Multinationals, Competition and Productivity Spillovers through Worker Mobility*

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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 that they have acquired. Theoretical models by Fosfuri et al (2001) and Glass and Saggi (2002) suggest that the direction and the intensity of the mobility of trained workers is affected by market conditions including the degree of product market competition. This, in turn, details an additional channel through which competition is likely to affect total factor productivity. In this paper, we take this hypothesis to the data 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 estimate several competing risks models to assess the impact of product market competition and absorptive capacity on worker mobility. We find that productivity spillovers arise only when workers move from domestic-owned multinational firms to domestic local firms. The spillover effects are economically important. Further, our results point out that competition affects the productivity of purely domestic plants adversely by reducing worker mobility.

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1 Introduction

A striking feature of the globalization in developed countries is that an increasing number of domestic firms have become multinational either through foreign acquisitions or through an expansion of greenfield activities abroad. This development has attracted interest both from researchers and policy-makers. Policy-makers tend to be skeptical towards foreign acquisitions as the "footloose" nature of multinationals is regarded as a threat to domestic jobs and job security. However, multinational firms and inward foreign direct investments are known to have many positive effects. In particular, multinationals tend to have some competitive advantage based on superior technology or other firm-specific knowledge and, therefore, inward FDI is believed to generate knowledge spillovers and productivity improvements which benefit the domestic economy.

The objective of this paper is to analyze whether multinational activity generates positive technology spillovers and under which conditions these spillovers occur. As it is well known, spillovers from multinationals (MNEs) may take several forms such as i) backward and forward linkages between MNEs and domestic firms, ii) demonstration effects which implies that domestic firms imitate the technology of MNEs and iii) worker mobility as former employees of MNEs join domestic firms and bring with them technological or other firm-specific knowledge (Blomström and Kokko, 1998). In this paper we focus on this third channel and we provide evidence on its economic importance as well as on whether this specific mechanism of technology diffusion responds to the degree of competition in the product market. Our paper departs from a theoretical formalization of spillovers by Fosfuri et al. (2001). In the context of a simple but useful two-stage oligopoly model they predict that the degree of competition is likely to play an important role in the occurrence of technology spillovers since the competitive stance in an industry affects differently the incentives multinationals have to keep trained workers as opposed to the incentives purely domestic firms have to hire them by paying higher wages. In addition, they also show that the absorptive capacity of the local firm affects the potential for FDI generating spillovers.

Our contribution to the scant literature on this issue is twofold. Firstly, we quantify the productivity differential in local plants between workers with multinational experience and workers without such experience (see also Görg and Strobl (2005) and Balsvik (2011)). This exercise allows us to provide a preliminary test of whether the transmission mechanism we are analyzing is indeed present in our data. Secondly, by estimating a set of multivariate duration models, we are the first to provide rigorous empirical evidence on the impact of product market competition on technology spillovers through worker mobility.

To reach our goals we exploit the availability of a large employer-employee panel data from Finland (FLEED) for 1990-2006. Our empirical results can be summarized as follow. Firstly, when applying the standard "within-group" methodology adopted in this literature, we find both economically large and statistically significant productivity differentials. Our estimates point out that workers with former multinational experience are 41.4% more productive than their colleagues without such an experience. Also, our qualitative findings are robust to less restrictive estimation methods which are consistent without assuming strict exogeneity for the inputs in the production function. Secondly, and accordingly to the predictions put forward by Fosfuri et al, we find that a less competitive environment seems to be conducive to more technology spillovers.

The structure of the paper is as follows. In Section 2 we provide a brief critical discussion on both the theoretical and the empirical literature on the specific issue we deal with in our paper. In Section 3 we describe the data sets we use and provide descriptive evidence on several aspects of worker mobility. Section 4 briefly illustrates our empirical strategy whereas in section 5 we present the econometric results. Section 6 concludes.

2 Relevant Literature

In their influential survey book on multinational firms, Barba Navaretti and Venables (2004) state that 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". This turns out to be the case since the entry of multinationals in a given domestic market potentially can bring about both the potential for technology spillovers to local firms and a change in the nature of competition in the industry. In their view this makes it very difficult to disentangle empirically the two effects on, let's say, the Total Factor Productivity (TFP) of local firms.

A potential solution to this problem, which has not been explored so far, is to look directly at 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. This approach is supported by a limited number of theoretical papers which provide explicit mechanisms through which product market competition can affect technology transfers from multinationals to local firms. Along this line, Fosfuri et al (2001) develop a simple but very instructive two-period oligopoly model. 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 for the trained worker from a local firm. If the latter is willing to pay a higher salary and therefore to hire the worker, it will enter the market and therefore compete with the multinational firm.

Clearly, the incentive for the latter to keep the worker depends on the toughness of competition in the second period. In particular, 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 industry profits are higher if both firms can use the technology. 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. Furthermore, their model also predicts that worker mobility, and therefore technology transfer, is more likely to occur when the absorptive capacity of the local firm is sufficiently high and when on-the-job training is general rather than specific.[1] As noted by Fosfuri et al (2001), however, testing such 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".[2]

In the last decade, however, the increased availability of linked employer-employee datasets 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, on the one hand, data availability makes it possible to build plant (or firm) specific measures for the share of workers in domestic plants with recent experience from multinationals. This

[1] Albeit not directly focussing 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 temptation not to offer a wage premium given that all other foreign subsidiaries are doing 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.

