

Addressing Keller's Critique: More on the Identification of Productive Technology Spillovers

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ABSTRACT

R&D activities by one industry can have positive effects on the productivity performance of other industries, as a consequence of technology spillovers. Multicollinearity problems, however, have precluded the identification of industries that have been responsible for the most important technology spillovers. This paper proposes an alternative estimation approach (Minimum Cross Entropy econometrics) to cope with these problems. For a number of manufacturing industries, rates of return to R&D expenditures by other industries are estimated on a bilateral basis. Furthermore, productivity effects of spillovers from the foreign counterparts of the industry are estimated. The analysis is done for eighteen industries in twelve OECD countries in the period 1976-1999.

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1. Introduction

Knowledge has some characteristics of a public good. It is partly nonrival and partly non-excludable, which implies that it can give rise to externalities. In mainstream theory, externalities often call for public policy. If the externalities are mainly positive, governments should take care of additional supply of the public good. Since most theories stress the positive externalities of knowledge, its purposeful production (for instance, by means of R&D activities) should be stimulated. Since the extent and nature of R&D activity varies considerably across industries, policy effectiveness would be helped considerably if the industries that generate the most important externalities (or, 'spillovers') could be singled out. Despite the by now vast empirical literature on this topic, one cannot but observe that this identification objective has still not been attained. This paper proposes a less traditional econometric approach, to come closer to the production of a matrix that indicates the productivity effects manufacturing industries experience as a consequence of R&D activities done in each of the other manufacturing industries. Productivity effects of foreign counterparts will also be estimated.

Due to econometric problems (i.e. multicollinearity), empirical research on productivity effects has so far relied on composite spillover variables. Constructing such variables involves the definition of a weighting scheme, to approximate the relevance of industry-specific contributions to the industry under consideration. Including relevance weights is important, since it is implausible to assume that the electronics industry will enjoy similar benefits from a euro spent on R&D in the food industry to those from a euro spent on R&D in the computer industry. Several weighting schemes have been proposed, based on different notions of technology flows channels. Studies like Los and Verspagen (2000) compared results for a couple of such composite variables to find out which type of spillovers would have the most prominent effects, but did not find very strong results. Keller (1997, 1998) went much further, by arguing that theoretically underpinned composite variables do not perform any better than composite variables based on randomly chosen weights. Although Keller's results were not left uncriticized, a very inconvenient situation emerged: almost all studies (see Nadiri, 1993, and Mohnen, 1996, for early surveys) agree that technology spillovers have substantial positive effects on productivity, but it is impossible to assess which industries are best at "radiating" productive spillovers.

This paper attempts to shed new light on the discussion, by adopting a non-classical regression approach, which does not suffer from the problems that led researchers using classical regression analysis to use composite spillover variables. Generalized Minimum Cross Entropy (GCE) econometrics can deal with multicollinearity in data (see the introduction by Golan *et al.*, 1996). We applied our GCE analysis on data for 12 developed countries, for the period 1976-

1999. The data on industry-level value added growth and labor inputs were taken from the very recent EU KLEMS (2007a, 2007b, 2008) database. OECD’s STAN-ANBERD dataset was used as the source for the industry-level R&D data. Our analysis gives indications about the main suppliers of technology spillovers for each of the 18 manufacturing industries for which we run the analysis.

The paper is organized as follows. Section 2 reviews the general setup of studies into the productivity effects of technology spillovers and discusses the current state of affairs. In Section 3, we give an introduction in the intuition behind MCE estimation and present the equations we will estimate using these techniques. Section 4 is devoted to a brief discussion of the data, after which the estimation results are presented in Section 5. Section 6 contains results for several robustness checks, in which we run the analysis with additional variables and for different definitions of labor productivity. Section 7 concludes.

2. A Brief Non-Chronological History of Spillover Effects Estimation

Since the early 1960s, many studies have tried to estimate the empirical importance of technology spillovers for productivity growth. Generally, these productivity studies start from a production function, most often an extended Cobb-Douglas specification. Not only the traditional production factors physical capital and labor are included, but also two kinds of R&D stocks: R&D investments by the unit (firm, industry, region or country) itself and R&D obtained through spillovers from other units (so-called indirect R&D). If we denote the former by R and the latter by IR , the production function looks like

$$Q_{jt} = A(IR)_{jt}^{\eta} K_{jt}^{\alpha} L_{jt}^{\beta} R_{jt}^{\gamma} \quad (1)$$

Q stands for value added, A is a constant, K indicates the stock of physical capital, L denotes employment, t is the time index and j is the unit index. The elasticities η , α , β and γ can be estimated, if sufficient observations on each of the variables are available. Alternatively, β can be measured as the labor share in total income (this approach is commonly known as ‘growth accounting’). If constant returns to scale with respect to capital and labor are imposed, α equals $1-\beta$. In this way, a measure for total factor productivity (TFP) growth is obtained, and this can be related to the changes in both R&D stocks.¹ Both approaches yield estimates for output elasticities with respect to indirect R&D, $(dQ/dIR) \cdot (IR/Q)$, or rates of return to indirect R&D, dQ/dIR . These are considered to be measures for the impact of spillovers. As explained by Van Meijl (1995), estimating a common rate of return is often less data-demanding than estimating a

¹ A third approach is to use the dual of the production function, i.e., the cost function. Changes in the costs per unit of output are regressed on changes in the prices and quantities of various inputs (see Bernstein and Nadiri, 1988).

common elasticity. Under the (admittedly strong) assumption that R&D stocks are not subject to depreciation, rates of return can be estimated by linking total factor productivity growth to R&D intensities, defined as RE/Q and IRE/Q (E indicates expenditures).²

In principle, the simplest way to estimate the influence of R&D efforts in other industries is the one applied by Bernstein and Nadiri (1988). They specify one indirect R&D variable for each of the (other) industries. For example, the decrease in unit costs in the U.S. chemical industry is related to the R&D expenditures of the industries that manufacture non-electrical machinery, electrical products, transportation equipment and scientific instruments. This approach lets the data speak for themselves to see which (other) industries influence the productivity of a particular industry. The method has one important drawback: most industry R&D budgets have risen during the last decades and are relatively high for the same set of countries, which causes huge multicollinearity problems. The method we propose below could be seen as a way of following up to the lead by Bernstein and Nadiri (1988), using an alternative regression technique.

Since classical regression analysis is not suitable to solve the problems encountered by Bernstein and Nadiri, many authors have proceeded along an alternative avenue of research. They continued in the way proposed much earlier already by Terleckyj (1974), using weights to construct aggregate indirect R&D investment variables (IRE):

$$IRE_j = \sum_i \omega_{ij} RE_i \quad \forall i \neq j \quad (2)$$

In this expression, i and j denote the ‘spillover producing’ and ‘spillover receiving’ units, respectively. The weights ω_{ij} are the crucial elements distinguishing the different approaches to measuring spillovers. They indicate to what extent the R&D undertaken by i may be considered to be part of the indirect R&D expenditures of j . A number of weighting schemes have been proposed. We will describe them briefly (see Los and Verspagen, 2007, for much more detailed discussions).³

Unit Weights

In his firm level study emphasizing the effects of intraindustry spillovers, Bernstein (1989) circumvents the weighting problem by setting all weights equal to one. So did Los and Verspagen (2000) in their attempt to evaluate the empirical performance of four different interindustry spillover measures. The most important disadvantage of this method is that no account is taken of the theory of spillovers, which argues that due to differences in technological opportunities, appropriability of knowledge, differences in trade intensities among industries etc., the weights should in fact be very heterogeneous.

