Harald Badinger and Peter Egger

Productivity spillovers across countries and industries: new evidence from OECD countries

Productivity Spillovers Across Countries and Industries: New Evidence From OECD Countries[*]

Abstract

This paper uses a translog approach to estimate intra- and inter-industry productivity spillovers transmitted through input-output linkages, distinguishing R&D and other (remainder) spillovers. For a panel of 12 OECD countries and 15 manufacturing industries from 1995-2005, first, we find that the estimated elasticity with respect to ‘own’ R&D amounts to 0.25 on average (which would be estimated to be lower if R&D were assumed to be additively separable from other inputs). Second, there are sizeable intra-industry and relatively small inter-industry R&D spillovers. Third, there are significant remainder spillovers, which are mainly of the intra-industry type and substantially amplify idiosyncratic technology shocks.

JEL classification numbers

L60, C21, F14

Keywords

Intra-industry spillovers, inter-industry spillovers, productivity, spatial econometrics, research and development

Word count: 10,183 (including footnotes, references and tables)

[*] We wish to thank the editor in charge (Jonathan Temple) and two anonymous referees for numerous helpful comments on earlier versions of this paper.

'... the transmission of technological change may also take the form of a circular process. Under such a configuration technological improvements have a magnified impact. ... All these repercussions – vertical or triangular – form part of a response mechanism that contributes to technological advancement.' (Balassa, 1961, p. 150)

I. Introduction

The process of economic integration after World War II has markedly intensified the interdependence of economic systems at all levels of aggregation – firms, industries, regions, and even countries. The reduction of barriers to transport and trade, improvements of infrastructure facilities, better availability of high-quality information and communication technologies, and access to new modes of specialization have induced sizeable growth in trade of both final and intermediate goods as well as foreign direct investment, which is widely held to have indirectly triggered productivity growth effects. Moreover, the mentioned modes of interaction have not only likely affected productivity locally but also the propagation of technology shocks within and across sectors, both nationally and internationally.

The goal of the present paper is to shed more light on the magnitude and transmission of these types of spillovers by providing a comprehensive empirical assessment of intra- and inter-industry productivity spillovers for a panel of 12 OECD countries and 15 manufacturing industries over the period 1995-2005. It builds on a strand of the literature that has originated and been heavily influenced by Coe and Helpman (1995), who started off a growing body of work assessing the magnitude and transmission channels of such spillovers at various levels – among firms, industries, regions, and countries.

Most of the previous work focuses on spillovers in a geographical dimension only.[1] Relatively few studies consider spillovers in other dimensions than just geographical space. And those studies which do so consider spillovers between firms or industries, but they typically assume these spillovers only happen within countries (see Morrison Paul and Siegel, 1999, or Cohen and Morrison Paul, 2005). Only a few studies consider spillovers across industries as well as countries or regions. Examples for the analysis of cross-country-and-

[1] See, e.g., Lichtenberg and van Pottelsberghe de la Potterie (1998), Aitken and Harrison (1999), Jacobs et al. (2002), Guellec and Van Pottelsberghe de la Potterie (2004), Keller (2004), Ebersberger and Lööf (2005), Hu et al. (2005), Branstetter (2006), Chen and Swenson (2007), Görg et al. (2006), Hale and Long (2006), Blonigen and Ma (2010), Lööf (2007), Keller and Yeaple (2009), Bloom et al. (2013).

sector spillovers are Bernstein and Mohnen (1997) and Keller (2002). Bernstein and Mohnen (1997) estimate spillovers from research and development (henceforth R&D) for selected manufacturing sectors between the US and Japan over the period 1962-1986. Keller (2002) considers knowledge spillovers between manufacturing sectors of eight major OECD countries over the period 1970-1991. A related strand of the literature (e.g., Cameron et al., 2005; Griffith et al., 2004) has established the role of R&D as a determinant not only of innovation rates but also of an industry's absorptive capacity, facilitating technology transfer and catching up to the technology frontier.

There is broad evidence that spillovers are associated with or structurally transmitted through import and export transactions, foreign direct investment, and that they decline with geographical distance also for other reasons (see Keller, 2004).

Earlier work on technology spillovers assumes that spillovers originate from observable factors, mainly R&D, and typically rests on the assumptions of Cobb-Douglas production technologies and of a linear separability of the impact of own and other (countries', regions', industries', or firms') R&D. Yet, there is broad evidence rejecting the assumption of Cobb-Douglas technologies at least at the level of sectors or firms (see, e.g., Christensen, Jorgenson, and Lau, 1973; Berndt and Khaled, 1979). If R&D is not separable from other production factors in a flexible production technology such as translog, not only its own effect but also the nature and magnitude of R&D spillovers will differ from Cobb-Douglas economies: not only will the magnitude of the overall effects likely be different (due to an omitted variables bias of the Cobb-Douglas estimates, if translog applies), but these effects will also vary with the level of the stock of R&D itself and also with the usage levels of other production factors. When ignoring spillovers from unobservable technology shifters and considering spillovers from R&D alone, one would generally underestimate the importance of technological interdependence at large.

Addressing these issues, the present paper goes beyond previous studies and considers not only knowledge spillovers associated with observable R&D but also "remainder" total-factor-productivity spillovers, the latter of which are modeled through a spatial econometric approach. It allows for, distinguishes between, and estimates the relative importance of two different channels of productivity spillovers, namely intra- versus inter-industry spillovers. Spillover effects are modeled as a decreasing function of economic (rather than merely geographical) distance, which we measure by using information on the domestic and international use of intermediate goods between industries. Furthermore, unlike most previous studies on R&D spillovers, we use a flexible translog production function approach, allowing the contributions of ‘own’ and ‘imported’ R&D to be potentially non-separable from other production factors.

As for estimation, we consider a spatial econometric framework suitable for the analysis of cross-sectional interdependence of the units of observation. In particular, we pursue a heteroskedasticity-robust two-step spatial generalized least-squares (GLS) estimation approach, introduced by Kelejian and Prucha (2010) for one mode of spatial interdependence and cross-section data. Since we consider a panel dataset and aim at distinguishing between intra- and inter-industry spillovers, we have to cope with two spillover channels and parameters of interdependence rather than a single one and with cross-sectional units of observation which are repeatedly observed over time. Hence, estimation of the spatial error process relies on Badinger and Egger (2015), which generalizes the first-order cross-sectional generalized method of moments (GMM) estimator by Kelejian and Prucha (2010) to panel data and higher-order spatial processes.

Our empirical results suggest the following conclusions. First, the assumption of Cobb-Douglas technology is clearly rejected by the data so that estimates obtained under that assumption would be biased. Second, there are sizeable knowledge spillover effects on the productivity within an industry, which amplify the output effect of ‘own’ R&D, whereas inter-industry knowledge spillovers are found to be smaller in magnitude. Third, there are significant remainder spillover effects unrelated to R&D but related to unobservable total-factor-productivity shifters. These spillover effects are transmitted through input-output relationships, predominantly among similar industries. As a result, total-factor-productivity shocks are amplified substantially through (primarily intra-industry) spillover effects and the associated repercussions.

The remainder of the paper is organized as follows. Section II lays out the basic empirical model and outlines the spatial econometric approach to modeling and estimating productivity spillovers with two transmission channels. Section III presents the estimation results for our panel of 12 OECD countries and 15 manufacturing industries over the period 1995-2005. Section IV summarizes the main findings and concludes.

II. Model Specification and Econometric Issues

The basic empirical model

For the sake of simplicity, it is useful to start with the outline of a model without R&D. Our point of departure is a translog production function using the physical capital stock (*K*) and labour (L) as primary input factors, which we denote as $\mathscr{F}(\ln K, \ln L)$. We will use indices i, k, and t to refer to countries, industries and time (years), respectively. For a single observation, the assumed production technology reads as follows:

$$\ln y_{ik,t} = \mathscr{F}(\ln K_{ik,t}, \ln L_{ik,t}) + \lambda_t + u_{ik,t} \text{ with } u_{ik,t} = \mu_{ik} + \varepsilon_{ik,t}. \tag{1a}$$

The dependent variable $\ln y_{ik,t}$ denotes (the log of) real value added in country i's industry k at t, λ_t denotes time-specific fixed effects, and $u_{ik,t}$ is a stochastic error term, which consists of a country-industry fixed effect, μ_{ik}, and a time-variant, idiosyncratic error term, $\varepsilon_{ik,t}$, which is independently distributed but allowed to be heteroskedastic. In the estimation, we will also consider a specification including country-year and industry-year fixed effects, $\lambda_{i,t}$ and $\lambda_{k,t}$, instead of common year effects, λ_t.

