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Abstract

Spillovers can arise when multinational firms (MNEs) train local employees who later join domestic firms, bringing with them part of the technological, marketing and managerial knowledge they have acquired. Fosfuri et al. (2001) suggest that the direction and the intensity of the worker mobility, and its associated spillovers, are affected by the degree of product market competition. In this paper, we assess empirically the importance of this hypothesis for the first time by using the Finnish longitudinal employeer-employee data. We first quantify the importance of spillovers via worker mobility by estimating augmented production functions. Second, we analyse the impact of product market competition and absorptive capacity on worker mobility by estimating several competing risks models. We find that productivity spillovers arise only when workers move from MNEs to purely domestic firms in high-tech industries. Further, in line with predictions of Fosfuri et al, our results show that competition reduces worker mobility. This details a channel through which competition may affect total factor productivity of purely domestic plants adversely.

Key words: spillovers, labour mobility, product-market competition, linked employer-employee data

JEL classification numbers: D22, D24, F23, J62

Tiivistelmä

Tuottavuuden ulkoisia sivuvaikutuksia voi syntyä, kun työntekijät siirtyvät monikansallisista yrityksistä paikallisten yritysten palvelukseen ja tuovat mukanaan osan edellisen työnantajan teknologia-, markkinointi- ja johtamisosaamisesta. Fosfuri et al. (2001) teoreettinen malli osoittaa, että tuotemarkkinakilpailu vaikuttaa työntekijöiden liikkuvuuden suuntaan ja intensiteettiin sekä siitä syntyviin sivuvaikutuksiin. Tutkimuksemme on ensimmäinen, jossa arvioidaan empiirisesti hypoteesin merkittävyyttä käyttäen suomalaista pitkittäistä työnantaja-työntekijä aineistoa. Ensiksi määritämme työtekijöiden liikkuvuudesta syntyvien ulkoisten sivuvaikutusten tärkeyttä estimoimalla laajennettuja tuottavuusfunktioita. Toiseksi analysoimme tuotemarkkinakilpailun ja absorptiokapasiteetin vaikutusta työntekijöiden liikkuvuuteen estimoimalla useita ”competing risk” -malleja. Tuloksemme osoittavat, että tuottavuuden sivuvaikutuksia syntyy ainoistaan silloin, kun työntekijöitä siirtyy monikansallisista yrityksistä paikallisiin yrityksiin korkeateknologia-aloilla. Lisäksi Fosfuri et al. ennusteiden mukaisesti tuloksemme osoittavat, että kilpailu vähentää työntekijöiden liikkuvuutta. Täten kilpailu voi vaikuttaa paikallisten yritysten tuottavuuteen haitallisesti.

Asiasanat: tuottavuuden ulkoiset sivuvaikutukset, työvoiman liikkuvuus, tuotekilpailu, yhdistetty työnantaja-työntekijä aineisto

JEL-luokittelu: D22, D24, F23, J62

1 Introduction

The entry of multinational firms and inward foreign direct investments are believed to bring productivity improvements in the domestic economy. Multinationals tend to have some competitive advantage based on superior technology or other firm-specific knowledge, and part of this knowledge is believed to spill over and to improve the productivity of the domestic firms. One channel for the spillover effects is worker mobility. Positive spillover effects may arise as former employees of MNEs join domestic firms and bring with them the technological, marketing and managerial knowledge that they have acquired (Blomström and Kokko, 1998). However, at the same time, the entry of multinationals in a given domestic market potentially changes the nature of competition in the industry which, in turn, may also bring about productivity improvements.

The existence of these two effects has been recognized theoretically by Fosfuri et al. (2001). They develop a simple and very instructive two-period oligopoly model. The model predicts that the degree of competition is likely to play an important role in the occurrence of technology spillovers since it affects differently the incentives of multinational and local firms to keep and to hire workers. However, the link between the degree of product competition and the extent of technology spillovers from multinationals to domestic firms has "rarely been explored in the literature as it raises complex methodological problems", as stated by Barba Navaretti and Venables (2004). In their view, it is very difficult to disentangle empirically the two effects on, e.g. the total factor productivity (TFP) of local firms. A potential solution to this problem, which has not been explored so far, is to look into the effect of product market competition on observables proxying for technology spillovers more directly, as opposed to more standard output measures such as firm TFP. In this paper, we adopt the approach of estimating the effects of worker mobility on firm TFP to empirically disentangle spillover effects and competition effects of the MNE impact.

Our paper departs from a theoretical formalization of spillovers by Fosfuri et al. (2001).[1] In the first period, a multinational firm provides training to a local worker and gains monopoly profits by using a superior technology. If the multinational keeps the trained worker in the second period, it also keeps gaining monopoly profits. However, in the second period the multinational firm faces competition from a local firm which realizes that it could also gain access to the technology by hiring the trained worker. If the latter is willing to pay a higher salary in order to hire the worker, it will enter the market and compete with the multinational firm. Clearly, the incentive for the multinational to keep the worker, by offering better conditions than the local firm, depends on the toughness of competition in the second period. In particular, worker mobility and technological spillovers are more likely to materialize –and therefore the monopoly ceases to exist–only when the "joint profit" effect does not hold, that is, when the sum of the gross profits of two duopolists using the technology is larger than

[1] Albeit not directly focusing on the role played by product market competion, Glass and Saggi (2002) also develop a theoretical model along similar lines. Their main conclusions can be summarized as follow. Firstly, the MNE has the incentive to prevent workers' mobility only when technology transfer is incomplete since the required wage premium would be larger - the more complete is technology transfer. Secondly, and possibly more interestingly, the presence of multiple MNEs increases the likelihood of workers' mobility whereas the presence of multiple local firms decreases it. The intuition for this second result is obvious. The incentive to prevent technology transfers is weakened by the presence of multiple MNEs since each of them has the incentive not to offer a wage premium presuming that all other foreign subsidiaries will do so. On the other hand, with many local firms competing in the same market, the benefit of restricting technology transfers is large since the MNE can increase the cost of all local competitors by paying the wage premium.

the gross profit of a monopolist. This is more likely to happen when the local and the multinational firm do not compete fiercely in the product market or sell in independent or vertically related markets. Fosfuri et al. (2001) also note that the extent to which technological spillovers occur depends on the nature of the technology and how easily it can be transferred. The model predicts higher labor mobility and more technological spillovers when the absorptive capacity of the local firm is sufficiently high and when on-the-job training is general rather than specific.

Our contribution to the literature on this issue is twofold. First, to the best our knowledge, we are first to analyze how worker mobility as a mechanism of technology diffusion responds both to the degree of competition in the product market and to the absorptive capacity of the local firms. As noted by Fosfuri et al. (2001), testing their predictions requires very disaggregated data, which explains why at the time of publication of their paper they claimed, and rightly so, that "this analysis has not been undertaken". To reach our goals, we exploit the availability of a large employer-employee panel data-set from Finland (FLEED) for 1990-2006. The possibility of following workers over time opens a completely new research dimension since we can model the mobility patterns from multinationals to local firms in a multivariate duration framework and test the hypotheses of interest in a rigorous way. Second, we provide additional evidence on the economic importance of productivity spillovers and when they arise. This allows us to test whether the transmission mechanism we are analyzing is indeed present in our data.

Our empirical results can be summarized as follows. First, productivity spillovers through worker mobility exist but are not economy-wide. Distinguishing between high-and low-tech industries by R&D expenditure, we find productivity spillovers, that are both economically large and statistically significant, only for high-tech industries. This is consistent with the transfer of technological knowledge through worker mobility. According to our estimates, workers with former multinational experience are 37 percent more productive than their colleagues without such an experience. Second, and in line with the predictions put forward by Fosfuri et al., a less competitive environment seems to be conductive to technology spillovers through worker mobility. Workers are more likely to move from multinational to non-multinational firms when the firms operate in a less competitive industry with higher price cost margins, or when the sending multinational firm and the receiving domestic firm operate in different industries. However, we find that competition inhibits worker mobility only in industries with productivity spillovers and has the opposite effect on transitions and in industries where spillover effects are absent. In addition, we find that the absorptive capacity of the local firm, measured in terms of productivity gap between the local and the multinational firms within the same industry, affects the potential for spillovers.

The structure of the paper is as follows. In the next section we briefly review the recent scant empirical literature on the relationship between worker mobility and productivity. Section 3 describes our data sets and provides descriptive evidence on several aspects of worker mobility. In Section 4 we present our empirical analysis, first the model and the results for quantifying the productivity spillovers and thereafter the econometric framework and the results for worker mobility. Section 5 concludes.

