Multinationals, competition and productivity spillovers through worker mobility

Published version:

DOI:10.1007/s10290-017-0304-2

Multinationals, Competition and Productivity Spillovers through Worker Mobility*

Katariina Nilsson Hakkala† Alessandro Sembenelli‡

December 10th, 2017

Abstract

Multinational firms are believed to impact the productivity of domestic firms through worker mobility. Fosfuri et al. (2001) suggest 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. We assess empirically the importance of the hypothesis by using the Finnish longitudinal employer-employee data. Consistent with the predictions of the model, we find that competition is negatively related to worker mobility but only in high-tech industries where productivity spillovers are present. Thus, our results detail a channel through which competition may negatively affect the productivity of purely domestic firms.

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

JEL classification numbers: D22, D24, F23, J62

*Financial support from the Academy of Finland (grant nr-134057) and Yrjö Jahnsson Foundation are gratefully acknowledged. For helpful comments and suggestions we are grateful to participants at ETSG Copenhagen 2011, Erwit/Efige Barcelona 2012, and seminar participants at University of Lund, University of Copenhagen, Helsinki Center for Economic Research (HECER), Labour Institute for Economic Research (PT) and VATT Institute for Economic Research.

†Aalto University and ETLA Research Institute of the Finnish Economy.

‡University of Torino and Collegio Carlo Alberto.

1 Introduction

The entry of multinational firms (MNEs) and inward foreign direct investments (FDI) 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 domestic firms. One channel for the spillover effects is worker mobility. Positive spillover effects may in fact 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, worker mobility within an industry cannot be thought of as exogenous since it might be affected, for instance, by the intensity of product market competition. If this is the case, competition could have an indirect effect on industry level productivity by potentially enhancing or hampering worker mobility and the diffusion of knowledge through this channel.

The existence of this indirect channel has been recognized theoretically by Fosfuri, Motta and Rønde (2001). They develop a two-period oligopoly model, which 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 the total factor productivity (TFP) of local firms. In this paper, we propose a solution to this problem by using a two-step approach. In the first step, we explore empirically the direct link between product market competition and worker mobility, while in the second step, we analyze on the effect of worker mobility on productivity. Although there is already established empirical evidence exploring our second step, the relationship between competition and mobility is far less investigated.[1]

Our paper departs from a theoretical formalization of spillovers by Fosfuri et al. (2001).[2] In the first period, a multinational firm provides training to a local worker and

[1]See the next section for a selected review of the recent empirical literature on these two issues.

[2]Glass and Saggi (2002) also develop a theoretical model along similar lines, but they do not directly focus on the role played by product market competion. 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

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 for the worker from a local firm which realizes that it could also gain access to the technology by hiring the trained worker. Competition for the worker is modelled as a first-price auction: the firm who offers a higher wage hires the worker and pays the wage it has offered. Clearly, the multinational firm has the incentive to offer more (less) than the local firm if the reduction in its profits following entry is larger (smaller) than the duopoly profits occurring to the local firm. A sufficient condition for this to be the case occurs when the so-called “joint profit” condition holds, that is, when the sum of the gross profits of two duopolists using the technology is larger than the gross profit of a monopolist. In turn, the duopoly profits are sufficiently high to assure the “joint profit” condition when the mode competition is not too intense (e.g. collusion vs Cournot vs Bertrand) or/and when the products offered by the two firms are not close substitutes (e.g. independent vs differentiated vs homogenous). As a consequence, the mobility of workers is more likely to be observed when the local and the multinational firm do not compete fiercely in the product market, or when they sell in independent or vertically related markets.

The same authors also note that the extent to which technological spillovers occur depends on the nature of the technology and how easily it can be transferred. In particular, 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. Firstly, we 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. This part of our analysis contributes to the literature on FDI and spillovers with new empirical evidence on the relationship between competition and worker mobility. 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

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.

local firms in a multivariate duration framework and test the hypotheses of interest in a rigorous way. Secondly, we also contribute to the recent growing literature on the economic importance of productivity spillovers, and on the conditions when they arise. This allows us to test whether the transmission mechanism that we are analyzing is indeed present in our data.

Our empirical results suggest that a more competitive environment restrains worker mobility. More specifically, 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. These results are consistent with the predictions put forward by Fosfuri et al. (2001). We also find that productivity spillovers through worker mobility exist but they are not economy-wide. By distinguishing between firms in high- and low-tech industries according to their level of R&D expenditures, we find productivity spillovers that are both economically large and statistically significant, but only for high-tech industries. According to our preferred estimates, workers with former multinational experience are 37 percent more productive than their colleagues without such an experience. This is consistent with the transfer of technological knowledge through worker mobility. We also 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 productivity spillovers.

The structure of the paper is as follows. In the next section, we briefly review the recent 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 two-step empirical analysis, first the econometric framework and the results for worker mobility and thereafter the model and the results for quantifying the productivity spillovers. 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.

The 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) study knowledge transfers in general without a specific focus on the dynamics between MNE**s** and domestic firms. They find that hiring workers from more productive firms implies gains amounting to a 0.35 percent productivity increase for the average firm one year after hiring. 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 percentile move up in the productivity distribution by the median firm in Danish manufacturing. On a related issue, Görg 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, Mohnen and Rouvinen (2009), Kaiser, Kongsted and Rønde (2011, 2015) and Parrotta and Pozzoli (2012) who find that the hiring of workers from R&D intensive or innovative firms is associated with improved performance or increased innovative activity by the hiring firms.

The studies by Poole (2013) and Pesola (2011) focus on workers and wages rather than on firms/plants and productivity. Poole (2013) finds evidence of 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. She 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 (2011) 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 related 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.

Finally, to the best of our knowledge, there is only one other paper that looks directly at the effects of competition on labor mobility (see Castillo et al, 2016). In particular, they exploit data on firm participation to an innovation support program in Argentina (FONTAT) and study workers mobility from participating to non-participating firms. They find that in industries where concentration is low non-participating firms are willing to pay a wage premium to acquire skilled workers which is higher than the premium participating firms are willing to pay to retain them. On the contrary, in more concentrated industries participating firms are willing to pay a higher wage premium than non-participating firms in order to prevent mobility.

As already mentioned, our primary and novel contribution to the previous literature is to analyze how worker mobility as a mechanism of technology diffusion from MNEs to local firms responds both to the degree of competition in the product market and to the absorptive capacity of the local firms. In addition, we also build on the approach proposed by Balsvik (2011) and test whether and in which type of industries worker mobility from multinationals to local firms generates productivity spillover effects in local firms. The productivity spillover analysis is obviously of paramount importance for the main 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.

