On the Robustness of R&D

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Abstract

Alternative models of productivity predict a range of its determinants besides that of research and development (R&D). We investigate the robustness of R&D *vis-à-vis* a dozen productivity determinants in a panel of 16 Organisation for Economic Co-operation and Development (OECD) countries through panel cointegration, bootstrap simulations and extensive sensitivity tests. Domestic knowledge stocks, international knowledge diffusion and human capital remain robust across all measures. The cross-country differences in accumulated knowledge stocks and human capital appear to explain productivity differences across countries.

JEL Classification: C2; O3; O4

Key Words: R&D Capital Stock; Multifactor Productivity; Heterogeneity; Panel Cointegration; Bootstrap Simulations

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1. Introduction

Motivated by the theoretical insights of new growth models, Coe and Helpman (1995, hereafter CH) analyze pooled aggregate data on R&D and productivity for a panel of 21 OECD countries plus Israel over the period 1971-1990. They report, *inter alia*, that domestic R&D capital and international R&D spillovers significantly explain domestic productivity, which supports knowledge-based growth models. CH's work breaks tradition with the previous empirical literature – primarily based on firm and/or industry-level (micro) data for a single country[1] – and inspired investigations on multicountry macro-panel data.

Ever since, macroeconometric investigations of R&D and productivity have proliferated. This growing literature engages with four main issues, namely, channels of international knowledge spillover, further determinants of productivity (i.e., omitted variables), econometric methodology and cross-country heterogeneity. Research on these issues is not mutually exclusive; a considerable overlap exists. We set the context by briefly summarizing it.

The bulk of the literature focuses on the potential channels of cross-border knowledge spillover. Typically, total imports (CH; Keller, 1998; Luintel and Khan, 2004), imports of capital goods (Xu and Wang, 1999; Luintel and Khan, 2009), inward and outward foreign direct investment (FDI) stocks and flows (Lee, 2006; Zhu and Jeon, 2007), information technology (Zhu and Jeon, 2007), bilateral exports (Funk, 2001), and technological proximity between nations (Park, 1999; Lee, 2006) are modeled as potential channels of cross-border knowledge transmission. These channels (ratios) form weights for the alternative measures of foreign knowledge stocks, and most of them are found to be significant conduits of international knowledge transmission.

Competing theoretical models predict several determinants of productivity that are external to the sources of knowledge (i.e., beyond measured R&D capital stocks) which makes the robustness of R&D an important issue. We denote the latter collectively as "non-R&D" determinants of productivity.[2] The literature addresses the robustness issue by augmenting R&D

capital stocks through measures of non-R&D determinants of productivity. To date, measures of human capital and productivity catch-up (Engelbrecht, 1997), import share (Edmond, 2001), and institutions (Coe, Helpman and Hoffmaister, 2009) appear to have been used to augment the R&D capital stocks in modeling productivity.[3] However, considering the long list of theoretically proposed determinants of productivity in the literature (see below), this issue appears somewhat under-researched; there is hence scope to extend this analysis. One of our aims is to do just that.

The econometric (methodological) issue has evolved with the advancement of panel data econometrics. CH applied OLS on pooled (panel) macro data and tested for the stationarity of residuals. Panel cointegration tests were not fully developed at the time. Following recent advances in panel data econometrics, interest in re-examining this issue surged. Some studies have applied up-to-date panel unit root and cointegration tests on CH's data and specifications, while others have investigated new and/or extended datasets employing these methods. Studies in this class include Kao *et al.* (1999), Edmond (2001), Lee (2006), and Coe, Helpman and Hoffmaister (2009), to name but a few. Overall, they find that productivity and R&D capital stocks are cointegrated and that CH's estimates are plausible despite their usage of OLS. The issue of parameter heterogeneity was recently raised by Luintel and Khan (2004). They show that cross-country parameters of the R&D and productivity relationship differ significantly, because countries differ in their accumulated knowledge stocks.

Our main objective is to extend this literature by providing a comprehensive and rigorous characterization of the empirical relationship between domestic productivity, domestic and foreign R&D capital stocks, human capital, and a broad range of other theoretically postulated and potentially important non-R&D determinants of productivity. Information on the robustness of R&D is important for growth and R&D-related policies. This paper complements as well as extends the existing literature in the following ways.

First, domestic productivity is modeled as a function of three different forms - business, public and foreign - of R&D capital stocks, human capital and a further 11 non-R&D determinants. The latter are predicted as potential determinants of productivity by various theoretical models of growth and development in the literature (see Section 2). We use four channels of international knowledge transmission, viz., bilateral R&D collaboration between countries, bilateral import ratio and the ratios of bilateral inward and outward FDI stocks. These channels are complementary in nature rather than substitutes. For example, imports, FDI and R&D collaboration are closely intertwined.[4]

We specify 13 models (specifications) consisting of one benchmark model, 11 individually augmented models and one jointly augmented model. The benchmark model includes the three forms of R&D and human capital as regressors. The 11 individually augmented models augment the benchmark model by one of the non-R&D determinants at a time. The jointly augmented model augments the benchmark model by the joint variations of all 11 non-R&D determinants, captured through a weighted principal component (WPC). Each of the 13 specifications is estimated in four alternative ways to capture the four different channels of international knowledge transmission. These 52 empirical models offer a rigorous and wide-ranging examination of the sensitivity of R&D and human capital *vis-à-vis* the other determinants of productivity.

Second, we model potential cross-country heterogeneity in knowledge-productivity relationships by explicitly modeling the role of the different levels of accumulated R&D stocks and human capital across countries. The idea is to examine whether a high knowledge base country, such as the United States (US), yields greater productivity benefits than a low knowledge base country like New Zealand.

Third, we apply the econometrics of non-stationary panel data. In addition, we conduct extensive simulations through a moving block bootstrap (MBB) procedure and scrutinize the small-sample properties of our results.

Finally, we conduct extensive sensitivity analyses *vis-à-vis*: (i) three (5%, 10% and 15%) depreciation rates for R&D capital stocks; (ii) three (3%, 5% and 8%) depreciation rates for stocks of public infrastructure; (iii) three measures of total factor productivity (TFP); (iv) country size in the sample; and (v) the size of the services sector in the economy. The latter is important because the extant R&D data mainly focus on manufacturing firms and do not yet offer sufficient coverage to the services sector (Gallacher, Link and Petrusa, 2005). Consequently, it may not fully proxy knowledge stocks of those countries that have a sizeable, well-developed services sector.

The rest of the paper is organized as follows. The next section discusses theoretical issues and empirical specification; data issues are covered in Section 3; econometric issues in Section 4; empirical results in Section 5 and sensitivity tests in Section 6. Section 7 summarizes the results and offers conclusions.

2. Theoretical issues and empirical specification

The endogenous growth models of Romer (1990a) and the quality ladder models of Grossman and Helpman (1991) and Aghion and Howitt (1992) theorize that innovations drive long-run aggregate productivity and economic growth. Based on these insights, CH specifies a basic R&D and productivity relationship as:

$$logP_{it}^{m} = \alpha_{1i} + \alpha_{1i}^{d} \log S_{it}^{d} + \alpha_{1i}^{f} \log S_{it}^{f} + \varepsilon_{1it}, \qquad (1)$$

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

Where "i" indicates the cross-sectional dimension and α_i captures the time-invariant fixed effects. P^m represents multifactor productivity; S^d and S^f denote domestic and foreign R&D capital stocks. Our benchmark model, which is in the spirit of CH, is:

$$logP_{it}^{m} = \alpha_{2i} + \alpha_{2i}^{b} \log S_{it}^{b} + \alpha_{2i}^{p} \log S_{it}^{p} + \alpha_{2i}^{f} \log S_{it}^{f} + \alpha_{2i}^{h} \log H_{it} + \varepsilon_{2it} \qquad (2)$$

Multifactor productivity (P^m) is measured as the difference between the log of output minus a weighted average of the log of labor and capital inputs. We employ three alternative measures of P^m. The first measure of P^m is obtained from the OECD (2008) which uses labor (total hours used) and capital (capital services) in its computation. The second measure (P^{ec}) is published by the European Commission (EC) which uses average real unit labor cost to compute labor input. Finally, we also compute the Solow residual-based measure of TFP (P^a) as: log P^a

= log GDP – 0.3 log K – 0.7 log L, which is common in the literature, where K is total net physical capital stock and L is total employment level. These alternative measures of aggregate productivity use different measures of labor and capital stock. The computations of P^{m} and P^{ec} use varying weights across countries, yet they maintain the assumption of constant returns to scale between labor and capital. The Solow residual maintains the same weights across sample countries as well as the assumption of constant returns to labor and capital.

In contrast to CH, we separate out total domestic knowledge stock into business (S_{it}^{b}) and public (S_{it}^{p}) sector knowledge stocks and include the stock of human capital (H) as an additional regressor. The separation of business- and public-sector knowledge stocks sheds light on the role of the sources of domestic knowledge stocks on productivity. Human capital is an extensively tested determinant of productivity (see, among others, Lucas, 1988 and 1993; Mankiw *et al.*, 1992; Romer, 1990a, b; Barro and Sala-i-Martin, 2003). However, Benhabib and Spiegel (2005) - following Nelson and Phelps (1966) - show that the role of human capital is more robust in respect of technology diffusion (i.e., the rate of catch-up) rather than a factor of production. We follow Coe *et al.* (2009) and directly input human capital as a factor production.

Theoretically, all three measures of R&D capital stocks exert positive effects on domestic productivity (see, among others, CH; Keller, 1998; Nadiri and Mamuneas, 1994). Consequently, we expect positive and significant parameters of all three sources of knowledge stocks *a priori*. The stock of human capital exerts a positive effect on productivity and economic growth. This is true for both the exogenous and endogenous growth models.[5]

We augment our benchmark model (equation (2)) by a further 11 determinants of productivity, postulated by different theoretical models in the literature. The latter include measures of information and communication technology (ICT), the stock of public physical infrastructure (Z), high-technology exports (X^{h}), high-technology imports (M^{h}), stocks of inward (F^{I}) and outward (F^{O}) FDI, the relative size of the services sector in the economy (SER) and a proxy variable for the business cycle (E). We also use three measures of financial development - private credit ratio (P^K), stock market capitalization ratio (S^{MC}) and stock market total value traded ratio (S^{MV}).

ICT is viewed as "general purpose technology" yielding network externalities (Schreyer, 2000) and capital deepening (Basu *et al.*, 2004), both of which boost labor and TFP. Indeed, ICT is found to have a significant effect on aggregate productivity and growth across OECD countries (O'Mahony and Van Ark, 2003 and 2005; Basu *et al.* 2004). Gordon (2000) credits ICT investments for the increase of TFP in the US during the latter half of the 1990s. The Council of Economic Advisors (2001) argues that the late 1990s surge in US labor productivity was mainly confined to *ICT*-intensive industries. Van Ark *et al.* (2002) report a large contribution of ICT in 12 European Union (EU) countries and the US. However, Basu *et al.* (op cit.) point out that the short-run (contemporaneous) effect of ICT on TFP may be negative, as reorganization and learning processes entail costs. We test for the long-run (cointegrating) relationship, hence expecting a positive association between ICT and productivity.

In the models of Arrow and Kurz (1970), and Grossman and Lucas (1974), infrastructure is viewed as an input to the private sector's production function. The "quality" and "size" of public infrastructure augment productivity and growth via cost reductions and/or improved specializations (see Gramlich, 1994, for a survey). On these theoretical grounds, we anticipate a positive effect of infrastructure on productivity.

In learning-by-doing models, access to export markets improves domestic productivity (see, among others, Bernard and Jensen, 1999; Clerides *et al.*, 1998; Eaton and Kortum, 2002). Domestic firms improve their specialization and productivity in providing the high product quality required by foreign markets. However, this effect may be more prominent among technological laggards. In order to capture this learning-by-exporting effect, we use the ratio of high-technology exports to total exports.

Imports are conduits of technology diffusion (Grossman and Helpman, 1991; CH; Keller, 1998 and 2004). Countries engaged in imports benefit from international knowledge spillovers.

