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Ioannis Bournakis[1], Dimitris Christopoulos[2], and Sushanta Mallick[3]

Abstract

Given the decline in growth momentum in the manufacturing sector in many OECD countries, the role of knowledge-based capital has emerged as a key driver for sustained growth. While empirical studies on estimating knowledge spillovers have usually been undertaken at the country level, the spillover effects can be more definitive only if the analysis is conducted at the industry-level. This paper therefore attempts to identify spillovers by disentangling technological innovations into intra- and inter-national knowledge innovations at industry level in driving per capita output growth. Our main findings are first, that there is evidence for a robust positive relationship between R&D, human capital and output growth across these countries at industry-level. Second, the potential of international spillover gains is greater in countries with higher human capital and in industries whose pattern of production is more R&D oriented, import intensive, and dependent on vertical FDI. Finally, significant heterogeneity is found between high and low-tech industries with high-tech group displaying greater knowledge spillovers, suggesting that low-tech industries need to be more innovative in order to absorb the technological advancements of domestic and international rivals.

JEL: F1, F6, O3, O4
Keywords: Knowledge spillover; Industry-level productivity; R&D

The authors

[1] Department of Economics and International Development, Middlesex University, London, NW4 4BT, UK; E-Mail: I.Bournakis@mdx.ac.uk
[2] Department of Economic and Regional Development, Panteion University, Syngrou Ave. 136, 176 71 Athens, Greece
[3] School of Business and Management, Queen Mary University of London, Mile End Road, London E1 4NS, UK

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1. Introduction

Productivity growth is widely regarded as the main source of welfare and economic prosperity. Over the last fifty years, economic literature has identified various sources of productivity growth in an attempt to understand why countries grow at a different rate. Historically, developed nations followed a strategy of physical and human capital deepening

[1] Department of Economics and International Development, Middlesex University, London, NW4 4BT, UK; Email: I.Bournakis@mdx.ac.uk
[2] Department of Economic and Regional Development, Panteion University, Syngrou Ave. 136, 176 71, Athens, Greece; E-mail: christod@panteion.gr
[3] School of Business and Management, Queen Mary University of London, Mile End Road, London E1 4NS, UK; Email: s.k.mallick@qmul.ac.uk

in stimulating growth and higher levels of per capita income (van Aark et al.(1993)) and Dougherty and Jorgenson (1996)). As countries approach the international technological frontier, to remain in a high growth trajectory must invest in the generation of new knowledge and ideas through R&D.[4] Investment in R&D is the main source of knowledge accumulation that vastly contributes to productivity growth at industry level, although human capital has been considered to disentangle productivity-raising innovation in aggregate level studies.

In parallel with the investigation of the channels that create new knowledge, the research agenda has focused on the importance of knowledge diffusion (see Hall et al. (2010) and Syverson (2011) for an update review in the topic) as an equally crucial driver of productivity growth. Keller (1998), Keller (2004) and León-Ledesma (2005) (among others) considered international trade as a driver for the diffusion of R&D spillover, which in turn boosts productivity growth. The diffusion of existing knowledge can also accelerate growth increasing the social return to R&D. The diffusion of knowledge can be either national or international in scope, with special importance to laggard countries as it provides access to technological expertise and advanced know-how without incurring the cost associated with research fertility. Although, the existence of knowledge spillovers is acknowledged in the growth process, various difficulties have been encountered in quantifying their contribution to output for a number of reasons. First, it is difficult to guarantee full appropriability of research, as knowledge is not always an excludable good and thus it cannot always be kept within the agent that bears the cost. In such a case, the social return to R&D[5] is usually bigger than it is initially expected. Second, it remains highly questionable as to through which transmission mechanisms the diffusion of knowledge takes place. The existing literature

[4] See Romer (1986) and Aghion and Howitt (1998) for some of the most original developments in the theory of endogenous growth. Also see Corrado and Hulten (2010) for a recent overview of this literature.
[5] The latter effect is of special interest to policy makers that design polices associated with R&D subsidies and R&D related tax exemptions.

suggests that knowledge dispersion still encounters substantial frictions which make the successful replication of best practices and ideas an uncertain process. The present study addresses the question about the size of knowledge spillovers and the precise mechanism through which these spillovers operate using industry level data, which is rather limited in the current empirical literature. We employ evidence from 14 OECD countries including not only manufacturing industries but also broader service sectors that have gradually increased their share in national production in many developed economies. One of the main goals of the present study is to identify whether knowledge and its associated spillover can be purely excludable goods and if not what sort of weighting measures can be applied to account for the possibility that innovative-enhancing efforts can benefit other national or international peers.

An equally important issue with the degree of "publicness" of knowledge and knowledge spillover is the role of human capital in absorbing the spillover. The implementation of knowledge spillovers is associated with the amount of tacit knowledge embodied in foreign commodities and foreign R&D stock. This type of knowledge cannot always be translated into gains for the domestic economy unless there is the required level of human capital to identify, assimilate and then utilise effectively the existing R&D spillovers. Persistent cross-country and cross-industry productivity differentials indicate that the evolution of the knowledge spillovers led growth process is not always straightforward. This implies that the current literature often overlooks the importance of the above issues. The present paper elaborates the role of human capital in the identification of spillover gains using industry level data which is more informative than country level often used in the knowledge spillovers literature.

The estimation of spillovers can be biased (Hall et al. (2009)) if the level of aggregation is too high or if one considers that all channels of knowledge transmission have the same potential in generating productivity gains. Most of the recent studies in the spillovers literature refer to country level evidence (Coe and Helpman (1995), Coe and Helpman and Hoffmaister (1997), Engelbrecht (1997, 2002), Keller (1998), van Pottelsberghe and Lichtenberg (2001)) overlooking the possibility that spillovers can also be intra-national. The latter consideration suggests that imitation of technology can occur across industries within the same country. This prospect can be examined only if one utilises industry level data which rarely has been common in the existing literature. We unveil the importance of intra-national R&D spillovers with industry level data that remove aggregation bias inherited in standard country level data.

Methodologically, we depart from a primal approach specifying a production function including human capital as a separate input. The technological parameter is then represented as function of national and international R&D spillovers. The primal approach was originally proposed in Griliches (1979) and relies on a production function framework augmented with an R&D stock input.[6] Nevertheless, studies adopting the primal approach neglect the role of knowledge spillovers in the empirical estimation treating them only as unobserved factors (Doraszelski and Jaumandreu (2013), Markus et al. (2013)). To capture the existence of knowledge spillovers, we rely on the *ad hoc* assumption that trade and FDI are the most important conduits of transmission given that international exchange of goods and factors embody substantial information.[7] Using firm-level data in a sample of 47 countries, Mallick and Yang (2014) find that the multinational parents' performance significantly influences the subsidiaries' performance. This suggests that there could be knowledge spillovers in the form of technology transfer from multinational corporations to subsidiary plants.

The present paper also contributes to the productivity measurement literature by applying parametric techniques in the estimation of output growth. The productivity

[6] Firm level studies that use this approach are Griliches and Regev (1995) for the US, Oulton (1996), Greenaway and Wakelin (2001) and Hígon (2007) for the UK and Hall and Mairesee (1995) for France.
[7] See for example, Carr et al. (2001) for a knowledge-capital model of the multinational enterprise which provides a tractable framework for testing the importance of foreign affiliates in the host country.

measurements derived from non-parametric growth accounting exercises are too restrictive and they do not allow accounting for the presence of imperfect competition and variations in the utilisation of inputs.[8] The behavioural framework of the present paper departs from a production function that is augmented with knowledge inputs relaxing some of the assumptions that underlie growth accounting measurements. The benefit from using this model is to disentangle real productivity changes from short term fluctuation of the quasi-fixed inputs. The existence of short-run variations from the full utilisation of inputs leads to productivity rigidities that can be mistakenly attributed to the state of technology. Similarly, growth accounting assumes that producers are always cost minimisers in the short run taking input shares in the production function as true approximations for the shares of input revenues to value added. This assumption does not hold in the presence of imperfect competition suggesting that input shares should be adjusted to cost rather than to revenue. In the econometric specification of the paper, utilisation of inputs and market power are tested empirically rather making a priori assumptions for their validity.

The remainder of this paper is organised as follows: section 2 presents the analytical framework, section 3 shows the measurement of knowledge capital and knowledge spillovers, section 4 discusses the econometric specification and results from baseline specifications, section 6 tests the robustness of the results implementing various sensitivity tests and section 7 concludes.

[8] Growth accounting (the Solow Residual) relies on a non-parametric technique which leads to the construction of a Total Factor Productivity (TFP) index (Good et al. (1996), Cameron et al. (2005), Kneller and Pisu (2007)). This index is then modelled as a function of potential productivity growth drivers (including knowledge inputs). The derivation of the TFP index presupposes the existence of strong assumptions (i.e. perfect competition in product and factor markets and full utilization of inputs) that often fail in real situations leading to biased estimates of productivity growth. Instead parametric techniques can address these issues less restrictively without avoiding, on the other hand, the potential cost of econometric bias. The empirical section of the paper discusses these issues in greater detail.