As is well known, the translog function with two inputs is given by $\mathscr{F}(\ln K_{ik,t}, \ln L_{ik,t}) = \mathbf{z}_{ik,t}\boldsymbol{\gamma}$, where $\mathbf{z}_{ik,t} = [\ln K_{ik,t}, \ln L_{ik,t}, \frac{1}{2}(\ln K_{ik,t})^2, \frac{1}{2}(\ln L_{ik,t})^2, \ln K_{ik,t} \ln L_{ik,t}]$ and $\boldsymbol{\gamma}$ is the corresponding parameter vector. Hence, the model in equation (1a) may be written as

$$\ln y_{ik,t} = \mathbf{z}_{ik,t}\boldsymbol{\gamma} + \lambda_t + u_{ik,t} \text{ with } u_{ik,t} = \mu_{ik} + \varepsilon_{ik,t}. \tag{1b}$$

In order to assess the role of R&D, we will add R&D as an explanatory variable. In particular, we include the (log of the) stock of knowledge capital, denoted by $RD_{ik,t}$, along with the other production factors in the translog form, $\mathscr{F}(\cdot)$. To estimate the role of R&D spillovers, we will use weighted averages of other countries' and industries' knowledge capital stocks, denoted as $\overline{RD}_{ik,t}$ and include them as well in the translog form. [2]

[2] There is a potential problem of double-counting of production factors, because R&D-related capital and labour may be counted as primary production factors and also as R&D expenditures. Moreover, value-added may be too small because R&D is subtracted as an intermediate expense (Schankerman, 1981). Given the lack of data on primary-factor employment in R&D versus the output production processes, this measurement problem cannot be addressed explicitly. However, the total cost share of R&D is only 5% on average (including royalty payments and other expenses), and what is used for estimation are not current expenditures on R&D but the R&D stock. Hence, we argue that in our specification the impact of current-period expenses on the primary-factor usage of R&D and, hence, the double-counting problem is small.

While our approach is closely related to that of Coe and Helpman (1995) and subsequent studies in that vein in general,[3] the following differences should be noted. First, Coe and Helpman (1995) use an index of total factor productivity as the dependent variable, which is calculated from a Cobb-Douglas production function by imposing the output elasticities of capital and labour in a first step. In contrast, our empirical approach builds on the more flexible translog production function, which allows for differences in output elasticities of the production functions across countries and industries, thereby mitigating the risk of an incorrect specification due to unobserved heterogeneity (see Yasar and Morrison Paul, 2007). In our framework, the (own and other countries' and industries') knowledge stock is a production factor that is not (log-)additively separable from capital and labour, unlike in Coe and Helpman (1995). Here, the elasticity of value added with respect to the knowledge stock depends on the inputs of capital and labour.

Second, we use industry rather than aggregate data, which allows us to distinguish between intra-industry spillovers, i.e., spillovers from knowledge stocks in the same industry from other countries ($\overline{RD}_{ik,t}^{\text{intra}}$), and inter-industry spillovers, i.e., spillovers from (domestic and foreign) knowledge stocks in other industries ($\overline{RD}_{ik,t}^{\text{inter}}$).

Hence, the most general specification of the chosen empirical model is given by:

$$\ln y_{ik,t} = \mathcal{F}(\ln K_{ik,t}, \ln L_{ik,t}, \ln RD_{ik,t}, \ln \overline{RD}_{ik,t}^{\text{intra}}, \ln \overline{RD}_{ik,t}^{\text{inter}}) + \lambda_t + u_{ik,t} \ , \tag{2}$$

with $u_{ik,t} = \mu_{ik} + \varepsilon_{ik,t}$ defined as before. The translog form of $\mathcal{F}(\cdot)$ as specified in equation (2) can again be specified by the linear form $\mathbf{z}_{ik,t}\boldsymbol{\gamma}$, which includes the variables as listed in (2), their squares, and interaction terms, making a total of 20 explanatory variables.

Finally, another novel feature of the present paper is that it tests for and estimates spillover effects unrelated to R&D (and other observables) but related to elements of total factor productivity, which are captured by the disturbance term $u_{ik,t}$. We do so by specifying a spatial regressive error process as will be outlined in more detail below.

Specification of spillover effects: a spatial econometric perspective

R&D spillovers

The construction of spillover terms is closely related to a spatial econometric framework. To make this explicit, define *N* as the number of country-industry observations, the $N \times 1$ vector $\mathbf{rd}_t = (RD_{ik,t})$, containing the observations of the knowledge stocks for all country-industry units in year *t*. The spillover term can then be defined as a so-called spatial lag of the variable $\mathbf{rd}_t$, namely $\overline{\mathbf{rd}}_t = \mathbf{Wrd}_t$, with elements $\overline{RD}_{ik,t} = \sum_{jl \neq ik} w_{ik,jl} RD_{jl,t}$. The time-invariant $N \times N$ matrix $\mathbf{W} = (w_{ik,jl})$ is a spatial weights matrix, whose elements measure the 'economic distance' between country *i*'s industry *k* and country *j*'s industry *l*.

To distinguish between intra- and inter-industry spillovers, we decompose $\mathbf{W}$ into two weights matrices, $\mathbf{W}^{\text{intra}} = (w_{ik,jl}^{\text{intra}})$ with nonzero elements for intra-industry relations only, and $\mathbf{W}^{\text{inter}} = (w_{ik,jl}^{\text{inter}})$ with nonzero elements for inter-industry relations only. Using these matrices to construct spatial lags of $\mathbf{rd}_t$, we obtain $\overline{\mathbf{rd}}_t^{\text{intra}} = \mathbf{W}^{\text{intra}}\mathbf{rd}_t$ and $\overline{\mathbf{rd}}_t^{\text{inter}} = \mathbf{W}^{\text{inter}}\mathbf{rd}_t$, which exhibit typical elements $\overline{RD}_{ik,t}^{\text{intra}}$ and $\overline{RD}_{ik,t}^{\text{inter}}$, respectively. We allow the strength of intra- and inter-industry spillovers to be different by estimating separate parameters on $\overline{\mathbf{rd}}_t^{\text{intra}}$ and $\overline{\mathbf{rd}}_t^{\text{inter}}$.

A precise definition of the elements of the weights matrices will be given below. For now, just note that the elements of $\mathbf{W}^{\text{intra}}$ and $\mathbf{W}^{\text{inter}}$ are zero along the main diagonal (to rule out self-influence) and measure the economic distance between cross-sectional units. We now proceed with the specification of the empirical model with special emphasis on spillover effects from unobservable total-factor-productivity shifters.

Remainder Spillovers

Previous studies on productivity spillovers have restricted their attention to knowledge spillovers. We do not expect the variables $\overline{\mathbf{rd}}^{\text{intra}}$ and $\overline{\mathbf{rd}}^{\text{inter}}$ to capture all possible spillover effects, though. First, since they will be constructed from private and business enterprise R&D, these terms do not account for knowledge spillovers related to public research. In addition, there are other types of intra- and inter-industry effects which are not (or only indirectly) related to knowledge transmitted through the use of intermediate goods. Such spillovers could be related to market structure, factor market characteristics, and other economic fundamentals with a potential impact on total factor productivity (Smarzynska Javorcik, 2004). An early discussion of such external economies across industries, including historical examples, is given by Balassa (1961, chapter 7). One example is that output pricereducing innovations in one industry will also increase demand for goods from input-producing industries, allowing firms in those industries to exploit economies of scale.

The productivity effects of such 'remainder' spillovers may be captured by a 'spatial' regressive error process. In the present paper, where we want to distinguish between intra- and inter-industry spillovers, we adopt the specification of a second-order spatial regressive error process, which is given – for year t – by

$$\mathbf{u}_t = \rho^{\text{intra}} \mathbf{W}^{\text{intra}} \mathbf{u}_t + \rho^{\text{inter}} \mathbf{W}^{\text{inter}} \mathbf{u}_t + \boldsymbol{\varepsilon}_t \,. \tag{3}$$

This specification implies that the equilibrium effect of productivity shocks to $\boldsymbol{\varepsilon}_t$ corresponds to $(\mathbf{I} - \rho^{\text{intra}} \mathbf{W}^{\text{intra}} - \rho^{\text{inter}} \mathbf{W}^{\text{inter}})^{-1} \boldsymbol{\varepsilon}_t$; provided that the inverse $(\mathbf{I} - \rho^{\text{intra}} \mathbf{W}^{\text{intra}} - \rho^{\text{inter}} \mathbf{W}^{\text{inter}})^{-1}$ exists, this captures and parameterizes Balassa's (1961, p. 150) key insight in the introductory quote.

