DO SPILOVERS MATTER WHEN ESTIMATING PRIVATE RETURNS TO R&D?

Markus Eberhardt, Christian Helmers, and Hubert Strauss*

Abstract—A large body of literature estimates private returns to R&D adopting the Griliches knowledge production function framework, which ignores the potential impact of spillovers on consistent estimation. Using a panel of twelve manufacturing industries across ten OECD economies, we investigate whether ignoring spillovers leads to bias in the estimated private returns to R&D. We compare results from a common factor framework, which accounts for spillovers and other unobserved shocks, to those from a standard Griliches approach. Our findings confirm that conventional estimates confound own-R&D and spillover effects, implying that spillovers cannot be ignored even when the interest lies exclusively in evaluating private returns to R&D.

Because the additive model is not really a very good description of knowledge production, further work on the best way to model the R&D input would be extremely desirable.

—Hall, Mairesse, and Mohnen (2009, 33)

I. Introduction

Firms invest in R&D to achieve productivity gains through innovations resulting from their investments. Thus from an aggregate economy perspective, R&D is seen as crucial in achieving productivity growth and has therefore received an enormous amount of attention from policymakers, academics, and the private business sector. As with any other 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, nonexcludability, and nonexhaustability, 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 essential, as R&D spending represents “one of the few variables which public policy can affect in the future” (Griliches, 1979, 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. But even once R&D is covered in core national accounts, another important issue closely linked to R&D will remain unaccounted for: knowledge spillovers. A vast economic literature attributes an eminent role to R&D in generating productivity gains and long-run growth owing to the generation of spillovers (Romer, 1990; Grossman & Helpman, 1991). 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 (that is, private) returns can be estimated without also accounting for the spillovers it induces.

Considering the importance of the subject, it is not surprising that a substantial number of empirical studies assessing the private and social returns to R&D at the country, regional, industry, and firm levels. A closer look at this literature, which is summarized in table A-1 in the online appendix, reveals that the most widely used approach is based on the knowledge production function originally proposed by Griliches (1979). In this approach, R&D stock is added as additional input to a Cobb-Douglas production function. This means that R&D is Hicks neutral as it shifts the production function without directly affecting returns to the standard inputs, labor and capital. This also implies that R&D enters the production function in an additively separable way, a convenient assumption as it allows direct estimation of output elasticities with respect to own-R&D, which are easily converted into returns to R&D. In the Griliches knowledge production function framework, any notion of spillovers is neglected in the empirical specification, a practice maintained in the most recent applications (see, for example, Doraszelski & Jaumandreu, 2008). In parallel to this approach, a large body of research concentrates on the contribution of spillovers to productivity, imposing a rigid structure on the spillover channels in constructing spillover variables based

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* Eberhardt: University of Nottingham; Helmers: Universidad Carlos III de Madrid; Strauss: European Investment Bank.

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1 In this paper, 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 nonprofit organizations (Edworthy & 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 that 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 A comprehensive overview of earlier work can be found in Cameron (1996); Hall et al. (2009) cover more recent studies.

5 Alternatively, returns to R&D can be obtained directly from using R&D expenditure, albeit under the restrictive assumption that knowledge does not depreciate (Hall et al., 2009).
on somewhat ad hoc assumptions. This practice reflects the general lack of a clear understanding about the precise channels through which (unobservable) spillovers occur.

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 error terms. If these unobserved factors are correlated with R&D, the resulting estimates of private returns to R&D are biased and inconsistent.

The dedicated knowledge spillover literature is largely 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 in a fashion akin to employing spatial weight matrices. Moreover, this approach implicitly assumes that cross-sectional correlation is exclusively generated by R&D spillovers. Hence, this approach may fail to produce unbiased and consistent estimates of private returns in case of empirical misspecification as it may not capture all of the cross-sectional dependence. This also implies that a statistically significant spillover variable may not represent genuine knowledge spillovers but rather reflect data dependencies more generally due to a host of other factors common to the countries and industries included in the sample.

In this paper, we adopt a more general common factor framework, 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 macrolevel when accounting for any unobserved heterogeneity, including local or global spillovers, and common shocks. This means that our results are not based on ad hoc assumptions about the structure of spillovers, and we do not assume that cross-sectional dependence is generated exclusively by knowledge spillovers. To implement our approach empirically, we use an unbalanced panel of ten OECD countries containing data for twelve manufacturing industries covering the period 1980 to 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 of the presence of knowledge spillovers and additional unobserved cross-sectional dependencies.

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 R&D or other spillover effects, or both), as well as technology homogeneity across countries or industries. This ensures that our conclusions do not merely reflect specific assumptions imposed on an unknown data-generating process.

Our findings suggest that when spillovers in the form of cross-sectional dependence are ignored, private returns to R&D are sizable; when we account for spillovers of unknown form, which may include factors other than merely R&D spillovers, private returns to R&D are at best modest. In our view, this finding is a strong indication of the presence of spillovers and the indivisibility of R&D from spillovers. If cross-sectional dependence due to knowledge spillovers 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 that of spillovers and a host of other phenomena. Our findings also suggest that commonly employed R&D spillover variables in the form of some weighted averages of R&D may, on the one hand, fail to adequately capture all of the cross-sectional dependence present in the data and, on the other, capture broader cross-sectional data dependencies than solely genuine knowledge spillovers.

The remainder of this paper is organized as follows. Section II discusses the theory underlying the Griliches knowledge production function at the heart of the literature. Section III discusses the theory on knowledge spillovers, as well as their empirical measurement. Section IV introduces the data set used for our analysis and provides descriptive statistics. Section V contains a description of our estimation strategy, and section VI presents the empirical results. Section VII concludes.

