universität wien

Diplomarbeit

Titel der Diplomarbeit

Labour Mobility and Knowledge Spillovers across Industries

Verfasser

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angestrebter akademischer Grad

Magister der Sozial- und Wirtschaftswissenschaften (Mag. rer. soc. oec.)

Wien, im November 2008

Studienkennzahl laut Studienblatt	A140
Studienrichtung:	Diplomstudium Volkswirtschaft
Betreuer:	Univ.Ass. PhD Neil Foster

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1 Abstract

This paper addresses the link between productivity and labour mobility. The hypothesis tested in the paper is that technology is transmitted across industries through the movement of skilled workers embodying human capital. The embodied knowledge is then diffused within the new environment creating spillovers and leading to productivity improvements.

A theoretical framework is presented wherein productivity growth is modelled through knowledge acquisition with respect to labour mobility. The empirical estimates confirm the existence of positive cross-sectoral knowledge spillovers and indicate that labour mobility has beneficial effects on industry productivity.

2 Literature Overview

The recent literature on endogenous growth emphasizes the importance of R&D as a source of national productivity growth and analyzes the spillover of the resulting knowledge and technology across firms, industries and countries. The extent of technology transfer is one of the key determinants of the world's distribution of productivity. If technology is easily diffused we would expect to find convergence across countries in terms of productivity, while a limited diffusion of technology favours divergence.

A large empirical literature has developed considering the extent of technology diffusion across firms, industries and countries. In this literature a number of channels of technology diffusion have been considered, including input-output linkages, trade, human capital, FDI and distance. Despite a theoretical foundation for diffusion being provided by the relatively recent development of endogenous growth theory a number of empirical papers on spillovers, particularly those on domestic spillovers, predate the development of endogenous growth models indicating the long-held belief in the importance of such diffusion (see for example, Gerschenkron, 1962)

Griliches (1979) broadly categorizes the spillovers channels into two main sources of potential externalities generated by R&D activities – rent spillovers and knowledge spillovers. Rent spillovers occur since the innovator cannot perfectly discriminate and prices as a result are not fully adjusted for quality improvements. Knowledge spillovers arise because of the imperfect appropriability of the knowledge associated with innovations (Cincera et al. 2001). The reasons are manifold: poor patent protection, reverse engineering practices and other knowledge leaks for example due to labour mobility all contribute to the dispersion of knowledge.

The recent literature on R&D spillovers has mainly focused on rent spillovers. The pioneering work of Terleckyj (1974) points out the importance of input/output relations for domestic technological spillovers. The estimated indirect effects of privately financed R&D on other industries are considerably larger than the direct effects on the industry conducting R&D. Terleckyj finds no comparable effects for government-financed industrial R&D. Despite the early stage of his framework he already includes human capital into the analysis. Another study of inter-industry spillovers was that of Bernstein and Nadiri (1988) who analyse five high-technology industries in the US and find that "variable costs for each industry was reduced by R&D capital spillovers"[1]. In their analysis they estimate the social rate of return to R&D through spillovers to be 77 to 150% greater than the private return and thus confirm the finding of Terleckyj (1974).

Coe and Helpman (1995) (henceforth CH) extend the approach adopted by Terleckyj (1974) to the international context using import weights rather than input-output weights to model how R&D is imported across countries. In their model TFP depends on the cumulative domestic R&D effort in an economy as well as on the foreign technological knowledge, transmitted through trade. Therefore countries trading primarily with partners having high levels of technological knowledge will benefit more from spillovers than countries whose trading partners have comparatively low levels of technological knowledge. They test their model on 22 OECD economies finding evidence in favour of the importance of international trade of goods and services for the diffusion of technology across countries.[2]

The method used by CH to calculate the foreign R&D stock has been criticized on a number of grounds. Lichtenberg and van Pottelsberghe de la Potterie (1996) (henceforth LP) for example correct the original specification of the foreign knowledge variable for country mergers. Keller (1998) questions the assertion that a country's benefit from knowledge created abroad is taken to be a trade-weighted average of foreign countries knowledge stocks. He compares the results of CH with those from assigning bilateral trade partners randomly and finds that regressions based on simulated data generate on average larger estimated foreign knowledge spillovers. Coe and Hoffmaister (1999) re-examine the work of Keller (1998) noting that the weights he constructs are essentially simple averages with a random error and that by choosing them completely randomly, the R&D spillover variable is no longer significant to explain TFP. They conceded however that the actual intensity of the trading relationship may be of limited importance because of the public good nature of knowledge.

A further important contribution to the debate has been made by Kao, Chiang and Chen (1999). They criticize the OLS estimation method used by CH under panel cointegration, which leads to a second-order asymptotic bias and hence to invalid standard

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[1] See Bernstein and Nadiri (1988) p.5f.

[2] This approach was extended to consider the importance of North-South spillovers by Coe, Helpman and Hoffmaister (1997).

errors. Alternative estimation procedures, such as Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS), have been designed to be able to calculate valid t-statistics. Kao and Chiang show that these estimation procedures have superior small-sample properties and by using the CH data set they find little evidence of significant international knowledge spillover effects through import flows. Later studies by Lee (2006) and Frantzen (2000) however support the role of trade as a source of spillovers even when taking cointegration into account. Lee reproduces the results of Kao et al. and then uses the method suggested by LP for the calculation of the foreign R&D stock whereupon he finds significant spillover effects through trade.

More important for the analysis in this paper are the studies focussing on inter-industry technology transmission. Most of the studies in this field use input-output relations in order to measure spillovers since they have been shown to perform better than technology flow matrices which indicate the usage of technology developed in other industries (Keller 2002). As mentioned before, the first studies in this field were done by Bernstein and Nadiri (1988) and Terleckyj (1974). More recently, Wang (2007) analyses trade related North-South and indirect South-South technology spillovers at the industry level. The results clearly show that North-South trade related R&D has substantial impact on TFP in the South. South-South trade also promotes technological spillovers but the effects tend to be smaller. Wang also looks at the importance of human capital for the absorptive capacity of a country and the findings suggest that human capital plays a significant role in facilitating spillovers (see also Engelbrecht, 2002). Furthermore increases in human capital in developing countries have a much larger impact on TFP than increases in R&D in the north. Similar studies have been conducted and confirmed the importance of the absorptive capacity for OECD countries by Engelbrecht (1997) and Frantzen (2000).

Human capital not only plays a role in absorptive capacity however, it is also a direct source of spillovers. Workers switching jobs between industries take their human capital with them and apply the prior obtained experience and knowledge in the new environment. Thus labour mobility is potentially a very important source of knowledge spillovers.

The focus of the knowledge spillovers analysis however has been on Foreign Direct Investment (FDI) and international spillovers (LP 1996, Lee 2006). Lee's above mentioned analysis (2006) is not only restricted to rent spillovers through trade but also analyses FDI flows and their importance for cross-country knowledge flows. His findings based on the DOLS estimation method contradict the results of LP (1996) who find significant effects of outward FDI. The results estimated by Lee are very similar to the ones found by LP as far as the significance of effect through FDI is concerned, but by using DOLS the importance of outward FDI becomes insignificant whereas inward FDI becomes significant. Intuitively, Lee's result can easily be followed, since the FDI home countries usually have higher levels of technological knowledge than the host countries.

Apart from the analysis of knowledge spillovers through FDI there have been some recent contributions to the empirical research regarding labour mobility. Since R&D efforts lead to product innovation as well as to an increase in the stock of human capital of the employees, workers moving to other companies create spillover effects by transferring human capital from one firm to another. Guarino and Tedeschi (2006) find that the proximity of industries is strongly related to inter-industry labour mobility – hence workers are able to use obtained technological knowledge in other related industries. With respect to technical employees Almeida and Kogut (1996) demonstrate by an analysis of patent data from the semiconductor industry that ideas are spread through mobility of key engineers. Since labour mobility involves a threat to the innovating firm, R&D intensive firms tend to have more durable employer-employee relationships and steeper wage curves (Moen 2000).

The literature on international knowledge spillovers through labour mobility is still sparse due to problems of data comparability and further research in this area is of great importance for the understanding of knowledge spillovers.

3 Innovation and Labour Mobility

Invention is a very risky process because the output – the creation of new information – can never be predicted perfectly from the inputs. Given that information is a nonrivalrous good which can be easily used by an unlimited number of economic entities with no marginal costs, the legal system has to protect innovations in order to make their production profitable. As long as the use of the information is exclusive, the owner can earn a monopoly rent, which compensates him for the risks and costs undertaken during the research process.