2. Theoretical Framework

2.1 The Production Function: The Benchmark Model

We assume a standard aggregate production function of the form:

$$Q_{i,c,t} = A_{i,c,t} \left(L\right)_{i,c,t}^{\alpha_1} \left(K\right)_{i,c,t}^{\alpha_2} \left(M\right)_{i,c,t}^{\alpha_3} \left(H\right)_{i,c,t}^{\alpha_4} \quad (1)$$

where *A*, *L*, *K*, *M* and *H* stand for Hicks neutral technical progress, labour, fixed capital, intermediate materials and human capital. Index $i = 1,...,I$ stands for industry, index $c = 1,...,C$ stands for country and index $t = 0,...,T$ stands for time. Shares of labour, fixed capital, intermediate materials and human capital are denoted by $\alpha_1,\ \alpha_2, \alpha_3, \alpha_4$. Under certain assumptions of perfect competition and constant returns to scale, these shares represent social marginal elasticities of output with respect to these inputs. The econometric estimation of (1) provides a modification of input shares to include the case of imperfect competition. As we include more than two inputs in the production function, the appropriate output measure is gross output instead of the standard measure of value added (Hígon, 2007). Taking logs and differentiating with respect to time, equation (1) becomes:

$$\Delta \ln Q_{i,c,t} = \Delta \ln A_{i,c,t} + \alpha_1 \Delta \ln L_{i,c,t} + \alpha_2 \Delta \ln\left(K\right)_{i,c,t} + \alpha_3 \Delta \ln\left(M\right)_{i,c,t} + \alpha_4 \Delta \ln\left(H\right)_{i,c,t} \quad (2)$$

where Δ is the first difference operator. Writing (2) in intensive forms, the left-hand side variable is output per unit of labour and the equation is written as:

$$\Delta \ln\left(\frac{Q}{L}\right)_{i,c,t} = \Delta \ln A_{i,c,t} + \alpha_2 \Delta \ln\left(\frac{K}{L}\right)_{i,c,t} + \alpha_3 \Delta \ln\left(\frac{M}{L}\right)_{i,c,t} + \alpha_4 \Delta \ln\left(\frac{H}{L}\right)_{i,c,t} \quad (3)$$

Next, we consider that the term of Total Factor Productivity (TFP) growth, $\Delta \ln A_{i,c,t}$ can be written as:

$$\Delta \ln A_{i,c,t} \equiv \Delta \ln TFP_{i,c,t} = \lambda_i + \eta_c + \gamma \ln\left(\frac{R}{L}\right)_{i,c,t=0} + \theta_h \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right)$$
$$+\rho_h \left[H_{i,c,t} \times \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right)\right] + u_{i,c,t} \tag{4}$$

Equation (4) states that TFP growth in industry *i*, in country *c*, at year *t* depends on industry's initial level of knowledge capital stock per worker $\left(\frac{R}{L}\right)_{t=0}$, and cross-country knowledge spillovers denoted by $R_{i,f,t}$, where f indexes the sender country of the R&D spillover. The first summation in (4) refers to cross-country knowledge spillovers in industry i weighted by w to capture the channel of knowledge transfer between the recipient country *c* and sender country *f* of the R&D spillover. The second summation captures absorptive capabilities of industry *i*, which is an interaction term between the index of knowledge spillover and human capital *H*. Effectively, such a term represents the amount of tacit knowledge embodied in foreign R&D stock whose beneficial effect on domestic output requires the existence of a critical amount of human capital in the recipient industry. Parameters θ and ρ capture the responsiveness of TFP growth with respect to knowledge spillovers and absorptive capacity, respectively. We use index *h* to indicate that there are various channels of knowledge spillovers each of them depending on the assumption one makes about the degree of "publicness" of knowledge and knowledge spillovers. [9] In equation (4), we use the knowledge stock in the beginning of the sample year instead of industry *i*'s contemporaneous value of R&D stock. This formulation provides two benefits, first reduces the degree of endogeneity bias between spillovers and industry's own R&D capital stock and second tests the presence

[9] The weighting measure w captures bilateral trade flows in industry i between c and *f*. Index h implies that there are different interpretations or versions of the spillover index subject to the assumptions made about the nature of knowledge and its associated spillover. A representative unit of trade flow does not always transfer the entire information included in foreign R&D stock. Likewise, the recipient agent does not always make available the entire information. Section 3 constructs four possible indexes to include all possible combinations.

of convergence process in the sample. Therefore, parameter γ shows a tendency towards convergence (divergence) to a common steady- state level of technology. If γ <0 (>0) then TFP growth rate across industries and across countries is inversely (positively) related to their initial level of R&D stock implying a convergence (divergence) process towards a common steady. Parameter λ_i and η_c capture unobserved industry and country specific idiosyncrasies that drive innovation. Finally, equation (4) is augmented with a stochastic error term with zero mean and constant variance (i.e. $u \sim IID(0,\sigma^2)$). The current framework adopts most of the key features of the primal approach (Rogers (2010)) and Ortega-Argiles et al. (2009))[10] in estimating output growth but knowledge and associated knowledge spillovers are specified as TFP drivers and not as direct inputs in the production function. This modification allows us further to examine whether the interaction of domestic human capital with foreign spillovers can generate substantial productivity gains.[11] Merging (3) with (4):

$$\Delta \ln\left(\frac{Q}{L}\right)_{i,c,t} = \lambda_i + \eta_c + \alpha_2 \Delta \ln\left(\frac{K}{L}\right)_{i,c,t} + \alpha_3 \Delta \ln\left(\frac{M}{L}\right)_{i,c,t} + \alpha_4 \Delta \ln\left(\frac{H}{L}\right)_{i,c,t} + \gamma \ln\left(\frac{R}{L}\right)_{i,c,t=0}$$
$$+\gamma \ln\left(\frac{R}{L}\right)_{i,c,t=0} + \theta_h \ln\left(\sum_{c\neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right) + \rho_h \left[H_{i,c,t} \times \ln\left(\sum_{c\neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right)\right] + u_{i,c,t} \qquad (5)$$

Parameter θ_h measures the responsiveness of output to knowledge spillovers via channel *h* while parameter ρ_h highlights the second role of human capital in the production, which is the utilisation of tacit knowledge embodied in foreign R&D stock. Equation (5) is the benchmark specification that will be augmented with a capacity utilisation term to control for

[10] See also Griliches (1979), Griliches (1980) and Griliches-Mairesse (1984) for earlier studies using the production function approach.

[11] See Eberhardt et al. (2013) for a different approach in the modelling of international knowledge spillovers. This approach remains agnostic concerning the nature and the channels of knowledge spillovers while focusing only on the establishment of an econometric correlation between output and unobserved factors which attributed to spillovers. We believe that this approach is problematic as it neglects the role of tacit knowledge embodied in spillovers that can be revealed only if observed measures of knowledge spillovers are interacted with human capital.

variation in the use of inputs, and it will be also modified to account for the presence of imperfect competition.

2.2 Adjusting Production Function for Capacity Utilization and Imperfect Competition

2.2.1 Utilisation Rate

Production function (1) implicitly refers to a full utilisation of the four inputs; nonetheless in the short run the use of the resources might deviate substantially from their long-run capacity. The utilization of inputs makes productivity highly pro-cyclical with TFP to be higher in booms as resources tend to be over-utilised while in recession TFP being lower due to under-utilization (Hall (1991)). Failing to adjust inputs for their actual use produces biased input estimates that can be mistakenly attributed to technological progress. Following the set-up of Basu and Kimball (1997), we assume that all inputs are quasi-fixed, so any change in the scale of inputs is associated with adjustment costs while it is feasible to change the intensity of inputs usage. Since we have already expressed all inputs relative to labour, capacity utilization can be viewed as a function of input intensities as follows:

$$U = f\left(\upsilon_K^{\varepsilon_{K,Q}}, \upsilon_L^{\varepsilon_{L,Q}}, \upsilon_H^{\varepsilon_{H,Q}}\right) \tag{6}$$

The superscripts in each utilization input denote the elasticity of output with respect to this input. The crucial issue regarding function (6) is that as the intensity of inputs is unobservable for the econometrician, the degree of utilization cannot be measured.[12] In our framework, the above methodologies are not applicable, as raw-material expenditures are directly used in the production function. To derive the degree of utilisation, we assume that changes in hours per worker are proportional to unobserved changes in both labour and

[12] Various approaches have been employed to measure input utilization including energy and material consumption (Burnside et al. 1995 and Basu et al. (2001)) as well as survey data on capacity utilization (Shapiro et al. (1996)). The rationale of using materials and energy as proxies of utilisation is that if capital utilization goes up then this is partly reflected in higher use of intermediate inputs.