II. The Knowledge Production Function

The output elasticity with respect to R&D capital, from which the private return to R&D is derived, is commonly estimated adopting a version of 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 knowledge capital $R$:

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

With $F(\cdot)$ assumed to be Cobb-Douglas, 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. Griliches then writes equation (1) as

\[ Y = AL^a K^{\beta} R^\gamma \exp^{\lambda t + e}, \]  

(3)

where \( A \) is a constant, \( t \) is a time index capturing a common linear trend \( \lambda \), and \( e \) is a stochastic error term. \( \alpha, \beta, \gamma \), and \( \lambda \) are parameters to be estimated. Equation (2) can be substituted into equation (3) to obtain output directly as a function of current and past R&D expenditure (Hall, 1996). In order to obtain an estimable equation, we take logarithms and use subscripts \( i \) and \( t \) to denote cross-sectional units and time, respectively,

\[ y_{it} = \alpha d_{it} + \beta k_{it} + \gamma r_{it} + \lambda t + \psi_i + e_{it}, \]  

(4)

where lowercase letters denote logarithms of the inputs in equation (3) and \( \lambda t \) is, more generally than above, a time-specific effect that is (for the sake of exposition) assumed to be common across countries and industries. \( e_{it} \) is an error term that contains random shocks to the production and knowledge accumulation processes. Equation (4) contains a measure for R&D capital stock, \( r_{it} \), instead of a lag polynomial of R&D expenditures; we discuss how the R&D capital stock \( (R) \) can be constructed from R&D expenditures \((R&D)\) in the online appendix, section B.4. In order to account for cross-section, unit-specific effects that remain constant over time, we also introduce \( \psi_i \). The coefficient \( \gamma \) measures the joint contribution of R&D to productivity and to output prices. \( \gamma \) therefore indicates the elasticity of output with respect to R&D capital:

\[ \gamma = \frac{\partial y}{\partial R} \cdot \frac{R}{Y}. \]

Accordingly, the gross private rate of return can be obtained as \( \rho^G = \gamma R \). Consequently, the net rate of return is \( \rho^N = \rho^G - d \), where \( d \) is the depreciation rate of R&D capital.

Griliches (1980) noted two important measurement problems with regard to equation (4). First, conventional measures of capital and labor also contain elements of R&D, which is thus double-counted because R&D workers are included in the total labor force head count and R&D-related investments in the overall capital stock figure. This was conventionally taken to imply that the coefficient associated with R&D stock is an estimate of the excess gross rate of return to R&D—the risk premium or supranormal profit of R&D investment over other investment. Second, since R&D is treated as an intermediate expense in the calculation of value-added, measured value-added is too small by that amount.

Schankerman (1981) discusses the disturbing impact of these mismeasurements in both a growth accounting and regression framework. Within the confines of the latter, he notes that the failure to recognize the double-counting of R&D inputs and the expensing of R&D can be framed as an omitted variable problem. He goes on to show that the omission of the share of R&D workers in total labor and of R&D-related investments in total investment leads to a downward bias on the R&D stock coefficient, which cannot be interpreted as “an excess return in any simple sense” (Schankerman, 1981; 456). The expensing bias resulting from the failure to account for R&D intensity may be either positive or negative, such that the sign of the combined bias is a priori ambiguous. Some of the existing empirical evidence in cross-section data suggests an overall downward bias in the coefficient of the R&D stock (Schankerman, 1981; Hall & Mairesse, 1995), although the significance of this bias in panel data sets accounting for fixed effects is subject to some debate (Cuneo & Mairesse, 1984; Hall & Mairesse, 1995; Guellec & van Pottelsbergh, 2004). Our strategy to deal with these econometric difficulties will be twofold. First, we show that the unobserved common factor model adopted in our empirics and detailed in section IIIB is theoretically appropriate to tackle the excess returns and expensing biases. Second, we follow Schankerman’s (1981) suggestion and investigate the significance of these biases in our data using both adjusted input values to account for double-counting and augmented empirical equations to account for expensing of R&D, with results discussed briefly in section VI and presented in more detail in the online appendix.

The overall validity of the Griliches knowledge production function approach rests on the assumption of perfectly competitive factor markets, full capacity utilization, and the absence of spillover effects, the last econometrically represented by the cross-sectional independence of the error term \( e_{it} \) in equation (4). While implied by our notation in the empirical setup described above, there is no obvious reason to require the input coefficients of the knowledge production function to be the same across countries or industries \((\alpha_i = \alpha, \beta_i = \beta, \gamma_i = \gamma)\). We investigate these issues in greater detail in the following sections.

### III. Knowledge Spillovers and Other Cross-Section Dependencies

In this section we introduce a second empirical literature that extends the Griliches knowledge production framework to measure productivity gains that arise from R&D spillovers. We discuss the main assumptions routinely made in this literature, primary among which is the specification of a known, additively separable, functional form that allows the estimation of separate coefficients associated with own-R&D and R&D spillovers, respectively. The approach rests on the assumption that any cross-sectional dependence present in

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7 Crepon, Duguet, and Mairesse (1998) stress that not innovation input (R&D) is supposed to affect productivity but innovation output. In common with a large number of empirical studies, they use patents as a measure for knowledge output. This, however, seems too narrow a measure, since knowledge output can also assume many other forms (new products, capital goods, or improved managerial practices). Since R&D underlies these different innovative outputs, it may be a better and more comprehensive measure of innovation than restricting the analysis to patented innovations.

8 Motivation for technology heterogeneity of this type can be taken from the “new growth” literature (Azriadi & Drazen, 1990; Banerjee & Newman, 1993), which has resulted in a limited empirical literature (see Eberhardt & Teal, 2011).
the data reflects R&D spillovers and that these are accurately captured by the coefficient associated with the spillover variable. In order to provide an answer to our research question—“Do spillovers matter when estimating private returns to R&D?”—that is not dependent on such ad hoc assumptions, we then introduce a more flexible encompassing empirical framework.