Potentially, technological laggards benefit more than technological leaders. Recent literature emphasizes the importance of trade in differentiated capital goods. We use the ratio of high-technology imports to total imports to capture this effect.

FDI is considered to generate technological externalities and to raise 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; Keller and Yeaple, 2009; Griffith *et al.*, 2006). Hence, we expect positive effects of FDI stocks on domestic productivity.

In recent years, the relative importance of the services sector in the aggregate output of OECD countries has increased significantly as has the sector's R&D activity. In the US, R&D performed by the services sector rose from 7 percent of total industrial sector R&D in the 1970s to 29 percent in 1990. A similar trend is evident across OECD countries, albeit with mixed magnitudes (see Jankowski, 2001). We control for this phenomenon by: (i) including the relative size of the services sector as one of the regressors in its own right; and (ii) re-estimating all models by controlling for the services sector.

Theoretical models predict that a well-functioning financial sector (banks and capital markets) boosts efficiency of investment, aggregate productivity and economic growth through its multifarious services. Financial development induces efficient allocation of capital and faster growth (Greenwood and Jovanovic, 1990); lowers monitoring and enforcement costs (Diamond, 1984); and eases risk diversification and shifts portfolios towards projects with higher expected returns (Devereux and Smith, 1994). A long list of theoretical models predicts that a well-functioning financial sector contributes to the allocation of resources, productivity and economic growth (Luintel and Khan, 1999; Levine, 2005; Luintel *et al.*, 2008).

Finally, we also capture the business cycle effect on domestic productivity through the rate of employment (E). Much of the literature predicts a pro-cyclical effect of the business cycle on productivity. Drawing from the preceding discussions, our augmented model for domestic productivity is:

$$LogP_{it}^{m} = \alpha_{3i} + \alpha_{3i}^{b}\log S_{it}^{b} + \alpha_{3i}^{p}\log S_{it}^{p} + \alpha_{3i}^{f}\log S_{it}^{f} + \alpha_{3i}^{h}\log H_{t} + \beta^{'} X_{it} + \varepsilon_{2it} \qquad (3)$$

where X is a vector containing 11 measures of non-R&D determinants of productivity outlined above, and $\beta_{(1x11)}$ is the parameter vector. Equation (3) has 15 covariates excluding the fixed effects. Although these 15 regressors may not exhaust all the potential productivity determinants available in the literature, they nevertheless represent a wide spectrum of key variables that are arguably sufficient to assess the robustness of R&D and human capital stocks. It is also important to note that some overlap between R&D and non-R&D determinants of productivity is likely as they exhibit positive correlation.[6] If knowledge stocks and human capital appear robust *vis-à-vis* these 11 non-R&D regressors, it is highly likely that they will pass other such tests. For example, Coe, Helpman and Hoffmaister (2009) report that including institutional factors does not alter the robustness of R&D.

We estimate equation (3) in a dynamic heterogeneous panel framework. The dynamic heterogeneous panel cointegration tests are powerful, and they are robust to cross-country parameter heterogeneity. Theoretically, estimation of the full system with all 16 variables would provide more stable and robust cointegrating relationships.[7] However, a number of issues arise in estimating such a large system. First, a system of 16 variables could potentially exhibit 15 cointegrating relationships (r) which require identification by suitable parametric restrictions. An identification mechanism, suggested by Pesaran and Sin (2002), would require r^2+1 parametric restrictions to obtain one over-identifying restriction to ensure the uniqueness of the identified cointegrating vectors. This implies a potential 226 parametric restrictions to obtain just one over-identifying restriction in equation (3). Experience suggests that such large numbers of restrictions are difficult to sustain statistically. Second, we have only 23 data points for each panel, hence estimation of such a large system is simply not feasible under the between-dimension estimator. Finally, the identification of economically meaningful cointegrating relationships among integrated processes through system estimation and normalization tests is meaningful when economic theory does not guide empirical specification sufficiently convincingly. The productivity relationship that we have is well specified in the literature; therefore, a single equation approach (e.g., Pedroni, 1999) would not compromise our purpose at hand. Hence, our estimation strategy is as follows.

First, we sequentially estimate equation (3) by incorporating only one variable of vector X at a time. This gives us 12 models – one benchmark model with four regressors (i.e., excluding $\beta' X_{it}$), and the remaining 11 augmented models with five regressors each (i.e., using one regressor at a time from vector X). Second, we jointly use all the regressors contained in vector X through the method of principal components. The 11 variables contained in vector X are all positively correlated pair-wise, except for the pair of inward FDI and employment rate. Theoretically, the variances of integrated processes are unbounded. In our case, tests confirm the WPC as I(1). Although the different covariates contained in vector X may influence domestic productivity differently, the usage of a principal component in summarizing the overall effects of several covariates is nonetheless relatively standard in the literature under both the stationary and non-stationary setup (Loayza, 2000; Levin, 2002; Luintel *et al.*, 2008; to name but a few), and follow the same.

Sample countries show considerable differences in their accumulated stocks of R&D and human capital (see Table 1). The US dominates in the ownership of knowledge stocks and the pool of scientists working in the R&D sector. Likewise, important cross-country heterogeneity is evident in the levels and growth rates of productivity. In our sample, the average annual growth rate of domestic productivity ranges between a minimum of 0.6 percent (Canada) to a maximum of 3.2 percent (Ireland); the sample mean is 1.1 percent. This gives rise to an interesting testable proposition of whether countries with high magnitudes of accumulated knowledge and human capital stocks yield higher productivity gains. If the evidence were affirmative, then countries with a smaller knowledge stock and less human capital would benefit by opting for policies that augment their stocks of knowledge and human capital. A formal test of this hypothesis requires specifications that directly allow for cross-country differences in knowledge and human capital stocks. Our specifications, which capture this, are:

$$LogP_{it}^{m} = \alpha_{4i} + \alpha_{4i}^{b}\log(S_{it}^{b} * \bar{S}_{i}^{b}) + \alpha_{4i}^{p}\log(S_{it}^{p} * \bar{S}_{i}^{b}) + \alpha_{4i}^{f}\log(S_{it}^{f} * \bar{S}_{i}^{b}) + \alpha_{4i}^{h}\log(H_{it} * \bar{S}_{i}^{b}) + \varepsilon_{4it} \quad (4)$$

$$LogP_{it}^{m} = \alpha_{5i} + \alpha_{5i}^{b}\log(S_{it}^{b} * \bar{S}_{i}^{p}) + \alpha_{5i}^{p}\log(S_{it}^{p} * \bar{S}_{i}^{p}) + \alpha_{5i}^{f}\log(S_{it}^{f} * \bar{S}_{i}^{p}) + \alpha_{5i}^{h}\log(H_{it} * \bar{S}_{i}^{p}) + \varepsilon_{5it} \quad (5)$$

$$LogP_{it}^{m} = \alpha_{6i} + \alpha_{6i}^{b}\log(S_{it}^{b} * \bar{H}_{i}) + \alpha_{6i}^{p}\log(S_{it}^{p} * \bar{H}_{i}) + \alpha_{6i}^{f}\log(S_{it}^{f} * \bar{H}_{i}) + \alpha_{6i}^{h}\log(H_{it} * \bar{H}_{i}) + \varepsilon_{6it} \quad (6)$$

where, $\bar{S}_{i}^{b} = T_{i}^{-1}\sum_{t=1}^{T_i} S_{it}^{b}$; $\bar{S}_{i}^{p} = T_{i}^{-1}\sum_{t=1}^{T_i} S_{it}^{p}$; and $\bar{H}_{i} = T_{i}^{-1}\sum_{t=1}^{T_i} H_{i,t}$. In equation (4), we interact all the covariates of our benchmark model - S_{it}^{b}, S_{it}^{p}, S_{it}^{f} and H_{it} - by country-specific mean levels of business-sector R&D capital stock.[8] Only interacted covariates appear in these specifications, because we employ a between-dimension dynamic heterogeneous panel estimator, which precludes the joint use of the level and interacted covariates due to perfect collinearity. While the lack of level variables in these specifications precludes a long-run relationship, they nonetheless reveal, *inter alia*, whether countries that are rich in knowledge and human capital reap higher productivity gains and whether there are complementarities, or a lack thereof, between different sources of R&D knowledge and human capital *vis-à-vis* domestic productivity.[9]

A positive and significant α_{4i}^{b} implies that countries with a large stock of accumulated business-sector R&D capital experience bigger productivity gains and vice versa. To illustrate this point, assume that two sample countries (A & B) in the panel have mean business-sector knowledge stocks of $\bar{S}_{A}^{b}$ and $\bar{S}_{B}^{b}$, respectively, such that $\bar{S}_{A}^{b} > \bar{S}_{B}^{b}$. From equation (4), this yields a point elasticity of $\alpha_{4i}^{b} * \bar{S}_{A}^{b}$ for country A and $\alpha_{4i}^{b} * \bar{S}_{B}^{b}$ for country B, necessitating higher point elasticity for country A due to its larger accumulated knowledge stock. These specifications reveal important information on whether high knowledge-base countries like the US or Germany reap more productivity gains than low knowledge-base ones like Greece or Spain.

Positive and significant α_{4i}^{p}, α_{4i}^{f} and α_{4i}^{h} imply that business-sector R&D capital complements public and foreign R&D capital stocks and human capital, respectively, in augmenting productivity. In equations (5) and (6), the benchmark model is interacted by country-specific mean levels of public-sector R&D capital stock ($\bar{S}_{i}^{p}$) and human capital ($\bar{H}_{i}$), respectively, and their parameters are to be interpreted correspondingly.[10]

3. Data

We analyze 16 OECD countries (see Table 1) and assemble data on three measures of productivity (the dependent variable) and 15 regressors discussed in Section 2. Consistent data on all these variables were not available for countries other than these 16, hence the sample. Data frequency is annual for a period of 23 years (1982-2004); we have a balanced panel of 368 observations. The data appendix lists all data series and their sources and computations.

Figure 1 about here

In Figure 1, we report bar charts of multifactor productivity, business- and public-sector R&D capital stocks and the stocks of inward FDI. Data exhibit large differences across sample countries. Domestic productivity growth rates range between 0.6 percent (Canada) to 3.2 percent (Ireland), which is a difference of over five-fold. There are huge differences in accumulated business- and public-sector knowledge stocks across OECD countries; the US completely dominates. Such cross-country differences are also evident among the non-R&D determinants of productivity. Since it is not feasible to provide bar charts for all variables due to limited space, we report summary statistics of some of the key variables in Table 1.

Table 1 about here

Table 1 shows important differences in the growth rates of productivity and their determinants across the sample OECD countries. The productivity of the US and the United Kingdom (UK) grew by around 1.3 percent during the sample period, while Japan, Germany and France experienced somewhat higher growth rates of 1.6 percent or so. The sample mean of business-sector R&D intensity (business-sector R&D expenditure-to-gross domestic product

(GDP) ratio) is 1.6 percent, but ranges from a minimum of 0.1 percent (Greece) to a maximum of 2.3 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 (Sweden); the sample mean is 0.7 percent. The stock of human capital, measured by average years of schooling, is lowest in Spain (7.6 years) and highest in the US (12.6 years). Foreign R&D capital stocks, public infrastructure, high-technology exports and imports, FDI and ICT also exhibit sharp cross-country differences, whereas financial development, proxied here by stock market capitalization, appears to be relatively smooth across countries.

To illustrate the time profile of our data series we plot P^m, S^b, S^p and S^f in Figure 2.

Figure 2 about here

The plotted foreign R&D capital stock is derived using the bilateral R&D cooperation coefficients as weights. All plots show an upward trend throughout the sample period, suggesting that they are probably non-stationary unit root processes. We confirm this through panel unit root tests in Section 5. The time profiles of these plots are also representative of other variables not reported here for space reasons.

4. Econometric Issues

Individual series of multicountry macro-panel data are widely reported to be unit root processes. This requires the application of panel unit root and cointegration tests in empirical scrutiny. These tests exhibit better power properties than the conventional time series tests when sample size is moderate. Further, panel estimators of cointegrating vectors are super-consistent and robust to endogeneity, measurement errors and dynamic heterogeneity (Pedroni, 1999).