In equations (2) and (3), we distinguish between intra- and inter-industry spillover parameters but not between domestic and international spillover parameters. However, we consider differences in the magnitude of domestic and international spillovers due to distance, trade costs, and border effects, through the use of intermediate goods which the weights matrices $\mathbf{W}^{\text{intra}}$ and $\mathbf{W}^{\text{inter}}$ are based upon. By way of contrast, differences between intra-industry and inter-industry spillovers are treated as qualitatively different in nature and are assumed to be associated with possibly different interdependence parameters ρ^{intra} and ρ^{inter}.

Specification of the weights matrix

In most applications, the elements of spatial weights matrices are specified as some decreasing function of geographical distance or of binary adjacency. However, often what would be required is a measure of economic distance. In particular, this is the case with two-dimensional data such as ours, exhibiting both country and industry variation. There, a focus on geographical distance would imply restricting one's interest to spillovers across countries and disregarding spillovers within versus across industries.

Hence, we pursue an alternative approach and use trade in intermediate goods as a measure of the intensity of interactions between countries' industries. This approach is inspired by Balassa's (1961) view of horizontal and vertical linkages between industries as a key source of productivity spillovers and the findings of Smarzynska Javorcik (2004) that input-output related linkages entail an important channel of spillovers at the firm level. In particular an input-output-based measure of interdependence spans both dimensions of our data, namely countries and industries. And since intermediate goods trade is highly correlated with final goods trade and factor flows, our specification of the weights matrices captures not only spillovers embodied in input-output flows, but also ones that relate to other spillover channels which are correlated with input-output linkages (such as trade and factor flows).

We are not the first to use input-output-based data to model interdependence of industries. For instance, Keller (2002) uses input-output data to construct knowledge spillover variables in his investigation of R&D spillovers between manufacturing industries of eight major OECD countries. Moretti (2004) investigates the effects of human capital spillovers on productivity and wages using US plant level data over the period 1982 to 1992 and rank indices based on the value of input-output flows.[4] A related approach by Cohen and Morrison Paul (2004) uses (total) trade between US states for the construction of the weighting matrix in their study of the spillover effects of public infrastructure investments.

We proceed by defining the elements of the (unnormalized) weights matrix $\mathbf{W}^0$ as the share of intermediate goods usage in production:

$$w^0_{ik,jl} = \frac{IO_{ik,jl}}{PROD_{ik}}, \tag{4}$$

where $IO_{ik,jl}$ is country i and industry k's use of intermediate goods from country j's industry l. The denominator in equation (4), $PROD_{ik}$, equals production (gross output) of country i's industry k. Hence, the weights matrix models the magnitude of the interactions between two industries by the intensity of the use of intermediate goods scaled by the respective industry's size. The weights matrices refer to the year 2000, corresponding to our sample midpoint. While data would also be available for the years 1995 and 2005, the assumption of time-invariant weights matrices is justified in light of the fact that input-output relations are fairly time-invariant. The average correlation coefficient of the rows of the weights matrices for 1995 (2005) and 2000 amounts to 0.95 (0.96).

While domestic input-output flows between industries ($IO_{ik,jl}$ for $i = j$) are available from the OECD's input-output database, international input-output flows ($IO_{ik,jl}$ for $i \neq j$)

[4] He allows for industry-specific parameter estimates, to test whether human capital spillovers decrease with an industry's economic 'distance' (captured by smaller levels of input-output flows) from manufacturing.

are only available at a gross basis (specific to $i, k,$ and l, i.e., total imported intermediates by industry for each importer-country *i* and industry-pair *kl*). We construct the missing data on $IO_{ik,jl}$ in (4) by adopting an assumption about the pattern of international trade in intermediate goods, which has been used in previous studies, namely that the pattern of international trade in intermediate goods in a particular industry is similar to that of total trade.[5] (See Appendix A for details.)

In order to distinguish between intra- and inter-industry spillovers, we split the $N \times N$ matrix $\mathbf{W^0} = (w^{0}_{ik,jl})$ into two $N \times N$ matrices $\mathbf{W}^{\text{intra},\mathbf{0}}$ and $\mathbf{W}^{\text{inter},\mathbf{0}}$, where $\mathbf{W^0_{intra}} + \mathbf{W^0_{inter}} = \mathbf{W^0}$. The elements of $\mathbf{W}^{\mathbf{intra},\mathbf{0}} = (w^{\text{intra},\mathbf{0}}_{ik,jl})$ have non-zero entries for $k = l$ and are 0 otherwise, capturing the decay of intra-industry interdependence in input-output space. The elements of $\mathbf{W}^{\text{inter},\mathbf{0}} = (w^{\text{inter},\mathbf{0}}_{ik,jl})$ are non-zero for $k \neq l$ and 0 otherwise, reflecting the decay of inter-industry interdependence in input-output space. The diagonal elements of $\mathbf{W}^{\text{intra},\mathbf{0}}$ and $\mathbf{W}^{\text{inter},\mathbf{0}}$ are zero by definition to rule out self-influence.

In order to ensure well-behaved asymptotics of the estimator it is necessary to use a normalization of the interdependence matrices (together with corresponding restrictions on the admissible parameter space).[6] Unlike most spatial econometric studies, which use row-normalized weights matrices, where each element of the un-normalized matrix is divided by the respective row sum, we use maximum normalization, where each element of the weights matrix is divided by the maximum row sum (or the maximum column sum, whichever is smaller). The advantage of this scalar normalization is that there is a single re-scaling factor for the autoregressive parameter leading to a specification that is equivalent to that corresponding to the un-normalized weights matrix (Kelejian and Prucha, 2010). In other words, unlike row normalization, this approach does not destroy the notion of absolute (e.g., economic) distance. A further advantage in the present application, which uses a second order spatial regressive process, is that it is irrelevant whether the two weights matrices are normalized individually or jointly (using the row sums of their sum). The final maximum

[5] A similar approach is used by Feenstra and Hanson (1999), who combine data on imports of final goods with data on total input purchases, to obtain a breakdown of imported intermediate inputs by industry for US data. Bergstrand and Egger (2010) provide evidence that at least aggregate trade among the OECD countries in intermediate goods behaves in a way remarkably similar to final goods trade.

[6] Strictly speaking, this applies only to the spatial regressive error process.

normalized weights matrices, which are obtained by dividing the unnormalized weights matrices $\mathbf{W}^{\text{intra},0}$, $\mathbf{W}^{\text{inter},0}$, and $\mathbf{W}^{0}=\mathbf{W}^{\text{intra},0}+\mathbf{W}^{\text{inter},0}$, by their respective maximum row (or column) sum, are referred to as $\mathbf{W}^{\text{intra}}$, $\mathbf{W}^{\text{inter}}$, and $\mathbf{W}$.

We emphasize that the distinction drawn between intra- and inter-industry spillovers depends on the level of disaggregation. In the present paper, the choice of 15 fairly highly aggregated 2-digit manufacturing industries (see Appendix A) is dictated by the high level of industry aggregation in internationally comparable input-output matrices. These 15 industries are clearly heterogeneous enough to regard any cross-industrial relationship to be of the 'inter-industry' type. However, one could argue that each of these 2-digit industries consists of sub-sectors that are distinct enough from each other to regard their relationships as 'inter-industrial' among similar industries. Hence, the estimated intra-industry spillovers capture both 'true' intra-industry spillovers as well as inter-industry spillovers among fairly similar industries.

Econometric issues

There are two main approaches to estimate spatial regressive models: maximum likelihood estimation (see Anselin, 1988; Lee, 2004) and GMM estimation (Kelejian and Prucha, 1999, 2008; Lee and Liu, 2006). A drawback of the maximum likelihood approach is that it is computationally cumbersome (particularly for large weights matrices), and it relies on relatively strong distributional assumptions of which one is that the error term $\boldsymbol{\varepsilon}$ is homoskedastic. Since heteroskedasticity is of concern in our data, we choose the GMM estimation framework, which is robust to heteroskedasticity in the idiosyncratic error term $\boldsymbol{\varepsilon}_t$ in equation (3), while allowing identification of the parameters ρ^{intra} and ρ^{inter}, which are of key interest in the present study.

The GMM estimation procedure for spatial models was introduced in a cross-sectional framework under homoskedasticity with a single spatial weights matrix or channel of interdependence by Kelejian and Prucha (1999). They suggest using a three-step estimation procedure. First, the main equation is estimated (ignoring spatial dependence in the error term) to obtain consistent estimates of the disturbances. Second, a GMM approach is used to estimate the spatial regressive parameter of the disturbance process (and the variance-covariance matrix of $\mathbf{u}$). Third, the main equation is re-estimated by feasible GLS. In an extension, Kelejian and Prucha (2010) also derive the joint asymptotic distribution of all model parameters (including the spatial regressive parameters) under general heteroskedasticity of $\boldsymbol{\varepsilon}$.