3 Data and Descriptive Statistics

3.1 Data

We use data from three different data-bases from Statistics Finland for the years 1990 to 2006. The main data-base 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 (LDMP), 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 industry codes, value added, capital stock, number of employees, wages, turnover/sales an R&D expenditure.[3] We restrict our analysis to manufacturing firms with at least 20 employees and to the period of 1997-2004.[4] 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.[5] Each individual is followed over time. An individual exits the data if he/she turns 70 years old, 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.[6] As it can be seen from Table 1, the number of non-multinational firms is more than twice as large as the number of multinational firms, but multinational firms tend to own several plants and 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,

[3]As a general rule, R&D data are collected for all enterprises with more than 100 employees and for a sample of enterprises with 10-99 employees.

[4]Register information on whether the firm is multinational is available from 1997 onward and information on start and end dates of employment spells 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 also included.

[5]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.

[6]Multinational firms include both foreign and domestically owned firms. In our econometric analysis we also investigate whether the type of ownership matters and we do not find significant differences.

multinationals have a smaller wage bill relative to turnover than domestic firms, use capital more intensively and invest in R&D more than purely domestic local firms. Finally, multinational firms are found to be more profitable as documented by the higher share of gross operating profits over turnover (PCM).

Tables 3 and 4 display statistics quantifying employees entering both 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 defined as the accumulated net number of entrants from current year and previous years as early as the data set allows (since 1990).[7] *New entrants* include the employees starting to work at the firm only in the current year. As can be easily detected by looking at Table 3, the share of *All entrants* increases over the period. It may be noticed that also the shares of *New entrants* slightly increase, but the increase is not monotonous over the time period. In Table 4, we distinguish *All entrants* to non-multinational firms according to whether the sending firm is multinational or not. We may note that the share of entrants coming from multinational firms increases more distinctly over time 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 entrants at entry year. Overall, MNEs are found to assume a larger share of female workers, employees with a longer education and a longer previous tenure than non-MNEs (see columns (i) and (v)). When we focus only on workers with previous tenure (see columns (ii) and (iii) for MNEs and columns (vi) and (vii) for non-MNEs), we observe that movers coming from MNEs are older, have a slightly longer education and a longer previous tenure.[8] This holds both for MNEs and for non-MNEs as destination firms. Also, the differences between the means are statistically significant for all variables. Overall, this evidence shows therefore not only that MNEs tend to assume on average more educated and experienced workers than non-MNEs but also that the subset of workers moving from MNEs to other firms (both MNEs and non-MNEs) is more educated and experienced than the subset moving from non-MNEs. In short, these results suggest that movers from MNEs are more qualified and therefore have the potential to transfer the knowledge acquired during the previous tenure.

In Tables 6 and 7, we finally provide descriptive 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

[7] *All entrants* is used to compute the shares of workers with and without multinational experience which enter the productivity equations. See Section 4.3. for the details.

[8] We include workers with a minimum of two years of tenure from the previous employer.

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.[9] We also observe an asymmetric pattern for the employees leaving non-MNEs. Comparatively a larger number is found to move to other non-MNEs than to MNEs. This overall pattern suggests that employees tend to change employers more frequently within the same type of firms.

Since our primary interest is to analyze whether worker mobility generates productivity spillovers in the non-multinational firms, Table 7 reports statistics on workers moving from multinational to non-multinational firms. We split the sample by the industry of the sending firms into low-tech and high-tech industries, since previous studies by Maliranta et al. (2009), Kaiser et al. (2011, 2015) and Parrotta and Pozzoli (2012) have found the hiring of workers from R&D intensive or innovative firms to be linked to better performance by hiring firms.[10] 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.[11] 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 this share is found to be higher in high-tech industries in most years. Although not conclusive, this observation is consistent with Fosfuri et al. model, which predicts that mobility is more likely to occur between firms operating in independent or vertically related markets. Also, the finding that the share of intra-industry mobility is lower in high-tech industries points out to the fact that within industry mobility is less frequent precisely in those industries where spillovers are more likely to materialize.

[9]A transition is identified when an employee changes both plant and firm identity codes of his/her employer between year t and t+1. In most mergers and acquisitions, codes of the plants belonging to the target firm remain unchanged while she gets a new firm code. This implies that mergers and acquisitions are not *per se* accounted as transitions of employees unless they are followed by restructuring causing employees to move to other plants and firms. In 2004 there was an increase in transitions from MNEs to MNEs (the last row of columns (iii) and (iv) in Table 6) and in the share of intra-industry transitions from MNEs to non-MNEs in high-tech industries (the last row of columns (v), (vi) and (vii) in Table 7) due to restructuring following company consolidations.

[10]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 on total sales in 1997). All other firms are defined as Low/Medium tech firms.

[11]In Table 7, industries are defined at the three-digit level and industry changes are defined accordingly. In the econometric section, our main results are based on intra- and inter-industry mobility at three-digit level, but we use also the two-digit level of industry in some specifications as robustness check.

4 Empirical Analysis

Our empirical strategy consists of two complementary sets of econometric estimates. The first part of the analysis serves the main purpose of this paper. In particular, we explore whether the evidence based on our data is in line with the hypotheses of Fosfuri et al. on the impact of competition on worker mobility. In the second part of the analysis, we estimate an augmented Cobb-Douglas production function with firm-level data. This allows us to establish whether worker mobility from multinationals to local firms has a positive effect on the total factor productivity of local firms. 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. More specifically, we apply the competing risks framework to the analysis of the effect of product market competition. 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.

4.1 Worker Mobility: Econometric Framework

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 destinations and therefore J associated latent durations, of which only the shortest is identifiable by the data. 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. These destinations are competing events. Unlike censoring, which merely precludes the view of the event of interest, a competing event precludes the occurrence of the primary event of interest altogether. If these latent durations were independently distributed, it would be, however, perfectly legitimate to apply the standard proportional hazards regression model exclusively to the transition of interest to estimate the impact of a change in a given covariate, x_k on the probability of leaving the initial state at or before time t (van den Berg (2005)). Economic theory, however, suggests that the durations are unlikely to be independent 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 expected to be related to different forms of mobility.