A number of panel unit root tests are proposed in the literature. Hlouskova and Wagner (2006) provide a comparative study of some of these tests through extensive Monte Carlo simulations. We implement a number of these panel unit root tests and, given the robustness of our results, only report those of Im, Pesaran and Sin (2003; hereafter IPS), Fisher-ADF (Maddala and WU, 1999) and Hadri (2000). The IPS test tests the null of a unit root for each cross-sectional unit in the panel, against the alternative that a fraction of cross-sections may contain a unit root. We choose the IPS test due to its generality, as it allows for the heterogeneity of: (i) persistence; (ii) dynamics; and (iii) error variance across groups. Further, it is a more general test than those that maintain stationarity across all groups under the alternative hypothesis.

The Fisher-ADF test, proposed by Maddala and Wu (1999), combines the p-values of each unit root test conducted on an individual member of the panel. They show that, under the null of a unit root for all N cross-sections, the quantity: $\sum_{i=1}^{N} \log(\pi_i)$ is asymptotically χ^2_{2N}; where π_i is the p-value of the unit root test on the i^{th} variable of the i^{th} panel member. Hardi's panel unit root test tests the null of stationarity against the alternative of the unit root, assuming a common persistence parameter across cross-sections. Although Hlouskosva and Wagner (2006) report that Hadri's test suffers from significant size distortion in the presence of autocorrelations, we nevertheless employ it, because it tests different null and alternative hypotheses compared to the earlier two tests. Hadri also derives autocorrelation and heteroskedasticity-consistent LM tests under the null of stationarity across all cross-sections.

Pedroni (1999) proposes seven residual-based tests of panel cointegration. Four of them are within-dimension tests that assume homogeneous cointegrating vectors across all panel members. The remaining three are between-dimension tests (referred to as group mean statistics), which allow heterogeneity of cointegrating vectors across all panel members. The distinction between these two sets of tests is crucial, because incorrect imposition of homogeneous cointegrating parameters would lead to the non-rejection of the null of non-cointegration even where the variables are cointegrated (Pedroni, 1999, p. 656). Given the heterogeneity in productivity levels and the factors determining them, we have no reason to believe that the cointegrating vectors across our panel of countries are homogeneous. Further, the between-dimension estimators exhibit lower size distortions than the within-dimension estimators (Pedroni, 2000). We therefore opt for the between-dimension tests. Of the three between-dimension panel cointegration tests, the group t-statistic is the most powerful (Pedroni, 2004). We report the group t-statistic and the group ρ-statistic derived by Pedroni (1999).[11]

Following Pedroni (1999 and 2001), we estimate the cointegrating parameters through Fully Modified OLS (FMOLS). Under this approach, the panel cointegrating vectors are essentially the average of the country-by-country time series estimates. Hence, the (small) size is a potential issue, which we address through bootstrap simulations. The integrated and cointegrated properties of our data and models preclude our treating the estimated residuals as identical independently distributed (i.i.d.) processes. Consequently, standard i.i.d. resampling schemes cannot be applied for bootstrap exercises. Instead, the Moving Block Bootstrap (MBB) procedure, proposed by Kunsch (1989) and Liu and Singh (1992), preserves such a data structure and is hence suitable. Further, Goncalves and White (2005) show that MBB procedures could be applied to processes with substantial memory (known as near epoch dependent processes).

A brief sketch of the MBB procedure is as follows. Consider a series $\{X_{Tt} : t = 1,...,T\}$; let ℓ be a block length such that $B_{t,\ell} = \{X_{Tt,} X_{Tt+1},..., X_{Tt+\ell-1}\}$ is the block of ℓ consecutive observations starting at X_{Tt}. The MBB draws b blocks randomly with replacement from the set of overlapping blocks $\{B_{1,\ell},..., B_{T-\ell+1,\ell}\}$ where $T = b\ell$. Letting $I_{T1},..., I_{Tb}$ as i.i.d. random variables distributed uniformly over $\{0,....,T-\ell\}$, we have $\{X^*_{Tt} = Z_{T,\tau_{nt}}, t = 1,...,T\}$, where τ_{nt} defines a random array $\tau_{nt} \equiv \{I_{T1}+1,...., I_{T1}+\ell,...., I_{Tb}+1,...., I_{Tb}+\ell\}$. We estimate ℓ by setting it equal to the highest order of the significant residual autocorrelation.

The residual resampling draws on the time dimension of the panel in order to match it with the nature of Pedroni's (2001) Panel FMOLS approach.[12] We generate 1,000 bootstrapped samples of residuals and, through our regression equation, 1,000 endogenous variables. We then compute 1,000 parameter vectors for each model through the FMOLS regressions on these pseudo-samples. The mean and median values of the simulated parameters and their distributions are derived. We also compute the empirical p-values for the estimated regression coefficients.

5. Empirical Results

Table 2 reports the results of panel unit root tests. Results in the first two columns relate to the null of a unit root for each member in the panel against the alternative that a fraction of a cross-section may contain a unit root. Neither test rejects the null at any conventional significance level (10 percent or better) for any of the data series in the panel. The Hadri test, which tests the null of stationarity, rejects the null for all series in the panel at very high levels of precision. Reported results pertain to the specifications that include country-specific intercepts. However, these results are robust to changes in deterministic components (inclusion of constants and linear trends or otherwise). All individual series in the panel are first-difference stationary.[13]

Table 2 about here

The overall finding from these tests is that all individual data series in the panel are unit root processes. It is worth stating that IPS, ADF-Fisher and Hadri panel unit root tests are first-generation tests that assume cross-sectional independence. The second-generation panel unit root tests allow for cross-sectional dependence (Gegenbach *et al.*, 2010, among others, provide an excellent comparative study of some of these tests). We assess whether our conclusion is robust to cross-sectional dependence by implementing the truncated version of the cross-sectionally augmented IPS (CIPS) test (Pesaran, 2007), which simultaneously accounts for cross-sectional dependence and residual serial correlation. Tests reveal that our findings are robust to cross-sectional dependence.[14] It is also worth noting that some of the model variables are ratios (bounded variables), hence their nonstationarity may look somewhat unexpected. However, Greenwood et al., (1997) provide theoretical justification for the possibility of trending great ratios, and our findings are not inconsistent with the literature.

Table 3 about here

Table 3 reports the results of cointegration tests and bootstrap summary statistics. Given the small sample size, we attach added importance to the simulated results and the mean values of the bootstrap parameters. The first half of the table contains the results of those empirical models that use bilateral import-weighted foreign R&D capital stocks (S^{fm}) computed at a 15 percent depreciation rate. The stock of public infrastructure (Z) used is based on a 3.0 percent depreciation rate, but results remain qualitatively the same at alternative depreciation rates (see Section 7). Panel A shows the results for the benchmark model (equation (2)). Both the group ρ -statistic and the group t-statistic firmly reject the null of non-cointegration at very high levels of precision, implying that domestic productivity, three forms of R&D capital, and human capital stocks are cointegrated in the panel. All the cointegrating parameters of the benchmark model are positive and highly significant, which conforms to theoretical priors. Both the asymptotic and the bootstrap p-values uphold the precision of the estimated parameters. The upper (U^B) and lower (L^B) bounds represent the threshold values of a 95 percent confidence band. Goncalves and White (2005) show that it is inappropriate to assess parameter significance by using bootstrapped standard error without further assumptions regarding its behaviour. Instead, they suggest deriving the distribution of the test statistic under the null. We derive the bootstrapped distribution of the t-statistic following their approach and test the significance of the finite sample parameter.

The finite sample results in panel A show that the point elasticity of public-sector R&D capital stock (0.193) is more than double that of business-sector R&D capital stock (0.089). Foreign-sector R&D capital stock has the smallest point elasticity (0.043). Human capital shows a point elasticity similar to that of public-sector R&D. However, this discrepancy between public- and business-sector R&D point elasticities largely disappears in the mean values of the simulated parameters, whereas human capital resumes a very high point estimate. This indicates that public- and business-sector R&D exert effects of a similar magnitude on domestic productivity. These results imply a downward bias in the regression estimate of the point estimate of human capital. Such a discrepancy between the regression estimates and the mean values of small-sample parameter distributions - which is apparent in other specifications as well -

highlights the importance of health checks through bootstrap simulations. Overall, our findings of significant positive effects for the three forms of knowledge stocks and human capital on domestic productivity are consistent with the existing literature (see, among others, CH; Engelbrecht, 1997).

Panel B contains the results of the augmented models. Each column of Panel B is obtained by augmenting the benchmark model through the regressor listed in the respective column. For example, the ICT column contains results where the benchmark model is augmented by the ICT variable. In the last column, the WPC that summarizes all 11 non-R&D regressors listed in Panel B augments the benchmark model. We compute eigenvectors from all 11 regressors for each country in the panel. The WPC is the weighted sum of all the eigenvectors that cumulatively explain total (100%) variation in the data; the proportion of total variation explained by each eigenvector is the respective weight.

The results reveal that all augmented models are cointegrated; both test statistics are highly significant and reject the null of panel non-cointegration. Thus, cointegration is evident under all three specifications - the benchmark model, the individually augmented 11 models and the model jointly augmented by the WPC. These results are symptomatic of a long-run equilibrium relationship between domestic productivity and its 15 determinants postulated by different theoretical models.

How well do the non-R&D determinants of productivity fare? Of the 11 covariates, seven – ICT, public infrastructure, stocks of inward and outward FDI, two measures of financial development (S^{MC} and S^{MV}) and the services sector of the economy – appear positive and significant when judged from empirical p-values. Asymptotic p-values show ICT and SER as insignificant and Z as marginal (significant at 9.95 only). The remaining four regression estimates – coefficients of high-technology export and import ratios, private-sector credit ratio and the proxy of business cycle – appear negative. However, the mean values of simulated parameters show that all regressors, except for high-technology export and import ratios and the business cycle proxy, are positive. The mean values of the simulated parameters associated with high-technology export and import ratios are very small. The business cycle proxy variable appears counter-cyclical, which does not conform to *a priori* expectation. The bootstrap results show some evidence of asymmetric upper and lower bounds with respect to a few parameters. Some mean and median values of the simulated parameters also differ. Overall, parameter distributions appear largely symmetrical. The last column reports the joint effect of all 11 covariates listed in Panel B, summarized by a WPC that is positive and significant. The parameter of the WPC shows a very high precision and indicates symmetric distribution.

How robust are domestic and foreign R&D and human capital stocks? The results of the benchmark model are extremely robust to every single augmentation. The coefficient of business-sector R&D ranges between a minimum of 0.017 and a maximum of 0.174 but always remains positive and significant across all 12 augmentations. Likewise, the parameters of public-sector R&D range between 0.071 and 0.284, those of foreign R&D between 0.010 and 0.057, and those of human capital between 0.045 and 0.439, all of them remaining positive and statistically significant. Domestic R&D capital stocks, international knowledge spillover and human capital appear robust to a wide spectrum of productivity determinants. This robustness holds irrespective of whether the other regressors are modeled individually or jointly through the summary measure of the WPC.

The second half of Table 3 reports the results of the empirical models that use bilateral R&D collaboration-weighted foreign R&D capital stocks (S^{fc}). As before, the group ρ-statistic and group t-statistic both reject the null of non-cointegration across all specifications. The benchmark model and all 12 augmented models are cointegrated.

The cointegrating parameters associated with business- and public-sector R&D capital stocks and human capital appear positive and significant, which confirms the earlier results. The regression coefficient of international knowledge spillover appears negative and insignificant asymptotically; however, this is overturned by bootstrap results, as the mean and median values of simulated parameters are both positive. The bootstrap results confirm bilateral R&D collaboration as a conduit of international knowledge transmission.

As before, the results of the benchmark model are robust to all augmentations. Of the 11 non-R&D regressors, all but two have positive and statistically significant cointegrating parameters. The exceptions are the high-technology import ratio and the services sector, which have negative coefficients. However, the mean and median values of simulated parameters are negative for three of the non-R&D determinants (namely, M^h, SM^v and E); the services sector appears positive. Overall, the distributions of simulated parameters echo the same message discussed above.

