling of the age group 25 to 64 proxies the stock of human capital (obtained from Bassanini and Scarpetta, 2002). We proxy the stock of public infrastructure by the stock of public physical capital stock constructed from government's gross fixed capital formation following the perpetual inventory method. Government's gross fixed investment data exclude expenditure on public R&D and military. [22] The relevant series to compute X^h and M^h are obtained from the OECD's STAN Indicators database. The control variable for the business cycle is computed as 1 minus the unemployment rate (see, Guellec and Van Pottelsberghe, 2004); data are obtained from OECD's ADB data base. Data on F^I and F^O are obtained from OECD and UNCTAD.

Figure 1: Multi-factor Productivity (2000=1)



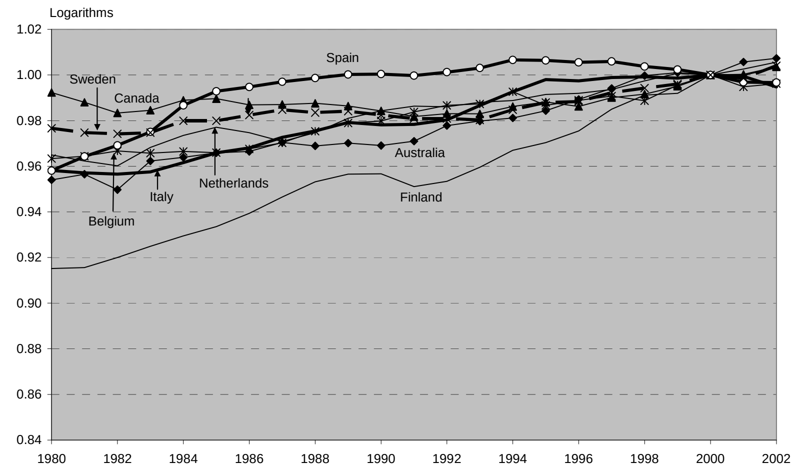
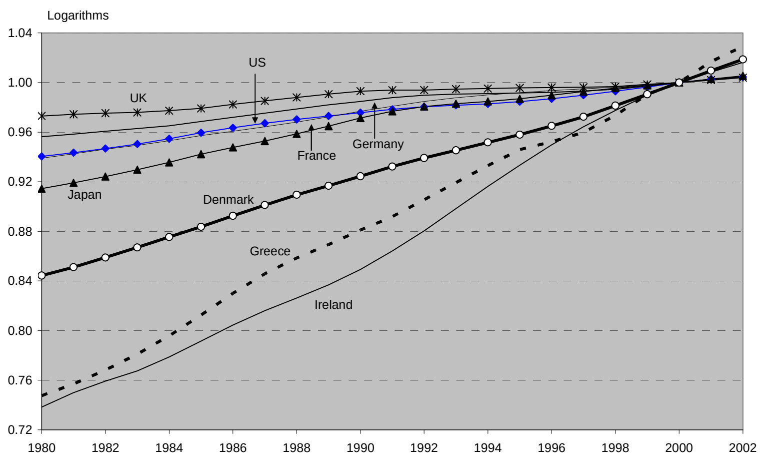


Figure 2: Business-sector R&D Capital Stocks (2000=1)