capital utilisation. Hours per worker can proxy for the utilization of capital as well as labour effort because shift premia create a link between capital hours and labour compensation (Basu et al., 2006).[13] We de-trend the series of hours per worker (*H*/*L*) using two different filters, namely Hodrick-Prescott (HP) (1997) and Christiano and Fitzgerald (CF) (2003). The former is widely used in the business cycles literature for estimating output gap (Baxter and King (1999)) while the second uses a random walk process to de-trend the series.

$$U^{\left(\frac{H}{L}\right)} = \ln\left(\frac{H}{L}\right)_{Actual} - \ln\left(\frac{H}{L}\right)_{Trend}$$

The term utilization rate is defined as:

$$\Delta \ln U = U_t^{\left(\frac{H}{L}\right)} - U_{t-1}^{\left(\frac{H}{L}\right)} \tag{7}$$

2.2.2 Mark-Ups

As mentioned earlier, the derivation of TFP from growth accounting exercises assumes perfect competition, which means that the observed input shares also represent social marginal elasticities. In the presence of market power in the product market, input-revenue shares are biased and instead the input-cost shares should be applied (Hall (1986)). To derive the share of inputs under conditions of imperfect competition we assume that producers have market power in goods market but they are price-takers in factor markets. The first order optimality condition is then given by:

$$p_{i,t} \frac{\partial Q_{i,t}}{\partial J_{i,t}} = \mu p_{i,t}^{J} \text{ , where } J{=}L,\ K,\ M \tag{8}$$

[13] This is based on the assumption that firms encounter adjustment costs for investing and hiring extra workers while they can freely change the intensity of hours worked of the existing labour.

Where $p_{i,t}$ and $p^J_{i,t}$ represent the price of goods and the price of production inputs *J*. Symbol μ stands for the price mark-up imposed upon marginal cost (MC). Under perfect competition, μ is equal to one when price equals MC, while when the value of mark-up is greater than one then the market departs from perfect competitive conditions. One can write input shares under conditions of imperfect competition as:

$$\varepsilon^{Q,J}_{i,t} = \mu \frac{P^J_{i,t} J_{i,t}}{P_{i,t} Q_{i,t}} = \mu_{i,t} \sigma^J_{i,t} \tag{9}$$

In equation (9) σ denotes the observed input share calculated from revenue while μ represents a price mark-up that measures the degree of imperfect competition. After controlling for capacity utilization and imperfect competition, the benchmark specification (5) becomes:

$$\begin{aligned} \Delta \ln\left(\frac{Q}{L}\right)_{i,c,t} = {} & \lambda_i + \eta_c + \mu\left[\sigma^K_{i,c,t} \Delta \ln\left(\frac{K}{L}\right)_{i,c,t} + \sigma^M_{i,c,t} \Delta \ln\left(\frac{M}{L}\right)_{i,c,t} + \sigma^H_{i,c,t} \Delta \ln\left(\frac{H}{L}\right)_{i,c,t}\right] + \kappa \Delta ln U_{i,c,t} \\ & \gamma \ln\left(\frac{R}{L}\right)_{i,c,t=0} + \theta_h \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right) + \rho_h \left[H_{i,c,t} \times \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right)\right] + u_{i,c,t} \end{aligned} \tag{10}$$

The first line in specification (10) is an extended production function that accounts for market power and cyclical use of production inputs as specified for example in Hall (1988) and Paquet and Robidoux (2001). Moreover, the present framework augments production function with sources of knowledge spillovers allowing them to interact with industry's own human capital. To simplify the notation, we re-write (10) as:

$$\begin{aligned} \Delta \ln\left(\frac{Q}{L}\right)_{i,c,t} = {} & \lambda_i + \eta_c + \mu\left[\Delta \ln F_{i,c,t}\right] + \kappa \Delta ln U_{i,c,t} + \gamma \ln\left(\frac{R}{L}\right)_{i,c,t=0} \\ & + \theta_h \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right) + \rho_h \left[H_{i,c,t} \times \ln\left(\sum_{c \neq f}^{C-1} w^i_{c,f} R_{i,f,t}\right)\right] + u_{i,c,t} \end{aligned} \tag{11}$$

with $\Delta \ln F_{i,c,t} = \sigma^{K}_{i,c,t} \Delta \ln \left(\frac{K}{L} \right)_{i,c,t} + \sigma^{M}_{i,c,t} \Delta \ln \left(\frac{M}{L} \right)_{i,c,t} + \sigma^{H}_{i,c,t} \Delta \ln \left(\frac{H}{L} \right)_{i,c,t}$

The estimation of this extended production function will provide information for the elasticity of growth of output per worker with respect to the following factors: market structure (μ), capacity utilisation (κ), initial R&D stock (γ), knowledge spillovers (θ_h) and absorptive capacity (ρ_h). Note Parameter θ will be estimated separately for each different channel of knowledge diffusion *h*. Finally, to obtain a more precise estimation for the role of human capital we run regressions for (11) reporting separate coefficients for $\Delta \ln \left(\frac{H}{L} \right)_{i,t}$.

3. Measurement of Knowledge Capital and Knowledge Spillovers

3.1 Knowledge Stock

To implement (11) we need a measure of knowledge capital, which is constructed by accumulating R&D expenditures over time. We use the perpetual inventory method to accumulate R&D stock as follows:

$$R_{i,t} = \left(1 - \delta\right) R_{i,t-1} + RDS_{i,t-1} \tag{12}$$

where *RDS* indicates R&D Spending[14] and δ is the depreciation rate of last year's R&D stock. The depreciation parameter δ is assumed to be common for all industries at 15%.[15] Using the perpetual inventory method we need to initiate the series of R&D stock considering a value for the stock of R&D capital at the first year of the sample. Assuming that R&D capital in the steady state behaves similarly to physical capital, then:

[14] R&D expenditure needs to be expressed in constant prices and thus values are converted into 2000 constant USD prices applying the GDP deflator.

[15] Hall et al. (2009) has shown that for a sufficiently long time series, R&D stock measures are insensitive to the choice of the depreciation rate.

$$\Delta R_t = 0 \Rightarrow RDS_{i,t} \approx \left(g_i + \delta\right) R_{i,t-1} \tag{13}$$

Therefore, we initiate the series of R&D capital stock with the following formula:

$$R_{i,t=0} = \frac{RDS_{i,t=0}}{g_i + \delta} \tag{14}$$

where g is the long run growth rate of R&D spending calculated as the average growth rate of R&D spending over the whole sample period.[16] The remaining part of this section defines the indices of domestic and international spillovers.

3.2 The Measurement of National and International Spillovers

The measure of R&D stock shown in equation (12) represents only industry *i*'s own R&D effort without incorporating the diffusion of R&D spillovers derived from R&D activity of other domestic counterparts. R&D is an expenditure that does not always lead to new inventions. In this case, R&D outcomes (whether successful or not) are not normally protected, which permits us to further explore whether R&D activity can generate substantial gains and through which channels these spillovers are diffused to other parties. To investigate these hypotheses a set of five indices is defined to capture the nature and the scope of R&D spillovers. Note these indices assume that different proportions of knowledge are transferred in the domestic industry depending on whether knowledge is viewed as a pure public or a pure private good but they do not address the issue of tacit knowledge embodied in foreign R&D. This crucial aspect also determines the effectiveness of international knowledge spillovers and it is captured here with the absorptive capacity term in equation (11), which

[16] Hall and Mairesse(1995) provides a similar representation based on the assumption that growth of real R&D expenditure is constant. Accordingly, R&D capital can be approximated by the equation:

$$R_t = \sum_{t=0}^{n} RDS_{t-1}(1-\delta)^n = RDS_{t=0}\sum_{t=0}^{n}\left[\frac{1-\delta}{1+g}\right]^n = \frac{RDS_{t=0}}{g+\delta}.$$

essentially examines whether the presence of human capital can decrypt the tacit knowledge incorporated in foreign R&D.

The first index refers to intra-national spillovers from R&D activity of other domestic counterparts (industries). According to this channel, there are domestic linkages which allows for inter-industry flows of R&D spillovers in parallel with the flow of commodities. We expect that the potential of domestic R&D knowledge spillovers to be analogous with the degree of similarity between industries. The degree of similarity between industries i and j refers to "technological proximity" in terms of production patterns and intensity of linkages (Branstetter (2001)).[17] We define the index of intra-national R&D spillovers as follows:

$$NR_{i,,c,t} = \sum_{i \neq j} \omega_{i,j,c} R_{j,c,t} \tag{15}$$

where ω is an element of the Leontief inverse matrix. The inverse matrix is generated from an input-output table that describes sales and purchases of commodities between industry i and j within the same country c. [18]

Coe and Helpman (1995) investigate the role of trade as a knowledge facilitator mainly via imports in intermediate raw materials (also see Yasar (2013)). The rationale is that imports increase contacts with foreign producers and thus can be appropriate conduits of international knowledge spillovers. This research revealed that a movement from autarky to free trade can also incorporate dynamic knowledge gains. A positive relationship between imports and R&D related spillovers is also found in Coe et al. (1997) and Ang and Madsen (2013). Keller (1998, 2000) shows that knowledge effects are independent from the volume of trade, and the identification of spillovers depends on the times series properties of the data

[17] R&D activity in industries of intermediate inputs supplier facilitates gains for downstream industries. The stronger is the degree of engagement between these two types of industries, the greater is the potential of R&D spillover.