2 Related Empirical Literature

In the last decade, the increased availability of linked employer-employee data-sets has allowed researchers to start opening the black box of technology spillovers and, in particular, to study the relevance of the worker mobility channel much more precisely. In fact, data availability has made it possible to build plant (or firm) specific measures quantifying the impact of the workers with previous experience from multinationals. These measures have been used in augmented productivity equations as a replacement for the standard, and far less accurate, proxy used in the older literature based on the share of output produced by multinationals operating in the same industry and/or in the same geographical area.

So far, previous empirical research has focused on the spillover effects without taking into account the possible simultaneous competition effects. Studies by Balsvik (2011) and Stoyanov and Zubanov (2012) have found positive firm-level productivity effects through employer mobility by using comprehensive employer-employee data sets respectively for Norway and Denmark. Balsvik provides a number of complementary pieces of empirical evidence which are broadly consistent with the existence of a channel for technology spillovers through worker mobility. She finds a large productivity differential (20 percent) in local plants between workers with MNE experience and their colleagues without such experience, even after controlling for unobserved characteristics of the workers. Coupled with the finding of a 5 percent premium for movers from MNEs to domestic plants, when compared to stayers in local plants with similar characteristics, she concludes that local firms do not fully pay for the value of the workers to the firm and thus worker mobility from MNEs to non-MNEs is found to be a source of knowledge externality in Norwegian manufacturing.

Stoyanov and Zubanov (2012) find that hiring workers from more productive firms is associated with gains amounting to a 0.35 percent productivity increase one year after hiring for the average firm. This increase in productivity lasts four years and the associated cumulative gain for four consecutive years is 1.64 percent which is equivalent to a 2.3 centile move up in the productivity distribution by the median firm in Danish manufacturing. On a related issue, Gorg and Strobl (2005) exploit firm-level data from Ghana with information on whether entrepreneurs were former employees of MNEs. Their overall analysis provides evidence that domestic firms run by entrepreneurs with experience from working for multinationals in the same industry are more productive and more likely to survive than other firms. There are also a number of studies specifically focusing on R&D spillovers. These include Maliranta et al. (2009) and Kaiser et al. (2011) who find that the hiring of workers from R&D intensive or innovative firms is associated with better performance by hiring firms.

Other relevant studies include Poole (2013) and Pesola (2007) who focus on workers and wages rather than on firms/plants and productivity. Poole (2013) finds evidence for positive wage spillovers by using Brazilian data. When workers leave multinationals and are rehired at domestic establishments, continuing domestic workers' wages increase. She also investigates where spillovers occur and how they are absorbed and finds that higher-skilled former multinational workers are better able to transfer information and higher-skilled incumbent domestic workers are better able to absorb information. Pesola (2007) analyzes the extent to which employees benefit from the knowledge they acquire in foreign-owned firms when moving to domestic firms and, in particular, whether this rent is associated to their educational level. She exploits a sample of the total Finnish linked employer-employee data set that we use. Her main finding suggests that previous tenure in a foreign firm has a positive effect on wages but only for workers located at the top of the distribution of educational levels. These results are consistent with the idea that domestic firms may want to pay higher wages to workers with multinational experience in order to gain access to their knowledge.

3 Data and Descriptive Statistics

3.1 Data

We use data from four different databases from Statistics Finland for the years 1990 to 2006. The main database is the Finnish Longitudinal Employer-Employee Data (FLEED). The data include all Finnish firms and all individuals of ages 15-70. The FLEED data are complemented with plant-level statistics from the Longitudinal Data on Plants in Manufacturing (LDPM), which include all manufacturing plants with at least five employees, and with firm register information on whether the firm is foreign or domestic-owned and on whether the firm is multinational. Firm and plant-level statistics include variables such as value added, capital stock, number of employees, wages, turnover/sales, R&D expenditure and industry.[2] We restrict our analysis to

[2] R&D data is collected from: i) enterprises that reported R&D activities in the previous inquiry; ii) enterprises that have received product development funding from TEKES (the Finnish Funding Agency for Technology and Innovation); ii) all enterprises with more than 100 employees and a sample of enterprises with 10-99 employees.

manufacturing firms with at least 20 employees and to the period of 1997-2004.[3] A domestic MNE is defined as a domestic firm with operations abroad and a foreign MNE is a firm with at least 20 percent of foreign ownership.[4] Each individual is followed over time. An individual exits the data if he/she turns 70 year, leaves the country or dies. The individual-level statistics contain detailed information on characteristics including education, occupation, annual earnings, gender, family status, work status and previous work history. All data sets are linked together with unique individual, plant and firm identifiers.

3.2 Descriptive Statistics

Tables 1 and 2 present some preliminary features of multinational and non-multinational firms in the manufacturing sector both at firm and plant level.[5] As can be seen from Table 1, the number of non-multinational firms is more than twice as large as the number of multinational firms, while the number of plants of multinational firms is almost as large as, or even larger than, the number of plants of non-multinational firms. This is obviously not unexpected since multinational firms tend to be larger and to own several plants. Despite the short time dimension of our panel, the initial picture changes substantially over the years since multinationals experience a much stronger growth rate

[3]Register information on whether the firm is multinational is available from 1997 onward and information on start and end date of employment exist until 2004 which restricts the period of analysis to 1997-2004. Firms which have more than 20 employees in 1997 but fall under this threshold in subsequent years are included.

[4]We check if our empirical results are sensitive to the choice of a 20 percent threshold by using alternative thresholds of ten and fifty percent. All our main findings are virtually unaltered.

[5]Multinational firms include both foreign and domestically owned firms. A large majority of manufacturing firms with more than 20 employees are domestically owned. In our econometric analysis we investigate whether the type of ownership matters.

in the number of firms and plants (39.9 percent and 29.8 respectively) compared to their domestic non-multinational counterparts (20.4 percent and 7.1 percent respectively).

As unanimously found in the literature, multinational firms appear to run much larger operations than purely local firms in terms of median number of employees, turnover and value added (see Table 2). When focusing on median values, multinationals have a larger wage bill relative to turnover than domestic firms. Also, multinational firms are found to use capital more intensively.[6] Furthermore, multinationals invest in R&D more than purely domestic local firms. This is not surprising, since domestic multinational firms tend to concentrate the bulk of their R&D activities in their home country and foreign multinationals tend to concentrate in industries where they can exploit their managerial expertise and superior technological skills. Finally, multinational firms are found to be more profitable as documented by the higher share of gross operating profits over turnover.

Tables 3 and 4 display statistics quantifying employees entering domestic non-multinational firms and multinational firms in the manufacturing sector. In Table 3 we distinguish all entrants and new entrants in the current year. All entrants is the accumulated net number of entrants from current year and previous years as early as the data set allows (since 1990). As expected, the share of all entrants increases over the period. For instance, the share of all entrants in non-multinational firms increases from 16.7 to 24.1 percent between 1997 and 2004. It may be noticed that also the shares of new entrants slightly increase, but the increase is not monotonous over the time period.

[6] In the productivity regressions we use plant-level data and capital is proxied by fixed capital stock computed by using the perpetual inventory methodology.

The share of accumulated entrants tends to be somewhat larger in multinational firms. One reason may be that multinationals were growing faster than the domestic firms during the period. In our productivity analysis, we focus on the effects of the accumulated number of entrants as there may be a lag in the impact. In the mobility section, we estimate the effect of competition and productivity gap on worker transitions in the current year. In Table 4, we distinguish the entrants to non-multinational firms by the source firm type. We may note that the share of entrants from non-multinational firms increases moderately over the period while the share of entrants coming from multinational firms increases more distinctly as multinational firms gain importance in the economy. In 2004, the share of workers in domestic firms with previous tenure in a MNE is as high as 6.4 percent.

Table 5 displays some characteristics of the entrants in both types of firms at the entry year. The MNEs employ a larger share of female workers, workers with a longer education and a longer previous tenure than domestic non-MNEs, but the differences are small thus indicating that there is no obvious evidence of selection of employees based on these observables.