The output of research is on the one hand information that is incorporated in goods, and on the other hand an increase in the human capital of research workers. The first part can, to a large extent, be codified or protected by patents. This doesn't hold true for what Zucker, Darby and Brewer (1998) have called *intellectual human capital*. Firm specific information, or knowledge, that is referring to patented innovations of the company may be protected by contracts, but not the full set of ideas that a worker acquires during the research process. Arrow already addresses this problem in his article "Economic Welfare and the Allocation of Resources for Invention" (1962) and states that "no amount of legal protection can make a thoroughly appropriable commodity of something as intangible as information".[3] He also identifies mobility of personnel among firms as a way of spreading

[3] see Arrow (1962), p.615

information and since these knowledge externalities decrease returns to R&D investment, they are a threat to firms.

This paper will take a closer look at these knowledge spillovers and will investigate to what extent knowledge acquired in a research intensive environment can be transferred across industries in the form of human capital. The first step will be to study the effects of R&D intensity on learning and turnover rates. This will be done by looking at the Pakes-Nitzan model whose implications have been tested by Moen (2000). The results are essential for the theoretical model that will be presented in chapter 4. Afterwards, labour mobility with respect to industry proximity, the second important pre-condition for the model in this paper will be examined.

3.1 R&D Intensity and Human Capital

The model by Pakes and Nitzan (1983) picks up the problem of hiring scientists when one takes explicit account of the fact that they may be able to use the information acquired during the project in a rival enterprise. The so called Pakes-Nitzan model is a two period model whose aim is to find optimal labour contracts for this kind of employment status. It is based on the assumption that both scientists and firms are aware of the fact that being part of a research project gives access to valuable information. As a result, researchers are therefore willing to accept an initial wage lower than their market value because they gain access to information that will raise their human capital stock. Once they have acquired the information the employer has to pay a higher wage reflecting their new market value in order to keep them from joining or setting up a rival. The theoretical model predicts that entrepreneurs are able to avoid knowledge outflows through labour mobility by sharing the monopoly rent with the workers.

Knowledge spillovers are not to be solely seen in a negative context from the point of view of the giving industry however,. They may also occur because of voluntary disclosure of information - examples are R&D collaborations, publications in technical and scientific papers or conferences. FDI is an example of an international transaction of knowledge from a home country, usually with higher stock of technological knowledge, to a host country. All these activities create knowledge spillovers that are due to voluntary disclosure of information.

The predictions of the Pakes-Nitzan model have been empirically analyzed by Moen (2000). He uses Norwegian data, which allows him to follow the working history of the entire working population from 1986-1995. The theoretical model leads to the conclusion, that turnover rates should be lower for more R&D intensive firms. Using descriptive analysis, Moen finds that R&D investment greatly reduces churning – the number of hires and quits above the level necessary to accomplish changes in the number of employees. Churning can be measured by the excess turnover rate, which is defined as separations out of jobs that continue divided by the number of continuing jobs. Since R&D intensive firms are more innovative they have to deal with a higher level of uncertainty which can lead to a higher than necessary fluctuation of staff. Those who stay are subject to a lower fluctuation however. The significance of this finding is confirmed by a simple tobit regression analysis which looks at the excess turnover rate with respect to the R&D intensity. Moen concludes that more innovative firms cultivate more durable employer-employee relationships.

Since possible knowledge outflows through labour mobility are an important factor in the determination of the future R&D investments, firms need to account for them. The finding shows that entrepreneurs are able reduce the negative external effects of flexible labour markets on R&D investment. This is a weak indicator in favour of the hypothesis that the R&D intensity of a firm affects human capital acquisition. The longer workers stay in a company the more human capital they acquire and the more valuable they become for a firm. Firm specific knowledge, which is defined as knowledge that has productive value in only one particular company, may be one factor that becomes increasingly important in more R&D intensive companies. Since employees always acquire firm specific knowledge disregarding the R&D intensity however, it should not play a major role. A more likely explanation for lower excess turnover rates would be that workers in more R&D intensive industries enhance their human capital levels with respect to the knowledge fields they are working in. Their ideas and insights partly flow into innovations or new products and are partly the basis for later inventions. If they move to another company their set of ideas travels with them and this means a knowledge leak for the firm. The empirically underlined findings of the model would indicate that in order to prevent knowledge leaks firms try to reduce labour mobility and that this effort increases with the R&D intensity of a firm. Therefore the knowledge leaks and thus the loss in human capital seems to be higher for R&D intensive firms.

The Pakes-Nitzan model predicts, that one of the major instruments to reduce excess turnover rates are wages. Moen also takes a look at this prediction and studies the effects of R&D on the earning profiles of technical staff. Since there is no complete historical information available on the career data he assumes constant R&D intensity of the worker's firms throughout the career. This seems plausible for his sample when looking at the transition matrix which shows that most of the job changes are done between firms with similar R&D levels.[4]

The findings support the theory and suggest that workers in R&D intensive firms accept a significant wage discount at the beginning of their career that transforms into a wage premium at the end of their career. Scientists and engineers starting in high R&D intensive firms, have on average 6.1 percent lower wages in their first year compared to low R&D intensive firms, but with 35 years of experience, the picture changes and they receive a wage premium of 6.8 percent.

These results are however most likely subject to an ability bias since one would expect people who learn more easily and thus have lower learning costs to self-select into more R&D intensive firms. Therefore the wage discount at the beginning of the career may be underestimated while the wage premium towards the end may be overestimated. Another interesting result is that "workers with technical or scientific education in R&D intensive firms who do not change employer, have higher wage growth throughout their career."[5]

The findings strongly support the theory that the R&D intensity of a firm affects learning opportunities for the employees. Workers are willing to accept job bundles with lower wages in view of better learning chances at the beginning of their career in order to increase their human capital stock and thus future productivity and wages. Hence it seems feasible to use R&D intensity as a proxy for human capital acquisition later in the empirical part of this paper.

After looking at R&D intensity of companies related to human capital accumulation wages and labour turnover, the next section of this paper will focus on the question of whether labour mobility and industry proximity are interrelated phenomena.

3.2 Labour Mobility and Industry Proximity

Pack and Paxson (1999) analyze this topic investigating whether flexible labour markets lubricate growth. They look at Taiwan, China because its sectoral structure has changed considerably over the past decades and the structural change has been accompanied by a high degree of inter-industry labour mobility. If labour mobility has enhanced growth, then turnover should not be random but workers should rather move to closer industries that can make better use of their accumulated human capital. Their hypothesis is "that workers acquire both general and industry-specific skills that can be transferred to other industries,

[4] See Moen (2000) p.10

[5] See Moen (2000) p.15

but that the degree to which skills are transferable varies across pairs of industries".[6] That means, that for example knowledge acquired in the rubber and plastics sector may be of value in the petroleum industry, but not applicable in the paper production sector. Therefore workers from the rubber and plastics sector are expected to move with a higher probability to the petroleum industry. Because of their valuable knowledge they should also earn higher wages there than workers coming from other industries.

Pack and Paxson use Input-Output tables as a measure of industry proximity to test whether workers are more likely to move to closer industries. Specifically workers should be more likely to move from an industry i to an industry j if

1. industry i supplies a large share of industry j's intermediate inputs
2. industry i receives a large share of its intermediate inputs from industry j
3. industries i and j use similar intermediate input bundles (correlation between input bundles)

The estimated equation takes the form

$$ln\,(N_{ijt}) = \delta_i + \theta_j + \mu_t + \beta z_{ijt} + \varepsilon_{ijt} \quad (1)$$

N_{ijt} denotes the number of workers who have moved from industry i to industry j at time t, δ_i, θ_j and μ_t are dummies for industry of origin, destination and time period and finally β estimates the effect of industry proximity z_{ijt} on labour mobility using the above measures. The major result is that the coefficients on proximity measures are all highly significant. If all three measures are included together they are still individually and jointly significant.

The size of the effects is fairly large. Using only measure 1 for example (see enumeration above), z_{ijt} equals the ratio of inputs purchased by sector j from sector i to total sales of sector j. The results using this measure indicate that the elasticity of N_{ijt} with respect to z_{ijt} is around 7.5. That would mean that a 1% increase of z_{ijt} leads to an increase in the number of workers moving from industry i to j by 7.8%.