[2] A preliminary, albeit informal, attempt to shed some light on this issue is in Smarszinka (2004). By using a firm-level data set from Lithuania, she finds evidence consistent with the presence of positive spillovers taking place only through backward linkages but she does not find evidence of spillovers occurring through either forward and, more importantly, horizontal linkage channel. She rationalizes her finding as follows: "Since multinationals have an incentive to prevent information leakage that would enhance the performance of local competitors, but at the same time may benefit from transferring knowledge to their local suppliers, spillovers from FDI are more likely to be vertical than horizontal in nature". Interestingly she also mentions in the conclusions the need for better data which allow the identification of individual firms as suppliers to multinationals as well as the need to learn more about host country and investor characteristics that determine the extent of spillovers operating through different channels.

measure can then be 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. On the other hand, and much more importantly for the purpose of this paper, the possibility of following workers over time opens a completely new research dimension since mobility patterns from multinationals to local firms can be modelled in a multivariate duration framework and hypotheses of interest can then be tested in a rigorous way.

Gorg and Strobl (2005) is probably the first empirical paper which looks directly at the effect of worker mobility on the performance of domestic firms. Unfortunately, the firm-level data from Ghana they exploit do not provide information on all workers in a firm since they only relate to the entrepreneurs. Still, their overall analysis provides evidence that domestic firms run by entrepreneurs who acquired experience by working for multinationals in the same industry are more productive than other firms. Balsvik (2011) is closer in spirit to our work. She exploits a fully fledged employer-employee data-set for Norway and is able to provide a number of complementary pieces of empirical evidence which are broadly consistent with the existence of a channel for technology spillovers through worker mobility. In particular she finds a large productivity differential (20%) in local plants between workers with MNE experience compared to 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.

Albeit less directly related to the topic we investigate in this paper, the availability of linked employer-employee data sets has also allowed researchers to investigate the wage policies set up by multinationals in host economies in a more rigorous way. By using detailed panel data for Portugal, Martin (2008) finds that movements from domestic to foreign firms are associated to sensible average pay increases of more than 10 percent. In addition, he also detects a–much smaller in size–selection effect arising from the fact that foreign firms typically hire workers that already enjoy an higher than average wage in their domestic firms. Finally, Pesola (2007) exploits a sample of the Finnish linked employer-employee data set as we use in our paper to analyze the extent to which employees with a multinational background 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. 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. In turn, this is 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 2004. The main database is the Finnish Longitudinal Employer-Employee Data (FLEED). The data includes all Finnish firms and all individuals of ages 15-70. The FLEED data is 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, sales and industry. We restrict our analysis to manufacturing firms with at least 20 employees and to the period of 1997-2004.[3] A foreign-owned MNE is a firm with at least 20 percent of foreign ownership.[4] Each individual is followed over time. Individuals exit 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 plant and firm identifiers.

3.2 Descriptive Statistics

Tables 1 and 2 present some preliminary features of domestic and foreign ownership in Finland both at firm and plant level. As it can be seen from a close inspection of Table 1, the vast majority of manufacturing firms with more than 20 employees is domestically owned. This is obviously not to be unexpected since foreign multinationals tend to concentrate in a limited number of industries in which they can exploit their managerial expertise and superior technological skills. For instance, in our first sample year, foreign multinationals account for 12.6 percent of the total number of firms and 12.0 percent of the total number of plants (see Table 1). As to domestically owned firms, those with some multinational activity account for an additional 21.8 percent and 34.6 percent of total firms and plants respectively. Despite the short time dimension of our panel, this initial picture changes substantially over the years since both foreign and domestic multinationals experience a much stronger growth rate in the number of firms (35.2 percent and 40.7 percent respectively) and plants (13.9 percent and 75.4 percent respectively) compared to their domestic non-multinational counterparts (12.7

[3]Register information on whether the firm is multinational is available from 1997 onward which restricts the period of analysis to 1997-2004.

[4]We check if our empirical results are sensitive to the choice of a 20 percent threshold by using alternative thresholds of 1, 10 and 50 percent. All our main findings are virtually unaltered.

percent and 7.1 percent respectively).

[Table 1 and 2 here]

As unanimously found in the literature, multinational firms, both foreign and domestic, appear to run much larger operations (from four to six times) than purely local firms in terms of both median turnover and value added (see Table 2). When computed as a share of turnover, foreign multinationals are also found to use labor–as proxied by the wage bill–less intensively than domestic firms, regardless of their multinational status. As to capital, here proxied by the bookvalue of fixed assets, the overall picture is less clear-cut. Still, when focusing on the median, foreign firms are found to use capital less intensively than domestic firms especially if we confine the comparison to those with some multinational activities.[5] Furthermore, foreign multinationals invest in R&D more than purely domestic local firms but less than domestic multinational firms. This is not surprising, since multinational firms tend to concentrate the bulk of their R&D activities in their home country. Finally, foreign-owned firms are found to be more profitable as documented by the higher share of gross operating profits over turnover. On the other hand, no striking differences emerge when comparing domestic multinationals with purely domestic firms.

[Tables 3 and 4 here]

Table 3 displays statistics quantifying employees entering domestic firms, domestic MNEs and foreign MNEs in the sample. We distinguish all entrants including entrants from previous years as early as the data set allows (since 1990) and new entrants in the current year. It may be noticed that the share of all entrants increases over the period, suggesting that worker mobility increases during the period. For instance, the share of all entrants increases from 15.1%

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

to 23.5% in purely domestic firms between 1997 and 2004. Similar patterns, although not as monotonous may be observed for the share of new entrants. In our productivity estimations we include the share of entrants from previous years, but in the mobility estimations we focus on the worker exit mobility in current year.