A. Knowledge Spillovers

Arrow (1962) pointed out that knowledge is distinct from the traditional production factors labor and physical capital. The distinguishing features are nonexcludability and nonrivalry of knowledge. These features lead to 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. The process of unintentional knowledge transmission from one actor to another is commonly referred to as knowledge spillovers.10 This implies that the return on investment in knowledge is partly private and partly public (Keller, 2004).

B. Spillovers in the Knowledge Production Function

Standard approaches. Given the fundamentally unobservable nature of knowledge spillovers, directly quantifying their magnitude is a difficult task. Within the production function framework, the most common approach in the literature proceeds in two steps; we assume 

$$i = 1, \ldots, N$$ industries within a single country for simplicity of exposition. First, TFP is estimated or computed from value-added and standard factor inputs labor and physical capital; in a second step, the resulting TFP estimates are regressed on an industry’s own R&D and some measure of knowledge spillovers:

$$\text{TFP}_i = g \left( R_{it}, \sum_{k=1}^{N} \omega_k R_{kt} \right),$$

where $$R_{it}$$ denotes the R&D stock of industry $$i$$ and the second term in parentheses captures spillovers received from all other industries, with $$\omega_k$$ some explicit weights structuring the relative importance of industries.11 This setup allows a differential impact of other industries’ R&D stocks on industry $$i$$’s productivity but comes at the cost of a rigid structure in the specification of $$\omega_k$$, usually based on somewhat ad hoc assumptions. Examples of the imposed structure for spillovers include input-output tables

$$10 \text{This phenomenon must not be confounded with targeted knowledge transfer, for example, technology transfer within (international) business groups.}$$

$$11 \text{By practical convention the weight on own-industry R&D is set to 0 ($$\omega_{0,k} = 0$$) in this computation.}$$

(Goto & Suzuki, 1989; Keller, 2002a), import weights (Coe & Helpman, 1995; Keller, 1998), inward-outward FDI or shares of foreign affiliates’ sales in domestic sales of an industry (van Pottelsberge & Lichtenberg, 2001; Baldwin, Braconier, & Forslid, 2005), geographic distance (Keller, 2002b), distance to technology frontier as measured by TFP differences (Griffith, Redding, & van Reenan, 2004; Cameron, Proudman, & Redding, 2005; Acemoglu, Aghion, & Zilibotti, 2006), and measures of technological proximity (Conley & Ligon, 2002; Guellec & van Pottelsberge, 2004).12

Equation (5) can be estimated as

$$\text{TFP}_i = \psi_i + \gamma R_{it} + \chi \sum_{k=1}^{N} \omega_k R_{kt} + \varepsilon_{it},$$

where lowercase letters denote logarithms and $$\varepsilon_{it}$$ is a stochastic shock. Equation (6) is commonly augmented with time dummies to purge additional correlation across industries, arising from common shocks (recessions, policy changes) that affect all industries in the same way. If the sample contains industry-level data from several countries, the specification usually also includes country fixed effects to capture country-specific effects.

The underlying assumptions made in this setup are worth emphasizing. Equation (6) assumes that spillovers affect TFP linearly as captured by the corresponding parameter $$\gamma$$. The spillover effect is additively separable from the own-R&D effect $$\gamma$$. More important, the model suggests that industry TFP levels are correlated exclusively because of R&D spillovers and that the spillover measure captures the nature of these spillovers appropriately, that is, conditional on $$\sum_{k=1}^{N} \omega_k R_{kt}$$, the residuals $$\varepsilon_{it}$$ are cross-sectionally independent. Furthermore, with special reference to the analysis of industry- or country-level data with a substantial time horizon, it is also assumed that the empirical specification captures the long-run equilibrium relationship and is not distorted by dynamic misspecification or neglect of salient time-series properties of the data. Econometrically, these assumptions translate into well-behaved, serially uncorrelated, stationary, and cross-sectionally independent regression residuals $$\hat{\varepsilon}_{it}$$.

In order to avoid empirical restrictions based on ad hoc assumptions about the nature of spillover channels as well as all of the other concerns raised above, we suggest an empirical strategy that can capture knowledge spillovers of unknown form, together with any other unobserved heterogeneities that may cause cross-sectional correlation, allows for heterogeneous production technology across industries and countries, and is concerned with the appropriate treatment of dynamics and time-series properties more generally.

Unobserved common factor framework. The common factor approach assumes that the error term as well as the

$$12 \text{Our literature review in table A-1 in the online appendix contains more details and additional studies.}$$
The cross-sectional dependence arises from the multifactor error structure, equation (7) without accounting for nonsymmetric structure. or economy to another following a complex, unknown, and asymmetric structure.