The second part of Pack and Paxson's paper looks at the effects of industry proximity on wages. Since wages are strongly related to productivity this analysis can be seen as an examination of the effects of industry proximity on the productivity of moved labour. Of course, when using wages one immediately faces the problem of a range of observable and unobservable factors that influence the variable apart from the criteria of interest. The

[6] See Pack and Paxson (1999) p.4

authors control for attributes like age, years of education, marital status, gender and a set of dummy variables for firm size, year and job tenure. The results support the hypothesis that a move to more similar industries produces larger wage gains. This is especially true when the industries' similarity is measured by method 3 when both industries use similar input bundles.

An alternative interpretation of the results of the paper is that industries that are closely linked due to input-output factors tend to locate in the same region. Therefore workers could be moving to closer industries not because their knowledge makes them more productive there, but because mobility costs are lower. This explanation is unlikely though when looking at wages, since workers that move to closer industries just because of lower mobility costs should not receive higher wages there.

Guarino and Tedeschi's study (2006) is somehow linked to this topic. Starting from the question of why there is a positive correlation between clustering and innovation activity they explore the linkage between knowledge spillovers and labour mobility in these clusters. The theoretical model leads to the conclusion that the presence of many similar firms in a small area can lead to labour poaching and to a high rate of labour mobility.

In this chapter we have now shown that the two main preconditions for the empirical model are fulfilled:

1. The empirically tested Pakes-Nitzan model suggests that R&D intensity is linked to human capital accumulation.
2. Pack and Paxson have shown that workers not only tend to move to "closer" industries, they are also more productive there.

4 Theoretical Model

The next section will provide a theoretical background for the empirical analysis. The framework fits into the category of endogenous growth models with the focus on labour augmenting knowledge spillovers. At the end of this section however the model will be extended to include rent spillovers thus explicitly modelling capital augmenting technological progress. To my knowledge, there exists no literature that tries to model growth through labour mobility and knowledge spillovers. In this framework, growth, which is measured by total factor productivity, will be expressed as a function of knowledge.

4.1 Value and Cost of Knowledge

We begin by assuming that there are n kinds of knowledge fields k_j. These fields are by definition separable – otherwise this problem would extend to an n dimensional space in order to be able to capture all the interdependencies which unnecessarily complicates the problem. However, the stock in each knowledge field can influence the abilities in the other fields – for example somebody who has knowledge in electrical engineering might be able to use this knowledge when working in machinery. Knowledge can be defined in a very broad sense so when referring to knowledge the ability of workers is also included. The unweighted value of a workers knowledge stock is given by

$$V(\vec{k}) = \prod_{f=1}^{n} k_f \tag{2}$$

Each industry has special requirements and therefore different need for certain types of knowledge. Chemical engineering skills are of little use for economic analysis but essential for chemical plant design. Thus each industry weights the knowledge fields differently and the weighted value for industry i is

$$V_i(\vec{k}, \vec{\omega}_i) = \prod_{f=1}^{n} {k_f}^{\omega_{fi}} \tag{3}$$

ω_{fi} represents the weighting of knowledge field f in industry i – values between 0 and 1 indicate logarithmic returns to knowledge, values larger than 1 increasing returns and values smaller than 1 would indicate decreasing returns to knowledge. Whereas the third possibility seems unlikely, the other two, namely logarithmic and increasing returns to knowledge are probable. An example for increasing returns would be computer related knowledge. Though a lot of research had been done before in this sector the knowledge was of little use for most industries 25 years ago. Continuous progress made them applicable and nowadays computers are indispensable in (almost) all industries. Similar effects could be observed in the field of nanotechnology in the future. A doubling in the knowledge stock in this sector may lead to a more than doubling of the value of this knowledge for some industry sectors. This however may only be true for a certain time span when a threshold is reached.[7]

[7] Increasing returns to knowledge at the beginning could also be due to a sigmoid function, but this case is not dealt with in this framework. However, one could assume that this weighting is only valid for a specific time horizon.

Dealing with increasing returns always poses the problem of a finite solution. This problem will be addressed by inverse Inada conditions with respect to the cost of knowledge acquisition. To be more specific in the empirical model presented later on the knowledge stock in certain fields is implicitly modelled as a function of the current R&D stock in an industry. The more a sector invests in R&D the higher the growth of knowledge in the fields linked to that sector. There are however a number of restrictions on the increase in knowledge. Firstly, the knowledge production function does not only depend on the R&D expenditures in this knowledge field, but also on innovation in other fields that either accelerate or simply enable progress. Simulations in the automobile industry or in economics as well as certain experiments in physics (e.g. particle accelerator in CERN) for instance would not be possible without today's computer power. Another example is the vast productivity increase in agriculture beginning in the 19^{th} century. The use of products of other sectors like machines and fertilizers lead to a decrease in the share of people working in the primary sector and enabled the emergence of the bourgeoisie. As a result, the growth of knowledge depends on the knowledge stock of other fields.

The second restriction refers to the costs of knowledge accumulation. Usually the following rule applies: the more common the knowledge, the cheaper it is to obtain. In order to increase a firm's or sector's knowledge, managers can either hire people from other sectors with the required skills, train already employed workers or invest in R&D. Training of course is only an option, if knowledge is already available and not protected by patents. The more specific the knowledge, the less people usually possess it and the more costly becomes the acquisition of this knowledge. It is therefore realistic to assume increasing costs of knowledge growth. If the knowledge is not yet available, R&D has to be undertaken, which is in general the most expensive form of knowledge acquisition meaning that the marginal cost of knowledge increases with respect to R&D is higher than the costs with respect to hiring or training.

Using the properties from above, it is reasonable to assume, that with given resource constraints at time *t*, there exists an upper bound for the knowledge stock that can be achieved. Expressed in mathematical terms this means that the assumed knowledge cost function with respect to knowledge is convex and limited, and has the inverse Inada condition properties. The function is also defined to be decreasing with respect to time, since knowledge already "created" through research can later be more cheaply obtained through training or the hiring of specialists. All the other variables that may influence the costs of knowledge like hiring are denoted by a point since they are not needed to show that there exists a finite solution.

$$c_{ft\cdot} = c(k_f, t, \cdot) \qquad \frac{\partial c(k_f,t,\cdot)}{\partial k_f} > 0,\ \frac{\partial c(k_f,t,\cdot)}{\partial t} < 0 \qquad \frac{\partial c(k_f,t,\cdot)}{\partial^2 k_f} > 0 \tag{4}$$

Inverse Inada conditions:

$$\begin{aligned} &c(0,t,\cdot) = 0 && \frac{\partial c(0,t,\cdot)}{\partial k_f} = 0 \\ &lim_{k_f \to k_{fmax}}\left(c(k_f,t,\cdot)\right) = \infty && lim_{k_f \to k_{fmax}}\left(\frac{\partial c(k_f,t,\cdot)}{\partial k_f}\right) = \infty \end{aligned} \tag{5}$$

With these properties defined a finite optimal level of R&D expenditures exists. After the definition of the environment, the next section will look at output and the relationship between productivity and knowledge. Starting from equation (3) the productivity and also an approximation of the wage of a worker r in a sector i can be defined by

$$p_{ri}(\overrightarrow{\gamma_1}, \overrightarrow{\gamma_2}, \vec{k}_r, \vec{\omega}_i, \vec{c}_r, \vec{\delta}) = \gamma_{1i} + \gamma_{2i} * \prod_{f=1}^{n} k_{rf}{}^{\omega_{fi}} * \prod_{h=1}^{m} c_{rh}{}^{\delta_h} \tag{6}$$

The productivity of a worker has a certain industry specific base level γ_{1i}. The usage of his industry weighted knowledge stock k is assumed to depend on his personal characteristics c. These characteristics can be anything that formed or influenced the workers incentives and attitude to work. Observable measures used for wage estimations by the empirical literature are often wage of the father, marital status, sex, age and so on.

The weighting δ_h of each of these personal characteristics is assumed to be the same across industries since they most likely affect the usage of the worker's knowledge stock in a similar way irrespective of the industry considered. When estimating this equation empirically the knowledge stock of a worker can be approximated by years of education and field of education as well as experience in certain sectors.