Table 4 reports results that use inward and outward FDI-weighted foreign R&D capital stocks, respectively, with a 15 percent depreciation rate.

Table 4 about here

Results in the upper half, pertaining to inward FDI-weighted foreign R&D capital stocks (S^{fI}), show that the benchmark model and all augmented models are cointegrated. Results are consistent with earlier findings that international knowledge travels through inward FDI as well. All parameters of the benchmark model are positive and significant, echoing the findings reported earlier. Their simulated mean and median values are all positive and are very close in magnitude. Of the 11 non-R&D determinants, the regression coefficients (cointegrating parameters) are positive and significant for all except the private credit-to-GDP ratio (P^K) and services sector (SER). However, the mean value of the bootstrap parameters is positive for all except import ratios and employment rate. As above, the majority of non-R&D determinants appear to exert a positive effect on productivity. This is further supported by the results in the last column – a positive and statistically significant joint effect of all 11 regressors captured by the WPC. The upper and lower bounds of simulated parameters show very few cases of asymmetry.

In the lower half of the table, the results are obtained from the models that use outward FDI-weighted foreign R&D capital stock (S^{fO}). The benchmark model and the entire set of augmented models are cointegrated. Judging by their bootstrapped p-values, all the cointegrating parameters are positive and statistically significant for the benchmark model. In Panel B, regression coefficients of all but two regressors (P^K and E) are positive and statistically significant. The mean values of simulated parameters are positive for all but M^h and E. Essentially, the results are similar to those in the upper half. Outward FDI is yet another conduit of cross-border knowledge spillover.

Overall, results of Tables 3 and 4 reveal that: (i) the three forms of R&D capital stocks and human capital are robust in explaining domestic productivity; and (ii) a large number of other determinants proposed by competing theoretical models are also significant and confirm theoretical predictions. Judging by the mean values of our bootstrap parameters, ICT, public infrastructure, stocks of inward and outward FDI, services sector and two measures of financial sector development (P^K and SM^C) show a positive effect in all specifications. The ratios of high-technology exports and stock market value traded are also positive in most (three out of four) specifications. Interestingly, the high-technology import ratio appears with a small but negative coefficient across all specifications. Theoretically, imports are viewed as conduits of technology diffusion. This is captured by the bilateral import ratios-weighted foreign R&D capital stocks, which is significantly positive. Therefore, this small (near zero) negative coefficient of import ratio may suggest that imports have no productivity role beyond knowledge diffusion. Employment rate (E) shows a counter-cyclical effect on productivity, indicating that it may not be a robust proxy for the business cycle.

Furthermore, whether the robustness of R&D, found above, remains for groups of some key variables - which capture important productivity channels such as openness, FDI and financial development - is an important issue. In order to assess this, we collate the non-R&D covariates in three separate groups encapsulating openness, FDI flows, and financial development. Openness is captured by jointly entering X^h and M^h; FDI flows are captured by the joint use of F^I and F^O; and financial development is captured by P^K and S^{MC}. When equation (2) is augmented by these groups of variables in turn, all signs and significance of estimated parameters appear very close to those in Tables 3 and 4, above, and the robustness of R&D stocks and human capital is maintained. [15]

How do our results compare with the literature? The finding of a robust positive and significant effect of domestic and foreign knowledge stocks on domestic productivity is consistent with those of CH, Keller (1998) and Luintel and Khan (2004), to name but a few. Findings that both business- and public-sector R&D affect domestic productivity positively reinforce the earlier results of Guellec and van Pottelsberghe (2004). Likewise, the robustness of human capital conform to those of Engelbrecht (1997) and Coe, Helpman and Hoffmaister (2009). In addition, ICT, public infrastructure, inward and outward FDI stocks, the services sector, high-technology exports and financial deepening all appear significant in explaining domestic productivity. These findings are consistent with a large body of theoretical and empirical literature discussed in section 2. [16] Interestingly, the direct inclusion of the import ratio appears negative suggesting that its positive productivity effect may only emanate as a conduit of knowledge spillover. Indeed, we find that the ratios of bilateral imports and inward and outward FDI stocks are important channel of knowledge spillovers. This is consistent with a voluminous literature (Lichtenberg and van Pottelsberghe, 1988; Lee, 2006; Zhu and Jeon, 2007; Xu and Wang, 1999; Luintel and Khan, 2009; Paci and Usai, 2009), which reports that knowledge spills across borders through different channels. The joint effect of all non-R&D determinants, captured through WPC, appears positive and significant across all specifications implying that, in addition to R&D and human capital, several factors in the economy also drive aggregate productivity.

Table 5 reports the results of models (4) to (6). They test whether countries with higher accumulated knowledge and human capital stocks experience greater productivity gains. The interacted covariates capture cross-country heterogeneity due to diversity in accumulated stocks.

Table 5 about here

The coefficients of interacted covariates, namely, $S^b * \bar{S}^b$, $S^p * \bar{S}^p$, and $H * \bar{H}$ are all positive and significant, which confirms that countries in possession of large knowledge and human capital stocks tend to benefit from high productivity gains. The coefficients of all the cross-product regressors - $S^p * \bar{S}^b$, $S^{fm} * \bar{S}^b$, $H * \bar{S}^b$; $S^b * \bar{S}^p$, $S^{fm} * \bar{S}^p$, $H * \bar{S}^p$; and $S^b * \bar{H}$, $S^{fm} * \bar{H}$, $S^{fm} * \bar{H}$ - are also positive and significant, indicating that the three sources of knowledge and human capital are complementary in augmenting productivity, although the magnitudes appear to be rather small. The central tendency of simulated parameters appears positive in all cases. The results, especially the bootstrap mean values of the parameters, are qualitatively similar across both measures of foreign knowledge stocks.

6. Sensitivity Analyses

All the results reported thus far are based on R&D capital stocks computed at a 15 percent depreciation rate. Our first sensitivity tests examine whether our results are susceptible to variations in depreciation rates. We re-estimate all the models by using R&D capital stocks measured at 10 and 5 percent depreciation rates and find that the results are robust to these variations. Table A1 reports results based on a 10 percent depreciation rate. Results pertaining to FDI-weighted foreign R&D capital stocks and a 5 percent depreciation rate are not reported to conserve space, but are available on request.

Results of mean-interacted models (Table 5), which reveal that higher levels of accumulated knowledge and human capital stocks yield greater productivity gains, are also robust to 10 and 5 percent depreciation rates. Table A2 reports results estimated at a 10 percent depreciation rate. Results obtained by using a 5 percent depreciation rate are qualitatively similar but are not reported to conserve space.

Second, we assess the sensitivity of our results to alternative measures of TFP. We re-estimate all specifications by employing a further two measures of productivity, namely, the TFP measure by the EC and our own calculation following the well-known Solow residual approach.

Table A3 reports results obtained from the use of these alternative productivity measures; again, results are robust.

Third, we examine whether our results are affected by the size of the countries in the sample. We re-estimate all models by dropping one country at a time from the sample. These results, reported in Table A4, appear robust to variations in the size of sample countries.

Fourth, we control for the services sector by directly including the relative size of the services sector in all the regressions reported in Tables 3 and 4, except for the SER column. Controlling for the services sector does not alter the reported results qualitatively. Finally, we use stocks of public infrastructure computed at 8 and 5 percent depreciation rates and find that the reported results remain qualitatively similar throughout these changes. For brevity, we do not report these two sets of results, but they are available on request. Overall, our main results are robust to a range of sensitivity tests.

7. Summary and Conclusion

We empirically examine the robustness of domestic knowledge stocks, international knowledge spillovers and human capital in driving productivity in a panel of 16 OECD countries. We capture 15 theoretical determinants (regressors) of productivity. They include three forms (business, public and foreign) of R&D capital stocks, human capital and a further 11 determinants of productivity. The latter include ICT, public infrastructure (Z), high-technology export (X^h) and import (M^h) ratios, ratios of inward (F^I) and outward (F^O) FDI stocks, the relative size of the services sector (SER), three measures of banking and capital market developments - private credit ratio (P^K),stock market capitalization ratio (S^{MC}),stock market total value traded ratio (S^{MV}) - and a proxy of business cycle (E). We estimate their individual, group, as well as joint effects on productivity. Four alternative measures of foreign R&D capital stocks based on the ratios of bilateral capital imports, R&D collaborations and inward and outward FDI stocks are computed to capture the different channels of international knowledge transmission.

It is well known that a significant disparity exists in the ownership of R&D and human capital across OECD (sample) countries. For example, the US dominates in terms of ownership of world knowledge stocks. We, therefore, directly test whether differing levels of knowledge and human capital stocks across nations lead to cross-country heterogeneity in productivity relationship (productivity parameters).

The long-run relationships between domestic productivity and its determinants are estimated through panel cointegration tests. The small-sample validity of the estimated cointegrating vectors is scrutinized through the MBB procedure. Results show that all variables in the panel are individually integrated (unit root) processes. All specifications (52 of them) are cointegrated, indicating a long-run equilibrium relationship between domestic productivity and the 15 determinants postulated by various theoretical models, as well as the four channels of international knowledge spillover.

Domestic R&D, international knowledge spillover and human capital remain robust in explaining productivity; their parameters remain positive and statistically significant throughout all augmentations. Most of the 11 non-R&D regressors also have a positive and significant effect. In particular, ICT, public infrastructure, inward and outward FDI stocks, the services sector of the economy, high-technology exports and financial deepening, appear as the main non-R&D determinants of productivity. Import ratio appears to affect productivity only as a conduit of knowledge spillover. However, the joint effect of all non-R&D determinants modeled through the WPCs appears to be positive and significant in all specifications. All four conduits of international knowledge transmission are also statistically significant.

We find that countries with higher levels of accumulated knowledge and human capital stocks tend to reap greater productivity gains than those with smaller knowledge and human capital bases. Our findings imply that countries like the US and Germany achieve higher productivity gains from their pool of R&D stocks and human capital than countries such as Spain and New Zealand. We also find that the three sources of knowledge stocks and human capital are complementary in augmenting productivity.

Extensive bootstrap simulations confirm that sample size, in most cases, is not an issue in relation to our results. They also pass an extensive range of sensitivity tests *vis-à-vis* depreciation rates for R&D capital and public infrastructure, alternative measures of TFP, country size and the relative size of the services sector in the economy. In conclusion, domestic knowledge stocks, international knowledge spillover and human capital appear as the robust determinants of domestic productivity across nations, yet a range of other factors also play an important role in explaining productivity.