We can illustrate the model setup in a simplified version of equation (4) with a single input $x_i$ and (for generality) heterogeneous technology parameter $\beta_i = \beta + \sigma_i$, where $\sigma_i \sim iid(0, \sigma^2)$. 

$$y_{it} = \beta_{i} x_{it} + u_{it}. \quad (7)$$

Cross-sectional dependence arises from the multifactor error structure and the assumed driving force of the input, 

$$u_{it} = \varphi_{i} f_{i} + \psi_{i} + \epsilon_{it}, \quad (8a)$$

$$x_{it} = \xi_{i} f_{i} + \pi_{i} g_{i} + \phi_{i} + \epsilon_{it}, \quad (8b)$$

where $\epsilon_{it}$ and $\epsilon_{i}$ are stochastic shocks. The setup assumes that latent processes drive both productivity and inputs, albeit not necessarily with the same strength (factor loadings $\varphi_{i}$ and $\pi_{i}$ differ from each other). The fact that the regressor as well as the error term share a common factor $f_{i}$ implies that if the factor loadings $\varphi_{i}$ and $\varphi_{i}$ are on average nonzero, estimating equation (7) without accounting for $f_{i}$ produces biased and inconsistent estimates of $E[\beta_{i}] = \beta$, as can be shown by simple substitution,

$$y_{it} = (\beta_{i} + \varphi_{i} \varphi_{i}^{-1}) x_{it} + \psi_{i} - \varphi_{i} \varphi_{i}^{-1} \phi_{i} + \epsilon_{it} - \varphi_{i} \varphi_{i}^{-1} \pi_{i} g_{i} + \varphi_{i} \varphi_{i}^{-1} \epsilon_{it} = \zeta_{i} x_{it} + \eta_{i} + \zeta_{it}. \quad (9)$$

This idea extends to multiple factors and the multivariate context, such as the Griliches knowledge production function where the main focus is on the coefficient of own-R&D: if the unobservable $f_{i}$ is merely a weak factor (representing local spillovers between a small number of industries), then the estimate of the $\beta$ coefficient may not be seriously biased; however, if we have multiple factors of the weak and strong type, the $\beta$ coefficient is not identified.\(^{13}\)

13 The literature on productivity analysis at the microlevel refers to this as transmission bias, which arises from firms’ reaction to unobservable productivity realizations when making input choices. Solutions to this problem are then sought via instrument design of one form or another (for a recent survey of the literature, see Eberhardt & Helmers, 2010).

As suggested above, the common factor framework can also account for the omitted variable bias arising from double-counting and expensing of R&D (Schankerman, 1981). If observed labor, capital stock, and value-added are mismeasured by the share of R&D workers in total labor ($s_{it}$), the share of R&D capital in capital ($\delta_{it}$), and the measured R&D intensity ($\delta_{it}$) respectively, then the true relationship can be represented in a variant of equation (4) (adapted from equation [10] in Schankerman, 1981) as

$$y_{it} = \alpha (l_{it} - s_{it}) + \beta (k_{it} - \delta_{it}) + \gamma r_{it} - \theta_{it} + \lambda_{i} + \psi_{i} + \epsilon_{it} + u_{it}, \quad (10)$$

$$= \alpha l_{it} + \beta k_{it} + \gamma r_{it} + \lambda_{it} + \psi_{it} - \alpha s_{it} - \delta_{it} + \epsilon_{it} + u_{it}. \quad (11)$$

where $\lambda_{i}$ and $\psi_{i}$ are time- and country-industry specific effects. Provided the omitted shares ($s$, $\delta$) and R&D intensity ($\theta$) each display some commonalities across a subset of country-industries (for example, increase over time in all R&D-intensive industries or increase within all industries of one country), the omitted variables in brackets can be represented by a combination of unobserved common factors (here, for simplicity, $h_{it}$, $i_{it}$, and $j_{it}$) with heterogeneous factor loadings (and a set of intercept terms):

$$y_{it} = \alpha l_{it} + \beta k_{it} + \gamma r_{it} + \lambda_{it} + \psi_{it} - \alpha s_{it} - \delta_{it} + \epsilon_{it} + u_{it}. \quad (12)$$

Since these common factors are correlated with the R&D stock (Schankerman, 1981), failure to account for their presence leads to the identification problem highlighted above. The omitted variable problem described as the source of the R&D double-counting and expensing bias can thus be accommodated econometrically in our encompassing empirical framework. We will nevertheless also estimate a version of equation (10) in which we use observed $s_{it}$, $\delta_{it}$, and $\theta_{it}$ to account for both double-counting bias and expensing bias (see section VIA).

\section*{IV. Data}

The data set comprises information on up to twelve manufacturing industries (SIC 15-37 excluding SIC 23)\(^{14}\) in ten countries (Denmark, Finland, Germany, Italy, Japan, Netherlands, Portugal, Sweden, United Kingdom, and the United States) over a time period of up to 26 years from 1980 to 2005, yielding 2,637 observations (see tables 1 and 2 for details).\(^{15}\) All of the results presented assume the country-industry as the unit of analysis (panel group member $i$), of which we have $N = 119$, yielding an average $T = 22.2$ time series observations per industrial sector. The data are taken from a number of sources, including the EU KLEMS data

14 We exclude industry SIC 23 (coke, refined petroleum products, and nuclear fuel) for which several countries do not report data.

15 The selection of countries is determined by data availability. Note that we use data for Germany only after its reunification in 1990.
set for the production data, the OECD for R&D expenditure, and Eurostat and the OECD for GDP deflators.

All monetary variables in our data set are expressed in million euros and deflated to 1995 price levels using either country- or industry-level deflators. 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, labor, and capital stock respectively. R&D stock is taken from KLEMS and extended to 2004 and 2005 using OECD data. In addition we construct the R&D capital stock series for Portugal, following the method adopted by KLEMS. We provide more details on data construction and assumptions made in the online appendix.

Table 3 contains descriptive statistics for the data sample used in our regression analysis. In figure 1 we provide box plots for value-added, physical capital stock, and R&D capital stock for the year 2005 (all deflated by million working hours), sorted by median value. As can be seen in the cross-country analysis of the left column, Japan is near the top for all three measures, whereas Portugal maintains the bottom position. The latter country aside, the distribution of value-added and physical capital stock per hour worked is relatively similar across these economies and has a narrow interquartile range, whereas the R&D capital stock per hour worked varies much more substantially. For the cross-industry analysis in the right column, we can note that the Chemicals industry (SIC 24) tops all three graphs, while Textiles (SIC 17-19) and Other Manufactures (SIC 36/37) can be found toward the bottom. Cross-industry variation is much stronger than cross-country variation and features more outliers, particularly for the R&D stock variable.

