DO SPILLOVERS MATTER WHEN ESTIMATING PRIVATE RETURNS TO R&D?*

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ABSTRACT

A large body of literature on the estimation of private returns to R&D adopts the Griliches knowledge production framework, ignoring the impact omitted spillover effects may have on consistent estimation. A separate body of literature is primarily interested in the presence and magnitude of spillovers but imposes a rigid ad hoc structure on the channels these can take, e.g. within-industry, within-country or determined by industry input-output matrices. In this paper we adopt a common factor approach which accounts for R&D spillovers without imposing any arbitrary structure on their nature and channels. At the same time we can account for other unobserved common processes which may affect countries or sectors differentially, e.g. economic shocks or business cycles, as well as heterogeneous evolution of TFP over time. Panel data from 12 industrial sectors of 12 OECD and EU countries (1980-2005) is used to arrive at unbiased estimates of private returns to R&D. Our results indicate the presence of substantial cross-sectional dependence in the residuals of the Griliches knowledge production function, pointing to the presence of knowledge spillovers. Further, our estimations suggest that when ignoring the presence of spillovers, R&D produces positive returns. However, when cross-sectional dependence is accounted for, we do not find any convincing evidence for positive private returns to R&D. These results suggest that spillovers may not be additively separable from own-R&D and need to be accounted for in the estimation even when the exclusive interest lies in obtaining estimates for private returns to R&D.

KEYWORDS: Productivity, R&D, Spillovers, Common Factor Model

JEL Classification: C23, D24, L16

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1 Introduction

Firms invest in R&D to achieve productivity gains through innovations resulting from their investments.[1] Thus from an aggregate economy perspective, R&D is seen as crucial in achieving productivity growth and has received an enormous amount of attention from policymakers, academics, and the private business sector.[2] As with any type of investment, investment in R&D depends on its expected return — in absolute terms as well as relative to other inputs. In addition, given the particular characteristics of knowledge, namely non-excludability and non-exhaustability, private and social returns to R&D generally do not coincide. This difference between private and social returns to R&D has motivated a range of policy interventions including direct subsidies and tax credit. From a policy perspective the question of the return to R&D is therefore essential as R&D spending represents *one of the few variables which public policy can affect in the future* (Griliches, 1979: p. 115).

Despite the crucial role of investments in R&D, national accounting does not record these in a way that reflects their perceived relevance for productivity growth, although this situation is about to change following an update of the System of National Accounts.[3] But even once R&D is accounted for in core national accounts, another important issue closely linked to R&D will still remain unaccounted for: knowledge spillovers. There is a vast economic literature attributing an eminent role to R&D in generating productivity gains and long-run growth owing to the generation of spillovers (Romer, 1990; Grossman and Helpman, 1991).[4] Notably, spillovers account for the difference between social and private returns to R&D. If spillovers are closely linked to R&D, the relevant question is whether the direct effect of R&D on productivity and its direct returns can be estimated *without* also accounting for the spillovers it induces.

Considering the importance of the subject, it is not surprising that there is a substantial number of empirical studies assessing the private and social returns to R&D at the country, regional, industry and firm-level.[5] A closer look at this literature reveals that the most widely used approach is the 'knowledge production function' originally proposed by Griliches (1979). In this approach R&D stock is added as additional input to a standard Cobb-Douglas production function. The corresponding estimates are elasticities of output with respect to R&D which can be converted into returns to R&D.[6] In the original Griliches knowledge production function, any

[1] We focus entirely on R&D conducted by the business enterprise sector.

[2] We use the terms productivity and TFP interchangeably throughout this paper to describe the residual of a production function.

[3] R&D is treated as an intermediate input for firms and as current consumption for governments and non-profit organizations (Edworthy and Wallis, 2007). Following the changes to the System of National Accounts in 2008 it is now recommended to treat existing and past R&D as an asset which is capitalized through 'satellite accounting'. The principal motivation for treating R&D expenditure as investment in National Accounting is to compute its contribution to growth in real GDP.

[4] See Uppenberg (2009) for an overview of this literature.

[5] A comprehensive overview of earlier work can be found in Cameron (1996), while Hall, Mairesse and Mohnen (2009) cover more recent studies. Recent relevant studies at the firm-level include Hall and Mairesse (1995), Mairesse and Hall (1996) and Doraszelski and Jaumandreu (2009). At the industry-level, important contributions include Griliches and Lichtenberg (1984) and Cameron, Proudman and Redding (2005). At the country-level, examples are Nadiri (1980), Lichtenberg (1992), Coe and Moghadam (1993) and Verspagen (1997).

[6] Alternatively, returns to R&D can be obtained directly from using R&D expenditure albeit under certain restrictive assumptions.

notion of spillovers is neglected in the empirical specification, a practice maintained in the most recent applications (see for example Doraszelski and Jaumandreu, 2009). In parallel to this, there is a vast body of research concentrating on the contribution of spillovers to productivity, imposing a rigid structure on the spillover channels in constructing 'spillover variables' based on *ad hoc* assumptions (see Section 3.2). This research indicates the presence and importance of spillovers within the production function framework.

This paper asks whether spillovers have to be accounted for within the Griliches knowledge production function framework even when the interest lies exclusively in the estimation of private returns to R&D. If spillovers are unobserved and go unaccounted in the empirical analysis, their presence can lead to correlation between cross-sectional units. Spillovers can therefore be regarded as omitted unobserved factors in the R&D variable as well as the error terms. If these unobserved factors are correlated, the resulting estimates of private returns to R&D are biased and inconsistent (Bai, 2009; Kapetanios et al, 2009).[7]

The dedicated knowledge spillovers literature, on the other hand, is unaware of the *econometric* importance of accounting for cross-section dependence for consistent estimation and instead concentrates on *establishing the impact* of spillover variables created based on *ad hoc* assumptions in a fashion akin to employing spatial weight matrices. This approach faces the question of whether a statistically significant spillover variable indeed points to knowledge spillovers or reflects data dependencies introduced by empirical misspecification of structural heterogeneity across countries and sectors.

In this paper we adopt a more general common factor approach, which allows us to remain agnostic about the nature and channels of this relationship: our primary interest is in establishing the private returns to R&D investment at the macro-level while accounting for *any* unobserved heterogeneities including local or global spillovers (Costantini and Destefanis, 2009; Kapetanios et al, 2009; Pesaran, 2009). To investigate this question empirically we use an unbalanced panel of 12 countries containing data for 12 two-digit manufacturing industries covering the period 1980-2005. We find strong evidence for cross-sectional dependence and the presence of a common factor structure in the data which we interpret as indicative for the presence of knowledge spillovers. We then compare and contrast the estimates for a Griliches knowledge production function across a number of different empirical specifications with inherently different assumptions about error term independence (lack of spillover effects) *as well as* technology homogeneity across countries and/or sectors. Our findings suggest that when spillovers in the form of cross-sectional dependence are accounted for, private returns to R&D are at best modest. In our view this finding is a strong indicator for the presence of spillovers and the indivisibility of R&D from spillovers. If cross-sectional dependence due to knowledge spillovers and/or additional unobserved heterogeneity is present in the data, estimates of the output elasticity with respect to R&D capital confound the direct effect of R&D on output with what in reality is a

[7]In order to address this issue, a spatial econometric approach would impose a specific structure on the spatial association between countries and/or industries by means of a spatial weight matrix, where the relevant 'space' can be defined in many ways such as geographical, technological, or input-output-based. However, if this fails to capture all of the cross-sectional dependence estimates remain biased.

combined effect of own-R&D, spillovers and a host of other phenomena.[8]

The remainder of this paper is organized as follows: Section 2 discusses the theory underlying the Griliches knowledge production function which is at the heart of the literature. Section 3 discusses the theory on knowledge spillovers as well as their empirical measurement. Section 4 introduces the dataset used for our analysis and provides descriptive statistics. Section 5 contains a description of the estimation approach taken and Section 6 presents the empirical results. Section 7 concludes.

2 The Knowledge Production Function

The output elasticity with respect to R&D (and thus the private returns to R&D) are commonly estimated adopting a version of the the Cobb-Douglas production function framework. Griliches (1979) assumes an augmented production function with value-added Y as a function of standard inputs labor L and tangible capital K as well as the additional input 'knowledge capital' R

$$Y = F(L, K, R) \tag{1}$$

The functional form of $F(\cdot)$ is assumed to be Cobb-Douglas, which implies that knowledge capital R is treated as a complement to the standard inputs. According to Griliches, the level of knowledge capital is a function of current and past levels of R&D expenditure

$$R = G[W(B)R\&D] \tag{2}$$

where $W(B)$ is a lag polynomial with B being the lag operator. Equation (2) describes the so-called knowledge production function: the functional relation between knowledge inputs and knowledge output.[9] Griliches then writes (1) as

$$Y = AL^{\alpha}K^{\beta}R^{\gamma}e^{\lambda t+\varepsilon} \tag{3}$$

where A is a constant, t is a time index capturing a common trend and ε is a stochastic error term. α, β, γ and λ are parameters to be estimated. Equation (2) can be substituted into Equation (3) to obtain output directly as a function of present and past $R\&D$ expenditure (Hall, 1996). In order to obtain an estimable equation, we take logarithms and use subscripts i

[8] In this paper, we focus on the standard Griliches knowledge production function rather than attempting to find an alternative and possibly more adequate specification accounting for both own-R&D and spillover effects which we leave for future work.

[9] Crepon et al. (1998) stress the point that not innovation *input* (R&D) is supposed to affect productivity, but innovation *output*. In common with a large number of empirical studies, Crepon et al. (1998) use patents as a measure for knowledge output. This however seems too narrow a measure, since knowledge output can also assume many other forms; for example it can be embodied in new products or capital goods, or disembodied in managerial practices which are not patentable. Since R&D is underlying these different innovative outputs, it may be a better and more comprehensive measure of innovation than restricting the analysis to patented innovations. At the same time, R&D may not even be broad enough because it only accounts for formal institutionalized forms of innovative effort.

and t to denote cross-sectional units and time respectively:

$$y_{it} = \psi + \alpha l_{it} + \beta k_{it} + \gamma r_{it} + \lambda t + \mu_i + e_{it} \tag{4}$$

where lower case letters denote logarithms of the inputs in Equation (2) and λt is a time-specific effect that is assumed to be constant across countries and sectors. e_{it} is an error term which contains random shocks in the relation described in Equation (2) as well as (3). Equation (4) contains a measure for R&D capital *stock*, r_{it}, instead of a lag polynomial of R&D expenditures. We discuss below how R&D capital stock (R) can be constructed from R&D expenditures ($R\&D$). In order to account for cross-section unit-specific effects that remain constant over time, we have also introduced μ_i into (4). The coefficient γ measures the joint contribution of R&D to productivity and to output prices of industry i. γ therefore indicates the elasticity of R&D capital, i.e., $\gamma = \frac{\partial Y}{\partial R}\frac{R}{Y}$. Accordingly the gross private rate of return can be obtained as $\rho^G = \gamma \frac{Y}{R}$. The net rate of return consequently is $\rho^N = \rho^G - \delta$ where δ is the depreciation rate of R&D capital. Note that so far we have not ruled out the shock e_{it} to be correlated with current input levels although we require it to be normally distributed and homoskedastic.[10]

In principle, Equation (4) is estimated without imposing any *a priori* parameter restrictions. If further analysis of the unobserved productivity residual is intended Total Factor Productivity (TFP) is 'backed out' in a second step imposing the estimated input parameter values. The validity of this approach rests on the assumption of perfectly competitive factor markets, full capacity utilization, as well as the absence of spillover effects — the latter is econometrically represented by the cross-sectional independence of error terms e_{it}, inputs and output in Equation (4) (Section 3 discusses these issues in more detail). In the growth accounting framework as laid out by Jorgenson and Griliches (1967), Jorgenson, Gollop and Fraumeni (1987), and Jorgenson, Ho and Stiroh (2005), the additional assumption of constant returns to scale is imposed on the input parameters. Under this additional assumption, output growth is equal to the income share-weighted growth of inputs and productivity. Once R&D is included in the production

[10] If the data required to construct R&D stocks is not available and returns to R&D are the primary concern, R&D expenditure can be used to recover $\rho^G = \gamma\frac{Y}{R}$ directly, albeit under the strong assumption of zero depreciation of R&D capital such that $\triangle R = R\&D$. This can be seen more clearly by first-differencing Equation (4) to obtain

$$\triangle y_{it} = \alpha\triangle l_{it} + \beta\triangle k_{it} + \gamma\triangle r_{it} + \lambda\triangle t + \triangle e_{it} \tag{5}$$

$$\text{where} \qquad \triangle r_{it} = r_{it} - r_{it-1} = \ln\left[\frac{R\&D_t + (1-\delta)R_{t-1}}{R_{t-1}}\right] = \ln\left[\frac{R\&D_t}{R_{t-1}} + (1-\delta)\right] \simeq \frac{R\&D_t}{R_{t-1}}$$

for δ approximately zero. This implies that $\gamma\triangle r_{it}$ can be replaced by $\rho^G\frac{R\&D}{Y}$ in Equation (5) since $\rho^G\frac{R_{t-1}}{Y_t}\frac{R\&D_t}{R_{t-1}} = \gamma\frac{R\&D_t}{R_{t-1}} = \gamma\triangle r$. Hence, levels of R&D intensity, i.e. R&D expenditure divided by value-added, are used instead of the R&D capital stock. Note that when using R&D capital, the output *elasticity* wrt R&D is assumed to be constant, whereas under the specification used to directly estimate private returns, the *rate of return* is the constant parameter. While the approach in Equation (5) dispenses with the construction of R&D stocks, it nevertheless does not dispense with the problem of choosing a depreciation rate for R&D because the coefficient ρ^G is an estimate of gross returns to R&D. Hence, to obtain net returns, the depreciation rate has to be subtracted from gross returns. Hall (2007) notices that using the formulation in Equation (5) to obtain gross returns to R&D leads to an underestimation of the true gross return. The magnitude of the bias depends on the ratio of growth of the R&D stock and the sum of R&D growth and the depreciation rate. Considering this problem and the fact that we have data on R&D capital stocks, we only estimate Equation (4) instead of adopting the approach described in Equation (5).

function, it is unclear whether the restriction of constant returns should be imposed on the aggregate production function, as knowledge is expected to lead to increasing returns (Romer, 1990). Moreover, both approaches make the assumption that all cross-sectional units have the same production function (parameter homogeneity), which may appear to be restrictive.