² This procedure is sometimes referred to as the ‘Terleckyj transformation’, after Terleckyj (1974).

³ See Griliches (1979, 1992) for classic contributions on channels through which innovations in one industry can affect the (sometimes misperceived) productivity performance of other industries. Van Pottelsberghe (1997) expresses views that are not in every sense in line with Los and Verspagen’s (2000, 2007) opinions.

Weights Based on Transaction Input or Output Shares

Early attempts to include spillovers in productivity analysis at the industry level (Terleckyj, 1974) used trade statistics to construct industry weights ω_j . Input-output tables are converted into tables of output coefficients. Such coefficients indicate the share of industry i 's output delivered to industry j . Next, R&D weights are set equal to the output coefficients, except for the diagonal elements. Terleckyj also calculated similar output coefficients from capital flow matrices to account for interindustry investment flows. In this output shares approach, 'second-round' effects might also be important. This occurs when spillovers are transmitted to industries down the production chain, for example, when advances in semi-conductors spill over to the computer industry, and from there to the banking industry (see, e.g. Sakurai *et al.*, 1997).

Input-output tables are also used to compute spillover measures in which the ω_j s are defined as the input coefficients a_{ij} . Wolff (1997), among others, used this measure in an interindustry context. In their highly influential international spillover study, Coe and Helpman (1995) construct a similar measure (using import weights). A disadvantage of these approaches is that only trade-related knowledge flows are taken into account. It is well-known that several other channels provide opportunities for technology spillovers.

Weights Based on Patent and Innovation Output Shares

Scherer (1982) pioneered another approach, because he felt that economic transactions often do not entail exchange of technology. A procedure based on true technological data should be used. First, he assigned a sample of patents granted in a certain period to an industry-of-origin, i.e., the producer of the technology described in the patent. Next, all patents were assigned to one or more industries-of-use, on the basis of information in the patent document.⁴ Finally, output shares were computed in a way directly comparable to the way output coefficients are constructed for traditional input-output tables based on economic transactions.

Numbers of innovations could be used as an alternative for patent counts. Sterlacchini (1989) used a large innovation survey undertaken by Robson *et al.* (1988). In this survey, innovations were assigned to an industry-of-origin (or industry-of-manufacture) and an industry-of-use. Next, he used this 'innovations input-output table' to calculate innovation share weights ω_j , denoting the share of innovations of industry i used by industry j . DeBresson *et al.* (1994) followed this lead. A disadvantage of both approaches is that the focus is on innovations traded between industries, usually embodied in product innovations. Knowledge flows not related to economic transactions are not considered. In this sense, the main disadvantage of input-output based weights is not addressed by these methods.

⁴ Johnson and Evenson (1997) proposed a concordance that maps patent classification codes assigned by the Canadian Patent Office onto industry codes, which enabled them to construct their matrix without the need to examine every patent document individually.

Weights Based on Patent Information Output Shares

Verspagen (1997a) derived different spillover measures from patent office documents. Using a concordance that maps patent classification codes onto manufacturing industry classes, Verspagen derived the industry most likely to have produced the knowledge described in the patent document, and the industries that have been most likely to benefit from this knowledge (not the patented product itself).⁵ This yielded a ‘patent information input-output table’ similar in format to the ones described above. The ω_{ij} s were then, set equal to the output coefficients of this table.

Verspagen constructed a second type of patent information input-output tables using patent citations. The patent citation output share weights method has the disadvantage that it relates to a very specific channel of spillovers and implicitly assumes that each cited patent is equally relevant to the spillover receiver.

Weights Based on Technological Proximity

The first spillover measure explicitly focusing on non-traded knowledge spillovers was constructed by Jaffe (1986). He argued that knowledge generated by R&D investments flows into a ‘spillover pool’, which is accessible to all firms. Some firms or industries benefit more from firm i 's contribution to the pool than others, because not all knowledge is relevant to their R&D. To measure the part of the contribution of the i th firm that is relevant to firm j , Jaffe (1986) used a ‘technological proximity’ measure:

$$\omega_{ij} = \frac{\sum_{k=1}^F f_{ik} \cdot f_{jk}}{\sqrt{\left(\sum_{k=1}^F f_{ik}^2 \cdot \sum_{k=1}^F f_{jk}^2 \right)}}, \quad (3)$$

Equation (3) gives the cosine of two vectors consisting of the shares of the F patent classes in the ‘patent portfolio’ of a firm. Goto and Suzuki (1989) chose a similar spillover measure in their productivity study at the industry level, but used Japanese information on the shares of product classes to which the R&D of an industry is devoted, instead of patent classes.⁶

⁵ Whereas a patent originating from the aircraft industry might have the airlines industry as its main beneficiary in terms of the use of the patented *product*, the main user of the *knowledge* documented in the patent might be the motor vehicles industry.

⁶ Comparable approaches can be found in Adams (1990), who used the shares of various categories of scientists in the research work force of an industry as determinants of its position ‘in technological space’, and in Los (2000), who proposed to compute weights analogously on the basis of columns of input-output tables.

A disadvantage of these methods is that symmetry is imposed, while it is very awkward to suppose that if industry i would generate knowledge useful for industry j , industry i will automatically benefit to the same extent from knowledge generated in j .

The discussion above shows that a number of approaches have been adopted to weight R&D expenditures to arrive at composite indirect R&D or spillover variables. The main result of most studies is that technology spillovers do have a substantive impact on productivity growth, irrespective of the weighting scheme applied. As a matter of fact, Keller (1997) claimed that most sets of *randomly* generated weights yielded virtually identical rates of return and goodness of fit statistics. Later on, in a critique of the influential article by Coe and Helpman (1995), he also claimed to find such a result for the effects of international R&D spillovers (Keller, 1998). This result got a lot of attention. Although Keller's claims had to be modified somewhat because of the peculiar way in which he had constructed his random weights, the bottomline was a negative one: Unit weights as discussed above did not yield better or worse results than sets of weights constructed along ways grounded in theory. This more or less led to a standstill with regard to this kind of research. Case study research into sources of technology for specific industries and countries largely replaced systematic comparisons.

In our view, not much more can be gained from the composite spillover variable approach. We feel, however, that new developments in non-classical econometrics make it possible to deal with data characterized by strong violations of the requirements for sensible application of classical least squares approaches. Hence, we propose to return to the original Bernstein and Nadiri (1988) approach of specifying an equation with several industry-specific R&D variables in the right hand side of the equation. These equations will be riddled with multicollinearity problems. Since Generalized Minimum Cross Entropy methods are capable of dealing with problems like these, we aim at estimating rates of return to R&D expenditures by individual industries, including by the industry considered (returns to "own" R&D).

3. The Minimum Cross Entropy Approach

In this section, the basics of Minimum Cross Entropy (CE) econometrics will be introduced. We will limit our discussion to methods used to obtain estimates for the type of linear regression models we use to assess the productivity effects of technology spillovers. More extensive introductions can be found in Kapur and Kesavan (1992) and Golan *et al.* (1996). The essential property of the CE principle is that estimates are derived from the probability distribution that is as similar as possible to an appropriate prior distribution, constrained by the condition that it is in line with the observed data and a very general distribution for the error terms. This is

fundamentally different from the classical least squares approach, in which several strong assumptions on the distribution of the error term must be taken for granted.