An alternative approach would be to use a spatial HAC approach for the error term **u** in equation (3), e.g., through a panel version of the estimator proposed in Kelejian and Prucha (2007). However, such an approach would not allow insights into the strength and channel of interdependence in **u**, i.e., the parameters ρ^{intra} and ρ^{inter}, which are of inherent interest to our study, since they capture effects of unobserved total-factor-productivity shifters. In a spatial HAC estimation framework, one is not interested in the spatial regressive parameters at all, but only in making standard errors on the coefficients of observable variables of interest and test statistics robust to spatial correlation in the disturbances. Hence, we have to rely on a framework, where the channel and strength of interdependence in those shifters can be identified.[7]

The estimation framework required in the present paper is more general than that of Kelejian and Prucha (2010) in two respects. First, we consider a fixed-effects panel-data model rather than a cross-sectional model. Second, we consider two channels of interdependence, which requires the specification of a second-order spatial regressive disturbance process. Hence, we rely on Badinger and Egger (2015), who generalize the cross-sectional, first-order, heteroskedasticity-robust estimator by Kelejian and Prucha (2010) to a random- and fixed-effects heteroskedasticity-robust panel data estimator for models with a higher-order spatial regressive disturbance process. To our knowledge, this is the only estimator available for fixed-effects models with higher-order spatial dependence and heteroskedasticity in $\boldsymbol{\varepsilon}$. It builds on the moment conditions introduced by Kapoor, Kelejian, and Prucha (2007), who consider estimation of first-order random-effects panel data models under homoskedasticity. Mutl and Pfaffermayer (2011) extend this estimator to cover fixed-effects estimation, sticking with the first-order framework and the assumption of homoskedasticity, however. The paper by Badinger and Egger (2015) goes beyond that of Mutl and Pfaffermayer (2011) by allowing for heteroskedasticity in $\boldsymbol{\varepsilon}$, deriving the distribution of the estimates of the spatial regressive parameters, and allowing fixed or random effects in the spatial regressive process.

[7] Another approach to estimating spillovers put forward by Eberhardt et al. (2013) allows for common time-specific shocks that have different effects across (country-industry specific) units. Relative to this approach, the present paper includes a full set of country-year, industry-year as well as country-industry fixed effects, which leads to a very high explanatory power so that there is virtually no room for unobservable factors to bias the model results to a large extent.

III. Estimation Results

Data and sample

In the following, we report estimates of alternative specifications of our empirical models derived in Section II. The cross-section dimension comprises $i = 1,\ldots,12$ OECD countries and $k = 1,\ldots,15$ ISIC-2-digit manufacturing industries, i.e., $N = 180$ cross-sectional observations, and the time period ranges from $t = 1995 - 2005$, such that we have a total of 1,980 observations. Real value added is measured in prices of the year 2000, and labour input in terms of total employment. Both variables are taken from the OECD STAN database. Capital and knowledge stocks are calculated from gross fixed capital formation and private and business enterprise R&D expenditures, respectively. The data on the former are from the OECD's STAN database and the data on the latter are from the OECD's ANBERD database. We use the perpetual inventory method to construct stocks from gross investment data. The weights matrices are based on input-output data, which are from the OECD's Input Output Database. For approximation of international input-output flows, we use the STAN bilateral trade database. A more detailed description of the sample and data is provided in Appendix A.

R&D spillovers, fixed effects estimation

Table 1 summarizes estimates of alternative specifications of our empirical model, including country-industry fixed effects and year dummies. We first consider the results for the main equation only. Since our empirical model contains up to 20 explanatory variables we only report the elasticities implied by the respective model (evaluated at sample means) and the corresponding standard errors, which are calculated using the delta method.

The baseline specifications of the panel data models in columns (1a)-(6a) of Table 1 with 1,980 observations (180 cross-sections -- 12 countries, 15 industries -- and 11 years) each include 180 (time-invariant) country-industry fixed effects, along with common year effects which are invariant in the cross section. One could argue that industries within a given country are all correlated with the national business cycle to some degree; moreover, a given industry could also be driven by similar shocks across countries, e.g., in the wake of technological progress or demand shifts. Hence, we also consider, for each model, a specification including country-year and industry-year fixed effects (i.e., interactions of the time dummies with country and industry dummies, respectively). The corresponding results of this demanding specification, which adds 250 variables to the 180 country-industry fixed-effects model, are reported in columns (1b)-(6b) of Table 1.

We start with the most parsimonious translog specification based on capital and labour variables only in column (1a). Evaluated at the sample mean, the implied average marginal effects are 0.537 with respect to the capital stock and 0.556 with respect to labour. We emphasize that the squares and interaction terms of capital and labour are jointly significant at 1% in column (1), indicating misspecification of the Cobb-Douglas model. Results for the specification in column (1b), which includes country-year and industry-year effects, are very similar.

< TABLE 1 >

To check the plausibility of the translog estimates we also consider the monotonicity properties by looking at the elasticities across observations. Reassuringly, only two out of 1,980 output elasticities with respect to capital are negative in column (1a); the elasticities with respect to labour are all greater than zero. The result that only a negligible share of the implied elasticities is negative also holds for all specifications considered in what follows (see Table 1, lower panel).

In a next step, we include the (log of the) own knowledge stock, assuming that it is additively separable (in logs) from capital and labour in columns (2a) and (2b) and the more general translog specification where knowledge is not separable from capital and labour and interacted with capital and labour as well as squared in columns (3a) and (3b). The assumption of additive separability of the knowledge stock is clearly rejected by the data (a result that holds true in all specifications considered): the squared knowledge stock and its interactions with capital and labour are jointly significant at 1%. The marginal effect of the knowledge stock on output as implied by the translog specification in column (3) amounts to 0.262. Hence, the (misspecified) model assuming additive separability of the technology in the knowledge stock in column (2) underestimates the effect of R&D with an elasticity of 0.175.[8] Comparing columns (2b) and (3b), the same conclusion holds for the models including country-year and industry-year effects, though the implied elasticity is found to be slightly smaller (0.229).

An implied elasticity to the 'own' knowledge stock of 0.229 to 0.262 is in the upper range of values found in previous (country) studies. For instance, Coe and Helpman (1995)

[8] Regarding the monotonicity properties of the translog function, all output elasticities with respect to capital and labour are greater than zero; the share of negative elasticities with respect to RD amounts to 6.1%.

estimate an elasticity of total factor productivity with respect to the domestic R&D stock ranging from 0.08 to 0.23. Coe, Helpman, and Hoffmeister (2009) obtain estimates of a similar magnitude. Guellec and van Pottelsberghe de la Potterie (2004), using panel data of 15 countries over the period 1980-1998 and assuming a constant-returns-to-scale (CRS) Cobb-Douglas production technology, obtain an elasticity of 0.13, which is close to our estimates when assuming that R&D is additively separable. In a recent study in the tradition of Coe and Helpman (1995), Madsen (2007) finds an elasticity of 0.07 for 16 OECD countries and the post-1950 period.

In a next step, we include the R&D spillover terms $\ln \overline{RD}^{\text{intra}}$ and $\ln \overline{RD}^{\text{inter}}$. Since the specification assuming additive separability is clearly rejected at the 1% level, both with or without country-year and industry-year effects, columns (4a) and (4b) report the estimates of the general translog specification.

In the baseline specification (4a), both spillover terms turn out statistically significant at 1% and the elasticity with respect to the own knowledge stock is hardly affected compared to column (3a). The results in column (4a) suggest that a uniform 1% increase in the knowledge stock of all observations leads to an increase in output of 0.530%, 0.240% of which is due to own R&D, 0.155% of which is due to intra-industry spillovers, and 0.135% of which is due to inter-industry spillovers. In other words, knowledge stocks are globally roughly twice as important due to spillover effects as in an isolated world without spillovers. This is broadly consistent with Keller (2002), who finds that an industry's own R&D and spillovers from other industries account for some half of the total effect. Guellec and Van Pottelsberghe de la Potterie (2004) find an elasticity with respect to foreign R&D of 0.45.

Adding country-year and industry-year effects in columns (4b) has no implications for the results regarding own R&D, whose implied elasticity is 0.222. Intra-industry R&D spillovers remain significant at 5% with a smaller elasticity of 0.085, whereas the inter-industry R&D spillover term in the main equation becomes insignificant.