3 Cross-sectional Dependence and Spillovers

3.1 Knowledge Spillovers

Arrow (1962) pointed out that knowledge is distinct from the traditional production factors labor and physical capital. The distinguishing features are (i) non-excludability, i.e., other actors cannot be excluded from accessing and using the knowledge produced by the original source and (ii) non-rivalry or non-exhaustability of knowledge, i.e., if one actor uses some specific knowledge, the value of its use is not reduced by other actors' use. These two distinguishing features lead to the third characteristic of knowledge, as pointed out by Griliches (1979), namely the fact that *we do not deal with one closed industry, but with a whole array of firms and industries which borrow different amounts of knowledge from different sources according to their economic and technological distance from them* (Griliches, 1979:103). Hence, knowledge spills over to other actors which do not pay the full cost of accessing and using the knowledge. This also implies that this phenomenon must not be confounded with *targeted* knowledge transfer, e.g. technology transfer to multinational corporation subsidiary plants. The process of knowledge transmission from one actor to another without deliberate action, is commonly referred to as 'knowledge spillovers'. As pointed out by Keller (2004), this also implies that the return to investments in knowledge is partly private and partly public.[11]

3.2 Incorporating Spillovers in the Knowledge Production Function

Given the fundamentally unobservable character of knowledge spillovers, directly quantifying their magnitude is a difficult task. To overcome this problem, empirical work on knowledge spillovers proposes a myriad of different spillover measures including approaches based on Input/Output tables (Wolff, 1997; Keller, 2002), patent citations (Jaffe, Trajtenberg and Henderson, 1993), human capital based measures (Breschi and Lissoni, 2001; Almeida and Kogut, 1999; Agrawal, Cockburn, and McHale, 2003), research cooperation (Cassiman and Veugelers, 2002; Abramovsky, Kremp, López, Schmidt, and Simpson, 2005), distance to technology frontier (Acemoglu, Aghion and Zilibotti, 2006; Griffith, Redding, and Van Reenen, 2004), so-called 'spillover pools' which quantify R&D activity in related industries (Basant and Fikkert, 1996; Griffith, Harrison and van Reenen, 2006) and measures of technological proximity (Jaffe, 1986; Bloom et

[11] Note that we are interested only in *ideas borrowed by research teams of industry i from the research results of industry j* (Griliches, 1979:104), i.e., knowledge spillovers in the form of knowledge moving from one industry to another. This is a distinct spillover concept from inputs that contain some form of externality if they are priced below their true quality price. This kind of spillover has been labeled 'rent spillovers' by Griliches (1979) and is not further discussed here. See Branstetter (2001) for a more detailed exposition of Griliches's argument.

al., 2005; Conley and Ligon, 2002; Orlando, 2004). The notion that knowledge spillovers are of great importance for productivity is a common thread through this myriad of approaches.

3.2.1 Standard Approaches

Within the production function framework, the most common approach in the literature to allow for spillovers is to compute TFP based solely on standard inputs labor and physical capital — commonly imposing constant returns to scale — and then in a second step to assume that TFP is a function of the knowledge stock within the sector or country and some measure of spillovers:[12]

$$\mathrm{TFP}_{it} = g\left(R_{it}, \sum_{k}^{N} R_{kt}\right) \tag{6}$$

where R_{it} denotes the R&D stock within sector i and R_{kt} with $i \neq k$ and $i = 1, ..., N$ denotes spillovers received from all other sectors. Equation (6) is estimated as:

$$\mathrm{tfp}_{it} = \psi + \gamma r_{it} + \chi \sum_{k}^{N} r_{kt} + e_{it} \tag{7}$$

where lower case letters denote logarithms and e_{it} is a stochastic shock. Note that Equation (7) assumes that spillovers affect TFP linearly as captured by the corresponding parameter χ.

In the approach described above, cross-sectional units are correlated exclusively because of correlation in R&D stocks r_{it} across units. Once spillovers are accounted for by the $\sum_k^N r_{kt}$ term, cross-sectional units are assumed to be independent which implies independence of e_{it} across units. Note that Equation (7) is commonly augmented with fixed effects and time dummies to purge additional correlation across cross-sectional units. However, this is only sufficient to eliminate any additional cross-sectional correlation under the assumption that the unobserved causes of cross-sectional dependence affect all cross-sectional units in the same way.

Importantly, in order to compute the spillover term $\sum_k^N r_{kt}$ in Equation (7), considerable structure is imposed on the cross-sectional dependence that spillovers are assumed to represent: the spillover variable is usually constructed as a weighted sum of cross-sectional units' R&D. This approach allows for a different effect of all other cross-sectional units' R&D on sector i through different weights but comes at the cost of rigid structure based on somewhat *ad hoc* assumptions. In order to avoid such restrictions, a novel alternative is to accept the unknown nature of cross-sectional spillovers (as well as other unobserved heterogeneities) and to adopt a multifactor error structure, where cross-sectional dependence is assumed to arise from unobserved common factors.

[12]See for example Griffith et al. (2004) who compute TFP using an index-number approach derived from the translog production function. Using the index number approach appears particularly appropriate when measurement error is small (van Biesebroeck, 2007). O'Mahony and Vecchi (2009) estimate TFP in a first step by estimating a Cobb-Douglas production function including R&D among inputs and then regress the resulting TFP measure on their spillover variables.

3.2.2 Unobserved Common Factor Framework

The unobserved common factor approach relies on latent factors in the error term as well as the regressors to account for cross-sectional dependence. Emerging from the panel time series literature over the recent years this approach has been primarily applied to macro panel data (Coakley, Fuertes and Smith, 2002; Pesaran, 2004; Coakley, Fuertes, and Smith, 2006; Pesaran 2006; Pesaran and Tosetti, 2007; Bai, 2009; Eberhardt and Teal, 2009b; Kapetanios et al, 2009).

The common factor approach regards cross-sectional dependence as the result of unobserved, time-varying omitted common variables or common shocks that affect each cross-sectional unit differently. Cross-sectional dependence leads to inconsistent estimates if regressors are correlated with the unaccounted common variables or shocks (Kapetanios et al, 2009). According to the common factor approach, the error term as well as right-hand-variables are assumed to contain a finite number of unobserved factors which can have a different impact on cross-sectional units.[13] Therefore, the error term is regarded as a linear combination of common time-specific effects with heterogeneous 'factor loadings' and an i.i.d. error term.[14]

To see the implications of cross-section dependence, rewrite the knowledge production function in Equation (4) omitting fixed effects and denoting the vector of inputs as $\mathbf{X}$:

$$y_{it} = \psi + \boldsymbol{\beta}'\mathbf{X}_{it} + \varepsilon_{it} \tag{8}$$

Note that we impose parameter homogeneity in the impact of observables for convenience of exposition. The structure of cross-sectional dependence is now described as

$$\mathbf{X}_{it} = \boldsymbol{\chi}_i\mathbf{f}_t + u_{Xit} \tag{9a}$$

$$\varepsilon_{it} = \boldsymbol{\varphi}_i\mathbf{f}_t + \mu_i + \lambda_t + u_{\varepsilon it} \tag{9b}$$

where $u_{Xit} \sim iid(0, \sigma^2_{Xi})$ and $u_{\varepsilon it} \sim iid(0, \sigma^2_{\varepsilon i})$. $\mathbf{f}_t$ contains a fixed number of unobserved common factors. The fact that regressors as well as the error term share a common factor implies that if the factor loadings are non-zero, estimating (8) without accounting for $\mathbf{f}_t$ produces biased and inconsistent estimates (see Eberhardt and Teal, 2009b and Bond and Eberhardt, 2009 for a detailed discussion). This means that in the presence of spillovers of the form given in ($9a$) and ($9b$) estimation of a standard empirical model as given in Equation (4) results in biased and inconsistent estimates. Coakley et al (2006) provide a set of Monte Carlo simulations to illustrate this point.

In order to test for the presence of such cross-sectional dependence, Pesaran (2004) proposes an extension of the Breusch and Pagan LM test for samples with large N and small T, which is based on the pairwise correlation coefficient of residuals obtained from ignoring the potential

[13] As detailed below, the setup is restricted to a finite number of 'strong' common factors (e.g. global shocks) but accommodates an infinity of 'weak' common factors (e.g. local spillovers). Since common factors are by construction orthogonal to each other the former assumption is easily justified: a change in the number of factors over time would represent an explosion in the variance of the observed variables made up of strong factors over time — a feature we do not observe in the data.

[14] Note that the error term may also display spatial dependence (Pesaran and Tosetti, 2007).

presence of cross-sectional dependence. For unbalanced panels, the test statistic of the the Cross-Section Dependence (CD) test is given by

$$CD = \sqrt{\left(\frac{2}{N(N-1)}\right)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\hat{\rho}_{ij}\right) \tag{10}$$

The pair-wise correlation coefficient $\hat{\rho}_{ij}$ is defined in an unbalanced panel setting as

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t\in T_i\cap T_j}(e_{it}-\bar{e}_i)(e_{jt}-\bar{e}_j)}{\sqrt{\sum_{t\in T_i\cap T_j}(e_{it}-\bar{e}_i)^2}\sqrt{\sum_{t\in T_i\cap T_j}(e_{jt}-\bar{e}_j)^2}} \tag{11}$$

where e_{it} is the OLS residual ignoring cross-sectional dependence. T_i denotes the set of years for which time series observations of the variables are available for unit i. The corresponding number of elements in the set is denoted by $\#T_i$ and hence $\bar{e}_i = \frac{\sum_{t\in T_i\cap T_j} e_{it}}{\#(T_i\cap T_j)}$. $T_{ij} = \#(T_i \cap T_j)$ is the number of observations used to estimate the correlation coefficient between the series of cross-sectional units i and j. Under the null hypothesis, e_{it} and e_{jt} are independently and standard normally distributed and serially uncorrelated, i.e. $H_0 : \rho_{ij} = \rho_{ji} = cov(e_{it}, e_{jt}) = 0$ $\forall i \neq j$. The alternative hypothesis is consequently $H_A : \rho_{ij} = \rho_{ji} \neq 0$ for some $i \neq j$. As shown in Pesaran (2004) for each $i \neq j$ and for $T_i > k+1$ (with k being the number of inputs) and $T_{ij} > 3$ it holds that $\sqrt{T}\hat{\rho}_{ij} \overset{T}{\Rightarrow} N(0,1)$. This implies that for $N \to \infty$, the CD test statistic is standard normally distributed.

If the null of global cross-sectional independence is rejected at reasonable significance levels, Pesaran (2006) suggests to account for cross-sectional dependence by using cross-section averages of the dependent and independent variables, where cross-section averages are defined as $\bar{\mathbf{y}}_t = N^{-1}\sum_{i=1}^{N}\mathbf{y}_{it}$ and $\bar{\mathbf{X}}_t = N^{-1}\sum_{i=1}^{N}\mathbf{X}_{it}$ $\forall t$. To see why augmenting Equation (4) can account for unobserved effects consider our pet-model in (8) in cross-section averages: given $\bar{e}_t = 0$ we obtain

$$\bar{y}_t = \bar{\psi} + \bar{\boldsymbol{\beta}}'\bar{\mathbf{X}}_t + \bar{\varphi}'\bar{\mathbf{f}}_t \tag{12}$$

which can be expressed as

$$\bar{\mathbf{f}}_t = \bar{\boldsymbol{\varphi}}^{-1}(\bar{y}_t - \bar{\psi} - \bar{\boldsymbol{\beta}}'\bar{\mathbf{X}}_t) \tag{13}$$

Hence, if $\bar{\boldsymbol{\varphi}} \neq 0$, the unobserved common factors are captured by cross-sectional means of y and $\mathbf{X}$ since $\bar{\mathbf{f}}_t \xrightarrow{p} \mathbf{f}_t$ as $N \to \infty$. In order to account for heterogeneous impact of the $\mathbf{f}_t$ across panel members, Pesaran (2006) suggests to augment the pooled fixed effects estimator by cross-section averages of the dependent and independent variables which can take different parameter estimates for each panel member i and are regarded as proxies for the linear combination of unobserved common factors. This allows the unobserved common factors to vary across cross-sectional units and yields a consistent estimator even in the case when regressors are correlated with the unobserved factors. This Common Correlated Effects Pooled estimator (CCEP) is then given by

$$y_{it} = \psi + \boldsymbol{\beta}'\mathbf{X}_{it} + \sum_{j=2}^{N}\phi_j D_j + \sum_{t=2}^{T}\sum_{j=1}^{N}\theta_{1i}(\bar{y}_t D_j) + \sum_{k=1}^{m}\sum_{t=2}^{T}\sum_{j=1}^{N}\boldsymbol{\theta}_{2i}(\bar{\mathbf{X}}_t D_j) + e_{it} \tag{14}$$

where $e_{it} \sim iid(0, \sigma^2)$, $\bar{y}_t$ and $\bar{\mathbf{X}}_t$ are cross-sectional means of the variables y and $\mathbf{X}$ for each t assuming m observed regressors. The first three terms on the right-hand-side are just a standard fixed effects estimator and the next two terms capture cross-sectional dependence through interaction terms of cross-section averages at time t and a set of N cross-section unit-specific dummies denoted as D. The $k+1$ interaction terms have dimension $NT \times N$. Pesaran (2006) further develops a Mean Group variant of this estimators, where the regression equation for each panel member is augmented with the cross-section averages for y and $\mathbf{X}$. By construction this Common Correlated Effects Mean Group estimator (CCEMG) allows for technology heterogeneity and differential impact of the unobservables across i.