If independency is not assumed, computing–and even signing– the marginal effect of interest is a much more difficult task which requires the estimation of multivariate duration models.[12] This is because the relevant CIF (Cumulative Incidence Function) will depend not only on the cause-specific hazard functions of the destination of interest but also on all other cause-specific hazard functions.[13] To overcome this problem we adopt the approach proposed by Fine and Grey (1999). Basically, they introduce the so-called sub-distribution hazard and show that the CIF–and therefore the implied marginal effects–can be easily computed as a function of the sub-distribution hazards of the event of interest only.[14] Their approach is semi-parametric in that the baseline sub-hazard of the event of interest is left unspecified, and the effects of covariates are assumed to be proportional.

Our purpose is to explore the empirical 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. 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 analyze the effect of the toughness of competition on the incentive for the multinational to keep the worker, we follow Aghion, Blundell, Griffith and Howitt (2005) and Nickell (1996) and we adopt the Lerner Index as main indicator of product market competition. This measure has several advantages over other observable competition indicators such as market shares or the Herfindahl concentration index. These other measures rely more directly on precise definitions of geographic and product markets, which is particularly difficult in our application, as multinational firms operate in international markets, so that market concentration measures based only on Finnish data

[12]The most popular framework is the so-called competing risks model. Recent surveys can be found in Putter et al (2006) for biostatistics and van den Berg (2005) for economics.

[13]However, Thomas (1996) shows 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.

[14]The main difference between the two hazard functions is that individuals leaving the initial state to another destination remains in the risk set for the sub-distribution hazard but leaves it instead for the cause-specific hazard.

may be extremely misleading. Operationally, we compute the price-cost margin at the firm level as operating profits net of the cost of capital divided by value added .[15] Operating profits are computed as value added minus wages and salaries and other personnel expenses. The cost of capital is assumed to be 0.085 for all firms and time periods (same as Aghion et al. assume). Our main competition measure is defined simply as the weighted average of the price cost margin across firms within the same three-digit industry:

$$InvCompetition_{jt} = \sum_i \frac{x_{ijt}}{\sum_i x_{ijt}} \frac{OP_{ijt} - CC_{ijt}}{VA_{ijt}} \tag{1}$$

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. A value of 0 indicates perfect competition (price equals marginal cost) while values above 0 indicate some degree of market power. As robustness, we also define an alternative competition measure, where the cost of capital is not included, as:

$$Alt\_InvCompetition_{jt} = \sum_i \frac{x_{ijt}}{\sum_i x_{ijt}} \frac{OP_{ijt}}{x_{ijt}} \tag{2}$$

As before larger values indicate larger operating profits and less fierce competition.

An obvious concern with our estimation model is that the firms' decisions affecting worker mobility are jointly determined with those affecting competition. When estimating competing risk models like ours, we therefore lack a fully satisfactory method of confronting the challenges of causal identification.[16] For this reason, we are careful not to interpret the estimated coefficients as consistent measures of the direct causal effect and focus instead on the differences in the estimated coefficients across industries or types of firms.

In addition to competition, we also aim to assess the importance of absorptive capacity of the receiving firm for intra-industry mobility. We therefore compute a firm-specific productivity gap measure (Prodgap) as:

$$Prodgap_{ijt} = TFP_{ijt} - \overline{TFP}_{jt} \tag{3}$$

[15] We use the measure of value added computed by Statistics Finland as corrected operating profit + wages and salaries + other personnel expenses.

[16] We refrain from using lags of potentially endogenous variables since its use is almost never justified on identification grounds (see e.g. Bellemare, Masaki and Pepinsky, 2015). In general, replacing contemporaneous with lagged regressors simply modifies the channel through which endogeneity biases estimates of causal effects.

where TFP_{ijt} denotes the total factor productivity of the multinational firm i in industry j at time t where worker is moving from and and $\overline{TFP}_{jt}$ denotes the average total factor productivity of non-multinational firms in industry j at time t.[17] As the main proxy for absorptive capacity, we use therefore the productivity gap between the sending MNE and the average domestic non-MNE firm in the same three-digit industry.[18] 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.[19] To sum up, the aim of the multivariate duration analysis is to determine whether and how *InvCompetition* and *Prodgap* are related to the probability of moving to a domestic firm, controlling for the other individual- and firm-specific covariates.

4.2 Worker Mobility: Results

In our estimations, we distinguish intra- and inter-industry mobility and mobility within low- and high-tech industries. We first identify those workers who are employed in a multinational in 1997 and we trace them over the entire sample period. Predictions received from the theory suggest that *InvCompetition* should enter with a positive sign in the specifications for intra-industry worker mobility, indicating that less fierce competition in the product market increases worker mobility between firms in the same industry. Since *InvCompetition* is defined at the industry of origin level, it is less obvious that the same relationship is expected to hold in inter-industry transitions. This would, however, be the case if, for instance, the replacement cost of the trained worker is assumed to be related to the degree of competition in the industry of origin.[20] In all regressions, we also include several standard individual level variables: age, gender, marital and parenthood status, educational level, income and regional location. Finally,

[17] Productivity is estimated at plant-level as described in section 4.3. 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) and output is used as weights. In multi-to-multi mobility regressions, we also use an alternative measure defined as the productivity gap between the sending MNE and the average of the MNEs in the same industry.

[18] We do so since we cannot include a direct measure of the productivity of the receiving firm. This is obviously not observable when there is no transition or when the transition is one of the competing events where the destination firm is not identified (enter unemployment or exit the labor market).

[19] 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 on our main results. These additional estimated equations are reported in Table A3 of the web appendix.

[20] In inter-industry mobility equations, variables capturing the degree of competition in the destination industry cannot be included since this piece of information is not available for all those workers who do not move over the sample period or who move to unemployment or out of the labor market.

this baseline model is augmented with (log) firm size and with a set of aggregate time dummies capturing aggregate business cycle effects.[21]

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 246,177 workers (corresponding to 1,131,913 observations), of which 1,748 (2,469) are found to move to a domestic non-multinational firm within the same 3-digit industry (the same 2-digit industry). We treat as competing events moves to a domestic non-multinational firm in a different 3-digit industry (11,305 workers), to a different multinational firm (33,636 workers), to unemployment (23,695) and out of labor market (23,550). All other observations are treated as censored.[22]

In our baseline specifications, we include all industries. Overall, results in Table 8 confirm received theoretical predictions. In the sub-distribution hazard function for the purely domestic firm destination state, the coefficients on the competition variable (*InvCompetition*) are positive and statistically significant in the specifications for intra-industry mobility (columns (i) and (ii)). This turns out to be the case regardless whether we compute mobility at the three- or the two-digit level. The results suggest that a less competitive environment with higher price-cost margins is associated to higher worker mobility between firms in the same industry, which is consistent with the theoretical predictions of Fosfuri et al. of competition affecting worker mobility adversely.