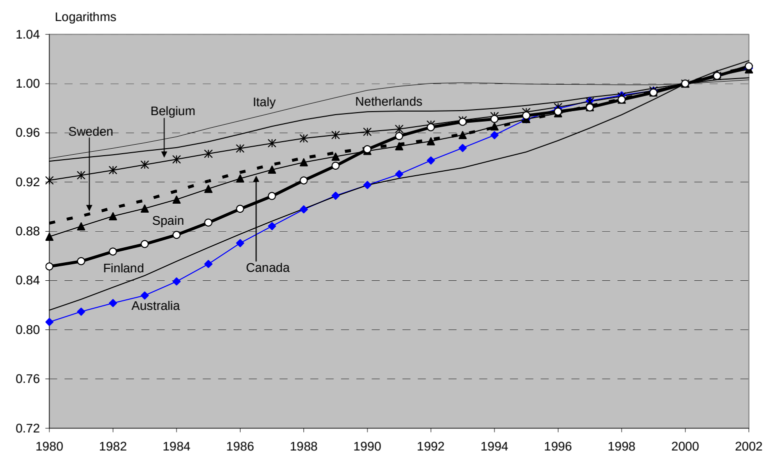
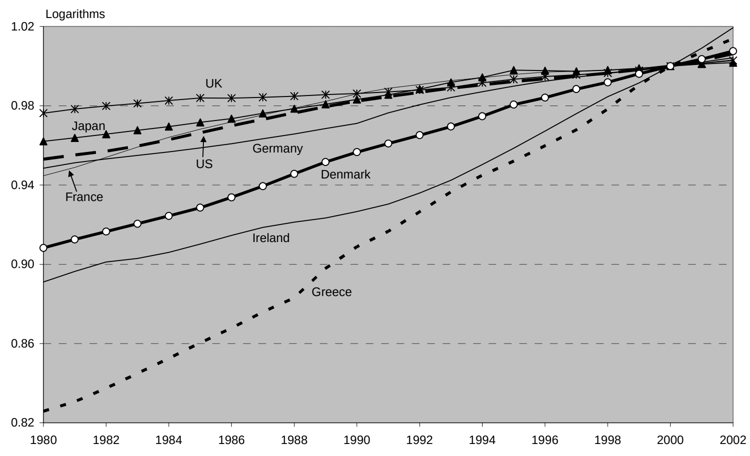


Figure 3: Public-sector R&D Capital Stocks (2000=1)



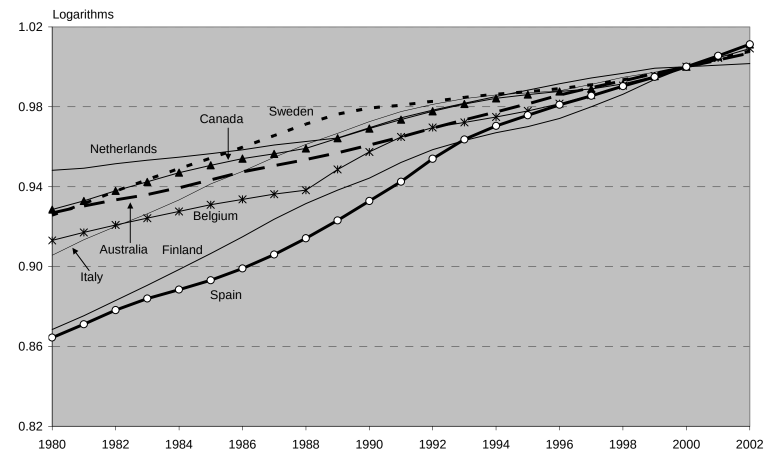
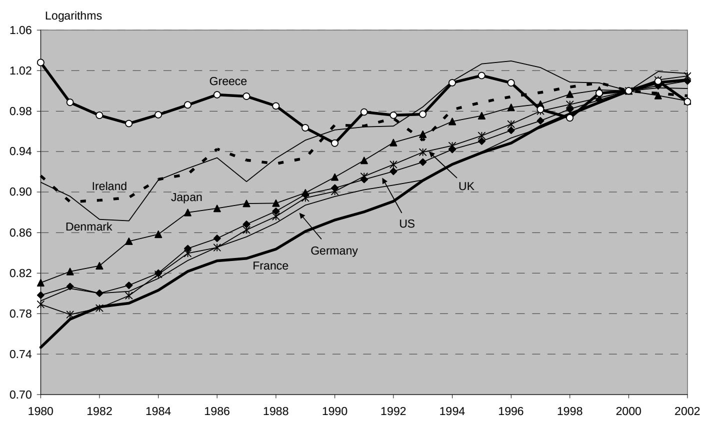
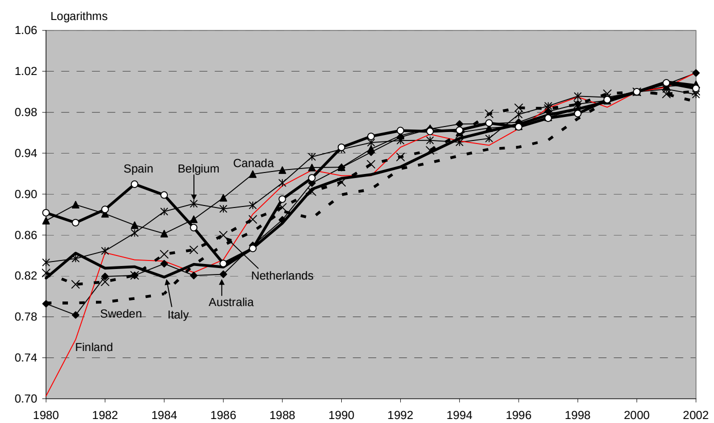