Applications of the CCE estimators to estimating production functions are still relatively limited. Eberhardt and Teal (2009a) investigate the implications of accounting for cross-sectional dependence of TFP in an agricultural production function at the country-level for a sample of 128 countries over the period 1961-2002. They apply Pesaran's CCE estimators and extend them through combinations with various weight matrices to mimic a more restrictive spatial association employed in spatial econometrics. Other empirical applications for estimators accounting for cross-section dependence include production function estimation for Italian regions (Costantini and Destefanis, 2009), trends for internal migration in Italy (Fachin, 2007), gravity models of internal trade in the EU (Serlenga and Shin, 2007), the 'natural resource curse' and development (Cavalcanti, Modaddes and Raissi, 2009) and a host of studies investigating Purchasing Power Parity (see Wagner, 2008).

4 Data

The data set comprises information on 12 manufacturing industries in 12 countries (Czech Republic, Denmark, Finland, Germany, Italy, Japan, Netherlands, Portugal, Slovenia, Sweden, United Kingdom, and the US) over a time period of up to 26 years from 1980 to 2005 — see Table 1 for details.[15] Unless indicated all of the results presented assume the country-sector as basic level of analysis (panel group member i). The data used in the analysis is taken from a number sources: the main source is the EU KLEMS data set.[16] R&D expenditure is taken from the OECD, GDP deflators come from Eurostat and the OECD.

We focus on 12 two-digit industries (SIC 15-37 excluding SIC 23) within the manufacturing sector, as shown in Table 2. We exclude industry SIC 23 (*Coke, refined petroleum products and nuclear fuel*) for which several countries do not report data.

[15]Note that we use data for Germany only after its reunification in 1990.
[16]See www.euklems.net.

4.1 Variables

Most of the data in our analysis comes from the EU KLEMS database (release March 2008). The EU KLEMS project produced an internationally comparable dataset on economic growth and productivity for all EU member states as well as other large non-EU economies such as the US and Japan, covering the period 1970-2005 for most countries. It contains output and input measures, including a breakdown of input components (e.g. ICT capital, non-ICT capital etc.). The KLEMS dataset has been constructed using data from national statistical offices which was harmonized according to standardized procedures to guarantee comparability across countries. The data is particularly useful for our purposes as it has been specifically created with a view to conducting growth accounting exercises and productivity analysis.

All monetary variables in our data set are expressed in million Euros[17] and are deflated to 1995 price levels using deflators either at the country or sector level. We use double-deflated value-added, total number of hours worked by persons engaged and total tangible assets by book value as our measures of output, labour and capital stock. R&D stock is taken from KLEMS and extended to 2004 and 2005. In addition we construct the R&D capital stocks for Portugal and Slovenia, following the method adopted by KLEMS. We provide more details on data construction and the assumptions made in the process in the Appendix.

4.2 Descriptive Statistics

Figure 1 plots the ratio of R&D capital to physical capital over the 26-year period 1980-2005. It shows that the ratio increased over time from around .26 in 1980 to .33 in 1990 to nearly 0.35 in 2005. The largest increases in relative size of R&D stocks and physical capital stocks occurred between 1986 and 1988 as well as 2003 and 2005. The individual evolution of R&D and physical capital stocks over this periods in Figure 2 reveals that the a comparatively lower growth rate in the latter creates the seemingly steep rise in relative R&D capital importance in the 1980s. Figure 3 shows box plots for value added as well as inputs across all countries included in the sample in 2005. The graph provides evidence for large variation in the sample, both across countries and within countries across sectors. Looking at the median by country, the US leads the sample in terms of value-added while Japan achieves slightly larger R&D capital stocks. To further investigate variation across sectors, Figure 4 shows box plots for the different sectors for 2005. The graph reveals considerable variation across countries for all sectors and inputs. The sectors with largest value-added are the high-tech industries Electrical and optical equipment (ISIC 30-33) and Chemicals and chemical products (ISIC 24). We also provide plots for value-added, physical and R&D capital stock deflated by the labour variable (million working hours) in Figure 5 Finally, Table 3 contains some descriptives statistics for the data used in the regression analysis.

In order to explore the presence of unobserved common factors in our data, we provide both the proportion of variance accounted for by the first two principal components (PCs) of each

[17] Where necessary, data were converted from national currencies to Euros using 1999 exchange rates taken from Eurostat. Only for Slovenia, the 2008 exchange rate was used.

variable as suggested by Coakley et al. (2006) and the results of the Pesaran (2004) test for the presence of cross-sectional dependence.[18] Results in Table 4[19] provide strong evidence for a factor structure in the data, especially in the two capital stock variables. The Pesaran (2004) CD test has been suggested as a reliable test in the case of strong cross-section dependence (Chudik et al, 2009), such as that of common factors considered here (see Moscone and Tosetti, 2009, for an overview of CSD tests). Results in Table 3 for variables in levels, first difference and residuals for AR(2) regression carried out at the country-sector level reject cross-section *in*dependence emphatically in all cases.

5 Estimation Strategy

5.1 Static Pooled Specification

We start by estimating the standard knowledge production function in Equation (4) using pooled OLS (POLS) ignoring spillovers, thus assuming that the corresponding error term is standard normal and i.i.d. The standard errors of our POLS estimates are computed using White's (1980) correction for heteroscedasticity. As discussed above, POLS estimates are unbiased and consistent as long as we rule out the presence of cross-section unit-specific effects as well as unobserved common factors that influence both the error term and the regressors. All pooled estimators impose parameter homogeneity, thus assuming that the production technology is the same in all sectors and across all countries — we will relax these assumptions below. In order to test for autocorrelation, we implement the Arellano and Bond (1991) serial correlation test, which does however assume cross-sectional independence.

As a second step, we implement a fixed effects (FE) estimator which accounts for cross-sectional unit-specific effects — the units in this case being country-sectors. The FE estimator yields consistent estimates when cross-sectional units have time-invariant unobserved characteristics which are correlated with the regressors. We then add time-specific fixed effects, i.e. we implement a two-way fixed effects (2FE) error component model which captures cross-sectional unit-specific and time effects.[20] If productivity parameters are homogeneous across country-sectors and there are unobserved common factors with *identical* impact on all units (homogeneous factor loadings), then the 2FE estimates are unbiased and consistent. As shown by Coakley et al. (2006), even if we allow for unobserved common factors that influence both the error term and the regressors and influence cross-sectional units differently (heterogeneous factor loadings), 2FE is still unbiased and consistent as long as $\boldsymbol{\chi}_i$ and $\boldsymbol{\varphi}_i$ in Equation (9a) and (9b) are

[18]The PCs are linear combinations of the data that account for the maximal amount of the total variation. The eigenvectors of the correlation matrix are the weights and the ordered eigenvalues over the cumulated eigenvalues give the variance proportion. The first PC often turns out to have equal weights and is therefore close to the cross-section mean of the data in each time-period.

[19]We present results from two different samples of different dimensions: PCA relies on balanced panels which forces us to drop some of the countries from this procedure since the data overlap would otherwise reduce to a mere handful of years. While the results cannot be claimed to extend to the country-sector series dropped, they are nevertheless indicative of the factor structure in this type of data.

[20]This is equivalent to a 2FE estimator implemented by regressing $(y_{it} - \bar{y}_i - \bar{y}_t + \bar{y})$ on $(\mathbf{X}_{it} - \bar{\mathbf{X}}_i - \bar{\mathbf{X}}_t + \bar{\mathbf{X}})$, where $\bar{y}_i = T^{-1}\sum_{t=1}^{T} y_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, $\bar{y} = (NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N} y_{it}$ and correspondingly for $\mathbf{X}$.

independent. A standard economic interpretation for the year fixed effects is that of a flexible, common TFP evolution over time.

As an alternative to using 2FE, we first-difference (FD) the data to obtain a specification using rates of change. As the FE estimator, the specification in first-differences purges time-invariant unit-specific effects. The problem, however, is that in the presence of measurement error, the FD-OLS estimates may be even more downward biased than the FE estimates (Griliches and Hausman, 1986).[21] To account for common time effects, we also include year-specific dummies, which were also shown to reduce the biasing impact of cross-section dependence (Bond and Eberhardt, 2009).

As a first step to explicitly account for spillovers in the estimation we adjust the FE specification to account for homogeneous cross-sectional dependence (CDFE).[22] Using this specification we account specifically for the presence of common factors, although the factor loadings are restricted to be the same across units within the same time period. This is very similar to the transformation carried out for the 2FE specification; if the assumption of homogeneous impact of unobserved common factors is violated these models both create data dependencies in the residuals introduced by the empirical misspecification.

Finally, we implement Pesaran's pooled CCE estimator (CCEP) as detailed above. This estimator allows for factor loadings to differ within the the same time period across cross-sectional units and regressors.

5.2 Dynamic Pooled Specification

The Arellano and Bond (1991) test statistics for our static specification in levels point to the presence of serial correlation in the residuals in most of the models investigated. We therefore assume an autocorrelated error term of the form $e_{it} = \rho e_{i,t-1} + \epsilon_{it}$. This expression for the error term can be used to rewrite Equation (4) as an autoregressive distributed lag model of order one, ARDL(1,1) where e_{it} is still assumed to be an error component of the form $e_{it} = \mu_i + \nu_t + v_{it}$. We estimate the dynamic model using OLS and country-sector fixed effects (FE) although Nickell (1981) has shown that the FE estimator yields inconsistent estimates for finite T. To avoid such bias, most commonly, the dynamic model is estimated applying the GMM estimators developed in Arellano and Bond (1992) and Blundell and Bond (1998). These estimators are considered to be attractive for two reasons: (i) they account for fixed effects μ_i by first-differencing the data, and (ii) they provide internal instruments by exploiting lags of the endogenous variables to

[21] The error term in Equation (4) captures pure measurement error in all the variables included in the model. However, if only inputs are measured with error, we expect a downward bias in the input coefficients, the well-known attenuation bias. The standard attenuation bias formula for OLS is plim $\hat{\beta}^{OLS} = \beta \left(\frac{\sigma^2_{x^*}}{\sigma^2_{x^*} + \sigma^2_u} \right)$ where $\sigma^2_{x^*}$ is the variance of the unobserved true input and σ^2_u is the variance of the measurement error. If $\sigma^2_u \neq 0$, $\hat{\beta}$ is biased and inconsistent with the downward bias being larger the larger $\sigma^2_u \neq 0$. The attenuation bias worsens if first-differences are used when the serial correlation in the true unobserved input measures is larger than serial correlation of the measurement error. There is no standard solution to address measurement error but we hope that by using EU KLEMS data, we avoid this problem as much as possible.

[22] This specification amounts to a transformation of the form $y_i - \bar{y}_i \; \forall t$ where $\bar{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$ is the cross-section mean of variable y at time t (the transformation is also referred to as cross-sectional 'demeaning'). The same transformation is applied to all inputs $\mathbf{X}$.

address endogeneity. A problem, however, is that the number of instruments increases quadratically in the length of the time series.[23] Roodman (2009) describes a number of problems that arise from a large instrument count relative to the sample size, most importantly 'over-fitting'. If there is a large number of instruments for a small number of endogenous variables, the instrument set may over-fit the endogenous variables. This results in instruments failing to purge endogeneous variables of their endogenous variation and yielding estimates biased in the direction of the pooled OLS results. Another issue concerns the estimation of the optimal weighting matrix in the two-step GMM estimator as a high instrument count can lead to imprecise estimates of the weighting matrix. This may lead to biased standard errors obtained in the second step of the estimation although parameter estimates are still unbiased and consistent.[24] A large instrument count can also weaken the power of the Hansen (1982) test of the instruments' joint validity (Bowsher, 2002). Considering these concerns and given our cross-section dimension of $N = 143$ and time-series length of $T = 25$ in the dynamic models, both consistency concerns and large instrument counts are problematic. For comparative purposes we apply the Arellano and Bond (1992) estimator (AB) as well as the Blundell and Bond (1998) estimator (BB) but collapse the instrument matrix as suggested in Roodman (2009). Like the other pooled models, static or dynamic, the AB and BB estimators assumes parameter homogeneity across panel units — note that if this assumption is violated no instrument (internal of external) exists which can satisfy both the conditions of validity and informativeness (Pesaran and Smith, 1995).

