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Productivity Effects of Knowledge Transfers through Labour Mobility

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The paper addresses the link between productivity and labour mobility. The hypothesis tested 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. The empirical analysis is based on household survey and industry-level data for a sample of 12 EU countries covering the years 1995-2005. The estimates document the importance of positive cross-sectoral knowledge spillovers and indicate that labour mobility has considerable beneficial effects on industry productivity. Possible endogeneity problems related to labour mobility are tackled by employing a two stage instrumental variables approach. Moreover we show that the spillover effects vary considerably by technology level of the giving industry. While workers moving away from high and medium-tech industries are found to produce positive productivity effects for the receiving industry, no effect is found for those coming from low-tech industries.

JEL: J24, J60, O47
Keywords: Knowledge Spillovers, Labour Mobility, Productivity, Human Capital, Industry Level

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1 Introduction

In the two decades before and after the millennium, we have experienced in almost all European countries a restructuring of industries with medium and high skilled workers moving away from low-tech to medium and high-tech industries. The essential question that arises is: What effect does this labour mobility have on industry productivity? Are those people able to make good use of their previously obtained knowledge or does this process possibly lead to negative productivity effects for higher tech industries?

The recent spillover literature provides estimates for the productivity effects of knowledge and technology transfers across firms, industries and countries. The main channels of technology diffusion that have been considered in the literature are trade (Coe and Helpman 1995), input-output linkages (Terleckyj 1974; Keller 2002a) and FDI (Lichtenberg and van Pottelsberghe de la Potterie 2001; Lee 2006). Labour mobility has also been analysed (Almeida and Kogut 1999; Guarino and Tedeschi 2006), though a theoretical framework and precise estimates are still missing. In this paper, we aim to fill this gap by building on previous efforts in the input-output and trade spillover literature.

Initial efforts at estimating the productivity effects of inter-industry R&D spillovers were made by Griliches (1973) and Terleckyj (1974). In their pioneering work, they underline the importance of domestic spillovers focussing on input-output relations as a transmission channel. Keller (2002a) follows this and other earlier studies (Bernstein and Nadiri 1988; Coe and Helpman 1995) and analyses the role of trade in advanced intermediate goods for technology transmission across industries and countries. The results suggest that spillovers from R&D activities of other industries are substantial and that the resulting productivity effect is approximately of the same magnitude as the one from the industry's own R&D efforts. The size of the spillover effect has been found to depend on the absorptive capacity of the industry or country however. A number of studies confirm that increases in human capital augment absorptive capacity and enhance productivity gains resulting from spillover effects (for developing countries see Engelbrecht 2002, Falvey et al. 2007 and Wang 2007 and for OECD countries see Engelbrecht 1997 and Frantzen 2000).

Related to the concept of absorptive capacity are spillovers through FDI and labour mobility. They arise because of the imperfect appropriability of knowledge associated with innovations (Cincera and van Pottelsberghe de la Potterie 2001). Arrow (1962) addresses this problem and states that "no amount of legal protection can make a thoroughly appropriable commodity of something as intangible as information". This becomes clear when looking at the two main outputs of innovative activities. The standard goal of applied research is the creation of information leading to the production of new goods. To a large extent, this usually non-rivalrous information can be codified by patents. Moreover, conducting R&D leads to an increase in the researchers' knowledge in the respective field (Zucker et al. 1998) and this intellectual human capital is very difficult to protect. Firm specific information or knowledge 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. Through R&D collaborations or mobility of personnel between firms, information is spread since workers apply and share the prior obtained experience and knowledge in the new environment.

Almeida and Kogut (1999) contribute to the empirical research regarding spillovers from labour mobility by demonstrating that the driving force for knowledge externalities is the mobility of technical key engineers and patent holders. Song et al. (2003) confirm this learning-by-hiring effect studying patenting activities in the semiconductor industry. The overall labour mobility pattern is found to be strongly related to the proximity of industries (Guarino and Tedeschi 2006). Workers are more likely to move to related industries as they are better able to use prior obtained technological knowledge there. Since labour mobility poses a threat to the innovating firm by reducing returns to innovative activity, firms need to account for them (Kim and Marschke 2005).

Moen (2005) has shown that R&D intensive companies are able to cultivate more durable employer-employee relationships as a result of steeper wage curves.

Regarding the connection between labour mobility and productivity, the literature is rather scarce. While the spillover literature has analysed human capital with respect to its importance for absorptive capacity, its role as a direct source of spillovers has been widely neglected in this strand of literature. A study by Thulin (2009) estimates the effect of labour mobility on regional wage growth and finds a positive effect. A very recent paper by Stoyanov and Zubanov (2012) looks a Danish manufacturing data and finds that firms that hire workers from more productive firms experience productivity gains one year after the hiring. To our knowledge, no estimates exist for the effects of domestic labour mobility spillovers on overall industries' productivity.

In the face of intensified labour mobility in the new economy, understanding spillover effects resulting from these transfers of human capital across industries is vital (Magnani 2008). Our study shortens this gap in the literature and provides estimates for the productivity effects of knowledge spillovers resulting from labour mobility. In particular we investigate to what extent knowledge acquired in a research intensive environment can be transferred across industries in the form of human capital. The estimation is carried out on a sample of 12 EU countries using a comparable dataset based on guidelines from Eurostat. The dataset does not however have information on cross-country labour mobility, which thus forces us to concentrate on job mobility across industries within each of the countries. The estimated empirical model is constructed on the basis of a theoretical model presented below. The basic model is then extended and re-estimated with separate coefficients for high, medium and low technology industries to account for the heterogeneity of the manufacturing sector. Furthermore, we control for spillovers resulting from improved intermediate products.

Another issue that we need to address is the possible endogeneity of labour flows. Looking at labour mobility, we identify two main reasons for job switches. First of all, workers may want to increase the match between the job requirements and their abilities and goals (Topel and Ward 1992). "Goal" can be defined as a rather broad term, including job plans for the future, work-life balance, the desire for learning opportunities and so on. In general, a better match in terms of abilities should lead to higher wages. This brings us to the second reason for job switches: many employees switch firms simply in order to receive higher wages. If some industries pay higher wages for the same qualification profile, this leads to endogeneity issues with respect to labour flows, which we address in our paper by employing an instrumental variable approach.

Last but not least we perform a counterfactual analysis. According to our theory, knowledge is transmitted across industries foremost via the mobility of medium and high skilled workers. In order to strengthen this hypothesis, productivity effects resulting from flows of lower skilled workers are estimated.

The remainder of the paper is set out as follows: section 2 provides a theoretical model, section 3 describes the datasets used, section 4 gives information on the empirical approach, section 5 reports main results and section 6 concludes.

2 Theoretical background

This section will provide the theoretical background for the empirical analysis. The framework fits into the category of endogenous growth models with the focus on labour augmenting knowledge spillovers. The goal is to provide estimates for the effects of labour mobility on an industry's productivity, in a similar manner to the recent literature on trade and input-output spillovers (Coe and Helpman 1995; Keller 2002a; Wang 2007).