Furthermore, the coefficients on *InvCompetition* are considerably smaller in the specifications for inter-industry mobility. This is coherent with our expectations since competition within the industry of origin is less obviously associated to the probability of observing worker transitions to other industries (columns (iii) and (iv)). Taken at its face value, however, the positive sign tells us that workers are more likely to move to other industries when profits in the industry of origin are higher. This might be the case, for instance, if the cost of replacing the worker is positively associated to the size of the monopoly profits. Firm size is also statistically significant and positive in the specifications for intra-industry mobility implying that workers are more likely to move from large firms to domestic firms in the same industry. The estimated parameters on age, gender, education and metropolitan Helsinki location are negative and statistically significant in the specifications for intra-industry mobility, implying that all these variables are associated to a slow down of the transition to purely domestic firms. Education and metropolitan Helsinki location have instead positive and signifi-

[21]See Tables A1 and A2 of the web appendix for summary statistics and correlation table of the covariates.

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

cant coefficients on inter-industry mobility suggesting that these factors accelerate the transition to purely domestic firms in other industries. Also, firm size has the opposite effect on inter-industry mobility slowing down the transitions.

Next, we split the sample in high- and low-tech industries and analyze further the effect of competition on intra-industry mobility at three-digit level of industries.[23] In addition to competition, we analyze the effect of the productivity gap on worker mobility.[24] The productivity gap is expected to enter with a negative sign, indicating that the smaller the productivity lead of a multinational firm in relation to non-multinational firms, the larger is the worker mobility between firms in the same industry. Here, we report only the main coefficients of interest. Full estimates are, however, available in Tables A4 and A5 of the web appendix.

Overall, results for the main measure of competition in Panel A in Table 9 confirm the theoretical predictions. In the subdistribution hazard function for the purely domestic firm destination state, the coefficient of *InvCompetition* variable is positive both in high- and low-tech industries, but it is larger in high- than in low-tech industries. Thus, these results suggest that a less competitive environment with higher price-cost margins is associated with a higher degree of worker mobility between multinational and non-multinational firms in the same industry both in high- and low-tech industries. Finally, the sign of the productivity gap is indeed negative and statistically significant, indicating that the smaller the absorptive capacity of non-multinationals is as compared to multinationals, the less likely are workers to switch from multinational to non-multinational firms.

We investigate the robustness of our results to the alternative measure of competition defined in equation (2) in section 4.1. The coefficients of this alternative measure of competition *(Alt_InvCompetition)* reported in Panel B in Table 9 are positive and statistically significant in the estimations for high-tech industries. Thus, our main findings turn out to be robust to an alternative proxy for the competitive environment in high-tech industries. This is not the case, however, in low-tech industries where the coefficients of *Alt_InvCompetition* are negative and, thus, opposite to the effects indicated in Panel A in Table 9.[25] However, the coefficient on productivity gap remains negative

[23] We employ worker mobility measured at the three-digit industries as the main definition of intra-industry mobility, since mobility measured at the two-digit level of industries is likely to include a substantial amount of *true* inter-industry mobility.

[24] The productivity gap measure is estimated separately for high- and low-tech firms. For multi-plant firms the productivity is computed as the output weighted average of high- and low-tech plants.

[25] This puzzle can be rationalized by noticing that the difference between the two measures is given by the cost of capital which in turn is a function of the level of capital. If in low-tech industries, local firms with an high level of capital are less likely to attract workers from multinationals, than we will observe a negative spurious correlation between *Alt_InvCompetition* and mobility. For this to be the

and significant when using the alternative measure of competition.

Obviously, the fact that our results for multi-to-non-multi mobility in high-tech industries, discussed so far, match well 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 analyzing whether our main findings also apply to other transitions or whether they are indeed specific to our destination state of interest. In Table 10, we report the results for worker transitions between multinational firms.[26] *InvCompetition* variable is negative and statistically significant both in high- and low-tech industries, indicating that a competitive environment with lower price-cost margins is associated with higher worker mobility between multinationals, which is opposite to the estimated effect on mobility from multinationals to non-multinationals. *Prodgap* enters with a negative sign in both industry groups. Taken at its face value, this implies that workers tend to move to other multinationals more often when purely local firms do not lag substantially behind in terms of productivity.[27] When including *Prodgap*, the coefficient of *InvCompetition* variable gets smaller, and it is less precisely estimated in high-tech industries.

Summarizing, our results for worker mobility from multinationals to non-multinationals are consistent with the theoretical predictions of Fosfuri et al. across different specifications in high-tech industries. In particular, more fierce product market competition and a weaker absorptive capacity are found to be adversely related to within-industry worker mobility from multinationals to local firms.

4.3 Spillover Effects: Econometric Framework

The mobility analysis provides evidence 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. In this sub-section we aim to establish whether worker mobility from multinationals to local firms generates productivity spillover effects in local firms. We start from the Cobb-Douglas production function:

$$Y_{it} = A_{it} L_{it}^{*\beta_l} K_{it}^{\beta_k} \quad i = 1, 2, ..., N; \; t = 1, 2, ...T \tag{4}$$

case capital and labor with multinational experience are required to be substitutes.

[26]For completeness we also report the results for transitions to unemployment and out of the labor market in the web appendix (Table A6).

[27]We also use as an alternative measure of the productivity gap the difference in productivity between the sending MNE and the average of MNEs in the same industry. The estimated coefficients for this alternative productivity gap measure are also negative but larger both in high-tech and low-tech industries. Results are reported in details in Table A7 of the web appendix.

where Y_{it}, K_{it} and L^*_{it} denote respectively production, capital stock and quality adjusted labor of plant i at time t. We follow the approach of Balsvik (2011) and define quality adjusted labor as equal to:

$$L^*_{it} = L^N_{it} + L^M_{it}(1+\gamma) = L_{it}(1+\gamma s_{it}) \tag{5}$$

where L^M_{it} and L^N_{it} denote labor with MNE experience and labor without such experience, $L_{it} = L^N_{it} + L^M_{it}$ 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 generated by the technology spillover embodied in L^M_{it}. The productivity term A_{it} is modelled as follows:

$$A_{it} = e^{\omega_{it}+u_{it}} \tag{6}$$

where ω_{it} denotes shocks to productivity that are potentially observed by firms when making their input decisions whereas u_{it} represents shocks to productivity that are instead neither observed nor predictable when input levels are chosen. By using equations (5) and (6), by taking logs and by using the approximation $\beta_l \ln L^{*\beta_l}_{it} = \beta_l \ln L^{\beta_l}_{it} + \beta_l \gamma s_{it}$, equation (4) can be rewritten in the following representation:

$$y_{it} = \beta_l l_{it} + \beta_l \gamma s_{it} + \beta_k k_{it} + \omega_{it} + u_{it} \tag{7}$$