Table 4 displays worker characteristics of the entrants in different types of firms at the entry year. The MNEs, both foreign and domestic, employ a larger share of female workers, workers with longer education and longer previous tenure than domestic non-MNEs, but the differences are small.

[Tables 5a and 5b here]

In Tables 5a and 5b, we display statistics quantifying the entrants to domestic firms and the separators from multinational firms, respectively. We focus on these statistics since our primary interest is to analyze whether worker mobility from MNEs to domestic firms generate productivity spillovers in the domestic firms. Most entrants seem to come from other purely domestic firms. The share of entrants from multinational firms, both foreign and domestically-owned, is smaller but increasing over our sample period. In particular, the share of workers moving from foreign (domestic) multinationals is 0.6 (0.3) per cent in 1997 and 2.7 (3.7) per cent in 2004. Thus, the scope for positive productivity spillovers may be increasing as well. As to separations, most workers moving to domestic firms are found to change industry in all years. For instance in 1997 (2004), the share of within-industry movers is 0.2 (0.2) per cent whereas the share of between-industry movers is 1.7 (1.0) per cent. This preliminary descriptive result is consistent with Fosfuri et al model which predicts that mobility is more likely to occur when firms sell in independent or vertically related markets.

4 Empirical Strategy

Our empirical strategy consists of two complementary sets of econometric estimates. Firstly, we estimate an augmented Cobb-Douglas production function with firm-level data. This first step serves two different purposes. On the one hand, 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. In the second step, 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 accomodates 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.[6]

4.1 Productivity Equations

We start from the following Cobb-Douglas production function:

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

[6] 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 Y_{it}, M_{it}, K_{it} and L^*_{it} denote respectively production, consumption of materials and services, capital stock and quality adjusted labor of plant i at time t. Quality adjusted labor is equal to

$$L^*_{it} = L^N_{it} + L^M_{it}(1+\gamma) = L_{it}(1+\gamma s_{it}) \tag{2}$$

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 (Balsvik, 2011) generated by the technology spillover embodied in L^M_{it}. The productivity term A_{it} is modelled as follows:

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

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.[7] By using equations (1), (2) and (3), 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 (1) can be rewritten in the following representation:

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

where y_{it}, m_{it}, l_{it}, and k_{it} are the logarithms of Y_{it}, M_{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

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

(m_{it}, 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. To take this endogeneity problem into account, we estimate equation (4) by using the standard within group transformation. This approach does not put any restriction on the conditional distribution of η_i with respect to all past, present and future input levels. It requires however 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.[8]

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. In order to obtain consistent estimates of the impact of labour mobility on productivity, controlling for unobserved heterogeneity, inputs' simultaneity and measurement errors, we rely on the GMM-system technique developed by Arellano and Bover (1995) and Blundell and Bond (1998).[9] This approach has become common in the empirical literature measuring productivity of MNEs and has been used by Griffith (1999a,b), Harris (2002), Harris and Robinson (2003) and Benfratello and Sembenelli (2006). As compared to previous papers (e.g. Görg and Strobl (2005) and Balsvik (2011)), we therefore contribute to this strand of literature by allowing for the share of workers with MNE experience to be sequentially exogenous as opposed to strictly exogenous.

Operationally, the idiosyncratic error u_{it} in equation (3) is redefined as the sum of a first

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

[9] GMM estimators have been found to produce large finite-sample biases when using the standard first-differenced estimator (Arellano and Bond, 1991) in the context of the estimation of production functions. These biases can be dramatically reduced by exploiting reasonable stationarity restrictions on the initial conditions process. See, for instance, Blundell and Bond (2000) and Blundell et al (2000).

order autoregressive productivity shock, v_{it}, and a serially uncorrelated measurement error, ε_{it}:

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

where

$$v_{it} = \rho v_{ti-1} + e_{it} \qquad |\rho| < 1 \tag{6}$$

and

$$e_{it}, \varepsilon_{it} \sim MA(0) \tag{7}$$

By using (3), (5) and (6) equation (1) can be rewritten in the following dynamic presentation:

$$\begin{aligned} y_{it} &= \rho y_{it-1} + \beta_m m_{it} - \rho\beta_m m_{it-1} + \beta_l l_{it} - \rho\beta_l l_{it-1} + \beta_l \gamma s_{it} - \rho\beta_l \gamma s_{it-1} + \\ &\quad + \beta_k k_{it} - \rho\beta_k k_{it-1} + \delta_t^* + \eta_i^* + w_{it} \end{aligned} \tag{8}$$

with

$$\delta_t^* = \delta_t + \rho\delta_{t-1} \tag{9}$$

$$\eta_i^* = \eta_i(1-\rho) \tag{10}$$

$$w_{it} = e_{it} + \varepsilon_{it} - \rho\varepsilon_{it-1} \qquad |\rho| < 1 \tag{11}$$

Finally, equation (8) is equal to:

$$\begin{aligned} y_{it} &= \pi_1 y_{it-1} + \pi_2 m_{it} + \pi_3 m_{it-1} + \pi_4 l_{it} + \pi_5 l_{it-1} + \pi_6 k_{it} + \pi_7 k_{it-1} + \\ &\quad + \pi_8 s_{it} + \pi_9 s_{it-1} + \delta_t^* + \eta_i^* + w_{it} \end{aligned} \tag{12}$$

subject to four non-linear restrictions $\pi_1\pi_2 = -\pi_3$, $\pi_1\pi_4 = -\pi_5$, $\pi_1\pi_6 = -\pi_7$, $\pi_1\pi_8 = -\pi_9$. We test whether these restrictions are rejected and choose the model accordingly. If the restrictions are not rejected we estimate the structural parameters by using minimum distance estimation techniques, and if they are rejected we estimate long-term effects treating equation (12) as an unrestricted autoregressive-distributed lag model.