In the model, output Y of an industry i is assumed to be produced according to a Cobb Douglas production function with the inputs labour L_i, information and communication technology (ICT) capital services K_{ICT} and non ICT capital services K_N.

$$Y_i = A_i\, K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta}\, L_i^{\gamma} \qquad \alpha+\beta+\gamma = 1 \qquad \alpha,\beta,\gamma > 0 \tag{1}$$

A_i is a positive constant and L_i denotes effective labour input in industry *i*. In the EU KLEMS database, which will be used for the subsequent empirical analysis, multifactor productivity (*MFP)* is estimated controlling for the inputs ICT and non-ICT capital services and the number of employees, differentiated by skill groups (Inklaar et al. 2008), that is:

$$MFP_i = \frac{Y_i}{K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta}({m_{ih}}^{\theta}{m_{im}}^{\mu}\, {m_{il}}^{\lambda})} \qquad \theta+\mu+\lambda = \gamma \qquad \theta,\mu,\lambda > 0 \tag{2}$$

where m_{ih}, m_{im} and m_{il} represent the numbers of high, medium and low skilled workers, with θ, μ and λ being the respective coefficients in the production function. The sum of these estimated coefficients is assumed to be equal to the coefficient γ of the effective labour input L in equation (1). Combining equations (2) and (1) leads to an industry specific multifactor productivity of

$$MFP_i = \frac{A_i\, K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta} {L_i}^{\gamma}}{K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta}({m_{ih}}^{\theta}{m_{im}}^{\mu}\, {m_{il}}^{\lambda})} = A_i \frac{{L_i}^{\gamma}}{{m_{ih}}^{\theta}{m_{im}}^{\mu}\, {m_{il}}^{\lambda}} \tag{3}$$

While the real labour productivity function L_i remains unobservable, it is clear that the productivity of workers does not solely depend on their initial education level as in the MFP measure, but also on experience. Working in a setting which provides access to valuable information increases the employee's human capital stock and thus their market value. The on-the-job learning curve is therefore influenced by the working environment as well as education and of course personal characteristics of the employee, though the latter are unlikely to matter at the aggregated industry level.

Once employees have acquired additional information, the employer faces the possibility of knowledge outflows as the employee might be tempted to join or set up a rival. Due to the imperfect appropriability of knowledge associated with innovation (Cincera and van Pottelsberghe de la Potterie 2001), the employer is unable to fully protect the firm's knowledge stock. Especially in research intensive working areas, labour mobility is a major knowledge diffusion channel, as state-of-the-art technologies are often tacit knowledge (Hoisl 2007; Winter 1987).

Pakes and Nitzan (1983) provide a theoretical framework for this dilemma of hiring scientists for R&D projects who might use the acquired knowledge afterwards in a rival enterprise. The solution to their theoretical model implies that scientists and engineers in R&D intensive firms accept a significant wage discount at the beginning of their career in the face of on-the-job learning opportunities. After some years of experience, this wage discount transforms into a premium, taking into account the increased market value of the employee. Similarly, Gersbach and Schmutzler (2003) state that firms can keep their employees from leaving by offering sufficiently high wages. These predictions were empirically tested and confirmed by Moen (2005). Additionally, Moen finds that innovative companies tend to cultivate more durable employer-employee relationships, indicating that the potential loss in human capital per worker seems to be higher for R&D intensive firms. These findings strongly support the theory that the R&D intensity of a firm affects learning opportunities for the employees. Hence it seems feasible to use R&D intensity as a proxy for human capital acquisition in our model.

We assume that workers start with a knowledge stock $\vec{h}_{i0}$, depending on their education level, which in our model will be approximated by years of schooling. While working in an industry, they gain access to its knowledge approximated by the R&D stock of the industry, R_i. The extent to which a worker has absorbed the industry's knowledge depends on the transferability of knowledge, β_s.[1] In an aggregate form, the approximated effective labour productivity function $\tilde{\bar{L}}_i$, accounting for the different skill composition and absent labour mobility can thus be written as

$$\tilde{\bar{L}}_i = \left({m_{ih}}^{\theta} * {m_{im}}^{\mu} * {m_{il}}^{\lambda} * \left(\bar{h}_{i0} * R_i\right)^{\beta_s}\right)^{\frac{1}{\gamma}} \tag{4}$$

where m_{ih}, m_{im} and m_{il} are again the numbers of high, medium and low skilled workers respectively, and $\left(\bar{h}_{i0} * R_i\right)^{\beta_s}$ represents the experience term, expressed as an increase in the human capital stock of the average worker through R&D. Differently put, that means that R&D effects productivity through an increase in the human capital stock of the employees. For reasons of empirical tractability we assume that the knowledge absorption capabilities from R&D depend linearly on years of schooling.

If workers now leave the firm and enter another company, they take ideas and past experiences with them, which they are likely to share with their new colleagues. Song et al. (2003) provide evidence for this learning-by-hiring effect using patent data from the American semiconductor industry. The degree to which skills are transferable however varies across pairs of industries. That means that for example knowledge acquired in the rubber and plastics sector may be of great value in the petroleum industry, but less applicable in the paper production sector. Hence workers from the rubber and plastics sector are more likely to move to the petroleum industry. More generally, workers are expected with a higher probability to move to "closer" industries where they can make better use of their accumulated human capital, where they are more productive and where they receive higher wages. Pack and Paxson (1999) analyse this topic and confirm that labour mobility patterns are strongly linked to industry proximity, measured by input-output linkages and/or similarity of inputs. They also look at the effects of industry proximity on wages, which can be seen

[1] Unfortunately, there is no complete working history available for the dataset. Therefore we can only include working experiences directly before the last employer switch into the estimations of the human capital stock.

as a proxy for worker productivity. The authors find that a move to more similar industries produces larger wage gains, controlling for observable factors like age, years of education, marital status, gender and a set of dummy variables for firm size, year and job tenure.

Based on these finding, we will use labour mobility patterns to provide information on knowledge flows between industries. A very important issue hereby is the usage of knowledge in the receiving industry. We have chosen to weight the transmitted human capital stock by labour flows only and decided against an additional weighting by industry proximity, which would be an extra measure of how well knowledge embodied in mobile workers can be used in the receiving industry. This was done for three reasons: Firstly, Pack and Paxson have shown that labour mobility patterns are closely related to industry proximity and thus these patterns already reflect the utility of knowledge in another industry. Secondly, Song et al. (2003) and Mowery et al. (1998) propose that mobility can be more likely to result in inter-firm knowledge transfer when "the hired engineers possess technological expertise distant from that of the hiring firm" – therefore weighting the knowledge flows by industry proximity might be counterproductive. Thirdly, firms usually do not employ people if their working history does not match the job description. Therefore 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 general industry proximity. In addition, job changes are only considered where people were already part of the workforce one year before. Thus, many changes occur voluntarily, strengthening the previous matching argument.