Finally, in Tables 6 and 7, we provide evidence on the transitions occurring between different types of firms. In Table 6, we analyze four different types of transitions; from MNEs to both non-MNEs and other MNEs and from non-MNEs to both MNEs and non-MNEs. The yearly transitions from MNEs to non-MNEs vary from 1.6 to 2.2 percent of total employees. The annual share of employees moving to other MNEs is larger and varies more over time.[7] We also observe a symmetric pattern for the employees leaving

[7] A transition is identified when an employee changes both plant and firm identity codes of their

non-MNEs. Comparatively, a larger number is found to move to other non-MNEs than to MNEs. This overall pattern suggests that employees tend change employers within the same type of firms.

In Table 7, we show statistics on workers moving from multinational to non-multinational firms. We do so since our primary interest is to analyze whether this type of worker mobility generates productivity spillovers in the non-multinational firms. We split the sample according to whether sending firms operate in low-tech industries as compared to high-tech industries, since previous studies by Maliranta et al. (2009) and Kaiser et al. (2011) have found the hiring of workers from R&D intensive or innovative firms to be linked to better performance by hiring firms. Furthermore, we separate inter- and intra- industry transitions since Fosfuri et al. (2001) predict worker mobility and spillovers to be more likely when the local and the multinational firm do not compete fiercely in the product market or sell in independent or vertically related markets.

It is obvious from Table 7 that most workers moving from MNEs to non-MNEs change industry.[8] For instance, in 1997, the share of inter-industry movers on total movers is 88.1 percent in low-tech and 92.3 percent in high-tech industries. This finding is not peculiar only to 1997 since the share is found to be higher in high-tech industries in most years. The observation is consistent with Fosfuri et al. model, which predicts that spillovers are likely to materialize and mobility is more likely to occur in industries where firms sell in independent or vertically related markets.

employer between year t and t+1. The ownership changes of plants when employee changes the firm but not the plant code are not included. The transitions when employees are moving to other firms and plants in connection with mergers and acquisition cannot be excluded. For instance, this could explain why the number of transitions from MNEs to MNEs almost doubled in 2000.

[8] Intra- and inter-industry mobility is defined at two-digit level of industries.

4 Empirical Analysis

Our empirical strategy consists of two complementary sets of econometric estimates. In the first part of the analysis, we estimate an augmented Cobb-Douglas production function with firm-level data. The productivity analysis serves two different purposes. It allows us to establish whether worker mobility from multinationals to local firms has a positive effect on the total factor productivity of local firms. This is obviously of paramount importance given the purpose of this paper. Indeed, finding no effect in our data would make the analysis of the effect of competition and absorptive capacity on worker mobility far less interesting, simply because the transmission channel going from competition to productivity via worker mobility would not be there. On the other hand, the estimation of production functions allows us to recover firm level measures of the technological distance of local firms from their multinational counterparts, this, in turn, being a proxy for absorptive capacity.

The second part of the analysis, where we test the hypotheses of Fosfuri et al. on the impact of competition on worker mobility, serves the main purpose of this paper. We model the mobility patterns from multinationals to local firms in a multivariate duration framework to analyze how worker mobility as a mechanism of technology diffusion responds to the degree of competition in the product market and to the absorptive capacity of the local firms. More specifically, we apply the competing risks framework to the analysis of the effect of product market competition and absorptive capacity on worker mobility from multinationals to local firms. This general transition model accommodates situations like ours that involve more than one destination and can be therefore interpreted as a multivariate duration model involving the joint specification and estimation of two or more hazard functions.[9]

4.1 Spillover Effects: Econometric Framework

We start from the following Cobb-Douglas production function:

$$Y_{it} = A_{it} L_{it}^{*\beta_l} K_{it}^{\beta_k} \quad i = 1, 2, ..., N; \; t = 1, 2, ...T \tag{1}$$

where Y_{it}, K_{it} and L_{it}^{*} denote respectively production, capital stock and quality adjusted labor of plant i at time t. Quality adjusted labor is equal to:

$$L_{it}^{*} = L_{it}^{N} + L_{it}^{M}(1+\gamma) = L_{it}(1+\gamma s_{it}) \tag{2}$$

where L_{it}^{M} and L_{it}^{N} denote labor with MNE experience and labor without such experience, $L_{it} = L_{it}^{N} + L_{it}^{M}$ and s_{it} is the share of total labour, L_{it} with MNE experience. In this context, the unknown parameter, γ can be interpreted as a positive productivity premium (Balsvik, 2011) generated by the technology spillover embodied in L_{it}^{M}. The productivity term A_{it} is modelled as follows:

$$A_{it} = e^{\delta_t + \eta_i + u_{it}} \tag{3}$$

[9] In our application a worker employed by a multinational firm could in fact alternatively: i) move to a local firm in the same industry or in a different industry, ii) move to a different multinational firm, iii) turn into self employment, iv) enter unemployment, v) exit the labor market.

where δ_t is a time specific intercept, η_i is the individual effect which in the present context can be thought of as unobserved plant characteristics that can be viewed as constant over the sample period, and u_{it} is the serially uncorrelated idiosyncratic error.[10] By using equations (1), (2) and (3), by taking logs and by using the approximation $\beta_l \ln L_{it}^{*\beta_l} = \beta_l \ln L_{it}^{\beta_l} + \beta_l \gamma s_{it}$, equation (1) can be rewritten in the following representation:

$$y_{it} = \beta_l l_{it} + \beta_l \gamma s_{it} + \beta_k k_{it} + \delta_t + \eta_i + u_{it} \tag{4}$$

where y_{it}, l_{it}, and k_{it} are the logarithms of Y_{it}, L_{it}, K_{it} respectively. To recover consistent estimates of the expected effect on productivity of the share of labor with MNE experience, s_{it}, holding all other variables fixed, reasonable identification assumptions have to be made. In particular, it seems sensible to assume that both standard input factors (l_{it}, k_{it}) and the labor share (s_{it}) are correlated with the individual effect (η_i). This allows for the possibility that plant and firm heterogeneity—if observable to managers even if not to the econometrician–matter in hiring decisions of workers with MNE experience.

Estimating equation (4) by the standard within group transformation does not put any restriction on the conditional distribution of η_i with respect to all past, present and future input levels, but it requires that all inputs are strictly exogenous with respect to the idiosyncratic component, u_{it} thus ruling out the possibility that managers adjust their input levels after observing past or present idiosyncratic productivity shocks.[11]

[10] We also allow for a less restrictive characterization of the idiosyncratic component of the error term. See equations (5) and (6).

[11] Note that this is the benchmark identification strategy adopted in Balsvik (2011).

Although within-group estimation of equation (4) controls for unobserved heterogeneity, the share of employees with MNE experience–as well as other input factors–are unlikely to be orthogonal to present and past idiosyncratic shocks. Indeed, profit-maximizing firms respond to productivity shocks by adjusting their inputs accordingly. Ignoring the correlation between the choice of inputs and the unobservable component of the error term would therefore yield inconsistent results.

In order to obtain consistent estimates of the impact of labour mobility on productivity, we rely on the estimation technique proposed by Levinsohn and Petrin (2003). This estimation method follows Olley and Pakes (1996) who develop an estimator that uses investment as a proxy for unobservable productivity shocks.[12] Levinsohn and Petrin (2003) point out that investment is lumpy and may not smoothly respond to the productivity shock, thus violating a basic condition for the validity of their approach. They show that using intermediate inputs can solve the simultaneity problem. In addition, the approach avoids truncating all the zero investment firms, since firms almost always report positive use of intermediate inputs like electricity or materials.

Operationally, the idiosyncratic error u_{it} in equation (3) is redefined as the sum of the transmitted productivity component, v_{it}, and an error term that is uncorrelated with input choices, ε_{it}:

$$u_{it} = v_{it} + \varepsilon_{it} \tag{5}$$

Demand for intermediate input m_{it} is assumed to depend on the firm's state variables

[12] This approach has been used in the related empirical literature on productivity spillovers and worker mobility by Stoyanov and Zubanov (2012).

k_{it} and v_{it}:

$$m_{it} = m_{it}(k_{it}, v_{it}) \tag{6}$$

Under monotonicity the demand function can be inverted, thus allowing v_{it} to be written as function of k_{it} and m_{it}:

$$v_{it} = v_{it}(m_{it}, k_{it}) \tag{7}$$

The unobservable productivity term is now expressed solely as a function of two observed inputs. Finally, Levinsohn and Petrin (2003) assume that productivity is governed by a first-order Markov process:

$$v_{it} = E(v_{it}|v_{it-1}) + \xi_{it} \tag{8}$$

where ξ_{it} is an innovation to productivity that is uncorrelated with k_{it}, but not necessarily with l_{it} which is part of the simultaneity problem. Under this set of assumptions, all unknown parameters in equation (4) can be consistently estimated by a two-step semi-parametric econometric approach.