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 input variables fixed, one has to solve the standard endogeneity problem arising from the fact that both standard input factors (l_{it}, k_{it}) and the labor share (s_{it}) are not orthogonal to the productivity shock, ω_{it}. This makes both the pooled OLS and the WG estimators biased and inconsistent.[28]

In order to obtain consistent estimates of the parameters of interest, we rely on the identification approach proposed by Levinsohn and Petrin (LP, 2003). In later work, Ackerberg et al. (ACF, 2015) argue that the technique developed by Levinsohn and Petrin suffers from collinearity problems and that the identification of the parameters of interest relies on an unintuitive set of assumptions. Both LP and ACF techniques share, however, a similar two-step semi-parametric econometric approach. Operationally, the main difference between the two is that whereas LP estimates β_l and γ in the first

[28]In order to be consistent the WG estimator would require $\omega_{it} = \omega_i$. As noted by Ackerberg et al. (2015), this is a very strong assumption since it would require the observed component of the productivity shock to be constant over time for each firm. This is however the benchmark identification strategy adopted in Balsvik (2011).

step and β_k in the second step, ACF estimates all parameters of interest in the second step.[29] Since we estimate a production function common to all or to large subsets of industries, we have to take into account the possibility that the composite error term $\omega_{it} + u_{it}$ includes an industry/time specific component which is not orthogonal to s_{it}. This potentially relevant endogeneity issue can be dealt with within the LP framework by simply adding a set of industry/time specific binary variables in the first step. A similar strategy is, however, precluded within the ACF approach where the coefficient on s_{it} is estimated in the second step. Indeed, the inclusion of time/industry specific binary variables would make the optimization problem in the second step computationally unfeasible because of the high number of estimated parameters. For this reason, we adopt the LP technique as our benchmark approach. However, we also briefly comment on the results obtained when using ACF applied to a model which excludes the industry/time set of binary variables.

4.4 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.[30] To take into account the possibility that technology spillovers occur only in high-tech industries, we also allow for the parameters of interest to differ between high-tech and low-tech firms. 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).[31] In some specifications, we also control for the length of previous tenure (MNE-tenure and non-MNE-tenure).[32]

Our basic results obtained when using the LP technique are summarized in Table 11. 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

[29]In their approach the purpose of the first step is only to recover estimates of ω_{it}.

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

[31]See Tables A8 and A9 for summary statistics and correlation table of the covariates.

[32]As explained in the previous section, our first step also includes industry/time specific binary variables. Industries are defined at the two-digit levels.

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.[33] 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 statistically insignificant (see columns (i) and (v)). However, for the plants of high-tech firms (column (iii)), the coefficient, γ_{MNE}, 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 Balsvik did not make the distinction between industries.[34]

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 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 lev-

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

[34]We also allowed for the possibility that the productivity premium associated to multinational experience in the previous job varies as a function of the length of the tenure in the current job. This might be the case if it takes time before the knowledge acquired in the previous firm is transferred and absorbed in the new firm. Overall, we do not find empirical support to the hypothesis that the productivity premium varies according to the number of years spent in the current job. For details see Table A10 in the web appendix.

els. 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.[35]

To sum up, results presented in Table 11 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.

5 Conclusions

In this paper, we exploit a large longitudinal employer-employee data set for Finland to analyze how product market conditions are related to 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

[35]As mentioned in the previous section, we have also estimated the same set of equations reported in Table 11, but without industry/time specific dummies in the first step, with the ACF methodology. Qualitatively, all our findings are fully confirmed. However, the implied productivity premiums turn out to be higher and perhaps implausibly so. For instance, when focusing on non-multinationals in high-tech industry it is as high as 84.8%. These additional results are available in Table 11 of the web appendix.

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.

To the best of our knowledge, we are the first to analyze empirically 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. Also, this occurs especially in high-tech industries, that is those industries where spillovers are more likely to materialize. Overall, this evidence is therefore consistent with the theoretical predictions coming from Fosfuri et al. model.

We also provide further 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 of knowledge spillovers through worker mobility is indeed present in our data, but rather than being economy-wide, it is specific to high-tech industries.

Altogether, our analysis presents evidence that competition is adversely related to worker mobility in industries with productivity spillovers, while it is positively or not correlated to worker transitions between firms and in industries where spillover effects are absent. More generally, this paper shows the presence of an additional, and possibly counter-intuitive, channel through which competition can affect productivity.

References

[1] Ackerberg D.A., K. Caves and G. Frazer (2015), "Identification Properties of Recent Production Function Estimators", *Econometrica*, 83 (6), pp 2411-2451

[2] Aghion, F., N. Bloom, R. Blundell, R. Griffith and P. Howitt (2005), "Competition and Innovation: An Inverted-U Relationship", *Quarterly Journal of Economics*, 120 (2), pp. 701–728.

[3] Balsvik R. (2011), "Is Labor Mobility a Channel for Spillovers from Multinationals? Evidence from Norwegian Manufacturing." *Review of Economics and Statistics*, 93 (1), pp. 285–297.

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

[5] Bellemare, M.F., T. Masaki, T.B. Pepinsky (2015), "Lagged Explanatory Variables and the Estimation of Causal Effects", available at SSRN: http://ssrn.com/abstract=2568724 or http://dx.doi.org/10.2139/ssrn.2568724

[6] Blomström M and A. Kokko (1998), "Multinational Corporations and Spillovers", *Journal of Economic Surveys,* 12 (2), pp. 247–277.

[7] Castillo, V., L. Figal-Garone, A. Maffioli, S. Rojo and R. Stucchi (2016), The Effects of Knowledge Spillovers through Labor Mobility, MPRA Working Paper Series, 69141

[8] Fine, J.P. and R.J. Gray (1999), "A Proportional Hazards Model for the Subdistribution of a Competing Risk", *Journal of the American Statistical Association*, 94(446), pp.496–509.

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

[10] Glass A. J. and K. Saggi (2002), "Multinational Firms and Technology Transfers", *Scandinavian Journal of Economics*, 104 (4), pp. 495–513.

[11] Görg H. and E. Strobl (2005), "Spillovers from Foreign Firms through Workers Mobility: An Empirical Investigation", *Scandinavian Journal of Economics*, 107 (4), pp. 693–709.