4.2 Mobility Equations

A worker operating in a multinational firm faces J distinct potential causes of transition. In the survival analysis literature, they are commonly labeled as risk factors. 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, it has to be taken into account that any "real world" situation involving two or more destination states or risks should be regarded as a multivariate model because the analysis involves the joint distribution of more than one duration. This makes it possible to relax the assumption that the hazard function does not depend on the destination state and to consider instead a less restrictive formulation in which–possibly independent– "competing risks" determine the worker tenure length in the multinational firm. More importantly for our purposes, it also avoids the risk of misinterpreting the estimated parameters of each estimated hazard function which conveys no information on the effect of a change in a given covariate on the likelihood of exit via option j since the sign of this effect also depends on the sign and size of all other sub-hazards.

To understand this important point, let $g_j(t)$ be the probability of leaving the initial state to option j in the interval $(t, t+dt)$. Furthermore, let $\lambda(t)$ be the overall hazard function, then

$$\lambda(t) = \sum_{j=1}^{J} g_j(t) \tag{13}$$

If risks are independent the expression in (14) simplifies further to

$$\lambda(t) = \sum_{j=1}^{J} \lambda_j(t) \tag{14}$$

where $\lambda_j(t)$ is the sub-hazard function for risk j.[10] We can therefore write the overall survival function as

$$S(t) = \exp\left[- \sum_{j=1}^{J} \int_0^t \lambda_j(s) ds \right] \tag{15}$$

What we are interested in this paper is to assess the impact of a change in a given covariate on the probability of leaving the initial state via risk j. To achieve this objective let define $f_j(t)$ as the density function of leaving the initial state at time t via risk j and P_j the probability of leaving the initial state via risk j. It follows that

$$P_j f_j(s) = \lambda_j(s) S(s) \tag{16}$$

Finally, if we integrate both sides over the range of s we obtain that

$$P_j = \int_0^t \lambda_j(s) S(s) ds \tag{17}$$

where P_j is simply the unconditional probability of leaving the initial state via risk j. As it is apparent from the expression in (18) this probability is a function of the parameters in all J risks trough the overall survival function, S and not only of λ_j. Thomas (1996) derives the general expression for the partial derivative of P_j with respect to x_j and shows that its sign is also a function of the parameters of all the hazards. Furthermore, he points

[10]Even if we omit it for simplicity, it must be borne in mind that each λ_j is a function of a vector of covariates $\mathbf{x}_j$, its corresponding parameter vector $\boldsymbol{\beta}_j$ and a vector of baseline parameters $\boldsymbol{\theta}_j$.

out that obtaining the implied marginal effects can be computationally demanding even for simple parametric models. To circumvent this problem he suggests to focus instead on the conditional probability of leaving the initial state via risk j at time t, $P_j(t)$, where

$$P_j(t) = \frac{\lambda_j(t)}{\lambda(t)} \tag{18}$$

As it can be easily seen this variable also depends on all sub-hazard functions. If all of them are of the proportional hazard form

$$\lambda_j(t) = \theta_j(t)\exp(\mathbf{x}_j'\boldsymbol{\beta}_j) \tag{19}$$

it can be proved that the $sgn(\partial P_j(t)/\partial x_j)$ is positive if $\beta_{ji} > 0$ and $\beta_{ji} > \beta_{ki}$ $\forall k \neq j$.[11]

The main aim of our analysis is to test the relevance of the two main hypothesis derived from the model of Fosfuri et al (2001). In particular, 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. Among the covariates we include price-cost margins (*pcm*) to test whether the incentive for the multinational to keep the worker depends on the toughness of competition.[12] Their model also predicts that worker mobility, and therefore technology transfer, is more likely to occur when the absorptive capacity of the local firm is sufficiently high. To capture this we compute a firm-specific productivity gap between the multinational and non-multinational firms (*prod_gap*). The productivity gap measures are based on our productivity estimations commente upon in section 6.1. Thus, the

[11] The same argument also applies to the unconditional marginal effect if one is willing to restrict all the baseline hazard parameters to be equal.

[12] 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 weighthed average of this across firms within the same three-digit industry.

main goal is to determine whether *pcm* and *prod_ gap* influence the probability of moving to a domestic firm, controlling for the other individual- and firm-specific covariates. As controlling covariates we include age, gender, marital and parenthood status, education level, income and location.

5 Econometric Results

5.1 Productivity Equations

Table (6) reports productivity equations for the sample of domestic non-multinational firms and the sample of multinational firms, including both foreign and domestically owned.[13] In addition to the standard input variables (materials, labor and capital) each equation includes several additional regressors, which represent the share of workers who have previously worked in a multinational (*MNE*, *high-education-MN*E, *low-education-MN*E*, domestic-MNE and foreign MNE,* respectively) and the share of other workers previously employed in non-multinational firms (*non-MNE*).[14] We believe that gaining experience that may become useful for the another firm takes some time, and include in the shares only workers with a previous tenure of at least 2 years.[15]

Obviously, we are mostly interested in the sign and size of γ_{MNE} as estimated on the sample of non-multinational firms since this is technology transmission channel we are focusing on. Indeed, this coefficient turns out to be positive and statistically significant at the 10 percent level (see column (i)). Furthermore, the magnitude of γ_{MNE} is economically sizeable since it implies a productivity premium as large as 0.414. This means that workers hired from

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

[14] High education is defined as more than 12 years of education and low education 12 years or less.