[18] We prefer this weighting for intra-national spillovers instead of taking national average R&D stock as potential pool of spillovers. Industrial linkages have been found to be of particular importance for technical progress and productivity (Wolff and Nadiri (1993)).

under study. Kao et al. (1999) cast doubt about the significance of trade related spillovers as they reveal no knowledge effects in a dynamic econometric specification. Funk (2001) stress the importance of weighting methods when one seeks to uncover import related spillovers. The previous findings suggest that the importance of trade as a mediator of spillovers remains highly controversial and it is associated –among other issues- with the nature of knowledge in the producing country as well as the nature of knowledge spillover in the recipient country.

To address the various controversies related to the measurement of international knowledge spillovers, we construct a set of indices using all possible combinations for the degree of "publicness" of knowledge stock and knowledge spillover (Falvey et al. (2004)). The issue of tacit knowledge embodied in foreign R&D spillovers is separate and it is associated with absorptive capacity in the recipient country. Absorptive capacity is measured with the use of interaction terms between spillover indices and human capital, the latter is defined as the number of workers with a tertiary education degree as a share of total employment. Similar approach has been used in Sena and Higon (2014) for a single country to capture regional differences in the industry-level educational attainment of the workforce in conditioning its capability of absorbing R&D spillovers. The first index assumes that R&D stock is a public good in the sender country and R&D spillover is a public good in the recipient country. This conceptualisation indicates that a unit of imports embodies the entire information of foreign R&D stock while this information becomes immediately available to all agents in the recipient country. The first index of international spillovers is written as:

$$ISP^{1}_{i,c,t} = \sum_{f} s^{i}_{c,f,t} R_{i,f,t} \tag{16}$$

where s stands for the bilateral import share between country c and f in industry i.

Import shares s in index (16) add up to one and they are not informative about the general trade orientation of industry i. To examine whether the potential of spillovers increase with trade orientation we assume that if two recipient countries have the same import share s

in industry *i* the benefit from international knowledge spillover is greater, the greater the industry *i*'s import intensity. In other words, we account for the degree of publicness of knowledge spillover in the recipient country using a measure of industry *i*'s import penetration. Therefore, the second index assumes that knowledge spillover from R&D is a private good in the recipient country while R&D stock remains a public good in the sender country.

$$ISP^{2}_{i,c,t} = \left(\frac{m_{i,c,t}}{x_{i,c,t}}\right)\sum_{f} s^{i}_{c,f,t} R_{i,f,t} \tag{17}$$

The ratio $\left(\frac{m_{i,c,t}}{x_{i,c,t}}\right)$ stands for import penetration.

The third index assumes that knowledge is a private good in the sender country while knowledge spillover is a public good in the recipient country. To represent the notion that not all R&D information is transferred in a unit of import we weight foreign R&D stock with foreign output. The index is written as follows:

$$ISP^{3}_{i,c,t} = \sum_{f} s^{i}_{c,f,t}\left(\frac{R_{i,f,t}}{x_{i,f,t}}\right) \tag{18}$$

The fourth index takes the case of having both private knowledge and private R&D spillover. In this specification, not all indigenous R&D knowledge is supposed to be embodied in imports received from the sender country *f* while the availability and diffusion of knowledge spillover in the recipient country depends on the degree of import penetration. This index is specified as follows:

$$ISP^{4}_{i,c,t} = \left(\frac{m_{i,c,t}}{x_{i,c,t}}\right)\sum_{f} s^{i}_{c,f,t}\left(\frac{R_{i,f,t}}{x_{i,f,t}}\right) \tag{19}$$

3.3 FDI Related Spillovers

Van Pottelsberghe and Lichtenberg (2001) propose the use of FDI measures as an alternative mechanism for knowledge transfer. Keller and Yeaple (2009) find that FDI related spillovers are more important than import related ones. Positive intra-industry spillovers are also found in Javorcik (2004) indicating that the advanced technological expertise and know-how of multinationals is transmitted via their affiliates and these benefits are then diffused in the host economy. Industry level evidence for the benefits of inward FDI are also found in Bitzer and Kerekes (2008). The present analysis investigates the importance of FDI as a conduit of knowledge transfer but also explores the existence of vertical FDI spillovers. The latter are derived from inward FDI activity in other domestic industries implying once again that downstream industries can benefit from the presence of FDI in their upstream industrial suppliers. Industrial linkages are measured as in index (15) with coefficients taken from a national input-output table. The two FDI related spillovers are specified as follows:

$$FDI_{i,c,t} = \frac{FDI^{inw}_{i,c,t}}{x_{i,c,t}} \tag{20}$$

$$VFDI_{i,c,t} = \sum_{i \neq j} \omega_{i,j,c} \left(\frac{FDI^{inw}_{j,c,t}}{x_{j,c,t}} \right) \tag{21}$$

To capture the relevant importance of FDI across industries, we weight FDI with gross output in the industry.

4. Data Coverage

The time period of the study refers to 1987-2007 covering 13 manufacturing industries (ISIC Rev.3 Classification) and 3 broader sectors, transport and communication, financial intermediation and real estate business activities (see Table 1). Production data are taken from EUKLEMS data base (2009 release) that cover up to 2007. The EUKLEMS data used are gross output (GO), total hours worked by employees (H_EMPE), intermediate material inputs (II) and gross fixed capital stock (GFCK). The exact methodology used for the construction of GFCK can be found in Timmer et al. (2007). Variables are expressed into constant 1995 prices using the following price deflators, output price index (GO_P) and material price index (II_P) and then converted into USD using PPP exchange rates from OECD-National Accounts.

Data for R&D expenditure are taken form OECD- ANBERD database. The time span of ANBERD is currently available up to 2007, which basically dictates the time coverage of the whole study. The series of R&D stock described in the previous section is generated from R&D expenditures expressed in 2000 USD prices converted with PPP exchange rates. The pool of foreign R&D stock is calculated from 18-OECD countries and data for bilateral import shares used in equations (16)-(19) are taken from STAN Bilateral Trade Data Base (2009).

Table 1: Data Coverage

Countries- Indexed with *c*	**Industry Code ISIC Rev3**	**Description**	**Foreign Partners used for the calculation of** $R_{i,f,t}$
Australia	15t16	Food	Australia
Austria	17t19	Textiles	Austria
Canada	20	Wood and Cork	Belgium
Denmark	21t22	Printing and Publishing	Canada
Spain	23	Coke	Denmark
Finland	24	Chemicals	Finland
Germany	25	Rubber and Plastics	France
Italy	26	Other non-Metallic Mineral	Germany
Japan	27t28	Basic Metals	Italy
Netherlands	29	Machinery	Ireland
Slovenia	30t33	Electrical and Optical Equipment	Korea
Sweden	34t35	Transport Equipment	Japan
UK	36t37	Other Manufacturing; Recycling	Netherlands
USA	I	Transport, Storage and Communication	Portugal
	J	Financial Intermediation	Spain
	K	Real Estate, Renting and Business Activities	Sweden
			UK
			USA

5. Empirical Analysis

5.1 Some Preliminary Statistics

Table 2 presents average statistics over the sample period by country and sector for the dependent variable, $\Delta\ln\left(\frac{Q}{L}\right)$. The most striking result in table 2 is that all industries maintain a positive growth rate of output per worker but not Business activities (sector K). The highest growth rate is in electrical and optical equipment (30t33), which is found to be 6% for the period under study. Looking at the growth rates of labour productivity by country, Germany is leading in this period with a national average across all sectors almost 4.5%. Very close to Germany is also Austria and Japan. To further understand the distribution of R&D stock among partners, we present in Table 2 average values of R&D stock for the 18 partners used in the analysis classified by industry. The leader in R&D is USA with an average stock in all sectors almost triple from Japan, which is the country with second highest value in the sample. In Europe the highest average value is in the UK followed by France and Germany. Figure A2 in the Appendix shows scatter plots of $\Delta\ln\left(\frac{Q}{L}\right)$ versus the four alternative knowledge spillovers. These preliminary plots reveal a positive link between output per worker and spillovers, which will be more systematically examined in the econometric estimation. Table A1 in the appendix summarises statistics for the remaining variables of the paper and Table A2 tabulates correlations between the four different spillover indices. As expected the correlation between the spillovers indices is high indicating that they should be entered interchangeably in the regressions to avoid problems of multi-collinearity.

