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Leaning from multinational companies through hiring: An empirical investigation.

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Learning from Multinational Enterprises:

Knowledge flows through labor mobility

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Abstract

Labor mobility is one mechanism through which technology and innovation from multinational enterprises (MNEs) may be transferred to non-multinational enterprises (non-MNEs). Previous research has predominantly focused at such transfers when MNEs from developed economies locate in less developed countries. The objective here is to investigate how labor mobility between MNEs and other firms in a developed economy impacts innovation and the reward to labor. The analysis is based on a unique Swedish employer-employee matched data set for the period 2001 to 2010 that enables us to trace employee mobility while controlling for a large number of other variables. We provide empirical evidence that hiring workers from MNEs, particularly domestically owned MNEs, generate strong knowledge spillovers to non-MNEs that translates into not only innovations but also higher wages. Further, we conclude that spillovers are mostly accounted for by higher-educated workers.

Keywords: Multinational enterprise; Labor mobility; knowledge spillover

JEL Codes: J61, O33, F23

I. Introduction

There is a large literature addressing how multinational enterprises (MNEs) influence technology, productivity and economic growth (Caves, 2007; Keller, 2000). MNEs possess 'firm specific asset' that can be transferred and utilized in their international units and may also spill over to domestic firms (Dunning, 2012; Markusen, 1995). The interest in how MNEs influence economic activities has been most pronounced in the North-South, or developed versus less-developed countries, perspective. Our focus is however different. We examine how non-MNEs within a developed economy may benefit from MNEs' specific asset by hiring workers previously employed at the MNEs. As labor move from MNEs to non-MNEs it can be expected they contribute with new knowledge that may improve innovation performance in the non-MNEs. As innovation is considered the engine of growth, the results from the empirical analysis contains important policy implications.

Hence, we take the theory of MNEs as endowed with specific knowledge and being a potentially important source of knowledge spillover as our departure point.[1] MNEs have been shown to possess specific knowledge related to management, innovation and production technology, which are used in an efficient way to build competitive advantages for these firms. Due to the potentially important spillover effect of such specific assets, the more contacts that other firms have with MNEs, the more benefit they can be expected to accrue from these interactions. Consequently, MNEs do not only bring physical investments which benefits economic growth, but even more important is their role in provide new knowledge and technology. Since new knowledge is primarily embodied in labor, mobility of workers implies that they may carry part of MNEs specific asset with them as they shift employer. Such spillover to the domestic firms can subsequently generate improved innovation capability, higher productivity and increased wages.

Even though these issues have been widely investigated in the North-South framework, much less attention has been directed towards how such knowledge spillover

[1] See the early contributions by, e.g. Hymer (1976), Dunning (1976) and recently contributions by Markusen (2004).

effects may present themselves in developed countries. We contribute to the literature on MNEs in the following ways. First, we provide detailed evidence on how multinational knowledge spillover through labor mobility may influence non-MNEs performance. Second, we implement data referring to both the individual, firm, industry and regional levels. Third, our analysis is not restricted to the manufacturing sector, rather we consider all sectors in the economy.

In the analysis we use a unique employer-employee matched data set that covers all individuals and firms from 2001 to 2010, taking all Swedish industries into account. Firms are distinguished in following ways: first, by the nationality of the firm, since nationality can be expected to affect corporate governance structures and firms' performance (Buckley & Strange, 2011). Second, firms are separated based on ownership of the firm to identify the firm specific-advantage hypothesis claimed to be associated with MNEs (Caves, 1974; Dunning, 1973; Koutsoyiannis, 1982; Markusen, 1995). In non-MNEs we split between firms belonging to a corporate group, for the reason that specific-advantage can also be expected to be transferred within such groups (Blanchard, Huiban, & Sevestre, 2005). We can then identify four types of firms: domestic-owned individual firms (DIFs), domestic-owned firms belonging to a Swedish corporate groups (DSCs), domestic-owned multinationals (DMNEs) and foreign-owned multinational firms (FMNEs).

In the empirical analysis we will first examine whether there seems to exist specific firm advantages for domestic and foreign MNEs. We find that that MNEs have higher wages than non-MNEs, which suggests there do exist such firm-specific advantages that in turn could generate knowledge spillovers as labor move from MNEs to non-MNEs. Next we track the movement of individuals among our four types of firms to test the spillover effect. The analysis support that hiring workers with MNEs experiences increase the innovation capability (measured as the number of patent applications and the number of patent citation) in the non-MNEs. In addition it is shown that hiring workers from domestic MNEs generates stronger spillover effects as compared to hire workers from foreign MNEs, and that higher educated employees are the dominant contributors to knowledge spillover. We also present some robustness tests through lagged measures of labor mobility and separate between levels of education to examine the causality. Finally, we observe that wage spillover for incumbents is primarily caused by labor flows from DMNEs.

This design of the analysis allows us to conclude that there exist firm specific advantages for MNEs, and that labor mobility is an important channel for potential knowledge spillover. Hence, hiring worker from MNEs can lead to knowledge spillover and more of innovative output, i.e. patent applications and paten citations. Assuming that heterogeneous knowledge is important for innovation creativity, the possibility for firms to hire workers from firms with different ownership structures could thus lead to increased spillovers across firms.

The rest of the paper is organized in the following way. The next section reviews previous research related to the issues addressed in this paper. Section three presents the dataset while section four develops the econometric model and and prsent the results. Causality issues are discussed in section five, the last section concludes.

II. Previous research

A. Multinational wage premium as spillover indicator

How MNEs compare to non-MNEs has been investigated implementing a host of different variables, where the most prominent would be growth gaps (Blonigen & Tomlin, 2001), wage gaps (Globerman et al., 1994), productivity gaps (Davies & Lyons, 1991) and technology gaps (Fors, 1997). As regards the issue being dealt with in the current analysis, several previous studies conclude that there exist a wage differential between MNEs and non-MNEs. That holds for both developed and developing countries.

Doms and Jensen (1998) found workers at foreign-owned manufacturing plants have 20 percent higher wages compared to workers at domestic-owned plants in developed countries.[2] Similarly, Aitken et al. (1996) reported about the same wage gaps

[2] The relatively few studies on developed countries are preoccupied with UK and the US, see e.g. Doms and Jensen (1998), Feliciano and Lipsey (1999) and Girma et al. (2001).

in developing countries.[3] In a previous study of Sweden, Bandick (2004) found that foreign-owned MNEs paid 7 percent higher wages than Swedish non-MNEs, while Swedish MNEs wage premium was 4 percent.

The reason for wage gaps is attributed MNE specific-advantage which had led to productivity and profitability gaps between MNEs and other firms. Markusen (1995) concludes the MNEs specific-advantages appear in four characteristics: high R&D/sales ratio; high knowledge worker share; relative new and complex products, and product differentiation. This also explains the superior performance of MNEs, i.e. only the most productive and innovative firms manage to be profitable in regions where they face limited information about market conditions as compared to local firms (Caves, 2007).

Another feature of MNEs is that they have higher capital intensities which may allow for to pay higher efficiency wages, since it is more costly for losing workers (Feliciano & Lipsey, 1999; Globerman et al., 1994).[4] Hiring workers with MNEs experience, non-MNEs are also willing to pay a higher wage for the reason that the worker might carry specific knowledge or technology belonging to MNEs which over time tends to increase productivity in the non-MNE. Simultaneously, MNEs could be willing to pay higher wages to prevent workers from leaving and thereby diluting firm-specific assets associated with MNEs proprietary technologies (Glass & Saggi, 2002). Wage gaps may obviously also indicate skill gaps, i.e. the skill requirements are different at MNEs than in non-MNEs. Other reasons for wage gaps could be a higher demand for labor (Fabbri et al., 2003) or because MNEs share profits internationally which allows them to pay higher wages to their workers in foreign affiliates (Budd & Slaughter, 2004).

B. Spillovers through worker mobility

Labor mobility as a spillover channel has been proved both theoretically (Fosfuri et al., 2001; Glass & Saggi, 2002) and empirically (Agrawal et al., 2006; Görg & Greenaway, 2004; Braunerhjelm et al., 2014). If knowledge is embodied in labor, hiring

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[3] For developing countries, e.g. Aitken et al., (1996), Mexico and Venezuela; and Sjöholm and Lipsey (2006), Indonesia.

[4] According to Griliches (1969)'s 'capital-skill complementarity hypothesis', capital intensive firm requires more human capital and more skilled labor. There is a positive correlation between capital intensity and wages.

new workers can obviously bring new knowledge which potentially have positive effects on productivity and innovation, thereby opening up for new business opportunities. Labor mobility can also enhance learning capacities and learning sharing in firms (von Hippel, 1987; Singh & Agrawal, 2011; Corredoira & Rosenkopf, 2010). Hoisl et al. (2007) shows how labor mobility has a positive effect on patenting activities. This is further stressed in Kaiser et al. (2011), showing that both firms losing employees (sourcing firms) and firms receiving employees (receiving firms) can benefit from labor mobility and improve the innovative performance, such as patent applications. Braunerhjelm et al. (2014) went further and found that the impact of labor knowledge flow is stronger if the sourcing firm (or receiving) is more innovative. Moreover, labor mobility that moves across regional borders cause stronger forward and backward knowledge flow.