Table 1: Descriptive Statistics (1982-2004 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 [7]		ICT [8]	FD [9]	Outward FDI[2]	Inward FDI[2]
	Growth Rate	Expenditure [Intensity]	Stocks	Expenditure [Intensity]	Stocks	Stocks	Stocks	Expenditure [Intensity]	Stocks	Imports Intensity	Exports Intensity	Intensity	Intensity	Stocks	Stocks
AU	1.4	2.8 [0.7]	12.7	3.1 [0.8]	17.5	2.6	11.9	9.3 [2.4]	181.9	21.6	4.8	2.9	0.6	67.8	108.1
BE	1.1	2.8 [1.2]	15.6	1.1 [0.5]	6.2	6.8	10.2	4.9 [2.2]	96.4	10.8	9.3	2.8	0.5	90.8	116.4
CA	0.6	6.7 [0.9]	33.1	5.2 [0.7]	28.8	11.5	12.7	17.1 [2.4]	242.5	17.2	8.8	2.2	0.9	160.8	165.2
DK	1.1	1.5 [1.1]	7.0	0.9 [0.7]	4.9	2.0	11.1	2.3 [1.7]	42.1	14.4	13.6	2.9	0.4	25.9	25.8
FIN	2.2	1.8 [1.5]	8.1	0.9 [0.8]	4.8	1.4	10.8	3.6 [3.3]	57.7	16.6	13.4	2.3	0.6	21.8	12.0
FR	1.4	18.2 [1.3]	103.2	11.2 [0.8]	65.7	11.1	10.4	41.4 [3.0]	656.4	16.4	17.5	1.9	0.4	247.8	186.2
DE	1.6	29.9 [1.7]	171.2	13.0 [0.7]	75.5	13.5	12.4	36.9 [2.2]	652.8	16.9	14.9	2.1	0.3	290.2	157.6
GR	1.2	0.2 [0.1]	0.9	0.5 [0.3]	2.5	1.0	9.3	5.1 [3.3]	73.0	10.7	3.8	1.2	0.3	6.5	19.7
IE	3.2	0.5 [0.6]	2.3	0.3 [0.4]	1.3	1.7	9.7	2.7 [3.9]	39.7	28.7	36.7	1.0	0.4	27.1	79.9
IT	0.8	7.5 [0.6]	43.2	6.5 [0.5]	35.8	7.8	8.6	38.3 [3.0]	596.2	13.8	9.7	1.9	0.3	122.0	87.9
JP	1.6	58.0 [2.0]	305.6	21.9 [0.8]	128.9	6.2	11.6	202.5 [7.1]	3157.1	14.6	28.7	2.5	0.8	161.5	22.5
NL	1.1	3.8 [1.0]	22.0	3.0 [0.8]	17.7	6.6	11.2	11.4 [3.1]	204.1	19.8	17.8	2.4	0.8	194.0	139.3
SP	0.7	2.9 [0.4]	14.0	2.6 [0.4]	12.7	4.9	7.6	24.8 [3.6]	317.1	14.1	7.8	2.2	0.4	93.1	133.4
SE	1.1	4.8 [2.3]	24.6	1.9 [0.9]	10.4	2.8	11.2	6.1 [3.0]	109.9	17.2	17.5	3.1	0.7	63.6	40.2
UK	1.3	16.5 [1.3]	100.7	8.1 [0.7]	49.5	11.9	11.2	18.9 [1.5]	350.0	20.7	24.5	2.8	1.6	447.5	275.8
US	1.2	145.8 [1.9]	809.0	52.2 [0.7]	298.0	24.3	12.6	253.6 [3.2]	3570.7	20.0	30.0	3.3	0.9	816.4	663.9
Mean	1.3	19.0 [1.6]	104.6	8.3 [0.7]	47.5	7.3	10.8	42.4 [3.5]	646.7	17.4	19.5	2.7	0.7	177.3	139.6

1. Average annual growth rate of multifactor productivity. 2. Billion constant (2000) PPP US dollars. 3. Intensity (business-sector R&D expenditure as a % of GDP). 4. Intensity (public-sector R&D expenditure as a % of GDP). 5. Human capital, proxied by the average years of schooling of the population group aged 25-64. 6. Public infrastructure, proxied by stocks of public physical capital stock and its intensity, is defined as public infrastructure expenditure as a % of GDP. 7. High-technology exports (imports) as a % of total exports (imports). 8. ICT investment-to-GDP ratio. 9. Financial development, proxied by stock market capitalization-to-GDP ratio.

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

Table 2: Panel Unit Root Tests			
	IPS [W-Stat]	ADF-Fisher [Chi-Square]	Hadri [Consistent Z-stat]
P^m	3.915 [1.000]	26.575 [0.738]	12.848 [0.000]
H	6.980 [1.000]	15.367 [0.994]	13.571 [0.000]
S^b	-0.081 [0.468]	35.084 [0.324]	13.493 [0.000]
S^p	3.776 [0.999]	16.865 [0.987]	13.672 [0.000]
S^{fc}	0.670 [0.749]	40.569 [0.142]	13.373 [0.000]
S^{fI}	2.038 [0.979]	14.797 [0.991]	12.413 [0.000]
S^{fO}	0.407 [0.657]	29.98 [0.467]	12.054 [0.000]
S^{fm}	1.055 [0.854]	24.358 [0.831]	12.565 [0.000]
ICT	-0.387 [0.350]	32.666 [.434]	7.921 [0.000]
F^I	5.188 [1.000]	10.790 [0.999]	11.848 [0.000]
F^O	5.070 [1.000]	9.950 [0.999]	12.233 [0.000]
M^h	-0.341 [0.367]	35.032 [0.3262]	12.506 [0.000]
X^h	1.779 [0.962]	26.263 [0.752]	11.370 [0.000]
SER	1.453 [0.927]	22.209 [0.902]	12.216 [0.000]
Z	6.143 [1.000]	12.650 [0.999]	13.093 [0.000]
P^K	1.912 [0.972]	28.247 [0.657]	8.084 [0.000]
S^{MC}	1.544 [0.939]	17.655 [0.964]	7.964 [0.000]
S^{MV}	1.410 [0.921]	21.084 [0.885]	8.277 [0.000]
E	-0.076 [0.469]	25.795 [0.773]	5.887 [0.000]
P^a	2.965 [0.999]	20.275 [0.946]	13.049 [0.000]
P^{ec}	2.197 [0.986]	27.738 [0.682]	13.034 [0.000]

Sample [1982-2004]. Exogenous variables: Individual effects. For the IPS and Fisher-ADF tests, the maximum lag length of 3 is set, and equation-specific lag lengths are chosen through Schwarz information criteria. W-Stat is the standardized $\bar{t}_{NT}$ test of IPS. ADF Fisher tests are χ^2 (32)-distributed. Altering the lag lengths does not change the qualitative nature of the results. The Hadri test is computed using Newey-West bandwidth selection and Bartlett kernel; the reported test statistic is a heteroskedasticity-consistent Z-statistic. Results of Hadri tests are robust to homoscedasticity and/or serial correlation in the error term.

Table 3: Panel cointegration tests and the FMOLS estimates of cointegrating parameters

	Panel A				**Panel B:** $LogP_{it}^{m}=\alpha_{3i}+\alpha_{3i}^{b}\log S_{it}^{b}+\alpha_{3i}^{p}\log S_{it}^{p}+\alpha_{3i}^{f}\log S_{it}^{f}+\alpha_{3i}^{h}\log H_{t}+\beta' X_{it}+\varepsilon_{3it}$											
Results based on bilateral imports-weighted foreign R&D stocks (S^{fm}).																
	S^{b}	S^{p}	S^{fm}	H	ICT	X^{h}	M^{h}	Z	F^{I}	F^{O}	P^{K}	S^{MC}	S^{MV}	E	SER	WPC
$\rho-statistic(pvalue)$	0.010				0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.001	0.002	0.001	0.001	0.000
$t-statistic(pvalue)$	0.000				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
β	0.089	0.193	0.043	0.197	1.141	-0.102	-0.069	0.049	0.024	0.041	-0.041	0.002	0.006	-0.170	0.227	0.047
	(0.000)	(0.000)	(0.000)	(0.000)	(0.368)	(0.000)	(0.000)	(0.099)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.162)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]	[0.000]
μ	0.121	0.115	0.004	0.303	0.315	-0.008	-0.006	0.151	0.004	0.006	0.002	0.001	0.001	-0.114	0.085	0.006
L^{B}	-0.067	-0.137	-0.042	-0.709	-2.744	-0.511	-0.392	-0.382	-0.027	-0.030	-0.097	-0.042	-0.036	-0.830	-0.614	-0.031
U^{B}	0.309	0.374	0.048	1.297	2.469	0.509	0.354	0.662	0.041	0.038	0.101	0.037	0.034	0.587	0.847	0.043
M^{D}	0.104	0.119	0.004	0.268	-0.420	-0.009	-0.004	0.230	0.002	0.004	0.006	-0.001	0.003	0.027	0.155	0.005
Results based on bilateral R&D collaboration-weighted foreign R&D stocks (S^{fc})																
	S^{b}	S^{p}	S^{fc}	H	ICT	X^{h}	M^{h}	Z	F^{I}	F^{O}	P^{K}	S^{MC}	S^{MV}	E	SER	WPC
$\rho-statistic(pvalue)$	0.001				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$t-statistic(pvalue)$	0.000				0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.115	0.000	0.000
β	0.133	0.188	-0.013	0.246	0.750	0.142	-0.089	0.259	0.019	0.046	0.003	0.030	0.022	0.154	-0.364	0.044
	(0.000)	(0.000)	(0.120)	(0.009)	(0.001)	(0.436)	(0.004)	(0.001)	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.085)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]
μ	0.098	0.114	0.010	0.269	0.324	0.024	-0.043	0.190	0.004	0.004	0.002	0.001	-0.002	-0.098	0.071	0.003
L^{B}	-0.108	-0.126	-0.043	-0.727	-2.695	-0.527	-0.448	-0.305	-0.031	-0.032	-0.117	-0.045	-0.046	-0.756	-0.582	-0.029
U^{B}	0.286	0.364	0.061	1.366	2.120	0.447	0.328	0.695	0.039	0.040	0.109	0.041	0.039	0.545	0.725	0.038
M^{D}	0.098	0.144	0.012	0.325	0.466	-0.070	-0.028	0.187	0.007	0.005	-0.007	-0.001	-0.002	-0.033	0.045	0.003

All variables are in logs. Panel A reports the results of benchmark model (equation (2)). Panel B reports results of augmented model; e.g., column ICT augments the benchmark model by the ICT variable. The group ρ - and group t-statistics are panel cointegration tests (Pedroni, 1999). The depreciation rates for S_{it}^{f} and Z are 15% and 3%, respectively. β -vector is the cointegrating parameter; μ and M^{D} are the mean and median values of bootstrap parameters; U^{B} and L^{B} are upper and lower bounds. 1,000 bootstrap parameters are computed. (.) are asymptotic and [.] are bootstrap p-values. The letters are derived by bootstrapping the distribution of the test statistics as suggested by Goncalves and White (2005). This implies that the bootstrapped mean value is significant despite having negative lower and positive upper bounds. For details on variables, see notes to Table 4.

Table 4: Panel Cointegration Tests and FMOLS Estimates of Cointegrating Parameters

	Panel A				Panel B											
Results based on bilateral inward FDI-weighted foreign R&D stocks (S^{fI})																
	S^b	S^p	S^{fI}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
$\rho - statistic(pvalue)$	0.001				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$t - statistic(pvalue)$	0.022				0.000	0.000	0.001	0.000	0.019	0.013	0.000	0.000	0.000	0.003	0.000	0.000
β	0.093	0.171	0.001	0.388	1.463	0.164	0.064	0.165	0.026	0.040	-0.065	0.021	0.010	0.009	-0.051	0.036
	(0.000)	(0.000)	(0.262)	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.040)	(0.000)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]
μ	0.104	0.123	0.001	0.374	0.145	0.013	-0.002	0.172	0.007	0.004	0.001	0.002	0.000	-0.065	0.041	0.005
L^B	-0.114	-0.165	-0.033	-0.843	-2.302	-0.612	-0.369	-0.451	-0.028	-0.027	-0.124	-0.033	-0.039	-0.656	-0.677	-0.031
U^B	0.324	0.427	0.035	1.603	2.489	0.579	0.433	0.736	0.043	0.041	0.099	0.037	0.041	0.592	0.675	0.041
M^D	0.119	0.123	0.001	0.371	-0.113	0.113	0.016	0.192	0.007	0.002	0.009	0.001	0.001	-0.082	0.097	0.004
Results based on bilateral outward FDI-weighted foreign R&D stocks (S^{fO})																
	S^b	S^p	S^{fO}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
$\rho - statistic(pvalue)$	0.000				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
$t - statistic(pvalue)$	0.022				0.002	0.000	0.002	0.000	0.014	0.076	0.000	0.000	0.000	0.004	0.000	0.000
β	0.071	0.161	0.005	0.665	1.723	0.007	0.026	0.196	0.022	0.047	-0.065	0.028	0.012	-0.066	0.030	0.036
	(0.000)	(0.000)	(0.427)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.212)	(0.011)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]
μ	0.106	0.128	0.002	0.320	0.143	0.003	-0.021	0.200	0.005	0.005	0.007	0.003	0.003	-0.019	0.035	0.006
L^B	-0.107	-0.148	-0.036	-0.871	-2.402	-0.545	-0.454	-0.363	-0.029	-0.030	-0.101	-0.031	-0.039	-0.685	-0.638	-0.032
U^B	0.314	0.398	0.035	1.404	2.611	0.525	0.366	0.740	0.039	0.042	0.122	0.043	0.043	0.653	0.748	0.041
M^D	0.117	0.121	0.003	0.213	-0.025	-0.011	-0.053	0.185	-0.001	0.007	0.004	0.007	0.003	0.032	0.127	0.007

The variables are: S^b = business-sector R&D capital stock; S^p =public-sector R&D capital stock; H = human capital; ICT =information and communication technology; X^h =ratio of high-technology exports to total exports; M^h =ratio of high-technology imports to total imports; Z = public physical infrastructure; F^I = stock of inward FDI; F^O = stock of outward FDI; P^K **=** ratio of private-sector credit by deposit money banks and other financial institutions to GDP; S^{MC} **=** stock market capitalization-to-GDP ratio; S^{MV} **=**stock market total value traded-to-GDP. ratio; E =employment rate; SER=value added of the services sector relative to GDP; WPC = weighted principal component. For other definitions please refer to the end notes of Table 3.