Figure 4: Foreign R&D Capital Stocks (2000=1)





[1] Exogenous growth models (e.g., Solow, 1956) treat technological progress exogenously whereas endogenous growth models (e.g., Romer, 1990a; Grossman and Helpman, 1991; Aghion and Howitts , 1992) endogenize innovations.

[2] A strand of empirical studies focuses on the role of different sources of R&D. Three distinct types of R&D – business sector, public sector and foreign R&D – are analyzed and, in general, they are reported to have significantly positive effects on domestic productivity and / or on the reduction of production costs (e.g., Cohen and Levinthal, 1989; Geroski, 1995; Nadiri and Mamuneas, 1994). It is argued that the public sector R&D focuses on “pure basic research” to advance the knowledge frontier whereas business sector R&D may lay equal emphasis on “applied research” and “experimental development”. Thus, different sources of R&D may have a different impact on productivity.

[3] Although in a minority, there are few exceptions to this consensus. Panel studies on firm and industry level data (Griliches and Lictchenberg, 1984; Jaffe, 1986; Bernstein, 1988; Verspagen, 1995) report that R&D elasticities are often statistically insignificant. Likewise, on the sources of R&D, Poole and Bernard (1992) report a significantly negative effect of military innovations on the multifactor productivity of Canada.

[4] The pair-wise correlation matrix, not reported here to conserve space, reveals a very high magnitude of correlation (coefficient of 0.90 or above) between all pairs of regressors except for the employment level. The latter is the only right hand side variable, which shows a somewhat lower magnitude of pair-wise correlation.

[5] A formal proof of omitted relevant variables resulting into biased parameter estimates and reduced standard errors of the parameters can be found, among others, in Greene (2003, pp. 149-151).

[6] Dummy variables are routinely used to capture some regional and / or country specific differences but our argument of heterogeneity is insightful and goes beyond the ability of dummy variables (see below).

[7] One exception is Luintel and Khan (2004) who argue and show that knowledge spillovers (β_3) may not be positive for the technology leader.

[8] Lucas (1993) and Romer (1990b) illustrate the different forms of human capital, e.g., human capital acquired through schooling, learning-by-doing and engaging in trade.

[9] For simplicity, only first order lags are shown in equation (1). In the estimation, we allow up to second order lags.

[10] Although, in specification (1) we allow for 10 theoretical determinants of productivity but this list is not exhaustive. We acknowledge that ICT (Vecchi and O’Mahony, 2003), financial deepening (Demetriades and Luintel, 1998; Townsend and Jeong, 2004), cross-

boarder flow of people (Barnebeck and Dalgaard, 2006) are some of the other variables which are viewed to affect domestic productivity. The lack of sufficiently long and consistent data series for the sample countries analyzed in this paper precluded us from using these variables. Moreover, the focus of this paper is to assess the robustness of the sources of knowledge in explaining productivity and we believe that augmenting three sources of knowledge by additional seven regressors is sufficient to accomplish the task at hand. In other words, if the sources of knowledge remain robust vis-à-vis these seven additional regressors then it is likely that they will remain so with respect to other variables as well.

[11] Pesaran et al., (2000) provide the theoretical basis for this modeling strategy and show that ignoring parameter heterogeneity results in biased and inconsistent parameters. They also find that when cross-country parameter heterogeneity is accounted in this manner, the non-linearity in macroeconomic relationships disappears. In other words, the econometric evidence of non-linearity in macroeconomic relationships may be due to the neglected heterogeneity.

