Intra- and Inter-Industry Productivity Spillovers in OECD Manufacturing: A Spatial Econometric Perspective

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Abstract

We adopt a spatial econometric approach to estimate intra- and inter-industry spillovers in total factor productivity transmitted through input-output relations in a sample of 13 OECD countries and 15 manufacturing industries. Both R&D spillovers as well as remainder, input-output-related linkage effects are accounted for, the latter of which we model by a spatial regressive error process. We find that R&D spillovers occur both horizontally and vertically, whereas remainder spillovers (i.e., ones through unobservable variables) are primarily of intra-industry type. Notably, these intra-industry remainder spillovers turn out economically more significant than R&D spillovers.

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> "*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 – among firms, industries, regions, and even countries. The removal 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 in final goods, foreign direct investment, and trade in components and intermediate goods (also referred to as outsourcing). This increase in economic interdependence is widely believed to have indirectly triggered productivity effects. Moreover, the mentioned modes of interaction have not only likely caused such productivity effects but also rendered their impact more global in nature. We suspect that – in a strongly integrated economic environment – productivity shocks, negative or positive, propagate more intensively both nationally as well as internationally.

The international economics literature on productivity spillovers roots in the seminal paper by Coe and Helpman (1995), which started off a growing number of studies assessing the magnitude and transmission channels of such spillovers (see Keller, 2004). While spillovers take place at various levels – among firms, industries, regions, and countries – the vast majority of previous work focuses on spillovers in a narrow, geographical sense, i.e., cross-border spillovers among regional or national entities. A much smaller number of studies considers spillovers between firms or industries. For instance, Smarzynska Javorcik (2004) and Görg, Hijzen, and Murakozy (2006) investigate the role of spillovers among firms associated with linkage effects that take place in a certain geographical neighborhood. There are hardly any studies on productivity spillovers across countries and industries. Notable exceptions are Bernstein and Mohnen (1997), who estimate bilateral R&D spillovers between selected US and Japanese manufacturing industries over the period 1962-1986, and Keller (2002) who considers knowledge spillovers between manufacturing industries of 8 major OECD countries over the period 1970-1991.[1]

The present paper investigates the role of intra- and inter-industry productivity spillovers within and among 13 OECD countries and 15 manufacturing industries. It goes beyond previous studies by considering not only knowledge spillovers (associated with research and development, henceforth referred to as R&D) but also other types of productivity spillovers. The latter are modeled by using a spatial econometric approach. We specify spillover effects as a decreasing function of economic (rather than merely geographical) distance, which we measure by using information on the domestic and international use and

[1] A comprehensive survey of more than one hundred empirical studies on economic growth with an emphasis on spillover effects, using conventional or spatial econometric techniques, is given by Abreu, De Groot, and Florax (2005). Strikingly, none of the studies included in the survey has used industry data. Early studies focusing on a single country or industry are Morrison Paul and Siegel (1999), who incorporate measures of intra-industry spillovers in a cost function framework for U.S. manufacturing, and Cohen and Morrison Paul (2005), who consider intra-and cross-industry spillovers for the U.S. food manufacturing sector.

delivery of intermediate goods between industries. Hence, our approach is inspired by Balassa's (1961) view on horizontal and vertical linkages between industries as a key source of productivity spillovers and findings of Smarzynska Javorcik (2004) at the firm level that linkage effects related to input-output relations entail an important channel of spillovers. The novelty of the paper is to allow for, distinguish, and estimate the relative importance of two different channels of total factor productivity spillovers, namely intra- versus inter-industry spillovers. As a workhorse model, we use a translog primary production function which accounts for domestic as well as imported R&D, following Coe and Helpman (1995) in the latter regard.

As for estimation, we consider a framework suitable for the analysis of cross-sectional interdependence of the units of observation. We adopt a generalized moments (GM) approach for 'spatially dependent' data by Kelejian and Prucha (2009), which is robust to heteroskedasticity. Since we aim at distinguishing between intra- and inter-industry spillovers, we draw on the generalization of Kelejian and Prucha (2009) by Badinger and Egger (2008) to the higher order case in order to cope with two spillover channels and parameters of interdependence rather than a single one.

Our empirical results suggest the following conclusions. First, there are sizeable knowledge spillover effects on productivity, with a dominant role of inter-industry spillovers. Second, stochastic productivity shocks unrelated to R&D are significantly transmitted through input-output relationships, but mainly between similar industries. As a result, productivity shocks are magnified through intra-industry spillovers and the associated repercussions.

The remainder of the paper is organized as follows. Section II lays out the basic empirical model. Section III outlines the spatial econometric approach to modeling and estimating productivity spillovers with two rather than a single transmission channel. (The detailed extension of the GM estimator by Kelejian and Prucha (2009) relegated to an Appendix.) Section IV presents the estimation results for our cross-section of 13 OECD countries and 15 manufacturing industries. Section V summarizes the main findings and concludes.

II. The Empirical Model

Our point of departure is a standard translog production function with two primary factors of production, labor and capital, and a parameter determining the level of total factor productivity (TFP).[2] An advantage of the translog form is its greater flexibility as compared to Cobb-Douglas or, more generally, a constant elasticity of substitution (CES) technology. It may also account for the variation in production functions across industries, since the first derivatives vary by observation. Thereby, it also mitigates endogeneity problems involved in

[2] We also experimented with other forms such as a generalized Leontief function as used by Thursten and Libby (2002). Ultimately, we opted for the translog form in our application, since the estimate of variance-covariance matrix under the generalized Leontief specification turned out as close to singular, and a model comparison in terms of the adjusted R^2 supported the translog form as compared to the generalized Leontief form with the data at hand.

estimating production functions (see Yasar and Morrison Paul, 2007).[3] In matrix notation, the assumed production technology reads as follows:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{u}, \tag{1}$$

where lower-case letters in bold face indicate vectors and **Z** refers to a matrix of explanatory variables. The cross-section available to us comprises i = 1,…,13 OECD countries and k = 1,…,15 ISIC-2-digit manufacturing industries, yielding $N = 195$ observations, and refers mainly to the year 1995.[4] A detailed list of the available countries and industries is given in Appendix A1. $\mathbf{y} \equiv [\ln y_{ik}]$ is an $N \times 1$ vector of log real value added in country i and industry k, measured in 1995 prices. **Z** is an $N \times Z$ matrix of explanatory variables where the column rank of **Z**, Z, may vary across the estimated specifications. $\boldsymbol{\gamma}$ is a $Z \times 1$ vector of unknown parameters, and $\mathbf{u} \equiv [u_{ik}]$ is an $N \times 1$ vector of disturbances.

Our empirical specifications will differ with respect to the definition of **Z** and the one of **u**, respectively. In any model estimated below, **Z** will include $\mathbf{l} \equiv [\ln L_{ik}]$, $\mathbf{k} \equiv [\ln K_{ik}]$, and the higher order terms $\mathbf{l^2} \equiv [\frac{1}{2}\ln^2 L_{ik}]$, $\mathbf{k^2} \equiv [\frac{1}{2}\ln^2 K_{ik}]$, $\mathbf{lk} \equiv [\ln L_{ik} \ln K_{ik}]$, where $\ln L_{ik}$ and $\ln K_{ik}$ denote inputs of primary production factors labor and physical capital, respectively, in country i and industry k expressed in natural logarithms.[5] The variable $\ln L_{ik}$ measures the logarithm of hours worked. For reasons of data availability, we approximate $\ln K_{ik}$ by a country and industry's logarithm of investment intensity, defined as the logarithm of gross fixed capital formation relative to value added.[6] This corresponds to the standard translog function in the two factors labor and capital.[7] Moreover, all models will include $\mathbf{Z}_{\boldsymbol{\alpha}}$, an

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[3] Given the absence of strong and convincing instruments for conditional factor demands, this is particularly important in our cross-section analysis, which precludes the use time lags as instruments unlike as with panel data (see Cohen and Morrison Paul, 2004).

[4] For our fairly comprehensive sample of OECD countries and the level of aggregation used, a panel approach is not feasible for reasons of data availability. On the one hand, the available series on some factor inputs such as expenditures on research and development (which are part of **Z**) are very short; the resulting panel would be highly unbalanced with data points unequally spaced in time, which is a serious problem with spatial models and may lead to inconsistent estimates. Second, the use of panel data would probably demand for a dynamic model and relatively long time series. Our estimates are to be interpreted as long-run relationships. (Pirotte, 1999, and Egger and Pfaffermayr, 2004, show that between estimates of dynamic models reflect long-run estimates.)

[5] It was not possible to estimate the technology parameters from a cost function, since the required data are not available for the sample of countries and industries we consider.

[6] Physical capital stock data are not available. One could approximate capital stocks by using the perpetual inventory method. But apart from introducing measurement error this would drastically reduce our sample size, since sufficiently long time series on real investment are not available for many of the cross-sectional units.

[7] In principle, one would wish to distinguish between inputs of skilled and unskilled labor. However, the available data do not permit such a distinction for the countries and industries covered here. It should be borne in mind that parameter estimates of variables which involve **l** refer to the joint input of skilled and unskilled labor.

$N \times 13$ selector (or dummy variable) matrix to allow for country-specific total factor productivity differences.

The models of particular interest to us will include R&D-related parts of total factor productivity such as $\mathbf{rd} \equiv [\ln RD_{ik}]$, where $\ln RD_{ik}$ reflects the logarithm of R&D intensity, defined as private and business enterprise R&D expenditures as share of value added, in country i and industry k.[8] Apart from 'own' R&D these models will include weighted averages of other industries' (logarithm of) R&D intensities to capture spillover effects: $\overline{\mathbf{rd}}_{\mathbf{intra}} \equiv \mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}\mathbf{rd}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}} \equiv \mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}\mathbf{rd}$, where the $N \times N$ weights matrices $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}} \equiv [w^{\mathbf{0}}_{\text{intra},ik,jl}]$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}} \equiv [w^{\mathbf{0}}_{\text{inter},ik,jl}]$ have elements $0 \leq w^{\mathbf{0}}_{\text{intra},ik,jl}$ and $0 \leq w^{\mathbf{0}}_{\text{inter},ik,jl}$, which determine the decay of interdependence within ~~a~~ (identical) 2-digit industries (*intra*-industry) and across industries (*inter*-industry), respectively, and will be defined in more detail in subsection 2 of section III below. Such a specification assumes that the production function is separable in $\mathbf{rd}$, $\overline{\mathbf{rd}}_{\mathbf{intra}}$, and $\overline{\mathbf{rd}}_{\mathbf{inter}}$, similar to the notion in Griffith, Redding and Van Reenen (2004). In that case one may think of the part of the model that is loglinear-additive in $\mathbf{Z}_{\boldsymbol{\alpha}}$, $\mathbf{rd}$, $\overline{\mathbf{rd}}_{\mathbf{intra}}$, and $\overline{\mathbf{rd}}_{\mathbf{inter}}$ to reflect total factor productivity. Appendix A1 provides a description of the sample of countries and industries as well as data sources and associated descriptive statistics of the variables in use.

We will also test for and estimate more flexible forms of the production function, using a translog-specification where the effects of an industry's own R&D ($\mathbf{rd}$) and R&D transmitted through intra- and inter-industry relationships ($\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$) are not separable from labor, capital, or each other. The economic interpretation of such a specification is that the marginal product of the production factors is a function of R&D and, in turn, the marginal effect of R&D on value added depends also on the input of labor and capital. In that case the regressor matrix $\mathbf{Z}$ includes the following additional higher order terms: the squares $\mathbf{rd^2} \equiv [\frac{1}{2}\ln^2 RD_{ik}]$; $\overline{\mathbf{rd}}^2_{\mathbf{intra}} \equiv [\frac{1}{2}(\overline{RD}_{\text{intra},ik})^2]$, and $\overline{\mathbf{rd}}^2_{\mathbf{inter}} \equiv [\frac{1}{2}(\overline{RD}_{\text{inter},ik})^2]$, and interactive terms $\mathbf{rd\,l} \equiv [\ln RD_{ik} \ln L_{ik}]$, $\mathbf{rd\,k} \equiv [\ln RD_{ik} \ln K_{ik}]$, as well as $\overline{\mathbf{rd}}_{\mathbf{intra}}\mathbf{l}$, $\overline{\mathbf{rd}}_{\mathbf{intra}}\mathbf{k}$, $\mathbf{rd}\,\overline{\mathbf{rd}}_{\mathbf{intra}}$, $\overline{\mathbf{rd}}_{\mathbf{inter}}\mathbf{l}$, $\overline{\mathbf{rd}}_{\mathbf{inter}}\mathbf{k}$, and $\mathbf{rd}\,\overline{\mathbf{rd}}_{\mathbf{inter}}$, which are defined analogously.

