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# JENA ECONOMIC RESEARCH PAPERS



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by

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# Technology Flows between Sectors and its Impact on Large-Scale Firms

Jürgen Antony\* Thomas Grebel†

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## Abstract

In this paper we highlight the importance of technology flows between sectors and their impact on the labor productivity of large-scale corporations. Based on theoretical considerations, we explore technological spillovers between the sectors of an economy. Large-scale corporations usually focus on certain sectors but make use of a wide range of technological knowledge from other sectors. Thereby, technological knowledge built up in sectors by continuous R&D activities does not spill over without bounds but is directed by firms' absorptive capacities. We use firms' patent portfolio to empirically calculate the sector affiliation and therewith the firms' absorptive capacities in order to estimate the impact of technology diffusion on labor productivity. Fortune 500 firms serve as data base.

*Keywords:* Technology Flows, Spillovers, Firm Productivity

*JEL Classification Number:* O33, O14,

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# 1 Introduction

The aim of this paper is to measure the influence of technology flows at the level of large scale corporations. Firms differ in their usage of new technologies. This is obviously due to the fact that they produce different products with different technological knowledge and different degrees in quality. There are several studies trying to measure the impact of technological flows on e.g. productivity. These studies mainly use data on an aggregate level and not on the firm level. Coe and Helpman (1995) in their pioneering study find evidence for the positive influence of R&D capital stocks of different countries on the total factor productivity of the OECD countries. There are several studies building on their idea: Lichtenberg and de la Potterie (1996), Xu (1999) and Xu and Wang (2000) try to identify different channels through which technological knowledge flows between countries. Keller (1999, 2002b) finds evidence for the impact of technology diffusion via different channels on the sector level for the G7 countries<sup>1</sup>. On the firm level Keller and Yeaple (2003) find evidence that US manufacturing firms profit from technology spillovers via imports and foreign direct investments (FDI). Multinationals often play a key role in those studies when explaining technology spillovers. A proxy that is commonly used is FDI which is induced by firms which engage in different countries. However, what seems to be unexplored in literature is the driving forces of such mechanism, i.e. the idea that such large-scale companies profit from different technologies in terms of productivity gains and that this effect eventually diffuses to their country of engagement.

The focus of our study we put on the impact of technology spillovers on large-scale firms. We investigate to what extend large companies engaged in different fields and sectors of an economy make use of new technologies and translate them into productivity gains, as this clearly is the underlying assumption of the idea that multinational firms contribute to the distribution of new technologies around the world. Our units of analysis are large manufacturing firms, i.e. the manufacturing firms of Fortune 500 firms. We measure their ability to absorb technological knowledge generated in different sectors. We assume that their patent portfolio reflects their actual knowledge base which marks their capacity to absorb external technology knowledge. We explicitly take account of the fact that Fortune 500 firms are multinational conglomerates of subsidiary firms that spread over various sectors.

Aside from the fact that a firm's patent portfolio reflects the firm's absorptive capacity to make use of different technologies, the patent portfolio also gives information about sector-specific technological knowledge which allows to determine its virtual sector affiliation, although firms may indicate to do business only in a certain sector. Thus actual spillovers to an individual firm are filtered by its absorptive capacities built up in the past, which is indicated by its patent portfolio. In other words, the firm's technological proximity to other sectors has a crucial influence on the technology flows between sectors. We elaborate on this idea with a theoretical multi-sector model as developed below, incorporating the idea of technology spillovers between

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<sup>1</sup>Other studies on the productivity effect of technology spillovers on the sector level are Jacobs, Nahuys and Tang (1999) for the Netherlands and Brecher et al. (1996) for the US and Canada.

sectors and usability of the outcome of this process by a large-scale firm. Empirically we measure the propensity of technology spillovers with a technology flow matrix as in Keller (2002b), based on patent statistics and a technology concordance scheme (see Evenson et al. 1991).

The paper is organized as follows: Section 2 presents the theoretical model highlighting the importance of technology spillovers for large-scale firms that generate technological knowledge in different sectors of the economy. These results are used to guide the empirical analysis in the subsequent sections. The way we measure spillovers is discussed in section 3, by referring to the related literature and the according methodology. Section 4 gives a description of our data base. Results are presented in section 5 before we end the paper with a conclusion.

## 2 The Model

This section considers an  $I$ -sector economy to highlight the importance of technology spillovers in determining labor productivity. We interpret technology as a set of differentiated input factors, be it tangible or intangible ones, that originate from different sectors but can be used under sector-specific transfer costs by any sector. Transfer costs for intangible input factors, such as technological knowledge, we consider as a firm's efforts to build up absorptive capacities. The usability of the differentiated input factors determines the degree of technology spillovers.

### 2.1 Production

Production takes place at several stages. Final goods and service which can be used for consumption and for the production of input factors are produced from sector goods according to a Cobb-Douglas technology, thus the macroeconomic production function for the model economy is given by

$$Y = \exp \left( \sum_{i=1}^I \alpha_i \ln Y_i \right), \quad \sum_i \alpha_i = 1,$$

where  $Y_i$  is production of sector  $i$ . The different sector goods are thus assumed to be imperfect substitutes. The price for the final good is normalized to one.

### 2.2 Sector Production

In each sector of the economy we assume a large number of firms standing in perfect competition with each other. The production function for a representative firm  $j$ ,  $j = 1, 2, \dots, J$ , in sector  $i$  in time period  $t$  is given by

$$Y_{i,j} = L_{i,j}^\alpha \int_0^A x_k^{1-\alpha} dk, \tag{1}$$

where  $L_{i,j}$  is the amount of labor employed in production by firm  $j$  in sector  $i$ .  $A$  is the set of intermediate input factors currently available to sector  $i$ ,  $x_k$  denotes the amount of the  $k$ th intermediate input factor used in production. The level of technology is thus determined by the set of intermediate input factors  $A$ . Since we assume perfect competition at the sector level prices equal marginal costs.