[12] Kaiser U., H. C. Kongsted and T. Rønde (2011), “Labor Mobility, Social Network Effects and Innovative Activity”, IZA Discussion Paper No. 5654.

[13] Kaiser U., H. C. Kongsted and T. Rønde (2015), “Does the Mobility of R&D Labor Increase Innovation?” *Journal of Economic Behavior & Organization*, 110 (2), pp. 91-105

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

[15] 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), pp. 1161–1191.

[16] Nickell S. J. (1996), “Competition and Corporate Performance”, *Journal of Political Economy*, 104 (4), pp. 724–746.

[17] Olley, G. S. and A. Pakes (1996), “The dynamics of productivity in the telecommunications equipment industry”, *Econometrica*, 64 (6), pp. 1263–1297.

[18] Parrotta, P. and D. Pozzoli (2012), “The effect of learning by hiring on productivity”, *RAND Journal of Economics* 43 (1), pp. 167-185

[19] Pesola, H. (2011), “Foreign Ownership, Labour Mobility and Wages”, *Scandinavian Journal of Economics,* 113 (3), pp. 637–664

[20] Poole, J. (2013), “Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility”, *Review of Economics and Statistics*, 95 (2), pp. 393–406.

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

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

[23] Thomas, J.M. (1996), “On the Interpretation of Covariate Estimates in Independent Competing Risks Models”, *Bulletin of Economic Research*, 48 (1), pp. 27–39.

[24] 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
Pric-cost margin**	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 criteria of Statistics Finland , see footnote 3. ** Defined as in equation (1).

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: All individuals moving to manufacturing firms with at least 20 employees are included.

Table 4. Descriptive statistics on workers' entry mobility - Entrants in non-MNEs 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: All individuals moving to non-multinational manufacturing firms with at least 20 employees are included.

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

	Entrants to non-MNEs						
	(i)		(ii)		(iii)		(iv)
	All entrants		Entrants with tenure from MNEs		Entrants with tenure from non-MNEs		Test of equality of means (ii) and (iii)
	Mean	Median	Mean	Median	Mean	Median	t-value
Age	31.6	29.0	39.7	39.0	38.3	38.0	8.83***
Education years	11.8	12.0	12.3	12.0	12.0	12.0	8.64***
Previous tenure in years	3.36	1.0	8.6	6.0	6.6	4.0	17.8***
Gender (share of female workers)	0.296		0.246		0.240		
Number of observations	91,254		9,521		5,703		
	Entrants to MNEs						
	(v)		(vi)		(vii)		(viii)
	All entrants		Entrants with tenure from MNEs		Entrants with tenure from non-MNEs		Test of equality of means (vi) and (vii)
	Mean	Median	Mean	Median	Mean	Median	t-value
Age	31.1	28.0	40.2	39.0	35.5	34.0	46.87***
Education years	12.4	12.0	13.0	12.0	12.6	12.0	15.31***
Previous tenure in years	3.90	1.0	8.6	5.0	6.0	4.0	33.40***
Gender (share of female workers)	0.350		0.297		0.280		
Number of observations	209,410		31,297		13,601		

Note: "With tenure" include entrants with a minimum of two years of tenure from the previous employer.

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
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
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: All individuals moving from manufacturing firms with at least 20 employees are included. 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
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
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: All individuals moving from manufacturing firms with at least 20 employees are included. 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. Intra- and inter industry mobility is defined at 3-digit level of industry classification (NACE rev 2).

Table 8. Mobility equations - Movers from MNEs to non-MNEs

	Intra-industry		Inter-industry	
Level of industry	3-digit	2-digit	3-digit	2-digit
	(i)	(ii)	(iii)	(iv)
InvCompetition	0.178***	0.155***	0.044**	0.050***
	(0.016)	(0.017)	(0.017)	(0.017)
Log firm size	0.351***	0.335***	-0.153***	-0.144***
	(0.017)	(0.013)	(0.006)	(0.006)
Age	-0.013***	-0.022***	-0.037***	-0.037***
	(0.003)	(0.002)	(0.001)	(0.001)
Gender	-0.229***	-0.197***	-0.187***	-0.186***
	(0.057)	(0.048)	(0.022)	(0.022)
Marital status	0.065	0.093**	0.035	0.023
	(0.055)	(0.047)	(0.022)	(0.023)
Parenthood status	-0.036	-0.036	-0.0002	-0.004
	(0.041)	(0.034)	(0.015)	(0.015)
Education	-0.050***	-0.046***	0.033***	0.037***
	(0.012)	(0.010)	(0.005)	(0.005)
Income	-0.064	0.024	-0.190***	-0.207***
	(0.048)	(0.044)	(0.016)	(0.016)
Location	-0.467***	-0.511***	0.248***	0.286***
	(0.080)	(0.069)	(0.025)	(0.025)
Wald test of joint sign.	2,953.24	2,914.64	13,120.75	13,092.76
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	1,131,913	1,131,913	1,131,913	1,131,913
No of subjects	246,177	246,177	246,177	246,177
No of failed	1,748	2,469	11,305	10,584
No. competing	92,186	91,465	82,629	83,350

Note: InvCompetition is defined as in equation (1). Year dummies are included. Firm-year clustered standard error (probability levels) in round (square) brackets. *** significant at the one,** at the five and *at ten percent level.

Table 9. Mobility equations - Movers from MNEs to non-MNEs within high- and low-tech industries

	High-tech		Low-tech	
Panel A	(i)	(ii)	(iii)	(iv)
InvCompetition	1.262***	1.339***	0.249***	0.242***
	(0.135)	(0.137)	(0.026)	(0.025)
Prodgap		-0.357***		-0.926***
		(0.076)		(0.063)
Wald test of joint sign.	1,686.68	1,765.15	1,637.82	1,555.14
	[0.00]	[0.00]	[0.00]	[0.00]
Panel B				
Alt_InvCompetition	1.047***	2.333***	-4.314***	-3.959***
	(0.540)	(0.541)	(0.619)	(0.597)
Prodgap		-0.338***		-0.913***
		(0.076)		(0.063)
Wald test of joint sign.	2,027.88	2,052.75	1717.00	1,638.37
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989
No of failed	551	551	949	949
No. competing	27,889	27,889	43,750	43,750

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3) for 3-digit industries. All the same control variables as in Table 8 are included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets. *** significant at the one, ** at the five and *at ten percent level.