Sarafidis and Robertson (2009) show that the Blundell and Bond (1998) GMM estimator yields inconsistent estimates for T fixed and $N \to \infty$ in the presence of cross-section dependence in the error process. As in all previous models, we therefore indicate the CD test statistics by Pesaran (2004) as these were shown to be valid in a dynamic panel setting. Yet, Pesaran's CD test may fail to reject the null of cross-sectional independence when factor loadings have zero mean across panel units (Sarafidis, Yamagata and Robertson, 2009). Sarafidis and Robertson (2009) suggest to include common time effects in the dynamic specification to reduce the bias of the GMM estimator in the presence of cross-section dependence. The remaining bias depends on the degree to which the effect of common factors differs across cross-section units. The intuition is as discussed above that time-demeaning removes part of the cross-section dependence from the error process.

5.3 Static Heterogeneous Specification

All of the above specifications assume that production technology is homogeneous across countries and sectors (or that the imposition of homogeneity does not affect the empirical estimation). Eberhardt and Teal (2009b) develop the impact of parameter heterogeneity on empirical estimation against the background of the cross-country growth literature, highlighting the adverse effect of misspecification of parameter heterogeneity on estimation and inference. Our empirical specifications considered include three variants:

[23] The number of elements in the estimated variance matrix of the moments is quadratic in the instrument count, which implies it is quadratic in T.

[24] Windmeijer (2005) devised a small-sample correction for this downward bias of standard errors.

- full heterogeneity: production technology can differ across countries and sectors;
- common production technology across countries within sectors; and
- common production technology across sectors within countries.

For the first of these we implement the Pesaran and Smith (1995) Mean Group estimator (MG), which allows for technology heterogeneity across countries. Cross-section independence is assumed, a linear trend term can capture country-sector-specific TFP evolution. Next up we employ the same estimator to data in deviation from the cross-section mean (CDMG). This allows for heterogeneous technology parameters but assumes that the unobserved common factors have the same impact in all country-sectors. Finally we employ the Mean Group variant of the Pesaran (2006) CCE estimators (CCEMG), which allows for parameter heterogeneity in the impact of observables and unobservables. For all three models we report the mean and robust mean estimate of the country-specific technology parameters. The robust mean employs weights based on the absolute residuals to reduce the impact of outliers on the mean estimate.[25]

For the heterogeneous country and sector technology specifications we employ POLS, 2FE (FE with $T-1$ year dummies, which is equivalent), CDFE and CCEP estimators to sector and country subsamples respectively. In effect we are conducting country regressions in the former and sector regressions in the latter. Conceptually these respresent halfway-houses between the pooled and heterogeneous specification discussed above: given the data limitations in the individual country-sector regressions it may be helpful for the data if we imposed somewhat more structure on the production process, whereby either countries or industrial sectors share the same production function. In an attempt to summarise the estimates from this exercise we also report the averaged estimates across sectors and countries respectively.

Given the data limitations it is difficult to identify appropriate alternatives for the heterogeneous parameter case whilst accounting for cross-section dependence: alternative estimators such as Bai (2009) or Bai, Kao and Ng (2009) estimate the unobserved common factors, which requires 'large N and T' — especially the latter is not given in this sample. There is also a concern with these approaches that they rely too heavily on the correct determination of the number of common factors present in the data Pesaran (2009): especially with regard to the notion of spillovers, it should be pointed out that the method by Bai and Ng (2002) to detect common factors is only appropriate for so-called 'strong' common factors (e.g. global shocks) in the data and neglects any 'weak' common factors (e.g. local spillovers, say, between two countries but not on a wider scale). In contrast, the CCE estimators are able to deal with a fixed number of 'strong' and an infinity of 'weak' common factors in the estimation since their impact is accounted for through the cross-section averages — see Kapetanios et al (2009) and Pesaran et al (2009) for more details. Finally, we cannot provide dynamic versions for the heterogeneous specifications as the short time-series dimension leads to dimensionality problems.

[25]We use robust regression to produce a robust estimate of the mean — see Hamilton (1992) for details.

6 Results

6.1 Pooled Models

Table 6 contains the results for POLS, FE, 2FE, CCEP, FD-OLS and FD-2FE when using a static specification. We can see that the FE model which does not account for any common factor — or indeed TFP growth over time — has a grossly inflated capital coefficient of around .75, considerably larger than the POLS estimate of .5 and out of line with macro evidence on factor income shares (Mankiw, Romer and Weil, 1992; Gollin, 2002). Once we allow for unobserved common factors the parameter estimates are much more in line with the macro data (2FE, CDFE, CCEP, FD-OLS). The standard CCEP estimator produces very sensible parameter estimates; our concern regarding this specification is the rejection of residual cross-section independence, the data property the estimator is intended to specifically address — possible explanations for this outcome are empirical misspecification with regard to dynamics or technology heterogeneity. We augment the CCEP estimator with a set of common year dummies to take out further covariation in the data and the diagnostics on cross-section independence are improved but at the expense of less precise parameter estimates. The FD-OLS estimator with year dummies has similarly favourable diagnostics although there is more evidence of higher-order serial correlation in the residuals (first order AR is to be expected).

In all models the coefficient on R&D capital stock is positive, albeit insignificant in our preferred static pooled models in columns [6] and [8] — this could be the result of measurement error interfering with a more precise estimation of the parameter coefficient (Hall and Mairesse, 1995). An explanation for the better performance of these estimator relates to the order of integration of the variables: if any of the inputs and/or output are I(1) series, misspecification can lead to nonstationary errors which may entail bias and certainly inefficiency. Most importantly the standard t-statistics for parameter estimates in this case are unreliable and tend to overstate their precision (Kao, 1999; Coakley et al, 2006; Bond and Eberhardt, 2009). Determining the order of integration in a panel of relatively moderate T is challenging, despite recent developments in the panel unit root testing literature. Our preliminary analysis (using the Pesaran (2007) CIPS, detailed results not reported) suggests that all the levels regressions with the exception of the CCEP are indeed subject to nonstationary residuals. The parameter estimates on the year dummies for the FD-OLS model (not reported) are mostly positive and statistically significant, implying (common) TFP growth of around 2 percent per annum in all countries, which seems reasonable — similar computations are not possible for the CDFE or CCEP models. It is important to note that in a variety of simulation setups we found the FD-OLS estimator augmented with year dummies to be consistent and efficient despite the presence of unobserved common factors with heterogeneous factor loadings (Bond and Eberhardt, 2009). Note that we also estimated the static specification lagging the labor input variable two periods to counter a possible transmission bias; although we find our results discussed above to remain largely unchanged.[26]

[26]Endogeneity arises under the assumption that industries receive an industry-specific productivity shock each period. Input choices are consequently based on these productivity realizations. If these shocks are observed

It is also worth noting that the R-squared for all the above models is very high (.999 in the CCEP models). This is a standard finding in macro panel data with a substantial time-series element — this diagnostic statistic thus loses any power to describe models as providing a better 'fit' for the data and we therefore do not present this statistic in any of the following empirical results.

Table 7 shows the results for OLS, FE, 2FE, AB, BB, CDFE and CCEP when using a dynamic specification. Given the Arellano and Bond (1991) residual tests in the static models it may be suggested that this represents the more appropriate empirical specification. The residual serial correlation tests for the dynamic specifications broadly seem to support this choice. In Panel (A) we do not impose any common factor restrictions arising from the ARDL(1,1) model; implied long-run coefficients are computed and reported in Panel (B), using the Delta method to establish standard errors. In Panel (C) the common factor restrictions are imposed and the validity of this choice is tested (COMFAC, H_0 imposition is valid). We begin our discussion with the results in Panel (A): with the exception of the AB and CCEP estimates, the lagged dependent variable carries very high coefficients, up to .98 in the POLS case, indicating high persistence in the data and pointing to potential nonstationarity. In terms of common factor restrictions the System GMM (BB) and CCEP models cannot reject their imposition — for all other models we therefore have to concentrate on the results in Panel (B). POLS yields an extremely high long-run output elasticity estimate for R&D, around .36, whereas this is insignificantly different from zero in the FE and 2FE models. For CDFE the same coefficient estimate is quite high again, at .16. Note that for all dynamic models the residual analysis for nonstationarity was fraught with difficulty, and we could therefore not obtain conclusive results from this analysis. Turning to the restricted models in Panel (C) we focus on the AB, BB and CCEP models. While the AB results are difficult to interpret (most likely due to the nonstationarity of the variable series) the BB yields a high lagged dependent variable estimate of .97. Labour and capital coefficients are in line with those of the preferred static models while the R&D coefficient is insignificant. The latter feature is more pronounced in the CCEP models, where long-run elasticities are almost exactly zero in the CCEP with year dummies. CD tests suggest that the AB, BB and CCEP with year dummies yield cross-sectionally independent residuals — in later versions of this paper we will investigate the power of the CD test in this data dimensions and consider alternatives.

Our pooled regression results for the static and dynamic models thus provide some evidence that accounting for cross-section dependence in the data leads to estimates for the output elasticity of R&D which are close to zero. In contrast to this, standard static FE or 2FE estimators suggest considerably higher and statistically significant coefficients, pointing to substantial

only by firms within the industry, but remain unobserved by the econometrician, standard OLS estimation suffers from biased and inconsistent estimates if inputs are not mean-independent from the omitted productivity variable (Marshak and Andrews, 1944). Contemporaneous correlation between input choices and the productivity shock is more likely to be present for inputs that adjust quickly. Commonly, labor is assumed to adjust quickly relative to physical capital which is accumulated over time, which points to a (stronger) bias of the labor coefficient. The microeconomic literature has proposed a range of estimation procedures to deal with the transmission bias at the firm level (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2006; Greenstreet, 2007; Blundell and Bond, 2000). Except for the Blundell and Bond (2000) approach, none of the micro-estimators appears to be appropriate for the estimation of an aggregate industry-level production function.

private returns to R&D.

6.2 Heterogeneous Parameter Models

We now turn to empirical models which allow for some degree of technology heterogeneity across sectors and/or countries. Table 8 presents results for the Mean Group-type estimators which are all based on country-sector level regressions — we now report the Pesaran et al (2009) t-statistic in brackets for each average coefficient and for comparative purposes also the Pedroni (1999) panel t-statistic. For each model we present two sets of results, namely simple and robust averages — the latter will be less affected by outliers and can be thought of as akin to median regressions. The capital coefficient collapses for the Mean Group models, which do not account for cross-section dependence in any way. It seems that in this model the linear trend (constant TFP growth) captures most of the variation in the data, to the detriment of capital and R&D stock. The CDMG model, which imposes a common impact of unobserved common factors, yields sensible technology coefficients, however the parameter on the R&D capital stock seems implausibly large. In this model over 70 percent of country-sector regressions reject constant returns to scale and there is some evidence of nonstationary residuals (as in the MG model). The CCEMG model provides mean capital and labor coefficients of .3 and .55 respectively, with the R&D stock coefficient insignificant. The robust mean is somewhat less precise for the capital coefficient. However, like in the pooled model case the Pesaran (2006) MG-type estimator strongly rejects cross-section independence in the residuals — as do the other two models. Other diagnostics seem to favour the CCEMG over the CDMG result: error normality, small(er) share of regressions residuals with a low Durbin-Watson d, and somewhat stronger evidence of stationary residuals.

Tables 10 and 11 present results from sector-level and country-level regressions for the POLS, 2FE, CDFE and CCEP models. Individual country- or sector-regression results can be seen to be imprecise or even nonsensical at times (e.g. capital coefficients in excess of unity). The heterogeneity introduced does not imply that each country- or sector-result can be seen as *a reliable estimate or test statistic*: as Pedroni (2007, p.440) explains, this interpretation is hazardous, since the "long-run signals contained in [limited] years of data may be relatively weak", such that one should refrain from country- or sector-specific policy implications unless the single time-series analysis for this specific country is deemed reliable. However, previous empirical analysis averaging over individual country regressions has frequently found that while country/sector estimates or tests where widely dispersed and at times economically implausible, averages represented very plausible results (Boyd and Smith, 2002; Baltagi et al, 2003). Our findings for the averaged sector- and country-regressions are summarized in Table 9, where we present the robust means from the 12 sector or country regressions next to those from the 143 (119 in the CCEMG case) country-sector regressions. It is notable that in the averaged country regressions the capital coefficients are inflated across the board in comparison with those from all previous results, with a parameter value of almost .8 in the CCEP case. Averaged sector regressions are in general quite imprecise and small in magnitude — both of these results suggest that the heterogeneity in industrial production is inadequately captured if we concentrate on sectors or countries alone, respectively. In most cases the coefficient on R&D is statistically insignificant.