The main idea is that a random variable (such as an estimator) z can take on K values (z_1, \dots, z_K), with unknown probabilities $\mathbf{p} = (p_1, \dots, p_K)$ and that some subjective non-sample information about \mathbf{p} is present in the form of a prior distribution $\mathbf{q} = (q_1, \dots, q_K)$. Following the formulation proposed by Kullback (1959), the cross entropy of these distributions \mathbf{p} and \mathbf{q} is:

$$I(\mathbf{p}, \mathbf{q}) = \sum_{k=1}^K p_k \ln(p_k / q_k) \quad (4)$$

The cross entropy function I measures the dissimilarity of the distributions \mathbf{p} and \mathbf{q} . This function reaches its minimum (zero) when \mathbf{p} and \mathbf{q} are identical. If some information (for example, observations on variables) is available, it can be used as one or more constraints in a linear programming model aimed at minimizing (4). If we denote the set of probabilities implied by the minimization procedures by $\tilde{\mathbf{p}}$, each piece of information will lead to a Bayesian update of this estimated distribution. The estimated value is found by computing the expected value of z given $\tilde{\mathbf{p}}$. It is important to note that even for a situation with only one observation, the CE approach yields an estimate of the probabilities, since this observation will generally lead to a difference between the priori \mathbf{q} and the posterior $\tilde{\mathbf{p}}$. Hence, in situations in which the number of observations is not large enough to apply classical econometrics, this approach can be used to obtain robust estimates of unknown parameters.

The problem at hand is the estimation of a linear model where a variable y depends on R explanatory variables x_r :

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \quad (5)$$

in which \mathbf{y} is the $(N \times 1)$ vector of observations for y , \mathbf{X} is the $(N \times R)$ matrix of observations for the R explanatory variables, $\boldsymbol{\beta}$ is the $(R \times 1)$ vector of unknown parameters $\boldsymbol{\beta} = (\beta_1, \dots, \beta_R)'$ to be estimated, and \mathbf{e} is the $(N \times 1)$ vector with random disturbances. As mentioned, each β_r is assumed to be a discrete random variable in the CE approach. A priori beliefs about their $K \geq 2$ possible realizations are included in the estimation procedure by means of support vectors $\mathbf{b}_r = (b_{r1}, b_{r2}, \dots, b_{rK})'$ with corresponding probabilities $\mathbf{p}_r = (p_{r1}, \dots, p_{rK})'$, for $r = 1, \dots, R$. The vectors \mathbf{b}_r are based on *a priori* beliefs about the likely values of the parameters. Now, vector $\boldsymbol{\beta}$ can be written as:

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_R \end{bmatrix} = \mathbf{B}\mathbf{p} = \begin{bmatrix} \mathbf{b}'_1 & \mathbf{0} & \cdot & \mathbf{0} \\ \mathbf{0} & \mathbf{b}'_2 & \cdot & \mathbf{0} \\ \cdot & \cdot & \cdot & \cdot \\ \mathbf{0} & \mathbf{0} & \cdot & \mathbf{b}'_R \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \dots \\ \mathbf{p}_R \end{bmatrix} \quad (6)$$

Then, given the vectors \mathbf{p}_r the initial estimate for each parameter is given by

$$\beta_r = \mathbf{b}'_r \mathbf{p}_r = \sum_{k=1}^K b_k p_{rk}; \quad r = 1, \dots, R \quad (7)$$

For the random term, a similar approach is followed. For the actual values contained in \mathbf{e} , we assume a distribution for each e_i , with a set of $Q \geq 2$ values $\mathbf{v}_i = (v_{i1}, \dots, v_{iQ})'$ with respective probabilities $w_i = (w_{i1}, w_{i2}, \dots, w_{iQ})'$.⁷ The prior distribution for \mathbf{v} will be denoted by \mathbf{u} . Now, we can write:

$$\mathbf{e} = \begin{bmatrix} e_1 \\ e_2 \\ \dots \\ e_N \end{bmatrix} = \mathbf{V}\mathbf{w} = \begin{bmatrix} \mathbf{v}'_1 & \mathbf{0} & \cdot & \mathbf{0} \\ \mathbf{0} & \mathbf{v}'_2 & \cdot & \mathbf{0} \\ \cdot & \cdot & \cdot & \cdot \\ \mathbf{0} & \mathbf{0} & \cdot & \mathbf{v}'_N \end{bmatrix} \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \dots \\ \mathbf{w}_N \end{bmatrix} \quad (8)$$

and the value of the random term for an observation i equals

$$e_i = \mathbf{v}'_i \mathbf{w}_i = \sum_{q=1}^Q v_{iq} w_{iq}; \quad i = 1, \dots, N \quad (9)$$

Consequently, model (5) can be transformed into:

$$\mathbf{y} = \mathbf{X}\mathbf{B}\mathbf{p} + \mathbf{V}\mathbf{w} \quad (10)$$

Now, the estimation problem for the unknown vector of parameters $\boldsymbol{\beta}$ is reduced to the estimation of $R + N$ probability distributions of the support vectors, and the following constrained cross entropy minimization problem can be solved to obtain these estimates:

⁷ The distribution for the errors is usually assumed symmetric and centered around 0. Therefore $v_{i1} = -v_{iQ}$. A usual procedure for giving values to this vector is following the so-called 3-sigma rule, which amounts to fixing the extreme bounds as ± 3 times the standard deviation of variable y . In our empirical analysis, we will assume identical a priori support vectors for each of the random disturbances.

$$\text{Min}_{\mathbf{p}, \mathbf{w}} I(\mathbf{p}, \mathbf{q}, \mathbf{w}, \mathbf{u}) = \sum_{r=1}^R \sum_{k=1}^K p_{rk} \ln(p_{rk} / q_{rk}) + \sum_{i=1}^N \sum_{q=1}^Q w_{iq} \ln(w_{iq} / u_{iq}) \quad (11a)$$

subject to:

$$\sum_{r=1}^R \sum_{k=1}^K x_{ri} b_k p_{rk} + \sum_{q=1}^Q v_{iq} w_{iq} = y_i; \quad i = 1, \dots, N \quad (11b)$$

$$\sum_{k=1}^K p_{rk} = 1; \quad r = 1, \dots, R \quad (11c)$$

$$\sum_{q=1}^Q w_{iq} = 1; \quad i = 1, \dots, N \quad (11d)$$

The restrictions in (11b) ensure that the posterior probability distributions of the estimates and the errors are compatible with the observations. The restrictions in (11c) and (11d) are just normalization constraints. The estimated value of β_r will be (cf. equation (7), but the vectors \mathbf{p} now reflect a posteriori distributions):

$$\beta_r = \sum_{k=1}^K b_k p_{rk}; \quad r = 1, \dots, R \quad (12)$$

Equation (12) provides point estimates for the coefficients. The GCE framework also offers opportunities to infer on the statistical significance of these point estimates. Golan (2001) shows that $H_0: \beta_r = 0$ (or to be more precise, a value very close to 0) can be tested for each r separately using the statistic:

$$\sum_{k=1}^K \frac{1}{q_{rk}} (\tilde{p}_{rk} - q_{rk})^2 \quad (13)$$

Under H_0 , the statistic in (13) asymptotically follows a χ_1^2 distribution, if an a priori probability close to one is chosen for the “spike” prior q_k corresponding to $\beta_r = 0$. Hence, by comparing the observed value for the statistic in (13) to critical values from the χ^2 distribution with one degree of freedom, we can assess if technology flows between specific pairs of industries led to productivity increases or not.

4. Data Issues

We use the methodology introduced above to estimate equations resembling production function (1), for 18 industries. The industry classification is given in Appendix A. Our choice for this specific aggregation level is mainly driven by data availability in the EU KLEMS (2007a,b, 2008) database, which is the most extensive set of data currently available. Despite the opportunities offered by this database, we are faced with some data restrictions. In order not to lose too much industry detail, we cannot include growth of capital intensities as a source of productivity growth. Although it does not fit standard mainstream production theory, one might argue that a lot of investment is induced by the emergence of improved or new capital goods. This would imply that parts of the returns to R&D carried out in capital goods industries are ‘misallocated’ to the investing industry if capital intensity is included as a separate determinant. In Section 5, we will test to what extent this effect has empirical relevance for the limited number of industries for which we actually have capital input data available.

Further, since the number of countries for which the required data are available is relatively small, we decided to consider three subperiods, 1976-1983, 1984-1991 and 1992-1999. This leaves us with 36 observations per industry, since data for Denmark, Finland, France, Germany, Ireland, Italy, Japan, The Netherlands, Spain, Sweden, the UK and the US have been available.⁸ In our benchmark regression, we assume that R&D activities are the sole driver of labor productivity growth, hence we do not include constants capturing “exogenous” productivity growth:

$$\left(\frac{\hat{Q}}{L} \right)_{ict} = \sum_{j=1}^{18} \beta_{ij}^D \frac{RE_{jct}}{Q_{ict}} + \varepsilon_{ict} \quad i = 1, \dots, 18; \quad (14)$$

The abovementioned subperiods are indicated by t . The left hand side of the equation represents the annual average labor productivity growth for industry i in country c , as taken from the EU KLEMS (2007a,b, 2008) database, variable LP_I (gross value added per hour worked, volume index).⁹ The right hand side of (14) contains eighteen R&D intensities and the corresponding rates of return (the β_{ij}^D coefficients). These refer to R&D expenditures by domestic industries, including the industry under consideration (i) itself.

All R&D expenditures were taken from OECD’s STAN-ANBERD database. In order to arrive at an industry-level classification compatible with the EU KLEMS productivity data some updating procedures comparable to EU KLEMS procedures had to be adopted, for instance in

⁸ The data for Japan were taken from EU KLEMS (2007a) and the data for Ireland and Sweden from EU KLEMS (2008). For the remaining countries, the data originate from EU KLEMS (2007b).

⁹ See Timmer *et al.* (2007) for an overview of the data and a description of construction procedures.

linking ISIC2 and ISIC3 industries to EU KLEMS industries.¹⁰ The value added figures were taken from EU KLEMS (2007a,b, 2008), variable VA. Both the R&D expenditures and the value added indicators are expressed in national currency and in current prices.¹¹ To arrive at average observations for the subperiods, the annual R&D expenditures for the eight year-periods were added and so were the value added figures, after which the ratios of the sums were computed.¹²

By adopting this specification, we assume that the rates of return to R&D remained equal over time. We acknowledge the restrictive nature of this approach, although mainstream economists would argue that profit-maximizing firms with rational expectations would lower their R&D expenditures in periods in which returns to a given level of R&D investments decline.

Alternatively, we could have opted for a specification in which we would have looked at just one, 24 year-period. To obtain a reasonable number of degrees of freedom, we should have assumed that industries within a few categories would have had identical rates of return to R&D. This approach was followed by Verspagen (1997a), who assigned industries to the categories “high-tech”, “medium-tech” and “low-tech”. We feel such an approach is more restrictive than ours, since it would imply that returns would be equal even though R&D activities in different industries are characterized by different degrees of uncertainty (and, therefore, risk).

We estimated equation (14) for 18 manufacturing industries. The industry classification can be found in the Appendix A.

5. Results

We first attempted to estimate (14) by means of traditional least squares techniques. For the sake of brevity, we do not present the full set of results. Discussion of a few results suffices to conclude that the estimation problem at hand is not suitable to be tackled by OLS. Estimated rates of return to R&D done in other industries range from -2357% to +3857%. Many of these huge (in an absolute sense) estimates appear not significant, however. The R^2 s range from 0.42 to 0.78. Thus, the results suggest that R&D intensities are able to explain a substantial part of labor productivity growth rates indeed, but no reasonable interpretation can be given to estimates for single coefficients. These results underline the inconvenient status quo that followed Keller’s (1997, 1998) critique outlined in Section 2.

In order to estimate equation (14) in an alternative way, we specified a minimum cross entropy problem shaped like equations (11). In the benchmark analysis, we took a common support vector with 3 elements (0.0, 0.5, 1.0) for all β_{ij}^D parameters, for all industries i . This

¹⁰ The R&D dataset is available from the authors on request.

¹¹ Note that we did not use PPPs to correct for international differences in the costs of R&D projects. See Dougherty *et al.* (2007).

¹² We could also have opted for a fully dynamic specification. This would have required the determination of a lag structure, which we consider an issue beyond the scope of this paper.

implies that we assume that the range of feasible rates of return for own R&D efforts in industry i is *a priori* the same as the rate of return to R&D expenditures in any other industry j . With this support vector we impose our belief that only nonnegative rates of return of R&D are feasible in the medium- to long-run and averaged over firms in a country. We cannot think of a reason why R&D activity in one sector could affect the medium-run labor productivity performance in an industry negatively. Additionally, we set an upper bound to the rates of return of 100%. For specifying the support vectors \mathbf{v}_i for the error term, a three-point vector centered around 0 has been used. The upper and lower bounds were set following the “3-sigma rule”, which implies wider bounds if the dependent variable shows a large dispersion. Applying the 3-sigma rule is common practice in empirical studies that apply entropy econometrics approaches (following Pukelsheim, 1994). In order to test for the significance of estimated rates of return by means of the test statistic given in equation (13), we specified a prior \mathbf{q} (0.999, 0.0005, 0.0005). The implied a priori rate of return very close to zero. If the observations draw the estimated distribution $\tilde{\mathbf{p}}$ far enough away from the prior with the large mass on 0.0, significant positive returns will follow.

Table 1 reports the results for the estimations of equation (14) obtained by GCE along the lines set out above. The estimates for the rates of return of the own R&D intensity in each industry are emphasized. The second row from below gives the scaled condition number (see Belsley, 1991, p. 56), which is an indicator of the extent to which multicollinearity is present. A rule of thumb suggested by Belsley (1991, p. 129) is to consider multicollinearity a serious problem if this number exceeds 30. As the results show, multicollinearity is a problem in all industries considered, which again justifies our reliance on an alternative estimation method.

The results on the main diagonal show that the rate of return to R&D conducted by the industry itself is significantly different from zero for five industries. These industries are “chemicals” (6), “office machinery” (12), “radio, tv and communication equipment” (14), “instruments” (15) and “motor vehicles” (16), which are all activities in which a lot of resources are spent on innovation (note that “chemicals” includes the production of pharmaceuticals). The rates of return are very high for “office machinery” (12) and “radio, tv and communication equipment” (14), up to about 70%. In the “other transport equipment” industry (17), we also find a point estimates larger than zero in the third digit, but this is not significant according to our yardstick. In all remaining industries, no results pointing towards positive labor productivity effects of own innovative activities can be found.

Table 1. GCE estimates of rates of return to R&D and R&D spillovers

(column headers indicate industries for which labor productivity growth is explained, rows refer to potentially spillover-generating industries)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Food products, beverages and tobacco	β_{1j}	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83*	0.00	0.00	0.00
Textiles, textile products, leather and footwear	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Wood and products of wood and cork	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pulp, paper, paper products, printing and publishing	β_{4j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coke, refined petroleum products and nuclear fuel	β_{5j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chemicals and chemical products	β_{6j}	0.06*	0.02	0.00	0.00	0.05	0.27*	0.07*	0.03	0.06*	0.04	0.05	0.58*	0.03	0.20*	0.00	0.03	0.01	0.03
Rubber and plastics products	β_{7j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Other non-metallic mineral products	β_{8j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Basic metals	β_{9j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fabricated metal products, except machinery and equipment	β_{10j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Machinery and equipment, n.e.c.	β_{11j}	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00
Office, accounting and computing machinery	β_{12j}	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.65*	0.00	0.00	0.00	0.16*	0.00	0.00
Electrical machinery and apparatus, n.e.c.	β_{13j}	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Radio, television and communication equipment	β_{14j}	0.04	0.00	0.03	0.66*	0.00	0.02	0.01	0.00	0.01	0.03	0.02	0.22*	0.03	0.72*	0.00	0.00	0.00	0.02
Medical, precision and optical instruments	β_{15j}	0.00	0.00	0.04	0.00	0.03	0.00	0.02	0.00	0.13*	0.00	0.01	0.59*	0.00	0.01	0.08*	0.00	0.00	0.01
Motor vehicles, trailers and semi-trailers	β_{16j}	0.01	0.00	0.00	0.00	0.01	0.29*	0.01	0.00	0.02	0.00	0.01	0.31*	0.00	0.24*	0.00	0.11*	0.03	0.00
Other transport equipment	β_{17j}	0.00	0.03	0.02	0.00	0.14*	0.00	0.04	0.00	0.21*	0.00	0.01	0.93*	0.00	0.00	0.27*	0.00	0.02	0.00
Furniture; manufacturing n.e.c.	β_{18j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Number of observations		36	36	36	36	33	36	36	36	36	36	36	35	36	36	36	36	36	36
Condition number		49	100	58	46	125	47	54	61	61	52	48	67	55	60	52	85	66	65
Correlation coefficient		-0.31	0.02	0.17	-0.15	0.33	-0.27	0.02	-0.34	0.38	0.18	0.01	0.01	0.02	0.39	0.19	0.23	0.07	0.02

* Estimates significantly different from 0.00075 at 10%;

Shaded cells on the main diagonal refer to productivity effects of “own” R&D.

Support vectors for all β_{ij}^D : (0.0, 0.5, 1.0); Associated prior distribution \mathbf{q} : (0.999, 0.0005, 0.0005).

As mentioned, we specified identical support vectors and associated prior distributions for the rates of return to “own” R&D and R&D spillovers. Since R&D is purposefully done by firms in an industry to enhance their own performance and spillovers are a by-product by definition, we expect to have a much smaller proportion of significant rates of return for the off-diagonal cells in a table like Table 1, than for those on the main diagonal. The results confirm this expectation: whereas 5 out of 18 (almost 30%) cells on the main diagonal are significantly positive, only 18 out of 306 (less than 6%) off-diagonal cells appear to share this property.

We find that many medium and high-tech industries generate productive spillovers to other industries. Our estimates show that R&D in the chemicals industry has a positive impact on productivity in “food products” (1), “rubber and plastics”(7), “basic metals” (9), “office machinery” (12) and “office machinery” (14). It is also interesting to see that “instruments” (15), “motor vehicles”(16) and “other transport equipment” (17, which includes shipbuilding and aircraft manufacturing) do not enjoy very strong positive productivity effects of their R&D activities, but that other industries benefit from the spillovers these industries generated. These effects might well reflect the downstream transmission of innovation rents, rather than pure knowledge spillovers. Somewhat surprisingly, the computer industry (12) did not generate such spillovers. A plausible explanation might be that the positive impacts of innovation in the computer industry are predominantly recorded in the services sector, which is not part of the subject of our analysis.

A number of low-tech industries such as “textiles” (2), “wood” (3), “glass and stone” (8) and “metal products” (10) do not benefit from any productive R&D or R&D spillover effects. As a consequence of this, the extent to which the right-hand side variables explain the labor productivity growth patterns is limited for many industries. Since conventional R^2 statistics are not bound in the $[0,1]$ interval in a GCE context, we present pairwise correlation coefficients between the predicted labor productivity growth rates and the actual growth rates to give an indication of the goodness of fit. We follow Arndt *et al.* (2002) in this respect.

Like in most empirical work, we also find some counterintuitive results, such as the rate of return from R&D in “motor vehicles” to productivity in “chemicals”, or the strong link between R&D in the “food” industry to labor productivity in “instruments”. Testing several (dynamic) specifications of the regression equation should prove a useful avenue for future research. In the next section, we will report on a number of simpler robustness analyses that might shed more light on the plausibility of the benchmark results presented above. We will mainly focus on the effects of omitted variables, such as spillovers from abroad, investment in physical capital and effects of increased schooling.

Table 2. Sensitivity of estimates of rates of return to R&D and R&D spillovers (wider support vector)

(column headers indicate industries for which labor productivity growth is explained, rows refer to potentially spillover-generating industries)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Food products, beverages and tobacco	β_{1j}	0.01	0.02	0.01	0.18*	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.83*	0.00	0.00	0.00
Textiles, textile products, leather and footwear	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
Wood and products of wood and cork	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pulp, paper, paper products, printing and publishing	β_{4j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coke, refined petroleum products and nuclear fuel	β_{5j}	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chemicals and chemical products	β_{6j}	0.11	0.00	0.00	0.00	0.02	0.33*	0.07	0.03	0.04	0.06	0.09	0.26*	0.04	0.13*	0.00	0.02	0.01	0.03
Rubber and plastics products	β_{7j}	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Other non-metallic mineral products	β_{8j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Basic metals	β_{9j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fabricated metal products, except machinery and equipment	β_{10j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Machinery and equipment, n.e.c.	β_{11j}	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.02	0.00	0.00	0.02	0.00
Office, accounting and computing machinery	β_{12j}	0.00	0.09	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.85*	0.02	0.00	0.00	0.18*	0.01	0.00
Electrical machinery and apparatus, n.e.c.	β_{13j}	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.03	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Radio, television and communication equipment	β_{14j}	0.05	0.00	0.03	0.62*	0.00	0.01	0.00	0.00	0.01	0.03	0.04	0.12	0.07	0.81*	0.00	0.00	0.00	0.02
Medical, precision and optical instruments	β_{15j}	0.00	0.01	0.07	0.00	0.05	0.00	0.06	0.00	0.18*	0.00	0.03	0.60*	0.00	0.01	0.09	0.00	0.00	0.05
Motor vehicles, trailers and semi-trailers	β_{16j}	0.00	0.00	0.00	0.00	0.01	0.24*	0.01	0.00	0.03	0.00	0.02	0.21*	0.01	0.20*	0.00	0.14*	0.03	0.00
Other transport equipment	β_{17j}	0.00	0.04	0.01	0.00	0.17*	0.00	0.05	0.00	0.18*	0.00	0.03	1.31*	0.00	0.00	0.27*	0.00	0.05	0.00
Furniture; manufacturing n.e.c.	β_{18j}	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Number of observations		36	36	36	36	33	36	36	36	36	36	36	35	36	36	36	36	36	36
Correlation coefficient		-0.32	0.08	0.25	-0.15	0.41	-0.27	0.07	-0.31	0.41	0.21	0.03	0.07	0.05	0.42	0.20	0.26	0.14	0.06

* Estimates significantly different from 0.0015 at 10%;

Shaded cells on the main diagonal refer to productivity effects of “own” R&D.

Support vectors for all β_{ij}^D : (0.0, 1.0, 2.0); Associated prior distribution \mathbf{q} : (0.999, 0.0005, 0.0005).

6. Sensitivity Analyses

The results documented in Table 1 might not be robust for several reasons. Omitted variables might play a role. We will discuss the effects of including a number of additional variables below. We would like to consider sensitivity to the support vectors chosen first, because these are very specific to the estimation technique we propose.

Table 2 presents the estimated results if the support vector has a larger maximum value than in the benchmark case. We increased the upper bound from 100% to 200%, to allow for the occasionally high rates of return to R&D (118-147%) found by Scherer (1982). The results show that the benchmark results are not very sensitive to this modification. One industry, “instruments” (15), appears not to have enjoyed significant productivity effects of its own innovative activities, but the point estimate is slightly higher than in the benchmark case. The most important implication of choosing a higher upper bound is the result that “chemicals” (6) does not yield a lot of spillovers to other industries, contrary to what we found before. In most cases, the level of significance dropped just below our threshold of 10%. In a qualitative sense, the width of the support vector does not appear to affect the results very much.

We start our sensitivity analysis with respect to omitted variables by including a variable related to technology generated abroad. The dataset contains a few small open economies for which foreign R&D activities might be an important source of spillovers affecting productivity growth. The limited number of observations led us to the decision not to estimate effects of international *inter*industry spillovers, but to focus on the effects of international *intra*industry spillovers (as opposed to, for example, Verspagen, 1997b). Neither did we include separate effects of R&D spillovers from individual countries, which would have been in the spirit of, among others, Coe and Helpman (1995). The effects of international intraindustry spillovers are captured by the rate of return β_i^F , estimated using an augmented version of (14):

$$\left(\frac{\hat{Q}}{L} \right)_{idt} = \sum_{j=1}^{18} \beta_{ij}^D \frac{RE_{jct}}{Q_{ict}} + \beta_i^F \frac{\sum_{d \neq c} RE_{idt}}{Q_{ict}} + \varepsilon_{ict} \quad i = 1, \dots, 18; \quad (15)$$

For the effects of foreign intraindustry spillovers, we do not exclude negative productivity effects. Business stealing effects of successful foreign R&D could lead to reduced labor productivity growth rates if labor markets do not react immediately to decreased output or a slower output growth rate. To reflect this, we choose (-1.0, 0.0, 1.0) as the support vector for the foreign spillovers coefficient. The results can be found in Table 3.

Table 3. Sensitivity of estimates of rates of return to R&D and R&D spillovers (inclusion of international R&D spillovers)
(column headers indicate industries for which labor productivity growth is explained, rows refer to potentially spillover-generating industries)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Food products, beverages and tobacco	β_{1j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Textiles, textile products, leather and footwear	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wood and products of wood and cork	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pulp, paper, paper products, printing and publishing	β_{4j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coke, refined petroleum products and nuclear fuel	β_{5j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chemicals and chemical products	β_{6j}	0.06*	0.01	0.00	0.01	0.06*	0.14*	0.05	0.02	0.05	0.03	0.03	0.64*	0.01	0.20*	0.03	0.04	0.01	0.02
Rubber and plastics products	β_{7j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other non-metallic mineral products	β_{8j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Basic metals	β_{9j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fabricated metal products, except machinery and equipment	β_{10j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Machinery and equipment, n.e.c.	β_{11j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00
Office, accounting and computing machinery	β_{12j}	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.63*	0.00	0.00	0.00	0.16*	0.00	0.00
Electrical machinery and apparatus, n.e.c.	β_{13j}	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Radio, television and communication equipment	β_{14j}	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.32*	0.02	0.72*	0.00	0.00	0.00	0.01
Medical, precision and optical instruments	β_{15j}	0.00	0.00	0.04	0.00	0.03	0.00	0.02	0.00	0.13*	0.00	0.01	0.55*	0.00	0.01	0.16*	0.00	0.00	0.01
Motor vehicles, trailers and semi-trailers	β_{16j}	0.01	0.00	0.01	0.00	0.01	0.17*	0.02	0.00	0.02	0.01	0.01	0.21*	0.01	0.24*	0.03	0.10*	0.03	0.02
Other transport equipment	β_{17j}	0.00	0.04	0.02	0.00	0.13*	0.01	0.04	0.00	0.21*	0.00	0.02	0.91*	0.00	0.00	0.25*	0.00	0.02	0.00
Furniture; manufacturing n.e.c.	β_{18j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Foreign spillovers from the same industry	β_j^F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of observations		36	36	36	36	33	36	36	36	36	36	36	35	36	36	36	36	36	36
Correlation coefficients		0.27	-0.08	0.26	0.34	0.31	-0.04	0.20	0.09	0.38	0.27	0.32	0.07	0.47	0.39	0.35	0.29	0.22	0.20

* Estimates significantly different from 0.00075 at 10%;

Shaded cells on the main diagonal refer to productivity effects of “own” R&D.

Support vectors for all β_{ij}^D : (0.0, 0.5, 1.0); Support vector for β_j^F : (-1.0, 0.0, 1.0); Associated prior distributions \mathbf{q} : (0.999, 0.0005, 0.0005).

A first important result is that we do not find significant rates of return to foreign intraindustry spillovers. Apparently, these are very close to zero.¹³ Inclusion of this variable adds to the explanatory power of the model, however, since the unweighted average of the correlation coefficients increases from 0.05 for the specification without international R&D spillovers to 0.24 for the specification including this potential source of productivity growth.

The inclusion of foreign intraindustry spillovers does not affect the result that own R&D has positive productivity effects in “chemicals”, “office machinery” and “radio, tv and communication equipment” only. The estimated rate of return of domestic R&D in “chemicals” (6) is reduced, from 27% to 14% as a consequence of foreign spillovers. Two implausible interindustry spillover effects that were identified in the benchmark are no longer detected: R&D in “radio, tv and communication equipment” (14) does not have a large positive impact on “paper” (4) and the same holds for spillovers from “food” (1) to “instruments” (15). We also find some positive domestic spillover effects that we did not detect before, from “chemicals” (6) to “fuels” (5). This rate of return is not extremely high and just significant at 10%. Apart from these changes, the results remain largely unchanged.

Another variable that is often considered as a driver of labor productivity growth is the accumulation of physical capital. In the long run, diminishing returns to investment might lead to almost zero effects, but over the 8-year periods we analyze high rates of investment might have an important impact. This might affect the estimated rates of return to R&D expenditures if part of the effects picked up by R&D in the benchmark equation should in fact be attributed to capital intensity growth. To investigate this issue, we estimated the following augmented version of (14):

$$\left(\frac{\hat{Q}}{L}\right)_{ict} = \sum_{j=1}^{18} \beta_{ij}^D \frac{RE_{jct}}{Q_{ict}} + \beta_i^K \left(\frac{\hat{K}}{L}\right)_{ict} + \varepsilon_{ict} \quad i = 1, \dots, 18; \quad (16)$$

To compute the average annual growth rate of capital intensities, the EU KLEMS variables H_EMP (hours worked by persons engaged) and CAP_QI (capital services volume index) have been used. The analysis could only be done for a subset of industries, since capital services data are lacking for a number of industries included in Table 1, 2 and 3. At a slightly higher level of aggregation, we can still consider the entire manufacturing sector, however. An important issue to be dealt with is the support vector and associated prior to be used for the capital elasticities β^K . We decided to choose these in such a way that the implied expected values equal the industry-

¹³ For four industries, the point estimate is negative. These are “fuels” (5), “office machinery” (12), “radio, tv and communication equipment” (14) and “motor vehicles” (16). Of course, the rates of return are very close to zero since the associated R&D intensities (all R&D expenditures in the same industry in 17 countries divided by the value added of the industry in the country considered) are very high. In terms of elasticities, the effects might well turn out to be sizable.

specific shares of capital compensation (variable CAP in the EU KLEMS database) in value added, averaged over the entire period. The lower bound of the support vector was set at zero, the center value at the expected value defined above and the upper bound at twice this expected value. As the prior, we used a uniform distribution (0.333, 0.333, 0.333). This choice prevents us from deciding whether the capital elasticity is significantly different from a specific value, but does not fix it too strongly at the capital share in value added. This allows for a useful analysis of the effects of including physical capital accumulation on the estimated rates of return to domestic R&D.

The results are documented in Table 4. The numbers of observations are lower than for the specifications we presented so far. This is due to lack of capital services data for Ireland, Japan and Sweden in the releases of the EU KLEMS database we use. The correlation coefficients are considerably higher than in the benchmark (the unweighted average over industries amounts to 0.19, as compared to 0.05 in the benchmark). For most industries, the estimated physical capital elasticity is far from the value implied by the average shares of capital compensation in value added. The sign of the deviations varies across industries. In “metals” (9+10), for example, our prior (0.27) is much higher than the GCE estimate (0.12), while in “machinery” (11) the estimate is much higher (prior: 0.24, GCE: 0.77). Generally speaking, the inclusion of capital does not have dramatic effects on the returns to own R&D, in the sense that similar industries appear to benefit from innovative efforts. In “chemicals” (6), the revenues of R&D are considerably lowered, however. In the benchmark (Table 1), we found a point estimate of 27%. Including capital, this value drops to 9%. The broad “electrical and optical equipment” industry (12-15) benefits from R&D done in the “radio, tv and communication equipment” (14) industry, which is an element of the broader industry considered. The broad “transport equipment” industry (16+17) appears not to enjoy labor productivity gains from its own R&D investments, whereas the “motor vehicles” part of this industry did in the benchmark.

Concerning interindustry spillovers, we find corroboration for most of our previous results. The chemicals industry is an important supplier of productive spillovers again, to “fuels” (5) and to “electrical and optical equipment” (12-15). Spillovers from the transportation equipment industries (16 and 17) are detected again, and “instruments” (15) is again identified as a provider of productivity-enhancing technology to other industries, notably “fuels” (5) and “machinery” (11). In general, the rates of return are somewhat smaller than in the benchmark. Moreover, some spillovers that feature in Table 1 do not show up after inclusion of changes in physical capital intensities as an explanatory variable, such as those from “chemicals” (7) to “food” (1).

Table 4. Sensitivity of estimates of rates of return to R&D and R&D spillovers (inclusion of capital elasticities)

(column headers indicate industries for which labor productivity growth is explained, rows refer to potentially spillover-generating industries)

		1	2	3	4	5	6	7	8	9+10	11	12-15	16+17	18
Food products, beverages and tobacco	β_{1j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Textiles, textile products, leather and footwear	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wood and products of wood and cork	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pulp, paper, paper products, printing and publishing	β_{4j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00
Coke, refined petroleum products and nuclear fuel	β_{5j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chemicals and chemical products	β_{6j}	0.00	0.00	0.00	0.00	0.11*	0.09*	0.02	0.01	0.00	0.00	0.07*	0.00	0.01
Rubber and plastics products	β_{7j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other non-metallic mineral products	β_{8j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Basic metals	β_{9j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fabricated metal products, except machinery and equipment	β_{10j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Machinery and equipment, n.e.c.	β_{11j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.26*	0.00	0.01	0.00	0.00
Office, accounting and computing machinery	β_{12j}	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Electrical machinery and apparatus, n.e.c.	β_{13j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Radio, television and communication equipment	β_{14j}	0.01	0.02	0.01	0.00	0.01	0.01	0.00	0.02	0.00	0.00	0.23*	0.00	0.01
Medical, precision and optical instruments	β_{15j}	0.00	0.01	0.05	0.00	0.14*	0.00	0.10	0.00	0.00	0.16*	0.02	0.00	0.05
Motor vehicles, trailers and semi-trailers	β_{16j}	0.00	0.00	0.00	0.00	0.00	0.32*	0.09	0.00	0.00	0.01	0.03	0.00	0.01
Other transport equipment	β_{17j}	0.00	0.02	0.01	0.00	0.25*	0.00	0.06	0.00	0.00	0.04	0.06*	0.00	0.00
Furniture; manufacturing n.e.c.	β_{18j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Capital intensity growth	β_k	0.57	0.32	0.26	0.31	0.61	0.95	0.63	0.25	0.12	0.77	0.36	0.11	0.13
Number of observations		27	27	27	27	24	27	27	27	27	27	27	27	27
Correlation coefficient		0.42	0.54	0.34	-0.01	0.41	-0.05	0.55	-0.16	-0.27	0.33	0.52	0.11	-0.31

* Estimates significantly different from 0.00075 at 10%;

Shaded cells on the main diagonal refer to productivity effects of “own” R&D.

Support vectors for all β_{ij}^D : (0.0, 1.0, 2.0); Support vector for β_j^K : industry-specific, lower bound 0.0; Associated prior distributions for β_{ij}^D like in Table 1, uniform for β_j^K .

Table 5. Sensitivity of estimates of rates of return to R&D and R&D spillovers (correction for differences in labor quality)
(column headers indicate industries for which labor productivity growth is explained, rows refer to potentially spillover-generating industries)

		1	2	3	4	5	6	7	8	9+10	11	12-15	16+17	18
Food products, beverages and tobacco	β_{1j}	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Textiles, textile products, leather and footwear	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wood and products of wood and cork	β_{2j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pulp, paper, paper products, printing and publishing	β_{4j}	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coke, refined petroleum products and nuclear fuel	β_{5j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chemicals and chemical products	β_{6j}	0.08*	0.01	0.00	0.07*	0.11*	0.16*	0.09*	0.03	0.03	0.06	0.10*	0.00	0.02
Rubber and plastics products	β_{7j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other non-metallic mineral products	β_{8j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Basic metals	β_{9j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fabricated metal products, except machinery and equipment	β_{10j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Machinery and equipment, n.e.c.	β_{11j}	0.01	0.05	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.01
Office, accounting and computing machinery	β_{12j}	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Electrical machinery and apparatus, n.e.c.	β_{13j}	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Radio, television and communication equipment	β_{14j}	0.05	0.00	0.04	0.02	0.00	0.01	0.00	0.00	0.01	0.05	0.27*	0.00	0.03
Medical, precision and optical instruments	β_{15j}	0.00	0.00	0.02	0.00	0.05	0.00	0.07*	0.00	0.00	0.00	0.01	0.00	0.00
Motor vehicles, trailers and semi-trailers	β_{16j}	0.00	0.00	0.00	0.01	0.01	0.50*	0.03	0.00	0.00	0.01	0.06	0.00	0.01
Other transport equipment	β_{17j}	0.00	0.01	0.00	0.01	0.17*	0.00	0.09*	0.01	0.00	0.01	0.01	0.00	0.00
Furniture; manufacturing n.e.c.	β_{18j}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of observations		24	24	24	24	22	24	24	24	24	22	24	24	24
Correlation coefficient		0.02	-0.16	-0.14	-0.31	0.27	-0.14	0.20	-0.32	-0.11	0.05	0.77	-0.11	0.42

* Estimates significantly different from 0.00075 at 10%;

Shaded cells on the main diagonal refer to productivity effects of “own” R&D.

Support vectors for all β_{ij}^D : (0.0, 0.5, 1.0); Associated prior distribution \mathbf{q} : (0.999, 0.0005, 0.0005).

Finally, we used information on the quality of labor inputs available from the EU KLEMS database to offer more indications of the robustness of our results. Its variable LAB_QI gives information about the labor services used in the activities of the industries. Labor services do not only take hours into account, but also the skills of the persons supplying these hours. It might be that changes in labor productivity expressed in terms of value added per hour worked (the indicator used in our benchmark estimations) are affected by increases in the quality of the labor force. If so, parts of labor productivity growth due to investments in schooling and related activities have been attributed to R&D and R&D spillovers in our benchmark. To correct for this potential omitted variable problem, we estimate equation

$$\left(\frac{\dot{Q}}{L^S}\right)_{ict} = \sum_{j=1}^{18} \beta_{ij}^D \frac{RE_{jct}}{Q_{ict}} + \varepsilon_{ict} \quad i = 1, \dots, 18; \quad (17)$$

The dependent variable indicates the growth of value added in excess of the growth of labor services. We present the results for equation (17) in Table 5. As a consequence of the limited availability of labor services data (especially for early years in our period of analysis), the number of observations is lower than in the benchmark.

The correlation coefficients show that correcting the labor input indicator does not lead to an increase in the explanatory power of the model. On average, the differences are negligible. The high correlation coefficient for the broad “electrical and optical equipment” industry (12-15), stands out. Apparently, differences in quality of labor and in R&D efforts do a good job in explaining differences in labor productivity performance. By and large, the results of the benchmark estimates are confirmed: rates of return to own R&D are nonsignificant in most industries, with the important exceptions of “chemicals” and “electrical and optical equipment”. “Chemicals” is the main supplier of productive spillovers again. As opposed to the benchmark, spillovers from this industry have also positive effects on labor productivity in “paper etc.” (4) and “fuels” (5). The transport equipment industries (16 and 17) also generate productive spillovers, like in the benchmark estimates. The implausibly high rate of return for “paper etc.” (4) to R&D done in “radio, tv and communication equipment” (14) as found in estimating the benchmark equation disappears, most probably as a consequence of dropping specific country-periods from the sample.

7. Conclusions

In this paper, we introduced a novel approach to the assessment of the impact of interindustry technology spillovers on labor productivity. In the late nineties, Keller (1997, 1998) published a very critical study about the results attained by this field, which had blossomed after the

emergence of R&D-driven economic growth in the decade before. Afterwards, the situation can best be characterized as a status quo: most scholars agree that technology spillovers play an important role in productivity growth, but there is no clear evidence of the impact of R&D conducted in specific industries on the productivity performance of others. This paper introduces an approach that might contribute to more knowledge concerning this important issue. Unlike the vast majority of empirical studies undertaken so far, we do not use classical least-squares estimation techniques, but rely on Generalized Minimum Cross Entropy (GCE) techniques. This toolbox of econometric methods is particularly geared towards situations in which data are ill-behaved. In studies linking productivity growth to sources of spillovers, multicollinearity is often a big problem, as a consequence of which it is impossible to estimate the effects of R&D done in individual industries. This paper is the first one to approach these problems using GCE techniques.

Our results derived from analyses of recent EU KLEMS productivity data and OECD R&D statistics show that with just a few exceptions, high-tech industries attain positive rates of return to their R&D investments (in the order of magnitude of 10% to 70%). Moreover, some industries benefit from innovation in many other industries, whereas others mainly rely on own R&D activities. We reported on a number of robustness checks, including estimating specifications with additional explanatory variables, such as intraindustry spillovers from abroad and changes in physical capital intensity changes. A robust finding is that the chemicals industry is an important generator of productive technology spillovers. To a somewhat lesser extent, this also holds for the transport equipment industry. The office machinery appears to attain a high rate of return on its own R&D activities, but does not contribute much to the performance of other industries. This could be due to our choice to focus on manufacturing industries. The most important spillover effects of the computer industry might be encountered in the services sector. This is a subject for future research.

Besides studying spillover effects in services, the analysis in this paper can be extended in various ways. In our view, addressing the specification of the R&D-productivity equation would be a prime candidate. We do not employ the full potential of our dataset in terms of dynamic analyses. It should be possible to replicate firm-level studies like Los and Verspagen (2000), especially because GME can deal with non-stationary series of observations without having to incorporate cointegration formulations and the like. Improved estimates of the productivity effects of interindustry technology spillovers could also lead to reasonable calibrations of dynamic Computable General Equilibrium models, providing policy makers with improved forecasts of the effects of targeted, industry-level innovation policies. Such calibrations based on econometric work seemed simply impossible after Keller's (1997, 1998) critique.

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Appendix A: Industry Classification*

nr.	Name	EUK	nr.	Name	EUK
1.	Food, beverages and tobacco	15t16	10.	Fabricated metal products	28
2.	Textiles, textile, leather and footwear	17t19	11.	Machinery, n.e.c.	29
3.	Wood and products of wood and cork	20	12.	Office, accounting and computing machinery	30
4.	Pulp, paper, paper products, printing and publishing	21t22	13.	Electrical machinery and apparatus, n.e.c.	31
5.	Coke, refined petroleum and nuclear fuel	23	14.	Radio, television and communication equipment	32
6.	Chemicals and chemical products	24	15.	Medical, precision and optical instruments	33
7.	Rubber and plastics	25	16.	Motor vehicles, trailers and semi-trailers	34
8.	Other non-metallic mineral products	26	17.	Other transport equipment	35
9.	Basic metals	27	18.	Manufacturing, n.e.c.	36t37

* EUK refers to industry classification numbers in EU KLEMS (2007a,b, 2008).