Figure 1: Sectoral Growth Rates of Output per Worker, 1987-2007

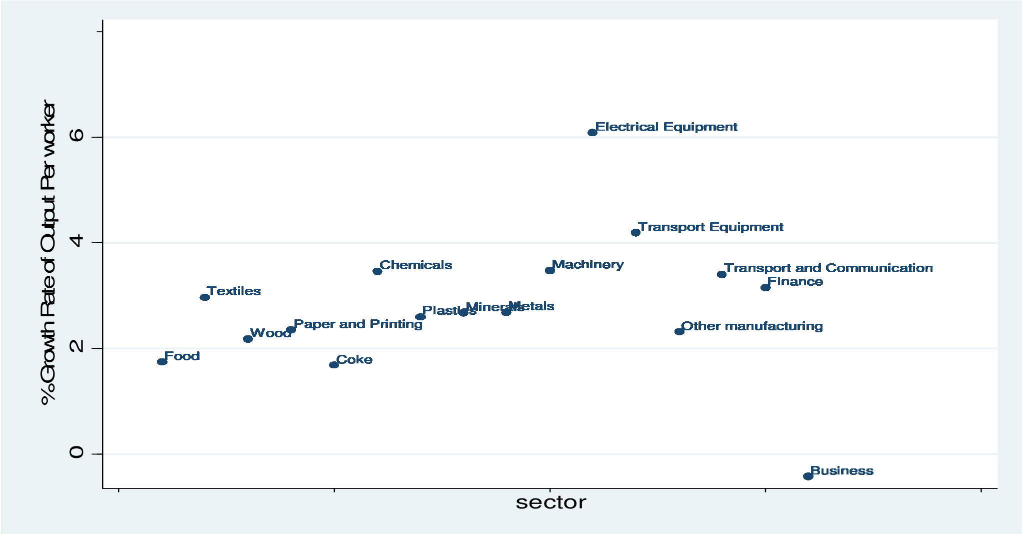

Table 2:R&D Stock in 18 OECD Countries, 1987-2007

Country	15t16	17t19	20	21t22	23	24	25	26	27t28	29	30t33	34t35	36t37	I	J	K	Average
Australia	1,369	475	159	570	78	3,073	235	380	3,793	1,134	3,890	3,149	491	1,370	1,541	3,573	1,580
Austria	516	72	64	165	595	360	230	149	233	253	1,180	416	68	29	391	904	352
Belgium	686	478	59	284	427	19,990	461	593	4,019	2,060	12,690	1,796	437	223	443	1,958	2,913
Canada	1,229	746	324	1,653	1,803	7,857	429	215	5,355	1,538	32,510	18,180	1,086	2,024	2,933	11,890	5,611
Denmark	837	35	26	47		3,484	155	1,483	257	1,757	3,339	1,012	380	603	227	2,802	1,096
Finland	710	167	225	508	213	3,757	364	357	1,315	2,303	6,437	993	146	723			1,301
France	3,553	1,129	139	810	10,830	62,030	5,080	2,341	12,010	9,123	81,150	107,800	1,635	3,448		7,116	20,546
Germany	4,256	2,865	656	1,253	4,091	46,320	5,799	7,870	5,528	60,590	41,900	61,820	1,068	1,537	1,184	2,233	15,561
Ireland	461	1,265	21	47		941	84	91	128	154	2,333	96	46	165	20	575	428
Italy	792	357	63	108	523	7,422	3,757	577	1,206	8,169	11,920	13,580	262	1,167	327	7,181	3,588
Japan	19,570	8,346	2,893	5,916	8,343	194,100	18,480	22,660	95,690	57,700	279,500	101,200	11,640	998	381	128,300	59,732
Korea	862	2,098	22	91	636	4,994	2,686	54	1,659	20,450	28,380	9,586	296	3,432	273	6,132	5,103
Netherlands	4,742	629	10	169	455	27,960	383	163	2,642	1,965	32,070	7,680	125	1,739	629	2,681	5,253
Portugal	67	46	15	158	68	164	3	14	44	76	357	81	4	174	66	278	101
Spain	934	302	24	255	421	7,489	752	503	1,635	1,800	8,353	8,945	577	1,159	110	3,059	2,270
Sweden	1,222	131	67	1,958	101	10,220	395	276	3,284	7,251	15,310	15,560	197	126	436	1,831	3,648
UK	5,117	1,532			13,960	71,070	1,275	2,341	18,440	15,950	91,120	78,490	1,214	31,090	1,212	24,230	25,503
USA	23,430	6,225	594	16,840	86,940	308,400	14,600	23,920	72,600	51,190	673,500	1,759,000	8,917	69,390	6,775	46,650	198,061

Notes: Values are in millions of 2000 PPP USD. The formulae for the construction of R&D stock are given in equations (12)-(14).

5.2 Econometric Specification

As already mentioned, the use of econometric techniques in estimating a production function offers the flexibility to remove some of the strong assumptions underlying the theory. Nevertheless, the econometric approach is not free of shortcomings and requires systematic analysis to avoid spurious results. Regarding the selection of an appropriate estimator, we start with a Pooled OLS (POLS). To estimate (11) using POLS presupposes that error terms are both uncorrelated over time and across cross-sections. Serial correlation is not a matter of concern as the production function has been specified in log differences. Nevertheless an augmented production function can be subject to unobserved macroeconomic shocks that commonly affect all industries within a country (and across countries) in a year *t*, thus raising issues of spatial dependence (i.e. $cov\left(u_{i,t}u_{j,t}\right) = \sigma_{i,j}$ for any industry $i \neq j$). To provide results robust in the presence of cross-sectional dependence we apply the panel corrected standard error (PCSE) estimator of Beck and Katz (1995), which is consistent for group-wise heteroscedasticity (i.e. $\mathrm{var}(u_i) = \sigma^2$) as well as for cross-section correlation in the error terms.

An OLS estimation of (11) can potentially suffer from two sources of bias. The first one is the existence of systematic feedback effects between output and production inputs. Although our specification is determined in first differences, the exogeneity assumption might still fail if one assumes that higher productivity is likely to impact on industry's future purchase of inputs. Under this condition we get: $E\left(u_{i,c,t+1} | \Delta \ln F_{i,c,t}\right) \neq 0$ where E is the conditional expectations operator. In other words, an unobserved mechanism can drive both the error term in (11) and the $\Delta \ln F_{i,c,t}$, causing simultaneity bias. A similar interpretation of endogeneity also applies for the spillover variables. To relax this moment condition we use an instrumental variable (IV) estimator. The second source of bias comes from unobserved measurement errors in all variables, especially those referring to the construction of R&D

stock and associated knowledge spillovers. We address measurement bias using an IV estimator, so next sub-section presents results from PCSE and IV.

5.3 Results from Baseline Specifications

The section of diagnostics tests in Table 3 reports the value of the Pesaran (2004) cross dependence (CD) statistic. The CD statistic is normally distributed under the null hypothesis that: $\mathrm{H}_0 : \varphi_{i,j} = \varphi_{j,i} = \mathrm{co}\,rr(u_{i,j}, u_{j,i}) = 0$, where φ is the correlation coefficient between two cross-sectional residuals u_i and u_j, for $i \neq j$. The test reported rejects the null at high levels of significance; hence, the PCSE is the recommended estimator to provide results robust in the presence of cross-sectional correlation in the residuals.[19]

We gradually estimate equation (11) starting from specifications that only include the linear terms of spillovers. Note, we do not include all the indices of international spillovers simultaneously to avoid multi-collinearity, as already discussed. More intiuitively, this process allows us to identify whether R&D and its spillovers are closer to the nature of public or private good.

The estimated parameter of $\Delta \ln F$ is μ in equation (11) and stands for a measure of market power. In all specifications of Table 3, the estimated coefficient is statistically greater than unity indicating the existence of market power.

[19] See Pesaran and Hashem (2006) and Eberhardt and Teal and Eberhardt et al. (2013) for alternative estimation methods in the presence of cross sectional dependence in panels.