In order to estimate the impact of this knowledge transfer through labour mobility on the productivity in the receiving sector, we include the knowledge stocks of the workers who moved to industry *i*. With this addition, the new approximated effective labour productivity function $\tilde{L}_i$ depends upon the human capital stocks of the workers staying in the industry (H_i^s) as well as the stocks of workers moving to the analysed industry (H_i^o). The two terms H_i^s and H_i^o, that is:

$$\tilde{L}_i = \left(m_{ih}{}^{\theta} * m_{im}{}^{\mu} * m_{il}{}^{\lambda} * \underbrace{\left(\frac{\bar{h}_{ii0} * R_i * l_{ii}}{l_i} \right)^{\beta_s}}_{H_i^s} \underbrace{\left(\sum_{\substack{j=1 \\ j \neq i}}^{J} \frac{\bar{h}_{ji0} * R_j * l_{ji}}{l_j} \right)^{\beta_o}}_{H_i^o} \right)^{\frac{1}{\gamma}} \tag{5}$$

where l_{ji} represents the number of workers moving from industry *j* to *i* and l_j stands for the total number of people employed in industry *j*. Accordingly l_{ii} denotes the people staying in industry *i*, $\bar{h}_{ij0}$ is the average education level of workers moving from industry *j* to industry *i* approximated by years of schooling and $\bar{h}_{ii0}$ the level of those staying in industry *i*, while R_i and R_j are the R&D stocks of the industries. Finally, β_o denotes the transferability of knowledge from the R&D stocks of other industries, made available through the movement of skilled workers embodying human capital. The two terms H_i^s and H_i^o enter in a multiplicative form as the knowledge stock of workers moving to the analysed industry diffuses within the new environment and has an effect on other workers as well.

H_i^s is defined similarly to the experience term in equation (4) but now weighted by the share of people staying in the industry l_{ii}/l_i. This weighting is applied because labour outflows create knowledge outflows that firms have to take into account. As a result, labour mobility out of the industry leads to a lower actual human capital stock of the analysed industry in our model. If we had assumed that knowledge in an industry is similar to a club good and can be used by all workers, 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 mostly private knowledge. As these ideas are the basis for future productivity increases, an outflow of this knowledge affects productivity increases negatively. Nonetheless, a sensitivity analysis based on the assumption that the knowledge remains completely in the industry is provided in the empirical section.

H_i^o represents the sum of the received human capital stocks from other industries weighted by the respective labour movements. The knowledge flows from industry *j* to *i* depends upon the number of people moving from *j* to *i* (l_{ji}), their average initial human capital stock and their past learning opportunities approximated by the R&D stock R_j of industry *j*.

The weighting as applied can be described or interpreted in a number of ways. We can say for example that industry *j*'s overall knowledge base $\bar{h}_j * R_j$ is weighted by the people moving from industry *j* to industry *i* (l_{ji}) scaled by the total number of workers originally employed in industry *j* (l_j). An alternative interpretation would be that the average human capital stock per worker in industry *j* ($\bar{h}_j * R_j / l_j$) is multiplied by the number of people l_{ji} switching from a job in industry *j* to one in industry *i*. Similar to the argument above, the assumption here is that the private nature of the employee's ideas and knowledge leads to a knowledge outflow if he leaves the industry.

A number of other possible weighting schemes could be considered. We discuss two alternatives here and explain why they are not suitable for our framework. One possibility would be to simple weight the human capital stock $\bar{h}_j * R_j$ by the level of workers moving from industry *i* to *j* without scaling the measure by l_j. With this specification we would need to make the strong assumption that knowledge is completely public however. This would mean that each worker moving from industry *j* would be able to transfer the whole knowledge stock to another industry which is in contrast to findings for example by Almeida and Kogut (1999) and Hoisl (2007).

A second possibility would be to scale by the number of people in the target industry (l_i) rather than the number in the origin industry (l_j). This is consistent with the idea of an inflow of knowledge to industry *i* expressed relative to the share of new labour. With different industry sizes, this is problematic however. If the industry of origin is small and the target industry big, then the resulting knowledge flow would be extremely small. Workers who move could be a large share of the people originally working in industry *j*, taking a great amount of tacit knowledge with them, but they would only be a small fraction of the people then working in *i*. Since the R&D stock already accounts for differences in industry size, this weighting would disproportionately diminish spillovers from small industries and not properly capture relative knowledge flows.

We can now substitute the real labour productivity function L_i in equation (3) by the approximated function $\tilde{L}_i$ of equation (5). Equation (6) now yields the starting point for our empirical analysis with MFP depending on a technology constant $\tilde{A}_i$ and the human capital variables H_i^s and H_i^o.

$$MFP_i \approx \frac{A_i\, K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta} L_i{}^{\gamma}}{K_{i_N}^{\alpha}\, K_{i_{ICT}}^{\beta}(m_{ih}{}^{\theta} m_{im}{}^{\mu}\, m_{il}{}^{\lambda})} = A_i * (H_i^s)^{\beta_s} * (H_i^o)^{\beta_o} \tag{6}$$

3 Data

3.1 Data Sources

The dataset used for the analysis contains 12 EU countries, namely Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden and the United Kingdom and covers the time period between 1995 and 2005. A number of sources were combined to setup the dataset. The multifactor productivity (MFP) indices were taken from EU KLEMS database (state March 2009), which provides data for the EU25 countries, Australia, Japan and the US at the industry level. The productivity indices were then multiplied with MFP levels which were estimated by Inklaar et al. (2008) for a subsample of the countries included in the EU KLEMS database.

The data on labour flows were taken from a sample of the EU Labour Force Survey by Eurostat covering the EU25 countries from 1995-2005. The adjusted employment series by Eurostat were used to correct for existing breaks in the series. The overall survey covers private households in the EU, EFTA and Candidate Countries with a sample size of 1.7 million individuals in 2004. The dataset holds information about the worker's age, education, occupation, gender and location on a NUTS2 level. It also provides some characteristics of the employer, such as size and industry classification. Furthermore the survey holds information on the industry the person has been working in one year before. Due to data limitations, the analysis focuses solely on inter-industry spillovers within countries. We expect cross-border flows to be relatively small compared to flows across industries within a country and so our expectation is that the results we have obtained would not be significantly affected. Our concentration on a fairly homogenous sample of developed countries would further lead us to believe that the issue of cross-border labour flows would have a limited effect on our results.

In order to identify the workers which are most likely the main source of knowledge spillovers, we use the International Standard Classification of Occupations (ISCO) and the International Standard Classification of Education (ISCED). With respect to occupation, 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". Additionally only medium and high skilled workers were used for the calculation of labour mobility patterns since they are most likely the main knowledge transmitter.

Average years of schooling $\bar{h}_{i0}$ for medium and high educated workers are calculated from the dataset of Barro and Lee (2010). Average years of schooling of medium educated workers are normalized to one in each country. The average initial human capital stock is then calculated by multiplying the normalized average years of schooling by the fraction of high and medium educated workers. Differences in initial education levels are picked up by country dummies.

The data on input-output linkages was taken from the newly constructed World Input-Output Database (WIOD), which covers the EU27 and 13 other major countries in the world. It contains data on 35 industries for each country over the period 1995-2005. In our analysis we restrict the sample to the manufacturing sector and to spillovers from these industries.

Finally data on research investment of the industries was taken from the STAN ANBERD database. The data in this dataset is at the industry classification ISIC Rev. 3 level and is compatible at the 2-digit level with NACE Rev. 1, which is used in the other databases. In order to make R&D investments comparable across time and countries, they were adjusted using purchasing power parity exchange rates and deflated using the gross fixed capital formation deflator taken from Eurostat. The initial R&D stock was calculated according to the commonly used formula provided by Griliches (1979) $R_o = RINV_0/(g + \delta)$, assuming a 10% depreciation rate. R_0 is the calculated R&D stock at the beginning of the sample and $RINV_0$ the R&D investment in that year, δ represents the assumed depreciation rate and g the growth rate of R&D investment over the analysed time period. The subsequent R&D stocks R are then calculated based on the perpetual inventory model and were used for the construction of the human capital variables.

Since one would expect knowledge to become obsolete faster in high technology sectors than in traditional, low technology sectors, we also present results from a sensitivity analysis in which we use different depreciation rates according to the technology level of the industry.

3.2 Descriptive Analysis

A general descriptive analysis of the data for countries and sectors is provided in TABLE 1. The Czech Republic experienced the highest productivity growth from 1995-2005, followed by Finland, Sweden and France. With respect to industries, "Electrical and optical equipment" and "Transport equipment" had the highest annual multifactor productivity growth rates with rates of 3.97% and 1.98% respectively. The industries "Coke, refined petroleum and nuclear fuel" and "Wood and products of wood and cork" as well as "Manufacturing n.e.c; recycling" had to be dropped because of large fluctuations in MFP across time. Especially in the case of "Coke, refined petroleum and nuclear fuel", these fluctuations occurred due to the high price volatility. These industries are also dropped from the countrywide manufacturing summary statistics in TABLE 1 (see Appendix TABLE A1 for MFP growth rates by industries and countries).

Regarding R&D investment, Finland (9.41%) and Denmark (8.04%) 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" has an R&D investment growth rate of 12.63 in Finland and 7.65 in Denmark (for more information on R&D investment across countries and sectors see Appendix TABLE A2). When examining total R&D investment in the sample we discover that "Electrical and optical equipment" (27.57%), "Transport equipment" (29.63%) and "Chemicals and chemical products" (22.82%) are by far the most important sectors for R&D investment and make up more than three quarters of all R&D investment in the sample.

TABLE 1

Summary statistics

code	Country / Industry	Average MFP growth*	Average R&D inv. growth*	Rel. size in terms of R&D**	Rel. size in terms of labour†	Rel. size in terms of VA‡
BE	Belgium	1.21	3.60	3.60	2.49	2.80
CZ	Czech Republic	3.63	3.24	0.68	4.10	1.23
DE	Germany	1.79	5.56	40.91	28.91	26.62
DK	Denmark	-0.38	8.04	1.63	1.58	1.64
ES	Spain	-0.57	4.85	2.86	9.18	7.25
FI	Finland	2.39	9.41	2.87	1.51	1.88
FR	France	2.13	2.33	19.31	14.57	15.19
IE	Ireland	1.59	-0.99	0.49	0.97	2.38
IT	Italy	-0.78	-1.53	5.47	15.55	15.09
NL	Netherlands	1.71	3.69	4.29	3.32	5.69
SE	Sweden	1.93	2.91	6.05	2.49	3.20
UK	United Kingdom	1.31	0.84	11.82	15.33	17.04
15t16	Food, beverages and tobacco	-0.05	3.09	2.05	11.40	13.31
17t19	Textiles, textile, leather and footwear	1.35	4.46	0.75	8.19	5.45
20	Wood and products of wood and cork	1.76	0.78	0.12	3.14	2.04
21t22	Pulp, paper, printing and publishing	0.77	2.54	0.56	8.51	9.35
23	Coke, refined petroleum & nuclear fuel	-11.35	-1.93	0.81	0.55	3.62
24	Chemicals and chemical products	1.43	3.68	22.82	6.53	12.35
25	Rubber and plastics	1.70	5.80	1.98	4.55	4.35
26	Other non-metallic mineral	1.20	1.98	1.09	3.78	4.45
27t28	Basic metals and fabricated metal	0.33	1.83	2.68	14.48	12.57
29	Machinery and equipment n.e.c.	1.07	4.23	9.22	11.40	8.92
30t33	Electrical and optical equipment	3.97	1.83	27.57	11.33	9.72
34t35	Transport equipment	1.98	5.16	29.63	10.16	9.36
36t37	Manufacturing n.e.c; recycling	0.62	2.59	0.71	5.98	4.52

Notes: All indicators in %; country figures do not include NACE 20, 23 and 36t37 for reasons of distortion; R&D investment is based on PPP adjusted USD data which was deflated using the GFCF deflator from Eurostat; *Mean annual average growth of value added MFP between 1995 and 2005, weighted by value added; **Based on R&D investment in 2000; †Based on total number of employees in 2000; ‡Based on gross value added in 2000 calculated from the WIOD database.

TABLE 2

High and medium educated workers moving from industry i to j in percent of all moving workers in the sample (average across years)

from \ to		15t16	17t19	20	21t22	23	24	25	26	27t28	29	30t33	34t35	36t37	D
15t16	Food, beverages and tobacco	9.06	0.17	0.05	0.18	0.00	0.22	0.17	0.07	0.26	0.23	0.23	0.14	0.13	10.91
17t19	Textiles, textile, leather and footwear	0.17	4.51	0.01	0.11	0.00	0.10	0.16	0.05	0.23	0.20	0.18	0.15	0.15	6.03
20	Wood and products of wood and cork	0.05	0.03	1.86	0.04	0.00	0.02	0.06	0.04	0.14	0.12	0.06	0.08	0.17	2.67
21t22	Pulp, paper, printing and publishing	0.14	0.09	0.04	7.15	0.03	0.15	0.10	0.06	0.23	0.24	0.23	0.13	0.12	8.73
23	Coke, refined petroleum & nuclear fuel	0.02	0.01	0.00	0.00	0.35	0.04	0.01	0.00	0.04	0.03	0.01	0.03	0.00	0.54
24	Chemicals and chemical products	0.23	0.08	0.02	0.16	0.06	4.95	0.20	0.08	0.17	0.21	0.20	0.10	0.07	6.53
25	Rubber and plastics	0.12	0.11	0.06	0.11	0.01	0.16	2.56	0.06	0.26	0.19	0.15	0.21	0.11	4.10
26	Other non-metallic mineral	0.05	0.04	0.06	0.06	0.00	0.09	0.11	2.27	0.19	0.14	0.10	0.08	0.05	3.25
27t28	Basic metals and fabricated metal	0.21	0.15	0.13	0.19	0.06	0.18	0.31	0.18	11.61	1.19	0.42	0.68	0.18	15.48
29	Machinery and equipment n.e.c.	0.22	0.14	0.07	0.24	0.04	0.20	0.22	0.10	1.41	9.65	0.61	0.52	0.16	13.57
30t33	Electrical and optical equipment	0.21	0.14	0.06	0.21	0.03	0.22	0.19	0.11	0.50	0.65	10.33	0.43	0.16	13.24
34t35	Transport equipment	0.16	0.08	0.04	0.09	0.01	0.09	0.23	0.07	0.65	0.47	0.43	6.97	0.23	9.52
36t37	Manufacturing n.e.c; recycling	0.12	0.13	0.18	0.07	0.01	0.08	0.12	0.08	0.22	0.19	0.26	0.24	3.74	5.43
D	Total Manufacturing	10.76	5.67	2.58	8.63	0.60	6.49	4.44	3.17	15.92	13.53	13.22	9.75	5.26	100.00

TABLE 2 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 workers having changed their job within the last year. Most changes of jobs occur within the same industry. Another crucial observation we can make is that there exists a positive net outflow of medium and high educated workers from all low technology industries to higher technology sectors. These annual 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. The technology classification was hereby 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).

4 Empirical model and estimation procedure

4.1 Baseline specification

Past studies have highlighted that research undertaken in one industrial sector is influenced by R&D activities of other sectors that spill over through various channels e.g. labour mobility, use of intermediate products, foreign direct investment, research cooperation, etc. (Bernstein and Nadiri 1988; Griliches 1979; Keller 2002a). In this section, the theoretical model will be used in order to set up an empirical model with the postulated hypothesis being that industries can profit from the R&D investments of other domestic sectors by hiring their workers and employing their human capital. The knowledge stock of workers coming from other sectors hereby has two effects on the productivity of the receiving industry. First, it influences productivity by adding more human capital incorporated in new employees (direct effect). In addition, the quality of the match between a worker and a job likely improves as workers move between employers and try different jobs (Topel and Ward 1992; Thulin 2009). Secondly, higher labour mobility increases the exposure of the incumbent workforce to knowledge of other workers. The new employees are likely to share their ideas, leading to potential inter-industry knowledge flows (a spillover effect). The direct effect is to some extent captured through the skill decomposition in the MFP function, the spillover effect however is completely absent therein.

With the theoretical model presented in section 2, we are in a position to estimate the size of this spillover effect from labour mobility in a manner similar to that done elsewhere in the spillover literature (Coe and Helpman 1995; Keller 2002a). Equation (6) from the theoretical model yields the starting point for our empirical investigation:

$$log\ MFP_{ict} = \beta_s\ log\ H_{ict}^{s} + \beta_o\ log\ H_{ict}^{o} + \alpha_t + \alpha_c + \alpha_i + \varepsilon_{ict} \tag{7}$$

where MFP_{ict} denotes the multifactor productivity of industry *i* in country *c* at time *t*, and β_s and β_o are the two coefficients to be estimated for the explanatory human capital variables. The construction of these variables follows directly from equation (5). 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, while a set of industry dummies α_i are included to account for differences in productivity across sectors due for example to automatisation possibilities that may vary by industry. Finally ε_{ict} denotes the error term. Note that we do not include labour flows on its own as a covariate. This is because the MFP function already accounts for the skill structure as the estimation of MFP uses information on workers differentiated by the education levels low, medium and high at the industry level. Thus, changes in the skill structure through labour mobility are already accounted for.

4.2 Cointegration issues

There are a couple of issues that have to be addressed and accounted for before moving on to the estimation. The primary concerns are cointegration, simultaneity and serial correlation. The standard OLS estimator is consistent even under panel cointegration but produces invalid standard errors due to a second-order asymptotic bias (Kao et al. 2000). Furthermore it suffers from an endogeneity bias. Newly available cointegration estimation techniques such as Dynamic OLS (DOLS) or Fully Modified OLS (FMOLS) correct for endogeneity biases and serial correlation and thus allow us to construct valid t-statistics (Banerjee 1999; Breitung and Pesaran 2005). These techniques have been employed in a number of articles in the spillover literature (Lee 2006; López-Pueyo et al. 2008; Coe et al. 2009) as well as in other strands of research.

First, we test for the existence of unit roots in the dataset using the Im-Pesaran-Shin test (IPS) (2003). If the null hypothesis of the IPS test cannot be rejected, it indicates that all panels have a unit root (H_0: $\rho_i = 0\ \forall i$). The alternative hypothesis is that at least one panel is stationary. In contrast to other tests such as the Levin-Lin-Chu test (LLC), the IPS test relaxes the assumption of a common ρ for the whole panel. TABLE 3 presents the results for the panel unit root tests. For *MFP* and H^s there is a strong indication that all panels contain a unit root. The fraction of non-stationary panels is not equal to zero for the spillover variable H^o as well as the input-output control variable *IO*.

TABLE 3

Panel unit root tests

	$ln(MFP_{cit})$	$ln\ (H^{s}_{cit})$	$ln\ (H^{o}_{cit})$	$ln\ (IO_{cit})$
Im-Pesaran-Shin test	2.7214	3.9994	-12.1752***	-2.0460**

The values represent W-t-bar statistics of the one-sided Im-Pesaran-Shin test (2003). The number of lags included in respective tests is chosen using the Akaike information criterion. ***, ** and * denote tests being significant at a 1, 5 and 10% level, respectively.

Given that the null hypothesis of stationarity in all panels could not be rejected for the MFP variable as well as the human capital stock H^s, we now perform Westerlund error-correction-based panel cointegration tests (Persyn and Westerlund 2008) to test for cointegration between log(MFP) and the rent spillover variables. The results are reported in TABLE 4 and indicate that MFP and the human capital stock of the analysed industry H^s are not only stationary, but also cointegrated. Although the time series are rather short (11 years), which poses a problem for the cointegration test, the results indicate cointegration for the panel as a whole. In order to obtain valid t-statistcs, we will therefore employ Dynamic OLS.

TABLE 4

Westerlund ECM panel cointegration tests

log(MFP)	log(H^s)	log(H^o)	log(IO)
Gt	-2.213***	-0.588	-0.776
Ga	-1.209	-0.885	-1.275
Pt	-7.444**	-5.947	-6.250
Pa	-1.350	-0.953	-1.111

A rejection of H_0 for the Ga and Gt test-statistics should be taken as evidence of cointegration of at least one cross-sectional unit. The Pa and Pt test statistics pool information over all the cross-sectional units and a rejection of H_0 provides evidence for cointegration for the panel as a whole. One lead and lag were included in the error-correction equations. ***, ** and * denote tests being significant at a 1, 5 and 10% level, respectively.

4.3 Other spillover channels

Another thing that we need to be concerned about is the fact that labour mobility is not the only source of spillovers between industries. To control for spillovers resulting from improved intermediate products, we follow the theoretical model of Keller (2002a) and extend our estimation equation (7) in order to include the input-output spillover variable IO_{ict}.

$$log\ MFP_{ict} = \beta_s\, log\, H_{ict}^{s} + \beta_o\, log\, H_{ict}^{o} + \beta_{io}\, log\ IO_{ict} + \alpha_t + \alpha_c + \alpha_i + \varepsilon_{ict} \tag{8}$$

Following the approach of Foster et al. (2012) we construct this variable by weighting the R&D stock, R_{jdt}, of the supplying industry j in country d at time t directly by the share of intermediate products used from this industry, ω_{icjdt}. These input-output weighted R&D stocks are then summed up over all supplying industries and countries for the analysed industry i in country c. This measure is supposed to control for rent spillovers both at the domestic and at the international level.

$$IO_{ict} = \sum_{d=1}^{C} \sum_{\substack{j=1 \\ j \neq i}}^{I} \omega_{icjdt} * R_{jdt} \tag{9}$$

4.4 Endogeneity of labour flows

Finally, we face the possibility of an endogeneity problem related to the labour flows. A major reason why workers move from one firm, and possibly industry, to another is simply the expectation of a better matching of their abilities with the needs of the employer (Topel and Ward 1992). People may also switch to another industry because of higher wages however, and this can create a simultaneity bias. In a perfectly competitive labour market, this does not happen, since the price for a specific qualification profile and workload should be the same across industries. Furthermore the recent heterogeneous firm literature stresses wage dispersion between firms within an industry rather than between industries (Davis and Haltiwanger 1991; Faggio et al. 2010; Helpman et al. 2012). Despite this, there are a number of reasons to expect mobility to respond to wages. One example of this is the recent literature suggesting that exporting firms are more productive and pay higher wages than non-exporters. Such a pattern could impact upon labour mobility patterns at the industry-level if firms in some industries have a higher propensity to export than others. Industry restructuring can also leave firms or even industries with a need for certain qualification profiles for which they are willing to pay a premium over other market participants. A downturn in a certain industry most likely results in lower productivity and in turn to lower labour inflows, which may create a correlation between productivity and human capital inflows, that is to some extent spurious.

In order to remove these biases, we perform a two-stage instrumental variable regression. In the first step, the decision of workers to stay or move to another industry is modelled. Then the predicted labour mobility values are summed up and plugged back into the estimation of equation (7). This procedure is similar to that used elsewhere, for example by Frankel and Romer (1999) in their study of trade and growth. As the sum of the normally distributed errors is still normally distributed, this aggregation should not lead to an estimation bias in the second stage.

$$\begin{aligned} log\ Mob_{aeojicrt} &= \beta_1\, log\ Lab_{jcrt-1} + \beta_2 log\ Lab_{icrt-1} + \sum_{a}^{A} \beta_{3a}\, age_a + \\ &+ \sum_{e}^{E} \beta_{4e}\, isced_e + \sum_{o}^{O} \beta_{5i}\, isco_o + \alpha_{ct} + \alpha_{cr} + \alpha_{ji} + \varepsilon_{aeoijcrt} \end{aligned} \tag{10}$$

Labour flows are estimated for each subcategory of workers of age a, with education level e and occupation o, which move from industry j to i in region r of country c at time t. The two main explanatory variables are the values of employment in the source (Lab_{jcrt-1}) and receiving (Lab_{icrt-1}) industries in the previous year at the regional level. Moreover, we use general inter-industry labour mobility patterns across countries by including interacted industry dummies of the receiving and source industry α_{ji}. By not using these patterns for each country separately, country specific industry relations are ignored (e.g. the movement of workers to an industry because of higher wages paid there specifically in that country).

A further dimension is the geographical aspect. Labour market legislation certainly differs over the analysed countries and changes over time. To account for changes in legislation and other factors that affect the labour mobility picture at the country level, country-time dummies α_{ct} are included. In addition to the differences across countries, mobility differs greatly by region. In dense areas labour mobility tends to be higher – thus we include dummies for NUTS2 regions α_{cr}.

Additionally, a number of characteristics of the workers are controlled for which likely influence the mobility of workers. As young people are more mobile, age is surely a major factor. Our dataset contains information on employees in the following groups $a \in A$ {15-24, 25-39, 40-54, 55-64, >65}. Furthermore, occupations based on the International Standard Classification of Occupations (ISCO) are used at the one digit level. Finally, workers are differentiated according to the education levels low, medium and high based on the International Standard Classification of Education (ISCED). Descriptive statistics from our dataset show that higher educated workers are less likely to switch industries. This is consistent with the theory that employers try to avoid knowledge outflows resulting from workers leaving the firm. These outflows are of course on average greater, the higher the education of the employee. Thus, firms are expected to prevent strong mobility of higher educated workers.

In order to be valid, the instruments have to be orthogonal to our productivity measure. As stated before, our MFP measure controls for education levels – thus including these as instruments does not pose a problem. Regarding the relationship between age, productivity and wages, the literature is not really consistent. When looking at piece-rates, a study of the U.S. Department of Labor (1957), analysing a broad range of industries finds that job performance increases until the age of 35 and steadily declines thereafter. This measure however is more related to low skilled workers, which are excluded from our study. Some papers cautiously point in the direction of a negative productivity-age relationship (Hellerstein et al. 1996; Kotlikoff and Gokhale 1992), others like Cardoso et al. (2011) suggest a positive relationship, even after controlling for wages, while others find no conclusive evidence at all (Hellerstein et al. 1999; Hellerstein and Neumark 1995). A number of studies find a form of inverted U-shaped work performance profile (Cardoso et al. 2011; Göbel and Zwick 2009; Crépon et al. 2003; Ilmakunnas et al. 1999). The peak with the highest productivity is however not clear and depending on the worker's skill level. Recent studies by Cardoso et al. (2011) and Göbel and Zwick (2009) find an increase in productivity until the mid 50ies and only a slight decrease in productivity afterwards. Cardoso et al. (2011) thus conclude that "older workers are, in fact, worthy of their pay". The reasons for this strong increase in firm productivity through older employees are their large knowledge stock and resulting spillovers to younger employees, a positive selection of older people which are still in the workforce as well as a usually better matching of their abilities with the needs of the employer compared to younger workers. Regarding the wage-productivity relationship, which is important to ensure orthogonality of age and MFP, this leaves us with no conclusive evidence. We thus do not expect this variable to bias our IV regression.

5 Results and Discussion

The following section provides estimates for the size of the spillovers. The first regression (i) in TABLE 5 shows the results of the basic equation (7). The coefficients can be interpreted as elasticities of multifactor productivity with respect to human capital stocks weighted by labour movement. β^s is a measure of the impact of the industry's own knowledge stock on MFP after adjusting for labour and thus human capital outflows. An industry can increase its own knowledge stock by investing more in R&D. Similarly β^o measures the degree to which industry *i* will profit from the human capital of other industries by hiring their workers. Basically there are two ways of increasing this spillover effect. First of all, the giving industry can enhance their R&D activities and thus add to their human capital stock. Assuming that the labour flows stay the same, this would lead to an increase in the knowledge flow. Secondly, the receiving industry can hire more workers from other industries or relatively more from those with higher human capital stocks.

The elasticities from estimation (i) indicate that the effect of knowledge built up in the industry itself β^{s} is around seven times larger than the productivity gains resulting from workers of other industries β^{o}. An annual increase in the human capital stock of around 3.5%, which can be observed in the sample over the analysed period, would, ceteris paribus, result in an overall 0.8% increase in productivity through labour mobility over ten years. The effect of the industry's own human capital stock, increased through R&D, results in a 5.8% higher MFP over the same time period (the human capital stock overall increased by a factor of 1.41, which is taken to the power of 0.164).

The provided estimates should be regarded as a lower bound to the true productivity effects since we are just able to consider labour movements from the year before and do not have information on the complete working history. Knowledge spillovers through labour mobility likely need more time to affect productivity in the new sector as workers need to first get acquainted with their new environment and the possibilities to bring in their knowledge may be somewhat limited during this period. Furthermore, knowledge sharing between employees does not happen overnight and knowledge spillovers also need time to affect productivity.

To account for the heterogeneity of the manufacturing sector, including both traditional and high technology industries, 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.

TABLE 5

Estimation results

	(i) DOLS	(ii) DOLS	(iii) DOLS	(iv) DOLS	(v) DOLS	(vi) OLS
β^{s}	0.164***		0.166***			
	(0.020)		(0.020)			
$\beta^{s\ hightech}$		0.205***		0.227***	0.246***	0.161***
		(0.029)		(0.033)	(0.030)	(0.022)
$\beta^{s\ medtech}$		0.170***		0.172***	0.183***	0.158***
		(0.021)		(0.021)	(0.022)	(0.019)
$\beta^{s\ lowtech}$		0.143***		0.127***	0.146***	0.126***
		(0.027)		(0.026)	(0.027)	(0.024)
β^{o}	0.023***	0.022***				
	(0.006)	(0.006)				
$\beta^{o\ hightech}$			0.012***	0.011**	0.015***	0.008***
			(0.005)	(0.005)	(0.005)	(0.003)
$\beta^{o\ medtech}$			0.020***	0.019***	0.018***	0.007**
			(0.006)	(0.006)	(0.006)	(0.004)
$\beta^{o\ lowtech}$			-0.008	-0.008	-0.006	0.002
			(0.007)	(0.007)	(0.007)	(0.004)
β^{io}					0.230***	
					(0.046)	
Country effects	yes	yes	yes	yes	yes	yes
Industry effects	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes
R^2	0.726	0.732	0.729	0.739	0.743	0.702
Observations	741	741	741	741	741	979

Standard deviations in parentheses. The dependent variable is ln(MFP). Coefficients are estimated using dynamic ordinary least squares (DOLS) with one lead and lag of the differenced human capital variables. <***>, <**> and <*> denote coefficients being significantly different from zero at a 1, 5 and 10% level, respectively.

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.

Quite striking is the fact that the productivity effects differ greatly by technology segment. High tech industries generate the highest productivity effects with respect to their own human capital stock, increased through R&D, while low tech industries produce the lowest ones. Taking again the 41% overall increase in human capital stock over the whole analysed period and the coefficients from estimation (iv), this leads to a productivity effect of 4.5% for low-tech, 6.1% for medium-tech and 8.1% for high-tech industries respectively. Turning to the spillover coefficients, we find that while the spillover coefficients for high and medium technology industries are positive and significant across specifications (ii) to (iv), they are insignificant (and negative) in low technology industries. Workers from medium and high tech industries possess a greater stock of state-of-the-art transferable knowledge and create higher spillovers, whereas workers from low tech industries seem to be able to use their prior obtained knowledge less in the new working environment. Thus the restructuring process which has taken place in Europe, with high and medium educated people moving away from low tech sectors, could have resulted in a negative impact on the productivity of other industries.

In a next step (v) we include spillovers through input-output linkages. The estimates suggest that spillovers arising from the use of intermediate products of other domestic and also international industries play an important role for productivity developments. The magnitude of the effect is similar to that found for industries' own human capital stocks, suggesting productivity effects of 8.3% over the analysed period of ten years. The coefficients for knowledge spillovers through labour mobility remain significant and are of a similar size.

Regressions (vii) to (ix) in TABLE 6 present the results of the two stage instrumental variable estimations. As there are various reasons for endogeneity problems related to labour mobility, we first estimate labour mobility flows, using the instruments shown in equation (10), and aggregate up the results in order to estimate the resulting productivity effects. The sample size decreases again due to the loss of one year, as the industry characteristics in t-1 are used as instruments for labour mobility flows. In the simple version of our model, presented in estimation (vii), the results stay very similar to the ones shown in estimation (i) before. Differentiating the human capital variables by technology segment again yields similar results for the industry's own human capital stock. Regarding spillovers from other industries, the productivity effect of worker inflows from high-tech industries however becomes stronger and of similar size to the one of medium-tech industries. Overall the results remain significant and underline the positive spillovers from labour mobility and intermediate inputs.

To complete the analysis, we perform a number of additional robustness checks. As noted in a footnote earlier, one can assume that knowledge produced in an industry is similar to a club good, an assumption different to the one employed above. In this case all knowledge can be codified or is completely shared with other employees and thus still remains entirely in the industry when essential employees move to another industry. This mobility would still create knowledge flows to other industries, but the industry itself would not lose knowledge. In regression (x) we examine this assumption by including the human capital variables of the analysed industry H^s solely without any mobility weighting. We observe that the elasticities of productivity with respect to human capital in the industry ($\beta^{s\ hightech}$, $\beta^{s\ medtech}$ and $\beta^{s\ lowtech}$) are lower as opposed to (iv) if we do not account for knowledge outflows through labour mobility. The changes however are minor as the industries' labour outflows per year are mostly below 10%. As another robustness check we also include the simple OLS regression (vi) in TABLE 5. The results are more or less in line with previous findings – however they suffer from serial correlation and cointegration bias.

TABLE 6

Instrumental variable estimations and robustness checks

	(vii) IV & DOLS	(viii) IV & DOLS	(ix) IV & DOLS	(x) DOLS β^s unweighted	(xi) DOLS diff. depr. rates	(xii) DOLS
β^s	0.155***					0.171***
	(0.023)					(0.020)
$\beta^{s\ hightech}$		0.212***	0.239***	0.220***	0.200***	
		(0.033)	(0.032)	(0.030)	(0.030)	
$\beta^{s\ medtech}$		0.157***	0.169***	0.170***	0.152***	
		(0.024)	(0.024)	(0.021)	(0.022)	
$\beta^{s\ lowtech}$		0.136***	0.129***	0.148***	0.122***	
		(0.031)	(0.032)	(0.027)	(0.027)	
β^o	0.023***					
	(0.007)					
$\beta^{o\ lowedu}$						-0.015**
						(0.007)
$\beta^{o\ hightech}$		0.016***	0.019***	0.012**	0.013**	
		(0.005)	(0.005)	(0.005)	(0.005)	
$\beta^{o\ medtech}$		0.017**	0.019***	0.017***	0.019***	
		(0.007)	(0.007)	(0.006)	(0.006)	
$\beta^{o\ lowtech}$		-0.002	0.000	-0.007	-0.004	
		(0.008)	(0.007)	(0.007)	(0.007)	
β^{io}			0.312***			
			(0.049)			
Country effects	yes	yes	yes	yes	yes	yes
Industry effects	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes
R^2	0.737	0.749	0.764	0.736	0.729	0.725
Observations	571	571	571	741	741	741

Standard deviations in parentheses. The dependent variable is ln(MFP). Coefficients are estimated using ordinary least squares (OLS) with robust standard errors and dynamic ordxinary least squares (DOLS) with one lead and lag of the differenced human capital variables. <***>, <**> and <*> denote coefficients being significantly different from zero at a 1, 5 and 10% level, respectively.

Furthermore, we perform a sensitivity analysis with respect to the depreciation rate. From TABLE 5 we can see in regressions (iii) and (iv) that the estimated spillover effect stemming from medium technology industries is higher than the one from high technology industries. Although a Wald test cannot reject the null hypothesis of these two coefficients being equal, we will show that the coefficients also depend on the depreciation rates chosen.

One would expect currently required and applied knowledge to change and become obsolete faster in high technology than in traditional, low technology industries. Therefore the ideas and experience that employees acquire during their work that could lead to future productivity increases also become obsolete faster in the more rapidly changing environment of high technology sectors. For this reason, we present a sensitivity analysis in TABLE 6, regression (xi) wherein we reproduce regression (iv) from TABLE 5 but use different depreciation rates according to the technology level of the industry. The depreciation rates for low, medium and high technology segments have been arbitrarily set to 7.5%, 10% and 12.5% respectively. The results of regression (x) show that the relative size of the coefficients for the different technology segments changes in comparison with the results shown in (iv) and high technology sectors become a more important source of knowledge spillovers.

The estimations in the literature for input-output spillovers should be looked at in this context. For the sensitivity analysis done in many papers (Coe and Helpman 1995; Keller 2002a), different depreciation rates are always used for the whole sample. By looking at knowledge in the textile industry and the computer industry it seems obvious that the assumption of one fixed depreciation rate across all sectors is not met.