Notice, however, that the additional country-year and industry-year fixed effects likely capture not only demand-side and business-cycle effects but also spillover effects to some extent. In that case, controlling for these effects could lead to a downward bias in the estimated magnitude of total spillovers. On the other hand, omitting some country-time-specific or industry-time-specific effects might lead to overestimating the role of spillovers. The change in the coefficients is supportive of this interpretation and would suggest the estimated R&D-related spillover effects in columns (4a) and (4b) could be seen as upper and lower bounds, respectively. A more conservative interpretation would be that R&D spillovers related to the weights matrices used in equations (2) and (3) mainly take place between similar industries and that the elasticity assumes a relatively small value below 0.1.

As one important robustness check related to R&D spillovers, columns (5a) and (5b) report the results for a specification where the R&D stocks are calculated under the assumption of a depreciation rate of 12% as in Hall and Mairesse (1995), rather than with 5% as in the baseline specifications. Reassuringly, the parameter estimates are very close to those in the baseline specification such that the qualitative results are not affected by this variation.

Regarding the scale properties of the estimated production function, we find that there are decreasing returns to scale with respect to capital and labour when holding R&D constant, and there are constant returns to scale (CRS) with respect to capital, labour, and knowledge together.

Productivity spillovers unrelated to R&D and spatial GLS estimates

We next consider estimates of the spatial regressive error process given in (3), capturing remainder spillover terms, and the spatial GLS estimates of the main equation. The reported standard errors are robust to heteroskedasticity in $\boldsymbol{\varepsilon}$, after spatial GLS transformation.

Column (1a) in Table 2 reports the GLS estimates corresponding to the preferred model in column (5) of Table 1 along with the estimates of the parameters of the spatial regressive error process. Both spatial regressive parameters turn out to be significant at 1%. We may check the stability of the spillover process by considering a global unitary shock in $\boldsymbol{\varepsilon}_t$, which implies a multiplier effect amounting to $(\mathbf{I}-\rho^{\text{intra}}\mathbf{W}^{\text{intra}}-\rho^{\text{inter}}\mathbf{W}^{\text{inter}})^{-1}\boldsymbol{\iota}_t$, where $\boldsymbol{\iota}_t$ is a vector of ones of size $N\times 1$. Stability of the model requires existence of $(\mathbf{I}-\rho^{\text{intra}}\mathbf{W}^{\text{intra}}-\rho^{\text{inter}}\mathbf{W}^{\text{inter}})^{-1}\boldsymbol{\iota}_t$ so that the response in outcome to a unitary shock in $\boldsymbol{\varepsilon}_t$ is finite. We may refer to the average value of $(\mathbf{I}-\rho^{\text{intra}}\mathbf{W}^{\text{intra}}-\rho^{\text{inter}}\mathbf{W}^{\text{inter}})^{-1}\boldsymbol{\iota}_t$ as the multiplier effect which amplifies shocks in idiosyncratic unobserved total-factor-productivity shifters due to cross-country and cross-industry spillovers. The estimates in column (1a) point to a sizeable multiplier effect of 3.4, suggesting that only part of the interdependence across countries and industries is due to R&D spillovers.

< TABLE 2 >

Comparing the magnitude of the spatial regressive coefficients for intra-industry and inter-industry spillovers, the estimates point to a dominant role of remainder intra-industry spillovers. Notice that the coefficients alone are not comparable, since what matters for the average spillover effect of a given shock is the coefficient times the respective entry in the spatial weights matrix. Hence, to make the estimated effects comparable, we need to rescale the coefficients. We do so by multiplying them by the average row sum of the respective weights matrices which corresponds to rescaling them such that the average row sum of each weights matrix is equal to one. After this adjustment, the ratio of the intra- to inter-spillover coefficients is equal to around three in most specifications. Regarding the feasible spatial GLS estimates in the main equation, the magnitude of the elasticity with respect to an increase in 'own' R&D is essentially unchanged and amounts to 0.263. The estimated spillover effects are slightly larger than in the unweighted expression, with a larger share attributed to intra-industry spillovers (0.233 of 0.377).

When country-year and industry-year effects are included in column (1b), the results hold up to a large extent under this specification. As in the unweighted regressions, the magnitude of spillover effects becomes smaller; the inter-industry R&D spillover term in the main equation becomes insignificant, whereas intra-industry R&D spillovers remain significant but turn out to be smaller than before with a coefficient of 0.14 compared to 0.23 in column (1a). The results regarding spillovers modeled through the spatial regressive error process are qualitatively unchanged: intra- and inter-industry spillovers both turn out to be statistically significant at 1%, where intra-industry spillovers are quantitatively larger with a spatial regressive coefficient of 1.88 (versus 0.54 for inter-industry spillovers). The total multiplier effect is reduced from 3.4 to 2.6.

The hypothesis of constant returns to scale is rejected when country-year and industry-year effects are included and the sum of the elasticities suggests decreasing returns to scale.

Overall, the results point to sizeable effects of own R&D as well as R&D spillovers, with a predominant role of intra-industry spillovers. Moreover, the findings indicate that there are sizable remainder intra- and inter-industry spillovers to total factor productivity which are unrelated to R&D.

Sensitivity analysis

We examine the sensitivity of the results with respect to alternative specifications. Columns (2a) and (2b) report the results when a depreciation rate of 12% for R&D stocks is assumed.

As in the unweighted regression the results turn out to be insensitive against variations in the depreciation rate to calculate knowledge stocks.

Columns (3a) and (3b) in Table 2 use weights matrices which are based on use plus delivery rather than use of intermediates only.[9] The spatial GLS estimates of the main equation are essentially unchanged. The remainder spillover effects turn out to be significantly larger, however; the spillover multiplier – i.e., the average value of $(\mathbf{I}-\rho^{\text{intra}}\mathbf{W}^{\text{intra}}-\rho^{\text{inter}}\mathbf{W}^{\text{inter}})^{-1}\boldsymbol{\iota}_t$ – is roughly doubled to 8.5 in comparison to a model that only uses a weights matrix based on the use of inputs. While these results should not be overstressed, this points to the relevance of delivery-related spillovers, which could be investigated in future research.

Finally, columns (4a) and (4b) show the results when using predicted weights matrices, whose elements are generated as predicted values from a 'geographical gravity model' to avoid endogeneity concerns (see Appendix B for a detailed description of the construction of the predicted weights matrices). The results suggest that this approach introduces measurement error, causing an attenuation bias in the main equation that reduces the estimated R&D spillover effects and renders inter-industry spillovers insignificant in both specifications. The reason is that the 'geographical gravity model' does not perform well in explaining the industry dimension of the input-output relations. Estimates of the error process become less precise when comparing column (6) to column (4), but they remain significant at the 1% level. Part of the knowledge spillovers appear now to be captured by the error process, where the spillover multiplier increases substantially to 10.6.

We admit that endogeneity of conditional factor demand is a concern in some empirical productivity studies (see Thursten and Libby, 2002). However, instrumental-variable procedures using outside instruments typically use much more parsimonious models than we do. Olley and Pakes (1996) as well as Doraszelski and Jaumandreu (2013) are examples of such studies, estimating productivity at the firm level. While Olley and Pakes (1996) adopt a nonparametric estimation strategy and rely on a firm's dynamic programming problem to back out productivity, Doraszelski and Jaumandreu (2013) pursue a parametric estimation strategy, assuming that information about current productivity is contained in static inputs and relying on parameter restrictions between the production function and the input demand equations. Both Olley and Pakes (1996) and Doraszelski and Jaumandreu (2013) assume Cobb-Douglas technologies which are (log-)linearly separable into the contributions

[9] Delivery matrices are generated as transposes of the use matrices.

of production factors and total-factor productivity. Accordingly, functional misspecification may be a concern in these studies.

To some extent, such concerns are avoided with a more flexible technology such as a translog or a generalized Leontief production function. Yet, then the number of potentially endogenous variables (up to 20 in our empirical models) is too large to proceed as in some of the studies proposing instrumentation. Moreover, our reading of the results is that endogeneity does not appear to be pronounced in previous work (e.g., Olley and Pakes-type estimates are often very close to Cobb-Douglas results which assume exogeneity of conditional factor demand). With the translog specification in this paper, the least-squares (LS) and feasible GLS estimates are fairly close, which is unlikely to be the case under pronounced endogeneity (see Wooldridge, 2006, p. 286, for an argument along those lines). Moreover, when judged against the results of previous studies on R&D spillovers using other econometric techniques, the elasticity estimates in the present paper lie in a plausible range. Finally, while the elasticity point estimates should not be overstressed, there is no reason to assume that endogeneity systematically biases the estimates of the *relative* role of intra- and inter-industry spillovers.