Combine the multinational enterprises theory that emphasize how competitiveness builds on knowledge endowments and firm-specific assets with labor mobility, Balsvik (2011) infers that workers with experience in MNEs can increase the productive for non-MNEs. Also Görg and Strobl (2005) suggest that firms are more productive than other domestic firms if their business owners have experience in MNEs. Poole (2013) find out there exist wage spillover in establishments if they have workers with MNEs experiences, which imply a potential improvement of the productivity or technology.

In summary, previous research have shown that wage differentials between MNEs and non-MNEs indicate a potential spillover source related to MNEs being endowed with firm specific-advantages. Labor mobility has been identified as a channel for knowledge spillover in the previous literature, which suggests a positive relationship between labor mobility from MNEs and non-MNEs innovative performance. Hence, based on previous theoretical contributions and to some extent empirical findings, we aim to test the following three hypotheses:

H1: The existence of a wage premium in MNEs can be expected to indicate potential spillover possibilities.

H2: Hiring workers from MNEs are expected to be positively associated with inflows of knowledge to receiving firms which would show up in higher innovation output.

H3: Hiring workers from MNEs are expected to generate positive wage spillover for incumbents, as proof of improvement of technology.

III. Data

We use a unique employer-employee dataset extracted the personal and firm data from the Statistics Sweden's Business Register since 1987, where the estimation period is 2001 to 2010 and the pre-sample period is 1987 to 2000. This dataset covers all employment in the Swedish labor market and all firms across different industries. The main variables of interest are the worker's serial ID number, annual salary wage before tax (SEK), age, gender, education level,[5] the years of work experience,[6] occupation status (business owners/employer) and foreign/Swedish background.[7]

----FIGURE 1----

On firm level, the main variable of interest is ownership structure. We split firms into four category base on the nationality of the firm and multinational characteristic: domestic-owned individual firms (DIFs), domestic-owned firms belonging to a Swedish corporate groups (DSCs), domestic-owned multinationals (DMNEs) and foreign-owned multinational firms (FMNEs).[8]

The other variables of interest on firm level are the firms' serial ID number, the size of firms, age, physical asset, capital intensity,[9] the industry classifications[10] and labor productivity.[11] We use the number of patent applications and the number of patent citations from the European Patent Office's PATSTAT database supplemented with

[5] The education levels are based on the Swedish Standard Classification of Education (SUN 2000) which adapted to the international classification ISCED 97 (International Standard Classification of Education).
[6] Experience is defined as the age minus the years of education minus seven.
[7] Swedish as defined according to Swedish Agency for Economic and Regional Growth (Tillväxtverket), as person born in Sweden with both parents born in Sweden. Immigrants are defined as person foreign born, born in Sweden with both foreign born parents, born in Sweden but with one foreign born parent.
[8] In our dataset, 88% firms are DIFs, 8% are DSCs, 2% are DMNEs and 2% are FMNEs.
[9] Capital intensity is defined as the value of physical asset divided by the number of employment.
[10] The industry classifications are based on the standard of Swedish industrial classification (SIC2007) which are completely identical to the first four levels of NACE Rev. 2. In this paper, we use the first level of SIC2007 to separate 21 sectors.
[11] Labor productivity is defined as the value of turnover divided by the number of employment.

patent data from the Swedish Patent Office as the measurement of innovation and matched firms' serial ID number. The definition and abbreviations are shown in Table 1.

----TABLE 1----

The individual level data can be matched with firm level data base on the firms' serial ID number. The main advantage of this employer-employee dataset is to tract all labor force across firms over time. The time-invariant worker's serial ID number and the firms' serial ID number can be used for controlling individual level and firm level unobservable heterogeneity. In the matched data sample, there are 22,453,569 employers distributed on 6,108,424 DIFs, 5,552,814 DSCs, 5,376,311 DMNEs and 5,416,020 FMNEs. The numbers of firms are 3,703,691 which can be classified into 3,261,131 DIFs, 316,543 DSCs, 61,909 DMNEs and 64,108 FMNEs.

Table 2 displays the firm separations base on ownership structures over ten years. The majority of firms are relatively small DIFs (3 employment on average) and they also have little physical assets and are poor innovators (patent applications and patent citations). The total amount of DIFs increases from 283,231 in 2001 to 371,830 in 2010.

The total number of DMNEs and FMNEs are similar around 6,000 and increase slightly in ten years, they have bigger size (90 employment on average), more physical asset and higher number of patent applications and patent citations. DMNEs show a higher level of innovation output than the FMNEs for both patent applications and patent citations. Finally, the total amount of DSCs increase from 26,362 in 2001 to 37,244 in 2010, with a median firm size (18 employees), the number of the patent applications and patent citations are higher than DIFs but lower than MNEs.

Table 3 displays the descriptive statistics of worker and firm separations from 2001 to 2010. On individual level, workers in MNEs have a higher income than DIFs and DSCs, DMNEs have a slightly higher average wage than FMNEs. Workers in MNEs have slightly higher education and longer experience. The means of gender and foreign/Swedish background do not show outstanding differences between MNEs and non-MNEs. On firm level, MNEs shows obvious advantages related to labor productivity and capital intensity, as compared to DIFs and DSCs. An interesting feature is DMNEs have higher wages, higher labor productivity, capital intensity and stronger innovation capability than FMNEs on average. Previous researches often found FMNEs to be more productive, having higher capital intensity and being more innovative than DMNEs[12]. Correlation matrix are provided in Table 12 and 13.

IV. Econometric Analysis

A. Multinational wage premium as spillover indicator

Considering MNEs as sources of spillover means one may expect either productivity or knowledge spillover when getting contacts with MNEs. We observe that FMNEs and DMNEs employ more highly educated workers and have more innovation output in table 3 which is consistent with the specific-advantage hypothesis and indicates a skill gap between MNEs and non-MNEs.

One way to observe the potential spillover source is to use the individual wage equation. We shall expect wage premiums for workers in MNEs for the reason that MNEs are more profitable and willing to pay higher wages to prevent workers leaving (Glass & Saggi, 2002), after controlling both individual and firm characteristics such as higher productivity. We address this problem with an individual wage equation using the employer-employee dataset control all individual and firm characteristics,

$$\begin{aligned} w_{i,t} &= \alpha + \beta_1 X_{i,t} + \beta_2 F_{j,t} + \beta_3 D_{ownership,j,t} + \beta_4 D_{industry,j,t} \\ &+ \beta_5 D_{time,j,t} + \beta_6 D_{region,j,t} + e_{i,t} \end{aligned} \tag{1}$$

Where $w_{i,t}$ is the logarithm of annual salary wage of person *i* in year *t*. $X_{i,t}$ is a vector of individual characteristic variables and $F_{j,t}$ is a vector of firm *j*'s characteristic variables. $D_{ownership}$ is the ownership structure dummies of four types firms: DIFs, DSCs, DMNEs and FMNEs. $D_{industry}$ is the industry dummies according to first digit of SIC2007 (21 sectors). D_{time} is the year dummies from 2001 to 2010. D_{region} is the regional dummies

[12] For wage gaps, e.g. Doms and Jensen (1998), Globermanet al. (1994), Feliciano and Lipsey (1999); for skill gaps, e.g. Howenstine and Zeile (1992), Blonigen and Tomlin (2001), Doms and Jensen (1998); for productivity gaps, e.g. Howenstine and Zeile (1992), Oulton (1998 a,b), Doms and Jensen (1998), Girma et al.(2001).

using FA-regions separations.[13] $e_{i,t}$ is the unobservable error term. On individual level, we control for the gender, foreign background (Swedish or immigrant), the logarithm of age and it square, the logarithm of years of education, the logarithm of years of experience. On firm level, we control for the logarithm of size, the logarithm of labor productivity and the logarithm of capital intensity.

The first three columns of table 4 display the OLS regression based on equation (1). In the first column, we do not control the individual and firms' characteristics and we can observe wage premiums in DSCs, DMNEs and FMNEs base on DIFs, FMNEs have the highest wage premium (29.4%) followed by DMNEs have the second wage premium (28.4%). In the second column, we control for personal characteristics, all wage premiums shrink, yet FMNEs still have the highest premium (21.9%). In the third column, we control for both personal and firm characteristics, FMNEs still have the highest premium (19.2%) but very close to DMNES (17.9%). The result is much higher than the result found by Balsvik (2011), it mainly because our result is based on DIFs than general non-MNEs. Our result is consistent with the result found by Heyman et al. (2007), in which they find 2% of the wage premium of FMNEs compare to DMNEs. Wage premium decrease, but persisted after we add more control variables include the regional, industry and year dummies. Therefore the wage premium is more a firm or individual specific phenomenon, rare than industry or region related.

For personal characteristics, being male and Swedish, higher education and longer experience will increase the wage. The wage will first increase and then decreased accompany with age increasing. For firm characteristics, bigger firms provide higher wages. High labor productivity and high capital intensity will also increase the wage.