4.2 Spillover Effects: Results

Given the purpose of this paper, we estimate plant-level productivity equations separately for the sub-samples of non-multinational and multinational firms, the latter including both foreign and domestic MNEs.[13] To take into account the possibility that technology spillovers occur only in high-tech industries, we also allow for the parame-

[13]Productivity estimations are carried out at the plant level since plant-level data for capital, labor and intermediate inputs are more detailed.

ters of interest to differ between high-tech and low-tech firms.[14] In addition to the standard input variables (labor and capital), each equation includes additional regressors measuring the share of workers who have previously worked in a multinational (MNE) and the share of workers previously employed in non-multinational firms (non-MNE). In some specifications, we also control for additional features of moving workers including the length of previous tenure (MNE-tenure and non-MNE-tenure), the level (MNE-higher-education and MNE-lower-education) and the type of education (MNE-technical-education and MNE-non-technical-education).

Our basic results are summarized in Table 8. Obviously, we are mostly interested in the sign and size of the coefficient of the labor share s_{MNE} and the associated parameter γ_{MNE} as estimated on the sample of non-multinational firms, since this is the technology transmission channel we are focusing on. Operationally, we define two versions of the labor share; in columns (i), (iii) and (v) the share s_{MNE} includes all workers who have been hired from MNEs, irrespective of the length of the previous MNE tenure. In columns (ii), (iv) and (vi) the share $s_{MNE-tenure}$ includes only workers hired from MNEs with a minimum of two years of previous MNE tenure.[15] The labor shares ($s_{non-MNE}$) and ($s_{non-MNE-tenure}$), are defined in the same way but for the employees hired from non-multinational firms.

For the total sample of non-multinational plants and for the sub-sample of plants belonging to low-tech firms, the coefficients γ_{MNE} and $\gamma_{MNE-tenure}$ turn out to be

[14] High-tech firms are defined as firms belonging to the tertiary of three-digit industries with the highest R&D expenditures (industries with more than 2.55% R&D expenditures of total sales in 1997) and the rest of the firms are defined as Low/Medium tech firms.

[15] Balsvik (2011) uses this definition of the labor share in her estimations. We have checked that our results are robust also for one year of tenure threshold.

statistically insignificant (see columns (i) and (v)). However, for the plants of high-tech firms (column (iii)), the coefficient is positive and statistically significant. Furthermore, it is economically sizeable since it implies a productivity premium as large as 0.372. This means that workers hired from MNEs contribute on average 37.2 percent more to the productivity of the plant than the incumbent workers. The result is similar for the $\gamma_{MNE-tenure}$ parameter, with a productivity premium of 35.9 percent associated to the employees with a minimum of two years of previous tenure in a MNE. This is higher than the productivity premium of 20 percent that Balsvik (2011) found workers with MNE experience contribute to the productivity of their plant as compared to workers without such experience. However, a major difference is that we find a premium only in the sub-sample of high-tech firms while she did not make such a distinction.

In order for our identification approach to be convincing, we also have to show that the productivity premium we estimate is peculiar to the type of worker mobility we are focusing on, that is the transitions from multinationals to domestic non-multinational firms. The first alternative explanation we have to rule out is therefore the possibility that what matters for the productivity of domestic non-multinational firms is simply the hiring of new employees, regardless of the characteristics of their previous work place. This might be the case, because of new hires have better skills or are likely to put more effort in order to get tenure or, more simply, to reveal their unknown ability type. The alternative hypothesis can be tested by looking at the parameters $\gamma_{non-MNE}$ and $\gamma_{non-MNE-tenure}$ as estimated for the plants of high-tech non-multinational firms (see columns (iii) and (iv)). It turns out that the estimated parameters are much smaller in size, or even negative, and not different from zero at conventional statistical levels. Taken at its face value, this finding corroborates the hypothesis that technology spillovers through worker mobility are associated to transitions from multinationals to domestic non-multinational firms, but not to transitions of workers between non-multinationals.

Another implicit basic assumption of our approach has been so far that the direction of spillovers through worker mobility is from multinationals to non-multinationals, and consequently, that spillovers are not relevant in the opposite direction. This need not to be the case, because multinationals and purely domestic firms might have complementary comparative advantages. For instance, multinationals could benefit from hiring workers with a more pronounced local background. If this is the case, $\gamma_{non-MNE}$ and $\gamma_{non-MNE-tenure}$ should enter with a positive sign in the equations estimated on the sample of multinational firms. This conjecture is not supported by the data since these parameters are not statistically different from zero (columns (vii)-(xii)). However, multinational firms seem to benefit from hiring workers from other multinationals. In fact the coefficients γ_{MNE} and $\gamma_{MNE-tenure}$ are positive and statistically significant in the estimations for the total sample of MNEs (columns (vii) and (viii)). However, the same parameters turn out to be statistically insignificant and much smaller in size (0.118 and 0.154 respectively) when estimated on the sub-sample of high-tech firms.

To sum up, results presented in Table 8 show that worker mobility from multinational firms to non-multinational firms in high-tech industries generate sizeable productivity effects. Furthermore, whether we include all former MNE employees or select only the employees with some minimum length of tenure matters only slightly for the size of the productivity premium. Finally, these estimated effects seem to be specific to the type of mobility we are interested into. Since our data allow us also to distinguish between foreign and domestic multinationals, we have analyzed whether ownership matters. Our results indicate that this distinction does not have any empirical relevance, neither for the total sample of plants nor for the two sub-samples of high-tech and low-tech plants.[16]

In Table 9 we focus on the role played by education as captured by complementary measures which are observable at the individual level. Previous research has argued that the ability of workers to transfer and apply new knowledge depends on education (Kaiser et al., 2011 and Poole, 2013). We distinguish workers with MNE experience in two ways: 1) by the length of education: lower educated workers have an education up to 12 years (equivalent of upper secondary education) and higher educated workers have an education longer than 12 years (equivalent of tertiary education), and 2) by the technical education: workers with technical education at upper secondary to tertiary level.[17]

Given the findings obtained so far, we focus on the high-tech sub-sample but we keep the distinction between non-multinationals and multinationals. In column (i) and (iv), shares are included separately for higher and lower educated workers, in columns (ii) and (v) shares are included separately for workers with technical and non-technical education and in columns (iii) and (vi) shares are included separately for workers with higher technical and non-technical education. Consistently with our previous findings, we do not find any effect for the sub-sample of multinationals since estimated parame-

[16] Results are not reported but available upon request.
[17] Definitions are according to the International Standard Classification of Education (ISCED).

ters are not significantly different from zero. When we turn to non-multinationals, the estimated productivity premium seems to be driven by the workers with technical education. Here, the productivity premium turns out to be as high as 80 percent (column (ii)). These results suggest that high-tech firms can better absorb and benefit from the knowledge of workers with technical education hired from MNEs. When we instead focus on education levels, punctual estimates suggest that the productivity premium exists and is considerable (48 percent) only for workers with a shorter education. The impact of highly educated workers is null. This result is somewhat surprising as we would expect high-tech firms to benefit from the human capital of the hired workers. A plausible explanation is that productivity spillovers are primarily attached to the knowledge acquired by employees with technical education who are working closer to the main production lines and R&D units, rather than by the group of highly educated employees including, in addition to engineers, other professional categories such as accountants, business administrators and lawyers. To investigate this hypothesis further, we split the share of highly educated workers by technical education (columns (iii) and (vi)). The impact of workers with higher technical education is positive, while the impact of workers with other higher education is negative, although it is not statistically significant.[18] The very large productivity premium suggests that the selective group of workers with higher technical education bring with them rather valuable knowledge.

[18] If we include the share of lower educated workers with MNE experience in columns (iii) and (vi), the punctual estimates are virtually the same. However, they are less precisely estimated since the share variables tend to be positively correlated.