Table 5: FMOLS Estimates of Mean-Interacted Specifications

	Panel A				**Panel B**				**Panel C**			
Estimation based on bilateral imports-weighted foreign R&D stocks (S^{fm})												
	$S_{it}^{b} * \bar{S}_{i}^{b}$	$S_{it}^{p} * \bar{S}_{i}^{b}$	$S_{it}^{fm} * \bar{S}_{i}^{b}$	$H_{it} * \bar{S}_{i}^{b}$	$S_{it}^{b} * \bar{S}_{i}^{p}$	$S_{it}^{p} * \bar{S}_{i}^{p}$	$S_{it}^{fm} * \bar{S}_{i}^{p}$	$H_{it} * \bar{S}_{i}^{p}$	$S_{it}^{b} * \bar{H}_{i}$	$S_{it}^{p} * \bar{H}_{i}$	$S_{it}^{fm} * \bar{H}_{i}$	$H_{it} * \bar{H}_{i}$
β	0.008 (0.000) [0.000]	0.021 (0.000) [0.000]	0.005 (0.000) [0.000]	0.009 (0.000) [0.000]	0.009 (0.000) [0.000]	0.021 (0.000) [0.000]	0.005 (0.000) [0.000]	0.014 (0.000) [0.000]	0.039 (0.000) [0.000]	0.080 (0.000) [0.000]	0.018 (0.000) [0.000]	0.071 (0.000) [0.000]
μ	0.012	0.013	0.000	0.026	0.013	0.012	0.000	0.025	0.051	0.051	0.001	0.118
L^{B}	-0.007	-0.012	-0.005	-0.079	-0.007	-0.014	-0.005	-0.088	-0.034	-0.051	-0.021	-0.334
U^{B}	0.030	0.038	0.006	0.134	0.030	0.038	0.006	0.142	0.131	0.159	0.023	0.567
M^{D}	0.010	0.013	0.001	0.021	0.013	0.009	0.000	0.028	0.048	0.047	-0.001	0.116
Estimation based on bilateral R&D collaboration-weighted foreign R&D stocks (S^{fc})												
	$S_{it}^{b} * \bar{S}_{i}^{b}$	$S_{it}^{p} * \bar{S}_{i}^{b}$	$S_{it}^{fc} * \bar{S}_{i}^{b}$	$H_{it} * \bar{S}_{i}^{b}$	$S_{it}^{b} * \bar{S}_{i}^{p}$	$S_{it}^{p} * \bar{S}_{i}^{p}$	$S_{it}^{fc} * \bar{S}_{i}^{p}$	$H_{it} * \bar{S}_{i}^{p}$	$S_{it}^{b} * \bar{H}_{i}$	$S_{it}^{p} * \bar{H}_{i}$	$S_{it}^{fc} * \bar{H}_{i}$	$H_{it} * \bar{H}_{i}$
β	0.013 (0.000) [0.000]	0.019 (0.000) [0.000]	-0.001 (0.120) [0.002]	0.026 (0.009) [0.000]	0.013 (0.000) [0.000]	0.019 (0.000) [0.000]	-0.001 (0.120) [0.002]	0.031 (0.009) [0.000]	0.057 (0.000) [0.000]	0.078 (0.000) [0.000]	-0.005 (0.120) [0.002]	0.098 (0.009) [0.000]
μ	0.010	0.012	0.001	0.027	0.010	0.013	0.001	0.027	0.041	0.049	0.004	0.114
L^{B}	-0.009	-0.014	-0.004	-0.078	-0.011	-0.015	-0.004	-0.078	-0.042	-0.056	-0.016	-0.316
U^{B}	0.030	0.038	0.006	0.133	0.030	0.038	0.006	0.133	0.125	0.158	0.025	0.537
M^{D}	0.008	0.011	0.001	0.035	0.010	0.011	0.001	0.019	0.041	0.049	0.002	0.144

Panels A, B and C report estimated results of models (4), (5) and (6) in the text, respectively. S^{b} and S^{p} denote, respectively, domestic business- and private-sector R&D capital stocks. H denotes human capital stocks. $\bar{S}_{i}^{b} = T_{i}^{-1}\sum_{t=1}^{T_i} S_{it}^{b}$; $\bar{S}_{i}^{p} = T_{i}^{-1}\sum_{t=1}^{T_i} S_{it}^{p}$; and $\bar{H}_{i} = T_{i}^{-1}\sum_{t=1}^{T_i} H_{i,t}$. Variable mnemonics are defined in the notes to Table 4.

Additional Results for Robustness

Table A1: : Panel cointegration tests and FMOLS estimates of the cointegrating parameter
R&D capital stocks at 10% depreciation rate

	Panel A				**Panel B**											
Results based on bilateral imports-weighted foreign R&D stocks (S^{fm}).																
	S^b	S^p	S^{fm}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
$\rho-statistic(pvalue)$	0.008				0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.000
$t-statistic(pvalue)$	0.000				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
β	0.019	0.258	0.041	0.208	1.594	-0.109	-0.102	-0.107	0.020	0.034	-0.037	0.015	0.024	-0.149	0.115	0.035
	(0.002)	(0.000)	(0.000)	(0.000)	(0.043)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.128)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.002]	[0.002]	[0.000]
μ	0.060	0.199	0.000	0.215	0.304	-0.031	-0.031	0.059	0.003	0.004	0.002	0.001	0.002	-0.056	0.017	0.005
L^B	-0.205	-0.151	-0.051	-0.950	-2.861	-0.576	-0.401	-0.600	-0.033	-0.030	-0.118	-0.041	-0.038	-0.778	-0.731	-0.032
U^B	0.320	0.548	0.048	1.334	2.230	0.530	0.327	0.653	0.036	0.036	0.115	0.039	0.039	0.629	0.743	0.039
M^D	0.091	0.204	0.000	0.267	-0.302	-0.046	-0.059	0.138	0.003	0.002	0.009	-0.001	-0.001	-0.089	0.065	0.005
Results based on bilateral R&D collaboration-weighted foreign R&D stocks (S^{fc})																
	S^b	S^p	S^{fc}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
$\rho-statistic(pvalue)$	0.001				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$t-statistic(pvalue)$	0.001				0.000	0.000	0.000	0.000	0.004	0.012	0.000	0.000	0.000	0.220	0.000	0.007
β	0.047	0.309	-0.018	0.123	1.097	0.074	-0.130	0.025	0.015	0.033	0.000	0.027	0.024	0.255	-0.563	0.035
	(0.002)	(0.000)	(0.002)	(0.054)	(0.000)	(0.103)	(0.000)	(0.248)	(0.000)	(0.000)	(0.160)	(0.000)	(0.000)	(0.252)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
μ	0.074	0.175	0.003	0.188	0.223	0.004	-0.039	0.049	0.002	0.004	0.001	0.001	-0.001	-0.038	0.003	0.004
L^B	-0.188	-0.212	-0.051	-0.864	-2.441	-0.497	-0.432	-0.508	-0.031	-0.030	-0.119	-0.039	-0.041	-0.647	-0.616	-0.031
U^B	0.345	0.524	0.053	1.279	1.867	0.527	0.343	0.620	0.039	0.038	0.121	0.035	0.039	0.592	0.705	0.042
M^D	0.095	0.197	0.000	0.166	-0.622	-0.039	0.020	0.086	0.002	0.003	-0.005	-0.002	0.000	0.034	-0.096	0.008

For all definitions, please refer to the end notes of Tables 3 and 4.

Table A2: : FMOLS estimates of the mean-interacted specifications
R&D capital stocks at 10% depreciation rate

	Panel A				Panel B				Panel C			
Estimation based on bilateral imports-weighted foreign R&D stocks (S^{fm})												
	$S^b_{it}*\bar{S}^b_i$	$S^p_{it}*\bar{S}^b_i$	$S^{fm}_{it}*\bar{S}^b_i$	$H_{it}*\bar{S}^b_i$	$S^b_{it}*\bar{S}^p_i$	$S^p_{it}*\bar{S}^p_i$	$S^{fm}_{it}*\bar{S}^p_i$	$H_{it}*\bar{S}^p_i$	$S^b_{it}*\bar{H}_i$	$S^p_{it}*\bar{H}_i$	$S^{fm}_{it}*\bar{H}_i$	$H_{it}*\bar{H}_i$
β	0.001	0.028	0.004	0.010	0.001	0.027	0.004	0.014	0.010	0.108	0.017	0.074
	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
μ	0.006	0.019	0.000	0.022	0.006	0.019	0.000	0.020	0.024	0.085	0.000	0.100
L^B	-0.022	-0.014	-0.005	-0.091	-0.021	-0.016	-0.005	-0.092	-0.098	-0.073	-0.021	-0.327
U^B	0.031	0.055	0.005	0.138	0.031	0.054	0.005	0.120	0.142	0.244	0.022	0.609
M^D	0.006	0.015	0.001	0.029	0.008	0.019	0.000	0.023	0.007	0.095	0.002	0.086
Estimation based on bilateral R&D collaboration-weighted foreign R&D stocks (S^{fc})												
	$S^b_{it}*\bar{S}^b_i$	$S^p_{it}*\bar{S}^b_i$	$S^{fc}_{it}*\bar{S}^b_i$	$H_{it}*\bar{S}^b_i$	$S^b_{it}*\bar{S}^p_i$	$S^p_{it}*\bar{S}^p_i$	$S^{fc}_{it}*\bar{S}^p_i$	$H_{it}*\bar{S}^p_i$	$S^b_{it}*\bar{H}_i$	$S^p_{it}*\bar{H}_i$	$S^{fc}_{it}*\bar{H}_i$	$H_{it}*\bar{H}_i$
β	0.005	0.030	-0.001	0.010	0.005	0.029	-0.001	0.014	0.021	0.129	-0.007	0.043
	(0.002)	(0.000)	(0.002)	(0.054)	(0.002)	(0.000)	(0.002)	(0.054)	(0.002)	(0.000)	(0.002)	(0.054)
	[0.000	[0.000	[0.002	[0.000	[0.000	[0.000	[0.002	[0.000	[0.000	[0.000	[0.002	[0.000]
μ	0.007	0.017	0.000	0.017	0.007	0.017	0.000	0.015	0.028	0.076	0.002	0.080
L^B	-0.019	-0.017	-0.005	-0.082	-0.019	-0.019	-0.005	-0.089	-0.086	-0.089	-0.020	-0.395
U^B	0.033	0.054	0.005	0.118	0.031	0.051	0.005	0.126	0.149	0.239	0.024	0.578
M^D	0.007	0.019	0.000	0.011	0.008	0.020	0.000	0.018	0.030	0.081	0.001	0.086

For definitions, please refer to the end notes of Table 5.