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

	High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)
InvCompetition	-0.211***	-0.078	-0.104***	-0.068***
	(0.067)	(0.066)	(0.025)	(0.021)
Prodgap		-0.223***		-0.498***
		(0.034)		(0.042)
Wald test of joint sign.	14,260.20	14,220.70	4,308.00	5,412.93
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989
No of failed	6,950	6,950	3,708	3,708
No. competing	21,490	21,490	40,991	40,991

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3) for 3-digit industries. All the same control variables as in Table 8 are included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets.
*** significant at the one, ** at the five and *at ten percent level.

Table 11. 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 -tenure		0.055		0.020		0.053		0.056		0.043		0.000
		(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)	
$\gamma_{non-MNE}$		0.081		0.028		0.080		0.094		0.058		0.000
$_{-tenure}$		(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: ln(value added). All regressions include industry-year interaction dummies in the first step.
***significant at the one, ** at the five and * at the ten percent level. Standard errors clustered on plants in parenthesis.

Web Appendix: Additional Tables

Table A1. Summary statistics of variables in mobility estimations

Variable	Mean	St. Dev.
InvCompetition	0.191	0.469
Alt_InvCompetition	0.125	0.055
Log firm size	6.980	1.484
Age	42.917	9.875
Gender	0.285	0.451
Marital status	0.596	0.491
Parenthood status	0.267	0.614
Education	12.036	2.204
Income	10.308	0.392
Location	0.126	0.332
Nr obs	1,131,913	

Table A2. Correlation table of variables in mobility estimations

Variable	InvCom.	Alt_InvC.	Log f. size	Age	Gender	Marital st.	Parent. st	Educat.	Income	Location
InvCompetition	1.000									
Alt_InvCompetition	0.163	1.000								
Log firm size	-0.079	0.230	1.000							
Age	-0.083	-0.120	-0.019	1.000						
Gender	0.014	0.015	-0.025	0.047	1.000					
Marital status	-0.016	-0.022	0.003	0.279	-0.038	1.000				
Parenthood status	0.031	0.038	0.009	-0.349	-0.072	0.151	1.000			
Education	0.065	0.082	0.089	-0.212	-0.075	0.058	0.146	1.000		
Income	-0.059	0.048	0.160	0.180	-0.334	0.143	-0.001	0.325	1.000	
Location	0.070	0.050	0.087	-0.028	0.074	-0.040	0.004	0.143	0.087	1.000
Nr obs					1,131,913					

Table A3. Mobility equations - Movers from MNEs to non-MNE with negative values of Prodgap not replaced

	High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)
InvCompetition	1.424***		0.216***	
	(0.148)		(0.030)	
Alt_InvCompetition		2.079***		-2.710***
		(0.518)		(0.602)
Prodgap-with negative values	-0.481***	-0.353***	-1.331***	-1.308***
	(0.060)	(0.046)	(0.047)	(0.048)
Wald test of joint sign.	1,696.11	2,159.36	1,861,85	2,041.54
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989
No of failed	551	551	949	949
No. competing	27,889	27,889	43,750	43,750

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3)
All the same control variables .as in Table 8 are included as additional regressors.
Firm-year clustered standard errors (probability levels) in round (square) brackets.
*** significant at the one, ** at the five and *at ten percent level.

Table A4. Mobility equations - Movers from MNEs to non-MNEs within high- and low-tech industries - Full estimates

	High-tech		Low-tech		High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
InvCompetition	1.262***	1.339***	0.249***	0.242***				
	(0.135)	(0.137)	(0.026)	(0.025)				
Alt_InvCompetition					1.047***	2.333***	-4.314***	-3.959***
					(0.540)	(0.541)	(0.619)	(0.597)
Prodgap		-0.357***		-0.926***		-0.338***		-0.913***
		(0.076)		(0.063)		(0.076)		(0.063)
Log firm size	-0.021	0.071	-0.492***	-0.288***	0.030	0.098	-0.512***	-0.311***
	(0.039)	(0.042)	(0.023)	(0.025)	(0.041)	(0.043)	(0.023)	(0.024)
Age	-0.002	-0.004	-0.013***	-0.014***	-0.005	-0.005	-0.014***	-0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Gender	-0.031	-0.018	-0.354***	-0.367***	-0.032	-0.033	-0.377***	-0.382***
	(0.091)	(0.091)	(0.082)	(0.083)	(0.090)	(0.090)	(0.083)	(0.083)
Marital status	0.178*	0.177*	0.037	0.042	0.175*	0.175*	0.034	0.038
	(0.097)	(0.097)	(0.075)	(0.075)	(0.097)	(0.097)	(0.075)	(0.075)
Parenthood status	-0.185**	-0.185**	0.020	0.024	-0.188**	-0.190**	0.020	0.020
	(0.077)	(0.077)	(0.054)	(0.054)	(0.078)	(0.078)	(0.054)	(0.054)
Education	-0.095***	-0.090***	-0.045***	-0.043***	-0.092***	-0.087***	-0.051***	-0.048***
	(0.021)	(0.021)	(0.017)	(0.017)	(0.021)	(0.021)	(0.017)	(0.017)
Income	-0.032	-0.019	-0.064	-0.021	-0.029	-0.014	0.003	0.045
	(0.051)	(0.054)	(0.093)	(0.099)	(0.053)	(0.056)	(0.098)	(0.104)
Location	-1.779***	-1.784***	0.115	0.180	-1.692***	-1.685***	0.093	0.170
	0.199	0.201	0.106	0.108	0.197	0.197	0.106	0.106
Wald test of joint sign.	1,686.68	1,765.15	1,637.82	1,555.14	2,027.88	2,052.75	1717.00	1,638.37
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989	73,696	73,696	136,989	136,989
No of failed	551	551	949	949	551	551	949	949
No. competing	27,889	27,889	43,750	43,750	27,889	27,889	43,750	43,750

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3) for 3-digit industries. Year dummies are included. Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table A5. Mobility equations - Movers from MNEs to MNEs within high- and low-tech industries - Full estimates

Industry	High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)
InvCompetition	-0.211***	-0.078	-0.104***	-0.068***
	(0.067)	(0.066)	(0.025)	(0.021)
Prodgap		-0.223***		-0.498***
		(0.034)		(0.042)
Log firm size	0.641***	0.695***	-0.185***	-0.064***
	(0.017)	(0.019)	(0.009)	(0.015)
Age	0.008***	0.008***	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Gender	-0.285***	-0.268***	-0.004	-0.006
	(0.030)	(0.030)	(0.041)	(0.041)
Marital status	0.018	0.015	0.042	0.043
	(0.029)	(0.029)	(0.038)	(0.038)
Parenthood status	0.028	0.027	-0.035	-0.032
	(0.018)	(0.018)	(0.030)	(0.030)
Education	0.029***	0.030***	0.018**	0.019**
	(0.006)	(0.006)	(0.009)	(0.009)
Income	0.294	0.304	0.802***	0.826***
	(0.021)	(0.021)	(0.047)	(0.047)
Location	-0.019***	-0.041***	-0.141**	-0.064***
	(0.029)	(0.029)	(0.057)	(0.015)
Wald test of joint sign.	14,260.20	14,220.70	4,308.00	5,412.93
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989
No of failed	6,950	6,950	3,708	3,708
No. competing	21,490	21,490	40,991	40,991

Note: InvCompetition defined as in equation (3) and Prodgap as in equation (5) for 3-digit industries. Year dummies are included. Firm-year clustered standard error (probability levels) in round (square)brackets.