Overall the heterogeneous parameter results have not changed our conclusion from the pooled models considerably, in that it seems that cross-section dependence plays an important role in the determination of private returns to R&D and that once these are accounted for the output elasticity wrt R&D is close to zero across a number of specifications. It is important to stress that our focus here is on the average result: while individual sectors or countries display large and statistically significant returns, the nature of our analysis requires us to focus on the averaged result to ensure comparability with the pooled model results.

7 Conclusion

In this study we asked whether returns to R&D can be estimated in a standard Griliches-type production function framework ignoring the potential presence of spillovers between cross-sectional units. Finding an answer to this question is relevant considering the vast amount of empirical work (a) implementing the Griliches-type production function under the assumption of absence of cross-sectional dependence and (b) specifically investigating spillovers originating from R&D.

Our results suggest the presence of a substantial amount of cross-sectional dependence in the residuals of a standard Griliches-type knowledge production function. Within a static framework, first-differencing the data and including a time trend eliminates the correlation among cross-sectional units in the panel and thus accounts satisfactorily for cross-sectional dependence. However, the coefficient associated with R&D falls considerably in magnitude relative to the POLS estimates and loses its statistical significance implying zero private returns to R&D. Within a dynamic setting, our preferred estimator, the Pesaran CCEP estimator, accounts for cross-sectional dependence but produces an estimate of the coefficient associated with R&D that is statistically not significantly different from zero. These findings suggest that conventional approaches produce estimates of the output elasticity with respect to R&D and thus of private returns to R&D that are positive and significant while model specifications accounting adequately for cross-sectional dependence produce R&D coefficients not different from zero implying zero returns to R&D.

While our analysis sheds some light on the importance of spillovers for the estimation of private returns to R&D, we do not recover a parameter associated with spillovers. Hence, we cannot make any statement regarding the magnitude of social returns to R&D. If social returns are the object of interest, more structure needs to be imposed on the nature of spillovers to be able to recover the corresponding parameter within a spatial econometric framework. Any such analysis thus involves necessarily the question of how to measure spillovers. We deliberately avoided addressing this question by adopting an agnostic common factor approach in order to escape the need to make somewhat *ad hoc* assumption on the by definition unobserved structure of spillovers. Yet, our results suggest that the commonly imposed *ad hoc* structure, i.e., some weighted average of R&D conducted by units contained in the sample, may fail to account for the cross-sectional dependence in the data which is generated by a complex interplay of a range of unobserved factors. We, therefore, regard the search for an appropriate specification of the knowledge production function, accounting for the true nature of cross-sectional interdependencies as the main challenge in the investigation of returns to R&D - both private and social.

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TABLES AND FIGURES

Figure 1: R&D Capital to Physical Capital Ratio 1980-2005

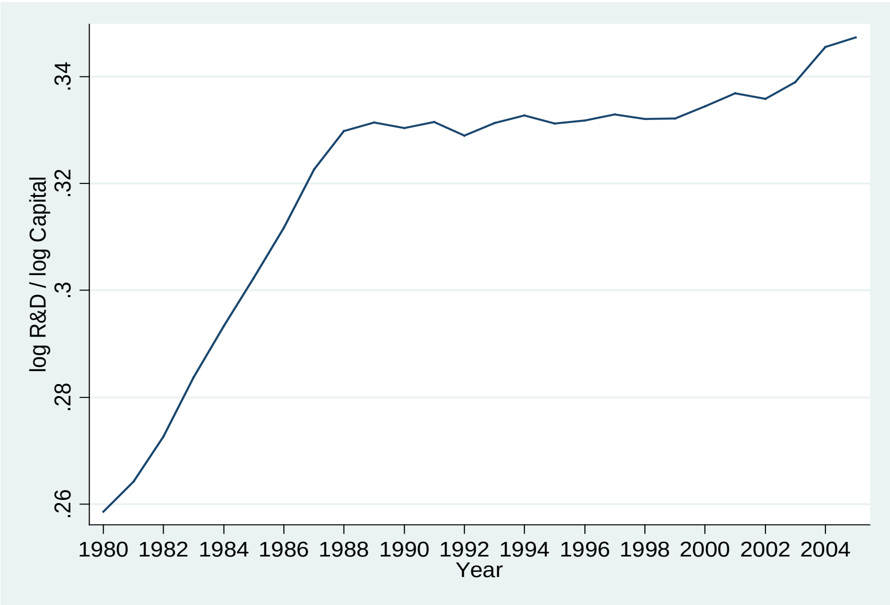
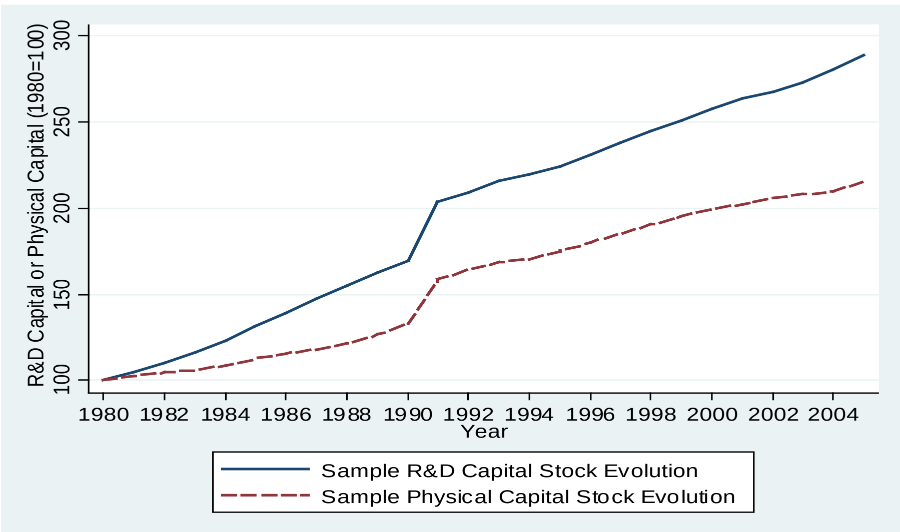


Figure 2: Evolution of R&D and Physical Capital Stock (1980 = 100)



Notes: The kink in 1991 is caused by Germany, a major innovator, entering our sample.

Figure 3: Input Variation across Countries for SIC 2-digit Industries (2005)

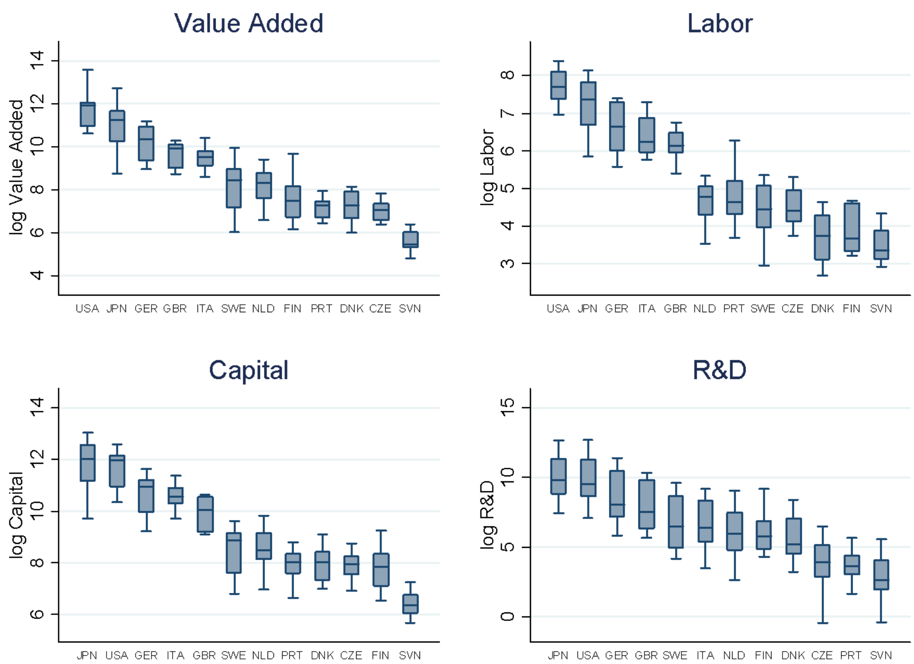


Figure 4: Input Variation across SIC 2-digit Industries (2005)

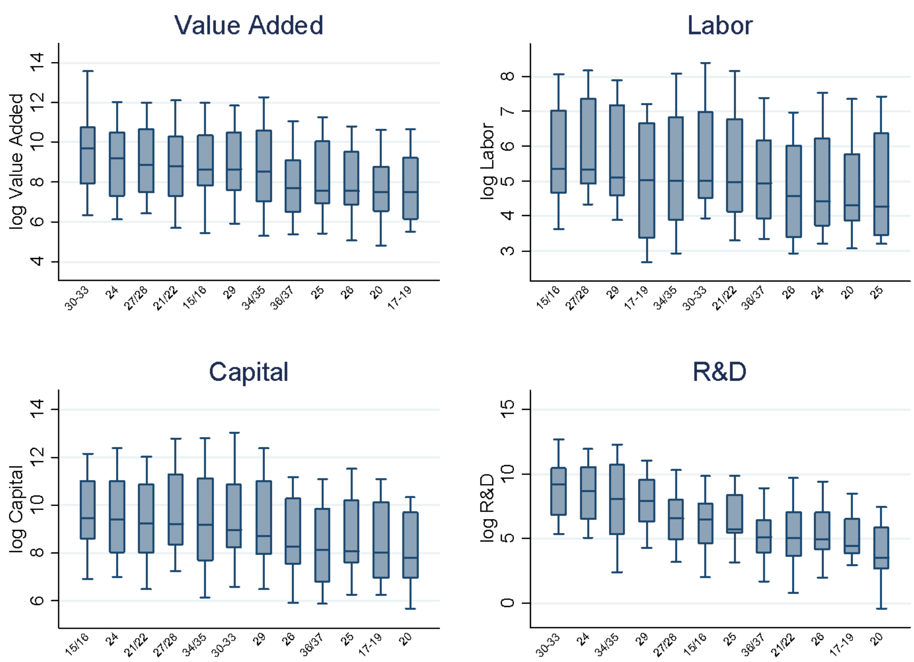
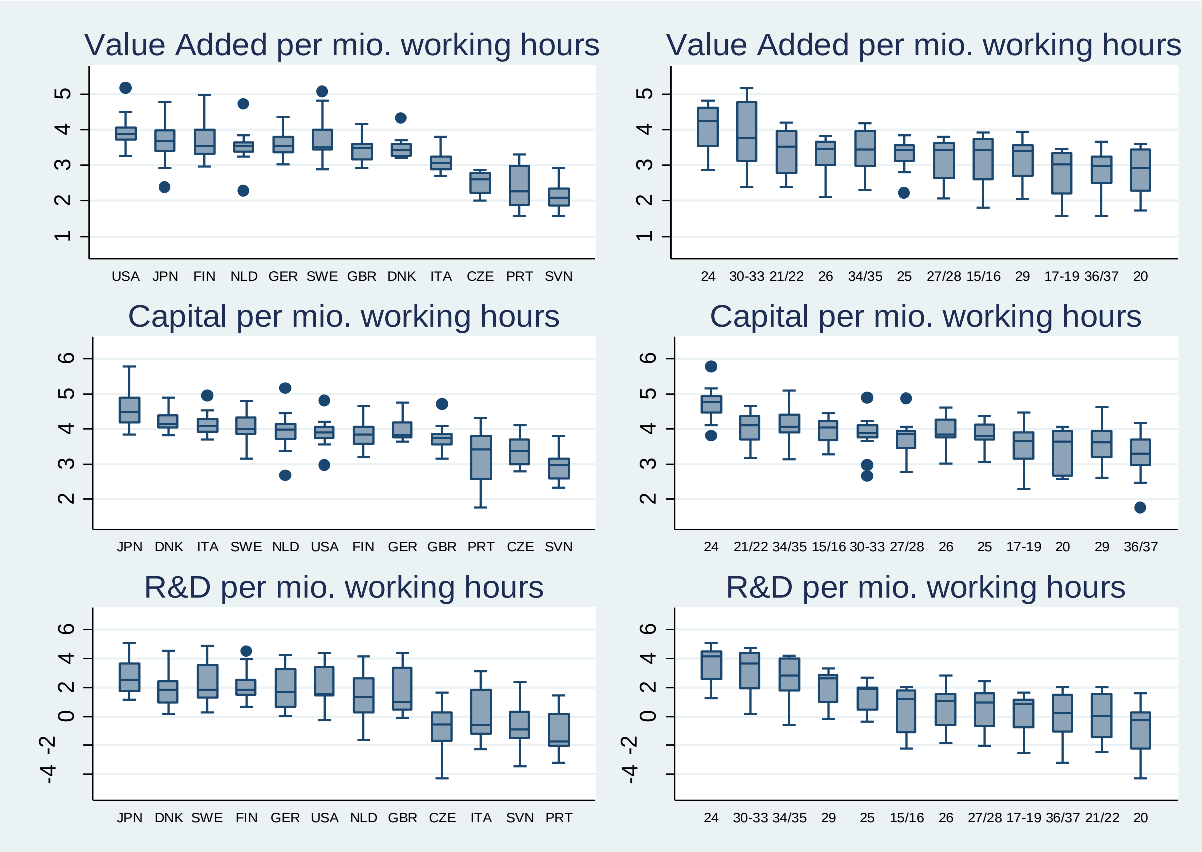


Figure 5: Labor-Deflated Input Variation across Countries & Industries



Notes: The data is transformed into mio. Euros per mio. working hours (in logs) and plotted in order of median value. The left column plots variation by country, the right column by SIC 2-digit industry. All data presented in this graph are for 2005.