As a means of preestimation analysis of the data, we investigate the time series and cross-section properties of all variables using panel unit root tests of the first (Maddala & Wu, 1999) and second generations (Pesaran, 2007), average cross-section correlation coefficients, as well as a formal test for cross-section dependence by Pesaran (2004). (Detailed results are presented in the online appendix.) We also employ these tests in our residual diagnostics for each of the empirical models presented below. The panel unit root tests suggest that all variables are integrated of order 1. The analysis of cross-section correlation indicates substantial dependence for the variables in levels as well as first differences.16

V. Estimation Strategy

By the nature of our research question, the empirical implementation will be carried out using different estimators, each of which will impose different assumptions about the underlying data-generating process, which can in part be tested using a range of diagnostic tests applied to the residuals (Banerjee, Eberhardt, & Reade, 2010). This ensures that our empirical findings do not simply mirror specific assumptions imposed by different empirical specifications and estimators. We employ the following general regression equation and use the scheme in table 4 to structure the different approaches into a common framework,

\[ y_{it} = \alpha_i l_{it} + \beta_i k_{it} + \gamma_i r_{it} + \lambda_i + \psi_i + e_{it} \]

where \( l, k, \) and \( r \) are labor, capital stock, and R&D stock (in logarithms).

A first distinction is to be made between common and heterogeneous parameter models: the former, pooled estimators, assume common technology parameters on factor inputs across all countries and industries (\( \alpha = \alpha, \beta_i = \beta, \gamma_i = \gamma \forall i \)), while the latter relax this assumption to varying degrees.18 Typical pooled estimators include the least

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16 Interestingly, testing the residuals from a pooled AR(2) regression for each of the variables cannot reject cross-section independence for value-added, labor and capital stock, whereas these tests do reject for residuals from country-specific AR(2) regressions. The R&D stock variable, however, displays substantial cross-section dependence throughout all of these testing procedures, possibly indicating the presence of R&D spillovers and other cross-section dependencies.

17 The empirical analysis was carried out in Stata 10, and we employed a number of user-written Stata routines: multipurt, xtcdd and xtmg by Markus Eberhardt (see Eberhardt, 2012); psecafd by Piotr Lewandowski; xtfisher by Scott Merryman; abar and xtabond2 by David Roodman; md_ar1 by Måns Söderbom. Routines are available through SSC or the authors’ personal web pages.

18 Our main focus is on the most flexible setup where each country-industry can have a different set of technology parameters. Results for alternatives (country- or industry-level homogeneity) are available on request.
Table 3.—Summary Statistics

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<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Minimum</th>
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<td>Labor (million hours worked)</td>
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<td>Physical Capital (million euro)</td>
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<td>242</td>
<td>459,870</td>
</tr>
<tr>
<td>R&amp;D Capital (million euro)</td>
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<td>846</td>
<td>39,998</td>
<td>0.4</td>
<td>328,954</td>
</tr>
<tr>
<td><strong>Logarithms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln Value-Added (ln (Y_{it}))</td>
<td>8.987</td>
<td>8.986</td>
<td>1.683</td>
<td>5.668</td>
<td>13.570</td>
</tr>
<tr>
<td>ln Labor (ln (L_{it}))</td>
<td>5.821</td>
<td>5.974</td>
<td>1.554</td>
<td>2.684</td>
<td>8.797</td>
</tr>
<tr>
<td>ln Physical Capital (ln (K_{it}))</td>
<td>9.431</td>
<td>9.584</td>
<td>1.669</td>
<td>5.487</td>
<td>13.039</td>
</tr>
<tr>
<td>ln R&amp;D Capital (ln (R_{it}))</td>
<td>6.881</td>
<td>6.741</td>
<td>2.505</td>
<td>−0.937</td>
<td>12.704</td>
</tr>
<tr>
<td><strong>Growth rates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ ln Value-Added</td>
<td>0.018</td>
<td>0.015</td>
<td>0.072</td>
<td>−0.412</td>
<td>1.081</td>
</tr>
<tr>
<td>Δ ln Labor</td>
<td>−0.015</td>
<td>−0.013</td>
<td>0.044</td>
<td>−0.269</td>
<td>0.185</td>
</tr>
<tr>
<td>Δ ln Physical Capital</td>
<td>0.020</td>
<td>0.017</td>
<td>0.031</td>
<td>−0.134</td>
<td>0.213</td>
</tr>
<tr>
<td>Δ ln R&amp;D Capital</td>
<td>0.037</td>
<td>0.031</td>
<td>0.064</td>
<td>−0.125</td>
<td>0.790</td>
</tr>
</tbody>
</table>

These descriptive statistics refer to the sample for \(N = 119\) country-industries (from 10 OECD countries), which in levels contains \(n = 2,637\) observations, average \(T = 22.2\) (range 1980–2005).

A second distinction is made between static and dynamic models, which is implemented for the common and heterogeneous technology models, respectively. Investigating long-run equilibrium relations in a static model without any lagged variables may oversimplify the dynamic adjustment of the system and may mistake short-run deviations for long-run effects. A first attempt at dealing with this is to specify a simple autoregressive distributed lag model (ARDL), which can be derived from equation (13) for \(\rho_i \neq 0\):

\[
y_{it} = \rho_0 y_{it-1} + \alpha_i \tilde{y}_{it} - \rho_i \alpha \tilde{y}_{it-1} + \beta_i k_{it} - \rho_i \beta \tilde{k}_{it} + \gamma_i r_{it} - \rho_i \gamma \tilde{r}_{it} + (\lambda_i - \rho_i \lambda_{i,t-1}) + (1 - \rho_i) \psi_i + u_{it}. \tag{14}
\]
industries. The distinction between static and dynamic Blundell and Bond (1998, BB). The latter deals with the mean group version without the nonlinear (common factor) restrictions. Apart from standard pooled estimators (POLS, 2FE) we also employ the dynamic micropanel estimator by Blundell and Bond (1998); CCEP: Pooled Pesaran (2006); CCE: common correlated effects; MG: Pesaran and Smith (1995) mean group; CDMG: cross-section demeaned mean group; CMG: Pesaran (2006) CCE mean group version.