4.2 Theoretical Background of the Empirical Model

When we now look at the aggregate level, the output of a firm or a sector is assumed to be produced according to a Cobb Douglas production function with the inputs labour, information and communication technology (ICT), capital services k_{ICT} and non ICT capital services k_N.

$$Y = A\, k_N^{\alpha}\, k_{ICT}^{\beta}\, l^{\delta}, \qquad \alpha + \beta + \delta = 1 \tag{7}$$

l is a function g_i of the productivity of the employees *r ∈ [1..m]*, l is in this case not equal to the sum of the productivities of the workers but a more complex function g_i, that takes spillovers between workers and synergy effects into account.

$$l_i(\overrightarrow{p_\iota}) = g_i\left(p_{1i}(\overrightarrow{\gamma_1}, \overrightarrow{\gamma_2}, \vec{k}_1, \vec{\omega}, \vec{c}_1, \vec{\delta}), \dots, p_{mi}(\overrightarrow{\gamma_1}, \overrightarrow{\gamma_2}, \vec{k}_m, \vec{\omega}, \vec{c}_m, \vec{\delta})\right) \tag{8}$$

It is straightforward to see that hiring affects the function by adding new workers to the function while training and R&D directly affects the knowledge stock $\vec{k}$ of the workers in the firm. Higher labour mobility makes the diffusion of knowledge easier and usually leads to a decrease in hiring costs and also training costs to some extent. On the other hand labour mobility makes R&D less profitable because of knowledge leaks – workers that increased their productivity within the firm switch to other companies and take their knowledge stock with them.

The empirical model that is presented in the next chapter tries to estimate the size of knowledge spillover effects through mobility of skilled labour in order to better explain the unobservable "real" aggregated labour productivity function g_i. This is done by looking at the effects of labour mobility on total factor productivity, which in this framework is defined as[8]

$$TFP = \frac{Y}{k_N^{\alpha}\, k_{ICT}^{\beta} \tilde{l}^{\delta}} \tag{9}$$

$\tilde{l}$ in this case stands for a function $\tilde{g}$ of aggregated employment data.

[8] The corrections made by Timmer et. al. (2008) concerning the TFP index are not accounted for.

Joining equations (9) and (7) and substituting from (8) and (6) leads to an industry specific total factor productivity of

$$TFP_i = \frac{Y_i}{k_N^\alpha \, k_{ICT}^\beta \tilde{l}^\delta} = \frac{A \, k_N^\alpha \, k_{ICT}^\beta \, l^\delta}{k_N^\alpha \, k_{ICT}^\beta \tilde{l}^\delta} = A_i \left(\frac{l_i}{\tilde{l}_i}\right)^\delta = A_i \left(\frac{g_i(\overrightarrow{p_i})}{\tilde{g}_i(m_i)}\right)^\delta \tag{10}$$

This equation will be the starting point for the later analysis.

In equilibrium, the marginal costs of each knowledge field in an industry i should be equal to the marginal returns in the industry:

$$\frac{\partial g_i(\overrightarrow{p_i})}{\partial k_f} = \frac{\partial c(k_f, t, \cdot)}{\partial k_f} \qquad \forall k_f \in [k_1, \dots, k_n] \tag{11}$$

With this information it is possible to calculate optimal stocks of knowledge for each worker at time t and rewrite the productivity of worker r in industry i in equilibrium as $\overline{p_{rit}}^*$. This is now only a function of exogenous variables, namely the industry specific weights ω_{fi} and the cost function $c(k_f, t, \cdot)$. The current productivity in equilibrium therefore depends on the current cost of knowledge and the equilibrium stock of knowledge at time t.

$$p_{rit}^* = \bar{f}_i(c(k_{r1}^*, t, \cdot), \dots, c(k_{rn}^*, t, \cdot), w_{1i}, \dots, w_{ni}) \tag{12}$$

Hence TFP can now be determined solely by exogenous variables. By taking the log of equation (10) we obtain

$$log(TFP_{it}) = \alpha * log(A_i) + (1-\alpha) * \Big(log\big(g_i(\overrightarrow{p_{it}})\big) - log\big(\tilde{g}(m_{it})\big)\Big) \tag{13}$$

At this stage, capital augmenting technological progress only appears as a factor A_{it} in the model and is capured by the constant in the empirical part. It would be interesting to include not only knowledge spillovers in the definition of output, but also rent spillovers. Starting from a more general definition of output where only labour and capital appear without differentiation into ICT and non-ICT capital services, capital k could be defined as a composite input of horizontally differentiate goods x of variety s

$$k = \left(\int_0^{n^e} x(s)^\alpha \, ds\right)^{\frac{1}{\alpha}} \tag{14}$$

where n^e represents the range of intermediate inputs which are employed in the sector

(Keller, 2002). In equilibrium the differentiated capital goods $x(s)$ are produced at level $\bar{x}$. In equilibrium we get the following equation:

$$log(TFP_{it}) = \alpha * (log(A_i) + log\, n^e) + (1-\alpha) * log\big(g_i(\overrightarrow{p_{it}})\big) - \\ - (1-\alpha) * log\big(\tilde{g}(m_{it})\big) \tag{15}$$

However, as shown in the model by Pack and Paxson (1999), labour mobility is closely linked to input-output relations between sectors, there will therefore likely be problems with the estimation of the effects due to problems of multicollinearity and small samples. Hence, this approach is left for future research.

5 Empirical Model and Construction of Variables

In this section, an empirical model will be presented that examines the effects of human capital mobility on productivity. The analysis focuses on intersectoral spillovers within a country. The hypothesis is that industries can profit from the R&D investments of other domestic sectors by hiring their workers. Therefore the model includes the industry's own R&D expenditures as well as the R&D investments of other sectors weighted by the share of workers coming from that sector.

According to general theory, the outcome of R&D undertaken in one industrial sector is influenced by R&D expenditures in other sectors that spill over through various channels (e.g. labour mobility, rent spillovers, knowledge exchange, etc). This means that there should exist a multiplicative relationship between the two variables in the model. In the case of labour mobility this hypothesis is supported by the data in the analysis.[9]

The theory behind this assumption is straightforward – the knowledge stock of workers coming from other sectors does not solely influence the productivity of the receiving sector by adding more human capital incorporated in new employees that are more productive (direct effect) – their knowledge is likely shared with other employees and will therefore diffuse within the firm and, if valuable, be used in production processes or applied in other parts of the firm (spillover effect).

The direct effect is to a large extent captured by wages since the expected productivity of the new worker is influenced by his education and working history, which is known to the

[9] The estimation of the basic equation (16) leads to an R^2 of 0.83 assuming a multiplicative relationship compared with 0.70 when assuming an additive relationship.

employer during the hiring process. Both the employer and the employee have expectations concerning the value of the new employee in the company, which are affected by signalling effects during the wage negotiations. However, there is asymmetric information on both sides - the new worker knows best about his abilities and job performance but little about the new environment and his opportunities for development therein, whereas the employer knows about the company background but has incomplete information about the workers capabilities. Therefore the wage will not fully capture the direct effects, but with time and reduced asymmetric information on both sides the wage should adjust with respect to the marginal productivity of the worker.

The size of the spillover effect is subject to corporate philosophy and the mode of operation. In a dog-eat-dog environment the workers usually see specific information as their advantage over other workers and are therefore not likely to share it. The better the corporate climate and the more team based the work is, the more the information will diffuse within the firm and thus create higher spillover effects. Another possible spillover effect would be if employees coming from other industries use their previous knowledge to produce things way beyond what is covered by their wage e.g. implementation of new production processes, acting as a catalyst for R&D projects, and so on.

With this formal specification the initial basic equation can be defined. The empirical model relates directly to equation (10) of the theoretical model in the sense that the knowledge spillovers estimated are a major part of the difference between the unobservable "real" aggregated labour productivity function g and the TFP function $\tilde{g}$.

$$log\,TFP_{cit} = \alpha_t + \alpha_c + \alpha_i + \beta^s\, logR^s_{cit-1} + \beta^o\, logR^o_{cit-1} + \varepsilon_{cit} \qquad (16)$$

The three dimensions of the equation are industry i, country c and time t. TFP_{cit} therefore denotes total factor productivity of industry i in country c at time t, α_t, α_c and α_i are dummy variables that control for fixed effects, ε_{cit} is an error term and finally β^s and β^o are the two coefficients to be estimated for the explanatory R&D variables. These are R^s_{cit}, which stands for weighted R&D investments of the currently analysed industry and R^o_{cit} which is a weighted sum of R&D investments of the other industries. For industry i the variable R^o_{cit} is created as a sum over the R&D investments of all other industries j weighted by the percentage of workers leaving the originating industry j in order to work in industry i.

$$R^{o}_{cit} = \sum_{\substack{j=1 \\ j\neq i}}^{J} R_{cjt} * \frac{l^{i}_{cjt}}{l_{cjt}} \tag{17}$$

R_{cjt} is the R&D stock of industry j in country c at time t, l^{i}_{cjt} represents the number of workers moving from industry j to i and l_{cjt} stands for the total number of people employed in industry j. That means that industry j's R&D stock is weighted by the fraction of people moving from industry j to industry i divided by the total number of workers originally employed in industry j.[10] Likewise the R&D stock of the currently analysed industry R^{s}_{cit} is weighted by the share of people not leaving the industry. This weighting is applied because labour outflows create knowledge outflows that firms have to take into account. As a result, labour mobility leads to a lower actual R&D stock of the current industry in the model[11].