Table 3: Results from Panel Corrected Standard Errors (PCSE) Estimator, Equation (11)

	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$
$\Delta\ln F$	1.128***	1.140***	1.131***	1.144***	1.128***	1.140***	1.132***	1.144***
	(75.46)	(66.29)	(76.36)	(66.88)	(75.57)	(66.19)	(76.57)	(66.80)
$\Delta\ln U$	0.082	0.078	0.075	0.070	0.083	0.078	0.075	0.070
	(1.62)	(1.49)	(1.50)	(1.38)	(1.63)	(1.50)	(1.50)	(1.38)
$\Delta\ln\left(\frac{H}{L}\right)$	0.012***	0.007*	0.012***	0.007*	0.010**	0.006	0.010**	0.007
	(2.68)	(1.65)	(2.68)	(1.65)	(2.31)	(1.36)	(2.41)	(1.46)
$\ln\left(\frac{R}{L}\right)_{t=0}$	-0.024	-0.030	-0.031	-0.039	-0.008	-0.017	-0.018	-0.032
	(-0.51)	(-0.66)	(-0.67)	(-0.84)	(-0.17)	(-0.36)	(-0.39)	(-0.69)
NR	0.095	0.142**	0.086	0.118*	0.129*	0.154**	0.094	0.090
	(1.41)	(2.20)	(1.26)	(1.78)	(1.85)	(2.28)	(1.38)	(1.32)
ISP^1	-0.001				-0.059			
	(-0.01)				(-0.50)			
ISP^2		-0.025				-0.096		
		(-0.30)				(-1.05)		
ISP^3			-0.029				-0.131	
			(-0.27)				(-1.17)	
ISP^4				-0.061				-0.156**
				(-0.83)				(-1.96)
Interaction Terms								
$NR\times\left(\frac{H}{L}\right)$					-0.007**	-0.006**	-0.003	-0.000
					(-2.23)	(-1.97)	(-1.55)	(-0.30)
$ISP^1\times\left(\frac{H}{L}\right)$					0.004***			
					(2.93)			
$ISP^2\times\left(\frac{H}{L}\right)$						0.003**		
						(2.73)		
$ISP^3\times\left(\frac{H}{L}\right)$							0.014***	
							(3.62)	
$ISP^4\times\left(\frac{H}{L}\right)$								0.009***
								(3.16)
N	3215	2994	3263	3042	3215	2994	3263	3042
adj. R^2	0.8940	0.8773	0.8937	0.8774	0.8945	0.8779	0.8943	0.8779
F	311.00	278.36	328.38	280.40	294.36	261.43	311.88	263.30
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CD Test	36.71	37.5	38.93	38.72				
p-value	(0.00)	(0.00)	(0.00)	(0.00)				
LL	-7168	-6682	-7280	-6793	-7159	-6674	-7270	-6785
BIC	14595	13613.	14819.	13835	14593	13612	14815	13836

Notes: All regressions include, industry and country fixed effects. Robust coefficients are reported in the presents of group-wise heteroscedasticity and cross-sectional dependence. *t* statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As expected, the impact of production inputs $\Delta \ln F$ on output is positive and statistically significant at 1% level of significance in all columns of Table 3. The degree of capacity utilization is however insignificant, indicating the lack of existence of cyclical effects in the utilisation of inputs or absence of adjustment costs that may affect productivity growth in the short–run.

The impact of industry's initial knowledge stock as measured by $\left(\frac{R}{L}\right)_{t=0}$ is negative but remains statistically insignificant across all columns. This means that between initial knowledge stock and industry output growth there is no relationship implying the absence of a convergence process. Regarding intra-national R&D spillovers NR_t the sign of this coefficient is positive, which is consistent with some earlier studies in the R&D spillovers literature (Branstetter (2001)). This finding suggests that innovative activity of other domestic counterparts incorporates growth-enhancing effects whose diffusion takes place through national production linkages as represented by the input-output matrix. This result implies the existence of national path dependence in the sense that a country that acquires a comparative advantage in an R&D sector can build upon that advantage eventually accelerating the strength of this advantage. This finding is rather supportive for the development of substantial research clusters among industries within a country while it contradicts key propositions of the neoclassical trade theory which predicts negative cross-industry productivity effects (Harrigan (1997), Nickell et al. (2008)).

Turning to the estimates of international spillovers, the results are negative and insignificant for all indices except ISP^4. However the effect turns positive and significant when the knowledge spillover variable is interacted with human capital, suggesting that countries with better human capital have the absorptive capacity to benefit more from knowledge spillover. Even the direct linear effect of human capital is also positive and significant. The magnitude of this interaction effect is somewhat bigger when knowledge is regarded as a private good in the sender (coefficient of ISP^3 is 0.014).

In Table 4, we consider all right hand side regressors of equation (11) as endogenous and use their lagged values up to 3 years as instruments. Having used an IV estimator, the second stage coefficients are presented in Table 4. Results in Table 4 are not qualitatively different from those reported in Table 3, which suggests that our spillover variables are truly capturing the spillover effect which turns significant in industries where absorptive capacity in the form of human capital is at a higher level.

Table 4: Results from IV Estimator, Equation (11)

	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$	$\Delta\ln\left(\frac{Q}{L}\right)$
$\Delta\ln F$	1.118***	1.146***	1.242***	1.167***	1.123***	1.177***	1.251***	1.214***
	(12.52)	(17.09)	(12.50)	(16.81)	(12.02)	(14.00)	(12.99)	(14.80)
$\Delta\ln U$	-0.031	-0.041	-0.085	-0.047	-0.027	-0.050	-0.092	-0.070
	(-0.30)	(-0.36)	(-0.76)	(-0.42)	(-0.26)	(-0.43)	(-0.87)	(-0.59)
$\Delta\ln\left(\frac{H}{L}\right)$	0.023	0.023	0.013	0.013	0.038	0.048	0.028	0.054
	(1.08)	(0.87)	(0.47)	(0.44)	(1.57)	(1.42)	(0.93)	(1.31)
$\left(\frac{R}{L}\right)_{t=0}$	1.074	0.833	-0.459	-0.625	1.473	1.708	0.836	1.197
	(0.85)	(0.62)	(-0.23)	(-0.66)	(1.09)	(1.04)	(0.34)	(0.73)
NR	0.066	0.089	-0.068	-0.037	0.153	0.152	-0.011	-0.009
	(0.65)	(1.03)	(-0.76)	(-0.61)	(1.33)	(1.39)	(-0.10)	(-0.12)
ISP^1	-0.014				-0.051**			
	(-0.46)				(-1.98)			
ISP^2		-0.020				-0.048*		
		(-0.56)				(-1.66)		
ISP^3			-0.111				-0.146	
			(-0.54)				(-0.78)	
ISP^4				-0.169				-0.021
				(-1.07)				(-0.09)
Interaction Terms								
$NR\times\left(\frac{H}{L}\right)$					-0.012*	-0.013	-0.004	-0.001
					(-1.74)	(-1.52)	(-1.40)	(-0.29)
$ISP^1\times\left(\frac{H}{L}\right)$					0.006*			
					(1.89)			
$ISP^2\times\left(\frac{H}{L}\right)$						0.006*		
						(1.68)		
$ISP^3\times\left(\frac{H}{L}\right)$							0.019**	
							(2.06)	
$ISP^4\times\left(\frac{H}{L}\right)$								0.014**
								(2.47)
N	2664	2484	2717	2535	2664	2484	2717	2535
adj. R^2	0.8901	0.8877	0.8960	0.8935	0.8762	0.8518	0.8874	0.8697
F	254.56	272.47	304.86	299.31	216.01	205.53	256.84	229.94
Hansen Test	10.34	11.20	8.03	9.35	8.75	8.57	7.12	8.70
p-value	0.59	0.51	0.78	0.67	0.79	0.80	0.90	0.80
LM Test	8.06	7.45	4.01	7.45	8.09	9.66	3.18	3.86
p-value	0.84	0.88	0.99	0.88	0.88	0.79	1.00	1.00

Notes: All regressions include, industry and country fixed effects. Instruments are lagged values of right-hand side regressors up to year (t-3). The null hypothesis of Hansen test is that instruments are valid and the null hypothesis of the LM test is that excluding instruments are correctly not included in the equation. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 Robustness Analysis

5.4.1 FDI Related Spillovers

This section examines the case that the conduit of international R&D spillovers is FDI. FDI can be an important vehicle of technology transfer as can contribute to the assimilation of new production and management techniques in the domestic economy. To explore the empirical validity of this argument, we consider whether FDI can provide access to gains from international R&D activities implicitly assuming that multinationals are usually more innovative intensive than domestic firms. This specification also assumes that the amount of knowledge and ideas transferred via the multinational subsidiaries and thus can be directly observed from any variable of FDI activity at the industry level. This is a common approach that can be frequently found in micro level studies (Xu (2000) and Aitken and Harrison (1999)). We replicate estimates of (11) using indices (20) and (21). These indices measure FDI and vertical FDI in industry i. Table 5 presents results from OLS with PCSE and IV estimators.

Table 5: FDI Related Spillovers

	PCSE (1)	PCSE (2)	PCSE (3)	PCSE (4)	IV (5)	IV (6)
$\Delta \ln F$	1.139***	1.142***	1.138***	1.138***	1.013***	0.928***
	(49.76)	(49.20)	(49.26)	(49.16)	(9.42)	(5.91)
$\Delta \ln U$	0.096	0.095	0.097	0.097	0.082	0.130
	(1.41)	(1.38)	(1.45)	(1.44)	(0.60)	(0.76)
$\Delta \ln \left(\frac{H}{L}\right)$	0.010**	0.009*	0.010**	0.010**	0.006	-0.016
	(1.99)	(1.86)	(2.12)	(2.05)	(0.18)	(-0.36)
$\left(\frac{R}{L}\right)_{t=0}$	-0.046	-0.069	-0.061	-0.063	-1.007	-2.677
	(-0.70)	(-1.08)	(-0.98)	(-1.02)	(-0.97)	(-1.17)
NR	0.100	0.101	0.093	0.090	-0.022	-0.045
	(1.45)	(1.47)	(1.34)	(1.30)	(-0.33)	(-0.50)
FDI	0.003	-0.004			-0.015*	
	(0.50)	(-0.79)			(-1.83)	
VFDI			0.065	-0.06		-0.362
			(1.18)	(-0.76)		(-1.56)
Interaction Terms						
$NR \times \left(\frac{H}{L}\right)$	0.000	0.000	0.000	0.000	0.001	0.002
	(0.05)	(0.14)	(0.27)	(0.12)	(0.66)	(0.91)
$FDI \times \left(\frac{H}{L}\right)$		0.01*			0.006**	
		(1.7)			(2.20)	
$VFDI \times \left(\frac{H}{L}\right)$				0.026*		0.091**
				(1.79)		(2.24)
N	2401	2401	2481	2481	2026	2098
adj. R^2	0.8675	0.8681	0.8672	0.8676	0.8700	0.7780
F	177.51	173.31	177.99	171.47	213.27	147.89
p-value	0.00	0.00	0.00	0.00	.	.
LL	-5332.06	-5326.68	-5496.31	-5492.25		
BIC	10920.99	10918.01	11250.57	11250.25	.	.
Hansen Test					10.02	4.16
p-value					0.12	0.66
LM Test					7.91	2.77
p-value					0.34	0.91

Notes: All regressions include, industry and country fixed effects. Robust coefficients are reported in the presents of group-wise heteroscedasticity and cross-sectional dependence. Instruments in the IV estimations are lagged values of right-hand side regressors up to year (*t*-3). The null hypothesis of Hansen test is that instruments are valid and the null hypothesis of the LM test is that excluding instruments are correctly not included in the equation. *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results from the linear terms of FDI and VFDI are statistically insignificant. Their interaction terms with human capital in columns (3) and (4) are positive and significant at 10%. When the model corrects for endogeneity with IV in columns (5) and (6), the interaction terms become statistical significant at the 5%. This is further evidence in favours of the absorptive capacity hypothesis implying that FDI enhances productivity gains only if the domestic economy has the capacity to absorb them effectively. Similarly, cross-industry FDI gains are high the higher is the level of human capital. Overall, the estimates form Table 5 show that FDI is beneficial only subject to a crucial level of domestic human capital otherwise the presence of FDI is likely to incorporate adverse competition effects that negative impact on industry's output per worker as suggested in column (5) by the coefficient of linear FDI term (-0.015).

5.4.2 Spillovers and Industry Group Heterogeneity

R&D spending is highly concentrated in a small numbers of industries indicating that the potential of international technology is likely to be restricted only within the group of industries that account for the largest share of innovative activity. The estimates presented above do not distinguish how different production patterns across industry groups can affect the importance of knowledge spillovers. To investigate whether knowledge spillovers differ across groups of different technological level we divide our sample into low and high tech industries following the OECD classification. We replicate results of Table 4 for import weighted knowledge spillovers (ISP^1, ISP^2, ISP^3) for low-tech and high-tech groups, which are shown in Tables 6 and 7 respectively.

Table 6: Low Technology Groups, Estimation of Equation (11)

	OLS	OLS	OLS	OLS	IV	IV	IV	IV
$\Delta \ln F$	1.105***	1.112***	1.110***	1.119***	1.137***	0.931***	1.325***	0.956***
	(61.69)	(50.68)	(62.81)	(51.51)	(6.16)	(7.11)	(5.27)	(6.30)
$\Delta \ln U$	0.040	0.037	0.031	0.028	-0.084	0.044	-0.223	0.016
	(0.67)	(0.60)	(0.53)	(0.47)	(-0.52)	(0.31)	(-0.97)	(0.12)
$\Delta \ln\left(\frac{H}{L}\right)$	0.011**	0.007	0.011**	0.006	0.017	-0.007	0.000	-0.027
	(2.11)	(1.23)	(2.11)	(1.20)	(0.53)	(-0.19)	(0.01)	(-0.46)
$\left(\frac{R}{L}\right)_{t=0}$	0.003	-0.002	-0.005	-0.013	2.623	0.982	5.748	-1.431
	(0.06)	(-0.04)	(-0.09)	(-0.24)	(1.23)	(0.80)	(1.03)	(-0.36)
NR	0.153*	0.169**	0.123	0.137*	0.027	0.149	-0.017	0.065
	(1.72)	(2.00)	(1.49)	(1.73)	(0.11)	(1.13)	(-0.09)	(0.76)
ISP^1	0.031				0.026			
	(0.19)				(0.34)			
ISP^2		0.032				0.001		
		(0.23)				(0.02)		
ISP^3			-0.049				0.839	
			(-0.38)				(0.84)	
ISP^4				-0.031				-0.477
				(-0.31)				(-0.45)
Interaction Terms								
$NR \times \left(\frac{H}{L}\right)$	-0.010**	-0.005	-0.004*	-0.001	-0.018	-0.004	-0.012	-0.001
	(-2.06)	(-1.14)	(-1.77)	(-0.70)	(-1.40)	(-0.54)	(-1.43)	(-0.61)
$ISP^1 \times \left(\frac{H}{L}\right)$	0.003*				0.005			
	(1.82)				(1.24)			
$ISP^2 \times \left(\frac{H}{L}\right)$		0.002				0.001		
		(0.94)				(0.25)		
$ISP^3 \times \left(\frac{H}{L}\right)$			0.012**				0.021	
			(2.08)				(1.42)	
$ISP^4 \times \left(\frac{H}{L}\right)$				0.007				0.012
				(1.61)				(1.08)
N	2211	2058	2259	2106	1955	1821	2007	1872
adj. R^2	0.8963	0.8745	0.8959	0.8747	0.8196	0.8616	0.4448	0.8452
F	225.89	183.27	238.60	183.81	107.08	136.72	55.26	135.17
p	0.00	0.00	0.00	0.00	.	.	.	.
LL	-4898.63	-4551.72	-5010.64	-4663.46				
BIC	10028.30	9324.70	10252.96	9548.84	.	.	.	.
Hansen Test					2.91	4.18	0.65	4.40
p-value					0.82	0.65	1.00	0.62
LM Test					4.28	4.67	1.87	1.66
p-value					0.75	0.70	0.97	0.98

Notes: All regressions include, industry and country fixed effects. Robust coefficients are reported in the presents of group-wise heteroscedasticity and cross-sectional dependence. Instruments in the IV estimations are lagged values of right-hand side regressors up to year (*t*-3). The null hypothesis of Hansen test is that instruments are valid and the null hypothesis of the LM test is that excluding instruments are correctly not included in the equation *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results from Tables 6 and 7 are consistent with the notion that knowledge spillovers vary greatly in strength across different groups of industries. Regarding domestic intra-national spillovers, coefficients are positive and statistically significant in all specifications for high tech group while for the low tech group both domestic and international knowledge spillover indices remain insignificant. Interestingly, coefficients of international knowledge spillovers now appear with a negative sign. These results indicate that international exchange of ideas tends to benefit mostly high tech industries while the scope of productivity gains for low tech group is rather limited. These results might also imply that low tech industries are weak in absorptive capacity mainly because of their limited R&D activity, which deteriorates their ability to convert into meaningful productivity gains from the technological advancements of domestic and foreign counterparts. The above findings are in line with the results from Keller (2001), who also highlights this as an issue of poor absorptive capacity derived from low levels of within industry innovative activity.