[15] We also experimented with a different number of minimun tenure years. All our overall results are broadly confirmed when we allow for at least one tenure year in the previous job.

MNEs contribute on average 41.4% more to the productivity of the plant than the incumbent workers.

However, 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, for instance, 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. This alternative hypothesis can be tested by looking at the parameter $\gamma_{non-MNE}$ as estimated in the sample of domestic non-multinational firms (see column (i)). It turns out that the estimated parameter is much smaller in size (0.045) 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.

The basic assumption of our approach so far has been 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 has not necessarily to be the case, however, because, for instance, multinational and purely domestic firms might have complementary comparative advantages. If this is the case, multinationals could benefit from hiring workers with a more pronounced local background. If this is the case $\gamma_{non-MNE}$ should enter with a positive sign in the equation estimated on the sample of multinational firms. This conjecture, however, is not supported by the data since this parameter is not statistically different from zero, albeit positively signed (0.304) as shown in column (iv).

Results presented in columns (i) and (iv) are based on the assumption that the productivity premium is a constant parameter. However, this might be too restrictive since it might depend on both worker and MNE characteristics. In order to shed light on this issue we allow this parameter to vary depending on the level of education of moving workers (column (ii) and (v)) or, alternatively, on whether the multinational firm workers move from is domestically or foreign owned (columns (iii) and (vi)). When we focus on non-multinationals (column (ii)), punctual estimates suggest that the productivity premium for workers with high education is larger (56.8%) compared to less educated workers (25.2%). However, the latter is not significantly different from zero at any conventional level whereas the former is significant only at 12 per cent level (see column (ii)). As to domestic as opposed to foreign multinationals, the coefficient for the share of workers with experience from foreign multinationals $\gamma_{foreign-MNE}$ is not significant. The effect of workers with experience from multinationals seems therefore to be driven by the workers previously working in domestic multinationals. Here the productivity premium turns out to be as high as 61.3% (column (iii)). Once again no effect whatsoever is found in the sample of multinational firms (column (v) and (vi)).

[Table 6 here]

All the results reported so far are based on the crucial assumption that inputs can be treated as strictly exogenous. This in turn rules out the possibility that firm managers may adjust input levels–including the share of workers with previous MNE experience–after observing present or past productivity shocks. In order to address this legitimate concern and to test–at least qualitatively–for the robustness of our previous findings to violations of the strict exogeneity assumption, we also report the GMM-system estimations of the dynamic model specified by equation (12) on the sample of non-multinational firms.

Table (7) shows the results for the model using earlier instruments dated t-2 for the equations in first differences and instruments dated t-1 for the equations in level. In all columns the test statistics indicate, as expected, that there is evidence of first but not of second order serial correlation when the 5% significant level is used as threshold. As for the Sargan-Hansen test, the validity of the instrument set is not rejected at the 1% significance level in all equations. However, the common factor restrictions implied by the theory are rejected in all equations. This in turn implies that we cannot impose these restrictions to our data and consequently we cannot recover the implied structural parameters. Nevertheless, we can still interpret our estimated model as an unrestricted autoregressive-distributed lag structure and compute the corresponding long-run effects. Rather comfortingly, the long run effect computed on the MNE variable (column (i)) turns out to be positive and significant at conventional statistical levels (1.306 with an associated standard error of 0.774). Analogously, when we allow the long run effect to vary depending on MNE nationality, it is the domestic-MNE effect which is found to be positive and significant (1.561 with an associated standard error of 0.871, see column (iii)). Needless to say, these additional findings are fully consistent with our previous results obtained with more restrictive estimation methods.

5.2 Mobility Equations

In assessing the effect of product market competition and absorptive capacity on worker mobility from multinationals to purely domestic 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.

In the first set of equations (Table 8) we distinguish two destination states: to a purely domestic firm (columns (i)-(ii)) and to a different multinational firm, regardless of its nationality (columns (iii)-(iv)). All other individuals are therefore treated as censored. Overall we have a sample of 202,936 individuals. Of those 9,610 are found to move to a purely domestic firm and 25,106 to a different multinational firm.

In order to test the predictions of Fosfuri et al (2001), we compute the time varying three-digit price-cost margin (PCM) of the multinational firm a given worker is employed by as proxy for the competitive environment. As main proxy for absorptive capacity, we use the productivity gap between the same MNE and the average domestic non-MNE firm in the same three-digit industry. 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.

Predictions from received theory suggest that PCM should enter with a positive sign and productivity gap with a negative sign in the purely domestic destination state sub-hazard function. In all regressions, we also include several standard individual level variables: age, gender, marital and parenthood status, educational level, income and location. Finally, this baseline model is augmented with (log) firm size and with a set of aggregate time dummies capturing aggregate business cycle effects.

Results in Table 8 confirm received theoretical predictions. In the sub-hazard function for the purely domestic firm destination state, the coefficient on the productivity gap is indeed negative and statistically significant in both columns ((i)-(ii)). Furthermore, the sign on the PCM variable is positive and statistically significant in both columns and thus consistent with theoretical predictions. The estimated parameters on age, gender and income are negative in all columns, implying that all these variables slow down the transition to purely domestic firms. On the other hand, the educational level and the Helsinki location, both enter with a positive sign. This, in turn, suggests that the increase in these two variables accelerates the transition to purely domestic firms.