Table A6. Mobility equations - Movers to other destinations in high- and low-tech industries

	Out of labor market				To unemployment			
	High-tech		Low-tech		High-tech		Low-tech	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
InvCompetition	-0.037***	-0.053	-0.130***	-0.130***	-0.015	0.106***	0.052***	0.045***
	(0.046)	(0.047)	(0.029)	(0.020)	(0.040)	(0.041)	(0.015)	(0.016)
Prodgap		0.079***		0.065***		-0.691***		-0.219***
		(0.035)		(0.020)		(0.044)		(0.021)
Wald test of joint sign.	5002.50	5012.91	11,116.39	11,116.39	6106.76	6595.18	14,422.74	14,373.95
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	275,088	275,088	640,996	640,996	275,088	275,088	640,996	640,996
No of subjects	73,696	73,696	136,989	136,989	73,696	73,696	136,989	136,989
No of failed	5,422	5,422	13,581	13,581	5,043	5,043	14,804	14,804
No. competing	23,018	23,018	31,118	31,118	23,397	23,397	29,895	29,895

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3) for 3-digit industries. All the same control variables as in Table 8 are included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table A7. Mobility equations - Movers from MNEs to MNEs with MNE productivity gap

	High-tech	Low-tech
	(i)	(ii)
InvCompetition	-0.424***	-0.098***
	(0.066)	(0.025)
Prodgap -to multinationals	-0.921***	-0.745***
	(0.065)	(0.084)
Wald test of joint sign.	14,557.60	4,595.20
	[0.00]	[0.00]
Observations	275,088	640,996
No of subjects	73,696	136,989
No of failed	6,950	3,708
No. competing	21,490	40,991

Note: InvCompetition defined as in equation (1) and Prodgap as in equation (3) where the nominator is the average productivity of multinationals in the 3-digit industry. All the same control variables as in Table 8 are included as additional regressors. Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table A8. Summary statistics of variables in productivity estimations

	Multinationals		Non-multinationals	
Variable	Mean	St. Dev.	Mean	St. Dev.
va	8.576	1.400	7.378	0.849
l	4.992	1.200	4.180	0.715
k	8.132	1.927	6.675	1.106
m	9.177	1.569	7.745	1.106
s MNE	0.076	0.148	0.036	0.079
s MNE-tenure	0.059	0.132	0.025	0.068
s non-MNE	0.133	0.166	0.164	0.160
s non-MNE-tenure	0.094	0.147	0.110	0.138
Nr obs	9,450		10,821	

Table A9. Correlation table of variables in productivity estimations

Variable	va	l	k	m	s MNE	s MNE-tenure	s non-MNE	s non-MNE-tenure
va	1.000							
l	0.873	1.000						
k	0.750	0.723	1.000					
m	0.842	0.802	0.747	1.000				
s MNE	0.112	0.075	-0.011	0.104	1.000			
s MNE-tenure	0.113	0.078	-0.004	0.098	0.962	1.000		
s non-MNE	-0.118	-0.118	-0.197	-0.122	-0.048	-0.060	1.000	
s non-MNE-tenure	-0.084	-0.089	-0.152	-0.094	-0.048	-0.057	0.935	1.000
Nr obs	20,271							

Table A10. Productivity estimations allowing for tenure effects

Tenure in the current job Number of years since entry	m = 1	m = 2	m = 3
	(ii)	(iii)	(iv)
s new MNE	0.420**	0.277*	0.192
	(0.214)	(0.158)	(0.149)
s old MNE	0.171	0.241	0.418**
	(0.201)	(0.230)	(0.194)
s all non-MNE	-0.011	-0.009	-0.008
	(0.090)	(0.091)	(0.094)
Structural parameters			
γ_{newMNE}	0.581**	0.383*	0.265
	(0.297)	(0.215)	(0.203)
$\gamma_{old\ MNE}$	0.237	0.333	0.577**
	(0.276)	(0.317)	(0.266)
$\gamma_{all\ non\_MNE}$	-0.015	-0.013	-0.300
	(0.124)	(0.126)	(0.348)
No. obs	2,127	2,127	2,127

Note: Dependent variable: ln(value added). Includes entrants with at least one year of previous tenure. All regressions include industry-year interaction dummies in the first step. Standard errors clustered on plants in parenthesis.

Table A11. Productivity estimations - ACF method

	Non-multinationals			Multinationals		
	Total	High-tech	Low-tech	Total	High-tech	Low-tech
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
l	0.809***	0.805***	0.791***	0.742***	0.964***	0.629***
	(0.029)	(0.040)	(0.030)	(0.038)	(0.038)	(0.034)
k	0.163***	0.115***	0.181***	0.256***	0.093***	0.317***
	(0.013)	(0.022)	(0.015)	(0.030)	(0.033)	(0.024)
s MNE-tenure	0.451**	0.681**	0.344	0.285	0.380	0.074
	(0.219)	(0.347)	(0.284)	(0.182)	(0.236)	(0.214)
s non-MNE	0.054	0.043	0.117	0.085	-0.136	0.002
-tenure	(0.085)	(0.167)	(0.099)	(0.218)	(0.340)	(0.209)
Structural parameters						
$\gamma_{MNE-tenure}$	0.561**	0.848*	0.434	0.391	0.397*	0.121
	(0.276)	(0.437)	(0.359)	(0.255)	(0.235)	(0.341)
$\gamma_{non-MNE-tenure}$	0.067	0.054	0.148	0.115	-0.139	0.003
	(0.105)	(0.208)	(0.124)	(0.301)	(0.339)	(0.335)
No. obs	10,821	2,127	8,694	9,450	2,554	6,893

Note: Dependent variable: ln(value added). *** significant at the one, ** at the five and * at the ten percent level. Bootstrapped standard errors in parenthesis.