One problem regarding to regression is the omitted variable bias. There might some unobservable time-invariant individual characteristics which cause the wage gaps. MNEs may also prefer worker with some features can we cannot observe. If there exist time-invariant omitted variables, which correlated with the variables in the regression, then fixed effects may provide controlling for time-invariant omitted variable bias. Since

[13] We introduce functional regions (FA-regions) as our spatial unit of measurement according to the Swedish Agency for Economic and Regional Growth (Tillväxtverket) and there are 72 FA regions in Sweden.

our sample consists all employment in Sweden, we shall assume independent effect for each person. We use the fixed effects panel regression by adding individual fixed effects as the following equation (2),

$$\begin{aligned} w_{i,t} &= \alpha + \beta_1 X_{i,t} + \beta_2 F_{j,t} + \beta_3 D_{ownership,j,t} + \beta_4 D_{industry,j,t} \\ &+ \beta_5 D_{time,j,t} + \beta_6 D_{region,j,t} + f_i + e_{i,t} \end{aligned} \tag{2}$$

Where f_i is the individual fixed effect for person *i*. The estimation of equation (2) are shown in the fourth column of table 4. After adding the individual fixed effect, the wage premium decreased largely, which indicates a workers selection exist in the MNEs. The wage premium for DSCs is 2.32% and DMNEs is 4.97%, and FMNEs still have the highest premium (5.52%). Our result is consistent with early empirical work, after controlling the firm size, industries, regional effects, time trends, or labor productivity, there is still a persistent wage gap between MNEs and non-MNEs (Feliciano & Lipsey, 1999; Girma & Görg, 2003).

The evidences show that there exists a wage premium for the workers in MNEs which suggests a potential spillover source. The descriptive statistics already has shown that MNEs have an advantage in productivity and innovation. Spillover occurs when a firm has some specific advantage over another firm, where the latter can benefit from contacts with the former firm. Conceivable spillover channels are learning, adaption, R&D cooperation or labor mobility. However, due to lack of data, spillover through labor mobility has been rarely discussed and therefore basically remained in a black box. Workers with experience in MNEs can increase the productivity for non-MNEs, yet the result only adopts for the manufacturing sector (Balsvik, 2011). Similarly, workers with MNEs experiences can cause a wage spillover in the firms that they move to (Poole, 2013). Also business owner with experience from MNEs can make enhance productivity in their firm (Görg & Strobl, 2005). Hence, labor mobility without question do cause spillover, but how and in what ways is still vague.

From the estimation of the individual wage equation, we can observe a persistent wage premium for FMNEs, DMNEs and DSCs compare to DIFs. The wage gap implies a potential spillover from high wage firms. In the next step, we shall test whether hiring workers from MNEs with such potential spillover positively associated with innovation output for receiving firms.

B. *Knowledge production function through labor mobility*

We use Cobb-Douglas production function to estimation knowledge spillover cause by labor mobility, while the production and innovation output can be express by physical capital (*K*) and human capital (*H*), the log-linearized Cobb-Douglas production could be as following

$$Y = \alpha \ln K + \beta \ln H \tag{3}$$

We apply the idea from Griliches (1967) and treat different types of labor have different weight. The new labor input here can be traced by the sourcing firms (working place in previous year)' ownership structures into four types: workers come from DIFs (L_{DIFs}), DSCs (L_{DSCs}), DMNEs (L_{DMNEs}), FMNEs (L_{FMNEs}) and stayers are workers who stay in the firm in previous year ($L_{stayers}$). The human capital can be express as following

$$H = \gamma_{DIFs} L_{DIFs} + \gamma_{DSCs} L_{DSCs} + \gamma_{DMNEs} L_{DMNEs} + \gamma_{FMNEs} L_{FMNEs} + L_{stayers} \tag{4}$$

Where γ is the weight premium relative to stayers for each types of labor. In the log-linearized Cobb-Douglas production, the regression can be express in following,[14]

$$\begin{aligned} Y_{j,t} &= \alpha \ln K_{j,t} + \beta_1 \ln L_{j,t} + \beta_2 s_{DIFs,j,t} + \beta_3 s_{DSCs,j,t} + \beta_4 s_{DMNEs,j,t} \\ &+ \beta_5 s_{FMNEs,j,t} + \beta_6 D_{industry,j,t} + \beta_7 D_{time,j,t} + \beta_8 D_{region,j,t} + f_j + e_{j,t} \end{aligned} \tag{5}$$

Where $Y_{j,t}$ is the output of firm *j* in year *t*, here we use the number of patent applications (citations) as innovation output to measure knowledge spillover. $K_{j,t}$ is the physical asset of firm *j* in year *t*. $s_{DIFs,j,t}$, $s_{DSCs,j,t}$, $s_{DMNEs,j,t}$ and $s_{FMNEs,j,t}$ are the share of new labor of firm *j* in year *t* from DIFs, DSCs, DMNEs, FMNEs. $D_{industry}$ is the industry dummies according to first digit of SIC2007 (21 sectors). D_{time} is the year dummies from 2001 to 2010. D_{region} is the regional dummies using FA-regions separations. $e_{i,t}$ is the unobservable error term. f_j is the firm fixed effect for firm *j*. We here also use firm's fixed

[14] For detail, see Appendix.

effect to control for time-invariant omitted variable bias for the reason that the firm's innovation can due to some unobservable variables rather than the spillover effect.

We use the number of patents applications and the number of patent citation as our dependent variables for innovation output and robust measurement. Patent application variable has been widely used as a proxy for innovation output innovation output (Alcacer & Gittelman, 2006; Griliches, 1990), even though invention may not always lead to innovation. It has an advantage as compared to patents granted by better capturing current innovation activities within the firms. We also use the number of patent citations as a robust measurement of innovation. It captures the value and quality of innovation output. Both dependent variables are counted data which can take only the non-negative integer values and include many zeros. The mean value of dependent variables are much lower than its standard deviation which indicates clear signs of overdispersion. Here we use constant dispersion negative binomial regression which is usually for over-dispersed count variables, such as patent applications.

C. Firm-specific heterogeneity

According to Blundell et al. (1995), a possible measure of the firm-specific heterogeneity in innovative capacity is the average number of innovations by the firm during a pre-sample period. Here, we choose 1987–2000 as our pre-sample period to estimate firm heterogeneity fixed effect as following:

$$FE_{j,t} = \frac{\sum_{t=1}^{T} P_{j,t}}{T} \tag{6}$$

Where $FE_{j,t}$ is the fixed effect for innovating capacity for firm j in year t. $P_{j,t}$ denotes the number of patent applications for firm j in year t. T represents the total number of years during the pre-sample period. We also include a dummy variable (*FEdum*) equal to one if firm had patent application during the pre-sample period and zero otherwise.

D. Results - Spillover by ownership effect

Table 5 displays the estimation result of the equation (5) of knowledge spillover through new hired worker with different experience from DIFs, DSCs, DMNEs and FMNEs. The dependent variable is the number of patent applications. Column 1 displays the estimation for all firms, the result are shown after controlling the effect of region, industry and year. Hiring new workers from four types of firms can all increase the number of patent applications when we include all observation. Column 2 to 5 are the separate regressions for different type of firms. Hiring workers with DMNEs experience have the strongest effect on innovation for non-MNEs (1.427 for all firms, 2.017 for DIFs, 1.819 for DSCs). New workers from FMNEs have a weaker effect for non-MNEs (1.114 for all firms, 1.741 for DIFs, 0.984 for DSCs). For DSCs, hiring workers from their own firm category is insignificant, the results are the same for DMNEs and FMNEs. For DMNEs, only hiring workers with FMNEs experience has a significant and positive effect on innovation (1.431). For FMNEs, workers from DSCs are significant and positive (1.392).

Table 6 rerun the estimations of equation (5) but use patent citations as a measurement of innovation quality (whereas patent applications refer to quantity). The results are however similar to those in Table 5. When all firms are included (Column 1), we find that hiring new workers from four types of firms all have positive effect on the number of patent citations. Workers come from DMNEs have the strongest effect on patent citations when all firms are considered (1.468) and DSCs (2.012). New workers from FMNEs have the strongest effect for DIFs (2.316). For DSCs, hiring workers from the same kind is again insignificant with regard to the number of patent citations. For DMNEs, only workers with FMNEs experience have a significant and positive effect on patent citations (1.413). For FMNEs, workers from DSCs are significant and positive (2.017).

Some results become insignificant with the control dummies for region, industry and time are inserted, which imply that firm’s innovation ability are also related to location, regional policy, industry specific asset and/or time trends. We find that the manufacturing industry has the strongest effect of all sectors, suggesting manufacturing industry has a stronger absorptive capacity to convert knowledge flows to innovation. Since we only use the first digit of industry classification, we cannot observe more details. Firm's heterogeneity fixed effect which measured by the logarithm of FE and FE dummy both show significant and positive effect on innovation performance. This indicates firms that already engaged in innovation activities will have better innovation performance in future and benefit more through labor mobility. Physical asset and firm size also play important roles in innovation, large firms benefit more through labor mobility channel and have the ability to convert knowledge into innovation.

The finding of spillover through labor mobility is interesting compared to earlier research results where it is always the case that FMNEs have stronger spillover. For non-MNEs, workers from DMNEs generates more spillover effect compare to FMNEs and cause more patent applications and patent citations. The reason might be that FMNEs have limited information about the local market and limited technology transfer between affiliates and headquarters, [15] which affect their profitability and innovation capacity (Caves, 2007). This could explain why FMNEs have lower average patent applications and patent citations than DMNEs (table 2). The other reason is that FMNEs are likely to have intentions not to lose workers or technology to their competitors, which could explain we find FMNEs have the highest wage premium.

Another interesting finding is that hiring worker from the same kind ownership structure have insignificant effect on innovation performance for corporate group firms (SCs and MNEs). We argued that workers from different types of firms carry more heterogeneous knowledge which is important for innovation performance and innovation uniqueness (Braunerhjelm et al., 2014).