Table A3: FMOLS estimates of the cointegrating parameter based on alternative measures of TFP

	Panel A				Panel B											
Results based on our own measure of TFP (P^a)																
	S^b	S^p	S^{fm}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
β	0.150	0.051	0.055	0.336	1.874	0.056	-0.031	-0.138	0.028	0.035	-0.039	0.034	0.028	-0.024	-0.200	0.050
	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.001)	(0.007)	(0.433)	(0.000)	(0.000)	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.002]	[0.002]	[0.000]
μ	0.105	0.126	0.004	0.240	0.314	-0.014	-0.025	0.170	0.003	0.004	0.004	0.000	0.000	-0.107	0.082	0.004
L^B	-0.073	-0.120	-0.039	-0.813	-2.912	-0.543	-0.372	-0.350	-0.032	-0.033	-0.106	-0.035	-0.036	-0.758	-0.613	-0.036
U^B	0.283	0.383	0.051	1.364	2.148	0.474	0.329	0.701	0.035	0.038	0.115	0.035	0.036	0.490	0.752	0.041
M^D	0.105	0.126	0.007	0.377	-0.127	0.039	-0.024	0.169	0.002	0.005	0.007	0.002	0.000	0.062	0.051	0.004
Results based on the European Commission's data on TFP (P^{ec})																
	S^b	S^p	S^{fm}	H	ICT	X^h	M^h	Z	F^I	F^O	P^K	S^{MC}	S^{MV}	E	SER	WPC
β	0.121	0.068	0.069	0.298	1.108	0.017	-0.068	-0.074	0.026	0.036	-0.067	0.025	0.022	-0.128	-0.168	0.050
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.012)	(0.030)	(0.115)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]	[0.000]
μ	0.103	0.130	0.005	0.290	0.311	-0.027	-0.020	0.172	0.004	0.004	0.007	0.001	-0.001	-0.098	0.077	0.004
L^B	-0.084	-0.129	-0.042	-0.890	-2.857	-0.500	-0.410	-0.307	-0.029	-0.032	-0.111	-0.032	-0.036	-0.846	-0.567	-0.031
U^B	0.281	0.373	0.049	1.362	2.057	0.418	0.317	0.694	0.038	0.039	0.129	0.033	0.034	0.533	0.677	0.040
M^D	0.105	0.119	0.005	0.308	-0.536	-0.007	-0.042	0.166	0.001	0.002	0.005	0.004	-0.003	-0.045	0.097	0.003

All the reported models are cointegrated. Panel cointegration tests with these alternative measures of TFP appear close to those reported in Tables 3 and 4. To economize on the size of the table, we do not report the results of cointegration tests. Data on P^{ec} are directly available from the EC. We compute P^a as: log P^a = log GDP – 0.3 log K – 0.7 log L; where K is total net physical capital stock and L is total employment level. For other definitions, please refer to the notes to Table 3. For variable mnemonics see Table 4.

Table A4: Panel Cointegration Tests and FMOLS Estimates of the Cointegrating Parameter															
	Panel A			**Panel B**											
	S^b	S^p	S^{fm}	H	ICT	X^h	M^h	Z	F^I	F^O	S^{MC}	S^{MV}	E	SER	WPC
Australia*	0.105	0.152	0.047	0.284	1.356	0.012	-0.052	0.011	0.028	0.043	0.011	0.010	-0.183	0.317	0.046
Belgium*	0.081	0.196	0.053	0.186	1.248	-0.075	-0.038	0.020	0.025	0.043	0.011	0.015	-0.174	0.238	0.045
Canada*	0.097	0.222	0.046	-0.033	1.608	-0.049	-0.034	0.091	0.019	0.029	0.009	0.014	-0.195	0.288	0.035
Denmark*	0.129	0.136	0.036	0.212	0.799	-0.036	-0.073	0.050	0.027	0.043	0.019	0.021	-0.164	0.152	0.047
Finland*	0.085	0.208	0.043	0.146	1.331	-0.114	-0.079	0.070	0.024	0.045	0.012	0.016	-0.156	0.282	0.045
France*	0.075	0.214	0.038	0.185	1.148	-0.100	-0.065	0.033	0.025	0.044	0.012	0.016	-0.186	0.240	0.045
Germany*	0.105	0.176	0.037	0.170	1.206	-0.103	-0.059	0.062	0.025	0.043	0.013	0.017	-0.177	0.196	0.045
Greece*	0.081	0.187	0.042	0.372	0.577	-0.204	-0.083	-0.041	0.023	0.039	0.008	0.015	-0.193	0.347	0.042
Ireland*	0.086	0.195	0.033	0.183	1.347	-0.093	-0.049	0.061	0.027	0.044	n.a.	n.a.	-0.166	0.218	0.047
Italy*	0.063	0.237	0.046	0.144	0.346	-0.189	-0.151	0.074	0.025	0.040	0.005	0.010	-0.111	0.134	0.044
Japan*	0.068	0.222	0.042	0.226	1.387	-0.050	-0.041	0.073	0.021	0.040	0.013	0.016	-0.250	0.232	0.038
Netherlands*	0.091	0.176	0.048	0.237	1.221	-0.126	-0.098	0.037	0.024	0.042	0.011	0.016	-0.146	0.253	0.044
Spain*	0.099	0.184	0.044	0.271	0.667	-0.195	-0.168	0.016	0.017	0.041	0.004	0.015	-0.122	0.097	0.041
Sweden*	0.069	0.225	0.046	0.231	1.399	-0.079	-0.024	0.081	0.023	0.044	0.016	0.017	-0.202	0.241	0.044
United Kingdom*	0.099	0.156	0.047	0.193	1.207	-0.120	-0.069	0.076	0.022	0.041	0.011	0.014	-0.188	0.176	0.043
United States*	0.085	0.200	0.045	0.143	1.406	-0.111	-0.030	0.075	0.035	0.037	0.010	0.017	-0.103	0.227	0.041

Note: * indicates exclusion of the country from the sample while computing these results. For example, Australia* denotes exclusion of Australia from the sample while estimating the results of the first row. The same structure applies for the results in other rows. All specifications are cointegrated. Again, to save space, we do not report these 16 sets of panel cointegration tests. Greece does not have data on S^{MC} and S^{MV}.

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Data Appendix

Data on multifactor productivity (P^m) are obtained from the OECD (2008). German data are available from 1991 only; we extrapolated pre-1991 data using the growth rate of the TFP series obtained from Timmer, Ypma and Van Ark (2003). However, dropping Germany from the sample does not change our results (see Section 6). Two further measures of TFP are used for robustness. The first one is our own measure of TFP (P^a) calculated as: log P^a = log GDP – 0.3 log K – 0.7 log L, where K is total net physical capital stock and L is total employment level. The second measure of TFP (P^{ec}) is published by the EC. Domestic business-sector R&D capital stocks (S^b) are calculated from business-sector R&D expenditure (E_b^{RD}), using the perpetual inventory method. Initial stock, S_0^b**,** is calculated as:

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

where δ denotes the depreciation rate, g is the average annual growth rate of E_b^{RD} over the sample, and $E_{b,o}^{RD}$ is the initial value of E_b^{RD}. This method of computing capital stocks requires making assumptions about the average life of capital stocks and depreciation rates, which do not always capture the complexity of different types of capital assets and the different depreciation rates affecting them. The issues of taxes on capital assets and the price of capital further complicate the matter. However, this method is widely used in the literature on the grounds of cost and convenience, and we do the same. All R&D capital stocks are computed using 15, 10 and 5 percent depreciation rates. Public-sector R&D expenditure (E_p^{RD}) is the total R&D expenditure of the government and higher education sectors. Public-sector R&D capital stocks (S^p) are generated from public-sector R&D expenditure (E_p^{RD}), applying the same approach as in equation (A1). Due to the lack of R&D deflators, R&D expenditure data are converted to constant prices by the GDP deflators. Initial capital stocks, S_o^b and S_0^p, are generated for the earliest year for which R&D expenditure data are available (their availability ranges from the late 1960s to early 1980s).

We compute four different measures of foreign R&D capital stocks using bilateral imports, bilateral R&D collaborations and stocks of bilateral inward and outward FDI as weights, following the approach suggested by Lichtenberg and van Pottelsberghe (1998). In this framework, the import ratio-weighted foreign R&D capital stock (S^{fm}) is:

$$S_{i,t}^{fm} = \sum_{j=1}^{N-i} (M_{ij,t} / Y_{j,t}) * S_{j,t}^{b} \qquad \text{(A2)}$$

where, Y_j denotes the GDP of country j and M_{ij} is the imports of country i from country j; throughout, 't' denotes time subscript. We use bilateral capital import ratios which include chemicals and related products (SITC 5), manufactured goods classified chiefly by material (SITC 6), machinery and transport equipment (SITC 7), and miscellaneous manufactured articles (SITC 8). Agro-industries and raw materials (SITC 0-4) are excluded. The bilateral R&D collaboration-weighted foreign knowledge stock (S^{fc}) is:

$$S_{i,t}^{fc} = \sum_{j=1}^{N-i} (PC_{ij,t} / TP_{i,t}) * S_{j,t}^{b} \qquad \text{(A3)}$$

where TP_i is country i's total patent applications and PC_{ij} is its joint patent applications with countries J, both filed at the EPO. Data on patent applications are obtained from the EPO. We compute 15X23 matrixes of bilateral patent cooperation coefficients for each sample country. Likewise, foreign R&D capital stocks based on inward (S^{fI}) and outward (S^{fO}) FDI stocks are computed as:

$$S_{i,t}^{fI} = \sum_{j=1}^{N-i} (FDI_{ij,t} / K_{j,t}) * S_{j,t}^{b} \qquad \text{(A4)}$$

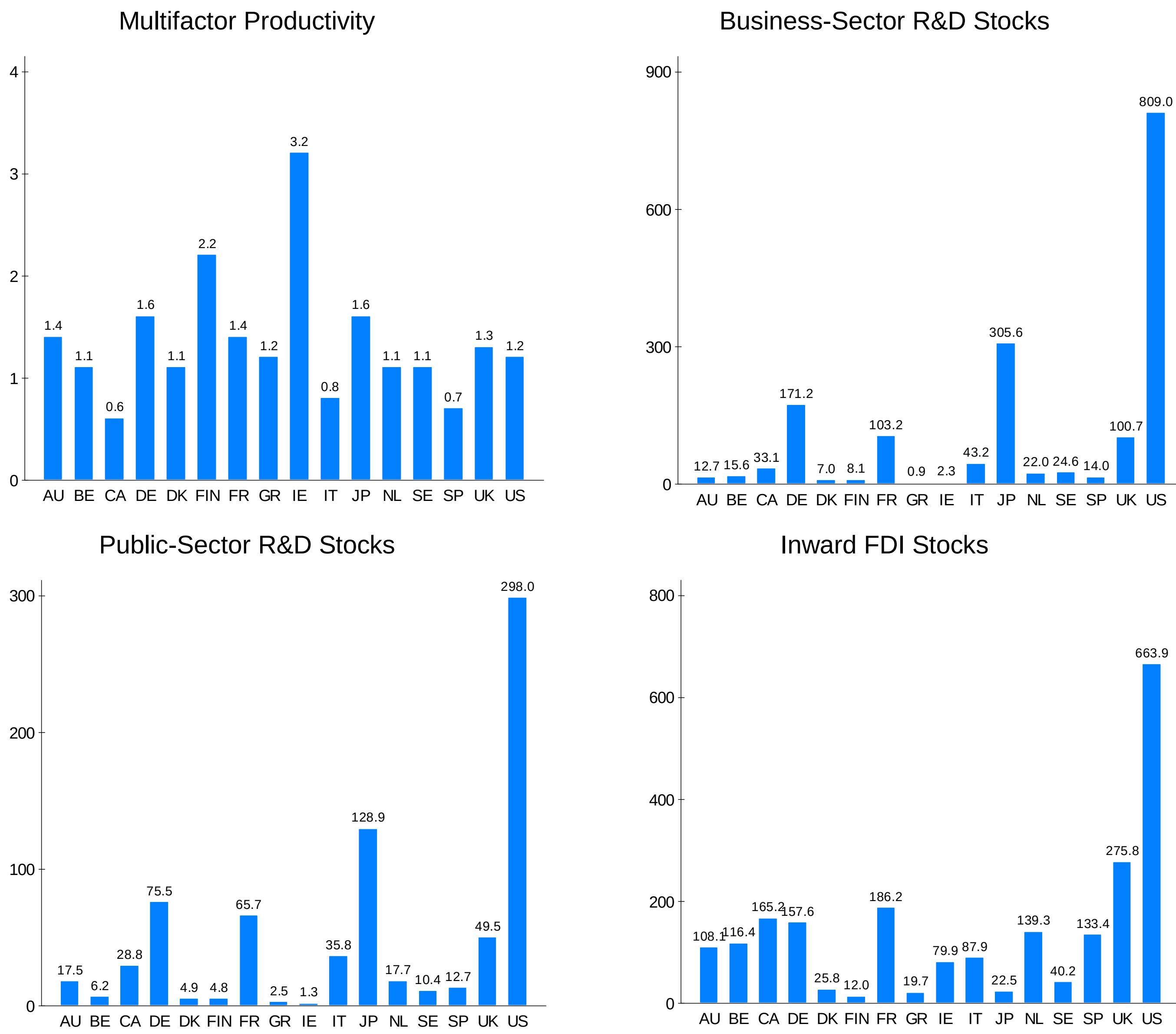
$$S_{i,t}^{fO} = \sum_{j=1}^{N-i} (FDO_{ij,t} / K_{j,t}) * S_{j,t}^{b} \qquad \text{(A5)}$$