IV. Conclusions

This paper considers the productivity effects of knowledge and "remainder" spillovers, using a panel of 12 OECD countries and 15 manufacturing industries. It allows for spillovers to cross both national and industrial boundaries and pays specific attention to the relative magnitude of intra- versus inter-industry spillovers that are transmitted through input-output relations. We allow such spillovers to be either related to R&D intensities or other, not further specified sources (such as total factor productivity or product-market characteristics), the latter of which are modeled using a spatial econometric approach.

Focusing on input-output relations and vertically-driven linkages, we hypothesize that spillovers between countries and industries decline with economic (rather than merely geographical) distance, which we measure by using information on the domestic and international use of intermediate goods between industries.

The results suggest that own R&D enhances productivity with an elasticity of some 0.26. One important result is that the impact of R&D on value added turns out to be non-separable from the other factors of production. Mistakenly assuming it to be linearly separable leads to underestimating the effect of own R&D on output. Furthermore, our results point to sizeable knowledge-spillover effects on productivity, which mainly take place within or among similar industries and turn out to be of the same importance as a country and industry's own R&D. In particular, a uniform increase in all countries' R&D stocks by 1% increases each country's productivity by 0.53%, approximately half of which is due to the direct effect of 'own' R&D, the other half caused by spillover effects from other countries.

Finally, there is also evidence for both statistically and economically significant remainder spillovers, which are unrelated to R&D, capital, and labour. The multiplier effect implied by our estimates suggests that a uniform productivity shock of 1% to all countries and industries increases each country's productivity by 4% in the long run. That amplification is predominantly due to intra-industry spillovers and the associated repercussions as transmitted though trade in intermediates (and final goods trade and FDI to the extent that they are correlated with intermediate goods trade) within the same or among similar industries. The larger role of intra-industry spillovers suggests that it is not mere geography but interactions within and among similar industries that predominantly account for the diffusion of technological progress.

References

Abreu, M., De Groot, H. L. F., and Florax, J. G. M. (2005). 'Space and growth: a survey of the empirical evidence and methods', *Région et Développement*, Vol. 21, pp. 13-44.

Aitken, B. and Harrison, A. (1999). 'Do domestic firms benefit from foreign direct investment? Evidence from Venezuela', *American Economic Review*, Vol. 89, pp. 605-618.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer, Dordrecht.

Badinger, H. and Egger, P. H. (2015). 'Fixed effects and random effects estimation of higher-order spatial autoregressive models with spatial autoregressive and heteroskedastic disturbances', *Spatial Economic Analysis*, Vol. 10, pp. 11-35.

Balassa, B. (1961). *The Theory of Economic Integration*. London: Allen & Unwin.

Bergstrand, J. H. and Egger, P. H. (2010). 'A general equilibrium theory for estimating gravity equations of bilateral FDI, final goods, and intermediate goods trade flows', in Brakman, S. and Bergijk, P. (eds), *The Gravity Model in International Trade: Advances and Applications*, Cambridge University Press, Cambridge, MA, pp. 29-70.

Bernstein, J. I. and Mohnen, P. (1998). ‘International R&D spillovers between U.S. and Japanese R&D intensive sectors’, *Journal of International Economics*, Vol. 44, pp. 315-338.

Berndt, E. R. and Khaled, M. S. (1979). ‘Parametric productivity measurement and choice among flexible functional forms’, *Journal of Political Economy*, Vol. 87, pp. 1220-1245.

Blonigen, B. A. and Ma, A. C. (2010). ‘Please pass the catch-up: the relative performance of Chinese and foreign firms in Chinese exports’, in: Feenstra, R. and Wei, S.J. (eds.). *China's Growing Role in World Trade*, 475-509, National Bureau of Economic Research.

Bloom, N., Schankerman, M., and van Reenen, J. (2013). ‘Identifying technological spillovers and product market rivalry’, *Econometrica*, Vol. 81, pp. 1347-1393.

Branstetter, L. (2006). ‘Is FDI a channel of knowledge spillovers? Evidence from Japanese FDI in the United States’, *Journal of International Economics*, Vol. 13, pp. 53-79.

Cameron, G., Proudman, J., and Redding, S. (2005). ‘Technological convergence, R&D, trade and productivity growth’, *European Economic Review*, Vol. 49, pp. 775-807.

Chen, H. and Swenson, D. L. (2007). ‘Multinational firms and new Chinese export transactions’, *Canadian Journal of Economics*, Vol. 41, pp. 596-618.

Christensen, L. R., Jorgenson, D. W., and Lau, L. J. (1973). ‘Transcendental logarithmic production frontiers’, *Review of Economics and Statistics*, Vol. 55, pp. 28-45.

Coe, D. T. and Helpman, E. (1995). ‘International R&D spillovers’, *European Economic Review*, Vol. 39, pp. 859-87.

Coe, D. T., Helpman, E., and Hoffmaister, A. W. (2009). ‘International R&D spillovers and institutions’, *European Economic Review*, Vol. 53, pp. 723-741.

Cohen, J. P. and Morrison Paul, C. J. (2004). ‘Public infrastructure investment, interstate spatial spillovers, and manufacturing costs’, *Review of Economics and Statistics*, Vol. 86, pp. 551-560.

Cohen, J. P. and Morrison Paul, C. J. (2005). ‘Agglomeration economies and industry location decisions: the impacts of spatial and industrial spillovers’, *Regional Science and Urban Economics*, Vol. 35, pp. 215-237.

Doraszelski, U. and Jaumandreu, J. (2013). ‘R&D and Productivity: Estimating endogenous productivity’, *Review of Economic Studies*, Vol. 80, pp. 1338-1383.

Eberhardt, M., Helmers, C., and Strauss, H. (2013). ‘Do spillovers matter when estimating private returns to R&D?’, *Review of Economics and Statistics,* Vol. 95, pp. 436-448.

Ebersberger, B. and Lööf, H. (2005). ‘Multinational enterprises, spillovers, innovation and productivity’, *International Journal of Management Research,* Vol. 4, pp. 7-37.

Feenstra, R. C. and Hanson, G. H. (1999). ‘The impact of outsourcing and high technology capital on wages: estimates for the United States, 1979-1990’, *Quarterly Journal of Economics,* Vol. 114, pp. 907-940.

Frankel, J. A. and Romer, D. (1999). ‘Does trade cause growth?’, *American Economic Review*, Vol. 89, pp. 279-399.

Görg, H., Hijzen, A., and Murakozy, B. (2006). ‘The productivity spillover potential of foreign-owned firms: Firm-level evidence for Hungary’, *GEP Research Paper,* No. 2006/08, University of Nottingham.

Griffith, R., Redding, S., and Van Reenen, J. (2004). ‘Mapping the two faces of R&D: Productivity growth in a panel of OECD industries’, *Review of Economics and Statistics*, Vol. 86, pp. 883-895.

Guellec, D. and Van Pottelsberghe de la Potterie, B. (2004). ‘From R&D to productivity growth: do the institutional settings and the source of funds of R&D matter?’, *Oxford Bulletin of Economics and Statistics,* Vol. 66, pp. 353-378.

Hale, G. and Long, C. (2006). ‘What determines technological spillovers of foreign direct investment: evidence from China’, *Federal Reserve Bank of San Francisco Working Paper,* No. 2006-13.

Hall, B. and Mairesse, J. (1995). ‘Exploring the relationship between R&D and productivity in French manufacturing firms’, *Journal of Econometrics,* Vol. 65, pp. 263-293.

Hu, A. G. Z., Jefferson, G. H., and Jinchang, Q. (2005). ‘R&D and technology transfer: firm-level evidence from Chinese industry,’ *Review of Economics and Statistics*, Vol. 87, pp. 780-786.

Jacobs, B., Nahuis, R., and Tang, P. J. G. (2002). ‘Sectoral productivity growth and R&D spillovers in the Netherlands’, *De Economist*, Vol. 150, pp. 181-210.

Kapoor, M., Kelejian, H. H., and Prucha, I. R. (2007). ‘Panel data models with spatially correlated error components’, *Journal of Econometrics*, Vol. 140, pp. 97-130.

Kelejian, H. H. and Prucha, I. R. (1999). 'A generalized moments estimator for the autoregresssive parameter in a spatial model', *International Economic Review*, Vol. 40, pp. 509-533.

Kelejian, H. H. and Prucha, I. R. (2007). 'HAC estimation in a spatial framework', *Journal of Econometrics*, Vol. 140, pp. 131-154.

Kelejian, H. H. and Prucha, I. R. (2010). 'Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances', *Journal of Econometrics* Vol. 157, 53-67.

Keller, W. (2002). 'Trade and the transmission of technology', *Journal of Economic Growth*, Vol. 7, pp. 5-24.