We also apply a lagged time structure in the estimation of the equation (5) to verify the direction of causality. The potential endogeneity arise if innovation is the reason for labor mobility. Workers might be attracted by more innovative firms. Or there exist an unobservable firms' characteristic will attract workers. We here adapt a lagged time structure of mobile workers. If the labor mobility cause the spillover, the spillover

[15] Gupta and Govindarajan (2000) suggest that the knowledge flow between overseas affiliates and headquarters have remained limited.

may take the form of positive externalities over time. Table 7 & 8 displays the estimation results of the equation (5) using one year lag of mobile labor. The dependent variables are the number of patent applications and the number of patent citations as of innovation quantity and quality. We find that the spillover effects are significantly positive and persistent for all firms. Hiring workers with DMNEs experience has the strongest effect on patent application and patent citation for DIFs and FMNEs. New workers from FMNEs have the strongest effect for DSCs and DMNEs. Hiring workers from the same kind ownership structure has insignificant effect for DSCs and FMNEs and small positive effect for DMNEs, which indicates the importance of heterogeneous knowledge for innovation capacity.

E. Results - Spillover by worker education level

The previous section provided evidence that knowledge spillover happened through labor mobility. Now we consider a somewhat different question: are higher education workers with MNEs experience more able to transfer firm-specific MNEs' asset to new firms? It seems reasonable to believe that more highly educated labor are more embodied with knowledge and thus more effective in generating spillover. We shall expect high knowledge workers to have a higher impact on spillover and we can observe a higher average education of workers in DMNEs and FMNEs (table 3). If we believe higher education workers are better in transferring technology we can distribute labor mobility in equation (5) on different educational levels. We split labor into the following two classifications, according to their educational level:[16]

1. *Workers with bachelor degree:* Workers holding a bachelor degree.
2. *Technicians with bachelor degree*: Workers holding a bachelor degree in natural, technical, agriculture or health science.

Hence we split the mobile labor share of newly hired workers, according to the classification:

[16] The education classification are based on SUN 2000 (the Swedish national standard for classification of education from July 2000).

$$
\begin{aligned}
H = {} & \gamma_{DIFs,D} L_{DIFs,D} + \gamma_{DIFs,ND} L_{DIFs,ND} + \gamma_{DSCs,D} L_{DSCs,D} \\
& + \gamma_{DSCs,ND} L_{DSCs,ND} + \gamma_{DMNEs,D} L_{DMNEs,D} + \gamma_{DMNEs,ND} L_{DMNEs,ND} \\
& + \gamma_{FMNEs,D} L_{FMNEs,D} + \gamma_{FMNEs,ND} L_{FMNEs,ND} + L_{stayers}
\end{aligned} \tag{7}
$$

Where index *D* indicates workers have a certain type of education and Index *ND* indicates workers does not have a certain type of education.

Table 9 displays the estimation result split worker by education according to the first classification. For the number of patent applications, the spillover effects are much stronger for the joiners holding a bachelor degree. Hiring workers from FMNEs have the strongest effect among all (2.820), followed by joiners from DMNEs (2.788). And for the number of patent citations, workers with DMNEs experiences have the highest impact (2.882), followed by joiners from FMNEs (2.870). The effect of joiners without bachelor degree are insignificant both for patent applications and patent citations.

Table 10 displays the estimation result that workers are split by education according to the second classification. New workers with a bachelor degree in natural, technical, agriculture or health science shows have higher impacts on firms' innovation output measured by patent applications and citations. Among them, hiring workers with DMNEs has the strongest effect for both patent applications and citations (3.333 and 3.234). Workers without a technical bachelor degree from DMNEs still have a positive and significant effect but much lower (0.788 and 0.847). Workers comes from FMNEs and DIFs with a technical bachelor degree have significant and positive effect, but not for the workers without such degree. For DSCs, both high and low educated workers have significant and positive effects.

When we consider the knowledge spillover with worker's education, highly educated movers generate more knowledge spillover and increase the number of patent applications and the number of patent citations. The result suggests that the education level of workers may play an important role for individual absorptive capacity, which affect the knowledge transfer from MNEs. High knowledge workers are better to learn the MNEs' special technological capital and transfer to new firms. In relation to ownership, high educated movers from MNEs generate more knowledge spillover compare the movers from non-MNEs, and workers from DMNEs contribute more to the new firms in innovation performance. The spillover effect from low educated worker in FMNEs is insignificant. The result may imply the 'firm specific asset' belonging to FMNEs such as technology or knowledge accumulation can only be acquired and transferred by highly educated workers. The reason could be the R&D department of FMNEs are often located in the headquarter abroad (Strandell, 2008). The FMNEs also invest less than domestic firms in the local market because they can rely on their parent firms and other subsidiaries for technology.

F. Results - Spillover for incumbents

The previous result shows that workers with MNEs experience, especially DMNEs, generate spillover when labor reallocates between firms which is converted into new knowledge and finally innovations. Workers from MNEs that bring knowledge or technology will enhance the productivity and innovation in the new firm. Moreover, increasing the technology and innovation shall increase the overall level of wages even for incumbents. We test the wage spillover effect of stayers cause through labor mobility:

$$\begin{aligned} w_{i,t} &= \alpha + \beta_1 s_{DOIFs,j,t} + \beta_2 s_{DOSCs,j,t} + \beta_3 s_{DOMNEs,j,t} + \beta_4 s_{FOMNEs,j,t} + \beta_5 X_{i,t} + \beta_6 F_{j,t} \\ &+ \beta_7 D_{ownership,j,t} + \beta_8 D_{industry,j,t} + \beta_9 D_{time,j,t} + \beta_{10} D_{region,j,t} + e_{i,t} \end{aligned} \tag{8}$$

As before $w_{i,t}$ is the logarithm of annual salary wage of person *i* in year *t*. $s_{DIFs,j,t}$, $s_{DSCs,j,t}$, $s_{DMNEs,j,t}$ and $s_{FMNEs,j,t}$ are the share of new labor of firm *j* in year *t* from DIFs, DSCs, DMNEs, FMNEs. $X_{i,t}$ is a vector of individual characteristics variables and $F_{j,t}$ is a vector of firm *j*'s characteristics variables. $D_{ownership}$ is the ownership structures dummies of four types firms: DIFs, DSCs, DMNEs and FMNEs. $D_{industry}$ is the industry dummies according to first digit of SIC2007 (21 sectors). D_{time} is the year dummies from 2001 to 2010. D_{region} is the regional dummies using FA-regions separations. $e_{i,t}$ is the unobservable error term.

Table 11 displays the wage spillover effect for incumbents cause by labor mobility, according to equation (8). The results show that labor mobility from MNEs increase the wage for stayers. Joiners from FMNEs and DMNEs cause wage spillover in the area of 25% when all observations are included. Note that new workers from DIFs and DSCs will decrease the wage for stayers. Hiring workers from DMNEs generates highest wage spillover for all kinds of firms except its own kind (25.2% for all firms, 9.6% for DIFs, 27.1% for DSCs, 9.8% for DMNEs, 11.1% for FMNEs). This is consistent with our early result, labor mobility from DMNEs generates the strongest knowledge spillover except when the sourcing firm is also a DMNEs. Again, it brings up the importance of heterogeneous knowledge which seem inessential for innovation. The result is the same for labor mobility from FMNEs. Workers from FMNEs cause 18.5% wage increase in DMNEs, but only 4.6% when they go to their own category, i.e. other FMNEs. The wage spillover presented the existence of knowledge transfers from MNEs to non-MNEs by increasing the productivity and innovation.

V. Causality

We have assumed that the labor mobility cause knowledge spillover and we have implemented three measures to control for the presence of potential endogeneity and omitted variable bias problem.

First, we design the research framework to verify the causality. We observe wage premiums for workers in DMNEs and FMNEs which imply there exist a potential spillover resource from the individual wage equation. The descriptive statistics also show DMNEs and FMNEs have more patent applications and patent citations compare to the DSCs and DIFs, which can be considered as a knowledge spillover resource. In the next step, the firm level regression shows that hiring new workers from MNEs have a positive effect on receiving firm’s innovation output measured both as patent applications and patent citations. We find that workers from DMNEs have a stronger spillover effect than workers from FMNEs. In the final step, we observe a wage spillover for stayers. That is, the more new workers from MNEs, the more stayers will gain in terms of increased wages. This implies that firms have benefited from the spillover which enables them to raise the average wage level.

Second, we employ a one year lagged measure of labor mobility for equation (5). This lagged time structure regression should detect causality problems. If labor mobility cause the knowledge spillover, we shall observe a persistent and positive effect. Our result shows a one year lagged workers with DMNEs and FMNEs experiences have significant and positive effect on patent applications and patent citations.

Third, we consider workers' education and the spillover effect. Highly educated workers are expected to generate more knowledge spillover than low educated workers. We split workers into two groups according to whether the workers have obtained a certain type of education. The result shows that both high-skilled and low-skilled workers can cause knowledge spillovers. Highly educated workers are however better in transferring the specific MNEs' asset to other firms and thereby raise innovation output.

We are also concerned about the potential for omitted variable bias. We calculate the firm-specific heterogeneity in innovative capacity using the patent application profile during pre-sample period as fixed effects. We use the fixed effects to control the time-invariant unobservable effect for firms. Based on the above described precautionary measures, we conclude the risk of potential endogeneity will not change the causal relationship between labor flows and innovation performance.

VI. Conclusion

In this paper, we find that MNEs have higher wages than non-MNEs, which suggests the existence of potential firm-specific advantages that may generate knowledge spillovers to other firms. We provide empirical evidence which supports the hypothesis that hiring workers with MNEs experiences increase the innovation capability measured as the number of patent applications and citations for non-MNEs. Furthermore, our result shows that hiring workers from DMNEs generates more spillover effects as compared to hiring workers from FMNEs which contrasts with previous research where the overall conclusion is that FMNEs accounts for most of the spillover effects. The result of wage spillover effect for incumbents is consistent with knowledge spillover through labor mobility, hiring workers from DMNEs have the strongest effect for both innovation and wage increase for incumbents.

We argue that reason is related to FMNEs having a disadvantage in knowing the local market and its distance to the headquarter. These reasons may lead to a lower innovation output compared to DMNEs. Meanwhile FMNEs have reasons to prevent workers leaving and transfer knowledge to their competitors, which can explain that the highest wage premium prevailed in the group of FMNEs. We also find that knowledge spillover from MNEs increases with the level of education. And that the importance of heterogeneous knowledge is essential for innovation creativity. Finally, the results also indicate that larger firms and firms having previous experience in innovation benefit more than other firms from labor mobility.

The main factor that the causes the spillover gap between DMNEs and FMNEs remains undefined. We can speculate and further research should aim at pinpointing the reasons to this wedge. Variables of interest to include could be levels of technology and whether that influences the difference of spillover. A plant level analysis could possibly contribute with more detailed information as firm level analysis conducted in the current paper.

References

Agrawal, A., Cockburn, I., & McHale, J. (2006). Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography, 6*(5), 571-591.

Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics, 88*(4), 774-779.

Aitken, B., Harrison, A., & Lipsey, R. E. (1996). Wages and foreign ownership a comparative study of Mexico, Venezuela, and the United States. *Journal of International Economics*, *40*(3), 345-371.

Balsvik, R. (2011). Is labor mobility a channel for spillovers from multinationals? Evidence from Norwegian manufacturing. *The Review of Economics and Statistics, 93*(1), 285-297.

Bandick, R. (2004). Do workers benefit from foreign wwnership? Evidence from Swedish manufacturing. Working Papers 2004:15, Örebro University, School of Business.

Blanchard, P., Huiban, J.P., & Sevestre, P. (2005). R&D and productivity in corporate groups: An empirical investigation using a panel of french firms. *Annales d'Economie et de Statistique*, (79-80), 461-485.

Blonigen, B. A., & Tomlin, K. (2001). Size and growth of Japanese plants in the United States. *International Journal of Industrial Organization, 19*(6), 931-952.

Blundell, R., Griffith, R. and J. Von Reenen (1995), Dynamic count data models of technological innovation, *The Economic Journal*, 105(429), 333–344.

Braunerhjelm, P., Ding, D., & Thulin, P. (2014), "Does labor mobility foster innovation? The case of Sweden.". Working Paper, presented at the Schumpeter Conference, Jena.

Buckley, P. J., & Strange, R. (2011). The governance of the multinational enterprise: Insights from internalization theory. *Journal of Management Studies, 48*(2), 460-470.

Budd, J. W., & Slaughter, M. J. (2004). Are profits shared across borders? Evidence on international rent sharing. *Journal of Labor Economics, 22*(3), 525-552.

Caves, R. E. (1974). Multinational firms, competition, and productivity in host-country markets. *Economica*, 41(162), 176-193.

Caves, R. E. (2007). *Multinational enterprise and economic analysis*. New York: Cambridge University Press.

Corredoira, R. and L. Rosenkopf (2010), "Should auld acquaintance be Forgot? The reverse transfer of knowledge through mobility ties", *Strategic Management Journal*, 31(2), 159–181.

Davies, S. W., & Lyons, B. R. (1991). Characterising relative performance: The productivity advantage of foreign owned firms in the UK. *Oxford Economic Papers*, 43(4), 584-95.

Doms, M. E. and J. B. Jensen (1998). Comparing wages, skills, and productivity between domestically and foreign-owned manufacturing establishments in the United States. *Geography and ownership as bases for economic accounting* (pp. 235-258). London: University of Chicago Press.

Dunning, J. H. (1973). The determinants of international production. *Oxford Economic Papers*, 25(3), 289-336.

Dunning, J. H. (1976). *Trade, location of economic activity and the MNE: A search for an eclectic approach*, England: University of Reading, Department of Economics.

Dunning, J. H. (2012). *International production and the multinational enterprise (RLE International Business)* (Vol. 12). New York: Routledge.

Fabbri, F., Haskel, J. E., & Slaughter, M. J. (2003). Does nationality of ownership matter for labor demands? *Journal of the European Economic Association, 1*(2-3), 698-707.

Feliciano, Z., & Lipsey, R. E. (1999). Foreign ownership and wages in the United States, 1987-1992. No. w6923. National bureau of economic research.

Fors, G. (1997). Utilization of R&D results in the home and foreign plants of multinationals. *The Journal of Industrial Economics*, *45*(3), 341-358.

Fosfuri, A., Motta, M., & Rønde, T. (2001). Foreign direct investment and spillovers through workers' mobility. *Journal of International Economics, 53*(1), 205-222.

Görg, H., & Greenaway, D. (2004). Much ado about nothing? Do domestic firms really benefit from foreign direct investment? *The World Bank Research Observer*, *19*(2), 171-197.

Görg, H., & Strobl, E. (2005). Spillovers from foreign firms through worker mobility: An empirical Investigation. *The Scandinavian Journal of Economics, 107*(4), 693-709.

Girma, S., & Görg, H. (2003). Blessing or curse? Domestic plants' survival and employment prospects after foreign Acquisition. IZA Discussion Papers 706, Institute for the Study of Labor (IZA).

Girma, S., D. Greenaway and K. Wakelin (2001). Who benefits from foreign direct investment in the UK? *Scottish Journal of Political Economy*, 48(2), 119-133.

Glass, A. J., & Saggi, K. (2002). Multinational firms and technology transfer. *The Scandinavian Journal of Economics*, *104*(4), 495-513.

Globerman, S., Ries, J. C., & Vertinsky, I. (1994). The economic performance of foreign affiliates in Canada. *Canadian Journal of Economics*, 27(1), 143-156.

Griliches, Z. (1969). Capital-Skill Complementarity. *Review of Economics and Statistics*, 51(4), 465–468.

Griliches, Z. (1967). Production functions in manufacturing: Some preliminary results. *The Theory and Empirical Analysis of Production* (pp. 275-340). National Bureau of Economic Research.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economie Literature*, 28(4), 1661-1707.

Gupta, A. K., & Govindarajan, V. (2000). Knowledge flows within multinational corporations. *Strategic Management Journal*, *21*(4), 473-496.

Heyman, F., Sjöholm, F., & Tingvall, P. G. (2007). Is there really a foreign ownership wage premium? Evidence from matched employer–employee data. *Journal of International Economics*, *73*(2), 355-376.

Hoisl, K. (2007), Tracing mobile inventors – the causality between inventor mobility and inventor productivity, *Research Policy*, 36(5), 619–636.

Howenstine, N. G., & Zeile, W. J. (1992). Foreign direct investment in the United States: Establishment data for 1987. *Survey of Current Business*, *72*(10), 44-78.

Hymer, S. H. (1976). The international operations of national firms: A study of direct foreign investment, MA: MIT press.

Kaiser, U., H. Kongsted and T. Rønde (2011). Labor mobility, social network effects, and innovative activity. IZA Discussion Paper (5654).

Keller, W. (2000). Do trade patterns and technology flows affect productivity growth? *The World Bank Economic Review*, *14*(1), 17-47.

Koutsoyiannis, A. (1982). *Non-price decisions: The firm in a modern context*. London: St. Martin's Press.

Markusen, J. R. (1995). The boundaries of multinational enterprises and the theory of international trade. *The Journal of Economic Perspectives*, 169-189.

Markusen, J. R. (2004). Multinational firms and the theory of international trade, MIT press.

Oulton, N. (1998a). Investment, capital and foreign ownership in UK Manufacturing, NIESR Discussion Paper, No. 141, August.

Oulton, N. (1998b). Labour productivity and foreign ownership, NIESR Discussion Paper, No. 143, September.

Poole, J. P. (2013). Knowledge transfers from multinational to domestic firms: evidence from worker mobility. *Review of Economics and Statistics*, *95*(2), 393-406.

Sjöholm, F., & Lipsey, R. E. (2006). Foreign firms and Indonesian manufacturing wages: An analysis with panel data. *Economic Development and Cultural Change*, *55*(1), 201-221.

Singh, J. and A. Agrawal (2011), "Recruiting for ideas: How firms exploit the prior inventions of new hires", *Management Science*, 57(1), 129–150.

Strandell, A. C. (2008). The international location of headquarters of multinationals. Working Paper, Swedish Institute for Growth Policy Studies, Stockholm.

Von Hippel, E. (1987), "Cooperation between rivals: Informal know-how trading", *Research Policy*, 16(6), 291–302.

Table1 Firm's definitions based on ownership structure

Firm's type by ownership structure	**Abbreviations**	**Definitions**
Domestic-owned individual firm	DIFs	Swedish individual firm
Domestic-owned firm belonging Swedish corporate groups	DSCs	Firms belong to Swedish enterprise group with no foreign daughters.
Domestic-owned multinational firms	DMNEs	Firms belong to Swedish enterprise group with foreign daughters
Foreign-owned multinational firms	FMNEs	Swedish daughters in a foreign group of enterprises

Table 2 Firm separations in period 2001-2010

	Number of firms				Average employment				Physical asset/1000				Patent applications				Patent citations			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
2001	283,231	26,362	6,219	5,480	3.06	18.73	96.36	90.11	882	20,276	74,001	43,920	0.014	0.093	3.068	2.584	0.147	0.726	34.036	30.565
2002	285,878	27,384	5,949	5,821	3.00	18.81	97.61	90.83	874	19,007	77,088	47,531	0.010	0.173	2.989	2.415	0.069	1.986	27.226	27.325
2003	289,734	28,279	5,813	6,002	2.94	19.42	94.63	89.15	880	18,722	75,808	50,763	0.009	0.118	3.342	2.162	0.067	0.940	25.367	20.895
2004	320,475	29,424	5,835	6,025	2.85	18.98	93.54	90.26	869	19,161	78,653	49,041	0.009	0.063	2.778	1.492	0.050	0.445	23.016	12.268
2005	327,013	31,337	6,014	6,178	2.87	17.77	93.24	87.72	881	19,567	70,479	54,133	0.008	0.077	3.129	1.760	0.057	1.154	23.911	12.889
2006	336,955	33,239	6,055	6,502	2.91	17.89	93.06	85.42	899	19,892	70,963	53,875	0.008	0.092	4.541	2.598	0.034	0.316	31.467	13.684
2007	342,170	33,516	6,233	6,693	2.94	18.42	88.52	88.99	928	19,990	76,416	55,179	0.013	0.071	4.587	2.310	0.038	0.163	19.528	11.756
2008	351,074	34,608	6,505	7,223	2.90	17.63	90.05	84.85	976	19,406	75,574	54,978	0.009	0.075	3.981	2.008	0.018	0.210	10.608	7.780
2009	352,771	35,150	6,514	7,108	2.79	17.28	81.11	84.59	922	21,947	76,258	58,627	0.002	0.013	1.188	0.537	0.002	0.018	2.906	1.320
2010	371,830	37,244	6,772	7,076	2.77	17.47	81.41	86.35	964	21,421	75,441	56,250	0.002	0.013	0.705	0.468	0.001	0.010	1.219	0.958

1= DIFs, 2= DSCs, 3= DMNEs, 4=FMNEs

Table 3 Worker and firm separations in period 2001-2010

	1		2		3		4	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Annual wage (SEK)	214,744.15	133,829.31	258,217.59	159,594.70	312,069.07	229,633.13	311,838.34	223,560.54
Female	0.38	0.49	0.39	0.49	0.32	0.47	0.35	0.48
Swedish	0.77	0.42	0.80	0.40	0.80	0.40	0.76	0.43
Age	39.74	13.25	41.31	13.05	41.93	12.25	41.45	12.07
Years of education	11.47	2.00	11.80	2.13	12.04	2.24	11.98	2.21
Years of experience	21.27	13.71	22.50	13.52	22.89	12.90	22.47	12.64
Number of workers	6,108,424		5,552,814		5,376,311		5,416,020	
FE	0.001	0.027	0.007	0.125	0.387	14.060	0.291	6.361
FE dummy	0.003	0.051	0.019	0.137	0.128	0.334	0.083	0.276
Physical asset	910,062.35	26,643,236.26	20,008,208.55	342,000,000.00	75,070,100.60	762,000,000.00	52,776,537.68	573,000,000.00
Patent applications	0.01	0.89	0.07	3.66	3.00	88.66	1.79	88.10
Patent citations	0.05	14.64	0.55	69.25	19.51	841.65	13.19	933.51
Firm size	2.90	29.90	18.18	123.16	90.73	472.80	87.66	418.04
Labor productivity	960,153.48	5,867,462.16	2,248,158.69	9,936,451.09	5,549,260.22	154,000,000.00	4,874,640.57	22,911,156.46
Capital intensity	400,426.59	8,634,981.08	1,582,120.80	15,113,358.31	3,574,491.66	179,000,000.00	1,681,959.63	23,652,577.51
Number of firms	3,261,131		316,543		61,909		64,108	

1= DIFs, 2= DSCs, 3= DMNEs, 4=FMNEs; labor productivity= turnover per employment; capital intensity= physical asset per employment

Table 4 Wage premiums in different ownership structures

	OLS			FE
	(1)	(2)	(3)	(4)
Dependent variable: Ln(income)				
Ownership (base on DIFs)				
DSCs	0.162***	0.116***	0.104***	0.0232***
	(245.78)	(207.57)	(176.25)	(53.37)
DMNEs	0.284***	0.203***	0.179***	0.0497***
	(392.57)	(331.39)	(230.28)	(91.03)
FMNEs	0.294***	0.219***	0.192***	0.0552***
	(393.52)	(346.11)	(248.82)	(99.60)
Female	-	-0.336***	-0.332***	-
		(-622.35)	(-618.29)	
Swedish	-	0.0986***	0.0948***	-
		(167.58)	(162.45)	
Age	-	7.921***	7.912***	5.267***
		(279.96)	(280.89)	(51.43)
Age^2	-	-1.076***	-1.074***	-0.754***
		(-309.96)	(-310.73)	(-40.67)
Education	-	0.977***	0.966***	2.594***
		(416.66)	(413.13)	(447.56)
Experience	-	0.243***	0.239***	0.415***
		(133.97)	(132.33)	(205.29)
Firm size	-	-	0.000166	0.0109***
			(1.32)	(104.42)
Labor productivity	-	-	0.0401***	0.00847***
			(120.66)	(62.15)
Capital intensity	-	-	0.00568***	0.00161***
			(60.41)	(26.24)
Year Dummy	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes
Regional Dummy	Yes	No	Yes	Yes
N	22,453,569	22,453,569	22,453,569	22,453,569

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by OLS regression with cluster robust standard errors. (Column 1-3) and panel regression with fixed effect and cluster robust standard errors (Column 4). Female and Swedish are binary variable. Age, the square of age, firm size are the logarithm of the real number. Education, experience, labor productivity and capital intensity are the logarithm of the real number plus one.

Table 5 Knowledge spillover (patent applications) through labor mobility

	(1)	(2)	(3)	(4)	(5)
	All firms	DIFs	DSCs	DMNEs	FMNEs
Dependent variable: Patent applications					
New workers from DIFs	0.927***	1.221***	1.015***	-0.214	-0.190
	(9.76)	(10.86)	(5.92)	(-0.80)	(-0.45)
New workers from DSCs	1.262***	1.446***	0.427	0.283	1.392**
	(11.32)	(8.16)	(1.90)	(0.68)	(2.80)
New workers from DMNEs	1.427***	2.017***	1.819***	0.113	0.694
	(7.65)	(11.19)	(7.30)	(0.62)	(1.50)
New workers from FMNEs	1.114***	1.741***	0.984**	1.431***	0.152
	(6.73)	(10.15)	(2.76)	(5.52)	(0.55)
Physical asset	0.0399***	0.0463***	0.0512**	0.0352**	0.0150
	(4.99)	(4.81)	(2.81)	(2.60)	(0.71)
Firm size	0.286***	0.451***	0.145***	0.165***	0.209***
	(11.40)	(12.94)	(3.79)	(5.10)	(3.45)
FE	0.863***	1.443***	1.452***	0.939***	0.986***
	(20.22)	(15.41)	(8.80)	(24.08)	(10.05)
FE dummy	3.531***	3.709***	3.298***	2.208***	2.469***
	(41.00)	(34.95)	(25.74)	(19.10)	(12.62)
Regional Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	3,703,691	3,261,131	316,543	61,909	64,108

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 6 knowledge spillover (patent citations) through labor mobility

	(1)	(2)	(3)	(4)	(5)
	All firms	DIFs	DSCs	DMNEs	FMNEs
Dependent variable: Patent citations					
New workers from DIFs	0.968***	1.320***	1.012***	-0.445	0.289
	(8.12)	(10.21)	(4.19)	(-1.26)	(0.69)
New workers from DSCs	1.243***	1.386***	0.444	0.116	2.017***
	(9.16)	(6.27)	(1.61)	(0.24)	(3.82)
New workers from DMNEs	1.468***	2.031***	2.012***	0.291	0.845
	(8.01)	(9.72)	(7.12)	(1.80)	(1.74)
New workers from FMNEs	1.108***	2.316***	0.790	1.413***	-0.0241
	(5.75)	(6.73)	(1.89)	(4.78)	(-0.07)
Physical asset	0.0325***	0.0437***	0.0485*	0.0299	0.00488
	(3.38)	(3.45)	(2.10)	(1.86)	(0.21)
Firm size	0.283***	0.495***	0.145***	0.150***	0.239***
	(10.51)	(11.52)	(3.36)	(4.24)	(3.48)
FE	0.907***	1.461***	1.430***	0.981***	1.088***
	(16.62)	(10.06)	(8.04)	(19.26)	(8.11)
FE dummy	3.722***	3.860***	3.548***	2.279***	2.563***
	(34.45)	(29.49)	(23.06)	(16.24)	(9.58)
Regional Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	3,703,691	3,261,131	316,543	61,909	64,108

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 7 Knowledge spillover (patent applications) through lagged labor mobility

	(1)	(2)	(3)	(4)	(5)
	All firms	DIFs	DSCs	DMNEs	FMNEs
Dependent variable: Patent applications					
L. New workers from DIFs	1.004***	1.396***	1.151***	0.351	-0.114
	(8.40)	(10.18)	(5.63)	(1.35)	(-0.28)
L. New workers from DSCs	1.331***	1.996***	0.00976	0.380	0.379
	(9.60)	(9.97)	(0.03)	(0.92)	(0.52)
L. New workers from DMNEs	1.684***	2.361***	1.510***	0.513**	0.900**
	(12.83)	(11.97)	(5.04)	(3.23)	(2.78)
L. New workers from FMNEs	1.094***	2.137***	1.911***	1.122***	0.177
	(5.37)	(8.79)	(5.12)	(3.47)	(0.61)
Physical asset	0.0418***	0.0663***	0.0599*	0.0321*	0.0117
	(4.29)	(5.04)	(2.47)	(2.16)	(0.51)
Firm size	0.305***	0.464***	0.165***	0.190***	0.244***
	(11.17)	(10.76)	(4.00)	(5.51)	(3.81)
FE	0.856***	1.445***	1.467***	0.924***	0.965***
	(18.26)	(13.14)	(8.28)	(23.28)	(9.32)
FE dummy	3.392***	3.577***	3.186***	2.112***	2.358***
	(36.52)	(28.13)	(22.04)	(17.15)	(11.55)
Regional Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	2,792,785	2,419,144	267,064	51,896	54,681

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 8 knowledge spillover (patent citations) through lagged labor mobility

	(1)	(2)	(3)	(4)	(5)
	All firms	DIFs	DSCs	DMNEs	FMNEs
Dependent variable: Patent citations					
L. New workers from DIFs	1.034***	1.486***	1.186***	0.404	0.295
	(6.82)	(9.12)	(5.12)	(1.16)	(0.74)
L. New workers from DSCs	1.325***	2.103***	-0.232	0.150	1.111
	(7.68)	(8.85)	(-0.57)	(0.27)	(1.50)
L. New workers from DMNEs	1.777***	2.672***	1.575***	0.664**	1.257***
	(10.69)	(12.49)	(4.50)	(2.96)	(3.46)
L. New workers from FMNEs	1.252***	2.284***	2.294***	1.345***	0.173
	(6.08)	(8.22)	(3.82)	(3.92)	(0.54)
Physical asset	0.0343**	0.0672***	0.0527	0.0329	-0.000689
	(3.03)	(3.83)	(1.70)	(1.89)	(-0.03)
Firm size	0.305***	0.497***	0.181***	0.169***	0.282***
	(10.01)	(9.36)	(3.70)	(4.38)	(3.79)
FE	0.888***	1.358***	1.463***	0.949***	1.076***
	(14.81)	(9.61)	(7.05)	(17.58)	(7.61)
FE dummy	3.569***	3.748***	3.420***	2.165***	2.469***
	(29.94)	(24.77)	(18.20)	(14.47)	(8.82)
Regional Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	2,792,785	2,419,144	267,064	51,896	54,681

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 9 Knowledge spillover of workers with different education

	(1)	(2)
	Dependent variable: Patent applications	Dependent variable: Patent citations
New workers from DIFs with bachelor degree	2.607***	2.671***
	(25.84)	(22.59)
New workers from DIFs without bachelor degree	-0.213	-0.400*
	(-1.44)	(-1.97)
New workers from DSCs with bachelor degree	2.516***	2.519***
	(14.67)	(12.49)
New workers from DSCs without bachelor degree	0.575***	0.391
	(3.39)	(1.78)
New workers from DMNEs with bachelor degree	2.788***	2.882***
	(10.38)	(11.08)
New workers from DMNEs without bachelor degree	0.432	0.366
	(1.70)	(1.44)
New workers from FMNEs with bachelor degree	2.820***	2.870***
	(15.32)	(12.98)
New workers from FMNEs without bachelor degree	0.151	0.0279
	(0.64)	(0.10)
Physical asset	0.0428***	0.0355***
	(5.52)	(3.79)
Firm size	0.307***	0.307***
	(11.94)	(11.14)
FE	0.837***	0.880***
	(19.88)	(16.78)
FE dummy	3.435***	3.609***
	(39.21)	(32.83)
Regional Dummy	Yes	Yes
Year Dummy	Yes	Yes
Industry Dummy	Yes	Yes
N	3,703,691	3,703,691

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 10 Knowledge spillover of workers with different education

	(1)	(2)
	Dependent variable: Patent applications	Dependent variable: Patent citations
New workers from DIFs with bachelor degree in natural, technical, agriculture or health science	3.180***	3.212***
	(24.87)	(21.05)
New workers from DIFs without bachelor degree in natural, technical, agriculture or health science	-0.0877	-0.233
	(-0.66)	(-1.29)
New workers from DSCs with bachelor degree in natural, technical, agriculture or health science	2.905***	2.852***
	(13.53)	(11.24)
New workers from DSCs without bachelor degree in natural, technical, agriculture or health science	0.747***	0.644***
	(5.00)	(3.38)
New workers from DMNEs with bachelor degree in natural, technical, agriculture or health science	3.333***	3.234***
	(16.31)	(12.54)
New workers from DMNEs without bachelor degree in natural, technical, agriculture or health science	0.788***	0.847***
	(3.69)	(3.84)
New workers from FMNEs with bachelor degree in natural, technical, agriculture or health science	3.138***	3.169***
	(12.93)	(10.65)
New workers from FMNEs without bachelor degree in natural, technical, agriculture or health science	0.376	0.289
	(1.73)	(1.10)
Physical asset	0.0427***	0.0353***
	(5.48)	(3.75)
Firm size	0.297***	0.297***
	(11.28)	(10.74)
FE	0.864***	0.908***
	(18.52)	(15.50)
FE dummy	3.411***	3.581***
	(39.78)	(32.33)
Regional Dummy	Yes	Yes
Year Dummy	Yes	Yes
Industry Dummy	Yes	Yes
N	3,703,691	3,703,691

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by Negative Binomial Regression with robust standard errors. Firm size is the logarithm of real number. FE dummy is the binary variable. Physical asset and FE are the logarithm of the real number plus one.

Table 11 Wage spillover for incumbents

	(1)	(2)	(3)	(4)	(5)
	All firms	DIFs	DSCs	DMNEs	FMNEs
Dependent variable: Ln(income)					
New workers from DIFs	-0.430***	-0.295***	-0.427***	-0.600***	-0.706***
	(-162.02)	(-86.55)	(-78.95)	(-82.88)	(-71.75)
New workers from DSCs	-0.0821***	-0.0486***	-0.0992***	-0.497***	-0.540***
	(-21.55)	(-8.34)	(-17.91)	(-35.60)	(-37.28)
New workers from DMNEs	0.252***	0.0961***	0.271***	0.0979***	0.111***
	(61.21)	(12.15)	(26.16)	(17.89)	(9.28)
New workers from FMNEs	0.252***	0.0305***	0.0927***	0.187***	0.0458***
	(64.24)	(3.94)	(9.34)	(14.96)	(9.02)
Female	-0.341***	-0.310***	-0.337***	-0.343***	-0.345***
	(-598.82)	(-304.17)	(-322.67)	(-308.19)	(-318.37)
Swedish	0.0966***	0.125***	0.0886***	0.0710***	0.0783***
	(156.46)	(114.19)	(75.27)	(61.01)	(68.68)
Age	8.477***	10.64***	9.591***	6.692***	6.596***
	(289.13)	(220.58)	(174.15)	(107.63)	(106.19)
Age^2	-1.151***	-1.431***	-1.289***	-0.926***	-0.910***
	(-320.44)	(-240.69)	(-191.25)	(-122.49)	(-120.56)
Education years	0.979***	0.618***	0.846***	1.169***	1.137***
	(402.06)	(143.18)	(187.84)	(250.17)	(244.85)
Experience	0.248***	0.104***	0.202***	0.355***	0.350***
	(129.86)	(33.50)	(56.53)	(86.96)	(84.80)
Firm size	0.0156***	0.0319***	-0.00127***	-0.00943***	-0.0201***
	(141.71)	(112.56)	(-4.99)	(-35.12)	(-69.69)
Labor productivity	0.0536***	0.0602***	0.0497***	0.0196***	0.0469***
	(126.59)	(86.77)	(70.43)	(27.58)	(65.59)
Capital intensity	0.00538***	0.00633***	0.00317***	0.00718***	0.00502***
	(49.31)	(36.18)	(17.27)	(30.52)	(19.68)
Regional Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	18,787,647	4,910,940	4,664,421	4,572,979	4,639,307

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by OLS with cluster robust standard errors. Female and Swedish are binary variable. Age, the square of age, firm size are the logarithm of the real number. Education, experience, labor productivity and capital intensity are the logarithm of the real number plus one.

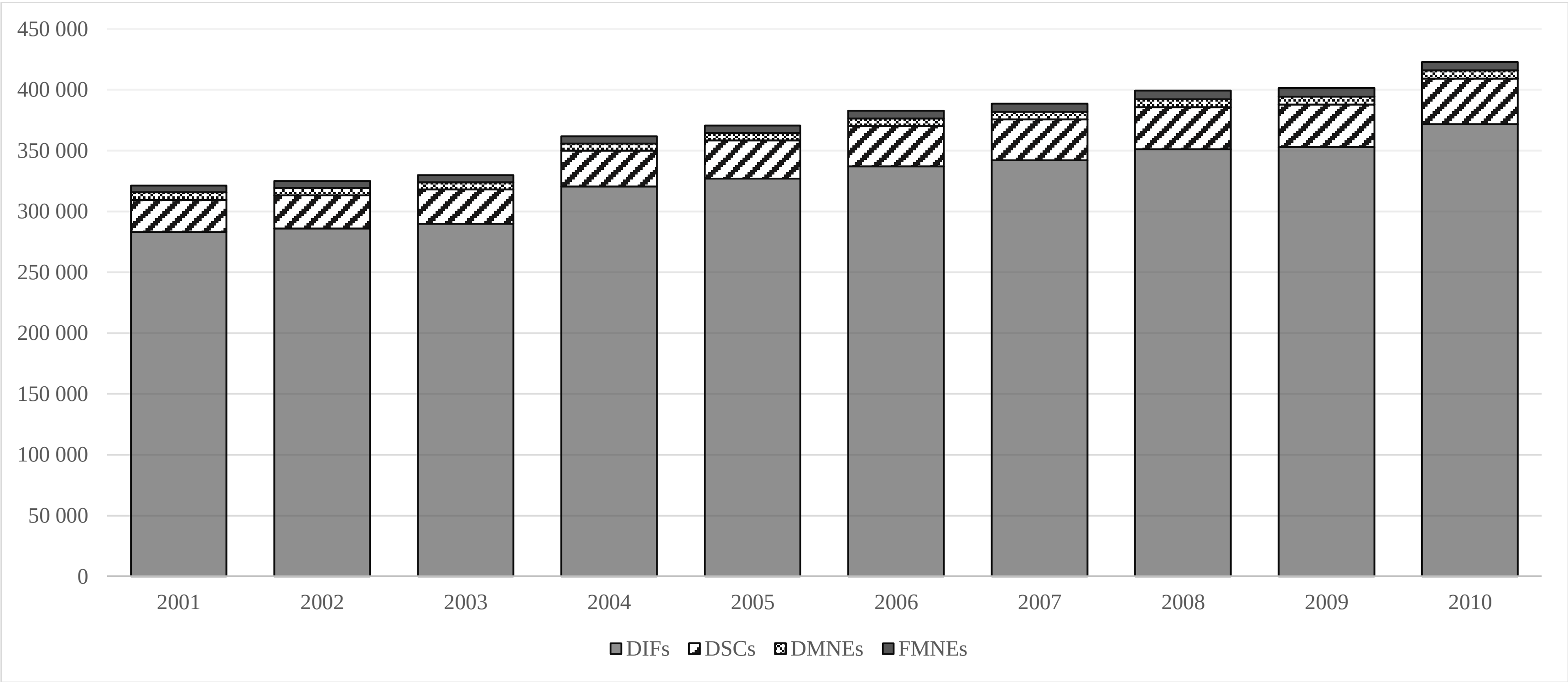
Table 12 Correlation matrix on individual level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Annual wage	1							
(2)	Female	-0.212	1						
(3)	Swedish	0.0517	-0.0297	1					
(4)	Education	0.2689	0.0613	-0.0057	1				
(5)	Experience	0.1762	-0.0683	0.0521	-0.3169	1			
(6)	Firm size	0.0358	0.0214	-0.0345	0.0317	0.0547	1		
(7)	Labor productivity	0.0812	-0.0141	0.011	0.0327	0.008	0.0171	1	
(8)	Capital intensity	0.0316	-0.011	0.0113	0.0049	0.0294	-0.0174	0.266	1

Table 13 Correlation matrix on firm level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Patent applications	1									
(2)	Patent citations	0.8733	1								
(3)	Physical asset	0.1125	0.0969	1							
(4)	Firm size	0.1789	0.1462	0.2488	1						
(5)	New workers from DIFs	-0.0003	-0.0002	0.0009	0.0092	1					
(6)	New workers from DSCs	-0.0001	-0.0001	0.0038	0.0104	0.0318	1				
(7)	New workers from DMNEs	0.0055	0.0045	0.0084	0.0218	0.0194	0.0219	1			
(8)	New workers from FMNEs	0.0022	0.0016	0.0073	0.0222	0.0231	0.0252	0.0296	1		
(9)	FE	0.7855	0.6984	0.093	0.1198	-0.0007	-0.0003	0.0061	0.0024	1	
(10)	FE Dummy	0.0614	0.0425	0.0606	0.1281	-0.0024	0.0062	0.0298	0.0216	0.0728	1

Figure 1 The number of firms in different ownerships structure



Appendix

Cobb-Douglas production function

We use Cobb-Douglas production function to estimation both productivity spillover and knowledge spillover cause by labor mobility, while the production and innovation output can be express by physical capital (*K*) and human capital (*H*). The log-linearized Cobb-Douglas production, the regression can be express in following,

$$Y = \alpha \ln K + \beta \ln H \tag{1}$$

We apply the idea from Griliches (1967) and treat different types of labor have different weight. The labor input here can be traced by the sourcing firms' ownership structures into four types: workers come from DIFs (L_{DIFs}), DSCs (L_{DSCs}), DMNEs (L_{DMNEs}), FMNEs (L_{FMNEs}) and stayers are workers who stay in the firm in previous year ($L_{stayers}$). The human capital equal to the sum of labor times weight

$$\begin{aligned} H &= \gamma_{DIFs} L_{DIFs} + \gamma_{DSCs} L_{DSCs} + \gamma_{DMNEs} L_{DMNEs} + \gamma_{FMNEs} L_{FMNEs} + L_{stayers} \\ &= L(\gamma_{DIFs} s_{DIFs} + \gamma_{DSCs} s_{DSCs} + \gamma_{DMNEs} s_{DMNEs} + \gamma_{FMNEs} s_{FMNEs} + s_{stayers}) \\ &= L(\gamma_{DIFs} s_{DIFs} + \gamma_{DSCs} s_{DSCs} + \gamma_{DMNEs} s_{DMNEs} + \gamma_{FMNEs} s_{FMNEs} + (1 - s_{DIFs} - s_{DSCs} - s_{DMNEs} - s_{FMNEs})) \\ &= L((\gamma_{DIFs} - 1) s_{DIFs} + (\gamma_{DSCs} - 1) s_{DSCs} + (\gamma_{DMNEs} - 1) s_{DMNEs} + (\gamma_{FMNEs} - 1) s_{FOMNEs} + 1) \end{aligned} \tag{2}$$

Where *s* is the share of each type of workers. Taking the natural logarithm of (2)

$$\begin{aligned} \ln H &= \ln\left[L((\gamma_{DIFs} - 1) s_{DIFs} + (\gamma_{DSCs} - 1) s_{DSCs} + (\gamma_{DMNEs} - 1) s_{DMNEs} + (\gamma_{FMNEs} - 1) s_{FMNEs} + 1) \right] \\ &= \ln L + \ln\left[(\gamma_{DIFs} - 1) s_{DIFs} + (\gamma_{DSCs} - 1) s_{DSCs} + (\gamma_{DMNEs} - 1) s_{DMNEs} + (\gamma_{FMNEs} - 1) s_{FMNEs} + 1 \right] \\ &\approx \ln L + \left[(\gamma_{DIFs} - 1) s_{DIFs} + (\gamma_{DSCs} - 1) s_{DSCs} + (\gamma_{DMNEs} - 1) s_{DMNEs} + (\gamma_{FMNEs} - 1) s_{FMNEs} \right] \end{aligned} \tag{3}$$

Plunge (3) into (1)

$$\begin{aligned} Y &= \alpha \ln K + \beta \left[\ln L + (\gamma_{DIFs} - 1) s_{DIFs} + (\gamma_{DSCs} - 1) s_{DSCs} + (\gamma_{DMNEs} - 1) s_{DMNEs} + (\gamma_{FMNEs} - 1) s_{FMNEs} \right] \\ &= \alpha \ln K + \beta \ln L + \beta (\gamma_{DIFs} - 1) s_{DIFs} + \beta (\gamma_{DSCs} - 1) s_{DSCs} + \beta (\gamma_{DMNEs} - 1) s_{DMNEs} + \beta (\gamma_{FMNEs} - 1) s_{FMNEs} \end{aligned} \tag{4}$$

For econometric analysis we can write as

$$\begin{aligned} Y_{j,t} &= \alpha \ln K_{j,t} + \beta_1 \ln L_{j,t} + \beta_2 s_{DIFs,j,t} + \beta_3 s_{DSCs,j,t} + \beta_4 s_{DMNEs,j,t} \\ &+ \beta_5 s_{FMNEs,j,t} + \beta_6 D_{industry,j,t} + \beta_7 D_{time,j,t} + \beta_8 D_{region,j,t} + f_j + e_{j,t} \end{aligned} \tag{5}$$

Where $Y_{j,t}$ is the output of firm *j* in year *t*, here we use the number of patent application (citations) as innovation output to measure productivity spillover and knowledge spillover. $K_{j,t}$ is the physical asset of firm *j* in year *t*. $s_{DIFs,j,t}$, $s_{DSCs,j,t}$, $s_{DMNEs,j,t}$ and $s_{FMNEs,j,t}$ are the share of new labor of firm *j* in year *t* from DIFs, DSCs, DMNEs, FMNEs. $D_{industry}$ is the industry dummies according to first digit of SIC2007 (21 sectors). D_{time} is the year dummies from 2001 to 2010. D_{region} is the regional dummies using FA-regions separations. $e_{i,t}$ is the unobservable error term. f_j is the firm fixed effect for firm *j*.