Table 1: Sample makeup

	Country	obs	share	years	CCEMG
CZE	Czech Republic	84	3%	1999-2005	
DNK	Denmark	312	11%	1980-2005	✓
FIN	Finland	312	11%	1980-2005	✓
GBR	Great Britain	308	11%	1980-2005	✓
GER	Germany	180	6%	1991-2005	✓
ITA	Italy	312	11%	1980-2005	✓
JPN	Japan	312	11%	1980-2005	✓
NLD	Netherlands	312	11%	1980-2005	✓
PRT	Portugal	121	4%	1995-2005	✓
SVN	Slovenia	72	3%	2000-2005	
SWE	Sweden	156	6%	1993-2005	✓
USA	United States	312	11%	1980-2005	✓

Notes: CCEMG refers to the countries included in the CCEMG regression.

Table 2: Industry descriptions

SIC	Description: Manufacture of	No. Obs.
15, 16	Food, beverages, tobacco	234
17, 18, 19	Textiles, textile products, leather and leather products	234
20	Wood and products of wood and cork	232
21, 22	Pulp, paper, paper products, printing and publishing	232
24	Chemicals and chemical products	234
25	Rubber and plastic products	223
26	Other non-metallic mineral products	234
27, 28	Basic metals and fabricated metal products	234
29	Machinery and equipment n.e.c.	234
30, 31, 32, 33	Electrical and optical equipment	234
34, 35	Transport equipment	234
36, 37	Manufacturing n.e.c.	234
Total		2,793

Notes: Sector SIC 23 (*coke, refined petroleum products and nuclear fuels*) is excluded from the analysis.

Table 3: Summary statistics

	Mean	Median	Std. Dev.	Min	Max
Levels					
Value Added (mio. Euro)	26288.9	7229.0	51444.2	104.4	782206.1
Labour (mio. hours worked)	869.6	292.4	1200.4	14.6	6611.9
Physical Capital (mio. Euro)	38295.3	10967.4	63149.6	241.6	459870.4
R&D Capital (mio. Euro)	12452.2	677.9	38980.6	0.3	328953.5
Logs					
ln Value Added	8.832	8.886	1.765	4.648	13.570
ln Labour	5.722	5.678	1.573	2.684	8.797
ln Physical Capital	9.298	9.303	1.724	5.487	13.039
ln R&D Capital	6.679	6.519	2.608	-1.157	12.704
Differences					
△ ln Value Added	0.019	0.016	0.074	-0.412	1.081
△ ln Labour	-0.014	-0.012	0.044	-0.269	0.185
△ ln Physical Capital	0.022	0.018	0.033	-0.134	0.297
△ ln R&D Capital	0.036	0.031	0.065	-0.128	0.790

Notes: These descriptive statistics refer to the sample for $N = 143$ country-sectors (12 countries), which in levels contains $n = 2,793$ observations, average $T = 19.5$ (range 1980-2005).

Table 4: Principal Component Analysis

	Panel A: Variables in Levels				
	$\ln Y$	$\ln L$	$\ln K$	$\ln R$	all four
$T = 9,\ N = 119$					
Variance expl. by 1st Component	0.592	0.603	0.858	0.805	0.706
Variance expl. by 2nd Component	0.167	0.233	0.091	0.125	0.155
Sum	0.760	0.836	0.948	0.930	0.862
$T = 24,\ N = 84$					
Variance expl. by 1st Component	0.668	0.565	0.820	0.811	0.707
Variance expl. by 2nd Component	0.129	0.165	0.103	0.135	0.131
Sum	0.797	0.730	0.922	0.946	0.838
	Panel B: Variables in First Diff.				
	$\Delta\ln Y$	$\Delta\ln L$	$\Delta\ln K$	$\Delta\ln R$	all four
$T = 8,\ N = 119$					
Variance expl. by 1st Component	0.270	0.381	0.384	0.420	0.350
Variance expl. by 2nd Component	0.202	0.182	0.307	0.228	0.218
Sum	0.472	0.563	0.691	0.648	0.568
$T = 23,\ N = 84$					
Variance expl. by 1st Component	0.233	0.227	0.253	0.389	0.187
Variance expl. by 2nd Component	0.116	0.144	0.188	0.120	0.155
Sum	0.349	0.371	0.441	0.509	0.342

Notes: For this approach we require a balanced panel across all sectors. We therefore employ two separate datasets: one with $T = 9$ time periods, $N = 119$ country-sectors represents the 'CCEMG sample. A second sample maximises on the number of time-series observations $T = 24$ time periods, $N = 84$ country-sectors, including only DNK, FIN, GBR, ITA, JPN, NLD and USA data.

Table 5: Pesaran (2004) CD Tests

Panel A: Variables in Levels				
	ln Y	ln L	ln K	ln R
avg ρ	0.22	0.24	0.51	0.32
avg $\lvert\rho\rvert$	0.59	0.59	0.79	0.77
CD	101.93	104.27	198.69	145.50
Panel B: Variables in FD				
	ln Y	ln L	ln K	ln R
avg ρ	0.13	0.15	0.16	0.02
avg $\lvert\rho\rvert$	0.30	0.31	0.36	0.39
CD	53.17	58.70	62.44	11.57
Panel C: AR(2) residuals				
	ln Y	ln L	ln K	ln R
avg ρ	0.10	0.11	0.08	0.04
avg $\lvert\rho\rvert$	0.32	0.32	0.33	0.30
CD	43.04	46.21	37.84	13.71

Notes: We present the average and average absolute correlation coefficients across the $N(N-1)$ sets of country series. CD reports the Pesaran (2004) cross-section dependence statistic, which is distribution $N(0,1)$ under the null of cross-section independence. In Panel C each of the four variables in levels is entered into a time-series regression $z_{it} = \pi_{1,i}z_{i,t-1} + \pi_{2,i}z_{i,t-2} + \pi_{t,i}t + \pi_{0,i} + \epsilon_{it}$, conducted separately for each country-sector i. The correlations and cross-section dependence statistic are then based on the residuals from these AR regressions.

Table 6: Static Production Functions

	POLS	FE	2FE	CDFE	CCEP	CCEP	FDOLS	FDOLS
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ln L_{it}	0.412	0.382	0.608	0.612	0.600	0.610	0.544	0.641
	[35.30]**	[13.13]**	[18.46]**	[19.47]**	[17.92]**	[17.41]**	[16.10]**	[18.25]**
ln K_{it}	0.529	0.748	0.492	0.553	0.282	0.117	0.511	0.309
	[41.36]**	[23.96]**	[11.04]**	[15.74]**	[5.97]**	[2.31]*	[9.68]**	[4.54]**
ln R_{it}	0.096	0.114	0.062	0.082	0.099	0.065	0.122	0.041
	[22.75]**	[8.35]**	[4.36]**	[7.21]**	[4.54]**	[2.90]**	[5.22]**	[1.56]
Year dummies	Included		Implicit			Included		Included
CRS	0.00	0.00	0.00	0.00	0.69	0.00	0.01	0.91
AB Test AR(1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB Test AR(2)	0.00	0.00	0.00	0.00	0.78	0.79	0.03	0.01
Order of integration	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
CD test	24.37	15.34	-1.51	2.28	8.92	-0.99	34.66	-0.11
(p)	(.00)	(.00)	(.13)	(.02)	(.00)	(.32)	(.00)	(.91)
Observations	2793	2793	2793	2793	2793	2793	2650	2650
R-squared	0.97	0.99	0.99	0.99	1.00	1.00	0.24	0.32

Notes: Absolute t-statistics in brackets, constructed from White heteroskedasticity-robust standard errors. *, ** Indicate significance at the 5% and 1% level respectively.
Abbreviations: FE — Fixed effects (country-sector dummies), 2FE — Two-way Fixed effects, CCEP — Pooled Common Correlated Effects estimator, FD-OLS — OLS with variables in First Differences.
CRS: p-value for H_0: Constant Returns to Scale (labour, physical capital and R&D capital). AB Test: Arellano and Bond (1992) test for autocorrelation (p-values). The order of integration is determined using the Pesaran (2007) CIPS Test, full results available on request. I(0) — stationary, I(1) nonstationary. CD Test: Pesaran (2004) test for cross-sectional dependence.

Table 7: Dynamic Production Functions

	POLS	FE	2FE	AB	BB	CDFE	CCEP	CCEP
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
PANEL A: UNRESTRICTED MODEL								
$\ln Y_{i,t-1}$	0.975	0.927	0.928	0.745	0.928	0.925	0.488	0.467
	[151.49]**	[68.13]**	[62.29]**	[8.46]**	[31.22]**	[67.62]**	[12.95]**	[12.19]**
$\ln L_{it}$	0.671	0.762	0.673	1.073	0.610	0.632	0.587	0.603
	[18.96]**	[20.90]**	[17.48]**	[6.16]**	[4.75]**	[18.00]**	[10.07]**	[10.31]**
$\ln L_{i,t-1}$	-0.661	-0.731	-0.623	-0.792	-0.634	-0.608	-0.349	-0.358
	[18.69]**	[20.25]**	[16.51]**	[5.60]**	[5.17]**	[17.61]**	[5.73]**	[5.85]**
$\ln K_{it}$	0.239	-0.002	0.037	-0.508	0.247	0.400	0.276	0.252
	[3.61]**	[0.03]	[0.48]	[1.85]	[1.68]	[10.20]**	[2.87]**	[2.58]*
$\ln K_{i,t-1}$	-0.234	0.046	-0.008	0.563	-0.182	-0.357	-0.102	-0.156
	[3.58]**	[0.64]	[0.11]	[2.07]*	[1.32]	[9.28]**	[1.16]	[1.77]
$\ln R_{it}$	0.065	0.025	0.015	-0.213	0.007	0.163	0.000	-0.014
	[2.43]*	[0.85]	[0.51]	[1.58]	[0.10]	[8.72]**	[0.01]	[0.43]
$\ln R_{i,t-1}$	-0.056	-0.024	-0.016	0.029	0.014	-0.151	0.040	0.039
	[2.12]*	[0.84]	[0.57]	[0.26]	[0.21]	[8.28]**	[1.27]	[1.17]
Year dummies	included		implicit	included	included	implicit		included
COMFAC	0.00	0.00	0.01	0.58	0.18	0.00	0.20	0.16
CRS	0.46	0.62	0.48	0.47	0.43	0.40	0.28	0.00
AB Test AR(1)	0.00	0.97	0.93	0.00	0.00	0.41	0.01	0.55
AB Test AR(2)	0.02	0.27	0.54	0.15	0.79	0.46	0.03	0.00
Sargan				0.00	0.00			
Order of integration	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)	I(1)/I(0)
CD-test	-0.62	25.76	-0.73	-0.92	-1.47	7.31	7.76	0.37
(p)	(.54)	(.00)	(.46)	(.36)	(.14)	(.00)	(.00)	(.37)
PANEL B: LONG-RUN COEFFICIENTS (UNRESTRICTED MODEL)								
Labour	0.418	0.437	0.700	1.102	-0.331	0.328	0.466	0.528
	[4.31]**	[3.20]**	[3.95]**	[2.19]*	[0.76]	[1.92]	[5.61]**	[5.46]**
Capital	0.198	0.607	0.402	0.217	0.894	0.578	0.340	0.141
	[1.33]	[6.00]**	[2.96]**	[0.55]	[2.86]**	[3.66]**	[3.54]**	[1.12]
R&D stock	0.356	0.011	-0.023	-0.723	0.286	0.160	0.080	0.016
	[4.16]**	[0.19]	[0.38]	[2.36]*	[1.96]*	[2.29]*	[1.96]*	[0.40]
PANEL C: $Y_{i,t-1}$ & LONG-RUN COEFFICIENTS (COMMON FACTOR RESTRICTIONS IMPOSED)								
$\ln Y_{i,t-1}$	0.977	0.963	0.947	0.854	0.973	0.929	0.517	0.495
	[190.40]**	[121.72]**	[80.58]**	[17.11]**	[55.82]**	[75.71]**	[14.84]**	[13.93]**
Labour	0.618	0.757	0.675	0.918	0.543	0.634	0.556	0.579
	[18.34]**	[20.93]**	[17.54]**	[6.23]**	[4.38]**	[18.23]**	[10.21]**	[10.66]**
Capital	0.294	0.055	0.130	-0.385	0.299	0.391	0.289	0.197
	[7.07]**	[0.94]	[2.09]*	[1.70]	[2.21]*	[10.14]**	[3.65]**	[2.32]*
R&D stock	0.138	0.043	0.030	-0.147	0.094	0.167	0.022	0.000
	[6.76]**	[1.63]	[1.17]	[1.14]	[1.67]	[9.07]**	[0.77]	[0.01]
Observations	2650	2650	2650	2507	2650	2650	2650	2650
R-squared	1.00	1.00	1.00			1.00	1.00	1.00

Notes: Absolute t-statistics in brackets, constructed from White heteroskedasticity-robust standard errors. *, ** Indicate significance at the 5% and 1% level respectively.
Abbreviations: FE — Fixed effects (country-sector dummies), 2FE — Two-way Fixed effects, AB — Arellano-Bond (1992) Difference GMM (instrument count: xx), BB — Blundell-Bond (1998) System GMM estimator (instrument count: XX), CDFE — Cross-sectionally demeaned FE, CCEP — Pooled Common Correlated Effects estimator, FD-OLS — OLS with variables in First Differences.
AB Test: Arellano and Bond (1992) test for autocorrelation (p-values). The order of integration is determined using the Pesaran (2007) CIPS Test, full results available on request. I(0) — stationary, I(1) nonstationary. COMFAC: p-value for H_0: Common factor restrictions valid. CRS: p-value for H_0: Constant Returns to Scale (labour, physical capital and R&D capital; applied to the long-run coefficients, COMFAC imposed based on test result). CD Test: Pesaran (2004) test for cross-sectional dependence.

Table 8: Static Production Functions: Country-sector averages

	MG		CDMG		CCEMG	
	[1]	[2]	[3]	[4]	[5]	[6]
	Mean	Robust	Mean	Robust	Mean	Robust
$\ln L_{it}$	0.407	0.614	0.634	0.610	0.554	0.641
	[3.18]**	[9.89]**	[5.90]**	[10.22]**	[7.08]**	[11.95]**
$\ln K_{it}$	-0.027	-0.049	0.332	0.343	0.282	0.178
	[0.19]	[0.52]	[3.29]**	[5.55]**	[2.10]*	[1.83]
$\ln R_{it}$	0.023	-0.022	0.182	0.163	0.057	0.053
	[0.26]	[0.40]	[4.87]**	[4.63]**	[0.73]	[0.96]
country trend	0.026	0.025				
	[3.52]**	[7.55]**				
# of CS	143	143	143	143	119	119
obs	2793	2793	2793	2793	2637	2637
reject CRS: # (share)	57	(40%)	102	(71%)	46	(39%)
Panel t-statistics						
labour		26.46**		34.10**		23.29**
capital		-0.69		26.67**		6.12**
R&D		-2.82**		20.31**		4.28**
trend		36.99**				
sign. trend		87				
Serial Correlation						
Ljung-Box	485.0	(.00)	885.6	(.00)	97.0	(1.00)
Durbin AR(1)	1059.9	(.00)	1229.6	(.00)	799.9	(.00)
Durbin AR(2)	1010.5	(.00)	1344.8	(.00)	1010.5	(.00)
BGod AR(1)	848.1	(.00)	937.1	(.00)	668.5	(.00)
BGod AR(2)	932.7	(.00)	973.8	(.00)	776.7	(.00)
Durbin-Watson	< 1.23	> 1.79	< 1.23	> 1.79	< 1.23	> 1.79
d statistic #	47	60	67	36	47	36
(in %)	33%	42%	47%	25%	39%	30%
Normality/Homosk						
Cameron & Trivedi (joint)	370.5	(.00)	419.3	(.00)	327.1	(.00)
Residuals I(1)						
no lags	-19.60	(.00)	-13.84	(.00)	-28.51	(.00)
1 lag	-5.50	(.00)	-2.64	(.00)	-22.63	(.00)
2 lags	3.63	(1.00)	6.54	(1.00)	-10.20	(.00)
3 lags	12.74	(1.00)	15.63	(1.00)	2.18	(1.00)
CSD						
Mean (abs) Correl. Coeff.	.05	(.25)	.01	(.26)	.01	(.23)
CD statistic (p)	25.98	(.00)	4.91	(.00)	4.95	(.00)

Notes: All parameter estimates presented are robust averages across N country-sectors. Absolute t-statistics in brackets, following Pesaran et al (2009). *, ** Indicate significance at the 5% and 1% level respectively.
Abbreviations: MG — Pesaran and Smith (1995) Mean Group estimator, CDMG — Cross-sectionally demeand MG, CCEMG — Pesaran (2006) Common Correlated Effects MG.
reject CRS: based on country-specific Wald test for H_0 of Constant Returns to Scale (labour, physical capital and R&D capital) — number of countries and share of sample rejecting H_0 reported. Serial correlation tests report Fisher (1932) statistics (p-values) except Durbin-Watson. dto. for Cameron and Trivedi (1991) test: H_0 normal and homosked. residuals. DW: Durbin-Watson test — # and share of panel units with > 1.79 ($d < 1.23$) — this is deemed to (be unable to) reject the null of first order serial correlation (under the strong assumption of exogenous regressors). Other serial correlation tests: H_0 of no serial correlation in the residuals. Residual I(1) tests following Pesaran (2007): H_0 nonstationarity. CD Test: Pesaran (2004) test for cross-sectional dependence (H_0 independent residual series). Panel t-statistic following Pedroni (1999).

Table 9: Production Functions: heterogeneous parameter models

	Country-sector regressions			Country regressions				Sector regressions			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	MG	CDMG	CCEMG	POLS	2FE	CDFE	CCEP	POLS	2FE	CDFE	CCEP
	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
$\ln L_{it}$	0.614	0.610	0.641	0.405	0.257	0.488	0.226	0.402	0.214	0.612	0.184
	[9.89]**	[10.22]**	[11.95]**	[11.34]**	[2.66]*	[5.81]**	[2.15]	[12.95]**	[1.84]	[5.45]**	[1.65]
$\ln K_{it}$	-0.049	0.343	0.178	0.478	0.693	0.623	0.776	0.421	0.353	0.386	0.430
	[0.52]	[5.55]**	[1.83]	[24.16]**	[5.59]**	[4.68]**	[6.06]**	[8.71]**	[3.34]**	[3.51]**	[3.96]**
$\ln R_{it}$	-0.022	0.163	0.053	0.047	0.090	0.067	0.106	0.205	0.127	0.123	0.143
	[0.40]	[4.63]**	[0.96]	[2.11]	[1.21]	[2.83]*	[1.65]	[6.16]**	[1.69]	[1.78]	[1.87]
trend	0.025										
	[7.55]**										
Sum	0.543	1.115	0.872	0.930	1.040	1.178	1.108	1.028	0.694	1.121	0.757
Avg n	19.5	19.5	22.2	232.8	232.8	232.8	232.8	232.8	232.8	232.8	232.8
N	143	143	119	12	12	12	12	12	12	12	12

Notes: Absolute t-statistics in brackets, following Pesaran et al (2009). *, ** Indicate significance at the 5% and 1% level respectively. In brackets: t-statistics following Pesaran et al (2009). Abbreviations: MG — Mean Group, CDMG — Cross-sectionally demeand MG, CCEMG — Common Correlated Effects MG. Avg n: number of observations for regressions from which these averages are constructed, N: number of panel units in the original regressions — country-sectors, sectors and countries respectively.

Table 10: Production Function Estimates: Sector regressions

POLS	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Food	Tex&C	Wood	Paper	Chem	Plastic	NonMet	Metals	MachEq	ElecOpt	Transp	NEC
$\ln L_{it}$	0.457	0.269	0.347	0.445	0.293	0.280	0.377	0.526	0.415	0.353	0.544	0.521
	[9.23]**	[6.89]**	[9.39]**	[12.35]**	[5.54]**	[4.91]**	[9.39]**	[12.95]**	[6.82]**	[3.42]**	[8.81]**	[19.79]**
$\ln K_{it}$	0.432	0.685	0.588	0.541	0.365	0.510	0.566	0.206	0.349	0.243	0.225	0.350
	[7.51]**	[15.20]**	[18.87]**	[13.67]**	[7.08]**	[9.45]**	[13.18]**	[4.30]**	[7.01]**	[2.17]**	[5.14]**	[11.38]**
$\ln R_{it}$	0.236	0.071	0.126	0.085	0.353	0.199	0.106	0.280	0.275	0.388	0.226	0.144
	[17.72]**	[7.21]**	[10.94]**	[9.32]**	[14.97]**	[10.52]**	[14.53]**	[15.78]**	[22.17]**	[9.85]**	[8.32]**	[12.14]**
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3
joint p	0.04	0.00	0.00	0.02	0.84	0.00	0.01	0.00	0.00	0.00	0.01	0.20
FE	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Food	Tex&C	Wood	Paper	Chem	Plastic	NonMet	Metals	MachEq	ElecOpt	Transp	NEC
$\ln L_{it}$	-0.287	0.612	0.495	-0.188	-0.340	0.091	0.388	0.167	0.421	-0.045	0.491	0.681
	[3.14]**	[9.02]**	[5.56]**	[1.38]	[2.69]**	[0.85]	[7.30]**	[1.17]	[5.32]**	[0.29]	[4.54]**	[9.41]**
$\ln K_{it}$	-0.072	-0.045	0.487	0.256	0.464	1.319	0.558	0.106	0.493	0.755	0.350	0.083
	[1.07]	[0.31]	[4.52]**	[3.33]**	[3.02]**	[13.20]**	[6.39]**	[1.11]	[8.08]**	[5.10]**	[4.34]**	[1.26]
$\ln R_{it}$	0.138	0.073	0.101	-0.039	0.467	-0.288	0.004	0.334	0.019	0.636	0.257	0.087
	[3.20]**	[3.10]**	[7.63]**	[1.06]	[9.49]**	[6.67]**	[0.11]	[5.82]**	[0.51]	[6.63]**	[4.47]**	[3.84]**
CRS	0.00	0.00	0.00	0.66	0.20	0.00	0.00	0.03	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-2	1-3	1-3	1-3
joint p	0.19	0.56	0.23	0.00	0.05	0.03	0.32	0.13	0.36	0.05	0.01	0.13
CDFE	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Food	Tex&C	Wood	Paper	Chem	Plastic	NonMet	Metals	MachEq	ElecOpt	Transp	NEC
$\ln L_{it}$	0.563	0.701	0.573	0.552	0.146	0.262	0.661	1.225	0.820	-0.142	0.909	0.891
	[5.08]**	[9.78]**	[10.07]**	[4.74]**	[1.03]	[2.86]**	[12.10]**	[14.68]**	[10.27]**	[0.78]	[8.61]**	[19.64]**
$\ln K_{it}$	0.126	0.381	0.456	0.275	0.392	1.180	0.689	-0.038	0.450	0.945	0.240	-0.003
	[1.16]	[3.25]**	[7.37]**	[3.81]**	[4.03]**	[10.65]**	[12.06]**	[0.46]	[7.47]**	[8.31]**	[3.52]**	[0.06]
$\ln R_{it}$	0.241	0.052	0.090	0.105	0.545	-0.248	-0.043	0.140	-0.055	0.555	0.222	0.133
	[4.57]**	[2.08]*	[6.89]**	[3.91]**	[10.36]**	[7.07]**	[1.36]	[2.80]**	[1.40]	[5.34]**	[4.82]**	[8.73]**
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-2	1-3	1-3	1-3
joint p	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
CCEP	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Food	Tex&C	Wood	Paper	Chem	Plastic	NonMet	Metals	MachEq	ElecOpt	Transp	NEC
$\ln L_{it}$	-0.390	0.549	0.685	-0.056	-0.267	0.205	0.253	-0.136	0.396	-0.035	0.366	0.608
	[5.15]**	[9.23]**	[11.23]**	[0.41]	[3.26]**	[1.71]	[5.53]**	[1.52]	[5.53]**	[0.28]	[.31]**	[7.65]**
$\ln K_{it}$	0.024	0.026	0.373	0.404	0.380	1.350	0.810	0.443	0.544	0.919	0.446	0.180
	[0.46]	[0.19]	[4.80]**	[7.45]**	[3.96]**	[17.73]**	[8.33]**	[6.04]**	[9.55]**	[7.30]**	[6.64]**	[3.72]**
$\ln R_{it}$	0.167	0.083	0.112	-0.044	0.510	-0.323	-0.017	0.326	0.042	0.574	0.258	0.087
	[4.38]**	[3.33]**	[7.97]**	[1.32]	[11.86]**	[6.79]**	[0.45]	[6.33]**	[1.32]	[6.36]**	[4.82]**	[3.78]**
CRS	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3
joint p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
obs	234	234	232	232	234	223	234	234	234	234	234	234

Notes: Robust t-statistics in brackets. Abbreviations: POLS — pooled OLS (with year dummies), 2FE — two-way Fixed Effects, CDFE — Cross-sectionally demeaned Fixed Effects, CCEP — pooled Common Correlated Effects.
CRS: Wald test for null of CRS in labour, capital and R&D (p-value reported). AB AR: Arellano and Bond (1991) Serial correlation test, we report for which lags (1-3) the null of independent errors is rejected. 'joint p' for Cameron and Trivedi (1991) test: H_0 normal and homoskedastic residuals