[12] In section 4, we explain why we opt for country-specific mean levels of $S_{i,t}^{b}$ ($\bar{S}_{i}^{b}$), $S_{i,t}^{p}$ ($\bar{S}_{i}^{p}$), $Z_{i,t}$ ($\bar{Z}_{i}$), and $H_{i,t}$ ($\bar{H}_{i}$) rather than the intensity measure in order to capture the cross-country heterogeneity in productivity parameters.

[13] In equation (2) if $\lambda_j = \delta_k^{'} = \theta_k^{'} = \varphi_k^{'} = \phi_k^{'} = 0$ holds for j=(1,.,5), then the relationship is static with homogeneous slope parameters. The autoregressive fixed effects model - common in the literature - holds if $\lambda_j = 0 \cup \delta_k^{'} = \theta_k^{'} = \varphi_k^{'} = \phi_k^{'} = 0$ for j=2,.,5. If $\lambda_j \neq 0 \cup \delta_k^{'} = \theta_k^{'} = \varphi_k^{'} = \phi_k^{'} \neq 0$, then the relationship is heterogeneous in both slope parameters and adjustment dynamics.

[14] In Table 1 Japan's stock of public infrastructure appears higher than that of the USA. This is due to the exclusion of public infrastructure expenditure by local governments. In USA, local governments account for a high proportion of these expenditures. We exclude infrastructure spending by local government to maintain data consistency across our sample countries (see footnote 7). This should not be a serious concern because in sensitivity checks, our results remain robust when we drop USA from the panel and re-estimate the model (see section 6).

[15] The per capita figures are readily calculated by dividing the relevant stock measures by the total labor force given in the last column of table 1.

[16] The first difference specification purges data of the fixed effects. However, there are other equally valid transformations – e.g., mean and/or orthogonal deviations – (see Arellano and Bond, 1991). We use mean deviations in equation (2).

[17] When only three sources of knowledge are allowed in regression (1), the estimated point elasticities are: 0.175 (0.095), -0.100 (0.391) and 0.049 (0.002), respectively, for S^{b}, S^{p} and S^{f}. Figures within parentheses are P-values.

[18] The country specific parameters are qualitatively similar across all three estimators except for the insignificance of F^I under the single equation GMM estimator. We do not report the country specific parameter associated with dynamic heterogeneous OLS and single-equation GMM estimators to conserve space. However, they are available on request.

[19] It is important to note that statistically significant parameters carry important information. Even if their signs do not conform to theoretical *priors*, a significant piece of information must receive due consideration in policy making hence the importance of these findings.

[20] Notes to Table 3 are as follows. AR(2) is the second order LM tests of residual serial correlation. Under GMM, these tests are on the first differenced residuals because of the transformation involved. α_i and γ_t are the fixed and time effects. Numbers (.) are p-values based on the robust standard errors under the null that the coefficient is zero. Sargan tests are χ^2[r] distributed under the null of instrument validity. S^b, S^p, U, X^h, M^h and H are GMM-instrumented setting $S \geq 3$; S^f and the mean-interacted regressors are treated exogenously. Reported results remain robust even when S^f and the mean-interacted regressors are instrumented by their lagged values. Variable definitions are given in the footnote to Table 2. The definition of mean values are: $\overline{V}_i = T_i^{-1}\sum_{t=1}^{T_i} V_{i,t}$ and $V_{i,t} \in (S_{i,t}^b, S_{i,t}^p, H_{i,t}, Z_{i,t})$.

[21] This measure of S^f reflects the extent of successful R&D collaboration between nations leading to patent applications at the EPO. It also reflects the view that knowledge spills over between countries through R&D collaboration.

[22] We acknowledge that this is a crude measure of public infrastructure. No data exist on governments' aggregate stock of physical infrastructure. Studies use measures such as road mileage, telephone lines, supply of electricity, number of airport terminals etc. However, such indicators of public infrastructure appear more suitable for developing countries but, for obvious reasons, are not appropriate for this analysis. Our sample of OECD countries may not show any significant variations in these measures of infrastructure during the late 20th and the early 21st century, which is our sample period. Except for the USA, it is difficult to find data on the fixed capital formation by local governments. Therefore, we use data on federal / central government to proxy public infrastructure.