4.3 Worker Mobility: Econometric Framework

The productivity analysis provides evidence that worker mobility from multinationals to local firms has a positive effect on the total factor productivity of local firms, but only in high-tech industries. This evidence gives a convincing reason to analyze further the transmission channel going from competition to productivity via worker mobility. Albeit the focus of this paper is on the role played by product market competition on the mobility from a multinational to a local firm, we have to take into account that a worker operating in a multinational firm faces J distinct potential causes of transition. In the survival analysis literature, these destination states are commonly labeled as risk factors. In our application a worker employed by a multinational firm could in fact alternatively: i) move to a local firm in the same industry or in a different industry, ii) move to a different multinational firm, iii) turn into self employment, iv) enter unemployment or v) exit the labor market.[19]

More formally, we can define J random variables $T_j (j = 1, ..., J)$ describing the duration until risk j is materialized. The obvious problem here is that only the smallest of all these durations, T is identifiable by the data since all other durations are censored. In fact, all is known is that their realizations are longer than T. In most economic applications, including ours, one is interested in one or more of the marginal distributions of the T_j. As pointed out by van den Berg (2005), under independency it would be perfectly legitimate to employ standard duration analysis for each of the T_j separately, treating the other random variables $T_i (i \neq j)$ as independent right-censoring

[19] Recent surveys of the so-called competing risks models can be found in Putter et al (2006) for biostatistcs and in van den Berg for economics (2005).

variables. However, economic theory often suggests that they are dependent. This can be the case, for instance, if they are affected by individual behavior and individuals are heterogenous. This is certainly the case in our application since workers differ because of both observable (e.g. age and gender) and unobservable (e.g. taste for mobility) characteristics and, in turn, these characteristics are likely to be associated to different forms of mobility. Under dependency and without additional structure or data neither the joint distribution of all T_j nor the net hazard rates of their marginal distributions can be identified.

This general non-identification result can be, at least partially, overcome by specifying semiparametric models that include observed–possibly time varying– individual characteristics, $\mathbf{x}$. The cause-specific hazard function, $\lambda_j(t)$, that is the hazard of failing from a given cause in the presence of competing events, can be estimated from the data. In general, however, the impact of a change in a given covariate, x_k on the probability of leaving the initial state via risk j (the so-called cumulative incidence function) is hard to calculate since this marginal effect not only depends on the effect of the covariate on cause j but also on the effects of the covariate on all other causes as well as on the baseline hazards for all other causes.[20] To overcome this analytical problem, in this paper we adopt the approach proposed by Fine and Grey (1999). They define a subdistribution hazard, $\overline{\lambda}_j(t)$ which differs from the standard cause-specific hazard, $\lambda_j(t)$. In detail, the risk set for the cause-specific hazard decreases whenever there is a failure of another cause. For the subdistribution hazard, individuals leaving the initial state

[20]Thomas (1996) shows, however, that with competing risks models of the proportional hazard type marginal effects can be signed if the estimated coefficient in the relevant cause-specific hazard function is larger than the corresponding coefficients in all other cause-specific hazard functions.

for another cause remain in the risky set instead. The advantage of modelling the subdistribution hazard is that the cumulative incidence function can be easily calculated as:

$$CIF_j(t) = 1 - \exp(-\int_0^t \overline{\lambda}_j(t)dt) \tag{9}$$

Finally, the model is semiparametric since the baseline subhazard, $\overline{\lambda}_{j,0}(t)$ is left unspecified while the effects of the covariates $\mathbf{x}$ are assumed to be proportional:

$$\overline{\lambda}_j(t) = \overline{\lambda}_{j,0}(t)\exp(\mathbf{x}'\boldsymbol{\beta}_j) \tag{10}$$

where $\boldsymbol{\beta}_j$ is a vector collecting the covariate effects on cause j.[21]

Our purpose is to test the relevance of the two main hypotheses derived from the model of Fosfuri et al. (2001). That is, whether worker mobility and technological spillovers are more likely to materialize when the local and the multinational firm do not compete fiercely in the product market or sell in independent or vertically related markets, and whether technology transfer is more likely to occur when the absorptive capacity of the local firm is sufficiently high. The competition is expected to be more intensive and, therefore, to have a negative effect on worker mobility between firms within the same industry, as compared to worker mobility between firms in different industries. We run separate regressions to assess whether the effect of competition differs for intra- and inter-industry worker mobility.

To test for the effect of the toughness of competition on the incentive for the multi-

[21] The competing risks model proposed by Fine and Grey (1999) is estimated by using the stsrreg stata command.

national to keep the worker, we include price-cost margins (PCM) among the covariates. Following Aghion et al. (2005) and Nickell (1996), the price cost margin we use at the firm level is measured by operating profits net of the cost of capital divided by value added. The cost of capital is assumed to be 0.085 for all firms and time periods (same as Aghion et al. assume). Our competition measure is simply the weighted average of this across firms within the same three-digit industry:

$$PCM_{jt} = \sum_i \frac{x_{ijt}}{\sum_i x_{ijt}} \frac{OP_{ijt} - CC_{ijt}}{VA_{ijt}} \tag{11}$$

where OP_{ijt}, CC_{ijt}, VA_{ijt} and x_{ijt} denote respectively operating profits, cost of capital, value added and output of firm i in industry j at time t. As robustness, we also define an alternative PCM measure as:

$$PCM_{jt} = \sum_i \frac{x_{ijt}}{\sum_i x_{ijt}} \frac{OP_{ijt}}{x_{ijt}} \tag{12}$$

In order to assess the importance of absorptive capacity of the receiving firm, we compute a firm-specific productivity gap measure (PRG) based on our productivity estimations commented upon in section 4.2. More specifically:

$$PRG_{it} = TFP_{ijt} - \overline{TFP}_{jt} \tag{13}$$

where TFP_{ijt} denotes the total factor productivity of multinational firm i in industry j at time t and and $\overline{TFP}_{jt}$ denotes the average total factor productivity of non-multinational firms in industry j at time t.[22] As the main proxy for absorptive capacity, we use the productivity gap between the sending MNE and the average domestic non-MNE firm in the same three-digit industry. In order to capture the impact of productivity lead of a multinational firm in relation to non-multinational firms, we replace negative values of the gap measure with zeros. Since this measure could be sensitive to extreme observations, particularly in small industries, we also use the same measure at the two-digit level as robustness check.[23] To sum up, the aim of the multivariate duration analysis is to determine whether and how PCM and PRG impact the probability of moving to a domestic firm, controlling for the other individual- and firm-specific covariates.

4.4 Worker Mobility: Results

In assessing the effect of product market competition and absorptive capacity on worker mobility between firms, we first identify those workers who are employed in a multinational in 1997, that is our first sample year, and we trace them over the entire sample period. Our main focus is on worker mobility in high-tech industries where we found evidence for productivity spillovers. We distinguish intra- and inter-industry mobility since Fosfuri et al. maintain that worker mobility and technological spillovers are more likely to materialize when the local and the multinational firm do not compete fiercely in the product market or when they sell in independent or vertically related market.

[22] For multi-plant firms productivity is computed as the weighted average of the estimated productivity of firm i's plants in industry j (either at 2- or 3-digit level of industries). Plant level productivity is estimated as described in section 3.1 and output is used as weights.

[23] In addition, we also rerun all estimated models presented in the next sub-section without setting equal to zero all negative values of the gap measure. This change has no effect whatsoever on all our main results.

Predictions received from the theory suggest that PCM should enter with a positive sign in the specifications for intra-industry worker mobility, indicating that less fierce competition increases worker mobility between firms in the same industry. The productivity gap is expected to enter with a negative sign, indicating that a smaller gap and larger absorptive capacity increases worker mobility between firms in the same industry. Since the measures of competition and productivity gap are defined at industry level, they are not expected to be related to inter-industry mobility in any particular manner. In all regressions, we also include several standard individual level variables: age, gender, marital and parenthood status, educational level, income and regional location. Finally, this baseline model is augmented with (log) firm size and with a set of aggregate time dummies capturing aggregate business cycle effects.

In the first set of equations, we define the mobility from multinational firms to a purely domestic firm in the same industry as the main destination state. Overall, we have a sample of 280,814 observations in high-tech industries. Of those, 544 workers are found to move to a domestic non-multinational firm within the same industry. We treat as competing events moves to a domestic non-multinational firm in a different industry (3,900 workers), to a different multinational firm (14,067 workers), to unemployment (5,173) and out of labor market (5,522). All other observations are treated as censored.[24] As mentioned in the previous section, we experiment with different definitions of our main variables of interest, PCM and productivity gap, and all our main findings are virtually unaltered.

[24]Transfer to self-employment are treated as sensored, since these transfers cannot be identified in a clear-cut way in the data.