A very important issue in equation (17) is the usage of knowledge in the receiving industry. The R&D stock as a proxy for the knowledge transmitted is only weighted by labour flows, not by industry proximity which gives a measure of how well the knowledge can be used in the receiving industry. This was done for two reasons: first of all Pack and Paxson have shown that labour mobility patterns are closely related to industry proximity and thus these patterns are already a measure of the closeness of two industries. The second argument is that only job changes are considered where people are already part of the workforce. Therefore, most changes occur voluntarily and thus people who move to industries which are not closely linked to the one of origin are most likely doing so because their new environment is able to make good use of their abilities regardless of the macroeconomic linkage.

There are a couple of issues that have to be addressed and accounted for before moving on to the estimations. The primary concerns are simultaneity and omitted variables. Demand shocks are an example of a set of effects that lead to a spurious correlation between productivity and R&D investments. The shock leads to lower revenues and usually higher

[10] Another possible weighting for the R&D stock of other industries would be the number of people moving from industry j to industry i as a share of the people working in industry i. With different industry sizes, this however is not a good measure of the knowledge outflow since the people who move may be a large share of the people originally working in industry j, but only a small fraction of the people then working in i. Therefore it would not properly capture relative knowledge outflow.

[11] If we had assumed that knowledge is a public good, it would remain completely in the industry. But the assumption in this framework is that the ideas and experience that employees acquire during their work is the basis for future productivity increases and thus an outflow of this knowledge affects productivity increases negatively.

stocks with similar input bundles since labour relations are not terminated immediately. Therefore the measured productivity of the industry falls. Under pressure, firms in general cut future-oriented expenses which include R&D investments. Therefore, we are able to observe a spurious correlation between productivity and research capital. A similar effect can be observed during booms – when output increases productivity also rises and during periods of high growth firms hire more workers. These workers coming from other sectors then create knowledge spillover effects that are likely overestimated.

The usual solution for this problem is the adoption of an instrumental variable (IV) approach. Due to the fact that there are no good instruments available, the second best solution in this case is to lag the explanatory variables in order to avoid simultaneity biases.

Year dummies α_t are included to account for global shocks that affect all countries and industries. Country fixed effects α_c control for differences in human capital, institutions or regulation in the labour market. Last but not least, a set of industry dummies α_i is included to account for differences in productivity across sectors for example due to automatisation possibilities that may vary by industry.

6 Data

6.1 Data Sources and Issues

The dataset used for the analysis contains 10 EU countries, namely Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden and the United Kingdom and covers the time period between 1995 and 2004.

Three main data sources were combined to the final dataset. The total factor productivity indices were taken from EU KLEMS database (state March 2008), which provides data for the EU25 countries, Australia, Japan and the US at the industry level. The productivity levels were normalized to 1997=100 and then multiplied with TFP levels for 1997 that were estimated by Inklaar, Timmer and Ark (2006) and that exist sector specifically only for a few countries.

The data on labour flows was taken from the EU Labour Force Survey by Eurostat which covers the European countries from 1995 until 2005. The adjusted employment series by Eurostat were used to adjust for the existing breaks in the series. Only medium and high skilled workers (based on ISCED) were included in the calculation of the labour flows, since they are most likely the main source of knowledge spillovers. Furthermore, the sample of observed workers was reduced with respect to the International Standard Classification of Occupations (ISCO). The major groups “clerks”, “service workers and shop and market sales workers” and “elementary occupations” have been excluded. The categories left in the final sample are “technicians and associate professionals”, “legislators, senior officials and managers”, “professionals”, “skilled agricultural and fishery workers”, “craft and related trades workers” and “plant and machine operators and assemblers” – these are considered the main source of knowledge spillovers in the manufacturing industries.

Finally, the data on research investments of the industries was taken from the STAN ANBERD database. In order to make R&D investments comparable across time and countries, they were adjusted using purchasing power paritiy exchange rates and deflated using the gross fixed capital formation deflator, which was taken from Eurostat. The initial stock of R&D was calculated according to the following commonly used formula using a 10% depreciation rate (different depreciation rates for high, medium and low technology industries are used later in a sensitivity analysis)

$$S_o = \frac{R_0}{g + \delta} \tag{18}$$

S_0 is the calculated R&D stock at the beginning of the sample and R_0 the R&D investment in that year, δ represents the assumed depreciation rate of R&D capital and g the logarithmic growth of the R&D investments over the analysed time period. The R&D stocks are then calculated based on the perpetual inventory model:

$$S_t = (1 - \delta) * S_{t-1} + R_{t-1} \tag{19}$$

In order to examine whether the variables are non-stationary which could lead to a spurious regression when estimated in levels, the panel unit root test developed by Levin, Lin and Chu (2002) is performed.

Table 1 – Stationarity tests

Levin-Lin-Chu (2002)	$\ln(TFP_{cit})$	$\ln(R^s_{cit})$	$\ln(R^o_{cit})$
no lags or trend included	0.1719	0.0000	0.0000
trend included	0.0000	0.0000	0.0000

The tests show that the two R&D stock variables are stationary but the TFP variable has a nonstationary behaviour. This is expected, since we are expecting an upward trend in productivity. When the test accounts for this trend, the null-hypothesis of nonstationary behaviour can also be rejected for the TFP variable. Since there are always time dummies included for every year, this trend is accounted for in the model.

6.2 Descriptive Analysis

A general descriptive analysis of the data for countries and sectors is provided in Table 2. The highest TFP growth rates in the sample are found in the sectors "Electrical and optical equipment" and "Chemicals and chemical products" with average annual growth rates of 4.68% and 1.72%. The only negative growth rate in the final sample with -0.08% can be found in the "Food, beverages and tobacco" sector. The industries "Coke, refined petroleum and nuclear fuel" and "Wood and of wood and cork" as well as "Manufacturing nec; recycling" had to be dropped because of huge fluctuations in TFP which occurred to some extent due to high price volatility. These industries also downward biased the manufacturing TFP growth rates of the countries in Table 2 and led to negative growth rates for Denmark, Spain and Italy (see Table 5A[12] for a detailed matrix on TFP growth rates for sectors and countries).

Considering R&D investment Denmark (8.93%) and Finland (10,11%) show extremely high annual growth rates. The share of non-public R&D funding in these two countries is far above the EU27 average and by looking at the data in more detail one finds that most investment has taken place in high technology sectors. "Electrical and optical equipment" for example has an R&D investment growth rate of 13.54 in Finland and 10.30 in Denmark (for more information on R&D investment across countries and sectors see Table 6A). When examining the industry shares in total R&D investment we discover that the sectors "Electrical and optical equipment" (29.69%), "Transport equipment" (26.94%) and "Chemicals and chemical products" (23.08%) invest by far the most in R&D and make up more than three quarters of all R&D investment in the sample.

[12] Tables denoted with an A can be found in the appendix at the end of this paper

Table 2 – Sample summary statistics

code	Country / Industry	Average TFP growth*	Average R&D inv. growth*	Relative size in terms of R&D**	Relative size in terms of labour***
BE	Belgium	0,80	3,36	3.24	2.70
DE	Germany	1,74	5,83	34.56	39.62
DK	Denmark	-0,43	8,93	0.99	2.08
ES	Spain	-0,64	5,58	2.62	4.89
FI	Finland	4,13	10,11	1.66	1.98
FR	France	2,11	2,91	21.29	16.49
IT	Italy	-1,17	-1,51	7.62	9.58
NL	Netherlands	1,82	3,52	3.98	3.92
SE	Sweden	3,71	4,82	5.57	1.55
UK	United Kingdom	1,08	0,91	15.38	17.18
15t16	Food, beverages and tobacco	-0.08	4.80	1.55	8.69
17t19	Textiles, textile, leather and footwear	1.08	5.26	0.63	5.38
20	Wood and of wood and cork	1.63	2.72	0.14	2.55
21t22	Pulp, paper, printing and publishing	0.32	3.33	0.70	8.78
23	Coke, refined petroleum & nuclear fuel	-2.96	-5.17	1.22	0.72
24	Chemicals and chemical products	1.72	5.19	23.08	7.92
25	Rubber and plastics	1.18	4.25	1.76	3.83
26	Other non-metallic mineral	1.14	2.87	1.07	3.13
27t28	Basic metals and fabricated metal	0.39	1.86	3.16	15.17
29	Machinery and equipment n.e.c.	0.98	4.35	9.47	13.37
30t33	Electrical and optical equipment	4.68	3.04	29.69	14.02
34t35	Transport equipment	1.38	3.27	26.94	11.40
36t37	Manufacturing nec; recycling	0.68	3.58	0.59	5.04

Notes: All indicators in percent. *Mean annual average growth between 1995 and 2005. **Based on USD PPP adjusted expenditures in 1995. ***Based on number of employees in 1997

Table 7A contains an overview of the labour mobility pattern within manufacturing. It shows the average annual percentage of workers in the sample moving from industry i to j. Included are all the workers who have changed their job within the last year. There is a pattern observable, namely that there exists a positive net outflow of workers from low technology industries like "Food, beverages and tobacco" or "Pulp, paper, printing and publishing" to higher technology sectors. The yearly industry net flows are mostly below 0.5% of the workers who switch jobs, but observed over a longer time period, this effect is not negligible.