Table 7: High Technology Groups, Estimation of Equation (11)

	OLS	OLS	OLS	OLS	IV	IV	IV	IV
$\Delta \ln F$	1.197***	1.204***	1.196***	1.203***	1.111***	1.071***	1.160***	1.140***
	(58.99)	(52.75)	(58.28)	(53.33)	(12.48)	(11.19)	(12.36)	(11.71)
$\Delta \ln U$	0.184***	0.179***	0.185***	0.178***	0.479*	0.558*	0.400	0.311
	(3.54)	(3.41)	(3.57)	(3.38)	(1.91)	(1.89)	(1.53)	(1.20)
$\Delta \ln\left(\frac{H}{L}\right)$	0.009	0.007	0.010	0.008	0.061**	0.057*	0.060*	0.047*
	(1.08)	(0.77)	(1.21)	(0.88)	(2.27)	(1.75)	(1.93)	(1.72)
$\left(\frac{R}{L}\right)_{t=0}$	0.046	0.052	0.012	-0.034	-0.174	0.277	-2.524*	-0.143
	(0.72)	(0.81)	(0.19)	(-0.56)	(-0.10)	(0.22)	(-1.74)	(-0.13)
NR	0.081	0.089	-0.033	-0.006	0.087	0.139	0.031	-0.016
	(0.56)	(0.56)	(-0.23)	(-0.04)	(0.28)	(0.48)	(0.12)	(-0.06)
ISP^1	-0.121				-0.175			
	(-0.67)				(-0.38)			
ISP^2		-0.057				0.204		
		(-0.35)				(0.37)		
ISP^3			-1.042***				-1.058**	
			(-3.70)				(-2.20)	
ISP^4				-0.456**				-0.405
				(-2.05)				(-1.00)
Interaction Terms								
$NR \times \left(\frac{H}{L}\right)$	-0.008	-0.008	-0.000	0.000	-0.007	-0.009	-0.027*	-0.003
	(-1.53)	(-1.58)	(-0.07)	(0.12)	(-0.90)	(-1.29)	(-1.77)	(-0.51)
$ISP^1 \times \left(\frac{H}{L}\right)$	0.004**				0.003			
	(2.41)				(0.74)			
$ISP^2 \times \left(\frac{H}{L}\right)$		0.005**				0.005		
		(2.46)				(1.24)		
$ISP^3 \times \left(\frac{H}{L}\right)$			0.010				0.053**	
			(0.99)				(2.02)	
$ISP^4 \times \left(\frac{H}{L}\right)$				0.010				0.013
				(1.28)				(1.28)
N	1004	936	1004	936	724	676	724	676
adj. R^2	0.8903	0.8833	0.8913	0.8827	0.9027	0.8974	0.8446	0.9069
F	212.83	200.10	207.04	190.93	146.78	145.28	119.93	158.43
p-value	0.00	0.00	0.00	0.00	.	.	.	.
LL	-2222.73	-2089.47	-2218.45	-2091.73				
BIC	4618.25	4343.13	4609.69	4347.67	.	.	.	.
Hansen Test					17.27	14.40	18.23	17.45
p-value					0.64	0.81	0.57	0.62
LM Test					4.89	9.69	7.59	8.54
p-value					1.00	0.98	1.00	0.99

Notes: All regressions include, industry and country fixed effects. Robust coefficients are reported in the presents of group-wise heteroscedasticity and cross-sectional dependence. Instruments in the IV estimations are lagged values of right-hand side regressors up to year (*t*-3). The null hypothesis of Hansen test is that instruments are valid and the null hypothesis of the LM test is that excluding instruments are correctly not included in the equation*t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusions

The present paper endeavours to analyse the impact of knowledge spillovers on output growth and how the absorptive capacity in each industry affects the impact of the technology spillovers. The methodology used is a primal approach directly derived from a production function. The key objective of the paper is to identify the importance of domestic and international spillovers and whether their effect on output growth depends on the degree of human capital. Through various specifications and robustness tests, the key findings of the paper is as follows: international knowledge spillovers are an important source of industry output growth via the absorptive-capacity hypothesis, that is the employment of skilled workers turns out to be a key channel through which knowledge spillovers tend to occur.

R&D spillover and human capital affect total factor productivity growth in the manufacturing sector across OECD countries, with evidence of a positive and significant direct effect of human capital and a positive and significant indirect effect of R&D spillovers reflecting own innovation and imitation of frontier technology. The interaction terms of trade-related foreign knowledge spillovers with human capital appear to be more robust in terms of statistical significance and the pattern persists even after controlling for endogeneity with IV approach. Knowledge and respective spillovers are not pure public goods, which imply that the potential of knowledge gains from research activity of international counterparts improves as the degree of import intensity increases. The importance of domestic spillovers and their interaction with human capital vanishes when controlling for endogeneity contrary to the pattern revealed for international knowledge spillovers. The message from these results is that foreign spillovers are present but their implementation from other counterparts calls for international policy coordination among countries in the area of investment in national scientific and industrial innovations.

Finally, significant heterogeneity found between high and low-tech industries. More importantly, spillovers found to be important only for output growth of the high-tech group, all sources of knowledge spillovers are weak for low-tech industries highlighting primarily the fact that low-tech industries are not innovative intensive thus become unable to absorb the technological advancements of domestic and international rivals. The importance of international spillovers in the presence of better human capital is more crucial for the high tech group while they do not seem to matter for the low tech group.

With regard to the role of inward FDI, the knowledge effect prevails only with the existence of human capital otherwise competitiveness effect outweighs the knowledge effects associated with FDI. The message is clear: multinational enterprises can boost output growth at the industry level only in conjunction with the presence of skilled workers. Similarly, the presence of positive spillovers from vertical FDI suggests that such vertical FDI flows should be promoted in order to upgrade an economy's absorptive capacity and move the economy to a higher steady state.

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Appendices

Figure A2: Output per worker versus Knowledge Spillovers

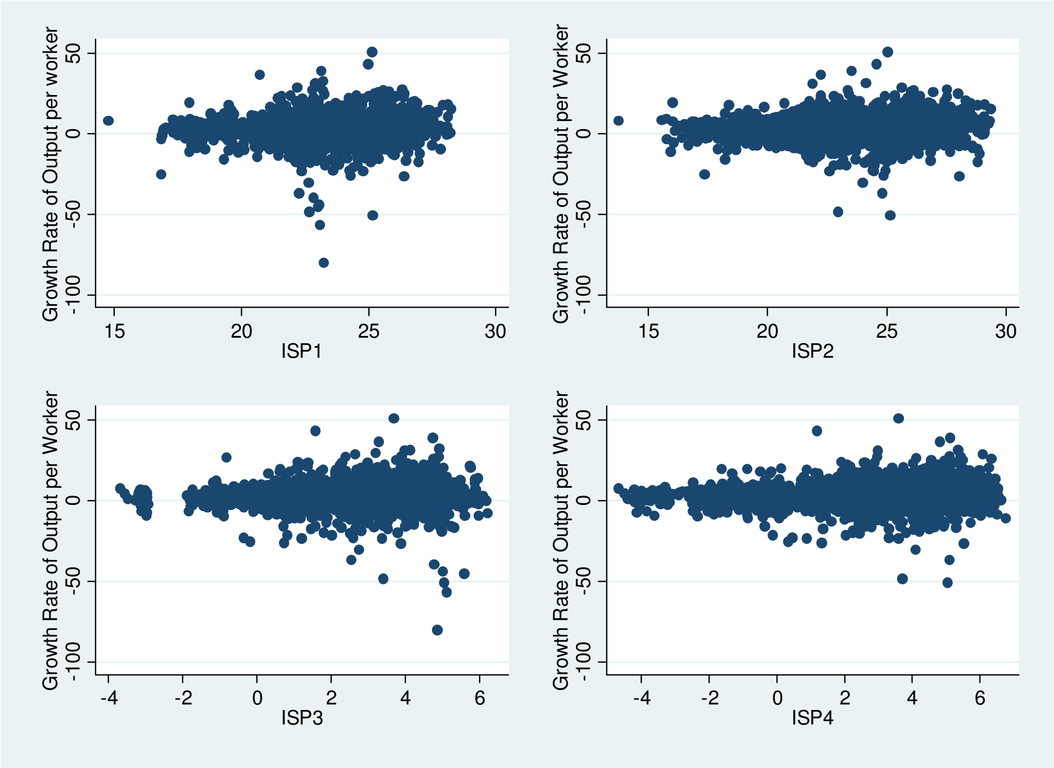

Table A1: Summary Statistics

Variable	Obs	Mean	SD	Min	Max
$\Delta \ln\left(\frac{Q}{L}\right)$	4320	2.78	6.51	-80.38	50.89
$\Delta \ln U$	4320	0.01	1.61	-19.70	34.92
$\Delta \ln F$	4160	2.16	5.30	-74.89	48.00
$\Delta \ln\left(\frac{H}{L}\right)$	4480	4.04	9.38	-47.65	77.21
$\left(\frac{R}{L}\right)$	4704	0.65	1.11	-3.94	1.92
NR	4661	6.04	2.46	-2.13	12.21
ISP^1	3397	22.99	1.93	14.77	28.26
ISP^2	3085	22.91	2.42	13.79	29.34
ISP^3	3445	2.75	1.66	-3.68	6.44
ISP^4	3133	2.59	2.15	-4.66	6.78

Table A2: Correlation Matrix of Knowledge Spillover Indices

	ISP^1	ISP^2	ISP^3	ISP^4	$ISP^1 \times H$	$ISP^2 \times H$	$ISP^3 \times H$	$ISP^4 \times H$
ISP^1	1.00							

ISP^2	0.92	1.00						
ISP^3	0.56	0.56	1.00					
ISP^4	0.56	0.73	0.89	1.00				
$ISP^1 \times H$	0.36	0.24	0.21	0.10	1.00			
$ISP^2 \times H$	0.38	0.28	0.22	0.14	1.00	1.00		
$ISP^3 \times H$	0.45	0.38	0.54	0.43	0.84	0.86	1.00	
$ISP^4 \times H$	0.48	0.54	0.56	0.60	0.68	0.72	0.92	1.00