Keller, W. (2004). 'International technology diffusion', *Journal of Economic Literature*, Vol. XLII, pp. 752-782.

Keller, W. and Yeaple, S. R. (2009). 'Multinational enterprises, international trade and productivity growth: firm level evidence from the United States', *Review of Economics and Statistics*, Vol. 91, pp. 821-831.

Lee, L. F. (2004). 'Asymptotic distribution of maximum likelihood estimators for spatial autoregressive models', *Econometrica*, Vol. 72, pp. 1899-1925.

Lee, L. F. and Liu, X. (2009). 'Efficient GMM estimation of high order spatial autoregressive models', *Econometric Theory*, Vol. 126, pp. 187-230.

Lichtenberg, F. R. and Van Pottelsberghe de la Potterie, B. (1998). 'International R&D spillovers: A comment', *European Economic Review*, Vol. 42, pp. 1483-1491.

Mankiw G., Romer, D., and Weil, D. (1992). 'A contribution to the empirics of economic growth', *Quarterly Journal of Economics*, Vol. 107, pp. 407-437.

Mayer, T. and Zignago, S. (2006). Notes on CEPII's distances measures. CEPII, Paris.

Moretti, E. (2004). 'Workers' education, spillovers and productivity: evidence from plant level production functions', *American Economic Review*, Vol. 94, pp. 656-690.

Morrison Paul, C. J., and Siegel, D. (1999). 'Scale economies and industry agglomeration externalities: A dynamic cost function approach', *American Economic Review*, Vol. 89, pp. 272-290.

Mutl, J. and Pfaffermayr, M. (2011). ‘The spatial random effects and the spatial fixed effects model: the Hausman test in a Cliff and Ord panel model’, *Econometrics Journal*, Vol. 14, pp. 48-76.

Olley, G. S. and Pakes, A. (1996). ‘The dynamics of productivity in the telecommunication equipment industry’, *Econometrica*, Vol. 64, pp. 1263-1297.

Schankerman, M. (1981). ‘The effects of double-counting and expensing on the measured returns to R&D’, *Review of Economics and Statistics*, Vol. 63, pp. 454-459.

Smarzynska Javorcik, B. (2004). ‘Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages’, *American Economic Review*, Vol. 94, pp. 605-627.

Thursten, N. K. and Libby, A. M. (2002). ‘A production function for physicians services revisited,’ *Review of Economics and Statistics*, Vol. 84, pp. 184-191.

Wooldridge, J. M. (2006). *Introductory Econometrics*, 3rd edition, South-Western, Mason, Ohio.

Yasar, M. and Morrison Paul, C.J. (2007). ‘International linkages and productivity at the plant: foreign direct investment, exports, imports and licensing’, *Journal of International Economics*, Vol. 71, pp. 373-388.

Appendix A. Data and Sample

Data sources

Our sample comprises a balanced panel with 180 cross-sectional observations, consisting of 12 countries (BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, ITA, NLD, NOR, SWE, USA) and 15 industries (see below), over the period 1995-2005, yielding a total of 1,980 observations. 95 observations on investment and R&D expenditures were missing for some countries and industries and were imputed from higher levels of aggregation. Data on real value added, gross fixed capital formation, and employment (persons engaged) at the industry level are taken from the OECD’s Structural Analysis (STAN) database. Data on R&D expenditures are from the OECD’s Analytical Business Enterprise Research and Development (ANBERD) database. Real values are based on industry-level value added deflators in terms of prices of the year 2000. Stocks of physical and knowledge capital are calculated using the perpetual inventory method, assuming a depreciation rate of 5%; for the depreciation used to construct knowledge stocks an alternative rate of 12% is considered. The initial capital stock in 1995 was calculated as investment in 1995 divided by the average annual growth of investment between 1995 and 2005 plus the depreciation rate (see Coe and Helpman, 1995). Input-output data to construct the weights matrices are based on the OECD's input-output database. The shares of bilateral imports in total imports at the industry level are calculated from the OECD's STAN bilateral trade database. Data on distances between countries and internal distance within countries as used for the 'geographical gravity model' on input-output use are from the Centre d'Etudes Prospectives et d'Informations Internationales' (CEPII) geographical database (http://www.cepii.fr/).

List of industries and summary statistics

< TABLE A1 >

Appendix B. Construction of Predicted Weights Matrices

The construction of the predicted weights matrices proceeds as follows. In a first step, the following 'geographical gravity model' is estimated:

$$\ln w^0_{ik,jl} = \kappa_{i,j} + \eta_{k,l} + \gamma_{k,l} \ln DIST_{i,j} + \omega_{ik,jl} \,,$$

where $w^0_{ik,jl}$ is the use of intermediates (as share of production) as defined in equation (5), $\kappa_{i,j}$ is a set of country-pair dummies (*i*,*j* = 1, …, 12) and $\eta_{k,l}$ is a set of industry-pair dummies (*k*,*l* = 1, …, 15). $DIST_{i,j}$ denotes average distance between countries *i* and *j* (or, for *j* = *i*, internal distance defined as $DIST_{i,i} = 0.67\sqrt{AREA_i / \pi}$); its parameter is allowed to vary across industry-pairs. The data source for distance $DIST_{i,j}$ is the CEPII database. There are 31,968 non-zero observations (of potentially 180×180 = 32400) and 592 parameters. Results indicate that the model performs reasonably well in predicting input-output flows. With an R^2 of 0.801 the model explains a substantial part of the variation in use intensity across countries and industries. However, notice that the choice of $DIST_{i,j}$ as the only continuous regressor leads to a prediction which works better at the country level than at the industry level.

The estimates are then used to generate the elements of the predicted (unnormalized) weights matrix $\hat{\mathbf{W}}^0$ as follows:

$$\hat{w}^0_{ik,jl} = \exp(\hat{\kappa}_{i,j} + \hat{\eta}_{k,l} + \hat{\gamma}_{k,l} \ln DIST_{i,j}) \,. \qquad \text{(A.14)}$$

The conditional expectation of $w^0_{ik,jl}$ is equal to $\exp(\hat{\kappa}_{i,j} + \hat{\eta}_{k,l} + \hat{\gamma}_{k,l} \ln DIST_{i,j})$ times $E[\exp(\omega_{ik,jl})]$. Under normality $E[\exp(\omega_{ik,jl})] = \exp[(\sigma^2_{ik,jl}/2)]$, where $\sigma^2_{ik,jl}$ is the variance of $\omega_{ik,jl}$ (see Frankel and Romer, 1999, p. 384). If $\omega_{ik,jl}$ is assumed to be homoskedastic, this correction factor is the same for all observations and can be dropped without consequences for the results regarding the normalized weights matrix.

For observations with zero entry, the predictions are set to zero as well. This corresponds to the notion of a two-part model for estimation of input-output use. The matrix $\hat{\mathbf{W}}^0$ is then split into two matrices $\hat{\mathbf{W}}^{\text{intra},\mathbf{0}}$ and $\hat{\mathbf{W}}^{\text{inter},\mathbf{0}}$ in exactly the same way as for the matrices for $\mathbf{W}^{\text{intra},\mathbf{0}}$ and $\mathbf{W}^{\text{inter},\mathbf{0}}$ based on actual values (see Section III). As before, $\hat{\mathbf{W}}^{\text{intra},\mathbf{0}}$

and $\hat{\mathbf{W}}^{\text{inter},\mathbf{0}}$, which are used as alternative weights matrices in the main equation to construct the R&D spillover terms, are rescaled (by a scalar) such that their average row-sum is equal to one, respectively.

The predicted weights matrices $\mathbf{W}^{\text{intra}}$ and $\mathbf{W}^{\text{inter}}$, which are used as alternative weights matrices in the spatial regressive error process, are then obtained by setting the main diagonal elements of $\hat{\mathbf{W}}^{\text{intra},\mathbf{0}}$ and $\hat{\mathbf{W}}^{\text{inter},\mathbf{0}}$ to zero and row-normalizing their elements.

TABLE 1.