Overall, results in Table 10 confirm received theoretical predictions. In the subdistribution hazard function for the purely domestic firm destination state, the coefficient on the PCM variable is positive and statistically significant in all specifications. These results suggest that a less competitive environment with higher price-cost margins is associated to worker mobility between firms in the same industry. This is consistent with the theoretical predictions of Fosfuri et al. of competition affecting worker mobility adversely. Furthermore, the sign of the productivity gap is indeed negative and statistically significant in all specifications, indicating that a larger productivity gap, indicating smaller absorptive capacity of non-multinationals as compared to multinationals, decreases worker transitions from multinational to non-multinational firms. The estimated parameters on parenthood status, education and metropolitan Helsinki location are negative and statistically significant in all columns, implying that all these variables slow down the transition to purely domestic firms. Of the other control variables, only marital status and firm size enter with a statistically significant positive effect, the latter suggesting that a larger firm size accelerates the transition to purely domestic firms. On the other hand, age, gender and income level, have not statistically significant impact on the transitions.

Obviously, the fact that our results so far fully match the theoretical predictions is not a direct test of the existence of the transmission channel we are interested in. A substantial step forward can be made by investigating whether our main findings also apply to other transitions or whether they are indeed specific to our destination state of interest. For this reason, in Table 11 we report the results for the transitions from multinational firms to three alternative destination states. The first column displays the results for the transitions from multinational firms in high-tech industries to other multinationals in the same industry.[25] The PCM measure is negative and significant in this specification, indicating the opposite result that a more competitive environment with lower price-cost margins increases worker mobility between multinational firms within the same industry. This, in turn, reinforces our previous conclusion that the negative effect of competition on labor mobility is present only in environments where technology spillovers have clearly been detected. The productivity gap enters with a positive sign in this equation. Taken at its face value, this implies that workers tend to move to other multinationals more often when purely local firms lag substantially behind.

The second column of Table 11 shows the results for the transitions from multinationals in high-tech industries to non-multinational firms in other, including both high- and low-tech, industries.[26] To the extent that our findings in Table 10 are truly associated to the transmission channel identified by Fosfuri et al, we should not expect the PCM in the sending industry to enter with a positive sign. Indeed, the industry-level competition measure enters with the opposite sign. Taken at its face value, this seems to suggest that competition in the sending industry makes workers more likely to move from multinationals to purely local firms operating in different industries. More importantly for our purpose, it points out that our main results do not hold across the board but are localized to the destination state we are focusing on. The sign on the produc-

[25] The competing events are: transitions to multinationals in other industries, to non-multinationals, to unemployment and out of labor market.

[26] Intra- and inter-industry mobility is defined at the two-digit industry level. The competing events are: transitions to non-multinationals in the same industry, to multinationals, to unemployment and out of labor market.

tivity gap is positive and smaller in size than in the regressions for multi-to-non-multi mobility as shown in Table 10, thus suggesting, as expected, that the productivity gaps within the industry matters less for inter-industry mobility.

The third column of Table 11 displays the results for intra-industry transitions from multinational to non-multinational firms in low-tech industries.[27] These are exactly those industries for which we do not find significant spillover effects. The coefficients on PCM and the productivity gap are both negative. Furthermore, they are both significantly different from zero at conventional statistical level. Once again, this is broadly coherent with our main message: competition inhibits worker mobility only in industries with productivity spillovers and has the opposite effect on transitions and in industries where spillover effects are absent. However, productivity gap seem to matter for worker mobility even in low/medium technology industries where spillover effects were not detected.

Finally, the findings on productivity summarized in section 4.2 point out to the peculiar role played by technical education in allowing the transmission of knowledge from multinationals to local firms. If this is the case, we should therefore expect competition and productivity gap to play a larger role in explaining worker mobility for this type of workers. To shed light on this issue we report additional equations in Table 12, where we interact the technical education dummy variable with the productivity gap (column (i)) and the PCM measure (column (ii)). In the first column, the coefficient on the interaction term is significant and has the opposite sign with respect to the coefficient

[27]The competing events are: transitions to non-multinationals in other industries, to multinationals, to unemployment and out of labor market.

on the productivity gap measure, thus reducing the effect of the productivity gap for technically educated workers from -0.846 to -0.620. In other words, absorptive capacity still increases worker mobility but less so for workers with technical education.

In the second column, the technical education dummy is interacted with the competition measure. Here, the competition measure and the interaction term have both positive signs indicating that the effect of competition may have somewhat larger impact on the mobility of workers with technical education (0.637 vs 0.708), but the interaction term is not statistically significant. The smaller impact of the productivity gap may indicate that technical education of the movers compensates for a larger productivity gap and a weaker absorptive capacity between firms.

5 Conclusions

In this paper, we exploit a large longitudinal employer-employee data set for Finland to test for the effect of product market conditions on worker mobility from multinational to domestic firms. In doing so, we first document the size of this phenomenon. Overall, purely domestic firms are found to hire mainly workers moving from other domestic firms. However, worker mobility from multinationals, both domestic and foreign, is not trivial and has grown substantially over our sample period. In 2004, for instance, the share of workers in domestic firms with previous tenure in a MNE is as high as 6.4 percent.

Secondly, we provide evidence that workers with previous tenure in a MNE are more productive compared to other workers employed in purely domestic firms. In particular, workers hired from MNEs in high-tech industries contribute on average 37 percent more to the productivity of the plant than the incumbent workers. This finding allows us to conclude that the transmission mechanism we are interested in is indeed present in our data.

Finally, to the best of our knowledge we are the first to test whether the degree of competition in an industry enhances or hampers the diffusion of technology through worker mobility. Our main results show that worker mobility from MNEs to local firms is more likely to occur when competition is low and when local firms are not too far from the technological frontier. This evidence is consistent with the theoretical predictions coming from Fosfuri et al. model. Our analysis presents further evidence that competition inhibits worker mobility only in industries with productivity spillovers and has the opposite effect on transitions and in industries where spillover effects are absent. More generally, this paper shows the presence of an additional, and possibly counter-intuitive, channel trough which competition can affect productivity.

References

[1] Aghion, F., N. Bloom, R. Blundell, R. Griffith and P. Howitt (2005), "Competition and Innovation: An Inverted-U Relationship", Quarterly Journal of Economics, 120, 701–728.

[2] Balsvik R. (2011), "Is Labor Mobility a Channel for Spillovers from Multinationals? Evidence from Norwegian Manufacturing." Review of Economics and Statistics, 93, 285–297.

[3] Barba Navaretti G. and A. J. Venables (2004), Multinational Firms in the World Economy, Princeton University Press.

[4] Blomström M and A. Kokko (1998), "Multinational Corporations and Spillovers", Journal of Economic Surveys, 12, 247–277.

[5] Fine, J.P and R.J Gray (1999), "A Proportional Hazards Model for the Subdistribution of a Competing Risk", Journal of the Amerian Statistical Association, 94, 496–509.

[6] Fosfuri A, M. Motta and T. Rønde (2001), "Foreign Direct Investment and Spillovers through Workers' Mobility", Journal of International Economics, 53, 205–222.

[7] Glass A. J. and K. Saggi (2002), "Multinational Firms and Technology Transfers", Scandinavian Journal of Economics, 104, 495–513.

[8] Gorg H. and E. Strobl (2005), "Spillovers from Foreign Firms through Workers Mobility: An Empirical Investigation", Scandinavian Journal of Economics, 107, 693–709.

[9] Ilmakunnas, P., M. Maliranta and H. Pesola (2009), "Spillovers From Multinationals to Domestic Firms: An Empirical Analysis of the Profitability Effects of Labor Flows", Aalto university, School of Economics, Mimeo.

[10] Kaiser U., H. C. Kongsted and T. Rønde (2011), "Labor Mobility, social network effects and Patenting Activity", IZA Discussion Paper No. 5654.

[11] Levinsohn, J. and A. Petrin. (2003), "Estimating production functions using inputs to control for unobservables", Review of Economic Studies 70(2), 317–342.

[12] Maliranta, M., P. Mohnen, and P. Rouvinen (2009), "Is inter-firm labor mobility a channel of knowledge spillovers? Evidence from a linked employer–employee panel". Industrial and Corporate Change 18 (6), 1161–1191.

[13] Martins P. S. (2011), "Paying More to Hire the Best? Foreign Firms, Wages and Worker Mobility", Economic Inquiry, 49 (2), 349–363.

[14] Nickell S. J. (1996), "Competition and Corporate Performance", Journal of Political Economy, 104, 724–746.

[15] Olley, G. S. and A. Pakes (1996), "The dynamics of productivity in the telecommunications equipment industry" Econometrica, 64, 1263–1297.