Table 4: Overview of Empirical Approach

<table>
<thead>
<tr>
<th>Technology Parameters:</th>
<th>Impact of Unobservables</th>
<th>Common</th>
<th>Heterogeneous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common</td>
<td>Static</td>
<td>POLS, FD</td>
<td>CCEP</td>
</tr>
<tr>
<td>Dynamic</td>
<td></td>
<td>POLS, BB</td>
<td>CCEP</td>
</tr>
<tr>
<td>Heterogeneous</td>
<td>Static</td>
<td>CDMG</td>
<td>MG, CMG</td>
</tr>
<tr>
<td>Dynamic</td>
<td></td>
<td>CMG</td>
<td>MG, CMG</td>
</tr>
</tbody>
</table>

Equation (14) is commonly estimated in an unrestricted version without the nonlinear (common factor) restrictions implied. Based on empirical testing, the long-run relationship in the data can then be evaluated either with or without restrictions. Apart from standard pooled estimators (POLS, 2FE) we also employ the dynamic micropanel estimator by Blundell and Bond (1998, BB). The latter deals with the problem of Nickell bias (Nickell, 1981) in a dynamic panel model with fixed effects, which yields inconsistent estimates in samples with limited data. Nickell bias can be captured by a combination of cross-sectional averages and unobservables over time is not constrained in any way and thus could be linear or nonlinear, stationary or nonstationary. In the lower panel of the table, the mean group estimator with variables in deviation from the cross-section mean (CDMG) maintains the same assumption about a common impact of unobservables across country-industries but allows for differential technology parameters.

The right column of table 4 contains estimators that allow for the impact of unobserved common factors to differ across countries and industries. Among the mean group type estimators in the lower panel of the table, the Pesaran and Smith (1995) mean group (MG) estimator can be augmented with country-industry specific linear trends, which allow for a differential impact of unobservables across country-industries while imposing linearity on their evolution. The Pesaran (2006) common correlated effects (pooled or mean group) estimators account for unobserved common factors with heterogeneous factor loadings by using cross-section averages of the dependent and independent variables as additional regressors. This allows for more flexibility as the impact of the unobserved common factors can differ across country-industries, while the evolution of these factors may be nonlinear or even nonstationary (Kapetanios, Pesaran, & Yamagata, 2011). To see the intuition behind this approach, consider the cross-section average of our pet model from equations (7), (8a), and (8b), replicated here for convenience.

\[ y_{it} = \beta_i x_{it} + \phi_i f_i + \psi_t + \epsilon_{it} \]  
\[ f_i = \psi^{-1}(\bar{y}_i - \bar{\psi} - \bar{\beta_i} \bar{x}_i), \]  
\[ y_{it} = \beta_i x_{it} + \phi_i \bar{y}_i + \psi_t + \epsilon_{it}, \]  
\[ y_{it} = \beta_i x_{it} + \pi_1 \bar{y}_i + \pi_2 \bar{x}_i + \pi_3 \epsilon_{it}, \]

where cross-section averages at time \( t \) are defined as \( \bar{y}_i = N^{-1} \sum_{t=1}^N y_{it} \) and \( \bar{x}_i = N^{-1} \sum_{t=1}^N x_{it} \). In words, as the cross-section dimension becomes large, the unobserved common factor \( f_i \) can be captured by a combination of cross-sectional averages of \( y \) and \( x \). Substitution for \( f_i \) in equation (15) yields

\[ y_{it} = \bar{y}_i + \bar{\psi} - \bar{\beta_i} \bar{x}_i + \epsilon_{it}, \]  
\[ y_{it} = \bar{y}_i + \pi_1 \bar{y}_i + \pi_2 \bar{x}_i + \pi_3 \epsilon_{it}, \]

As can be seen, the parameters of \( \bar{y}_i \) and \( \bar{x}_i \), as well as the intercept \( \pi_1 \), must be country-industry specific to capture the heterogeneity in the factor loadings \( \phi_i \). In the heterogeneous technology version of the estimator (CMG), where we allow for \( \beta_i \neq \beta \), this is achieved by construction since each factors provided their impact does not differ across country-industries. For the empirical models in equations (13) and (14), this would imply \( \lambda_a = \lambda_i \). The evolution of the unobservables over time is not constrained in any way and thus could be linear or nonlinear, stationary or nonstationary. In the lower panel of the table, the mean group estimator with variables in deviation from the cross-section mean (CDMG) maintains the same assumption about a common impact of unobservables across country-industries but allows for differential technology parameters.

We also considered the Arellano and Bond (1991) estimator, which commonly performs poorly when data are highly persistent (results available on request).

If this assumption is violated, no instrument (internal or external) exists that can satisfy both the conditions of validity and informativeness (Pesaran & Smith, 1995).

Note that in standard fashion in all but the POLS models, we account for time-invariant unobservables (fixed effects) using dummy variables or model transformations such as first differencing.