Estimation results, fixed-effects estimates of the production function

Factors	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
K	0.537***	0.471***	0.423***	0.346***	0.235***	0.252***	0.208***	0.190***	0.221***	0.203***
	(0.025)	(0.028)	(0.027)	(0.031)	(0.031)	(0.034)	(0.033)	(0.036)	(0.033)	(0.036)
L	0.556***	0.568***	0.503***	0.488***	0.528***	0.491***	0.566***	0.527***	0.579***	0.541***
	(0.033)	(0.050)	(0.033)	(0.049)	(0.032)	(0.048)	(0.033)	(0.049)	(0.033)	(0.049)
RD			0.175***	0.177***	0.262***	0.229***	0.240***	0.222***	0.186***	0.177***
			(0.017)	(0.020)	(0.018)	(0.021)	(0.019)	(0.021)	(0.016)	(0.018)
$\overline{RD}^{\text{intra}}$							0.155***	0.085**	0.129***	0.094***
							(0.033)	(0.051)	(0.027)	(0.045)
$\overline{RD}^{\text{inter}}$							0.135***	-0.106	0.125***	-0.113
							(0.042)	(0.070)	(0.038)	(0.059)
Fixed effects	no	yes	no	yes	no	yes	no	yes	no	yes
RD add. separable	-	-	yes	yes	no	no	no	no	no	no
CRS-test (*p*-value)	0.165	0.688	0.264	0.092	0.463	0.601	0.705	0.269	0.714	0.153
Monotonicity										
K	0.101	0	0.051	0	0	0	1.364	5.606	0	0
L	0	0	0	0	0	0	0	0	0.606	5.455
RD	-	-	-	-	6.061	2.323	8.333	1.465	10.756	2.576
SEE	0.121	0.110	0.118	0.108	0.112	0.105	0.110	0.103	0.111	0.103
Adj. R^2	0.991	0.993	0.992	0.993	0.993	0.994	0.993	0.994	0.993	0.994

Notes: The dependent variable is log value added, ln*Y*. All models are based on a panel of 1,980 observations (12 countries, 15 industries, 1995-2005). The reported values are implied mean elasticities, and the standard errors are calculated using the delta method. The specifications in columns (a) include country, time, and year effects, the specifications in columns (b) include country-year and industry-year effects. The specifications in columns (5a) and (5b) are as in columns (4a) and (4b), assuming a depreciation rate of 12% rather than 5% for R&D. CRS test in columns (2)-(5) refers to *K*, *L*, and *RD*. Monotonicity reports the share of negative elasticities, implied by the estimates, SEE is the estimated standard deviation of the error term **u**. ***, **, * indicate significance at 1, 5, and 10%.

TABLE 2

Estimation results, spatial GLS fixed-effects estimates of the translog production function

Factors [1)]	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
K	0.239***	0.207***	0.485***	0.471***	0.245***	0.219***	0.257***	0.199***
	(0.048)	(0.036)	(0.047)	(0.049)	(0.048)	(0.036)	(0.047)	(0.039)
L	0.483***	0.454***	0.263***	0.216***	0.471***	0.387***	0.490***	0.470***
	(0.047)	(0.049)	(0.045)	(0.036)	(0.049)	(0.050)	(0.048)	(0.054)
RD	0.263***	0.225***	0.204***	0.182***	0.271***	0.226***	0.221***	0.222***
	(0.026)	(0.023)	(0.020)	(0.020)	(0.025)	(0.024)	(0.025)	(0.025)
$\overline{RD}^{\text{intra}}$	0.233***	0.140***	0.191***	0.136***	0.244***	0.172***	0.067**	0.151***
	(0.046)	(0.053)	(0.041)	(0.046)	(0.051)	(0.056)	(0.048)	(0.058)
$\overline{RD}^{\text{inter}}$	0.144***	-0.091	0.132***	-0.091	0.120**	-0.101	0.062	-0.094
	(0.064)	(0.072)	(0.054)	(0.062)	(0.066)	(0.070)	(0.085)	(0.080)
Fixed effects	no	yes	no	yes	no	yes	no	yes
CRS-test (p-value)	0.734	0.038	0.287	0.000	0.771	0.004	0.641	0.074
Monotonicity								
K	2.727	6.162	0	0	3.535	5.252	0	7.374
L	0	0	1.967	6.464	0	0	0.202	0
RD	4.293	0.808	7.929	1.515	4.242	1.061	0.667	1.111
Error process								
ρ^{intra}	2.178***	1.846***	2.212***	1.853***	2.495***	2.204***	1.691***	1.980***
	(0.004)	(0.000)	(0.003)	(0.015)	(0.021)	(0.040)	(0.009)	(0.000)
ρ^{inter}	0.487***	0.465***	0.577***	0.532***	0.441***	0.321***	1.243***	0.637***
	(0.021)	(0.000)	(0.028)	(0.027)	(0.021)	(0.022)	(0.020)	(0.000)
Spatial multiplier	3.400	2.379	3.932	2.509	8.500	3.050	10.625	4.572
Intra/inter-industry	3.032	3.97	2.60	2.36	3.875	4.703	1.167	2.666
SEE	0.110	0.103	0.111	0.103	0.110	0.103	0.111	0.103
R^2	0.993	0.993	0.992	0.993	0.992	0.993	0.992	0.992

Notes: The dependent variable is log value added, ln$Y$. Table 2 reports feasible spatial GLS fixed-effects estimates of alternative model specifications, implied by the estimates of the spatial regressive error process in equation (3). The reported parameters are implied mean elasticities, and the standard errors are calculated using the delta-method and robust to heteroskedasticity in ε_t. Optimally-weighted GMM estimates of the error process in equation (3). The 'spatial multiplier' is implied by the average of the elements of the vector $(\boldsymbol{I} - \rho^{\text{intra}}\mathbf{W}^{\text{intra}} - \rho^{\text{inter}}\mathbf{W}^{\text{inter}})^{-1}\boldsymbol{\iota}$, where $\boldsymbol{\iota}$ is an $N \times 1$ vector of ones. The row 'Intra/inter-industry' reports the ratio of the estimates of ρ^{intra} and ρ^{inter} after scaling the coefficients by the average row sum of $\mathbf{W}^{\text{intra}}$ and $\mathbf{W}^{\text{inter}}$, respectively. R^2 is the squared correlation between actual and predicted values.

TABLE A1

List of industries and summary statistics

ISIC Rev3	Industry	Productivity VA per person	Investment intensity % of value added	R&D intensity % of value added	Total use of intermediate goods[1)] % of production		Intra-industry use % of total use		Domestic use % of total use	
15-16	Food products, beverages and tobacco	117,303	17.34	1.48	12.48	(25.83)	30.89	(66.61)	28.61	(65.51)
17-19	Textiles, textile products, leather and footwear	88,089	11.44	1.31	16.76	(30.53)	35.01	(64.33)	26.98	(59.92)
20	Wood and products of wood and cork	94,950	18.83	0.55	15.04	(28.41)	31.47	(63.72)	26.05	(60.85
21-22	Pulp, paper, paper products, print.and publishing	140,787	17.32	0.66	16.24	(32.47)	42.72	(71.35)	29.45	(64.71)
23	Coke, refined petr. products and nuclear fuel	339,435	25.58	3.03	6.15	(11.14)	38.75	(66.18)	35.62	(64.46)
24	Chemicals and chemical products	249,732	18.60	14.83	25.09	(35.47)	52.87	(66.67)	26.46	(47.99)
25	Rubber and plastics products	117,976	18.01	2.77	31.65	(37.38)	9.44	(23.33)	35.32	(45.24)
26	Other non-metallic mineral products	120,573	17.53	1.45	15.37	(24.07)	14.54	(45.42)	44.78	(64.73)
27	Basic metals	142,043	22.56	2.19	27.02	(37.68)	39.89	(56.90)	34.09	(52.74)
28	Fabricated metal products	106,699	14.00	1.23	26.65	(37.00)	6.71	(32.79)	41.93	(58.17)
29	Machinery and equipment, n.e.c.	120,195	11.99	5.93	32.59	(38.77)	19.50	(32.33)	46.58	(55.09)
30-33	Electrical and optical equipment	137,817	18.29	19.57	25.93	(35.40)	45.95	(60.42)	31.45	(49.80)
34	Motor vehicles, trailers and semi-trailers	141,706	20.26	9.41	41.71	(51.84)	35.18	(47.85)	24.18	(39.00)
35	Other transport equipment	117,277	13.72	13.69	38.35	(46.66)	27.80	(40.66	32.63	(44.63
36-37	Manufacturing n.e.c.	78,801	12.66	1.15	28.81	(32.33)	4.76	(15.15	22.64	(31.08
	Column averages	140,892	17.21	5.28	23.99	(33.67)	29.03	(50.25)	32.45	(51.82)

Notes: Statistics are simple country averages and refer to the sample midpoint (2000). Value added (VA) is measured in prices (at US$) of the year 2000. Investment intensity is the share of gross fixed capital formation in value added in %. R&D intensity is private and business enterprise R&D expenditures as a share of value added. The category 'Intra-industry use' in the penultimate pair of columns excludes domestic intra-industry use, and the category 'Domestic use' in the last two columns includes domestic intra-industry use.