Intermediate input factors are produced linearly from final output of the economy and depreciate fully after use. Free entry into the market for intermediate factors requires prices to equal marginal costs. These factors are assumed to have some sector specific components which make them most productive in the sector for which they were originally designed. However, other sectors can use these factors as well but with a lower productivity. We model this sector dependence by making use of “iceberg” transport or transfer costs between sectors. An intermediate input factor originating from sector  $l$  and used by sector  $i$  requires  $\tau_{l,i}$  units of final output for being produced. For these transfer costs we assume the structure  $\tau_{i,i} = 1$  and  $\tau_{l,i} > 1$  for all  $l \neq i$ . Hence, the price for an intermediate input factor originating from sector  $l$  and used by a firm in sector  $i$  equals  $\tau_{l,i}$

The demand for the  $k$ th intermediate input factor originating from sector  $l$  by sector  $i$  is derived from the usual marginal productivity condition and is given by

$$x_{i,k} = p_i^{\frac{1}{\alpha}} \tau_{l,i}^{-\frac{1}{\alpha}} (1 - \alpha)^{\frac{1}{\alpha}} L_i, \quad (2)$$

where  $p_i$  denotes the price for sector  $i$  goods and  $L_i = \sum_j L_{i,j}$ . Using this demand function in the production function for a firm  $j$  in sector  $i$  and aggregating over all firms as well as integrating over the different intermediate input factors, yields production in reduced form as

$$Y_i = p_i^{\frac{1-\alpha}{\alpha}} (1 - \alpha)^{\frac{\alpha}{1-\alpha}} \sum_{l=1}^I A_l \tau_{l,i}^{-\frac{1-\alpha}{\alpha}}, \quad (3)$$

where  $A_l$  denotes the set of intermediate input factors originating from sector  $l$ .

Since the technology for final good production is Cobb-Douglas, relative prices between sector  $i$  and sector  $l$  are given by

$$\frac{p_i}{p_l} = \frac{\alpha_i}{\alpha_l} \frac{Y_l}{Y_i}. \quad (4)$$

We assume that labor is mobile in the long run so that workers can move between sectors until wages between sectors equalize. This yields a distribution of the exogenously given labor force of the economy,  $L$ , between sectors given by  $L_i = \alpha_i L$ . As the price for final output in the economy is normalized to one, this implies a price for sector  $i$  goods in terms of final output of

$$p_i = \left( \sum_{l=1}^I A_l \tau_{l,i}^{-\frac{1-\alpha}{\alpha}} \right)^{-\alpha} \left[ \prod_{l=1}^I \alpha_l^{\alpha_l} \left( \sum_{n=1}^I A_n \tau_{n,l}^{-\frac{1-\alpha}{\alpha}} \right)^{\alpha \alpha_l} \right]. \quad (5)$$

Using this result in the production function (3) gives sector production as

$$Y_i = (1 - \alpha)^{\frac{1-\alpha}{\alpha}} L_i \left( \sum_{l=1}^I A_l \tau_{l,i}^{-\frac{1-\alpha}{\alpha}} \right)^{\alpha} \left[ \prod_{l=1}^I \alpha_l^{\frac{1-\alpha}{\alpha} \alpha_l} \left( \sum_{n=1}^I A_n \tau_{n,l}^{-\frac{1-\alpha}{\alpha}} \right)^{(1-\alpha)\alpha_l} \right] \quad (6)$$

and hence, labor productivity in sector  $i$  is given by

$$\frac{Y_i}{L_i} = (1 - \alpha)^{\frac{1-\alpha}{\alpha}} \left( \sum_{l=1}^I A_l \tau_{l,i}^{-\frac{1-\alpha}{\alpha}} \right)^{\alpha} \left[ \prod_{l=1}^I \alpha_l^{\frac{1-\alpha}{\alpha} \alpha_l} \left( \sum_{n=1}^I A_n \tau_{n,l}^{-\frac{1-\alpha}{\alpha}} \right)^{(1-\alpha)\alpha_l} \right] \quad (7)$$

In this result the effect of technology progress can clearly be seen. Labor productivity in sector  $i$  is affected by the availability of technology through two main channels. The first is the accessibility through the sector itself and is determined by how sector  $i$  can use technologies originating in other sectors. The second channel operates through a price effect. If other sectors have better access to the available technologies, their relative production increases and, hence, their relative price decreases through shrinking production costs. Due to this, the relative price of sector  $i$  goods increases as well as the nominal marginal product of intermediate input factors and thus raises the output per worker in sector  $i$  as shown in equation (7).<sup>2</sup>

### 2.3 Large-Scale Firms

So far the analysis examined labor productivity for a representative firm in one specific section. Large-scale firms such as Fortune 500 firms are usually active in several sectors. A way of modeling such an activity by using the above results is to assume that a large-scale corporation consists of many firms which are possibly active in different sectors. Thus, such a corporation is a conglomerate of different firms for which (7) is valid. Let  $\mu_i$  denote a portfolio weight which gives the fraction of ordinary labor employed in a multinational firm in sector  $i$  in total employment. Then aggregate labor productivity for such a firm,  $\frac{Y_{LS}}{L_{LS}}$ , is given by

$$\begin{aligned} \frac{Y_{LS}}{L_{LS}} &= \sum_{i=1}^I \mu_i \frac{Y_{i,j}}{L_{i,j}} = \\ &= (1 - \alpha)^{\frac{1-\alpha}{\alpha}} \sum_{i=1}^I \mu_i \left( \sum_{l=1}^I \tau_{l,i}^{-\frac{1-\alpha}{\alpha}} A_l \right)^{\alpha} \prod_{l=1}^I \left[ \alpha_l^{\frac{1-\alpha}{\alpha} \alpha_l} \left( \sum_{n=1}^I \tau_{n,l}^{-\frac{1-\alpha}{\alpha}} A_n \right)^{\alpha_l(1-\alpha)} \right] \end{aligned} \quad (8)$$

## 3 Measuring Spillovers

The starting point of the empirical analysis is equation (8) which gives the per capita production of a multinational firm, depending on the technological knowl-

<sup>2</sup>These two effects are already mentioned by Griliches (1979) who distinguished pecuniary effects from technological spillovers. Although it is easy to make this distinction on a theoretical bases, it can hardly be overcome by an empirical one, as we will see in the empirical part of this paper.

edge emerging in the different sectors of the economy. To empirically track this equation, we need to answer three basic aspects: firstly, how can we measure technology spillovers; secondly, what is the means of technology flows and thirdly, to which extent can spillovers flow in order to affect, if at all, a firm's labor productivity. Hereto, we clarify how we intend to measure knowledge in general and firm knowledge in specific in order to deliver some empirical evidence for the determinants of technology spillovers.

### 3.1 Related Literature

The first generation models of technology spillover generally used a non-parametric approach in constructing variables that account for technology flows between sectors and countries. These variables usually are weighted sums of R&D capital stocks (perpetual inventory method). Coe and Helpman (1995) study technology flows between OECD countries and their impact on total factor productivity in an inter-country context.

Others use data on input-output or capital flows to proxy the potential spillover pool. In this vein Keller (2002) as well as Terleckyj (1974) and Griliches (1979) model spillovers as a weighted sum of R&D stocks computed from the past expenditures on R&D.

A large strand of literature builds on patent data in order to proxy knowledge generated by innovators. In contrast to using R&D data the challenge in using patent data was always the difficulty to attribute the codified technological knowledge to specific industry sectors to measure the impact on a sector basis. This has been overcome by the Yale technology concordance scheme (Evenson et al. (1991)) which uses the information by the Canadian Patent Office that assigned to every patent the sector of origin and use of a new technology according to the ISIC classification. Such technology flow matrices have been used among others by Keller (2002b), Los and Verspagen (1999), Fikkert (1997), Evenson (1997) and Verspagen (1997).<sup>3</sup> When applying a concordance scheme such as the Yale concordance to match IPCs with ISIC sectors, this results in a spillover matrix between sectors.

Irrespective of how we measure the stock of technological knowledge and hence, the potential spillover pool of technological knowledge, there has to be a means of transmission that substantiates the actual flow of knowledge. Using intermediary goods as input factors, as we do in our theoretical model, one may think of an embodied technological progress. As a consequence, the pecuniary spillover to downstream sectors is not separable from spillovers induced by spillovers from disembodied technological knowledge (Griliches (1979)). Even if we cannot conciliate this issue to a full extent, we try to partially remedy this by interpreting and measuring input factors as distinct sector-specific knowledge blocks of firms. In other words, we

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<sup>3</sup>For a test of the accuracy of this concordance see Kortum (1997). For possible interpretations Verspagen (1997) gives ideas how to construct matrices capturing R&D spillovers between sectors. Both use the International Patent Classification (IPC) codes of a granted patent. To each patent a main IPC as well as supplementary IPC-codes are assigned. Verspagen (1997) suggests to interpret the main classification as indicating the source technology field of a patent and the supplementary IPCs as the possible fields of technology usage.



think of intermediary goods as knowledge blocks firms build up internally. And these knowledge blocks we deduce from the firms' individual patent portfolio. Using the Yale concordance scheme will render such sector-specific knowledge blocks by firm. This also implies in correspondence to our model that an increase in input factors, that is, an increase in a firm's technological diversity should have a positive impact on its productivity (Nesta (2007)). Hence, the actual means of transmission of technological knowledge is embedded in the firms' multi-sectoral activities.

Finally, the actual flow of spillovers needs clarification. The extent to which potential spillovers flow to the unit under investigation, be it countries, sectors or firms, respectively, is not equivalent to all. The more distance there is to some knowledge, the less intensive spillovers will be. The question about weights is addressed. What determines a firm's absorptive capacity. Coe and Helpman (1995) use bilateral trade shares to weight technology flows on a country level. Keller (2001a) offers a survey of the literature on some refinements of this approach. Lichtenberg und Pottelsberghe de la Potterie (1996) choose FDI as weights, whereas Xu and Wang (1999) take bilateral import shares in capital intensive goods. Xu (2000) uses data on multinational firms to construct weights. Keller (1999) applies the methodology of Coe and Helpman (1995) to different sectors of the G7 countries instead of on the whole economy. Keller (2002b) elaborates a technology flow matrix to weight sector-level spillovers and bilateral industry-specific import shares as country-level weights in order to analyze total factor productivity on the sectoral level for OECD countries. A recent approach emerged from the work in Keller (2002a) where the technology available to a country is modeled by a weighted sum of R&D stocks but with the weights estimated instead of deterministically computed from the data. In a nonlinear regression analysis, Keller uses parameterized exponential functions to measure the geographical distance between countries in order to model technology spillovers between sectors of the OECD countries. Keller (2001b) extends this approach by not only including geographical distance in the weight functions but also sector specific trade measures, FDI and communication channels to explain differences in total factor productivity. Jaffe (1986) uses a vector of patent applications over different technology classes for an individual firm to locate its position in technology space. As a measure of technological proximity between two firms he proposes the concentrated correlation between the elements of two such vectors, which renders the pairwise proximity of firms.

Since our focus is put on technology spillovers on a sector level, we think it best to use the Yale Technology Concordance scheme to calculate weights for firm-specific spillovers. As pointed out above, the concordance scheme generates sector weights out of the patent portfolio of an individual firm. These weights can be interpreted as a firm's sector affiliation; or, in the wake of our theoretical model, those weights tell us which sectoral-specific knowledge blocks a firm uses in order to produce their final goods and along with it, to which extent a firm is ready to absorb technological knowledge on a sectoral level.

### 3.2 Methodology

In this section we develop an econometric model adequate to estimate the relationship (8) which links per capita production to technology spillovers. The technique we use to construct the technology variable is taken from the empirical work on technology diffusion cited above. The models we estimate are based on equation (8) and are of the form

$$y_p = \beta_0 + \ln(S_p) + \gamma z_p + \varepsilon_p, \quad (9)$$

with

$$S_p = \sum_{i=1}^I (\mu_{p,i} E_i)^{\alpha_i},$$

where  $y_p$  is the logarithm of per capita production of the  $p$ th firm using sales as a proxy for output.  $S_p$  denotes firm  $p$ 's potential spillover pool.  $z_p$  is the vector of covariates and  $\gamma$  the corresponding coefficient vector.  $\varepsilon_p$  is the usual error term.  $\beta_0$  and  $\alpha_i$  are parameters to be estimated.  $\mu_{p,i}$  indicates a weighting factor taking into account the firm's absorptive capacities towards sector  $i$ . This weight is derived from the firm's patent portfolio using the Yale Technology Concordance scheme, i.e. we calculate the implied shares of the firm's patents in the total number of its patents originating from 22 two-digit ISIC sectors.

$E_i$  measures the effective knowledge capital available to a firm active in sector  $i$ . However, this number is not only determined by R&D expenditures by that sector. An innovation achieved through R&D in one sector is often used by other sectors as well because technology in general is transferable albeit at possible costs. Therefore we try to measure what a sector's effective state of technology is by using the Yale Technology Concordance again. We use a representative annual patent portfolio in the considered time span (see section on data) extracted from the European Patent Office (EPO) database<sup>4</sup> to see to what extend patents originating from one ISIC sector are used by other ISIC sectors. Let  $T$  denote the technology flow matrix described above. Its rows correspond to the sector of manufacture of technology and its columns to sectors of use. A typical element  $t_{li}$  of this matrix gives the importance of sector  $l$  in producing technology for use in sector  $i$ . We define relative importance  $t_{li}^r$  as  $\frac{t_{li}}{\sum_{i=1}^I t_{li}}$  which corresponds to our theoretical concept of  $\tau_{l,i}^{-\frac{1-\alpha}{\alpha}}$  giving the transferability of technology from sector  $l$  to sector  $i$ . We then calculate the effective state of technology for sector  $i$  as

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<sup>4</sup>ESPACE ACCESS, European and PCT International Patent Application Bibliography with patents WO-1978/000001-2007/150079 and EP-A-0000001-1871158.

$$E_i = \sum_{l=1}^I t_{li}^r R_l,$$

where  $R_l$  is the R&D capital stock of sector  $l$ .  $R_l$  is computed from past expenditure for R&D in sector  $l$  using the perpetual inventory method. Therefore

$$R_{l,t} = (1 - \delta)R_{l,t-1} + I_{l,t-1}, \quad (10)$$

where  $I_{l,t}$  denotes R&D expenditures in sector  $l$  in the year  $t$  and  $\delta$  is the rate of obsolescence taken as the usual 15% per year. The initial stock of knowledge by sector we calculate according to Griliches and Mairesse (1983) and Griliches and Clark (1984), as

$$R_{l0} = I_{l0}/(g_l + \delta),$$

where  $g$  is the average annual growth rate of R&D expenditures in sector  $l$ . To emphasize: each firm has idiosyncratic absorptive capacities concerning the potential knowledge spillover pool as provided by the effective sector knowledge capital. The weight to take into account absorptive capacities is proxied by the affiliation of firm  $p$  to sector  $i$  labeled as parameter  $\mu_{p,i}$ . Conclusively, the actual knowledge that spills over to firm  $p$  is the weighted sum over all sectors' effective knowledge capital scaled by the spillover parameter  $\alpha$ .

In the following, we test the hypothesis, implied by result (8), which forms the basis for the methodology outlayed above on the non-linear effects of the diffusion of technological knowledge on labor productivity. Of interest are the parameters  $\alpha_i$  as they measure the impact of effective knowledge capital on labor productivity. Allowing all  $\alpha_i$  to be different would result in a large number of parameters to be estimated. For simplification we distinguish only between two different values  $\alpha_l$  and  $\alpha_h$  which capture the impact from effective knowledge capital from low and high tech sectors. Low (high) tech sectors are characterized by an R&D intensity below (above) the OECD average.

In our estimations we work with a simplified linear version of the model (9). For this we define two alternative measures of the spillover pool,  $S_{p,l}$  and  $S_{p,h}$  which are defined as

$$S_{p,l} = \sum_{i=1}^I \Upsilon_{l,i} \mu_{p,i} E_i,$$

$$S_{p,h} = \sum_{i=1}^I \Upsilon_{h,i} \mu_{p,i} E_i.$$

Here,  $\Upsilon_{l,i}$  and  $\Upsilon_{h,i}$  are two indicator variables taking the value 1 if the sector  $i$

belongs to the low tech sectors and 0 otherwise.

## 4 Data

The database we use is a compilation of a patent and a financial data set.<sup>5</sup> The source of the former is the US Patent and Trademark Office (USPTO) offered by the National Bureau of Economic Research (Hall, et al. 2001), consisting of more than 3 million US patents since 1963. The latter were selected from the 1997 edition of Worldscope Global Researcher (WGR). The focus was put on the Fortune 500 (August 1998) firms. Since most of the largest companies do business in non-manufacturing sectors such as banking and insurance, only 162 companies as the largest manufacturing corporations were selected. All financial data are deflated into 1996 US dollars with the Implicit Price Deflator provided by the OECD. The lack in data on firm consolidation in the USPTO patent data set was overcome by using the Who owns Whom 2000 Edition. Thus, more than 300000 patents were identified. The technological knowledge is thereby encoded with the international technology classification (IPC). After cleaning the data set it remains an unbalanced panel data set of 106 companies observed between 1987 and 1996, which is equivalent to 866 observations.

Labour productivity we measure by the log of deflated sales over the number of employees. To control for firm size, we take the net value of property plant and equipment ( $C$ ). The number of employees is used as a proxy for labor ( $L$ ). Of course, it would be desirable to measure the actual value added, hours of work, wages and compensation in order to specify productivity more precisely, but this information is not provided by firms. As a proxy for knowledge capital of the individual firm ( $E$ ), we follow Griliches and Mairesse (1983) and Griliches and Clark (1984) and use the cumulated stock of past patent applications applying the permanent inventory method with a 15% obsolescence rate per year:  $E_{p,t} = \dot{g}(1 - \delta)E_{p,t-1}$  with  $\dot{g}_{p,t}$  as the number of patent grants of firm  $p$  in year  $t$  and  $\delta$  for the obsolescence of knowledge.<sup>6</sup> Furthermore, to measure the impact of R&D activities of other sectors on firms' labor productivity, we use OECD data on sectoral R&D spending as an explanatory variable. ( $E_{OECD}$ ) labels sectoral knowledge capital applying the perpetual inventory method as described above. ( $E_{p,OECD}$ ) is different for all firms, as we subtract firm R&D from ( $E_{OECD}$ ) for each firm  $p$ .

Thus, we intend to uncouple the endogeneity problem arising from knowledge capital on the firm level and the sectoral knowledge capital. On the sector level, we calculate the knowledge capital from R&D investment ( $R$ ) on the two-digit ISIC level, which serves as the potential spillover pool of the respective sectors. Aside from these long-term effects on productivity, we control for short-term changes in R&D activity by introducing R&D intensity measured by  $R$  over  $Y$ . Moreover, to allow for increasing returns we introduce labor ( $L$ ) as a further control variable.

Table 1 shows the corresponding descriptive statistics.

<sup>5</sup>Parts of the data have generously been provided by Lionel Nesta who collected the data together with Pari Patel.

<sup>6</sup>Compare Nesta (2007).

[Table 1 about here.]

Taking a closer look at the data: the 106 firms spread over 12 sectors (International Standard Industry Classification (ISIC) on a two digit level). All firms deliver indications about their principle business in the following sectors: Food (15, 4 firms), Tobacco products (16, 1 firm), Chemicals (24, 28 firms), Rubber and plastics (25, 1 firm), Other non-metallic mineral products (26, 2 firms), Basic metals (27, 6 firms), Fabricated metal products, except machinery and equipment (28, 4 firms), Machinery and equipment (29, 20 firms), Office, accounting and computing machinery (30, 12 firms), Electrical machinery and apparatus (31, 5 firms), Radio, television and communication (32, 8 firms), Medical precision and optical instruments (33, 3 firms), Other transport equipment (35, 4 firms) and furniture (36, 1 firm). Table 2 gives a general picture on the sectoral decomposition.

[Table 2 about here.]

The correlation matrix of the variables is depicted in table 3. Note, that we divided sectoral knowledge capital into two groups ( $e_{low}$  and  $e_{high}$ ). Given that all Fortune 500 deliver indications about the principle sector they do business in. We analogously categorized the ISIC-sectors into low and high-tech sectors, i.e. sectors with an below-average R&D-intensity account for low-tech sectors and vice versa. Correspondingly,  $e_{low}$  denotes the knowledge capital generated in low-tech ISIC-sectors and  $e_{high}$  the knowledge capital of high-tech ISIC-sectors.

[Table 3 about here.]

## 5 Results

To test equation 9, several econometric specifications have been formulated. To begin with, we executed within regressions of our pooled sample as shown in table 4. In all models we control for unobserved heterogeneity. All variables enter the estimation model in logs and minuscules indicate logarithmic magnitudes. In all regression we include fixed firm and time effects. We sequentially introduced the explanatory variables. In the first column we introduce net capital per employee to control for effects of capital intensity. Not surprisingly, an increasing capital intensity has a positive effect on labor productivity. R&D intensity measured by R&D expenditure per employee is added in column two in order to test whether short-term changes in R&D activities have an impact on labor productivity. Indeed, R&D activities do have a positive effect. A persistent commitment in research and development, however, is a crucial long-term input factor within a firm and therefore should also have a labor-productivity augmenting impact. Continuous R&D expenditure induces the growth of a firms' stock of knowledge. As the coefficient (0.136) in model (3) shows, it is significant.

In our theoretical model, we assume constant returns to scale. To relax this assumption in order to test scale effects, labor is introduced in the fourth model. Seemingly, Fortune 500 firms have to cope with decreasing returns to scale. This might be put

into perspective by the fact that we use a very restrictive concept of input factors owing to the limits of our data base, so we cannot examine the contribution of material input, which might bring the results closer to constant or rather increasing returns to scale. More to this point will be discussed later on.

Up to this point, we have basically introduced control variables. All coefficients are highly significant and deliver robust results. The aim of this paper is to shed some light on the diffusion of technological knowledge between sectors. The last column in table 4 offers first insights.<sup>7</sup> Overall, it especially is the knowledge capital generated in high-tech sectors that explains productivity gains to a significant extent. The coefficient of low-tech sector contrarily takes a negative sign but remains insignificant. This may be due to a possibly negligible R&D-activity by low-tech sectors. These preliminary results show that we observe a positive effect of spillovers on labor productivity which appears to be consistent with the literature.

[Table 4 about here.]

Now we will focus on the actual structural form of our theoretical model: Equation (9) states a non-linear setting. Table 5 contains two general non-linear models tested on the data. In both models we introduced the same control variables as in the within regressions in table 4. Furthermore, a non-linear term is added substantiating spillovers. The non-linear models (A) and (B) take the form:

$$(y - l)_{p,t} = \beta_0 + \beta_1(r - l)_{p,t} + \beta_2 l_{p,t} + \beta_3 e_{p,t} + \ln(S_p) + \varepsilon_p.$$

In Model (A) we have imposed the restriction  $\alpha = \alpha_l = \alpha_h$  assuming that effective sectoral knowledge capital  $E_i$  weighted by firm-specific absorptive capacity  $\mu_{p,i}$  has a positive impact on the firm-level labor productivity  $(y - l)_{p,t}$  regardless of the sector of origin. In the non-linear model (B) we distinguish between spillovers coming from low- and high-tech sectors, respectively, i.e.  $\alpha_l$  and  $\alpha_h$  are allowed to differ.

Moreover, in both non-linear settings we run regressions on the whole data set as well as on subsets. The decomposition separates low- and high-tech firms. Firms with a below average R&D intensity count as low-tech firms, firms with an above average R&D intensity belong to high-tech firms. Thus, we can differentiate knowledge flows. The regression runs in non-linear model (A) render all coefficients with a highly significant impact on labor productivity. Capital intensity, R&D intensity and knowledge capital have a throughout positive effect. Introducing labor, the estimates suggest decreasing returns to scale. But as already pointed out in the within regressions above, we did not include possible explanatory variables such as material input which might shift those estimates closer to constant or even increasing returns to scale. Nonetheless, what clearly can be stated: high-tech firms are closer to increasing returns than low-tech firms. Concerning spillovers from sectoral knowledge

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<sup>7</sup>As mentioned above, R&D expenditure of OECD countries account for more than 90% of worldwide R&D spending. The sectoral knowledge capital we calculated by using the Yale Technology Concordance scheme in contrast to firms' knowledge capital, where we used Jaffe's measure along with the permanent inventory method. Thus, we try to circumvent endogeneity problems.

capital: in general, total spillovers ( $\alpha_1$ ) are positive (0.098) but diminishing with a growing (worldwide) knowledge capital. Comparing subsets, the parameter values suggest that low-tech firms (0.122) profit more from external knowledge than high-tech firms (0.083).

[Table 5 about here.]

Trying to disentangle knowledge flows even further, the non-linear model ( $B$ ) supports even more our hypothesis of the labor-productivity-augmenting nature of spillovers. All coefficients of the control variables (column (3) to (6) in table (5)) remain consistent with the previous findings. The spillover parameter is now separated into spillovers from the low-tech sectors ( $\alpha_l$ ) and spillovers from the high-tech sectors ( $\alpha_h$ ). Considering the whole data set (column (4)), knowledge spillovers from low-tech sectors (0.122) appear to be higher than from high-tech sectors (0.101). However, when we look at the sub samples, evidently, it is the low-tech firms (column (6)) that profit more from spillovers by other sectors than high-tech firms (column (5)), although these gains by low-tech firms is higher from other low-tech sectors than from high-tech sectors. On the contrary, high-tech firms, though absorbing external technological knowledge, generally profit less from external technological knowledge than low-tech firms. Productivity gains of high-tech firms by spillovers from low-tech sectors remain positive but insignificant. This supports the hypothesis that technology diffusion is tentatively downstream. The returns from internal knowledge capital is higher in high-tech firms than in low-tech firms.

## 6 Conclusion

This paper investigated technology spillovers and their effects on labor productivity on the firm level. A simple equilibrium model is developed to substantiate the rationale underlying our empirical work. The model is governed by the transferability of technological knowledge between sectors subject to firm-specific absorptive capacities. The model shows that via price effects not only matters the accessibility to technology within a single sector, but even more the accessibility of technology across sectors matters in terms of gains in labor productivity.

To test the outcome of our analytical model the world's largest firms (Fortune 500) served as the database. Using patent data we constructed a measure of accessibility of technology and of sector affiliations of particular firms. By using aggregated data on R&D expenditures of the OECD countries decomposed with respect to manufacturing sectors, we found a significant impact of technological spillovers on labor productivity of large-scale firms that hold knowledge of different sectors of the economy.

The results support the hypotheses derived from our theoretical model and are consistent with the literature on technology flows and spillovers. Technology spillovers play a significant role in large-scale firms' labor productivity. Given the considered input factors, scale effects appear to be diminishing though near to constant returns. Presumably, when including remaining input factors such as material goods, large-scale firms may face increasing returns.

Low-tech firms experience higher productivity gains from other low-tech sectors than from high-tech sectors. Spillover effects from both types of sectors are always higher for low-tech firms than for high-tech firms. This is caused by spillovers as well as by price effects. Within the scope of the empirical data, both effects cannot be fully separated. This way, the results support the downstream argument of spillovers. Even more so, since spillovers for high-tech firms from low-tech sectors, though being positive, are insignificant.

In summary, technology spillovers matter in all sectors and they have a positive effect on firms' labor productivity.



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## Appendix

Derivation of result (3): From (2) it follows that

$$x_{i,k}^{1-\alpha} = p_i^{\frac{1-\alpha}{\alpha}} \tau_{l,i}^{-\frac{1-\alpha}{\alpha}} (1-\alpha)^{\frac{1-\alpha}{\alpha}} L_i^{1-\alpha}. \quad (11)$$

Integrating over all variants  $k$  and taking account of symmetry across variants in each sector yields

$$\int_0^A x_{i,k}^{1-\alpha} dk = p_i^{\frac{1-\alpha}{\alpha}} (1-\alpha)^{\frac{1-\alpha}{\alpha}} L_i^{1-\alpha} \sum_{l=1}^I A_l \tau_{l,i}^{-\frac{1-\alpha}{\alpha}}. \quad (12)$$

Premultiplying this result with  $L_i^\alpha$  gives the production function in reduced form as in (3).

Derivation of result (5): The price for final output is normalized to one. Therefore it holds due to the Cobb-Douglas production function for final output that

$$1 = \prod_{l=1}^I \left( \frac{p_l}{\alpha_l} \right)^{\alpha_l}, \quad (13)$$

$$1 = \frac{p_i}{\alpha_i} \prod_{l=1}^I \left( \frac{p_l \alpha_i}{p_i \alpha_l} \right)^{\alpha_l}. \quad (14)$$

Wage equality across sectors demands the marginal product of labor to equalize across sectors, i.e.  $\alpha p_i \frac{Y_i}{L_i} = \alpha p_l \frac{Y_l}{L_l}$ . Due to the Cobb-Douglas structure of final good production it holds that  $\alpha_l p_i Y_i = \alpha_i p_l Y_l$ . From these two conditions it directly follows that  $\frac{L_i}{L_l} = \frac{\alpha_i}{\alpha_l}$

Now

$$\frac{p_i}{p_l} = \frac{\alpha_i}{\alpha_l} \frac{Y_l}{Y_i}, \quad (15)$$

$$= \frac{\alpha_i}{\alpha_l} \left( \frac{p_l}{p_i} \right)^{-\frac{1-\alpha}{\alpha}} \frac{L_l \sum_n A_n \tau_{ln}^{-\frac{1-\alpha}{\alpha}}}{L_i \sum_n A_n \tau_{in}^{-\frac{1-\alpha}{\alpha}}}. \quad (16)$$

Which results in

$$\frac{p_i}{p_l} = \left( \frac{\sum_n A_n \tau_{ln}^{-\frac{1-\alpha}{\alpha}}}{\sum_n A_n \tau_{in}^{-\frac{1-\alpha}{\alpha}}} \right)^{\alpha}. \quad (17)$$

Using this expression in (14) gives

$$1 = \frac{p_i}{\alpha_i} \prod_{l=1}^I \left( \frac{\sum_n A_n \tau_{ln}^{-\frac{1-\alpha}{\alpha}}}{\sum_n A_n \tau_{in}^{-\frac{1-\alpha}{\alpha}}} \right)^{\alpha} \alpha_l \left( \frac{\alpha_i}{\alpha_l} \right)^{\alpha_l}, \quad (18)$$

which implies

$$p_i = \left( \sum_n A_n \tau_{in}^{-\frac{1-\alpha}{\alpha}} \right)^{-\alpha} \prod_{l=1}^I \left[ \alpha_l^{\alpha_l} \left( \sum_n A_n \tau_{ln}^{-\frac{1-\alpha}{\alpha}} \right)^{\alpha \alpha_l} \right] \quad (19)$$

Inserting this result into the reduced form production function (3) yields (6).

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Table 1: Descriptive statistics (pooled sample)

Variable	Observed	Average	S.D.	Max	Min
$C_p$	866	116250	643610	7669917	30.05
$R_p$	866	17639	110940	1664540	16
$Y_p$	866	396830	1909900	16600000	467.16
$L_p$	866	106480	110710	813000	647
$E_p$	866	7.1252	1.1274	9.4	2.39
$E_{p,OECD}$	866	86497	82640	320007	49.6588

C: net value of plant and equipment; R: R&D expenditure of firms;  
Y: sales; L: number of employees; E: knowledge capital of firms;  
 $E_{OECD}$ : knowledge capital of OECD sectors.

Table 2: Sectoral decomposition of the main variables (1987-1996)

ISIC	P	Y	L	Y/L	R/Y	E	E <sub>OECD</sub>
15 <sup>a</sup>	4	36363.9	224447.8	0.16886	0.0147466	432.6806816	2465.273
16 <sup>b</sup>	1	50311.71	162000	0.3103119	0.0084084	841.3434841	128.6875
24 <sup>c</sup>	27	539029.2	59983.78	14.37946	0.0656333	1473.893769	141255.5
25 <sup>d</sup>	1	12904.4	100274.6	0.1298152	0.0282183	817.2949127	15176.81
26 <sup>e</sup>	2	13110.63	71131	0.2429783	0.0238536	705.8304127	12929.75
27 <sup>f</sup>	6	12375.6	41567.81	0.639261	0.0181214	450.8627638	19291.47
28 <sup>g</sup>	4	9187.032	38251.07	0.2537707	0.0291629	458.6328505	11929.38
29 <sup>h</sup>	20	556973.8	174044.4	6.16448	0.0423905	1032.582268	46996.84
30 <sup>i</sup>	12	25696.11	112521.9	0.2609813	0.0699057	2190.902854	73113.93
31 <sup>j</sup>	5	28920.43	178208.7	0.1500111	0.0502106	2627.53126	45166.09
32 <sup>k</sup>	8	25043.54	123424.1	0.2188044	0.0739916	2210.115377	111103.2
33 <sup>l</sup>	3	2447107	87124.65	22.73517	0.0626321	1092.423607	52022.63
35 <sup>m</sup>	4	1219938	85048.65	32.10563	0.052773	669.1083465	264799.9
36 <sup>n</sup>	1	5987.872	46130	0.1282019	0.0156383	458.5182066	3888.15
Mean (Sum)	(106)	396825.5	106482.8	7.483797	0.0533834	1242.849492	86497.18

P: number of firms; Y: sales (in millions of 1996 US\$); L: number of employees; Y/L: deflated sales per employee (thousands of 1996 US\$); R/L: R&D expenditure per employee; E: knowledge capital generated by individual firms; E<sub>OECD</sub>: total knowledge capital of selected OECD sectors.

<sup>a</sup>Food products and beverages

<sup>b</sup>Tobacco products

<sup>c</sup>Chemicals and chemical products

<sup>d</sup>rubber and plastics products

<sup>e</sup>Other non-metallic mineral products

<sup>f</sup>Basic metals

<sup>g</sup>Fabricated metal products, except machinery and equipment

<sup>h</sup>Machinery and equipment

<sup>i</sup>Office, accounting and computing machinery

<sup>j</sup>Electrical machinery and apparatus

<sup>k</sup>Radio, television and communication equipment

<sup>l</sup>Medical precision and optical instruments

<sup>m</sup>Other transport equipment

<sup>n</sup>Furniture, manufacturing

Table 3: Correlation matrix (1997-1996); pooled sample (N=866)

	$y-l$	$e$	$l$	$e_{low}$	$e_{high}$	$C$	$r-l$
$y-l$	1						
$e$	-0.1667	1					
$l$	-0.2945	0.5162	1				
$e_{low}$	0.0694	0.044	-0.0404	1			
$e_{high}$	-0.0139	0.0397	0.1121	0.3695	1		
$C$	0.8727	-0.0885	-0.107	0.0179	-0.0711	1	
$r-l$	0.8597	0.0639	-0.1967	-0.1032	-0.0919	0.7808	1

$y-l$ : natural logarithm of deflated sales per employee;  $e$ : natural logarithm of firm knowledge capital;  $l$ : logarithm of labor;  $c-l$ : natural logarithm of gross capital per employee;  $l$ : natural logarithm of labor;  $e_{low}$ : natural logarithm of knowledge capital by low-technology sectors;  $e_{high}$  natural logarithm of knowledge capital by high-technology sectors;  $C$ : net value of plant and equipment;  $r-l$ : natural logarithm of R&D per employee.



Table 4: Spillover and productivity (pooled sample)

Dependent variable: log of sales per employee					
Within Regression	(1)	(2)	(3)	(4)	(5)
$C/L$	0.06 [0.006]***	0.042 [0.005]***	0.042 [0.005]***	0.028 [0.004]***	0.028 [0.004]***
$r - l$		0.285 [0.041]***	0.282 [0.041]***	0.199 [0.031]***	0.197 [0.031]***
$e_p$			0.136 [0.029]***	0.275 [0.033]***	0.259 [0.033]***
$l$				-0.324 [0.046]***	-0.324 [0.045]***
$s_{p,l}$					-0.001 [0.010]
$s_{p,h}$					0.051 [0.017]***
Constant	-1.489 [0.030]***	-0.15 [0.196]	-1.096 [0.288]***	1.173 [0.464]**	0.88 [0.470]*
Observations	862	862	862	862	862
Adjusted R-squared	0.72	0.78	0.79	0.82	0.82
F-test	41.73	64.83	67.51	108.69	98.09

(\*\*, \*\*\*) significant at 10%(5%,1%) level of significance;  
Fixed firm and time effects included, heteroskedasticity robust standard errors in brackets.

Table 5: Non-linear regressions (pooled sample)  
 Dependent variable: log of sales per employee

	Non-linear model (A)			Non-linear model (B)		
	(1) all firms	(2) high-tech	(3) low-tech	(4) all firms	(5) high-tech	(6) low-tech
$C/L$	0.026 [0.002]***	0.032 [0.003]***	0.015 [0.003]***	0.026 [0.002]***	0.033 [0.003]***	0.015 [0.003]***
$r - l$	0.215 [0.017]***	0.268 [0.025]***	0.15 [0.024]***	0.215 [0.017]***	0.267 [0.025]***	0.15 [0.024]***
$e_p$	0.314 [0.022]***	0.318 [0.030]***	0.277 [0.033]***	0.315 [0.022]***	0.314 [0.031]***	0.281 [0.034]***
$l$	-0.344 [0.025]***	-0.217 [0.035]***	-0.445 [0.035]***	-0.344 [0.025]***	-0.216 [0.035]***	-0.446 [0.035]***
$S_p (\alpha_1)$	0.098 [0.015]***	0.083 [0.020]***	0.122 [0.023]***			
$S_p (\alpha_l)$				0.122 [0.030]***	0.123 [0.114]	0.133 [0.033]***
$S_p (\alpha_h)$				0.101 [0.017]***	0.094 [0.037]**	0.121 [0.024]***
Constant	-14.431 [3.220]***	-12.244 [4.582]***	-14.341 [4.554]***	-14.553 [3.224]***	-12.38 [4.600]***	-14.662 [4.612]***
Observations	858	419	439	858	419	439
R-squared	0.82	0.89	0.61	0.82	0.89	0.61

\*(\*\*, \*\*\*) significant at 10%(5%,1%) level of significance;

Fixed firm and time effects included, heteroskedasticity robust standard errors in brackets.