As explained in section 4.2, the sign of the impact of a covariate on the probability of leaving the initial state via mobility to a purely domestic firm is not given by the sign on the same covariate in the purely domestic firm destination state sub-hazard function. For this reason, we also report (column (iii)-(iv)) the sub-hazard functions for the multinational destination state. As it can be easily seen, the estimated parameters on PCM are positive, statistically significant and larger in size compared to the domestic firm destination state. This additional finding does not allow us to conclude unambiguously that less competition increases the probability of moving to a purely domestic firm.

[Table 8 here]

In the second set of estimates, we further distinguish between destination to a domestic firm operating in the same three-digit industry and to a domestic firm operating in a different three-digit industry. In this way we aim to capture whether the effect of competition and absorptive capacity on worker mobility differ when the destination firm is competing in the same as opposed to a different three-digit industry. Indeed, Fosfuri et al (2001) predict that technological spillovers are more likely to materialize when the local and the multinational firm do not compete fiercely in the same product market or sell in independent or vertically related markets. Thus, the degree of competition–as measured by the industry level price cost margin–should indeed have a greater effect on worker mobility in the same industry.

[Table 9 here]

The results for intra-industry mobility are displayed in columns (i)-(ii) and for inter-industry in columns (iii)-(iv) in Table 9. Our results on the effect of the competitive stance are coherent with the theoretical predictions. Lack of competition, as measured by price-cost margin, is found to have a positive and significant effect on both inter- and intra-industry mobility. However, the size of the effect is much larger on the latter, as one would expect.[16] Analogously, the productivity gap enters with a negative sign in both sets of equations. Once again the size of the effect is larger on intra-industry mobility. Thus, technological distance seems to deter intra-industry mobility more than inter-industry mobility.

6 Conclusions

In this paper we exploit a large longitudinal employer-employee dataset 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%.

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 contribute on average 41.4% more to the productivity of the plant than the incumbent workers. This preliminary finding allows us to conclude that the transmission mechanism we are interested in is indeed present in our data.

Finally, or main results point out 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

[16] Note also that the size is also larger compared to the multinational destination state (table 8, columns (iii) and (iv)). Therefore we can unambiguosly conclude that less competition has a positive probability on observing transitions to the intra-industry domestic non-MNE destination state.

Fosfuri et al model. More generally, this paper shows the presence of an additional, and possibly counterintuitive, channel trough which competition can affect productivity.

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7 Tables

Table 1. Number of sample firms and plants by firm ownership

	Firms	Non-MNEs	Domestic MNEs	Foreign MNEs	Plants	Non-MNEs	Domestic MNEs	Foreign MNEs
1997	1,880	1,234	410	236	2,813	1,453	972	338
1998	2,039	1,332	431	276	2,981	1,546	970	465
1999	2,140	1,409	429	302	3,042	1,616	922	504
2000	2,125	1,377	441	307	3,007	1,570	938	499
2001	2,264	1,489	448	330	3,188	1,680	955	553
2002	2,194	1,393	483	318	3,095	1,547	995	553
2003	2,184	1,347	525	312	3,137	1,520	1,034	583
2004	2,287	1,391	577	319	3,256	1,556	1,107	593

Table 2. Descriptive statistics on sample firms by ownership (1997-2004 mean and (median))

	Non-MNEs	Dom-MNEs	For-MNEs
Turnover	6302.6	123194.3	50861.5
	(3312.6)	(16762.3)	(19120.1)
Employees	48.1	368.1	222.8
	(30.6)	(111.7)	(96.2)
Value Added	2164.5	30499.0	14505.9
	(1289.5)	(5417.4)	(5906.3)
Wages/Turnover	0.268	0.352	0.233
	(0.247)	(0.191)	(0.176)
Capital/Turnover	0.458	1.866	1.900
	(0.246)	(0.289)	(0.237)
R&D/Turnover	0.023	0.032	0.024
	(0.003)	(0.009)	(0.010)
PCM	0.047	0.030	0.400
	(0.162)	(0.181)	(0.247)

Note: Gross operating profits are computed as averages for firms in three-digit industries with at least 5 firms.

Table 3. Descriptive statistics on workers entry mobility

	Entrants in Domestic Firms				Entrants in Domestic-MNEs				Entrants in Foreign-MNEs			
	All entrants		New entrants		All entrants		New entrants		All entrants		New entrants	
	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed
1997	11,317	0.151	6,702	0.089	26,572	0.171	18,063	0.116	49,587	0.155	4,156	0.084
1998	12,203	0.165	7,055	0.095	27,784	0.175	15,795	0.100	9,667	0.172	5,409	0.096
1999	12,870	0.172	7,328	0.098	27,723	0.186	12,898	0.087	10,931	0.180	5.941	0.098
2000	13,817	0.190	8,322	0.114	31,353	0.194	16,428	0.102	12,238	0.201	6,853	0.112
2001	15,090	0.211	8,812	0.123	29,242	0.192	17,037	0.112	14,576	0.209	8,331	0.120
2002	13,478	0.213	7,482	0.118	30,148	0.199	16,643	0.110	13,813	0.210	7,858	0.120
2003	13,601	0.219	6,519	0.105	34,884	0.217	17,081	0.106	13,150	0.205	6,450	0.101
2004	14,718	0.235	6,819	0.109	35497	0.222	14,636	0.092	12,871	0.204	5,367	0.085

Table 4. Entrants characteristics at entry year, mean (median)

	Non-MNEs	Dom-MNEs	For-MNEs
Gender (share of female)	0.296	0.355	0.335
Age	31.6	30.8	31.6
	(29.0)	(28.0)	(29.0)
Education years	12.7	13.1	13.0
	(12.0)	(12.0)	(12.0)
Previous tenure	3.36	3.93	3.36
	(1.0)	(1.0)	(1.0)

Table 5a. Descriptive statistics on entrants to domestic firms

	From Domestic Firms		From Domestic MNEs		From Foreign MNEs	
	Number	Share of employed	Number	Share of employed	Number	Share of employed
1997	9,687	0.129	244	0.003	486	0.006
1998	9,710	0.131	938	0.013	615	0.008
1999	9,658	0.128	1296	0.017	826	0.011
2000	10,021	0.138	1609	0.022	1217	0.017
2001	10,662	0.149	2018	0.028	1470	0.021
2002	9,636	0.152	1732	0.027	1321	0.021
2003	9,421	0.152	1931	0.031	1457	0.023
2004	9,924	0.158	2339	0.037	1664	0.027

Note: Some entrants have missing information about firm type and are not reported in this table.

Table 5b. Descriptive statistics on separators from MNEs

Entry/Exit	to domestic Firms		to other employment		to domestic firms in the same industry		to domestic firms in the different industry	
	Number	Share of employed	Number	Share of employed	Number	Share of employed	Number	Share of employed
1997	3895	0.019	11,761	0.057	404	0.002	3491	0.017
1998	3040	0.014	11,944	0.056	286	0.001	2754	0.013
1999	3384	0.016	11,749	0.056	459	0.002	2925	0.014
2000	3011	0.014	16,037	0.072	402	0.002	2609	0.014
2001	2215	0.010	8,177	0.037	247	0.001	1968	0.012
2002	2465	0.011	8,690	0.040	363	0.002	2102	0.009
2003	2361	0.011	8,261	0.037	411	0.002	1950	0.009
2004	2753	0.012	13,028	0.058	547	0.002	2206	0.010

Table 6. Productivity estimation (Within-Group).

	Non-multinationals			Multinationals		
	(i)	(i)	(iii)	(iv)	(v)	(vi)
m_t	0.488***	0.488***	0.488***	0.442***	0.443***	0.442***
	(0.024)	(0.024)	(0.024)	(0.042)	(0.042)	(0.042)
l_t	0.358***	0.358***	0.358***	0.434***	0.433***	0.434***
	(0.023)	(0.023)	(0.023)	(0.053)	(0.053)	(0.053)
k_t	0.022***	0.022***	0.022***	0.011	0.012	0.011***
	(0.006)	(0.006)	(0.006)	(0.017)	(0.017)	(0.017)
MNE_t	0.148*			-0.087		
	(0.086)			(0.121)		
$non\text{-}MNE_t$	0.016	0.015	0.017	0.132	0.127	0.132
	(0.079)	(0.079)	(0.079)	(0.105)	(0.105)	(0.105)
$high\text{-}education\text{-}MNE_t$		0.204			-0.307	
		(0.132)			(0.193)	
$low\text{-}education\text{-}MNE_t$		0.090			0.127	
		(0.167)			(0.105)	
$domestic\text{-}MNE_t$			0.219*			-0.069
			(0.120)			(0.157)
$foreign_t$			0.041			-0.119
			(0.117)			(0.176)
Structural parameters						
γ_{MNE}	0.414*			-0.201		
	(0.243)			(0.282)		
$\gamma_{non-MNE}$	0.045	0.043	0.047	0.304	0.486	0.305
	(0.221)	(0.220)	(0.221)	(0.248)	(0.491)	(0.247)
$\gamma_{high-education-MNE}$		0.568			-0.709	
		(0.369)			(0.461)	
$\gamma_{low-education-MNE}$		0.252			0.252	
		(0.467)			(0.467)	
$\gamma_{domestic-MNE}$			0.613*			-0.159
			(0.341)			(0.364)
$\gamma_{foreign-MNE}$			0.113			-0.275
			(0.327)			(0.410)
No. obs	10,900	10,900	10,900	9,749	9,749	9,749
R2	0.88	0.88	0.88	0.80	0.80	0.80

Note: Dependent variable log(output). 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 7. Productivity estimations (GMM).