Our main goal is to model and estimate productivity spillovers as determinants of total factor productivity and to consider whether such spillovers take place only within 2-digit industries (*intra*-industry spillovers) or also between different types of industries (*inter*-industry spillovers).

We do not expect the variables $\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$ to capture all possible spillover effects; on the one hand they reflect only private and business enterprise R&D and do not account for knowledge spillovers related to public research. In addition, there are other types

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[8] Similar to capital stocks, it is not feasible to include the stock of knowledge here. The reason is that the available time series of R&D expenditures are of unequal length, unequally spaced in time, and short for most cross-sectional units so that stocks of knowledge can not be constructed by using the perpetual inventory method. Moreover, industry-level depreciation rates and price indices are not available. While the use of intensities rather than stocks allows us to estimate productivity effects of knowledge and associated spillovers, the corresponding parameters need to be interpreted differently from a specification which employs (capital or R&D) stocks. This issue will be discussed below.

of intra- and inter industry effects which are not or only indirectly related to knowledge transmitted through the use of intermediate goods. An early discussion of such external economies across industries, including historical examples, is given by Balassa (1961, chapter 7). One example is that output price-reducing innovations in one industry will also increase demand for goods from input-producing industries, allowing firms in those industries to exploit economies of scale. More generally, Balassa (1961, p. 150) points out that "*the transmission of technological change may also take the form of a circular process [between industries]. 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 as the economy grows.*"

As a result, part of the spillovers in our model will be reflected in the $N \times 1$ error term vector $\mathbf{u}$. In econometric terms, $\mathbf{u}$ is expected to exhibit 'spatial' correlation (i.e., interdependence across units of observations), which we will talk about in more detail in the subsequent section.

III. Modeling Intra- and Inter-Industry Productivity Spillovers: A Spatial Econometric Perspective

1. General Remarks

With cross-sectional data, it is infeasible to estimate the individual elements of $N \times N$ matrices of interdependence. But rather, it is necessary to adopt an assumption about the channel(s) and the structure of interdependence, captured by the elements of so-called spatial weights (or linkage or interdependence) matrices (see Anselin, 1988, Kelejian and Prucha, 1999, Anselin, 2003).

2. Specification of the Weights Matrices for Intra- and Inter-industry Spillovers

In most applications, the elements of weights matrices are specified as some decreasing function of geographical distance or as function of adjacency. With two-dimensional data such as ours (exhibiting country and industry variation), using a geographical spillover channel would unnecessarily restrict spillovers to occur in the country dimension but not across industries. In our application, the inclusion of fixed country effects even washes out all cross-country spillovers which are identical across industries (such as ones related to geographical adjacency).

Since productivity spillovers, which are the subject of this study, take place between firms, we use trade in intermediate goods – the bulk of trade between firms – as a measure of the extent and intensity of interactions both within and across industries. This approach is inspired by Balassa's (1961) view on horizontal and vertical linkages between industries as a key source of productivity spillovers and findings of Smarzynska Javorcik (2004) that input-output related linkages entail an important channel of spillovers at the firm level. Our input-output-based measure of interdependence naturally spans both dimensions of our data, namely countries and industries.[9]

[9] An exception is Cohen and Morrison Paul (2004), who use measures of (total) trade between US states for the construction of the weighting matrix in their study on spillovers effects of public infrastructure investments.

However, we are not the first to use input-output-based data to model interdependence of industries. Moretti (2004) investigates the effects of human capital spillovers on productivity and wages using US plant level data over the period 1982 to 1992, using rank indices based on the value of input output flows. 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. An important difference to our study is that Moretti rules out cross-country spillovers and focuses on a single channel (inter-industry) rather than two channels (intra- versus inter-industry) of interdependence. Keller (2002) also uses input-output data to construct knowledge spillover variables in his investigation of R&D spillovers between manufacturing industries of 8 major OECD countries. Our study goes beyond that of Keller (2002) by considering not only knowledge spillovers but also other types of spillovers captured in the disturbance term **u**, which we account for by using a spatial econometric approach as will be outlined in more detail below.

To construct the matrices of interdependence (the 'spatial weights' matrices), we employ the production share of trade in intermediate goods. Specifically, define the elements

$$w^0_{ik,jl} = \frac{IO_{ik,jl}}{PROD_{ik}}. \tag{2}$$

The numerator $IO_{ik,jl}$ denotes exchange of intermediate goods between country *i's* industry *k* and country *j*'s industry *l*. We consider two alternative measures of input-output flows: use of intermediate goods and use-plus-delivery of intermediate goods.

$IO_{ik,jl}$ in (2) is constructed as follows. Domestic input-output flows between industries are available from the OECD's input-output database. International input-output flows are only available at a gross basis (total imported intermediates by industry for each importer-country and industry-pair). Accordingly, we have to adopt an assumption about the pattern of international trade in intermediate goods. We follow various examples in the literature by assuming that the foreign trade pattern of intermediate goods in a particular industry is similar to that of total trade.[10] (See Appendix A1 for details.)

The denominator in equation (5), $PROD_{ik}$, equals production (gross output) of country *i'*s industry *k*. Hence, the corresponding weights matrix models the magnitude of the interactions between two industries by the intensity of the use (or use-plus-delivery) of intermediate goods scaled by the respective industry's size.

One contribution of this paper is to assess whether there are differences between intra- and inter-industry spillovers. This will be achieved by splitting up the $N \times N$ matrix $\mathbf{W^0} = [w^0_{ik,jl}]$ into two $N \times N$ matrices $\mathbf{W^0_{intra}}$ and $\mathbf{W^0_{inter}}$, where $\mathbf{W^0_{intra}} + \mathbf{W^0_{inter}} = \mathbf{W^0}$. The elements of $\mathbf{W^0_{intra}}$ correspond to $w^{\mathbf{0}}_{\text{intra},ik,jl} = w^{\mathbf{0}}_{ik,jl}$ for $k = l$ and 0 otherwise, capturing the

[10] 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 (2007) provide evidence that at least aggregate trade among the OECD countries in intermediate goods behaves remarkably similar to final goods trade.

decay of intra-industry interdependence in input-output space. $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ contains elements $w^{\mathbf{0}}_{\text{inter},ik,jl} = w^{\mathbf{0}}_{ik,jl}$ for $k \neq l$ and 0 otherwise, reflecting the decay of inter-industry interdependence in input-output space. Notice that the diagonal elements of $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ do not need to be zero and those of $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ are zero by definition. To ensure that the parameter estimates associated with the weighting matrices used in the estimation are directly comparable, we divide the elements of the original weighting matrices $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ by the respective average row-sum. Of course, such a division by a scalar is merely a reparameterization, which leaves the magnitude of the implied effects and inference unaffected. Hence, for simplicity of notation, we continue to refer to these matrices, which are normalized by the average row-sum, as $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ in the following.

As will become clear below, in the estimation of the spatial regressive error process it is necessary to use a normalization of the interdependence matrices together with corresponding restrictions on the admissible parameter space in order to ensure well-behaved asymptotic behavior of the parameter estimates. We follow the standard approach in the literature on spatial regressive processes and use row-normalized weights matrices, where each element of the unnormalized matrices $\mathbf{W}^{\mathbf{0}}$, $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ is divided by the respective row sum, such that the elements of each row sum up to unity. (See, e.g., Lee and Liu (2009) for a similar approach with a higher order spatial autoregressive model.) We refer to these $N \times N$ matrices as $\mathbf{W}$, $\mathbf{W}_{\mathbf{intra}}$ and $\mathbf{W}_{\mathbf{inter}}$, respectively, and maintain throughout that their diagonal elements are zero so that $w_{ik,ik} = w_{\text{intra},ik,ik} = w_{\text{inter},ik,ik} = 0 \quad \forall i,k$.

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 A1) 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 is made up of sub-sectors that are distinct enough from each other to regard their relationships as 'inter-industrial' among similar industries. Hence, the figures about intra-industry spillovers should be interpreted as an upper bound, capturing true intra-industry spillovers as well as inter-industry spillovers among fairly similar industries.

3. R&D Spillovers

Our approach to modeling R&D spillovers builds on Coe and Helpman (1995). They use (aggregate) data from 21 OECD countries and Israel over the period 1971 to 1990 to estimate the contributions of the domestic knowledge capital stock and (bilateral import share weighted) foreign knowledge stocks to total factor productivity. A large number of studies has extended and econometrically refined this seminal procedure by Coe and Helpman (1995). (See Keller, 2004, for a survey of the literature.)

While our estimation framework is closely related to that of Coe and Helpman (1995), there are also some differences. First, we use industry rather than aggregate data and distinguish between intra- and inter-industry spillovers. Second, while Coe and Helpman (1995) use a TFP index as the dependent variable, which is calculated from a Cobb-Douglas production function by imposing the income shares of labor and capital in a first step, our estimation builds on a more flexible translog production function approach. Finally, we use (the log of) R&D intensity, defined as share of R&D expenditures of value added, rather than R&D capital stocks as an explanatory variable for reasons of data availability (see section II).

As indicated before, our empirical model includes not only an industry's 'own' R&D intensity $\mathbf{rd}$, but also the spatial lags $\overline{\mathbf{rd}}_{\mathbf{intra}} \equiv \mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}\mathbf{rd}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}} \equiv \mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}\mathbf{rd}$, which can be interpreted as R&D spillovers transmitted through intra- and inter-industry relationships. In line with previous studies on R&D spillovers the elements of $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ are based on the use of intermediates between industries. Note that the average row-sum of both matrices $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ is equal to 1. As a consequence, in the specification where R&D is assumed to be separable from labor and capital, the (average) intra- and inter-industry transmitted productivity spillover effect of a simultaneous, uniform increase in all industries' R&D intensity by one percent can be read off directly from the parameters of $\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$. In the more general case, where R&D is not separable, the spillover effects are equal to the derivatives of $\mathbf{y}$ with respect to $\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$, which will then also depend on the values of the other inputs and parameters of the interaction terms.

$\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$ reflect intra-industry and inter-industry spillovers, respectively, at the national and international level. Notice that we implicitly restrict the parameters of domestic and international spillovers to be equal (both for intra- and inter-industry R&D spillovers). This assumption appears to be justified for spillovers among the developed and highly integrated OECD countries. Differences in the magnitude of domestic and cross-border spillovers are mainly due to distance, trade costs, and border effects, which are already reflected in the magnitude of domestic versus international input-output flows (use of intermediate goods), which the spillover weights matrices are based upon. By 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.

4. Remainder Productivity Spillovers in the Residuals

In our application, there are (significant) productivity spillovers that work through channels other than the import of knowledge. These spillovers are reflected in the residuals. While previous studies on productivity have focused on knowledge spillovers, this paper allows for linkage effects channeled through input-output relationships which are not related to knowledge or R&D. Such spillovers could be related to market structure, factor market characteristics and other economic fundamentals with a potential impact on total factor productivity (Balassa, 1961; Smarzynska Javorcik, 2004). The productivity effects of such 'remainder' spillovers may be captured by a 'spatial' regressive error process, where we distinguish again between two channels of interdependence: remainder intra-industry spillovers through the matrix $\mathbf{W}_{\mathbf{intra}}$ and remainder inter-industry spillovers through the matrix $\mathbf{W}_{\mathbf{inter}}$ (see section 2). Since we do not rule out that remainder spillovers (i.e., ones associated with unobservable variables related to total factor productivity) are also transmitted through delivery of intermediates, the elements of the matrices $\mathbf{W}_{\mathbf{intra}}$ and $\mathbf{W}_{\mathbf{inter}}$ are based on use-plus-delivery of intermediates between industries. The spatial regressive process of $\mathbf{u}$ is determined as

$$\mathbf{u} = \rho_{\text{inter}} \mathbf{W}_{\mathbf{intra}} + \rho_{\text{inter}} \mathbf{W}_{\mathbf{inter}} + \boldsymbol{\varepsilon} . \qquad (3)$$

With row-normalized matrices $\mathbf{W}_{\mathbf{intra}}$ and $\mathbf{W}_{\mathbf{inter}}$, what matters is another industry and country's *relative* (rather than the *absolute*) weight for a given country-industry dyad. Moreover, the two channels of interdependence obtain the same ex-ante 'weight' in terms of their row sums in the error process, such that their relative importance is reflected in the parameter estimates of ρ_{intra} and ρ_{inter}, respectively.

Regarding the model specification, the interdependence parameters (ρ_{intra}, ρ_{inter}) have to be restricted to lie in the interval $0 \leq |\rho_{\text{intra}}| + |\rho_{\text{inter}}| < 1$ under row-normalization and the main diagonal elements of both $\mathbf{W}_{\mathbf{intra}}$ and $\mathbf{W}_{\mathbf{inter}}$ have to be zero as mentioned before. The latter implies that we cannot incorporate domestic intra-industry spillovers in the spatial regressive specification of the residual $\mathbf{u}$ for econometric reasons. Accordingly, the weights matrix $\mathbf{W}_{\mathbf{intra}}$ captures only international intra-industry spillovers, whereas $\mathbf{W}_{\mathbf{inter}}$ reflects both domestic and international inter-industry spillovers.

To check the sensitivity of the results with respect to the choice of the weights matrix, we will consider two alternative specifications below: first, we use a weights matrix which is based on use (rather than use-plus-delivery) of intermediate goods; second, to address endogeneity concerns, we consider the case of a weights matrix whose elements are based upon the predicted values from a gravity-type model for input-output flows. (See subsection 3 in section IV and Appendix A3 for details.)

Regarding estimation, two approaches dominate the literature: maximum likelihood estimation (see Anselin, 1988; Lee, 2004) and generalized method of moments estimation (Lee and Liu, 2006; Kelejian and Prucha, 2008). 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 indeed turns out to be important in our data as we will show below, we choose the GM estimator by Kelejian and Prucha (2009) to obtain consistent estimates of the interdependence parameters. The estimation approach is briefly sketched in formal accounts in Appendix A2.1.

Kelejian and Prucha (2009) consider only one channel and parameter of interdependence. Building on Badinger and Egger (2008), who generalize the estimator by Kelejian Prucha (2009) for models with higher order spatial regressive processes, Appendix A2.2 outlines the econometric issues involved in the estimation of the second order process as specified in equation (3).[11] We refer the interested reader to the working paper version of this paper and Badinger and Egger (2008) for a Monte Carlo simulation study showing that the estimator based on the extended moment conditions performs reasonably well, even in small samples.

[11] This approach is related to the ones of Bell and Bockstael (2000) and Cohen and Morrison Paul (2007), who also consider GM estimation of higher order spatial regressive error processes but assuming homoskedastic residuals. However, apart from technicalities, there is a conceptual difference between our approach and the ones of Bell and Bockstael (2000) and Cohen and Morrison Paul (2007). In our case, the different weights matrices refer to qualitatively different relationships – intra- versus inter-industry – among units in the sample rather than different geographical 'bands' (or gradual differences in neighborhood) there.

IV. Estimation Results

Our estimates of the empirical models derived in section II are based on the aforementioned cross-section, consisting of 13 OECD countries and 15 manufacturing industries (making a total of 195 observations) and refer (mainly) to the year 1995.

1. R&D Spillovers

Table 1 summarizes estimates of the parameters for alternative empirical models. We first consider the results for the main equation only, i.e., the estimates of γ in equation (1), and then turn to remainder spillovers in the error process, i.e., ρ_{intra} and ρ_{inter}, in equation (3). Inference for the estimates of γ is based on robust standard errors, which account for the spatial regressive structure of the error term and the heteroskedasticity in $\boldsymbol{\varepsilon}$. (See Appendix A2 for details.)

We start with the most parsimonious translog specification based on capital and labor variables only (except for country dummies, which are included in all models) in column (1).[12] Notice that the non-linear terms $\mathbf{l}^2$, $\mathbf{k}^2$, and $\mathbf{lk}$ are jointly significant at 10 percent in column (1), indicating that the production function would be misspecified by a Cobb-Douglas model. Evaluated at the sample mean, the implied average derivatives are 0.507 with respect to the log of the investment intensity and 0.872 with respect to the log of labor. Recovering the output elasticity with respect to the capital stock and labor from our estimates would require additional assumptions about the particular form of the production function. While the parameter estimates are in a plausible range,[13] we do not pursue this issue further here and turn to our main goal, i.e., the estimation of productivity spillovers.

< Table 1 >

We proceed by stepwise including the R&D variables, assuming additive separability of the R&D terms in a first step. Column (2) shows the results when only the (log of) 'own' R&D intensity – captured by vector **rd** – is included as additional regressor ('own' here refers to the same country and industry). The corresponding coefficient turns out to be significant at five percent, reflecting an elasticity of 0.032, which is below the effect obtained in previous (country) studies.[14] For instance, Coe and Helpman (1995) estimate an elasticity of total factor

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[12] Including industry dummies is not feasible with the data at hand, since they are highly collinear with the covariates in the model. However, the goodness of fit increases only moderately in a model with industry dummies as compared to our more parsimonious specifications. We thus opt for the latter model and pool the constants across industries.

[13] For example, if we interpret the parameters using the steady-state of a standard neoclassical growth model and imposing a parameter for the log of labor equal to unity (which is close to our average estimate), the output elasticity with respect to the capital stock (α) can be recovered from the relation $\varepsilon_s = \frac{\alpha}{1-\alpha}$, where ε_s is the elasticity of output with respect to the investment-ratio. For the estimate of ε_s in column (1), this would imply an average output elasticity with respect to the capital stock of 0.336.

[14] Recall that the estimated elasticity with respect to the R&D intensity does not directly measure the elasticity with respect to the knowledge stock.

productivity with respect to the domestic R&D stock, ranging from 0.08 to 0.23. In the most 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. That we obtain a smaller estimate is not too surprising, since we use disaggregated data; we will return to this point below.

In a next step we include the R&D spillover terms $\overline{\mathbf{rd}}_{\mathbf{intra}} = \mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}\mathbf{rd}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}} = \mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}\mathbf{rd}$, allowing their parameters to differ. As can be seen from column (3), both $\overline{\mathbf{rd}}_{\mathbf{intra}}$ and $\overline{\mathbf{rd}}_{\mathbf{inter}}$ enter significantly at the one percent level. Moreover, an F-test clearly rejects the restriction that $\gamma_{\overline{\mathbf{rd}}_{\mathbf{intra}}} = \gamma_{\overline{\mathbf{rd}}_{\mathbf{inter}}}$ at one percent. In light of the fact that the average row sums of the weights matrices $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ are equal to 1, the coefficients suggest that inter-industry R&D spillovers are roughly twice as important as intra-industry R&D spillovers.

In terms of magnitude the estimates imply that a simultaneous increase in all industries' R&D (i.e., including own R&D) by one percent induces spillover effects (both across industries as well as within the same industry) on total factor productivity by 0.15 percent (0.043 of which is due to own R&D, 0.072 of which is due to inter-industry spillovers, and 0.036 of which is due to intra-industry spillovers).

Turning to the effect of country *i*'s and industry *k*'s "own" R&D we have to bear in mind that $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ contains nonzero diagonal elements. Hence, in terms of our notation, the average direct effect of own R&D on productivity is given by $\gamma_{\mathbf{rd}}$ (the direct effect of 0.043) plus $\gamma_{\overline{\mathbf{rd}}_{\mathbf{intra}}}$, multiplied with the average of the main diagonal elements of $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$, the latter reflecting the effect of domestic intra-industry spillovers taking place within the respective industry (0.027). The effect on an industry's productivity of an increase in R&D by one percent in all *other* industries – that is the productivity effect due to spillovers except those induced by the same industry and country – amounts to 0.080. This is consistent with the results by Keller (2002), who finds that an industry's own R&D and spillovers from other industries account for some half of the total effect.

Based on our assumption that the parameters are equal for domestic and international relationships (see the discussion in subsection 2 of section III), the sums of the weights expressing domestic and international (intra- and inter-industry) relations can be used to infer the relative magnitudes of domestic versus international spillovers. With an average domestic share of some 0.75 and 0.79 percent in total intra-industry and inter-industry use of intermediate goods, this implies that some three quarters of the R&D spillovers take place domestically. If we exclude spillover effects within the same industry (domestic intra-industry spillovers), domestic spillovers still account for some two thirds of all spillover effects. Again this is fairly close the estimates by Keller (2002), who finds that some 60 percent of all spillover effects stem from domestic industries.

We next turn to the results for the specification assuming that effects of R&D are non-separable from the other factors of production. Column (4) includes only own R&D (**rd**) and the corresponding interaction terms, which turn out jointly significant at one percent. The implied average elasticity is somewhat larger than that obtained in column (2). Column (5a) reports the estimates where the R&D spillover terms (and the corresponding interactions) are included as well. The qualitative conclusions are very similar to those obtained from column (3), though a larger effect is assigned to own R&D with an implied average elasticity of 0.067 and inter-industry spillovers with an implied average elasticity of 0.042, whereas intra-industry spillovers are smaller in magnitude (0.003) and statistically insignificant.

The specification of the main equation given in column (5a) is our preferred model. The fit is satisfactory with an adjusted R^2 of 0.972 and a standard error of 0.234. Note that throughout all models, the Ramsey-test statistic is insignificant. We may interpret this as an indication of the absence of strong endogeneity problems with our specification. We now turn to a discussion of the results regarding the spatial regressive error process of **u**.

2. Remainder Productivity Spillovers

The lower panel of Table 1 reports the Moran's I test for spatial correlation in **u** and a series of LM tests suggested by Anselin, Bera, Florax, and Yoon (1996) for specification search with spatial econometric models. For the data at hand, the results point to the importance of spatial autocorrelation in the error term but not the dependent variable in all models. It should be noted, however, that the LM tests assume that the error term $\boldsymbol{\varepsilon}$ is homoskedastic and that there is only a single mode of interdependence (i.e., first-order spatial correlation through **W**). Since some of our models include a second-order spatial regressive error process (through $\mathbf{W}_{\mathbf{intra}}$ and $\mathbf{W}_{\mathbf{inter}}$) and heteroskedasticity in $\boldsymbol{\varepsilon}$ is pronounced in all specifications according to standard Breusch-Pagan tests (see Table 1) the test statistics should only be regarded as indicative of spatial correlation in the error term. Estimation and inference regarding the GM estimates of ρ are based on Kelejian and Prucha (2009); for the second order models, estimation and inference for the GM estimates of $\rho_{\mathbf{intra}}$ and $\rho_{\mathbf{inter}}$ are based on the generalization by Badinger and Egger (2008). (See Appendix A2 for details.)

In columns (1)-(5a), we report the interdependence coefficient when assuming a first-order spatial regressive error process, i.e., $\mathbf{u} = \rho\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}$, along with the estimates of ρ_{intra} and ρ_{inter}, assuming a second-order process as reflected in equation (3).[15]

In our preferred specification in column (5a), the estimate of ρ is approximately 0.430. This is supportive of the arguments by Balassa (1961) that technological improvements have a magnified impact on productivity. The coefficient suggests that a unitary productivity shock in all industries is amplified by a factor of 1.754 in the long run, accounting for spillovers to other industries and their repercussions. A comparison of the spatial correlation tests and the estimates of ρ in columns (4) and (5a) (or columns (1) and (3) for separable R&D) in Table 1 indicates that remainder spillovers become less important – but do not become insignificant – in response to the inclusion of the R&D spillover terms in the main equation. Hence, part – yet not all – of the interdependence across countries and industries identified in columns (1)-(5a) is due to R&D spillovers channeled through national and international input-output relationships.

[15] In Table 1, estimates of ρ are reported in the row denoted by $\mathbf{Wu}$ while ones of $\rho_{\mathbf{intra}}$ and $\rho_{\mathbf{inter}}$ are summarized in the rows labeled $\mathbf{W}_{\mathbf{intra}}\mathbf{u}$ **and** $\mathbf{W}_{\mathbf{inter}}\mathbf{u}$, respectively. Since the GM procedures applied here are based on first-step (least squares) estimates of **u** from the main equation, we may report the GM estimates of ρ along with ones of ρ_{intra} and ρ_{inter} in columns (1) to (5a) of Table 1.

Using the specification in column (5a), we now take a closer look at remainder productivity spillovers as captured in the residuals. The corresponding analysis is based on the least squares residuals of the model in column (5a) and summarized in columns (5a)-(5c) in Table 1. We first allow the spatial autoregressive parameter to vary between intra- and inter-industry relations as in equation (3). (Results for the systematic part of the model, i.e., the main equation, are the same across columns (5a)-(5c) except for the estimates of the robust standard errors.) Compared with the estimate of ρ, the estimate of ρ_{intra} (measuring productivity effects transmitted through international intra-industry use of intermediate goods) is positive and statistically significant, while that of ρ_{inter} (measuring productivity effects transmitted through both domestic and international inter-industry use of intermediates) is close to zero and actually insignificant – it actually is slightly negative, according to the center panel of column (5a). We regard this result as strong evidence of a dominance of intra- over inter-industry spillovers unrelated to R&D.

Our interpretation of the role of intra- versus inter-industry interdependence is also supported by the results from two alternative specifications of the error process, which assume $\rho_{\text{intra}} = 0$ and, alternatively, $\rho_{\text{inter}} = 0$ in columns (5b) and (5c), respectively. If only inter-industry spillovers are allowed as in column (5b), the estimate of ρ_{inter} is positive but very small and not significantly different from zero. In contrast, if only intra-industry spillovers are allowed as in column (5c), the estimate of ρ_{intra} is about the same as in column (5a) and highly significant. Hence, our analysis of nested spillover effects suggests that there are no (or only negligible) inter-industry spillovers associated with the stochastic part of total factor productivity, after accounting for intra- and inter-industry spillovers in R&D.

3. Feasible GLS Estimates and Sensitivity Analysis

Having obtained an estimate of the error process, efficiency of the estimates of the model parameters can be improved by a generalized least squares (GLS) approach. Kelejian and Prucha (2009, p. 22) suggest applying a standard Cochrane-Orcutt transformation to (1):

$$\mathbf{y}^* = \mathbf{Z}^*\boldsymbol{\gamma} + \mathbf{u}^*. \tag{4}$$

In the second-order case, we have $\mathbf{y}^* = (\mathbf{I} - \rho_{\text{intra}}\mathbf{W}_{\text{intra}} - \rho_{\text{inter}}\mathbf{W}_{\text{inter}})\mathbf{y}$, $\mathbf{Z}^* = (\mathbf{I} - \rho_{\text{intra}}\mathbf{W}_{\text{intra}} - \rho_{\text{inter}}\mathbf{W}_{\text{inter}})\mathbf{Z}$, and $\mathbf{u}^* = (\mathbf{I} - \rho_{\text{intra}}\mathbf{W}_{\text{intra}} - \rho_{\text{inter}}\mathbf{W}_{\text{inter}})\mathbf{u} = \boldsymbol{\varepsilon}$. The corresponding transformation for the case of a first-order spatial regressive error process is obtained by replacing the transformation matrix $(\mathbf{I} - \rho_{\text{intra}}\mathbf{W}_{\text{intra}} - \rho_{\text{inter}}\mathbf{W}_{\text{inter}})$ with $(\mathbf{I} - \rho\mathbf{W})$. As is evident from these definitions, the transformed model depends on ρ_{intra} and ρ_{inter}. The feasible generalized least squares (FGLS) estimator of $\boldsymbol{\gamma}$ is obtained by replacing ρ_{intra} and ρ_{inter} with their estimates (based on the least squares residuals). To account for the (remaining) heteroskedasticity in $\boldsymbol{\varepsilon}$, robust standard errors are used for inference regarding $\boldsymbol{\gamma}$. In Table 2, GM estimates and inference regarding ρ_{intra} and ρ_{inter} are based on the FGLS residuals of the main (untransformed) equation. For more details on the econometric issues, see Appendix A2.

< Table 2 >

The FGLS results for our preferred specification of the main equation (Table 1, column 5a) with a second order spatial regressive process are given in column (1a) of Table 2. Since the GM estimates again suggest that remainder inter-industry spillovers are insignificant, we proceed with a discussion of column (1b), where ρ_{inter} is restricted to zero. Compared with the least squares estimates, the estimate of the implied elasticity with respect to own R&D becomes smaller and amounts to 0.028, whereas that of inter-industry R&D spillovers increases to 0.037. Regarding the relative role of intra- versus inter-industry R&D spillovers, the qualitative results do not change: inter-industry R&D spillovers are highly significant and dominate intra-industry spillovers, which turn out insignificant at conventional levels. Regarding remainder productivity spillovers, the GM estimate of ρ_{intra}, which is now based on the FGLS residuals (referring to the untransformed model), amounts to 0.649, is highly significant and points to a multiplier effect of a uniform, incipient one-percent productivity shocks of around 2.850 percent.

Next, we infer the sensitivity of the results[16] with respect to alternative weights matrices for interdependence in the spatial regressive error process. In both cases we report the estimates using a second order spatial regressive process, and proceed with a restricted specification of the error process where appropriate.

Column (2) provides FGLS estimates using weights matrices $\mathbf{W}_{\text{intra}}$ and $\mathbf{W}_{\text{inter}}$, which are based on use rather than use-plus-delivery shares. Again, remainder inter-industry spillovers turn our insignificant, such that we proceed with a model entertaining a first-order spatial regressive error process in $\mathbf{W}_{\text{intra}}$. As can be seen from column (2b), the results are virtually identical to those in column (1b), where the weights matrices are based on use-plus-delivery shares.

As a second robustness check, we consider the results when the use-plus-delivery based weights matrix in the main equation and the error process is generated from the predicted values of a gravity model, including country-pair dummies, industry-pair dummies, and distance between countries (or internal distance for domestic use-plus-delivery intensities) as determinants of use-plus-delivery intensities across industry-country-pairs. This approach aims at avoiding the potential endogeneity of intermediate goods flows, similar to an instrumental variable model.[17] Appendix A3 gives a more detailed description of the construction of the predicted weights matrix, referred to as $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{inter}}$ as well as $\hat{\mathbf{W}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}_{\mathbf{inter}}$. Columns (3a) and (3b) in Table 2 report the results, using $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{inter}}$ to construct the R&D spillover terms in the main equation and $\hat{\mathbf{W}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}_{\mathbf{inter}}$ as weights matrices in the error process. Again, our findings are qualitatively and quantitatively similar to the results using the original weights matrices, which are based on actual values.

[16] Table 2 reports the results for the specification where R&D is assumed to be non-separable. The corresponding results and differences for the specification where R&D is assumed to be separable are qualitatively very similar as for the least squares estimates. (See the discussion in subsection 1 of section IV).

[17] Our approach is inspired by that of Frankel and Romer (1999), who use (the country-specific sum) of predicted bilateral trade flows from a 'geographical' gravity model as an instrument in a cross-country regression of per capita income on (endogenous) trade and country size.

We admit that endogeneity of conditional factor demand is a concern in empirical productivity studies.[18] However, instrumental variable procedures using outside instruments typically use much more parsimonious models than we do (typically, they rely on Cobb Douglas technologies and specify value added primarily as a (log-)linearly separable function of primary production factors capital and labor only; see Olley and Pakes, 1996). Accordingly, functional misspecification may be a concern in some of these studies. This is avoided with a more flexible technology such as a translog or a generalized Leontief production function at hand. Yet, then the number of potentially endogenous variables 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. First, the Ramsey-test is insignificant in all models and, hence, does not point to misspecification. Second, the LS and FGLS estimates are fairly close, which is unlikely to be the case under pronounced endogeneity (see Wooldridge, 2006, p. 286). Third, judged against the results of previous studies on R&D spillovers using other econometric techniques, our parameters estimates are in a plausible range (see subsection 1 of section IV,). Finally, while the point estimates of the parameters 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, which is the focus of our paper.

V. Conclusions

This paper considers the productivity effects of knowledge and other type of spillovers, using a cross-section of 13 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 product or factor market characteristics). To account for the latter, we adopt a spatial econometric approach.

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

In our estimation of knowledge spillovers, we extend the empirical analysis by Coe and Helpman (1995) along three lines. First, we use industry rather than country data. Second, we test for differences in intra- and inter-industry spillovers related to R&D. Third, we allow for remainder spillovers beyond those embodied in R&D, which are not further specified but hypothesized to be related to input-output linkages as well. For the latter, allowing intra-industry spillovers to differ from inter-industry spillovers requires a spatially autoregressive model for residuals with two rather than a single channel of interdependence. Suitable for our dataset with cross-sectional interdependence and pronounced heteroskedasticity, we use an extension of the heteroskedasticity-robust GM estimator by Kelejian and Prucha (2009), which allows for two spillover channels and parameters of interdependence (intra- and inter-industry spillovers).

The results suggest that own R&D enhances productivity and also point to sizeable knowledge spillover effects on productivity, transmitted through both inter-industry and intra-industry use of intermediate goods. Inter-industry R&D spillovers dominate intra-industry

[18] See Thursten and Libby (2002).

spillovers, which turn out much smaller and even insignificant in some specifications. There is also evidence for sizable remainder spillovers which are not related to R&D but also transmitted through input-output linkages. However, statistically significant remainder spillovers are only found within or among very similar industries; there is no evidence of inter-industry spillovers unrelated to R&D. Shocks to total factor productivity unrelated to knowledge are amplified by roughly a factor of two through intra-industry spillovers and the associated repercussions. The results may be interpreted as evidence of an even stronger intra-industry spillover mechanism for shocks to total factor productivity which are unrelated to knowledge than for ones that are embedded in knowledge.

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Appendix A1. Data and Sample

A1.1 Data Sources

Our final sample is determined by data availability and comprises 13 countries (CAN, CZE, DEU, DNK, ESP, FIN, FRA, GBR, ITA, NLD, NOR, POL, USA) and 15 industries (see below). Of the 195 observations, data on investment and R&D expenditures is missing for some countries and industries such that 170 observations remain. 20 of the 25 missing observations were imputed from higher levels of aggregation; the other missing values were approximated, using the ratio of a variable's value in the particular industry to the average value across all available industries. Data on value added (in 1995 prices) and employment (hours worked) are taken from the Groningen Growth and Development Center (GGDC). Investment data are from the OECD Structural Analysis (STAN) database. Data on R&D expenditures are from the OECD's Analytical Business Enterprise Research and Development (ANBERD) database. The cross-section data refer to 1995, a choice dictated by the availability of input-output tables, which refer to the period around 1995. Investment- and R&D intensities are averages over the longest available time span over the period 1990-2000. Data on distances between countries and internal distance within countries are from the CEPII database (http://www.cepii.fr/).

Input-output data to construct the weights matrix are from the OECD input-output database. International input-output flows by industry are assumed to exhibit the same bilateral trade pattern as total trade. Information on the level of imported intermediate goods (i.e., international use of intermediates) of industry k from industry l is combined with bilateral import shares in total imports of industry k. Exports of intermediate goods (i.e., international delivery of intermediates) of industry k to foreign industries l are assumed to be symmetric to imports of industry l from foreign industries k and combined with bilateral export shares in total exports in industry k.[19] The shares of bilateral import and exports in total trade at the industry level are calculated from the OECD's STAN bilateral trade database.

A1.2 List of Industries and Summary Statistics

< Table A1 >

[19] The relevance of this approximation is reduced by the fact that all weights matrices based on delivery of intermediate goods are row-normalized; as a consequence, the more relevant assumption is that bilateral export shares in total exports are equal to bilateral shares in intermediate goods exports. In addition, we consider weights matrices which are based on the use of intermediate goods only in the sensitivity analysis.

Appendix A2. Econometric Issues

Estimation of the main equation (1), i.e, $\mathbf{y} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{u}$, is standard. The least squares (LS) estimator is $\hat{\boldsymbol{\gamma}} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{y}$ and the generalized least squares (GLS) estimator is given by $\hat{\boldsymbol{\gamma}}^* = (\mathbf{Z}^{*\prime}\mathbf{Z}^*)^{-1}\mathbf{Z}^{*\prime}\mathbf{y}^*$, where the asterix indicates the use of transformed matrices[20], which depend on the spatial regressive parameter ρ (or ρ_{intra} and ρ_{inter} in the second order case). The feasible generalized least squares (FGLS) is defined as $\hat{\hat{\boldsymbol{\gamma}}}^* = (\tilde{\mathbf{Z}}^{*\prime}\tilde{\mathbf{Z}}^*)^{-1}\tilde{\mathbf{Z}}^{*\prime}\tilde{\mathbf{y}}^*$, where the ~ indicates that the GM estimate $\tilde{\rho}$ (or the estimates $\tilde{\rho}_{\text{intra}}$ and $\tilde{\rho}_{\text{inter}}$) are used to calculate the transformed matrices. In the following we outline the GM procedure to obtain estimates of the spatial regressive parameters of the error process.

A2.1 Estimation of First Order Spatial Regressive Error Process

Consider the model with a first order spatial autoregressive error process (SAR1):

$$\mathbf{u} = \rho\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}, \qquad \text{(A.1)}$$

where **X** is a matrix of explanatory variables and $\boldsymbol{\varepsilon}$ is a stochastic error term. Having obtained consistent estimates of **u** from the main model, the generalized moments (GM) estimator by Kelejian and Prucha (2009) can be used to estimate the spatial regressive parameter ρ in equation (A.1). It is based on the following moment conditions, which rely on independently though not necessarily identically distributed disturbances ε_i and some restrictions on the properties of the weights matrix:

$$N^{-1}E[\bar{\boldsymbol{\varepsilon}}'\bar{\boldsymbol{\varepsilon}} - Tr\{\mathbf{W}diag_{i=1}^{N}[(E\varepsilon_i^2)]\mathbf{W}'\}] = 0, \text{ and} \qquad \text{(A.2a)}$$

$$N^{-1}E\bar{\boldsymbol{\varepsilon}}'\boldsymbol{\varepsilon} = 0, \qquad \text{(A.2b)}$$

where $\bar{\boldsymbol{\varepsilon}} = \mathbf{W}\boldsymbol{\varepsilon}$; *N* is the total number of observations and *Tr* is the trace operator. Alternatively, the moment conditions can be written as

$$N^{-1}E(\boldsymbol{\varepsilon}'\mathbf{A}_1\boldsymbol{\varepsilon}) = 0, \text{ or} \qquad \text{(A.3a)}$$

$$N^{-1}E(\boldsymbol{\varepsilon}'\mathbf{A}_2\boldsymbol{\varepsilon}) = 0, \qquad \text{(A.3b)}$$

where $\mathbf{A}_1 = \mathbf{W}'\mathbf{W} - diag_{i=1}^{N}(\mathbf{w}_{.i}'\mathbf{w}_{.i})$ with $\mathbf{w}_{.i}$ denoting the *i*-th column of $\mathbf{W}$, and $\mathbf{A}_2 = \mathbf{W}$.

Substituting for $\boldsymbol{\varepsilon} = (\mathbf{I}-\rho\mathbf{W})\mathbf{u}$ yields a two equation system in ρ and ρ^2. Its empirical counterpart is given by:

$$\tilde{\boldsymbol{\pi}} - \tilde{\boldsymbol{\Pi}}\boldsymbol{\eta} = \boldsymbol{\upsilon}, \qquad \text{(A.4)}$$

where $\boldsymbol{\eta} = [\rho, \rho^2]'$ and the elements of the 2×1 vector $\tilde{\boldsymbol{\pi}}$ and the 2×2 Matrix $\tilde{\boldsymbol{\Pi}}$ can be calculated from the estimates of **u** and the elements of the weights matrix **W**; $\boldsymbol{\upsilon}$ can be regarded as a vector of regression residuals. The GM estimator of ρ is now defined as weighted nonlinear least squares estimator based on (A.4). It is obtained by solving

$$\tilde{\rho} = \underset{\rho}{argmin}\, [(\tilde{\boldsymbol{\pi}} - \tilde{\boldsymbol{\Pi}}\boldsymbol{\eta})'\tilde{\boldsymbol{\Psi}}^{-1}(\tilde{\boldsymbol{\pi}} - \tilde{\boldsymbol{\Pi}}\boldsymbol{\eta})], \qquad \text{(A.5)}$$

where $\tilde{\boldsymbol{\Psi}}^{-1}$ is (a consistent estimate of) the optimal weighting matrix (defined below), ensuring asymptotic efficiency of $\tilde{\rho}$.

A2.2 Estimation of Second Order Spatial Regressive Error Process

Kelejian and Prucha (2009) consider only one homogenous parameter ρ in the spatial regressive process. Badinger and Egger (2008) consider a more general specification, which allows for *M* heterogeneous parameters in the spatial autoregressive process:

[20] For the definition of the transformed series see equation (4) and the surrounding discussion.

$$\mathbf{u} = \sum_{m=1}^{M} \rho_m \mathbf{W}_m \mathbf{u} + \boldsymbol{\varepsilon}, \tag{A.6}$$

where the matrices $\mathbf{W}_m$ have the same dimension as $\mathbf{W}$ in (A.1).[21] In the present paper, we have a second order process with

$$\mathbf{u} = \sum_{m=1}^{2} \rho_m \mathbf{W}_m \mathbf{u} + \boldsymbol{\varepsilon} = \rho_1 \mathbf{W}_1 \mathbf{u} + \rho_2 \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon}, \tag{A.7}$$

where we have set $\rho_1 \equiv \rho_{\text{intra}}$, $\mathbf{W}_1 \equiv \mathbf{W}_{\text{intra}}$, $\rho_2 \equiv \rho_{\text{inter}}$, and $\mathbf{W}_2 \equiv \mathbf{W}_{\text{intra}}$.

The generalized GM estimator can be obtained by recognizing that – using the same assumptions as in Kelejian and Prucha (2009) – the moment conditions given by (A.3a) and (A.3b) must hold for each matrix $\mathbf{W}_m$, $m = 1,2$

$$N^{-1}E[\bar{\boldsymbol{\varepsilon}}_m' \bar{\boldsymbol{\varepsilon}}_m - Tr\{\mathbf{W}_m diag_{i=1}^{N}[(E\varepsilon_i^2)]\mathbf{W}_m'\}] = 0 \text{, and} \tag{A.8a}$$

$$N^{-1}E\bar{\boldsymbol{\varepsilon}}_m' \boldsymbol{\varepsilon} = 0, \tag{A.8a}$$

where $\bar{\boldsymbol{\varepsilon}}_m = \mathbf{W}_m \boldsymbol{\varepsilon}$. The moment conditions can be written alternatively as

$$N^{-1}E(\boldsymbol{\varepsilon}'\mathbf{A}_{1m}\boldsymbol{\varepsilon}) = 0, \tag{A9a}$$

$$N^{-1}E(\boldsymbol{\varepsilon}'\mathbf{A}_{2m}\boldsymbol{\varepsilon}) = 0, \tag{A.9b}$$

for m = 1, 2, where $\mathbf{A}_{1m} = \mathbf{W}_m'\mathbf{W}_m - diag_{i=1}^{N}(\mathbf{w}_{.i,m}'\mathbf{w}_{.i,m})$ with $\mathbf{w}_{.i,m}$ denoting the i-th column of $\mathbf{W}_m$, and $\mathbf{A}_{2m} = \mathbf{W}_m$.

From the specification of the error term in (A.7) it follows that

$$\boldsymbol{\varepsilon} = \mathbf{u} - \sum_{m=1}^{2} \rho_m \mathbf{W}_m \mathbf{u} = \mathbf{u} - \rho_1 \mathbf{W}_1 \mathbf{u} - \rho_2 \mathbf{W}_2 \mathbf{u} = \mathbf{u} - \rho_1 \bar{\mathbf{u}}_1 - \rho_2 \bar{\mathbf{u}}_2, \tag{A.10a}$$

$$\bar{\boldsymbol{\varepsilon}}_m = \mathbf{W}_m \boldsymbol{\varepsilon} = \mathbf{W}_m \mathbf{u} - \rho_1 \mathbf{W}_m \mathbf{W}_1 \mathbf{u} - \rho_2 \mathbf{W}_m \mathbf{W}_2 \mathbf{u} = \bar{\mathbf{u}}_m - \rho_1 \bar{\bar{\mathbf{u}}}_{m1} - \rho_2 \bar{\bar{\mathbf{u}}}_{m2}, \tag{A.10b}$$

where we use the following definitions:

$\bar{\mathbf{u}}_m = \mathbf{W}_m \mathbf{u}$, $\bar{\bar{\mathbf{u}}}_m = \mathbf{W}_m \mathbf{W}_m \mathbf{u}$, and $\bar{\bar{\mathbf{u}}}_{m1} = \mathbf{W}_m \mathbf{W}_1 \mathbf{u}$, $\bar{\bar{\mathbf{u}}}_{m2} = \mathbf{W}_m \mathbf{W}_2 \mathbf{u}$.

Substituting (A.10a)-(A.10b) into the moment conditions (A.8a)-(A.8b) or (A.9a)-(A.9b) we obtain the following four equation system:

$$\boldsymbol{\pi} - \boldsymbol{\Pi}\boldsymbol{\eta} = \mathbf{0},$$

where $\boldsymbol{\eta} = [\rho_1, \rho_2, \rho_1\rho_2, \rho_1^2, \rho_2^2]'$ and the elements of $\boldsymbol{\pi} = [\pi_1, \pi_2, \pi_3, \pi_4]'$ and $\boldsymbol{\Pi} = [\pi_{i,j}]_{i=1,\dots,4,j=1,\dots,5}$ are defined as follows:[22]

$$\pi_1 = N^{-1}E\{\bar{\mathbf{u}}_1'\bar{\mathbf{u}}_1 - Tr[\mathbf{W}_1 diag_{i=1}^{N}(u_{i,N}^2)\mathbf{W}_1']\} = N^{-1}E(\mathbf{u}'\mathbf{A}_{11}\mathbf{u}). \tag{A.11}$$

$$\pi_2 = N^{-1}E(\mathbf{u}'\bar{\mathbf{u}}_1) = N^{-1}E(\mathbf{u}'\mathbf{A}_{21}\mathbf{u}).$$

$$\pi_3 = N^{-1}E\{\bar{\mathbf{u}}_2'\bar{\mathbf{u}}_2 - Tr[\mathbf{W}_2 diag_{i=1}^{N}(u_i^2)\mathbf{W}_2']\} = N^{-1}E(\mathbf{u}'\mathbf{A}_{12}\mathbf{u}).$$

$$\pi_4 = N^{-1}E(\mathbf{u}'\bar{\mathbf{u}}_2) = N^{-1}E(\mathbf{u}'\mathbf{A}_{22}\mathbf{u}).$$

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[21] A similar extension of the moment conditions, although for the case of homoskedasticity as in Kelejian and Prucha (1999), is used by Bell and Bockstael (2000) as well as Cohen and Morrison Paul (2007).

[22] In the scalar expressions $\bar{u}_{m,i}$, the first subscript m refers to the matrix by which $\mathbf{u}$ is premultiplied and the second subscript i refers to the unit of observation.

$$\pi_{1,1} = 2N^{-1}E\{\bar{\bar{\mathbf{u}}}_1'\bar{\mathbf{u}}_1 - Tr[\mathbf{W}_1 diag_{i=1}^N(\bar{u}_{1,i}u_i)\mathbf{W}_{1,}']\} = 2N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{11}\mathbf{u})$$

$$\pi_{1,2} = 2N^{-1}E\{\bar{\bar{\mathbf{u}}}_{12}'\bar{\mathbf{u}}_1 - Tr[\mathbf{W}_1 diag_{i=1}^N(\bar{u}_{2,i}u_i)\mathbf{W}_{1,}']\} = 2N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{11}\mathbf{u}).$$

$$\pi_{1,3} = -2N^{-1}E\{\bar{\bar{\mathbf{u}}}_1'\bar{\bar{\mathbf{u}}}_{12} - Tr[\mathbf{W}_1 diag_{i=1}^N(\bar{u}_{2,i}\bar{u}_{1,i})\mathbf{W}_1']\} = -2N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{11}\mathbf{W}_2\mathbf{u}).$$

$$\pi_{1,4} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_1'\bar{\bar{\mathbf{u}}}_1 - Tr[\mathbf{W}_1 diag_{i=1}^N(\bar{u}_{1,i}^2)\mathbf{W}_1']\} = -N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{11}\mathbf{W}_1\mathbf{u}).$$

$$\pi_{1,5} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_{12}'\bar{\bar{\mathbf{u}}}_{12} - Tr[\mathbf{W}_1 diag_{i=1}^N(\bar{u}_{2,i}^2)\mathbf{W}_1']\} = -N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{11}\mathbf{W}_2\mathbf{u}).$$

$$\pi_{2,1} = N^{-1}E[\mathbf{u}'\bar{\bar{\mathbf{u}}}_1 + \bar{\mathbf{u}}_1'\bar{\mathbf{u}}_1] = N^{-1}E[\mathbf{u}'\mathbf{W}_1'(\mathbf{A}_{21}' + \mathbf{A}_{21})\mathbf{u}].$$

$$\pi_{2,2} = N^{-1}E[\mathbf{u}'\bar{\bar{\mathbf{u}}}_{12} + \bar{\mathbf{u}}_2'\bar{\mathbf{u}}_1] = N^{-1}E[\mathbf{u}'\mathbf{W}_2'(\mathbf{A}_{21}' + \mathbf{A}_{21})\mathbf{u}].$$

$$\pi_{2,3} = -N^{-1}E(\bar{\bar{\mathbf{u}}}_{12}'\bar{\mathbf{u}}_1 + \bar{\bar{\mathbf{u}}}_1'\bar{\mathbf{u}}_2) = -N^{-1}E[\mathbf{u}'\mathbf{W}_2'(\mathbf{A}_{21}' + \mathbf{A}_{21})\mathbf{W}_1\mathbf{u}].$$

$$\pi_{2,4} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_1'\bar{\mathbf{u}}_1] = -N^{-1}E[\bar{\mathbf{u}}_1'\bar{\bar{\mathbf{u}}}_1] = -N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{21}\mathbf{W}_1\mathbf{u}).$$

$$\pi_{2,5} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_{12}'\bar{\mathbf{u}}_2] = -N^{-1}E[\bar{\mathbf{u}}_2'\bar{\bar{\mathbf{u}}}_{12}] = -N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{21}\mathbf{W}_2\mathbf{u}).$$

$$\pi_{3,1} = 2N^{-1}E\{\bar{\bar{\mathbf{u}}}_{21}'\bar{\mathbf{u}}_2 - Tr[\mathbf{W}_2 diag_{i=1}^N(\bar{u}_{1,i}u_i)\mathbf{W}_2']\} = 2N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{12}\mathbf{u}).$$

$$\pi_{3,2} = 2N^{-1}E\{\bar{\bar{\mathbf{u}}}_2'\bar{\mathbf{u}}_2 - Tr[\mathbf{W}_2 diag_{i=1}^N(\bar{u}_{2,i}u_i)\mathbf{W}_2']\} = 2N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{12}\mathbf{u}).$$

$$\pi_{3,3} = -2N^{-1}E\{\bar{\bar{\mathbf{u}}}_{21}'\bar{\bar{\mathbf{u}}}_2 - Tr[\mathbf{W}_2 diag_{i=1}^N(\bar{u}_{2,i}\bar{u}_{1,i})\mathbf{W}_2']\} = -2N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{12}\mathbf{W}_2\mathbf{u}).$$

$$\pi_{3,4} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_{21}'\bar{\bar{\mathbf{u}}}_{21} - Tr[\mathbf{W}_2 diag_{i=1}^N(\bar{u}_{1,i}^2)\mathbf{W}_2']\} = -N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{12}\mathbf{W}_1\mathbf{u}).$$

$$\pi_{3,5} = -N^{-1}E[\bar{\bar{\mathbf{u}}}_2'\bar{\bar{\mathbf{u}}}_2 - Tr[\mathbf{W}_2 diag_{i=1}^N(\bar{u}_{2,i}^2)\mathbf{W}_2']\} = -N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{12}\mathbf{W}_2\mathbf{u}).$$

$$\pi_{4,1} = N^{-1}E[\mathbf{u}'\bar{\bar{\mathbf{u}}}_{21} + \bar{\mathbf{u}}_1'\bar{\mathbf{u}}_2] = N^{-1}E[\mathbf{u}'\mathbf{W}_1'(\mathbf{A}_{22}' + \mathbf{A}_{22})\mathbf{u}].$$

$$\pi_{4,2} = N^{-1}E[\mathbf{u}'\bar{\bar{\mathbf{u}}}_2 + \bar{\mathbf{u}}_2'\bar{\mathbf{u}}_2] = N^{-1}E[\mathbf{u}'\mathbf{W}_2'(\mathbf{A}_{22}' + \mathbf{A}_{22})\mathbf{u}].$$

$$\pi_{4,3} = -N^{-1}E(\bar{\bar{\mathbf{u}}}_2'\bar{\mathbf{u}}_1 + \bar{\bar{\mathbf{u}}}_{21}'\bar{\mathbf{u}}_2) = -N^{-1}E[\mathbf{u}'\mathbf{W}_2'(\mathbf{A}_{22}' + \mathbf{A}_{22})\mathbf{W}_1\mathbf{u}].$$

$$\pi_{4,4} = -N^{-1}E[\bar{\mathbf{u}}_1'\bar{\bar{\mathbf{u}}}_{21}] = -N^{-1}E(\mathbf{u}'\mathbf{W}_1'\mathbf{A}_{22}\mathbf{W}_1\mathbf{u}).$$

$$\pi_{4,5} = -N^{-1}E[\bar{\mathbf{u}}_2'\bar{\bar{\mathbf{u}}}_2] = -N^{-1}E(\mathbf{u}'\mathbf{W}_2'\mathbf{A}_{22}\mathbf{W}_2\mathbf{u}).$$

The GM estimate of $\tilde{\boldsymbol{\rho}} = [\rho_1\ \rho_2]$ is obtained by solving the nonlinear optimization problem

$$\tilde{\boldsymbol{\rho}} = [\tilde{\rho}_1\ \tilde{\rho}_2]' = \underset{\rho_1, \rho_2}{argmin}\ [(\tilde{\boldsymbol{\pi}} - \tilde{\boldsymbol{\Pi}}\boldsymbol{\eta})'\tilde{\boldsymbol{\Psi}}^{-1}(\tilde{\boldsymbol{\pi}} - \tilde{\boldsymbol{\Pi}}\boldsymbol{\eta})], \qquad (A.12)$$

where $\tilde{\boldsymbol{\pi}}$ and $\tilde{\boldsymbol{\Pi}}$ are the estimates of $\boldsymbol{\pi}$ and $\boldsymbol{\Pi}$, whose elements are obtained from (A.11) by suppressing the expectations operator and replacing the disturbances **u** by their estimates. $\boldsymbol{\Psi}^{-1}$ is the optimal weighting matrix, which is equal to the the variance-covariance matrix of the moment vector.[23] Since the optimal weighting matrix depends on the unknown parameters ρ_1

[23] In the general case with endogenous regressors, the optimal weighting matrix $\boldsymbol{\Psi}$ is not identical to the variance-covariance matrix of the moment vector, which is due to the fact that the GM estimator is based on estimated rather than the true disturbances. (See Kelejian and Prucha, 2009, and Badinger and Egger, 2008.)

and ρ_2 as will become clear in its definition below, the identity matrix can be used as weighting matrix instead to obtain initial consistent estimates.

A2.3 Asymptotic Properties of Parameter Estimates

In the following we state the asymptotic variance-covariance matrix of the estimates of the parameters of the main model and the spatial regressive error process, which is robust to heteroskedasticity. The first order case is treated in Kelejian and Prucha (2009). Badinger and Egger (2008) have extended the results for the case of a higher order model of arbitrary (finite) order. The present paper is a special case with a second order process and no spatial lag (or other endogenous regressors). The reader is referred to Badinger and Egger (2008) for a detailed statement of the assumptions and the proofs of the subsequent results.

A2.4 Asymptotic Normality of LS estimate $\hat{\boldsymbol{\gamma}}$ and FGLS estimate $\hat{\hat{\boldsymbol{\gamma}}}^*$

In light of Theorem 4 and Lemma 1 in Badinger and Egger (2008) the following result holds for the least squares estimator of model (1):

$$\hat{\boldsymbol{\gamma}} \overset{a}{\sim} \mathrm{N}(\boldsymbol{\gamma}, N^{-1}\boldsymbol{\Omega}_{\tilde{\gamma}}) \text{ with } \boldsymbol{\Omega}_{\tilde{\gamma}} = \mathbf{P}'\boldsymbol{\Psi}_{\Delta\Delta}\mathbf{P}\text{, where}$$

$$\mathbf{P} = \mathbf{Q}_{\mathbf{ZZ}}^{-1}\text{, with } \mathbf{Q}_{\mathbf{ZZ}} = \lim_{N\to\infty}(N^{-1}\mathbf{Z}'\mathbf{Z})\text{,}$$

$$\boldsymbol{\Psi}_{\Delta\Delta,N} = N^{-1}\mathbf{F}'\boldsymbol{\Sigma}\mathbf{F} \text{ with } \mathbf{F} = (\mathbf{I} - \sum_{m=1}^{2}\rho_m\mathbf{W}_m')^{-1}\mathbf{Z}\text{,}$$

and $\boldsymbol{\Sigma} = diag_{i=1,\ldots,N}(E\varepsilon_i^2)$.

For the FGLS estimator it holds that (compare Theorem 4 and Lemma 2 in Badinger and Egger, 2008):

$$\hat{\hat{\boldsymbol{\gamma}}}^* \overset{a}{\sim} \mathrm{N}(\boldsymbol{\gamma}, N^{-1}\boldsymbol{\Omega}_{\hat{\hat{\gamma}}^*}) \text{ with } \boldsymbol{\Omega}_{\hat{\hat{\gamma}}^*} = \mathbf{P}^{*\prime}\boldsymbol{\Psi}^*_{\Delta\Delta}\mathbf{P}^*\text{, where}$$

$$\mathbf{P}^* = \mathbf{Q}_{\mathbf{Z}^*\mathbf{Z}^*}^{-1} \text{ with } \mathbf{Q}_{\mathbf{Z}^*\mathbf{Z}^*} = \lim_{N\to\infty}(N^{-1}\mathbf{Z}^{*\prime}\mathbf{Z}^*)\text{, and}$$

$$\boldsymbol{\Psi}_{\Delta\Delta,N} = N^{-1}\mathbf{F}^{*\prime}\boldsymbol{\Sigma}\mathbf{F}^*\text{, and } \mathbf{F}^* = \mathbf{Z}^*.$$[24]

Estimates of $\boldsymbol{\Omega}_{\tilde{\gamma}}$ and $\boldsymbol{\Omega}_{\hat{\hat{\gamma}}^*}$ are obtained using $\tilde{\mathbf{P}} = (N^{-1}\mathbf{Z}'\mathbf{Z})^{-1}$, $\tilde{\mathbf{F}} = (\mathbf{I} - \sum_{m=1}^{2}\tilde{\rho}_m\mathbf{W}_1')^{-1}\mathbf{Z}$ or $\tilde{\mathbf{P}}^* = (N^{-1}\tilde{\mathbf{Z}}^{*\prime}\tilde{\mathbf{Z}}^*)^{-1}$ and $\tilde{\mathbf{F}}^* = \tilde{\mathbf{Z}}^*$ respectively. Finally, $\tilde{\boldsymbol{\Sigma}}_N = diag_{i=1,\ldots,N}(\tilde{\varepsilon}_i^2)$ where $\tilde{\boldsymbol{\varepsilon}} = (\mathbf{I} - \sum_{m=1}^{2}\tilde{\rho}_m\mathbf{W}_m)\tilde{\mathbf{u}}$ with $\tilde{\mathbf{u}}$ corresponding to the LS or FGLS residuals.

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[24] Note that if there is no spatial regressive error process ($\rho_1 = \rho_2 = 0$ such that $\mathbf{u} = \boldsymbol{\varepsilon}$) and under homoskedasticity of $\boldsymbol{\varepsilon}$ (i.e., $\boldsymbol{\Sigma} = \sigma_\varepsilon^2\mathbf{I}$), the expressions $N^{-1}\boldsymbol{\Omega}_{\tilde{\gamma}}$ and $N^{-1}\boldsymbol{\Omega}_{\hat{\hat{\gamma}}^*}$ boil down to the standard LS and FGLS variance-covariance matrices $\sigma_\varepsilon^2\mathbf{Z}'\mathbf{Z}$ and $\sigma_\varepsilon^2\mathbf{Z}^{*\prime}\mathbf{Z}^*$.

2. Asymptotic Normality of $\tilde{\boldsymbol{\rho}}$

For the (optimally weighted) GM estimate $\tilde{\boldsymbol{\rho}} = [\tilde{\rho}_1 \; \tilde{\rho}_2]$, it holds in light of Theorem 2 in Badinger and Egger (2008) that

$$\tilde{\boldsymbol{\rho}} \overset{a}{\sim} \mathrm{N}(\boldsymbol{\rho}, N^{-1}\boldsymbol{\Omega}_{\tilde{\boldsymbol{\rho}}}) \text{ with } \boldsymbol{\Omega}_{\tilde{\boldsymbol{\rho}}} = (\mathbf{J}'\boldsymbol{\Psi}^{-1}\mathbf{J})^{-1}.$$

The matrix $\mathbf{J} = \frac{\partial}{\partial \boldsymbol{\rho}'}\boldsymbol{\Pi}\boldsymbol{\eta} = \boldsymbol{\Pi}\mathfrak{B}$, where $\mathfrak{B}$ is a 5×2 matrix, defined as:

$$\mathfrak{B} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \rho_2 & \rho_1 \\ 2\rho_1 & 0 \\ 0 & 2\rho_2 \end{bmatrix}$$

The (inverse of the) optimal weighting matrix $\boldsymbol{\Psi}$ is of dimension 4×4 and defined as $\boldsymbol{\Psi}_N = (\boldsymbol{\psi}_{pq,N})$, $p,q = 1,2$, i.e., it consists of four 2×2 blocks

$$\boldsymbol{\psi}_{pq,N} = \begin{bmatrix} \psi^{11}_{pq,N} & \psi^{12}_{pq,N} \\ \psi^{21}_{pq,N} & \psi^{22}_{pq,N} \end{bmatrix}$$

with elements

$$\psi^{11}_{pq,N} = \frac{1}{2}N^{-1}Tr[(\mathbf{A}_{1p} + \mathbf{A}'_{1p})\boldsymbol{\Sigma}(\mathbf{A}_{1q} + \mathbf{A}'_{1q})\boldsymbol{\Sigma}],$$

$$\psi^{12}_{pq,N} = \frac{1}{2}N^{-1}Tr[(\mathbf{A}_{1p} + \mathbf{A}'_{1p})\boldsymbol{\Sigma}(\mathbf{A}_{2q} + \mathbf{A}'_{2q})\boldsymbol{\Sigma}],$$

$$\psi^{21}_{pq,N} = \frac{1}{2}N^{-1}Tr[(\mathbf{A}_{2p} + \mathbf{A}'_{2p})\boldsymbol{\Sigma}(\mathbf{A}_{1q} + \mathbf{A}'_{1q})\boldsymbol{\Sigma}],$$

$$\psi^{22}_{pq,N} = \frac{1}{2}N^{-1}Tr[(\mathbf{A}_{2p} + \mathbf{A}'_{2p})\boldsymbol{\Sigma}(\mathbf{A}_{2q} + \mathbf{A}'_{2q})\boldsymbol{\Sigma}].$$

Appendix A3. Construction of Predicted Weights Matrices

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

$$\ln w^0_{ik,jl} = \kappa_{i,j} + \eta_{k,l} + \gamma_{k,l}\ln DIST_{i,j} + \omega_{ik,jl}, \tag{A.13}$$

where $w^0_{ik,jl}$ is the use or the use-plus-delivery intensity as defined in equation (5), $\kappa_{i,j}$ is a set of country-pair dummies (*i*,*j* = 1, …, 13) 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 $DIST_{i,k}$ is the CEPII database (see Mayer and Zignago, 2006).

The model in (A.13) has potentially 619 parameters. For use-plus-delivery intensities, there are 37094 non-zero observations (of potentially 195×195 = 38025). One could avoid losing observations by employing a Poisson quasi-maximum likelihood model as suggested by Santos Silva and Tenreyro (2006). However, the latter obtains very similar effects in our case. Results indicate that the model performs reasonably well in predicting input-output flows. With an R^2 of 0.809 the model explains a substantial part of the variation in use-plus-delivery intensity across countries and industries. Hence, model (A.13) serves our purpose well, given our goal to generate exogenous weights from predicted values.

The parameter estimates of model (A.13) are then used to generate the elements of the predicted (unnormalized) weights matrix $\hat{\mathbf{W}}^0$ as follows:

$$\hat{w}^0_{ik,jl} = \exp(\hat{\kappa}_{i,j} + \hat{\eta}_{k,l} + \hat{\gamma}_{k,l} \ln DIST_{i,j})\,.^{25} \tag{A.14}$$

For observations with a zero entry, the predictions are set to zero as well. The matrix $\hat{\mathbf{W}}^0$ is then spilt up into two matrices $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{inter}}$ in exactly the same way as for the matrices for $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$ based on actual values (see subsection 2 of section III). As before, $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{intra}}$ and $\hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{inter}}$, which are used as alternative weights matrices in the main equation to construct the R&D spillover terms, are rescaled such that their average row-sum is equal to one respectively.

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

[25] 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 $E[\exp(\omega_{ik,jl})]$ (see Frankel and Romer, 1999, p. 384). Under normality $E[\exp(\omega_{ik,jl})] = \exp[(\sigma^2_{ik,jl}/2)]$, where $\sigma^2_{ik,jl}$ is the variance of $\omega_{ik,jl}$. Since ω is modelled as homoskedastic, this correction factor is the same for all observations and can be dropped without consequences for the results regarding the final row-standardized weights matrix.

Table 1. Estimation Results, Least-squares Estimates of the Systematic Part of the Model and GM Estimates of the Remainder Spillover Process in the Residuals

	(1)	(2)	(3)	(4)	(5a)	(5b)	(5c)
l	1.628^{***}	1.667^{***}	1.688^{***}	1.738^{***}	1.704^{***}	1.704^{***}	1.704^{***}
	(0.327)	(0.338)	(0.332)	(0.243)	(0.274)	(0.267)	(0.299)
k	2.783^{***}	2.978^{***}	2.321^{***}	2.542^{***}	2.149^{***}	2.149^{***}	2.149^{***}
	(0.928)	(0.909)	(0.730)	(0.850)	(0.635)	(0.635)	(0.643)
$\mathbf{l}^2$	-0.040^{*}	-0.040^{*}	-0.045^{*}	-0.028^{*}	-0.039^{**}	-0.039^{**}	-0.039^{**}
	(0.022)	(0.023)	(0.023)	(0.017)	(0.017)	(0.017)	(0.018)
$\mathbf{k}^2$	-0.387	-0.406	-0.317	-0.424^{**}	-0.335^{**}	-0.335^{**}	-0.335^{**}
	(0.262)	(0.270)	(0.213)	(0.200)	(0.140)	(0.140)	(0.150)
l k	-0.099^{**}	-0.112^{**}	-0.086^{**}	-0.121^{***}	-0.057	-0.057	-0.057
	(0.049)	(0.047)	(0.040)	(0.041)	(0.038)	(0.037)	(0.039)
rd		0.032^{**}	0.043^{**}	-0.112	-0.137	-0.137	-0.137
		(0.016)	(0.017)	(0.222)	(0.202)	(0.199)	(0.204)
$\overline{\mathbf{rd}}_{intra}$			0.036^{***}		0.057	0.057	0.057
			(0.014)		(0.162)	(0.159)	(0.154)
$\overline{\mathbf{rd}}_{inter}$			0.072^{***}		-0.185	-0.185	-0.185
			(0.016)		(0.136)	(0.132)	(0.134)
$\mathbf{rd}^2$				-0.020	0.012	0.012	0.012
				(0.019)	(0.026)	(0.025)	(0.023)
rd l				0.038^{***}	0.026^{**}	0.026^{**}	0.026^{**}
				(0.014)	(0.012)	(0.012)	(0.012)
rd k				-0.139^{***}	-0.060^{*}	-0.060^{*}	-0.060^{*}
				(0.038)	(0.032)	(0.032)	(0.031)
$\overline{\mathbf{rd}}^2_{intra}$					0.016^{*}	0.016^{*}	0.016^{*}
					(0.009)	(0.008)	(0.008)
$\overline{\mathbf{rd}}_{intra}$ **l**					-0.002	-0.002	-0.002
					(0.009)	(0.009)	(0.009)
$\overline{\mathbf{rd}}_{intra}$ **k**					0.012	0.012	0.012
					(0.026)	(0.027)	(0.025)
$\overline{\mathbf{rd}}^2_{inter}$					0.012	0.012^{*}	0.012^{*}
					(0.007)	(0.007)	(0.006)
$\overline{\mathbf{rd}}_{inter}$ **l**					0.006	0.006	0.006
					(0.007)	(0.007)	(0.008)
$\overline{\mathbf{rd}}_{inter}$ **k**					0.089^{***}	0.089^{***}	0.089^{***}
					(0.024)	(0.024)	(0.024)
rd $\overline{\mathbf{rd}}_{intra}$					-0.019	-0.019	-0.019^{*}
					(0.012)	(0.013)	(0.012)
rd $\overline{\mathbf{rd}}_{inter}$					-0.008	-0.008	-0.008
					(0.010)	(0.010)	(0.009)
$\overline{\mathbf{rd}}_{intra}\overline{\mathbf{rd}}_{inter}$					0.021^{***}	0.021^{***}	0.021^{***}
					(0.008)	(0.007)	(0.007)
Elasticities [1)]							
l	0.872^{***}	0.869^{***}	0.905^{***}	0.906^{***}	0.951^{***}	0.951^{***}	0.951^{***}
	(0.050)	(0.051)	(0.038)	(0.044)	(0.029)	(0.030)	(0.026)
k	0.507^{***}	0.493^{***}	0.402^{***}	0.470^{***}	0.379^{***}	0.379^{***}	0.379^{***}
	(0.075)	(0.074)	(0.075)	(0.068)	(0.066)	(0.067)	(0.061)
rd		0.032^{**}	0.043^{**}	0.043^{***}	0.067^{***}	0.067^{***}	0.067^{***}
		(0.016)	(0.017)	(0.016)	(0.017)	(0.018)	(0.015)
$\overline{\mathbf{rd}}_{intra}$			0.036^{***}		0.003	0.003	0.003

			(0.014)		(0.015)	(0.015)	(0.014)
$\overline{\mathbf{rd}}_{\text{inter}}$			0.072^{***}		0.042^{***}	0.042^{***}	0.042^{***}
			(0.016)		(0.015)	(0.015)	(0.013)
Adj. R^2	0.957	0.958	0.963	0.965	0.972	See (5a)	See (5a)
$\hat{\sigma}_u$	0.303	0.300	0.277	0.272	0.234	See (5a)	See (5a)
Ramsey [2)]	(0.776)	(0.415)	(0.698)	(0.231)	(0.256)	See (5a)	See (5a)
Error Process							
$\mathbf{Wu}$ [3)]	0.482^{***}	0.468^{***}	0.351^{**}	0.445^{***}	0.358^{**}		
	(0.215)	(0.218)	(0.188)	(0.210)	(0.225)		
$\mathbf{W}_{\text{intra}}\mathbf{u}$ [4)]	0.543^{***}	0.533^{***}	0.557^{***}	0.487^{***}	0.470^{***}	0 (imposed)	0.472^{***}
	(0.096)	(0.098)	(0.098)	(0.094)	(0.081)		(0.067)
$\mathbf{W}_{\text{inter}}\mathbf{u}$ [4)]	-0.070	-0.050	-0.150	-0.041	-0.079	0.048	0 (imposed)
	(0.239)	(0.253)	(0.192)	(0.240)	(0.220)	(0.190)	
$\hat{\sigma}_\varepsilon$	0.292	0.290	0.273	0.265	0.230	0.234	0.210
Breusch-Pagan [5)]	(0.028)	(0.003)	(0.014)	(0.008)	(0.020)	(0.021)	(0.017)
Moran's I	6.172^{***}	5.867^{***}	4.824^{***}	5.921^{***}	5.446^{***}	2.455^{**}	7.281^{***}
LM-Error	9.241^{***}	7.314^{***}	3.417^{*}	7.128^{***}	4.641^{**}	0.019	39.190^{***}
LM-Error^R	4.911^{**}	4.523^{**}	1.903	3.785^{*}	1.804	1.032	18.076^{***}
LM-Lag	6.345^{***}	3.430^{***}	2.123	5.117^{***}	6.185^{**}	1.663	32.014^{***}
LM-Lag^R	2.015	0.639	0.609	1.774	3.348^{*}	2.676	10.899^{***}

Notes: Dependent variable is ln$Y$. All models based on a cross-section of 195 observations (13 countries, 15 industries). ***, **, * indicate significance at 1, 5, and 10 percent. Heteroskedasticity-robust standard errors in parenthesis. All models include country-specific fixed effects. $\hat{\sigma}_u$ and $\hat{\sigma}_\varepsilon$ are asymptotic standard errors of $\mathbf{u}$ and $\boldsymbol{\varepsilon}$. [1)] Implied elasticities of Y with respect to L and K and with respect to a uniform increase in **rd** by 1 percent; standard errors calculated using the delta-method. [2)] Ramsey-test reports p-value of squared predicted value $\hat{\ln}^2 Y$. [3)] Optimally weighted GM estimate of ρ assuming a SAR1 process (i.e., $\rho_{\text{intra}} = \rho_{\text{inter}} = \rho$), based on least squares residuals. [4)] Optimally weighted GM estimates of ρ_{intra} and ρ_{inter} assuming a SAR2 process as given in equation (3), based on least squares residuals. [5)] Breusch-Pagan test for heteroskedasticity in epsilon. Spatial correlation tests, referring to model $\mathbf{y} = \phi\mathbf{Wy} + \mathbf{Z}\boldsymbol{\gamma} + \mathbf{u}$, $\mathbf{u} = \rho\mathbf{Wu} + \boldsymbol{\varepsilon}$, are as follows. Superscript R refers to "robust". Small sample corrected Moran's I: H_0: $\phi = 0$, $\rho = 0$; LM-Lag: H_0: $\phi = 0$ under $\rho = 0$; LM-Lag^R: H_0: $\phi = 0$, ρ unrestricted; LM-Error: H_0: $\rho = 0$ under $\phi = 0$; LM-Error^R: H_0: $\rho = 0$, ϕ unrestricted (Anselin, Bera, Florax, and Yoon, 1996).

Table 2. Estimation Results, FGLS Estimates of the Systematic Part of the Model and GM Estimates of the Remainder Spillover Process in the Residuals and Sensitivity Analysis

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
$\mathbf{l}$	1.992***	2.004***	2.028***	1.999***	1.804***	1.825***
	(0.268)	(0.251)	(0.270)	(0.242)	(0.235)	(0.216)
$\mathbf{k}$	2.282***	2.307***	2.278***	2.263***	2.091***	2.111***
	(0.746)	(0.593)	(0.775)	(0.582)	(0.683)	(0.567)
$\mathbf{l}^2$	-0.059***	-0.060***	-0.062***	-0.061***	-0.054***	-0.055***
	(0.017)	(0.016)	(0.018)	(0.015)	(0.014)	(0.014)
$\mathbf{k}^2$	-0.406***	-0.409***	-0.411**	-0.408***	-0.502***	-0.498***
	(0.154)	(0.130)	(0.164)	(0.134)	(0.149)	(0.135)
$\mathbf{l\,k}$	-0.079*	-0.080**	-0.079*	-0.075**	-0.050	-0.053
	(0.044)	(0.035)	(0.046)	(0.034)	(0.039)	(0.034)
$\mathbf{rd}$	-0.205	-0.209	-0.206	-0.194	-0.116	-0.122
	(0.208)	(0.183)	(0.212)	(0.180)	(0.230)	(0.195)
$\overline{\mathbf{rd}}_{intra}$	0.036	0.036	0.033	0.036	0.056	0.058
	(0.167)	(0.140)	(0.175)	(0.139)	(0.129)	(0.110)
$\overline{\mathbf{rd}}_{inter}$	-0.067	-0.067	-0.063	-0.070	-0.109	-0.104
	(0.133)	(0.116)	(0.137)	(0.115)	(0.094)	(0.086)
$\mathbf{rd}^2$	0.018	0.020	0.023	0.021	0.045	0.047*
	(0.026)	(0.021)	(0.028)	(0.021)	(0.033)	(0.028)
$\mathbf{rd\,l}$	0.030**	0.031***	0.031***	0.030***	0.028**	0.028***
	(0.012)	(0.011)	(0.012)	(0.010)	(0.012)	(0.010)
$\mathbf{rd\,k}$	-0.066**	-0.063**	-0.063*	-0.065**	-0.086**	-0.082**
	(0.033)	(0.028)	(0.035)	(0.029)	(0.037)	(0.033)
$\overline{\mathbf{rd}}^2_{intra}$	0.021**	0.021***	0.021**	0.021***	0.018***	0.018***
	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)	(0.006)
$\overline{\mathbf{rd}}_{intra}\,\mathbf{l}$	-0.002	-0.002	-0.002	-0.003	-0.010	-0.010
	(0.011)	(0.009)	(0.012)	(0.009)	(0.009)	(0.008)
$\overline{\mathbf{rd}}_{intra}\,\mathbf{k}$	0.035	0.034	0.035	0.034	0.015	0.013
	(0.027)	(0.022)	(0.028)	(0.023)	(0.021)	(0.019)
$\overline{\mathbf{rd}}^2_{inter}$	0.012*	0.012**	0.012*	0.013**	0.013***	0.013***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.004)	(0.004)
$\overline{\mathbf{rd}}_{inter}\,\mathbf{l}$	0.006	0.006	0.007	0.006	-0.001	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
$\overline{\mathbf{rd}}_{inter}\,\mathbf{k}$	0.042*	0.043**	0.039	0.044**	0.042***	0.041***
	(0.025)	(0.020)	(0.026)	(0.020)	(0.016)	(0.015)
$\mathbf{rd}\,\overline{\mathbf{rd}}_{intra}$	-0.020*	-0.020**	-0.021*	-0.021**	-0.035***	-0.035***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
$\mathbf{rd}\,\overline{\mathbf{rd}}_{inter}$	-0.012	-0.011	-0.012	-0.012*	-0.031***	-0.030***
	(0.009)	(0.007)	(0.009)	(0.007)	(0.010)	(0.009)
$\overline{\mathbf{rd}}_{intra}\,\overline{\mathbf{rd}}_{inter}$	0.023***	0.023***	0.023***	0.023***	0.008	0.008*
	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)
Elasticities 1)						
$\mathbf{l}$	0.915***	0.914***	0.913***	0.913***	0.935***	0.934***
	(0.028)	(0.022)	(0.030)	(0.023)	(0.027)	(0.025)
$\mathbf{k}$	0.164***	0.163***	0.150**	0.175***	0.227***	0.221***
	(0.060)	(0.049)	(0.063)	(0.050)	(0.055)	(0.048)
$\mathbf{rd}$	0.028*	0.028**	0.025	0.029**	0.053***	0.052***
	(0.016)	(0.013)	(0.017)	(0.013)	(0.020)	(0.017)
$\overline{\mathbf{rd}}_{intra}$	0.012	0.011	0.013	0.013	0.014	0.015
	(0.016)	(0.012)	(0.016)	(0.012)	(0.015)	(0.013)
$\overline{\mathbf{rd}}_{inter}$	0.037**	0.036***	0.036**	0.038***	0.044***	0.043***

	(0.015)	(0.011)	(0.015)	(0.011)	(0.015)	(0.013)
Adj. R^2	0.967	0.967	0.967	0.968	0.968	0.968
$\hat{\sigma}_u$	0.252	0.252	0.256	0.251	0.250	0.251
Ramsey [2)]	(0.939)	(0.954)	(0.726)	(0.793)	(0.791)	(0.826)
Error Process						
$\mathbf{W}_{\mathbf{intra}}\mathbf{u}$ [3)]	0.657^{***}	0.649^{***}	0.685^{***}	0.627^{***}	0.574^{***}	0.585^{***}
	(0.103)	(0.046)	(0.103)	(0.048)	(0.091)	(0.058)
$\mathbf{W}_{\mathbf{inter}}\mathbf{u}$ [3)]	-0.170	0 (imposed)	0.050	0 (imposed)	-0.062	0 (imposed)
	(0.257)		(0.175)		(0.241)	
$\hat{\sigma}_\varepsilon$	0.240	0.184	0.246	0.185	0.241	0.197
Breusch-Pagan	(0.025)	(0.017)	(0.026)	(0.010)	(0.006)	(0.021)
Moran's I	5.446^{***}	7.281^{***}	4.716^{***}	7.445^{***}	4.456^{***}	6.524^{***}
LM-Error	4.641^{**}	39.190^{***}	2.730^{*}	40.662^{***}	2.378	30.263^{***}
LM-Error^R	1.804	18.076^{***}	1.547	22.511^{***}	0.538	12.433^{***}
LM-Lag	6.185^{**}	32.014^{***}	1.918	26.455^{***}	3.762^{*}	24.520^{***}
LM-Lag^R	3.348^{*}	10.899^{***}	0.735	8.304^{***}	1.922	6.691^{***}

Notes: See Table 1. Column (1a)-(1b): FGLS estimates with heteroskedasticity-robust standard errors (compare columns (5a) and (5c) in Table 1). Columns (2a)-(2b): FGLS estimates, with $\mathbf{W}$ ($\mathbf{W}_{\mathbf{inter}}, \mathbf{W}_{\mathbf{intra}}$) based on use rather than use plus delivery shares. Columns (3a)-(3b): Weighing matrices based on predicted values from gravity model, i.e., $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}} = \hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{inter}}$ and $\mathbf{W}^{\mathbf{0}}_{\mathbf{intra}} = \hat{\mathbf{W}}^{\mathbf{0}}_{\mathbf{intra}}$ for construction of R&D spillover terms, and $\mathbf{W} = \hat{\mathbf{W}}$ ($\mathbf{W}_{\text{inter}} = \hat{\mathbf{W}}_{\text{inter}}$ and $\mathbf{W}_{\text{intra}} = \hat{\mathbf{W}}_{\text{intra}}$) in error process (see Appendix A3). R^2 refers to original model (generalized R^2). [3)] Optimally weighted GM estimates of ρ_{intra} and ρ_{inter}, assuming a SAR2 process as given in equation (3), based on FGLS residuals.

Table A1. List of Industries and Summary Statistics

ISIC Rev3	Industry	VA/ hour $/hour	Investment intensity percent of value added	R&D intensity percent of value added	Total use of intermediate goods percent of production	Inter-industry use	Domestic use percent of total use	domestic intra-industry use
15-16	Food products, beverages and tobacco	30.18	17.89	1.05	24.24	31.35	90.35	63.13
17-19	Textiles, textile products, leather and footwear	18.64	10.81	0.83	29.60	32.38	82.81	55.85
20	Wood and products of wood and cork	21.45	16.31	1.13	26.28	36.75	86.46	56.14
21-22	Pulp, paper, paper products, print.and publishing	33.09	19.04	0.55	32.94	24.43	82.21	63.05
23	Coke, refined petr. products and nuclear fuel	73.66	32.38	1.33	10.93	41.63	85.45	50.82
24	Chemicals and chemical products	54.01	21.12	10.47	30.64	37.49	70.98	39.41
25	Rubber and plastics products	28.93	18.45	2.23	33.83	76.26	69.50	18.88
26	Other non-metallic mineral products	30.47	19.20	1.21	22.56	57.47	83.96	37.40
27	Basic metals	39.93	20.67	2.18	36.86	35.43	76.58	47.10
28	Fabricated metal products	24.28	13.66	0.99	34.47	72.81	80.78	24.07
29	Machinery and equipment, n.e.c.	27.84	11.23	4.51	36.67	67.15	75.03	21.73
30-33	Electrical and optical equipment	30.71	15.43	13.50	37.09	42.42	66.62	32.73
34	Motor vehicles, trailers and semi-trailers	31.16	25.77	8.73	50.22	53.10	63.72	25.87
35	Other transport equipment	26.11	15.11	15.73	40.84	65.95	69.42	19.42
36-37	Manufacturing n.e.c.	20.17	11.93	0.73	30.96	83.98	84.59	13.03
	Column averages	32.71	17.93	4.34	31.88	50.57	77.90	37.91

Notes: Statistics are simple country averages. VA is value added in 1995 prices, 1995 US$. Investment intensity is share of gross fixed capital formation in value added in percent. R&D intensity is private and business enterprise R&D expenditures as share of value added. Use of intermediate goods corresponds to (average) row sum of unnormalized weights matrix $\mathbf{W}^{\mathbf{0}}$ (including domestic intra-industry use). Inter-industry use corresponds to average row sum of $\mathbf{W}^{\mathbf{0}}_{\mathbf{inter}}$. Domestic use corresponds to intra- and inter-industry use from industries of the same country. Domestic intra-industry use corresponds to main diagonal elements of $\mathbf{W}^{\mathbf{0}}$.