where K_j is country J's capital stock, generated from non-resident fixed capital formation using the perpetual inventory method at an 8.0 percent depreciation rate. FDI_{ij} is country i's FDI stock originating in country j; FDO_{ij} is country J's FDI stocks originating in country i. Data are expressed in constant 2000 prices using the GDP deflator. The relevant weights for all foreign knowledge stocks are computed using three-year moving averages to avoid yearly fluctuations. Human capital (H) is proxied by the average years of schooling of the 25-64 age group. Bassanini and Scarpetta (2002) kindly provided data for the period up to 2000; we extrapolate the last four observations. We acknowledge that this is only a rough measure of human capital, but we do not have any suitable alternative measures. Data on ICT investment consist of non-resident investment in hardware, communications equipment and software. They are expressed as a percentage of GDP. High-technology exports (X^h) and imports (M^h) are expressed as a percentage of total exports and imports, respectively. We follow the OECD's (2007) definitions of high-technology items of trade, which include: pharmaceuticals (ISIC.2423); office, accounting and computing machinery (ISIC.30); radio, TV and communications equipment (ISIC.32); medical, precision and optical instruments (ISIC.33); and aircraft and spacecraft (ISIC.353). Service sector (SER) is measured as the value added of the service sector relative to GDP. The service sector consists of ISIC Rev.3 industries from 50 to 90. The proxy for the business cycle is the rate of employment (E).

Stocks of public infrastructure (Z) is generated from government's fixed capital formation (I^{gov}) using the perpetual inventory method (equation (A1)). I^{gov} is converted to constant 2000 PPP US dollars using the fixed capital formation deflator. Measures of Z based on 3, 5 and 8 percent depreciation rates are generated. Data on stocks of inward (F^{I}) and outward (F^{O}) FDI are published by the United Nations Conference on Trade and Development (UNCTAD) in current US dollars. They are converted to constant PPP dollars using GDP deflator and PPP exchange rates. Banking sector development is proxied by the ratio of private-sector credit by deposit money banks and other financial institutions to GDP (P^{K}). Two measures of capital market development are the stock market capitalization-to-GDP ratio (S^{MC}) and the stock market total value traded-to-GDP ratio (S^{MV}). They are well-known measures of financial sector development (see Beck and Levine, 2002; Luintel *et al.*, 2008).

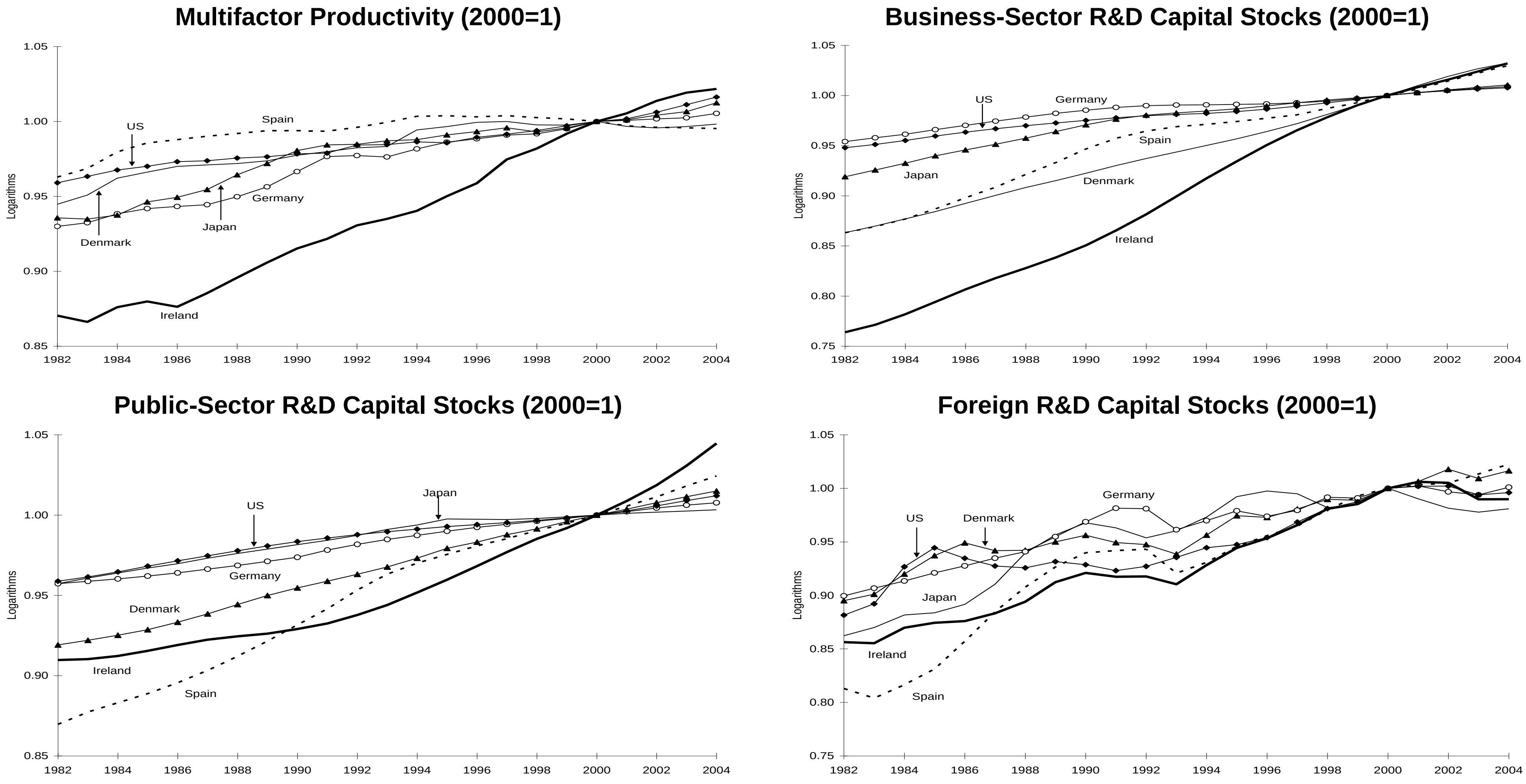
Data	**Sources**
Multifactor productivity and ICT	Multifactor Productivity Database (OECD)
Total factor productivity, capital stocks	AMECO Database (European Commission)
R&D expenditure	Research and Development Database (OECD)
Human capital	Bassanini and Scarpetta (2002)
High-technology exports and imports, and total exports and imports	STAN Bilateral Database (OECD)
Stocks of total inward and outward foreign direct investment	UNCTAD's foreign investment database
Private-sector credit by deposit money banks and other financial institutions to GDP, stock market capitalization to GDP and stock market total value traded to GDP	World Bank
Service sector value added	STAN Indicators Database (OECD)
GDP, GDP deflator, total employment level, employment rate, PPP exchange rate, government fixed capital formation and its deflator, non-resident fixed capital formation and its deflator, investment	Analytical Database (OECD)
Bilateral imports	International Trade by Commodities Statistics Database (OECD)
Patent applications at the European Patent Office	Patent Database (OECD)

Figure 1:



Note: R&D and FDI data are in constant PPP$ and 1982-2004 mean values. Country codes: Australia (AU), Belgium (BE), Canada (CA), Denmark (DK), Finland (FIN), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Japan (JP), Netherlands (NL), Spain (SP), Sweden (SE), United Kingdom (UK) and United States (US)

Figure 2



For visual ease of cross-country comparisons, these plots are normalized at 2000=1.

[1] See, among others, Griliches and Mairesse, 1990; Hall and Mairesse, 1995, and the review by Griliches (1988).

[2] We acknowledge that it is not always convincing to lump all other determinants of productivity except for the three forms of R&D capital stocks as non-R&D determinants. For example, it is hard to segregate ICT from its knowledge content, and similar arguments may apply in other cases. However, for the sake of convenience, and without any prejudice, we denote them as "non-R&D" determinants throughout.

[3] Of course, productivity has been separately modelled as a function of a range of other variables, like cross-border flow of people (Andersen and Dalgaard, 2006) and structural composition of the economy (Moro, 2007), to name but a few. However, our focus here is on those studies that augment R&D capital stocks by other (non-R&D) determinants.

[4] We acknowledge that there are other channels of knowledge spillover, e.g., international student flows (Park, 2004; Le, 2010), indirect trade-related knowledge spillovers (Lumenga-Neso *et al.*, 2005), information technology (Zhu and Jeon, 2007), telephone traffic (Wong, 2004), to name but a few.

[5] 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.

[6] As expected, the R&D and non-R&D determinants shown in equation (3) are positively correlated except that employment rate (E) shows negative correlations with inward FDI (-0.107) and inward FDI-weighted foreign knowledge stocks (-0.019).

[7] It is well known that a higher dimensional system produces more stable cointegrating relationships and that the joint inclusion of all relevant variables also makes estimates robust to potential misspecification bias - e.g., the exclusion of relevant variables.

[8] It is often argued that R&D intensity measures capture cross-country differences in R&D activity. However, Khan and Luintel (2006) illustrate that intensity measures fail to capture the full extent of disparity in R&D activity across sample countries. Instead, they show that the mean levels of R&D activity better capture such differences; hence we use the mean levels of S_{it}^{b}, S_{it}^{p} and H_{it} to capture cross-country heterogeneity.

[9] The dynamic heterogeneous panel estimators do provide country-specific parameters however, they are not informative as to the potential complementary between various sources of knowledge stocks and human capital as specified in equations (4) to (6).

[10] Our specifications capture within-country variations and are similar in spirit to Beck and Levine (2002). Luintel *et al.* (2008) elaborate on the alternative specifications involving interacted covariates.

[11] For brevity, we do not outline these test statistics; however, they are detailed in Pedroni (1999). Alternative panel cointegration tests proposed by Kao (1999), Kao, Chiang and Chen (1999) and McCoskey and Kao (1998) all assume homogeneous cointegrating vectors across panel members, and are hence less appealing in the present context.

[12] As stated above, Pedroni's panel estimates are essentially the mean of the country-specific FMOLS estimates of Philips and Hansen (1990).

[13] We do not report the results of panel unit root tests on the first differenced data; however, the results are available on request.

[14] The truncated CIPS tests resume t-ratios of 1.237, 0.881 and -2.543, respectively, for models without deterministic components, with a constant, and with a constant and a linear time trend. In order to reject the null of a unit root in the panel, these t-ratios must be negatively signed and significant. The respective 5 percent critical values reported by Pesaran (2007) for a panel of N=15 and T=20 are -1.65, -2.26 and -2.78. Clearly, the null of unit root in the panel cannot be rejected in any case.

[15] We do not report these results to conserve space; however, they are available on request. Yet another group is the ICT and Services Sector (ICT and SER), which is addressed in Section 6 (last paragraph). R&D and human capital remain robust to the joint use of these two variables as well. We thank an anonymous referee for suggesting these specifications.

[16] For example, our findings on ICT are consistent to those of Gordon (2000) and O'Mahony and van Ark, (2005); those on FDI are inconformity with Griffiths et al., (2006) and Keller and Yeaple (2009).