[16] Pesola, H. (2007), "Foreign Ownership, Labour Mobility and Wages", HECER Discussion paper series, 175.

[17] Poole, J. (2013), "Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility", Review of Economics and Statistics, 95 (2), Pages 393–406.

[18] Putter, H., M. Fiocco and R.B Geskus (2006), "Tutorial in Biostatistics: Competing Risks and Multi-state Models", Statistics in Medicine, 26, 2389–2430.

[19] Smarzynska Javorcik B. (2004), "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In search of Spillovers through Backward Linkages", American Economic Review, 94, 605–627.

[20] Stoyanov, A. and N. Zubanov (2012), "Productivity Spillovers Across Firms through Worker Mobility", American Economic Journal: Applied Economics, 4 (2), 168–198.

[21] Thomas, J.M. (1996), "On the Interpretation of Covariate Estimates in Independent Competing Risks Models", Bulletin of Economic Research, 48, 27–39.

[22] van den Berg, G.J (2005), "Competing Risks Models", IFAU Working paper series, 25.

Table 1. Non-multinational and multinational firms and plants

	Firms					Plants				
	Total	Non-MNEs		MNEs		Total	Non-MNEs		MNEs	
		Number	Share	Number	Share		Number	Share	Number	Share
1997	2,304	1,614	0.701	690	0.299	2,813	1,453	0.517	1,310	0.466
1998	2,473	1,725	0.698	748	0.302	2,981	1,546	0.519	1,435	0.481
1999	2,589	1,796	0.694	772	0.298	3,042	1,616	0.531	1,426	0.469
2000	2,690	1,868	0.694	802	0.298	3,007	1,570	0.522	1,437	0.478
2001	2,776	1,930	0.695	828	0.298	3,188	1,680	0.527	1,508	0.473
2002	2,814	1,915	0.681	880	0.313	3,095	1,547	0.500	1,548	0.500
2003	2,854	1,915	0.671	913	0.320	3,137	1,520	0.485	1,617	0.515
2004	2,950	1,944	0.659	965	0.327	3,256	1,556	0.478	1,700	0.522

Note: Manufacturing firms with at least 20 employees and their plants. The total number of firms can exceed the sum of multinational and non-multinational firms since some firms lack information about their multinational status.

Table 2. Descriptive statistics on non-multinational and multinational firms (1997-2004 mean and median)

	Non-MNEs		MNEs	
	Mean	Median	Mean	Median
Turnover	6,302.6	3312.6	95,092.4	17,677.3
Employees	48.1	30.6	311.6	103.5
Value Added	2,164.5	1289.5	24,285.6	5635.1
Wages/Turnover	0.268	0.247	0.306	0.185
Capital/Turnover	0.458	0.246	1.880	0.269
R&D/Turnover*	0.024	0.003	0.028	0.009
PCM**	0.046	0.162	0.174	0.207
No of obs	16,623		7,564	

Note: Manufacturing firms with at least 20 employees. * R&D data are collected for the firms that fulfill the selection criterias of Statistics Finland, see footnote 3. ** Defined as in equation 11.

Table 3. Descriptive statistics on workers' entry mobility

	Entrants in non-MNEs				Entrants in MNEs			
	All entrants		New entrants		All entrants		New entrants	
	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed
1997	15,819	0.167	5,078	0.054	43,817	0.181	11,563	0.048
1998	17,125	0.181	5,907	0.063	47,702	0.188	12,383	0.049
1999	18,215	0.190	6,186	0.064	50,268	0.202	13,879	0.056
2000	19,867	0.207	7,379	0.077	56,122	0.213	16,789	0.064
2001	20,381	0.222	6,495	0.071	63,268	0.236	24,206	0.090
2002	18,947	0.227	5,206	0.062	59,410	0.227	12,297	0.047
2003	18,254	0.227	4,746	0.059	59,484	0.231	10,728	0.042
2004	19,236	0.241	5,155	0.064	60,740	0.235	12,500	0.048

Note: Includes entrants coming from any other employer to manufacturing firms with at least 20 employees.

Table 4. Descriptive statistics on workers' entry mobility - entrants to non-MNE by source

	All entrants in non-MNEs			
	from MNEs		from non-MNEs	
	Number	Share of employed	Number	Share of employed
1997	967	0.010	13,578	0.144
1998	2,273	0.024	13,583	0.144
1999	2,934	0.031	13,569	0.141
2000	3,833	0.040	14,503	0.151
2001	4,502	0.049	14,484	0.158
2002	4,162	0.050	13,555	0.162
2003	4,435	0.055	12,782	0.159
2004	5,086	0.064	13,134	0.164

Note: Includes entrants coming from multinational firms to manufacturing firms with at least 20 employees.

Table 5. Characteristics of entrants at entry year (1997-2004 mean and median)

	Non-MNEs		MNEs	
	Mean	Median	Mean	Median
Age	31.6	29.0	31.1	28.0
Education years	11.8	12.0	12.4	12.0
Previous tenure in years	3.36	1.0	3.90	1.0
Gender (share of female workers)	0.296		0.350	

Table 6. Descriptive statistics on annual transitions of workers

	From MNEs to non-MNEs		From MNEs to MNEs		From non-MNEs to non-MNEs		From non-MNEs to MNEs	
	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed
1997	3,895	0.016	6,328	0.026	3,799	0.040	1,679	0.018
1998	4,600	0.018	9,613	0.038	3,917	0.041	1,449	0.015
1999	5,380	0.022	8,884	0.036	4,898	0.051	2,606	0.027
2000	5,444	0.021	17,644	0.067	4,389	0.046	1,851	0.019
2001	4,494	0.017	7,082	0.026	3,857	0.042	1,444	0.016
2002	4,567	0.017	6,419	0.025	3,210	0.038	1,580	0.019
2003	4,486	0.017	6,614	0.026	3,349	0.042	1,155	0.014
2004	5,305	0.021	11,669	0.045	4,126	0.052	1,583	0.020

Note: Includes employees moving from manufacturing firms with at least 20 employees to any other firms. Some individuals lack information about the multinational status of their new employer and are therefore missing. Transitions of employees due to ownership changes of plants or firms are excluded.

Table 7. Descriptive statistics on annual worker separations from MNEs to non-MNEs

	Low/medium-tech industries				High-tech industry			
	Total		Share of		Total		Share of	
	Number	Share of employed	Intra-industry	Inter-industry	Number	Share of employed	Intra-industry	Inter-industry
1997	2,476	0.016	0.119	0.881	1,419	0.017	0.077	0.923
1998	2,835	0.017	0.079	0.921	1,765	0.020	0.081	0.919
1999	3,038	0.019	0.125	0.875	2,342	0.024	0.085	0.915
2000	3,074	0.018	0.129	0.871	2,370	0.025	0.032	0.968
2001	2,634	0.015	0.088	0.921	1,860	0.019	0.041	0.959
2002	2,753	0.017	0.123	0.877	1,814	0.019	0.035	0.965
2003	2,851	0.018	0.147	0.853	1,635	0.017	0.060	0.940
2004	3,254	0.020	0.097	0.903	2,051	0.022	0.211	0.789

Note: See Table 6

Table 8. Productivity estimations

	Non-multinationals						Multinationals					
	Total		High-tech		Low-tech		Total		High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
l	0.676***	0.676***	0.724***	0.722***	0.666***	0.666***	0.595***	0.595***	0.734***	0.734***	0.551***	0.551***
	(0.021)	(0.020)	(0.038)	(0.038)	(0.023)	(0.021)	(0.022)	(0.023)	(0.036)	(0.032)	(0.027)	(0.028)
k	0.129***	0.131***	0.131***	0.132***	0.137***	0.137***	0.116***	0.116***	0.118**	0.119**	0.123***	0.123**
	(0.035)	(0.031)	(0.034)	(0.033)	(0.036)	(0.036)	(0.030)	(0.028)	(0.051)	(0.052)	(0.035)	(0.037)
s MNE	0.121		0.269**		0.064		0.139*		0.087		0.114	
	(0.078)		(0.135)		(0.102)		(0.075)		(0.095)		(0.097)	
s MNE-tenure		0.137		0.259**		0.085		0.186**		0.113		0.156
		(0.086)		(0.131)		(0.125)		(0.077)		(0.101)		(0.118)
s non-MNE	0.041		-0.019		0.050		0.053		0.087		-0.008	
	(0.038)		(0.092)		(0.050)		(0.062)		(0.086)		(0.080)	
s non-MNE		0.055		0.020		0.053		0.056		0.043		0.000
-tenure		(0.048)		(0.103)		(0.051)		(0.079)		(0.107)		(0.089)
Structural parameters												
γ_{MNE}	0.179		0.372**		0.095		0.233**		0.118		0.207	
	(0.116)		(0.185)		(0.154)		(0.127)		(0.130)		(0.177)	
$\gamma_{MNE-tenure}$		0.203		0.359**		0.128		0.313**		0.154		0.283
		(0.129)		(0.181)		(0.189)		(0.129)		(0.139)		(0.217)
γ_{non_MNE}	0.060		-0.026		0.074		0.088		0.118		-0.014	
	(0.057)		(0.127)		(0.076)		(0.105)		(0.118)		(0.144)	
$\gamma_{non-MNE-tenure}$		0.081		0.028		0.080		0.094		0.058		0.000
		(0.071)		(0.142)		(0.077)		(0.133)		(0.147)		(0.163)
No. obs	10,821	10,821	2,127	2,127	8,694	8,694	9,450	9,450	2,554	2,554	6,893	6,893