Finally, a counterfactual analysis is performed. We have assumed that knowledge is transmitted across industries foremost via the mobility of medium and high skilled workers. This hypothesis is put to the test by estimating productivity effects similar to regression (i), but with flows of lower skilled workers. Since these workers are not expected to transmit much state-of-the-art knowledge across industries, productivity effects from these flows should be minor. In fact, we find that a movement of lower skilled workers affects productivity in the target industry negatively in the subsequent year as can be seen in regression (xii) in TABLE 6. Note that changes in the overall skill composition are already accounted for. Therefore this is not a direct affect resulting from a higher stock of lower skilled workers, but an indicator that the adjustment costs to the new job outweigh knowledge transmission effects for lower skilled workers.

6 Conclusions

Recent growth literature has emphasised the importance of domestic as well as international 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 theoretical findings that were recently substantiated by empirical evidence, a theoretical model is developed that explains changes in productivity with respect to growth in human capital stocks and labour mobility.

The empirical analysis documents the importance of labour mobility that goes hand in hand with the diffusion of knowledge across industries for productivity growth. The estimates suggest that spillovers through labour mobility overall increased productivity in the sample by 0.8% over the analysed period. The estimate has to be seen as a lower bound to the true effect of labour mobility, as we are able to only consider labour movements to other industries from the year before. The knowledge diffusion in the receiving industry will usually take more time and the effects on productivity will only follow thereafter.

Given the heterogeneity of the manufacturing sector, including both traditional and high technology segments, the spillover effects were then estimated separately for high, medium and low technology industries. The results confirm the hypothesis that spillover effects differ considerably by technological classification of the giving industry. Workers moving away from the medium and high technology segment of the manufacturing sector are found to create substantial productivity effects to other industries, whereas those from low technology industries induce no significant spillovers.

Due to endogeneity problems associated with the analysis – a downturn in an industry for example might lead to lower labour inflows – a two stage instrumental variable approach is employed. First, labour mobility patterns are estimated using characteristics of the source and receiving industry as well as regional information. Then these flows are used to again investigate the productivity effects resulting from the associated knowledge spillovers. The results using this method confirm the previous findings and underline their robustness. Furthermore, we perform a number of robustness checks and control for spillovers through intermediate use. Again, the existence of positive productivity effects stemming from the mobility of higher educated workers is confirmed.

Finally a counterfactual analysis reveals that the application of our model to the flows of lower skilled workers results in negative spillovers, indicating that for lower skilled workers, adjustment costs to the new job dominate knowledge transmission effects.

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9 Appendix

TABLE A1

Average annual MFP growth in % (1995-2005)

nace2		BE	CZ	DE	DK	ES	FI	FR	IE	IT	NL	SE	UK	mean
15t16	Food, beverages and tobacco	-0.03	-1.62	0.26	-1.47	-1.91	4.44	-0.03	3.26	-1.61	0.93	-1.06	-0.29	-0.05
17t19	Textiles, textile, leather and footwear	2.20	3.33	2.62	0.15	-1.67	1.54	2.60	2.45	-2.00	2.35	0.40	2.59	1.35
20	Wood and products of wood and cork	2.56	3.40	2.73	1.33	-1.47	3.31	4.47	3.49	1.66	-0.88	3.50	-0.89	1.76
21t22	Pulp, paper, printing and publishing	-0.18	2.67	0.10	0.14	0.30	2.13	0.93	3.24	-1.08	0.94	0.14	-0.22	0.77
23	Coke, refined petroleum & nuclear fuel	-6.57	-30.59	-3.83	-11.92	-2.40	3.50	4.86	4.47	-23.68	5.74	5.78	-1.10	-11.35
24	Chemicals and chemical products	-0.40	0.63	3.95	3.27	-0.98	2.54	0.31	0.62	0.72	3.77	2.50	1.52	1.43
25	Rubber and plastics	2.98	9.87	1.63	-0.39	-0.16	-0.85	7.35	0.54	-0.29	0.81	0.79	-0.04	1.70
26	Other non-metallic mineral	-0.96	4.76	1.95	0.94	0.95	2.79	0.99	-1.91	0.31	0.28	1.74	2.43	1.20
27t28	Basic metals and fabricated metal	1.09	-0.68	0.76	-1.46	-0.44	1.43	0.58	1.47	-0.29	1.05	-1.00	2.14	0.33
29	Machinery and equipment n.e.c.	2.62	4.03	0.78	-1.62	-0.49	0.50	4.26	-0.31	-1.27	1.74	1.55	1.71	1.07
30t33	Electrical and optical equipment	3.24	7.40	4.31	0.17	-1.45	12.35	4.71	4.09	-1.05	0.82	20.87	2.84	3.97
34t35	Transport equipment	2.30	7.44	1.96	-2.40	0.09	0.55	2.30	2.85	-0.87	4.91	3.82	1.13	1.98
36t37	Manufacturing n.e.c; recycling	1.45	0.34	-0.11	-1.79	0.35	0.85	0.60	0.74	0.02	1.05	4.46	-0.11	0.62

TABLE A2

Average annual growth of R&D investment by country and industry in % (1995-2005)

nace2		BE	CZ	DE	DK	ES	FI	FR	IE	IT	NL	SE	UK	mean
15t16	Food, beverages and tobacco	6.53	8.09	5.49	9.09	7.78	4.00	4.04	-5.62	-1.65	0.39	-1.71	0.81	3.09
17t19	Textiles, textile, leather and footwear	6.58	7.63	5.26	26.54	11.41	2.83	-0.07	-27.06	10.47	6.95	0.72	-5.36	4.46
20	Wood and products of wood and cork	14.20	10.62	-2.94	11.18	11.65	-0.22	-0.94	0.27	-3.63	5.16	2.70		0.78
21t22	Pulp, paper, printing and publishing	-3.46	-4.54	3.85	1.57	8.52	3.44	-1.65	-17.93	6.16	6.15	1.74		2.54
23	Coke, refined petroleum & nuclear fuel	-9.78	-30.93	0.82		3.23	-1.24	0.93		-25.43	-16.52	4.88	-2.15	-1.93
24	Chemicals and chemical products	4.37	1.78	5.24	11.33	6.63	5.67	3.35	2.99	-3.98	4.34	2.16	1.70	3.68
25	Rubber and plastics	5.00	7.63	8.79	9.67	3.18	6.85	6.35	-13.25	1.25	3.20	-1.32	-3.78	5.80
26	Other non-metallic mineral	1.87	11.11	1.63	0.20	8.23	-7.01	2.72	0.01	6.96	3.97	-1.78	-5.02	1.98
27t28	Basic metals and fabricated metal	2.48	-3.81	5.17	6.98	7.17	7.35	-1.61	-7.07	-6.79	0.78	6.32	-6.53	1.83
29	Machinery and equipment n.e.c.	4.47	1.56	5.51	0.91	7.05	2.85	2.75	-0.37	6.35	9.13	1.55	-0.49	4.23
30t33	Electrical and optical equipment	1.69	8.19	2.87	7.65	-0.89	12.63	0.12	-0.65	-4.29	3.19	3.46	-1.92	1.83
34t35	Transport equipment	4.23	2.95	7.61	0.46	4.98	4.15	3.47	-12.50	-0.58	-0.02	3.48	2.76	5.16
36t37	Manufacturing n.e.c; recycling	-4.31	-8.10	2.66	-17.05	8.79	12.09	5.46	-3.92	4.59	2.18	12.23	-0.63	2.59