23 These estimators are remarkably robust to structural breaks, lack of cointegration, and certain serial correlation.

24 Note that in the case of multiple covariates, we construct cross-section averages for each in turn: \( \bar{x}_{1i}, \bar{x}_{2i}, \ldots, \bar{x}_{ki} \).
country-industry is estimated separately. In the pooled version (CCEP), the cross-section averages need to be interacted with country-industry dummies so that each country-industry can have a different parameter on the cross-section averages. Both estimators can accommodate a fixed number of strong common factors and an infinite number of weak common factors (Chudik et al., 2011), where the former can be thought of as common global shocks and the latter as local or regional spillover effects. The focus of this estimation approach is to obtain unbiased estimates for $\beta$ or the mean of the heterogeneous $\beta_i$; since various averages of the unknown parameters are contained in $\pi_1$, $\pi_2$, and $\pi_3$, these cannot be interpreted and should be seen as merely accounting for the cross-section dependence in the data.

VI. Results

In the following, we discuss the empirical results from our study of ten OECD economies with up to twelve manufacturing sectors each. We follow the scheme in table 4, beginning with common technology models (static, dynamic), then moving on to heterogeneous technology models (static, dynamic). Within each of these four groups, estimators differ in their assumptions about cross-section dependence and common factors. In order to evaluate rival empirical models, we use a number of diagnostic tests, including a Wald test of constant returns to scale ($\alpha + \beta + \gamma = 1$), serial correlation tests (in the static models only), common factor restriction tests (in the dynamic models only), residual cross-section correlation tests (Pesaran, 2004), and residual stationarity tests (Pesaran, 2007). In addition we provide the root mean squared error (RMSE) statistic for each regression model to indicate a measure for goodness of fit.

A. Common Parameter Models

Table 5 contains the results for standard pooled panel estimators in their static specification (POLS, 2FE, FD), as well as for the CCEP estimator in its standard version and augmented with common year dummies. All five models yield statistically significant and sensible parameter estimates for capital and labor inputs, ranging from .2 to .5 and .45 to .65, respectively. The coefficient of the R&D stock is large and highly significant in the POLS case and, to a lesser extent, in the 2FE and CCEP models. Although of relatively similar magnitude, the R&D coefficient in the FD model is not significant at the 5% level. All parameter estimates are economically plausible.

Turning to the diagnostics, it is suggested that POLS and 2FE yield nonstationary residuals, and we therefore cannot rule out spurious results, even in a panel regression (Kao, 1999). Serial correlation is present in all five models (AR(1) is to be expected in the FD case), and, curiously, the residual CD tests for cross-section independence seem to reject in case of CCEP estimators. The measure of fit indicates that the FD and CCEP models have similar residual standard deviations, which are much smaller than those for the POLS and 2FE models.

Our interpretation of these results is that the standard pooled models in levels (POLS, 2FE) are seriously misspecified, given their serially correlated and nonstationary residuals. Since these models do not seem to suffer from cross-sectionally correlated residuals and the FD yields more favorable diagnostics, we suggest that the source of the misspecification derives either from the (lack of) dynamics or the erroneous pooling of all country-industries (common technology). The CCEP models fail to address the concerns for erroneous pooling of all country-industries (common technology). The CCEP models have similar residual standard deviations, with common year dummies so that each country-industry can have a different parameter on the cross-section averages.

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Table 6 turns to the results for the dynamic specifications. In order to ease comparison with the static results, we report only the long-run coefficients implied by the common factor restrictions (ARDL model estimates based on equation [14] are available on request). Implied long-run coefficients for capital and labor vary substantially across the five models presented, from .1 to .9 and -.5 to .7, respectively. All but the POLS model in column 1 result in very low or statistically insignificant R&D capital. For the POLS estimator, it seems that identification of capital stock in the presence of R&D stock is challenging, and although the diagnostic tests indicate some favorable residual diagnostics, these results are still somewhat questionable. The identification problem highlighted in equation (9) is most likely the culprit for this outcome. The poor performance of the BB estimator (negative, albeit insignificant, labor coefficient), relying on lagged levels variables as instruments for contemporaneous
first differences and on lagged differences for levels, highlights the persistence and likely nonstationarity of the data. The two CCEP estimators yield similar results, with R&D capital insignificant and around .03.

Diagnostics for these models seem to suggest that only the 2FE and CCEP models yield stationary residuals, with the popular micropanel estimator (BB) fails the instrument validity (Sargan) test. Since we take the possibility of cross-section dependence (spillovers, common shocks) explicitly into account in the models in columns 4 and 5 in table 6, we see a substantial reduction in the coefficient of R&D capital, and we can no longer detect a statistically significant impact. Given their favorable diagnostics, our preferred dynamic pooled models are the standard and augmented CCEP in columns 4 and 5.

We argued in section IIIB above that the concerns over double-counting and expensing of R&D should be alleviated in a panel model accounting for unobserved common factors. We nevertheless also offer results that are obtained from explicitly correcting the input variables and value-added for mismeasurement following Schankerman (1981). However, the data required to correct for double-counting and expensing are available only for a subset of countries, industries, and time periods. Hence, the sample used to explore the effect of explicitly correcting the data is less than 30% of the size of the original sample. This lack of data allows us only to implement the static specification of our pooled model for which we estimate two specifications: directly correcting the input variables and augmenting the specification with the omitted variables. Furthermore, the CCEP estimators were dropped since their use would have led to a further halving of the sample while it is also unlikely that these estimators would perform as expected in the resulting short-T panel (average T = 7.5). To briefly summarize, we find that the results obtained from the corrected data suggest some downward bias in the R&D coefficient, mostly due to double-counting, but produce statistically insignificant R&D coefficients (except for POLS). The models, which add , and to the regression, show very little impact on the R&D capital coefficient throughout. A more detailed discussion of the approach and the corresponding results is relegated to the online appendix.