	Non-multinationals		Non-multinationals		Non-multinationals	
	(i)		(ii)		(iii)	
y_{t-1}	0.467***	(0.081)	0.464	(0.078)	0.464	(0.079)
m_t	0.195**	(0.078)	0.233***	(0.074)	0.273***	(0.069)
m_{t-1}	0.056	(0.057)	0.027	(0.057)	0.024	(0.054)
l_t	0.653***	(0.160)	0.728***	(0.133)	0.617***	(0.128)
l_{t-1}	-0.300***	(0.113)	-0.351***	(0.092)	-0.288***	(0.093)
k_t	-0.035	(0.068)	-0.056	(0.066)	-0.004	(0.057)
k_{t-1}	0.010	(0.042)	0.025	(0.042)	-0.010	(0.037)
MNE_t	0.738	(0.780)				
MNE_{t-1}	-0.042	(0.572)				
$non\text{-}MNE_t$	0.562	(0.398)	0.545	(0.327)	0.474	(0.377)
$non\text{-}MNE_{t-1}$	-0.629	(0.433)	-0.525	(0.341)	-0.574	(0.380)
$high\text{-}education\text{-}MNE_t$			0.739	(0.708)		
$high\text{-}education\text{-}MNE_{t-1}$			-0.304	(0.493)		
$low\text{-}education\text{-}MNE_t$			-0.547	(1.314)		
$low\text{-}education\text{-}MNE_{t-1}$			1.284	(0.986)		
$domestic\text{-}MNE_t$					1.347**	(0.668)
$domestic\text{-}MNE_{t-1}$					-0.511	(0.539)
$foreign_t$					0.202	(0.758)
$foreign_{t-1}$					0.161	(0.515)
Long-term effects						
Materials	0.471***	(0.086)	0.486***	(0.077)	0.488***	(0.078)
Labour	0.662***	(0.157)	0.703***	(0.145)	0.614***	(0.134)
Capital	–0.047	(0.058)	–0.057	(0.056)	-0.026	(0.047)
MNE	1.306*	(0.774)				
non-MNE	-0.126	(0.350)	0.037	(0.309)	-0.186	(0.290)
high-education-MNE			0.811	(0.822)		
low-education-MNE			1.374	(1.027)		
domestic-MNE					1.561*	(0.871)
foreign					0.679	(0.681)
AR(1)	0.000		0.000		0.000	
AR(2)	0.097		0.083		0.144	
Hansen	0.407		0.547		0.547	
No. of obs	8,213		8,213		8,213	

Note: Dependent variable log(output). AR(1) and AR(2) test for first- and second-order autocorrelation (reported p-values). Hansen is a test for overidenfying restrictions (reported p-values). All regressions include year and industry (2–digit)-year interaction dummies. *** significant at the one, ** at the five and * at the ten percent level. Robust (the Windmeijer bias-corrected) standard errors in parenthesis. Common factor restrictions tested and rejected in equation (i) and therefore long-run effects are reported for both equations.

Table 8. Mobility Equations (Movers from MNEs to domestic non-MNEs and to other MNEs)

	Multi to non-multi		Multi to multi	
	(i)	(ii)	(iii)	(iv)
Age	-0.036***	-0.035***	-0.022***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
Gender	-0.178***	-0.191***	0.064***	0.090***
	(0.024)	(0.024)	(0.015)	(0.015)
Marital status	0.011	0.015	0.065***	0.065***
	(0.024)	(0.024)	(0.016)	(0.015)
Parenthood status	0.006	0.003	0.010	0.009
	(0.015)	(0.015)	(0.009)	(0.009)
Education	0.040***	0.044***	0.115***	0.120***
	(0.005)	(0.005)	(0.003)	(0.003)
Income	-0.470***	-0.476***	0.180***	0.188***
	(0.022)	(0.022)	(0.017)	(0.017)
Location	0.205***	0.199***	0.612***	0.644***
	(0.029)	(0.029)	(0.016)	(0.016)
Log firm size	-0.171***	-0.155***	0.095***	0.115***
	(0.007)	(0.008)	(0.005)	(0.005)
Productivity gap 3-digit	-0.128***		0.147***	
	(0.021)		(0.011)	
Productivity gap 2-digit		-0.228***		0.046***
		(0.026)		(0.011)
Price-cost margin	0.106***	0.112***	0.146***	0.143***
	(0.015)	(0.015)	(0.007)	(0.007)
Wald test of joint sign.	13,613.83	13,639.90	39,735,02	41,372.84
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	866,980		866,980	
Subjects	202,936		202,936	
Dom. firm dest. state	9,610		25,106	
For. firm dest. state	25,106		9,610	

Note: All regressions are estimated in Stata11. Year dummies and categorical size variables as additional regressors.

Firm-year clustered standard errors (probability levels) in round (square) brackets.

Table 9. Mobility Equations (Movers from MNEs to domestic non-MNE)

	Intra-industry		Inter-industry	
	(i)	(ii)	(iii)	(iv)
Age	-0.013***	-0.014***	-0.039***	-0.038***
	(0.004)	(0.004)	(0.001)	(0.001)
Gender	-0.164**	-0.168***	-0.174***	-0.188***
	(0.067)	(0.066)	(0.025)	(0.025)
Marital status	0.118*	0.124*	-0.007	-0.003
	(0.067)	(0.067)	(0.026)	(0.026)
Parenthood status	-0.010	-0.012	0.011	0.008
	(0.045)	(0.045)	(0.016)	(0.016)
Education	-0.049***	-0048***	0.053***	0.057***
	(0.014)	(0.014)	(0.006)	(0.006)
Income	-0.282***	-0.256***	-0.475***	-0.483***
	(0.072)	(0.075)	(0.022)	(0.022)
Location	-0.303***	-0.316***	0.261***	0.254***
	(0.097)	(0.097)	(0.030)	(0.030)
Log firm size	-0.278***	-0.260***	-0.150***	-0.134***
	(0.022)	(0.024)	(0.008)	(0.008)
Productivity gap 3-digit	-0.616***		-0.068***	
	(0.061)		(0.022)	
Productivity gap 2-digit		-0.704***		-0.170***
		(0.071)		(0.026)
Price-cost margin	0.180***	0.175***	0.061***	0.071***
	(0.016)	(0.016)	(0.019)	(0.018)
Wald test of joint sign.	2,872.35	2,934.94	11,901,40	12,002.87
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	866,980		866,980	
Subjects	202,936		202,936	
Dom. firm dest. state	1,321		8,289	
For. firm dest. state	33,395		26,427	

Note: All regressions are estimated in Stata11. Year dummies and categorical size variables as additional regressors.

Firm-year clustered standard errors (probability levels) in round (square) brackets.