Finally Table 8A provides information on the average tenure of jobs across countries and sectors. While Denmark has by far the lowest average job tenure with 10.1 years, Germany and France show the highest tenure in the sample with 13.1 and 13.0 years. Across the years the average current job tenure stays relatively constant with around 12.2 years across the sample. During the early 2000s recession there is a slight decrease of around 2% observable. These fluctuations are for sure more apparent when looking at the average job duration, which cannot be calculated with the current dataset since it includes no data on past employment status.

7 Estimation Results

The following section provides estimates for the size of the spillovers. Acknowledging that a part of the knowledge effects found could be due to rent spillovers and vice versa, the coefficients should be considered an upper bound for the true size of the knowledge spillovers.

The first regression (i) in Table 3 shows the estimation results of the basic equation (16). The estimated coefficient of the industry's own R&D stock β^{s}_{cit} with a value of 0.1294 is around 5 times higher than the gains from the knowledge of other industries β^{o}_{cit} which is estimated as 0.0278 – both coefficients are highly significant. The coefficients can be interpreted as elasticities of total factor productivity with respect to labour movement weighted R&D investment. β^{s}_{cit} is a measure of the impact of the industry's own knowledge stock on TFP after adjusting for labour and thus knowledge outflows. Similarly β^{o}_{cit} measures the degree to which industry i will profit from the R&D investment of other industries by hiring their workers and thus by employing their human capital stock. This effect increases if the giving industries enhance their R&D activities and thus add to their human capital stock. A coefficient of 0.0278 for β^{o}_{cit} in estimation (i) therefore implies that a 1 percent increase in the R&D stock of medium technology firms increases total factor productivity in the receiving industry by 0.028 percent. Since the R&D investments are weighted by labour movements in the model, the receiving industry can profit in a similar way from the human capital stock of other sectors by simply hiring more workers from those industries.

Table 3 – Estimation results

	(i)	(ii)	(iii)	(iv)	(v)
β_{cit}^{s}	0.1294*** (6.69)		0.1304*** (7.05)		0.1167*** (5.18)
$\beta_{cit}^{s\ \mathrm{high}}$		0.1492*** (5.13)		0.1612*** (5.74)	
$\beta_{cit}^{s\ \mathrm{med}}$		0.1427*** (7.41)		0. 1410*** (7.32)	
$\beta_{cit}^{s\ \mathrm{low}}$		0.0666*** (2.55)		0.0749*** (2.83)	
β_{cit}^{o}	0.0278*** (3.62)	0.0276*** (3.62)			0.0651*** (5.22)
$\beta_{cit}^{o\ \mathrm{high}}$			0.0166*** (2.70)	0.0175*** (2.81)	
$\beta_{cit}^{o\ \mathrm{med}}$			0.0200** (2.23)	0.0179** (1.98)	
$\beta_{cit}^{o\ \mathrm{low}}$			0.0099** (1.99)	0.0089* (1.77)	
R^2	0.8317	0.8338	0.8331	0.8349	0.8316
F-statistic	151.03	150.70	142.40	142.86	130.57
Observations	709	709	709	709	528

t-statistics in parentheses. The dependent variable is ln(TFP). All regressions include unreported dummies for years, countries and industries. Coefficients are estimated using ordinary least squares (OLS) with robust standard errors. <***>, <**> and <*> denote coefficients being significantly different from zero at a 1, 5 and 10 percent level, respectively. Estimations (ii), (iii) and (iv) are simple extensions of equation (16) by new R&D terms.

Given the heterogeneity of the manufacturing sector, including both traditional and high technology sectors, the empirical model was then extended and re-estimated with separate coefficients for high, medium and low technology industries. The knowledge spillovers from other industries have been differentiated by providing industry. The classification was done according to that developed by the OECD (2005). The high technology segment consists only of the industry “Electrical and optical equipment” (30–33). The medium technology sectors in the sample are “Chemicals and chemical products” (24), “Rubber and plastic products” (25), “Other non-metallic mineral products” (26), “Basic metals and fabricated metal products” (27–28), “Machinery and equipment (n.e.c.)” (29) and “Transport equipment” (34–35). Finally, the low-tech category includes “Food products, beverages and tobacco” (15–16), “Textiles, textile products, leather and footwear” (17–19) and “Pulp, paper, paper products, printing and publishing” (21–22).

In regression (ii), separate coefficients were estimated for the industry's own knowledge stock differentiated by technology segments (high, medium and low-tech). Regression (iii) subsequently uses coefficients for knowledge spillovers from other industries split up by technology level. Finally in estimation (iv) both original coefficients β^{s}_{cit} and β^{o}_{cit} were estimated for each technology segment.

As expected, the coefficients for high and medium technology industries are larger than those of low technology sector. The estimated spillover effect from the medium technology industry is found to be higher than that from the high technology industry however, though the difference is not found to be significant. This finding can in general have various backgrounds - one being that the medium technology industries are not as specialized as the high technology ones and the knowledge gained there can therefore be better used in other sectors. As shown later, the coefficients depend on the depreciation rates chosen. Higher depreciation leads to lower initial R&D stocks and greater fluctuations in the sample. Since one would expect knowledge to depreciate more in high technology sectors than in traditional, low technology sectors, it is feasible to use different depreciation rates for the R&D investments. The sensitivity analysis presented in Table 4 addresses this issue and shows that the size of the coefficients relative to each other changes as a result.

The last estimation (v) uses 3-year averages of the labour weighted R&D stock variables. These averages increase the time that R&D investments can influence TFP. The coefficient for knowledge spillovers from other industries increases from 0.0278 to 0.0651. This indicates, that especially knowledge spillovers through labour mobility need more time to affect productivity in the new sector. This could be due to the fact that workers need to get acquainted with their new environment first. During this period they might not be as productive and their possibilities to bring in their knowledge may be limited.

The next set of results presented in Table 4 deals with the sensitivity analysis. The depreciation rates for low, medium and high technology sectors have been arbitrarily set to 7.5%, 10% and 12.5% in order to assume more realistic depreciation rates for knowledge. These different rates have been chosen since the currently required and applied knowledge changes more quickly in high than in low technology sectors. Therefore also the ideas and experience that employees acquire during their work that could lead to future productivity increases becomes obsolete faster in the more rapidly changing environment of high technology sectors.

Table 4 – Sensitivity analysis

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
β_{cit}^{s}	0.1294*** (6.69)		0.1167*** (5.18)	0.1365*** (7.63)		0.1238*** (5.72)
$\beta_{cit}^{s\ \mathrm{high}}$		0.1612*** (5.74)			0.1929*** (7.04)	
$\beta_{cit}^{s\ \mathrm{med}}$		0.1410*** (7.32)			0.1478*** (7.88)	
$\beta_{cit}^{s\ \mathrm{low}}$		0.0749*** (2.83)			0.0826*** (3.28)	
β_{cit}^{o}	0.0278*** (3.62)		0.0651*** (5.22)	0.0261*** (3.73)		0.0624*** (6.04)
$\beta_{cit}^{o\ \mathrm{high}}$		0.0175*** (2.81)			0.0185*** (2.87)	
$\beta_{cit}^{o\ \mathrm{med}}$		0.0179** (1.98)			0.0172* (1.92)	
$\beta_{cit}^{o\ \mathrm{low}}$		0.0089* (1.77)			0.0093** (2.03)	
R^2	0.8317	0.8349	0.8316	0.8341	0.8379	0.8351
F-statistic	151.03	142.86	130.57	154.29	147.83	134.69
Observations	709	709	528	709	709	528

t-statistics in parentheses. The dependent variable is ln(TFP). All regressions include unreported dummies for years, countries and industries. Coefficients are estimated using ordinary least squares (OLS) with robust standard errors. <***>, <**> and <*> denote coefficients being significantly different from zero at a 1, 5 and 10 percent level, respectively. Estimations (ii) and (v) are simple extensions of equation (16) by new R&D terms.

Regressions (i), (ii) and (iii) were taken from above and use a depreciation rate of 10% throughout the sample whereas (iv), (v) and (vi) are based on the same equations but use different depreciation rates depending on the technology level. The regressions (iii) and (vi) again use 3-year averages of the labour weighted R&D stock variables and have therefore a reduced sample size. The results of regression (v) show, that the relative size of the coefficients for the different technology sectors changes in comparison with the previous results and high technology sectors become the most important source of knowledge spillovers. Generally the coefficients become more significant in all three compared estimations, which is a result in favour of the assumption of different depreciation rates.

The estimations in the literature for rent as well as knowledge spillovers should be looked at in this context. Usually a fixed depreciation rate is assumed across all sectors but by looking at knowledge in the textile industry and the computer industry it seems obvious that this assumption is not met. The sensitivity analysis mostly done uses different depreciation rates for the whole sample. Using higher rates leads to a lower initial R&D stock and therefore increases the volatility of the R&D stock. Moreover, if the variable is highly correlated with TFP, also the significance of the estimates increases.

Overall, the results in Table 3 and Table 4 are robust to changes in the model and confirm the importance of knowledge spillovers on productivity growth.

8 Concluding Remarks

Recent growth literature has emphasised the importance of domestic as well as international rent spillovers across industries. The paper tries to establish a role for knowledge spillovers through the mobility of a higher educated workforce in this framework. Based on recent theoretical findings that were confirmed by empirical evidence, a theoretical endogenous growth model is developed that explains labour productivity with respect to knowledge acquisition. The empirical analysis confirms the importance of human capital transferred across industries as a source for knowledge spillovers. Due to the fact that labour mobility is closely linked to input-output relations as shown by Pack and Paxson (1999) this finding provides evidence suggesting that part of the estimated productivity effects of rent spillovers are in fact due to labour mobility.

Given the heterogeneity of the manufacturing sector, including both traditional and high technology sectors, the model was then extended and re-estimated with separate coefficients for high, medium and low technology industries. The results confirm the assumption that industries with a low technological level create lower knowledge spillovers to other sectors than medium and high technology industries.

There are a number of issues left to be addressed in future work. An important concern should be the magnitude of the spillover effects that can be attributed to rent spillovers and knowledge spillovers respectively. However the simultaneous estimation of the two effects is likely to lead to a multicollinearity problem since labour mobility and input-output relations are highly correlated and this difficulty can only be overcome with larger panel datasets. The estimation would also profit from the use of micro-level data that provides firm-level data and more information on the working history of the population. This would reduce the distortion in the calculation of the human capital stocks of the workforce and thus improve the estimation results for the knowledge spillovers. On the other hand it would be interesting to find a method to estimate the size of the negative external effects for firms that arise because of labour mobility and in particular with respect to research and development.

This paper is meant to be a first step in the direction of estimating knowledge spillovers through labour mobility and should point out the importance of the mobility of human capital that goes hand in hand with the diffusion of knowledge into other industries for economic growth. Hopefully it will prove useful for future work in this research field and encourage the pursuit of this topic.

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10 Appendix

Table 5A – Average annual TFP growth in percent (1995-2005)

nace2		BE	DE	DK	ES	FI	FR	IT	NL	SE	UK	mean
15t16	Food, beverages and tobacco	-0.03	0.26	-1.47	-1.91	4.44	-0.03	-1.61	0.93	-1.06	-0.29	-0.08
17t19	Textiles, textile, leather and footwear	2.20	2.62	0.15	-1.67	1.54	2.60	-2.00	2.35	0.40	2.59	1.08
20	Wood and of wood and cork	2.56	2.73	1.33	-1.47	3.31	4.47	1.66	-0.88	3.50	-0.89	1.63
21t22	Pulp, paper, printing and publishing	-0.18	0.10	0.14	0.30	2.13	0.93	-1.08	0.94	0.14	-0.22	0.32
23	Coke, refined petroleum & nuclear fuel	-6.57	-3.83	-11.92	-2.40	3.50	4.86	-23.68	5.74	5.78	-1.10	-2.96
24	Chemicals and chemical products	-0.40	3.95	3.27	-0.98	2.54	0.31	0.72	3.77	2.50	1.52	1.72
25	Rubber and plastics	2.98	1.63	-0.39	-0.16	-0.85	7.35	-0.29	0.81	0.79	-0.04	1.18
26	Other non-metallic mineral	-0.96	1.95	0.94	0.95	2.79	0.99	0.31	0.28	1.74	2.43	1.14
27t28	Basic metals and fabricated metal	1.09	0.76	-1.46	-0.44	1.43	0.58	-0.29	1.05	-1.00	2.14	0.39
29	Machinery and equipment n.e.c.	2.62	0.78	-1.62	-0.49	0.50	4.26	-1.27	1.74	1.55	1.71	0.98
30t33	Electrical and optical equipment	3.24	4.31	0.17	-1.45	12.35	4.71	-1.05	0.82	20.87	2.84	4.68
34t35	Transport equipment	2.30	1.96	-2.40	0.09	0.55	2.30	-0.87	4.91	3.82	1.13	1.38
36t37	Manufacturing nec; recycling	1.45	-0.11	-1.79	0.35	0.85	0.60	0.02	1.05	4.46	-0.11	0.68

Table 6A – Average annual growth of R&D investment per sectors and country in percent (1995-2005)

nace2		BE	DE	DK	ES	FI	FR	IT	NL	SE	UK	mean
15t16	Food, beverages and tobacco	7.43	5.03		8.50		5.70	3.73	-1.57			4.80
17t19	Textiles, textile, leather and footwear	-0.71	2.78		12.47	3.51	1.09	13.11	4.55			5.26
20	Wood and of wood and cork	-12.51	-2.93	14.86	14.66	1.88	0.89	-7.43	5.57	9.54		2.72
21t22	Pulp, paper, printing and publishing	-10.90	8.92		10.96	3.84	1.44	1.54	11.53	-0.71		3.33
23	Coke, refined petroleum & nuclear fuel	5.74	-0.89		0.96	-1.04	-1.20	-25.08	-23.73	1.72	-2.96	-5.17
24	Chemicals and chemical products	4.85	5.21	11.50	7.65	5.87	4.46	-1.30	4.36	7.93	1.38	5.19
25	Rubber and plastics	5.13	8.77	10.88	3.60	7.72	10.02	2.25	1.03	-5.73	-1.21	4.25
26	Other non-metallic mineral	-0.91	4.55	8.55	7.45	-5.88	1.36	8.25	7.69	-0.50	-1.88	2.87
27t28	Basic metals and fabricated metal	5.05	5.41	5.37	9.02	7.54	-2.64	-6.38	-1.62	4.51	-7.71	1.86
29	Machinery and equipment n.e.c.	3.46	4.81	1.77	6.62	3.83	3.19	7.19	10.27	-0.80	3.13	4.35
30t33	Electrical and optical equipment	1.10	3.13	10.30	0.26	13.54	1.51	-5.24	3.26	5.06	-2.53	3.04
34t35	Transport equipment	2.82	8.46		5.75	3.07	2.82	-1.73	0.19	5.11	2.93	3.27
36t37	Manufacturing nec; recycling	-1.48	-4.94		7.62	12.92	8.99	5.09	-5.02		5.43	3.58

Table 7A – Average percentage over countries and years of workers moving from industry i to j

from \ to	15t16	17t19	20	21t22	23	24	25	26	27t28	29	30t33	34t35	36t37	D
15t16	8.71	0.20	0.05	0.20	0.03	0.44	0.18	0.16	0.32	0.27	0.26	0.18	0.09	11.10
17t19	0.15	4.05	0.03	0.11	0.00	0.05	0.15	0.03	0.23	0.13	0.14	0.14	0.19	5.39
20	0.05	0.01	2.15	0.06	0.00	0.02	0.06	0.05	0.14	0.20	0.06	0.15	0.20	3.16
21t22	0.18	0.05	0.09	9.27	0.02	0.17	0.15	0.11	0.20	0.22	0.22	0.14	0.13	10.94
23	0.01	0.01	0.00	0.01	0.31	0.02	0.01	0.00	0.05	0.03	0.02	0.03	0.00	0.48
24	0.35	0.12	0.03	0.15	0.05	4.36	0.18	0.05	0.14	0.21	0.14	0.09	0.10	5.96
25	0.08	0.16	0.04	0.10	0.00	0.18	2.22	0.06	0.30	0.27	0.23	0.14	0.06	3.84
26	0.06	0.06	0.12	0.04	0.00	0.06	0.13	2.08	0.28	0.19	0.09	0.12	0.03	3.27
27t28	0.23	0.13	0.19	0.23	0.04	0.27	0.37	0.20	11.05	1.57	0.53	0.72	0.25	15.77
29	0.21	0.11	0.07	0.35	0.05	0.23	0.17	0.12	1.96	9.21	0.69	0.64	0.14	13.96
30t33	0.19	0.14	0.07	0.23	0.02	0.31	0.16	0.11	0.58	0.81	9.68	0.39	0.10	12.79
34t35	0.12	0.04	0.06	0.05	0.00	0.14	0.17	0.03	0.63	0.70	0.40	5.96	0.17	8.47
36t37	0.10	0.15	0.27	0.10	0.01	0.07	0.19	0.05	0.25	0.15	0.17	0.33	3.04	4.87
D	10.44	5.22	3.18	10.91	0.53	6.31	4.14	3.05	16.12	13.96	12.62	9.03	4.49	100.00

Table 8A – Average current job tenure in years and deviation from the average sectoral job tenure (1995-2005)

nace2	BE	DE	DK	ES	FI	FR	IT	NL	SE	UK	mean
15t16	10.53 (-3.77%)	11.59 (5.89%)	10.49 (-4.14%)	10.12 (-7.54%)	11.55 (5.49%)	11.02 (0.72%)	11.18 (2.17%)	11.92 (8.86%)	10.81 (-1.20%)	10.24 (-6.49%)	10.9
17t19	11.25 (2.11%)	12.75 (15.70%)	9.66 (-12.34%)	9.39 (-14.82%)	12.45 (12.95%)	11.90 (7.98%)	10.03 (-9.01%)	10.76 (-2.32%)	11.75 (6.59%)	10.27 (-6.83%)	11.0
20	10.02 (-8.63%)	11.59 (5.70%)	10.06 (-8.26%)	9.55 (-12.94%)	11.61 (5.86%)	11.85 (8.10%)	10.78 (-1.66%)	12.71 (15.93%)	11.38 (3.81%)	10.10 (-7.92%)	11.0
21t22	10.58 (-10.11%)	12.45 (5.84%)	11.44 (-2.78%)	9.58 (-18.58%)	14.38 (22.20%)	11.76 (-0.03%)	11.30 (-3.94%)	11.75 (-0.12%)	14.28 (21.39%)	10.13 (-13.87%)	11.8
23	15.63 (0.31%)	16.07 (3.16%)	12.20 (-21.69%)	17.82 (14.39%)	16.40 (5.29%)	15.87 (1.85%)	15.84 (1.69%)	16.42 (5.41%)	15.23 (-2.25%)	14.31 (-8.17%)	15.6
24	12.21 (-1.02%)	14.27 (15.67%)	9.04 (-26.70%)	12.12 (-1.79%)	13.66 (10.70%)	12.90 (4.59%)	12.04 (-2.40%)	14.29 (15.83%)	11.49 (-6.85%)	11.35 (-8.02%)	12.3
25	10.46 (-3.74%)	11.83 (8.82%)	9.57 (-11.89%)	10.80 (-0.64%)	10.79 (-0.70%)	12.29 (13.07%)	10.52 (-3.16%)	10.99 (1.16%)	11.61 (6.84%)	9.81 (-9.75%)	10.9
26	12.24 (1.79%)	13.47 (12.01%)	9.86 (-18.01%)	10.59 (-11.96%)	10.94 (-9.00%)	13.88 (15.38%)	10.77 (-10.46%)	13.01 (8.15%)	13.74 (14.28%)	11.77 (-2.18%)	12.0
27t28	13.12 (7.78%)	13.58 (11.60%)	9.78 (-19.61%)	11.51 (-5.45%)	12.16 (-0.10%)	12.73 (4.62%)	11.20 (-7.96%)	12.88 (5.82%)	12.98 (6.65%)	11.76 (-3.36%)	12.2
29	11.68 (-4.41%)	13.88 (13.59%)	10.91 (-10.77%)	11.46 (-6.24%)	12.55 (2.69%)	13.98 (14.37%)	10.99 (-10.08%)	11.77 (-3.71%)	13.62 (11.45%)	11.38 (-6.88%)	12.2
30t33	12.08 (8.20%)	12.42 (11.26%)	9.10 (-18.52%)	10.81 (-3.19%)	8.81 (-21.15%)	13.19 (18.16%)	11.07 (-0.84%)	13.09 (17.21%)	11.05 (-1.07%)	10.04 (-10.06%)	11.2
34t35	12.30 (-7.77%)	14.45 (8.32%)	10.18 (-23.66%)	13.32 (-0.14%)	13.60 (1.96%)	16.21 (21.50%)	13.54 (1.49%)	13.39 (0.41%)	13.69 (2.62%)	12.71 (-4.73%)	13.3
36t37	10.18 (-5.19%)	12.13 (12.90%)	9.50 (-11.55%)	9.44 (-12.10%)	11.67 (8.66%)	11.75 (9.44%)	10.28 (-4.30%)	11.40 (6.16%)	11.70 (8.97%)	9.34 (-13.01%)	10.7
D	11.7	13.1	10.1	11.0	12.0	13.0	11.2	12.5	12.6	11.0	11.8

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Z U S A M M E N F A S S U N G

Diese Arbeit analysiert die Verbindung zwischen Produktivität und Arbeitsmarktmobilität. Die darin getestete Hypothese besagt, dass technologisches Wissen durch die Bewegungen von Fachkräften in der Form von Humankapital über Industrien verbreitet wird. Das Wissen diffundiert daraufhin im neuen Umfeld und führt zu Produktivitätssteigerungen.

Basierend auf neuesten theoretischen Erkenntnissen, die empirisch bestätigt wurden, wird ein endogenes Wachstumsmodell entwickelt, das die Produktivität von Arbeit im Hinblick auf Wissensakkumulation erklärt. Sodann bestätigen die Ergebnisse der empirischen Analyse die wichtige Rolle des Humankapitals als eine Quelle für Wissenstransfers. Da Arbeitsmarktbewegungen eng mit Input-Output Verbindungen von Industrien verknüpft ist, deutet dieses Ergebnis darauf hin, dass die in der Literatur geschätzten Produktivitätseffekte von Spillover Effekten aus Renten in Wirklichkeit zum Teil durch Wissenstransfer entstehen.

Aufgrund der Heterogenität der Produktionsindustrien wird das Modell danach erweitert und mit separaten Koeffizienten für Hoch-, Mittel- und Niedrigtechnologiesektoren geschätzt. Die Resultate bestätigen die Annahme, dass Industrien mit einem niedrigen technologischen Niveau auch niedrigere Wissenstransfers erzeugen als Industrien mit einem höheren technologischen Level.

Diese Arbeit ist ein erster Schritt zur Schätzung der Produktivitätseffekte aus Wissenstransfers im Hinblick auf Arbeitsmarktmobilität und soll deren Bedeutung für wirtschaftliches Wachstum hervorheben.

SUMMARY

This paper addresses the link between productivity and labour mobility. The hypothesis tested in the paper is that technology is transmitted across industries through the movement of skilled workers embodying human capital. The embodied knowledge is then diffused within the new environment creating spillovers and leading to productivity improvements.

Based on recent theoretical findings that were confirmed by empirical evidence, a theoretical endogenous growth model is developed that explains labour productivity with respect to knowledge acquisition. The empirical analysis confirms the importance of human capital transferred across industries as a source for knowledge spillovers. Due to the fact that labour mobility is closely linked to input-output relations, this finding provides evidence suggesting that part of the estimated productivity effects of rent spillovers are in fact due to labour mobility.

Given the heterogeneity of the manufacturing sector, including both traditional and high technology sectors, the model was then extended and re-estimated with separate coefficients for high, medium and low technology industries. The results confirm the assumption that industries with a low technological level create lower knowledge spillovers to other sectors than medium and high technology industries.

The paper is meant to be a first step in the direction of estimating knowledge spillovers through labour mobility and should point out the importance of the mobility of human capital that goes hand in hand with the diffusion of knowledge into other industries for economic growth.