B. Heterogeneous Parameter Models

In our results for the static and dynamic models in tables 7 and 8, we focus on the most flexible specification where each country-industry is allowed to follow a different production function. We also investigated intermediate models using country- or industry-level regressions, which yielded qualitatively similar results regarding R&D capital stock (available on request).

The average labor coefficients in our static results in table 7 are again quite similar across all models—between .56 and .70—and thus close to the macroeconomic data on factor
time series dimension available: these models are estimated with between eight and seventeen covariates in the CDMG and trend-augmented CMG models, respectively. Due to this dimensionality problem, we are forced to drop a number of countries (GER, PRT, SWE) from the analysis in the CMG models; results for the MG and CDMG in this reduced sample were qualitatively very similar to those presented, so we report results for the larger sample for these two models. Given these data problems, we view these results only as tentative evidence and merely highlight the similar patterns to the static heterogeneous models discussed above: CDMG yields a spuriously high R&D coefficient due to the imposition of common impact of unobservables across country-industries; once this assumption is relaxed in the CMG models in columns 3 and 4, the coefficient drops substantially in magnitude and is no longer statistically significant. Diagnostic tests again suggest that MG and CDMG yield possibly non-stationary residuals, and all models raise some concerns over residual cross-section dependence.

In summary, our empirics have paid particular attention to residual cross-section dependence, which in economic terms can be interpreted as knowledge spillovers or other unobserved shocks but econometrically raises serious concerns regarding the consistency of the regression estimates. We offer a number of alternative specifications for the empirical model, allowing for dynamics as well as technology heterogeneity across countries. We find across these alternatives that models that yield a large and statistically significant coefficient of own-R&D are seriously misspecified (nonstationary, serially correlated, or cross-sectionally dependent residuals). In contrast, once our diagnostic tests are more favorable, the coefficient of own-R&D always drops considerably and becomes statistically insignificant. We take this as a clear indication that spillovers, be they true knowledge spillovers or other common shocks, matter and cannot be ignored even when the interest lies exclusively in estimating private returns to R&D.

### VII. 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 knowledge spillovers between cross-sectional units as well as other cross-section dependencies. Finding an answer to this question is relevant considering the vast amount of empirical work either implementing a Griliches-type production function under the assumption of cross-section independence or investigating knowledge spillovers, assuming a known, additively separable functional form for R&D and spillovers and positing that no other cross-section dependencies are captured by the R&D spillover variable. Our main claim is that

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26 We also conducted these MG-type regressions (static and dynamic) using (outlier-robust) weighted averages instead of the unweighted averages reported in tables 7 and 8. Findings are qualitatively identical and confirm that our results are not driven by outliers.

27 The results reported are based on long-run coefficients calculated from the average coefficients in the ARDL model. When we calculate long-run coefficients in each industrial sector and average these, the results are qualitatively the same.
the Griliches framework is inadequate even when the analysis focuses exclusively on private returns to R&D.

Using data for twelve industrial sectors in ten OECD countries, our results suggest the conventional Griliches-type knowledge production function model is indeed seriously misspecified, with diagnostic tests pointing at nonstationary and serially correlated residuals. Across static and dynamic as well as pooled and heterogeneous parameter models, we can trace a pattern whereby estimators that explicitly account for cross-section dependence and are robust to variable nonstationarity yield substantially lower coefficients for the R&D capital stock, which are statistically insignificant in most cases. These findings suggest that conventional approaches imply large and significant private returns to R&D, while specifications accounting for cross-section dependence imply relatively limited private returns to R&D.

These results may be explained by at least two types of arguments and, most likely, by a combination of the two. First, R&D is a worthwhile undertaking. Yet its value stems from a complex mix of own R&D successes and spillovers received rather than from a clearly identifiable stream of returns to an industry’s own R&D investment. Once we account for spillovers, private returns to R&D are modest. Second, the empirical approach taken here accounts not just for knowledge spillovers but for any other cross-section dependencies, including other types of productivity spillovers unrelated to R&D as well as the impact of common shocks. The true social return to R&D investment is likely to substantially higher. It is partly the result of interactions between factor inputs, as well as between countries and industries. Therefore, it cannot be extracted in a ceteris paribus fashion as is common in a knowledge production function building on additive separability and focusing on private returns.

Our analysis therefore offers two conclusions. First, even when the objective is to identify only private returns to R&D, spillovers cannot be ignored. Second, including only measures capturing R&D spillovers in the empirical equation is unlikely to account appropriately for a cross-sectional dependence that is commonly generated by the complex interplay of a range of unobserved processes. Instead, the coefficient associated with the R&D spillover variable is likely to at least in part capture common shocks and cross-sectional dependence that arises for reasons other than genuine knowledge spillovers. The common factor approach adopted in our analysis offers a way of recovering private returns by stripping the estimates from any other confounding factors.

While our analysis sheds some light on the importance of spillovers and other causes of cross-section correlation in the estimation of private returns to R&D, we do not recover a parameter associated with spillovers and therefore cannot make any statements regarding the 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 necessarily involves 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 ad hoc assumptions about the unobserved structure of spillovers. In our mind, the search for a more appropriate specification of the knowledge production function that accounts for the true nature of cross-sectional interdependencies and allows identification of private and social returns to R&D should be regarded as the main challenge for the investigation of returns to R&D in years to come.

28 The practical problem consists in splitting knowledge spillovers from common shocks and other cross-section dependencies. For instance, the use of the CCE estimator in a dedicated spatial econometric model fails to recognize that the cross-section averages included in the specification already account for both common shocks and spillovers. It is, however, anticipated that theoretical developments in this field of research will offer appropriate alternative methods in the near future.

REFERENCES


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