Table 11: Production Function Estimates: Country regressions

POLS	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	CZE	DNK	FIN	GBR	GER	ITA	JPN	NLD	PRT	SVN	SWE	USA
$\ln L_{it}$	0.418	0.525	0.551	0.518	0.481	0.534	0.345	0.266	0.298	0.259	0.388	0.269
	[7.25]**	[14.69]**	[14.45]**	[13.24]**	[15.27]**	[21.17]**	[7.31]**	[8.03]**	[10.83]**	[6.81]**	[9.11]**	[5.36]**
$\ln K_{it}$	0.476	0.448	0.463	0.595	0.460	0.411	0.638	0.816	0.461	0.484	0.512	0.735
	[9.63]**	[14.10]**	[13.21]**	[16.80]**	[15.05]**	[13.98]**	[12.22]**	[24.65]**	[9.98]**	[7.31]**	[10.74]**	[14.61]**
$\ln R_{it}$	-0.034	0.041	0.150	-0.005	0.080	0.035	0.014	-0.039	0.051	0.118	0.190	0.030
	[3.09]**	[4.26]**	[7.34]**	[0.58]	[8.71]**	[5.56]**	[0.53]	[3.80]**	[2.49]*	[7.01]**	[9.04]**	[2.00]*
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1,3	1-3	1-3	1-3
joint p	0.02	0.00	0.00	0.23	0.00	0.00	0.48	0.00	0.00	0.00	0.00	0.00
2FE	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	CZE	DNK	FIN	GBR	GER	ITA	JPN	NLD	PRT	SVN	SWE	USA
$\ln L_{it}$	0.233	0.610	0.124	-0.002	0.396	0.346	0.959	-0.164	0.213	0.396	0.420	-0.084
	[1.02	[12.31]**	[2.19]*	[0.03]	[5.47]**	[3.50]**	[10.67]**	[2.25]*	[0.71]	[3.39]**	[1.38]	[0.74]
$\ln K_{it}$	0.833	0.409	1.632	0.645	0.716	0.354	0.377	0.911	0.217	0.844	0.547	1.374
	[6.78	[5.49]**	[18.51]**	[9.03]**	[5.56]**	[5.87]**	[2.90]**	[11.00]**	[1.38]	[8.16]**	[3.48]**	[7.94]**
$\ln R_{it}$	0.200	0.140	0.028	0.273	-0.141	0.042	0.508	0.012	0.030	-0.066	0.495	-0.263
	[2.14]*	[4.36]**	[0.90]	[8.88]**	[5.99]**	[2.92]**	[4.47]**	[0.25]	[0.49]	[1.17]	[5.18]**	[4.23]**
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1,3	1-3	1-3	1-3
joint p	0.02	0.00	0.00	0.23	0.00	0.00	0.48	0.00	0.00	0.00	0.00	0.00
CDFE	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	CZE	DNK	FIN	GBR	GER	ITA	JPN	NLD	PRT	SVN	SWE	USA
$\ln L_{it}$	0.366	0.685	0.110	0.114	0.509	0.622	0.980	0.464	0.482	0.841	0.453	0.323
	[1.08]	[9.43]**	[1.90]	[1.55]	[8.83]**	[12.86]**	[8.19]**	[7.98]**	[2.17]*	[4.75]**	[1.64]	[3.50]**
$\ln K_{it}$	0.813	0.191	1.575	0.831	0.833	0.349	0.268	0.771	0.414	0.393	0.449	1.367
	[3.27]**	[2.78]**	[15.86]**	[12.88]**	[12.89]**	[8.76]**	[2.20]*	[10.74]**	[2.97]**	[2.18]*	[2.97]**	[8.59]**
$\ln R_{it}$	0.118	0.114	-0.004	0.113	-0.066	0.057	0.093	0.075	0.090	-0.014	0.410	-0.202
	[1.75]	[3.50]**	[0.16]	[3.37]**	[2.31]*	[5.39]**	[1.46]	[2.49]*	[1.95]	[0.26]	[4.91]**	[3.60]**
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB AR	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3	1-3
joint p	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CCEP	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
global	CZE	DNK	FIN	GBR	GER	ITA	JPN	NLD	PRT	SVN	SWE	USA
$\ln L_{it}$	0.103	0.839	0.212	-0.066	0.374	0.256	1.058	-0.261	0.203	0.407	0.377	-0.003
	[0.47]	[11.43]**	[4.12]**	[1.53]	[12.86]**	[2.17]*	[12.85]**	[3.97]**	[0.56]	[3.40]**	[1.35]	[0.03]
$\ln K_{it}$	0.935	0.362	1.518	0.756	0.775	0.464	0.281	1.102	0.326	0.821	0.680	1.465
	[8.56]**	[5.99]**	[17.18]**	[10.73]**	[10.70]**	[12.46]**	[1.94]	[15.88]**	[2.92]**	[7.34]**	[5.89]**	[10.25]**
$\ln R_{it}$	0.198	0.107	0.085	0.269	-0.112	0.065	0.508	0.043	0.020	-0.068	0.495	-0.122
	[1.97]*	[3.57]**	[2.57]**	[6.77]**	[5.37]**	[4.63]**	[3.81]**	1.05]	[0.30]	[1.14]	[5.37]**	[2.19]*
CRS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00	0.00
AB AR	-3	1-3	1-3	1-3	1-2	1-3	1-2	1-3	1	1,3	1-3	1-3
joint p	0.87	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.11	0.00	0.00
obs	84	312	312	308	180	312	312	312	121	72	156	312

Notes: Robust t-statistics in brackets. Abbreviations: POLS — pooled OLS (with year dummies), 2FE — two-way Fixed Effects, CDFE — Cross-sectionally demeaned Fixed Effects, CCEP — pooled Common Correlated Effects.
CRS: Wald test for null of CRS in labour, capital and R&D (p-value reported). AB AR: Arellano and Bond (1991) Serial correlation test, we report for which lags (1-3) the null of independent errors is rejected. 'joint p' for Cameron and Trivedi (1991) test: H_0 normal and homoskedastic residuals

APPENDIX

A Variable construction

A-1 Output — Value added

We use value added as a measure of industry output mainly in order to achieve comparability with the existing literature and because value-added is more closely related to profitability than sales. EU KLEMS reports both gross output and intermediate inputs in current prices. We therefore construct double-deflated value-added by subtracting real inputs from real output. This practice is preferable over using single-deflated value-added, i.e. deflated nominal value-added, as a measure for output, since it avoids the situation where differential price movements across countries generate the false impression of productivity changes. EU KLEMS also provides the necessary sector-level deflators which represents an advantage as for some sectors, expectations of price changes would likely be different to the general level of inflation.[27] This is an important issue because if inadequate deflators are used, industry output may appear to grow slower. Since this is most likely in sectors that are R&D-intensive, the contribution of R&D to output growth would be underestimated (Hall, 1996).[28]

A-2 Labour input

As a measure of labor input, EU KLEMS provides the total number of hours worked by persons engaged. The availability of such information is an advantage of EU KLEMS over other data sets as usually the number of full-time equivalent employees has to serve as a proxy possibly aggravating the problem of measurement error (see for example Hall and Mairesse, 1996; Wakelin, 2001).

A-3 Capital input

Ideally, a measure of current capital services instead of capital stocks, i.e., a flow measure instead of a stock measure, should be used in productivity analysis (Jorgenson and Griliches, 1967).[29] The EU KLEMS data set provides such a measure for capital services in index form. However, since we do not have any data on R&D capital services, we prefer to use physical capital stocks as a proxy for capital services.[30] This is acceptable under the assumption that the quantity of an asset held by a sector is proportional to the quantity of the corresponding service obtained from that asset. For this to be the case, the aggregate of an industry's capital holdings should

[27]Hall and Mairesse (1996) also show for sales as the output measure that usage of sector-level deflators increases the elasticity with respect to R&D substantially for their sample of US firms. Their explanation is the hedonic price index used in the US for the computing sector.

[28]At the same time, if quality improvements in inputs are not accounted for, the contribution of R&D to output growth may be overestimated (see Griliches, 1992; Hall and Mairesse, 1995).

[29]The flow of productive services coming from the cumulative stock of past investments is called capital services of an asset.

[30]Lichtenberg and van Pottelsberghe (1998) have shown that using an index is identical to using volumes in a fixed effects specification. However, both approaches are different when using OLS.

represent an average over the various different vintages and age groups of the capital employed within the sector. That this assumption may approximately hold in practice is supported by empirical work, for example, by Wallis and Turvey (2009) for the UK.

Capital input is measured as total tangible assets by book value recorded annually. EU KLEMS provides several measures for tangible assets including total tangible assets, gross fixed capital formation (GFCF), ICT assets, and non-ICT assets. We use total tangible assets and deflate them using a sector level producer price index.

A-4 R&D expenditure and stocks

We use R&D stocks in our analysis. It is well known that R&D takes time to translate into innovation and it is therefore the ensemble of past and current R&D expenditures that should matter for productivity rather than merely current expenditure. At the same time past knowledge also depreciates, hence, simply specifying lagged R&D expenditure *levels* to account for the dynamic nature of R&D may be misleading. The combination of knowledge accumulation and depreciation is also the underlying rationale for Equation (2) in the Griliches knowledge production framework (see Section 2): the notion that more recent vintages of R&D investment matter more for the knowledge stock than older ones is captured by the log polynomial specification.

EU KLEMS provides R&D stocks for 19 countries for the period 1980-2003. However, the overlap with the available tangible capital stock data is not perfect leaving us with 10 countries for which both R&D stocks and physical capital data are available. In order to increase the number of countries in the sample, we constructed R&D capital stocks for Portugal and Slovenia for which R&D data is available. These R&D stocks were computed using the OECD Analytical Business Enterprise Research & Development (ANBERD) data (update May 2009) which only accounts for business enterprise R&D.[31] EU KLEMS also uses ANBERD to construct R&D stocks and we followed their methodology for Portugal and Slovenia applying the perpetual inventory method (PIM) assuming that the R&D stock evolves according to the following equation of motion:[32]

$$R_{it} = (1-\delta)R_{it-1} + \mathrm{R\&D}_{it} \tag{15}$$

where R&D denotes real R&D flows and R the corresponding stock. In order to implement equation (15), δ has to be determined. In line with EU KLEMS, we assume a depreciation rate of 12 percent, which is slightly lower than the commonly assumed 15 percent (Hall and Mairesse, 1995; Hall, 2007). Moreover, the depreciation rate is assumed to be the same across sectors and constant over time. As noted by Hall and Mairesse (1995), the actual rate chosen, however, seems to be of little relevance for estimation. The reason is the same that also justifies the use

[31] ANBERD is an attempt undertaken by the OECD to correct for a range of difficulties that arise in working with official R&D data including uneven coverage of sectors across countries, uneven methods of allocating R&D in multiproduct firms to individual industries, confidentiality constraints to reporting of data (particularly in smaller countries), classification issues, and notably differences in the treatment of the R&D services industry (ISIC rev.3 Division 73) (OECD, 2009).

[32] PIM has been widely applied in the empirical literature to construct R&D stocks (see for example Hall and Mairesse, 1995).

of the following formula to compute the initial capital stock

$$\begin{aligned} R_{i1} &= \text{R\&D}_{i0} + (1-\delta)\ \text{R\&D}_{i-1} + (1-\delta)^2\ \text{R\&D}_{i-2} + ... \\ &= \sum_{t=0}^{\infty}(1-\delta)^t\ \text{R\&D}_{i-s} = \text{R\&D}_{i0}\sum_{t=0}^{\infty}\left[\frac{1-\delta}{1+g_i}\right]^t = \frac{\text{R\&D}_{i0}}{\delta+g_i} \end{aligned} \tag{16}$$

where g_i denotes the sector-specific growth rate of R&D capital stock. Contrary to other authors, such as Hall and Mairesse (1995), we do not assume a value for g_i but compute it using the first seven years for which R&D expenditure is observed. As long as the growth rate and the depreciation rate do not change dramatically within sectors over time, they will be captured by sector-specific effects in any regression. Hence, the elasticity of output with respect to R does not depend on the choice of δ.[33]

In addition to constructing R&D capital stocks for Portugal and Slovenia, we extended the R&D stocks computed by EU KLEMS for all other countries to cover 2004 and 2005 as well, using ANBERD data and PIM described above. We used GDP deflators as proxies for R&D-specific deflators to obtain real R&D expenditures prior to computing the stock variables. We acknowledge a potential measurement problem arising from this choice (see Edworthy and Wallis, 2007) but at present no viable alternative data is available.

Despite efforts undertaken by the OECD to produce internationally comparable R&D data, important differences across countries in their attribution of R&D across industries remain, including data collection, changes in classification and annual data coverage (OECD, 2009). For our data, the problem in international comparability arises from the fact that countries do not report R&D data uniformly by product field but some rather by main activity. Countries also differ in their treatment of R&D conducted in the 'R&D services' sector ISIC 73. Our set of countries contains countries that follow either the product field or main activity approach, a mixture of both or both: Denmark, Germany, Italy, Japan, Netherlands, Portugal, Slovenia and the US follow the main activity approach. Whereas Finland, Sweden, and the UK follow the product field approach. Only the Czech Republic reports data both by product field and main activity. This difference in the allocation of R&D spending across industries still contaminates cross-country comparability of R&D expenditures and stocks.[34]

Finally, note that in two cases R&D stocks represent the bottleneck in terms of data availability: for Slovenia, R&D capital stocks are only available from 2000 onwards and for the Czech Republic only from 1999 onwards.

[33]Note that we carried out a robustness check of all our results where we excluded the first six years of data which we had used to compute g_i in order to reduce the effect that the assumption imposed on initial conditions has on the value of the computed R&D stock. This reduces the sample size by a third to data from 1986-2005. Our results are broadly robust to this sensitivity check.

[34]For a detailed discussion see Helmers, Schulte and Strauss (2009).