Note: Dependent variable log(value added). All regressions include year and industry-year interaction dummies.*** significant at the one, ** at the five and * at the ten percent level. Standard errors clustered on plants in parenthesis.

Table 9. Productivity estimation - Human capital in high-tech sample

	Non-multinationals			Multinationals		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
l	0.722***	0.724***	0.727***	0.741***	0.733***	0.739***
	(0.044)	(0.036)	(0.038)	(0.037)	(0.041)	(0.038)
k	0.132***	0.131***	0.132***	0.115*	0.118**	0.116**
	(0.038)	(0.033)	(0.036)	(0.058)	(0.065)	(0.058)
s MNE-higher-edu	0.055			0.396		
	(0.397)			(0.226)		
s MNE-lower-edu	0.345**			-0.074		
	(0.172)			(0.128)		
s MNE-technical-edu		0.577***			0.207	
		(0.200)			(0.137)	
s MNE-non-technical-edu		-0.176			-0.124	
		(0.245)			(0.228)	
s MNE-technical-higher-edu			0.859*			0.297
			(0.395)			(0.259)
s MNE-non-technical-higher-edu			-1.024			0.533
			(0.395)			(0.572)
s non-MNE	-0.017	-0.017	-0.012	0.084	0.087	0.090
	(0.085)	(0.086)	(0.079)	(0.077)	(0.080)	(0.091)
Structural parameters						
$\gamma_{MNE-higher-edu}$	0.077			0.535		
	(0.549)			(0.305)		
$\gamma_{MNE-lower-edu}$	0.478**			-0.099		
	(0.237)			(0.172)		
$\gamma_{MNE-technical-edu}$		0.797***			0.283	
		(0.272)			(0.188)	
$\gamma_{MNE-non-technical-edu}$		-0.243			-0.169	
		(0.340)			(0.312)	
$\gamma_{MNE-technical-higher-edu}$			1.183*			0.402
			(0.663)			(0.353)
$\gamma_{MNE-non-technical-higher-edu}$			-1.409			0.722
			(1.271)			(0.770)
$\gamma_{non-MNE}$	-0.024	-0.024	-0.017	0.114	0.119	0.122
	(0.118)	(0.119)	(0.110)	(0.105)	(0.110)	(0.125)
No. obs	2,127	2,127	2,127	2,554	2,554	2,554

Note: Dependent variable log(value added). All regressions include year and industry-year interaction dummies. *** significant at the one, ** at the five and * at the ten percent level. Standard errors clustered on plants in parenthesis.

Table 10. Mobility equations - Movers from MNEs to non-MNEs within high-tech industries

	High-tech intra-industry destination state			
	(i)	(ii)	(iii)	(iv)
Age	-0.008	-0.009	-0.007	-0.008
	(0.005)	(0.005)	(0.005)	(0.005)
Gender	-0.001	-0.021	-0.021	-0.037
	(0.092)	(0.091)	(0.090)	(0.090)
Marital status	0.176*	0.181*	0.169*	0.173*
	(0.097)	(0.097)	(0.097)	(0.097)
Parenthood status	-0.175**	-0.181**	-0.178**	-0.183**
	(0.077)	(0.077)	(0.077)	(0.078)
Education	-0.082***	-0.083***	-0.084***	-0.087***
	(0.022)	(0.022)	(0.021)	(0.021)
Income	-0.034	0.051	0.017	0.026
	(0.056)	(0.058)	(0.056)	(0.058)
Location	-1.654***	-1.629***	-1.664***	-1.644***
	(0.196)	(0.198)	(0.197)	(0.198)
Log firm size	0.155***	0.167***	0.133***	0.135***
	(0.040)	(0.040)	(0.040)	(0.041)
Productivity gap 3-digit	-0.723***		-0.607***	
	(0.070)		(0.067)	
Productivity gap 2-digit		-0.687***		-0.503***
		(0.078)		(0.072)
Price-cost margin*	0.653***	0.671***		
	(0.042)	(0.043)		
Price-cost margin**			1.853***	1.615***
			(0.562)	(0.548)
Wald test of joint sign.	1,795.24	1,727.13	1,956.43	1,959.55
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	280,814	284,982	280,814	284,982
No of subjects	74,284	74,284	74,284	74,784
No of failed	544	555	554	555
No. competing	28,662	28,993	28,662	28,993

Note: *Our main measure of PCM, defined as in equation (11). **Defined as in equation (12). Year dummies included as additional regressors.
Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table 11. Mobility Equations - Testing the model by looking at alternative destination states

	High-tech Multi-to-Multi Intra-Industry	High-tech Multi-to-non-Multi Inter-Industry	Low/Medium-tech Multi-to-non-Multi Intra-Industry
Age	0.008***	-0.028***	-0.014***
	(0.002)	(0.002)	(0.004)
Gender	-0.287***	-0.196***	-0.389***
	(0.030)	(0.037)	(0.083)
Marital status	0.017	-0.042	0.035
	(0.029)	(0.038)	(0.075)
Parenthood status	0.028	0.038	0.016
	(0.018)	(0.025)	(0.054)
Education	0.028***	-0.016*	-0.046***
	(0.006)	(0.008)	(0.017)
Income	0.293***	-0.079***	-0.052
	(0.020)	(0.024)	(0.101)
Location	-0.014	0.007	0.117
	(0.029)	(0.040)	(0.108)
Log firm size	0.658***	-0.110***	-0.434***
	(0.017)	(0.012)	(0.027)
Productivity gap 3-digit	0.015	0.069**	-0.284***
	(0.022)	(0.029)	(0.041)
Price-cost margin*	-0.297***	-0.149***	-4.771***
	(0.067)	(0.034)	(0.651)
Wald test of joint sign.	14,354.34	3,726.21	1938.64
	[0.00]	[0.00]	[0.00]
Observations	280,814	280,814	654,892
No of subjects	74,284	74,284	139,340
No of failed	6,951	3,900	951
No. competing	22,265	25,316	44,879

Note: *Our main measure of PCM, defined as in equation (11). Year dummies included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table 12. Mobility Equations - Looking at the role of technical education

	Multi to non-multi intra-industry destination state	
Age	-0.007	-0.007
	(0.005)	(0.005)
Gender	-0.063	0.060
	(0.095)	(0.096)
Marital status	0.178	0.178*
	(0.097)	(0.097)
Parenthood status	-0.173**	-0.173**
	(0.077)	(0.077)
Education	-0.094***	-0.095***
	(0.026)	(0.026)
Income	-0.037	0.039
	(0.055)	(0.056)
Location	-1.635***	-1.637***
	(0.197)	(0.197)
Log firm size	0.152***	0.153***
	(0.040)	(0.040)
Prod gap 3-digit	-0.846***	-0.716***
	(0.095)	(0.070)
Price-cost margin*	0.680***	0.637***
	(0.043)	(0.044)
Technical education	-0.004	0.109
	(0.132)	(0.109)
Prod gap*Techn edu	0.226*	
	(0.127)	
PCM*Techn edu		0.071
		(0.068)
Wald test of joint sign.	1,799.52	1,797.86
	[0.00]	[0.00]
Observations	280,814	280,814
No of subjects	74,284	74,284
No of failed	554	554
No. competing	28,662	28,662

Note: *Our main measure of PCM, defined as in equation (11).
Year dummies included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets.