Learning from Multinational Enterprises: Imitation or Innovation*

(Job Market Paper)

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Abstract

A key issue in the analysis of knowledge spillover concerns the patterns of diffusion of new technologies. We estimate the spillover effect from technological leaders Multi-National Enterprises (MNEs)) to technological followers (non-MNEs) through labor mobility. We distinguish two types of spillover: novel innovative and imitation based on whether non-MNEs apply the same patents that are owned by MNEs. Using employer-employee panel data on Swedish firms for a 10-year period, we find empirical evidence that spillover through hiring workers previously employed at the MNEs leads to more imitation but less novel innovation. We also find that heterogeneous spillover effects can be expected by the source of the spillover. Spillover from competitors induces imitation, while spillover from non-competitors generates novel innovation.

Keywords: Multinational Enterprise; Labor Mobility; Knowledge Spillover

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1 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 knowledge' that can be transferred and utilized in their international units and may also spillover to domestic firms (Dunning, 2012; Markusen, 1995). While many empirical studies appear to support the presence of technology spillover from MNEs, there remains a major problem. It is well known that spillovers will not only stimulate novel innovation but also induce imitation; however, the latter effect are rarely tested. Early general equilibrium models had emphasize the importance of imitation activity (Paul S. Segerstrom, 1990; Grossman and Helpman, 1993; HELPMAN, 1993). Robert J. Barro (1997) develop a model of technological diffusion through imitation. In their model, technology leader deterministically invent new varieties of goods. Technology followers imitate the good because copying is chapter than innovation. Novel innovation without doubt is the engine of economic growth, but imitation at lower cost might decrease the benefit from novel innovation and affect the entire economy. Aghion et al. (1997) present a model of imitation and find when ease of imitation goes to infinity the growth rate falls to zero. However, lower level of imitation will enhance the growth.

In this paper, I develop a methodology to identify the spillover effects from technological leaders (MNEs) to technological followers (Non-MNEs) through the labor mobility channel. I identify the empirical impact of these two types of spillovers: novel innovation based on own inventive activity and imitation, and argue that heterogeneous effects can be expected by the source of the spillover. 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 technology. Due to the potentially important spillover effect of such specific knowledge, the more contacts that other firms have with MNEs, the more benefit they can expect to accrue from these interactions. Since knowledge is primarily embodied in labor, the

[1]See the early contributions by Hymer (1976); Dunning (1977) and recently contributions by Markusen (2004).

mobility of workers implies that employees may carry part of the MNEs specific knowledge with them as they shift employer. Such spillover to domestic firms has been widely investigated, but much less attention has been directed towards whether spillover from MNEs stimulates novel innovation or induces imitation.

This paper contribute to the literature on technology spillover in the following ways. First, by implementing individual level data for the entire Swedish private sector, we provide solid evidence on how knowledge spillover through labor mobility from MNEs influences the performance of other firms. 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. We apply the idea from Griliches (1967) and treat workers with MNEs and non-MNEs experience with different weight. The spillover from workers with MNE experience can be differentiated in two parts: spillover due to mobility and spillover from MNE experience. The possible identification of spillover from MNE experience can be calculated through the differential effect of hiring workers from MNEs over workers from non-MNEs.

Second, we distinguish the spillovers for two types of innovative activity – novel innovation and imitation – using information on the distribution of patenting across technology fields. Imitation is defined as the patent application within the patent classes in which the sourcing firm (MNEs) had been active in the last 3 years, other patent application are defined as novel innovation. Previous research often observe positive spillover as a increase total factor productivity or patent count. However our result are different, we find MNE experience most induce imitation rather than innovation.

Third, we argue that heterogeneous spillover effects can be expected by the source of the spillover.We distinguish spillover source base on the five-digit coding according to Swedish Standard Industrial Classification: spillover from market rivalry (in the same industry), spillover from technology neighborhood (in the related industry), and spillover from non-competitors (in other industry). The spillover source are important for the reason that knowledge flow from some sources may well be beneficial for imitation, but less for innovation. We find spillover from market rivalry or technology neighborhood is more likely to generate imitation. Only spillover from non-competitors can stimulate novel innovation.

The paper is organized such that the next section reviews previous research related to the issues addressed in this paper. Section three presents the dataset, section four develops the econometric model, and section five presents the empirical estimation. The paper then concludes.

2 Literature Review

Spillover from MNEs to non-MNEs has been widely investigated in the North-South framework between developing and developed countries. In this paper, the North-South framework had been extended to a developed country where North and South indicate technology followers and technology leaders. MNEs, by virtue of their access to technological centers all over the world to access to technology, have an important source of competitive advantage (Almeida, 1996; Dunning, 1996; Dunning and Wymbs, 1999; Fors, 1997; Frost, 1996; Pearce, 1999). Knowledge require innovation is tacit and uncodified, that is difficult to transfer of verbalizing. Technology leaders (MNEs) acquire tacit knowledge that cannot be duplicated by technological followers (non-MNEs). Non-MNEs could hire highly skilled workers from MNEs and gain access to the new technology through spillover.

2.1 Spillover from MNEs

MNEs are technologically more advanced than non-MNEs. How MNEs compare to non-MNEs has been investigated implementing a host of different variables, where the most prominent would be growth gaps (Blonigen and Tomlin, 2001), wage gaps (Globerman et al., 1994), productivity gaps (Davies and Lyons, 1991) and technology gaps (Fors, 1997). Markusen (1995) concluded that the MNEs specific advantages appear to exhibit four characteristics: high R&D/sales ratio, high knowledge worker share, relatively new and complex products, and product differentiation. Only the most productive and innovative firms manage to be profitable in regions where they have limited information about market conditions as compared with local firms (Caves, 2007). Another feature of MNEs is that they have higher capital intensities, which may allow for higher efficiency wages (Feliciano and Lipsey, 1999; Globerman et al., 1994)[2]. Hiring workers with MNE experience, non-MNEs may be willing to pay higher wages in order to benefit from the specific knowledge or technology that the worker has acquired at the MNE. Over time, such a mechanism would be expected to increase productivity in the non-MNE.

Simultaneously, MNEs could be willing to pay higher wages to prevent workers from leaving and, thereby, dilute firm-specific assets associated with MNEs proprietary technologies (Glass and Saggi, 2002). Regarding the issue for the current analysis, several studies concluded that there exists a wage differential between MNEs and non-MNEs that holds for both developed and developing countries. Doms and Jensen (1998) found that workers at foreign-owned manufacturing plants have 20 percent higher wages compared to workers at domestic-owned plants in developed countries[3]. Aitken et al. (1996) reported similar wage gaps in developing countries[4].

In a 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 in relation to other Swedish firms. Wage gaps may also indicate skill gaps, i.e., the skill requirements are different at MNEs than they are 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 and Slaughter, 2004). Poole (2013) recently used individual wages as an indicator of technology spillover and linked them to firm performance[5].

[2]According to Griliches (1969), the capital-skill complementarity hypothesis implies that the demand for human capital increases in capital deepening, leading to a positive correlation between capital intensity and wages.

[3]Relatively few studies on developed countries primarily build on data from the UK and the US. See Doms and Jensen (1998); Feliciano and Lipsey (1999); Girma et al. (2001).

[4]For developing countries, see Aitken et al. (1996) Mexico and Venezuela; and Sampson (2007) on Indonesia.

[5]For wage gaps, see Doms and Jensen (1998); Globerman et al. (1994); Feliciano and Lipsey (1999); for skill gaps, see Howenstine and Zeile (1992); Blonigen and Tomlin (2001); Doms and Jensen (1998); for productivity gaps, see Howenstine and Zeile (1992); Oulton (1998); Oulton et al. (1998); Doms and

2.2 Spillovers through Worker Mobility

Labor mobility as a spillover channel has been proved both theoretically (Fosfuri et al., 2001; Glass and Saggi, 2002) and empirically (Agrawal et al., 2006; Görg and Greenaway, 2004; Braunerhjelm et al., 2014). If tacit knowledge is embodied in labor, hiring new workers can obviously bring new knowledge, which potentially has positive effects on productivity and innovation and, thereby, opens up for new business opportunities. Labor mobility can also enhance learning capacities and learning sharing in firms (von Hippel, 1987; Singh and Agrawal, 2011; Corredoira and Rosenkopf, 2010). Hoisl (2007) showed how labor mobility has a positive effect on patenting activities. Combining the multinational enterprises theory that emphasizes how competitiveness builds on knowledge endowments and firm-specific assets with labor mobility, Balsvik (2011) inferred that workers with experience in MNEs could increase the productivity for non-MNEs. In addition, Görg and Strobl (2005) suggested that firms are more productive than other domestic firms are if their business owners have experience in MNEs. Most of the literature has implied positive productivity for technology spillover.

2.3 Spillovers: Novel Innovation or Imitation

Spillovers can be regarded as positive externalities. However, they can generate both novel innovation based on own inventive activity and imitation, but the latter effect is neglected in the literature. Non-MNEs can choose to imitate by hiring a worker from MNEs that have already innovated. Imitation will usually have a lower cost than executing novel innovation (Mansfield et al., 1981). However, spillovers may also induce novel innovative activity if labor mobility transfers novel ideas. Spillovers from MNEs may affect both imitation and performance of original innovations. The early studies usually explain innovation using the number of patents or innovation counts, but a variable standing for imitation is rarely discussed. We propose measures of spillovers for novel innovation and imitation.

Jensen (1998); Girma et al. (2001).

In summary, previous research has shown a potential spillover source related to MNEs that is endowed with firm-specific advantages. Labor mobility has been identified as a channel for non-MNEs to receive knowledge spillover. Spillovers from MNEs may result in both imitation and novel innovations. Hence, we hypothesize that spillovers from MNEs through labor mobility can be both an input for imitation as well as for novel innovation.

3 Data

We use a unique employer-employee dataset extracted from the individual and firm data of the Statistics Sweden's Business Register since 1987, where the estimation period is 2001 to 2010. This dataset covers all employment in the Swedish labor market and all firms across different industries. On individual level, the dataset contains following variables: worker's serial ID number, annual salary wage before tax (SEK), age, gender, education level[6], the years of work experience[7], occupation status (business owners/employer) and foreign/Swedish background[8].

On firm level, we split firms into three category based on the nationality of the firm and multinational characteristic: non- multinational firms (non-MNEs), domestic-owned multinationals (Domestic-Owned Multi-National Enterprises (DMNEs)) and foreign-owned multinational firms (Foreign-Owned Multi-National Enterprises (FDMNEs))[9]. The definition and abbreviations are shown in Table 1[10]. The other variables on the firm level are the size of the firms, age, physical asset, the industry classifications[11]. We use the patent applications from the European Patent Office's PATSTAT database supplemented with

[6]The education levels are based on the Swedish Standard Classification of Education (SUN2000) which adapted to International Standard Classification of Education (ISCED1997).

[7]Experience is defined as the age minus the years of education minus seven.

[8]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.

[9]See Bandick (2004) for motivating the distinction between foreign- and domestically owned MNEs

[10]In our dataset, 96% firms are non-MNEs, 2% are DMNEs and 2% are FDMNEs.

[11]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.

patent data from the Swedish Patent Office as the measurement of innovation variables. 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. We are able to identify labor mobility between sourcing firms (MNEs) and receiving firms (non-MNEs).

3.1 Define R&D Worker

In this paper, we only focus on the labor movement of R&D workers. High educated workers are considered as knowledge carrier who are able to transfer new technology and get access to the knowledge of MNEs. We use detailed measures of R&D workers, both function and formal occupation. We define R&D workers according to their educational level and job classification[12]:

1. Workers holding a bachelor degree in natural, technical, agriculture, or health science.

2. Workers whose jobs are classified as professional, technicians, of associate professionals all involved in R&D.

Table 2 displays the descriptive statistics for R&D worker separation from 2001 to 2010. In the dataset, there are 1,901,767 observations in non-MNEs, 1,480,099 in DMNEs, and 1,504,390 in FDMNEs. R&D workers in MNEs have higher incomes than non-MNEs and FDMNEs have a slightly higher average wages than DMNEs. R&D worker in MNEs do not show differences in the year of education or experience. The means of gender and foreign versus Swedish background do not show outstanding differences between MNEs and non-MNEs.

[12]The education classification are based on SUN2000, job classification are based on Swedish Standard Classification of Occupations (SSYK). The first digit of job classification are: 1, Legislators, senior officials and managers; 2, Professionals; 3, Technicians and associate professionals; 4, Clerks; 5, Service workers and shop sales workers; 6, Skilled agricultural and fishery workers; 7, Craft and related trades workers; 8, Plant and machine operators and assemblers; 9, Elementary occupations; 0, Armed forces.

3.2 Dependent Variables

We use patent applications from the European Patent Offices PATSTAT database supplemented with patent data from the Swedish Patent Office as the measurement of spillover. The patent application variable has been widely used as a proxy for innovation output (Alcacer and Gittelman, 2006; Griliches, 1990), even though invention may not always lead to innovation. It has an advantage when compared to patents granted by better capturing current innovation activities within the firms. The dataset allows splitting patent applications into two components:

1. Patent application within the patent classes in which the souring firm (MNEs) had been active in the last 3 years.

2. Patent application within the patent classes in which the souring firm (MNEs) has not been active in the last 3 years.

We use the definition of component 1 to measure novel innovation and component 2 for imitation. The dependent variables are measured as the count of patent applications of innovation or imitation. For example, if labor mobility from MNEs induces non-MNEs to apply the same patents that are owned by MNEs, we measure this type of spillover as imitation. If non-MNEs apply different types of patents, we call this type of spillover novel innovation[13].

3.3 Firm Fixed effect

According to Blundell et al. (1995), firm-specific heterogeneity in innovative capacity can be controlled by the mean number of innovations during the pre-sample period. Here, we choose 1987 – 2000 as our pre-sample period to estimate firm heterogeneity, but we

[13]The patent classes International Patent Classification (IPC), where technology classes being constructed from the 639 categories. For example, labor mobility happened between receiving firm i and sourcing firm j. If firm i apply a patent in the same patent classes owned by firm j during the 3 year prior to a given year, it means that firm i follows the same technology direction that has been owned by firm j. Hence, this patent is defined as an imitation. If firm i decides to invent something new that differs from the sourcing firm, the patent counts as an novel innovation

also follow the suggestion by Kaiser et al. (2011) and extend the pre-sample estimator by Blundell et al. (1995) to account for the proportion of patent applications in a given year[14]:

$$\ln FE_{i,t} = \ln \left[\frac{\sum_{t=1}^{T} \frac{P_{i,t}}{P_t}}{T} \right] \tag{1}$$

$P_{i,t}$ denotes the number of patent applications for firm i in year t and P_t is the total number of patent applications for all firms in year t. T represents the total number of years during the pre-sample period (1987 – 2000). Therefore, if firm i innovates during a year in which few other firms innovate, it will carry a higher weight in the average innovative capacity of the firm.

Table 3 displays the summary statistics of non-MNEs with at least one R&D workers. There are 145,164 non-MNEs in the dataset with 18 employers and 2.63 R&D workers on average. Only 2 percent of firms had patenting history. The mobile worker variable are the share between the number of R&D workers from difference sourcing and the number of total R&D workers in the firm. The summary statistics shows non-MNEs hiring more workers with non-MNEs experience than workers with MNEs experience. Among workers from MNEs, most mobile worker are from non-competitors (in other industry). The mean value of dependent variable imitation and novel innovation are 0.09 and 0.12. Firm average education, experience and individual fixed effect are used to control the human capital, while individual fixed effect are calculated through individual wage equation. A correlation matrix is provided in Table 4.

4 Analytical Framework

We consider the empirical implications of knowledge spillovers from MNEs to non-MNEs through labor mobility, using the Cobb-Douglas production function. We apply the idea

[14]We have also run regressions using the original pre-sample estimator by Blundell et al. (1995), and the results are basically unaltered.

from Griliches (1967) and treat different workers with different weight. The production function with two type labor inputs as follows:

$$Y = K^{\alpha} H^{\beta} = K^{\alpha} \left[(A_M L_M)^{\sigma} + (A_O L_O)^{\sigma} \right]^{\frac{\beta}{\sigma}} \tag{2}$$

where Y, K and H are respectively, output, physical capital, and human capital. L_M and L_O are different types of labor with two separate technology terms, A_M and A_O. In this paper, we make the assumption that workers are identical but with different experience. The labor input here can be divided by former working experience into two types: workers with experience from MNEs (L_M) and workers without such experience (L_O). Identical workers means two types of workers are perfect substitutes in production (where $\sigma = 1$). The parameters A_M and A_O capture the weight for the different experience. Under perfect substitution, human capital (H) is linear.

$$H = A_M L_M + A_O L_O \tag{3}$$

Under the spillover hypothesis we can assume that workers with experience from MNEs (L_M) would be weighted by a positive premium ($\frac{A_M - A_O}{A_O} > 0$) which measure the spillover effect.

$$H = A_M L_M + A_O L_O = A_O L + (A_M - A_O) L_M = \left(1 + \frac{A_M - A_O}{A_O} \frac{L_M}{L} \right) A_O L \tag{4}$$

In the log-linearized Cobb-Douglas production, the regression can be expressed as follows[15]:

$$\begin{aligned} y_{j,t} = \alpha \ln K_{j,t} + \beta \ln L_{j,t} + \beta \ln A_{O_{j,t}} + \beta \frac{A_M - A_O}{A_O} \frac{L_M}{L} \\ + D_{industry,j,t} + D_{time,t} + D_{region,j,t} + e_{j,t} \end{aligned} \tag{5}$$

where $y_{j,t}$ is the output of firm j in year t. Here, we use the number of patent ap-

[15] See appendix for more details.

plications (citations) as innovation output to measure knowledge spillover. $K_{j,t}$ is the physical asset of firm j in year t. $\frac{L_M}{L}$ is the share of labor that has MNE experience in firm j in year t. $D_{industry,j,t}$ is the industry dummies according to the first digit of SIC2007 (21 sectors). $D_{time,t}$ is the year dummies from 2001 to 2010 control for business cycles. $D_{region,j,t}$ is the regional dummies using FA-regions separations[16]. $e_{i,t}$ is the unobservable error term. Region, time and industry fixed effect are commonly used in the spillover literature for controlling business cycles, industry, and geographical concentration (Heyman et al., 2007). I constructed the measure for the share of workers with MNE experiences by measuring the newly hired workers from MNEs. These mobile workers who worked in MNEs in the previous year $t-1$ are expected to contain some MNE experience and transfer to new firms.

We have assumed that the workers with MNEs generate spillover to production. First, we make the assumption that workers are identical. One cannot rule out another explanation, namely, that mobile worker are better educated or selected on some unobservable characteristics. Hence, we might observe a higher A_M and an upward bias for spillover. We focus on the labor mobility of R&D workers who at least hold a bachelor's degree and are involved in R&D. Table 2 displays the individual characteristics in non-MNEs based on their mobility status. The result does not show significant differences between "stayers" and mobile workers in regards to education, experience, and fixed individual effect (capture the unobservable characteristics)[17]. Mobile workers are slightly younger and have less experience. The distribution of education is plotted in the Figure 1. There is no significant difference between the distribution of stayers and mobile workers. Mobile workers come from MNEs and workers from non-MNEs have a similar distribution in education. The distribution of experience is plotted in the Figure 2. Stayers have a flatter distribution and mobile workers shift to the left side. The result indicates movers have slightly less experience than stayers do. Mobile workers come from MNEs and work-

[16]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.

[17]See appendix for details.

ers from non-MNEs also have the similar distribution in education. The distribution of individual fixed effect is plotted in Figure 3. The distribution of mobile workers shifts to the left side. The result indicates movers have smaller fixed effect than stayers, which may imply that non-MNEs are hiring workers from the lower distribution. Mobile workers coming from MNEs and workers from non-MNEs also have a similar distribution in education.

Second, the spillover from workers with MNE experience can be differentiated in two parts: spillover due to mobility and spillover from MNE experience. The possible identification of spillover from MNE experience can be calculated through the differential effect of hiring workers from MNEs over workers from non-MNEs. We can rewrite the production function with three type labor inputs: L_M is the share of workers from MNEs (weighted by A_M), L_N is the share of worker from non-MNEs (weighted by A_N), and others L_O (weighted by A_O).

$$\begin{aligned} y_{j,t} = \alpha \ln K_{j,t} + \beta \ln L_{j,t} + \beta \ln A_{O_{j,t}} + \beta \frac{A_M - A_O}{A_O} \frac{L_M}{L} + \beta \frac{A_N - A_O}{A_O} \frac{L_N}{L} \\ + D_{industry,j,t} + D_{time,t} + D_{region,j,t} + e_{j,t} \end{aligned} \tag{6}$$

Based on the early distribution, we can believe that mobile workers from MNEs and non-MNEs have a similar distribution for education, experience, and fixed effect. If the innovation increase is only caused by more productive mobile labor, we shall observe equal weighted workers with experience from MNEs and workers from non-MNEs ($\frac{A_M - A_O}{A_O} = \frac{A_N - A_O}{A_O}$). Otherwise, we can calculate the spillover from MNEs by taking the difference ($\frac{A_M - A_O}{A_O} - \frac{A_N - A_O}{A_O}$).

Third, firms having more workers with higher educations will present better innovation outcomes, which will lead to an upward bias in the estimated coefficients. The estimation of spillover parameter $\frac{A_M - A_O}{A_O}$ also depends on the weight AO. We can use three measures to calculate the weight for human capital: average year of education, average year of experience, and average individual fixed effect.

The dependent variables are counted data that can take only non-negative integer values and may include many zeros. The mean values of dependent variables are much lower than their standard deviations, which is a clear signs of over dispersion. Here we use constant dispersion negative binomial regression, which is usual for over-dispersed count variables, such as patent applications. In order to avoid a direct simultaneity bias between the dependent and the explanatory variables, we also used lagged labor input.

5 Empirical Result

5.1 Spillover through Labor Mobility

Table 5 displays the estimated result of Equation 4 of knowledge spillover through workers for imitation. The dependent variable is the number of patent applications of imitation (similar patent application as MNEs). In columns 1 to 4, we estimate spillover for the non-MNEs with no patent history. The reason we split the firm base on their pre-sample patent activity is that prior innovation activity could largely affect their future innovation. Column 1 indicates that both workers with non-MNE experience and MNE experience have positive and significant effect imitation for non-MNEs. The estimated coefficient of workers with MNE experience is 2.012, combined with the coefficient of R&D worker (0.868). We can calculate that the weight for workers with MNE experience (L_M) is 2.32 and that the weight for workers with non-MNE experience (L_N) is 0.85 at 0.1% significance. The result indicates mobile workers with MNE experience are weighted three times more heavily than workers with non-MNE experience in contributing to imitation. The difference between mobile worker from MNEs and non-MNEs is 1.46, implying a positive premium for MNE experience. Column 2 presents the result when we use a lagged measurement of labor mobility to avoid a direct simultaneity bias. The coefficient of workers from MNEs decreases and the coefficient of workers from non-MNEs increases. The difference between mobile workers from MNEs and non-MNEs reduces to 0.89, but is still positive and significant.

In column 3, we split the share of workers with MNEs into two types: workers with DMNE experience and workers with FDMNE experience. The coefficient for the share of workers with DMNE experience is larger than that for the workers with FDMNEs experience. We can calculate weight for workers with DMNE experience at 2.6 and for workers with FDMNE experience at 1.9. If there emerges some aberration that leads to an increase in both labor mobility and innovation output, this will lead to an upward bias in the estimation. We control for this possible aberration by using the lagged share of labor. The results are presented in column 4. The difference between mobile worker from DMNE and non-MNE is 1.02, and the difference between mobile worker from FDMNE and non-MNE is 0.71. The result indicates that there exists a spillover from MNE that contributes significantly to a firm's imitation.

In columns 5 to 8, we only estimate the non-MNE with a patent history and use the pre-sample estimator (FE) to control the firm-specific heterogeneity in innovative capacity. The results are quite robust whether non-MNEs had patent or not. Column 5 indicates that both workers with non-MNE experience and MNE experience have positive and significant effect on imitation for firms that had a patent history. The difference between mobile workers from MNEs and non-MNEs is 0.66, implying a positive spillover for imitation by MNE experience. When we take the lagged labor mobility in column 6, the difference increases to 1.48. In columns 6 and 8, we split the share of workers with MNEs into two types: workers with DMNE experience and workers with FDMNE experience. Workers with FDMNE experience generate stronger spillover for imitation. The difference weight between workers with FDMNE experience and workers from non-MNE is 1.03. If we take the lagged labor, the difference increases to 2.03. The results indicate for non-MNE, the labor mobility from MNEs can generate spillover of imitation. The effects are stronger for firms that did not have any patenting history. One reason could be because firms with no innovation history are technology followers and imitation will usually be cheaper for these firms than executing their own R&D.

Table 6 displays the estimation result of Equation 4 for knowledge spillover through workers for novel innovation. The dependent variable is the number of patent applications of novel innovation (different from patent applications for MNE). Column 1 indicates that workers with both non-MNE experience and with MNE experience have positive and significant effect on novel innovation. We can calculate the weight for workers with

MNE experience (L_M) as 2.0 and the weight for workers with non-MNE experience (L_N) as 1.93 at 0.1% significance. The difference between mobile worker from MNE and non-MNE is 0.07, implying a positive but quite small spillover for novel innovation due to MNE experience. Column 2 presents the results when we use a lagged measurement of labor mobility. The difference between mobile workers from MNE and non-MNE becomes almost zero. We further split workers with DMNE experience and workers with FDMNE experience in column 3. We can calculate the difference weight for workers with DMNE experience as 0.61 and for workers with FDMNE experience as -0.77 compared to workers from non-MNEs. Only workers with DMNE experience have a positive spillover effect for novel innovation. Column 4 presents the results using a lagged share of labor. The differences between a mobile worker from MNE and a non-MNE are nearly zero. The results indicate that labor mobility from MNEs generate weak spillover on novel innovation compared to labor mobility from non-MNEs. In column 5 to 8, we only estimate the non-MNEs with a patent history. The results are quite robust, spillover stimulates novel innovation for firm had innovation history and the firm did not. Column 5 indicates only workers with non-MNE experience show a positive and significant effect on novel innovation. The difference of weight between workers from MNEs and workers from non-MNEs are either negative in column 5 or weakly positive in column 6. In columns 7 and 8, we find that workers with experience from DMNE have a positive and significant effect on novel innovation. Workers with experience from FDMNE have negative effect for novel innovation, and the coefficient is insignificant if we take lagged labor. The difference between workers from non-MNEs and worker from DMNE is -0.46 in column 7 and 4.15 if we take lagged labor in column 8.

The results are robust across the two specifications of the dependent variables. We find that spillovers with MNE experience contribute significantly to a firm's imitation output, but have a weak effect on novel innovation. In the empirical analysis, we do not control for the home country effect. The spillover from FDMNEs could be different if the headquarters are located in different countries. The geographical distance between headquarters and the local market could lead to different technology transfer. Yet our data do not have information to control that. Among the control variables, the number of R&D workers and pre-sample estimator show a positive effect for imitation and novel innovation. More R&D workers and higher accumulated knowledge associate with a higher absorption capacity for spillover and a higher ability to transfer the knowledge inflow into innovation output.

5.2 Spillover Controlling Human Capital

In the last section, we did not control the different human capital between firms and assume R&D workers are identical (A_O is normalize to one). Now we weight the labor input by three variables: average education, average experience, and average fixed effect.

Table 7 displays the estimation result of Equation 4 of knowledge spillover through workers for imitation after controlling for human capital. We first look at firms with no patent history. In column 1, we find that firms' average education will decrease the spillover effect for both workers with non-MNE and MNE experience. The early estimation is upward bias due to heterogeneous human capital. The difference between mobile workers from MNEs and non-MNEs is 1.94, implying a positive spillover for imitation by MNE experience. The results are unchanged when we use firms' average experience and average individual fixed effect to control human capital. The difference between mobile worker from MNEs and non-MNEs is 1.5 (column 2) and 1.39 (column 4). When we control all three types of human capital, the difference in weight is 1.31, which is similar to the results in Table 5 (1.46).

Columns 5 to 8 present the result when we use a lagged measurement of labor mobility to avoid a direct simultaneity bias. The difference in weight between MNEs and non-MNEs is 1.29 (control education), 0.91 (control experience), 0.81 (control fixed effect), and 0.99 (control for all three). The results are robust compared with the early result of 0.89 (Table 5, column 2).

Table 8 displays the estimation result for non-MNEs that applied patent application before sample period. The spillover for imitation is still significant and positive. After controlling all three for human capital, the difference in weight between MNEs and non-

MNEs is 0.71 (column 4), while the early result is 0.66 (Table 5, column 5). When we use lagged labor input, the result does not change much (1.21). The results indicate a persistent spillover for imitation.

Table 9 presents the spillover effect for novel innovation. The results are robust whether we control the human capital or not. For firms with no patent history, the different weights between MNE experience and non-MNE experience is 0.29 and 0.23 (lagged labor input) after controlling for all three human capital variables.

The result for firms that had patent application before the sample period is the same. In Table 10, we can observe that MNE experience has positive but insignificant effect for novel innovation. The weight for MNE experience is smaller than for non-MNE experience, which indicates the labor mobility from MNE does not induce novel innovation. In column 5 to 8, we use lagged labor input. The MNE experience becomes significant, but the spillover effect for novel innovation is still weak and near zero.

The results are quite robust across different human capital control. The reason is that it can both reduce the coefficient of workers with MNE experience and workers with non-MNE experience. Hence, the different weight between these two does not change much. The results indicate that spillover from MNE experience is more likely to induce imitation than innovation. Spillover for imitation is stronger for firms that did not have any patent history before the sample period. We argue the reason is that non-MNE with no innovation activities is the technology laggard and information from MNEs is more valuable for the technology laggard.

5.3 Spillover from Different Sources

We found that spillover from MNEs induces both strong imitation and weak novel innovation. The results question which sources of spillover lead to imitation or innovation. The heterogeneous spillover effects can be expected from different sources. If spillover ease imitation from MNEs, the spillover source is likely from the same or a related industry. We distinguish spillover base on the five-digit coding according to Swedish Standard Industrial Classification 2007: spillover from market rivalry (in the same industry), spillover from technology neighborhood (in the related industry), and spillover from non-competitors (in other industry). If receiving firms (non-MNE) and sourcing firms (MNEs) have the same five-digit code, we consider them as market rivals. If receiving firms (non-MNEs) and sourcing firms (MNEs) only have the same first digit (first category), we consider them as in the same technology neighborhood. Otherwise, we consider the spillover is from other sourcing. We split the worker with MNE experience into the three categories based on their sourcing.

Table 11 displays the estimation result of equation (4) for non-MNEs with no patent history with human capital controlling. The dependent variable is imitation here. The results are robust for different kinds of human capital controlling. In columns 1 to 4, we find both worker from non-MNEs and workers with MNE experience in a related industry and other industries have significant effect on imitation. The difference between mobile workers from MNEs and non-MNEs is positive, implying that spillovers induce imitation. MNE experience in other industries has a stronger effect on imitation. If we take a one-year lag of labor input, the results are unchanged. MNE experience both in a related industry and in another industry can stimulate imitation.

Table 12 displays the estimation result for non-MNEs that had a patent history. In columns 1 to 4, we find workers both from non-MNEs and workers with MNE experience in same industry have a positive effect on imitation. The difference between mobile workers from MNEs in same industry and non-MNEs is positive, implying that spillover induce imitations. If we take a one-year lag of labor input, only MNE experience in a related industry can induce imitation. Compare the different results, we find spillover from same or related industry is more likely to generate imitation. For those firms that had no patent history, spillover from other industry could also induce imitation. One explanation is that since these firms did not have a direction of innovation, any market potential could induce them to imitate.

Table 13 displays the estimation result for novel innovation. For Non-MNEs with no patent history, workers from both non-MNEs and workers with MNE experience in other industries have positive effect on novel innovation. The difference between mobile workers from MNEs and non-MNEs is positive, implying that spillover from non-competitors induces novel innovation. If we take a one-year lag of labor input, both MNEs in the related industry and MNEs in other industries are significant. However, workers with experience from MNEs in the related industry show a smaller weight compared to workers from non-MNEs; hence, this type spillover has a negative weight for novel innovation. Only the workers with experience from MNEs in the other industries can induce novel innovation, but the effects are quiet small.

Table 14 displays the estimation result for non-MNEs with patenting history. In columns 1 to 4, only workers from non-MNEs have a positive effect on novel innovation. If we take a one-year lag of labor input, MNEs in other industry are also significant. MNE experience in other industries also has a higher weight than non-MNEs, indicating that this type of spillover can induce novel innovation.

For novel innovation output, we find that only spillover from other industries has a positive effect. Knowledge inflow from different industries could provide more demand and market information for other types of invention, which would lead firms to innovation.

5.4 Econometric Results for Three High-Tech Industries

A straightforward extension of the methodology is to examine particular industries with more innovation. Perhaps spillover effects were contradicted in the high-tech sectors, and our results might be due to biases induced by heterogeneous sectors. Table 15 displays the patent distribution over 21 industries according to Swedish Standard Industrial Classification 2007, with 93% of patent application belonging to the firms in the following industries: manufacturing, professional, scientific, and technical activities, and activities of extraterritorial organizations and bodies. We examined the three most innovative sectors in Tables 15 to 18. Overall, the qualitative results are robust: significant technology spillovers are found in all three sectors for both imitation and novel innovation. We find that only spillover from other industries has a positive effect on novel innovation. Spillover from the same or related industries is more likely to generate imitation. For those firms having no patent history, spillover from other industries could also induce imitation. For novel innovation, we find only spillover from other industry have positive effect. The coefficient of imitation is smaller than in the pooled results, and the coefficient of novel innovation is larger than in the pooled results. Result indicate that labor mobility with MNE experience induces more novel innovation and less imitation for firms in high-tech industries than for firms in other industries.

6 Conclusion

This paper investigates and analyses spillover effects and focuses on the differences between spillovers attributable to novel innovation and those attributable to imitation. Innovation is positively associated with economy growth. However, spillovers from innovation lead to imitations that might be received negatively and lead to intense competition.

We have assumed that labor mobility causes knowledge spillover and we have implemented a measure to isolate the spillover effect due to prior experience with an MNE. We compare the labor mobility from non-MNEs and MNEs, and we take the difference of the coefficient. The paper provides empirical evidence that spillovers through labor mobility from MNEs mostly induce imitation rather than innovation. Through hiring workers from MNEs, non-MNEs can learn from the knowledge possessed by workers from prior MNEs and imitate the same technology that belongs to MNEs. In the patent production function, we controlled three types of human capital: the average year of education in the firm, the average year of experience in the firm, and the average individual fixed effect.

We found that the heterogeneous spillover effects could be expected from different sources. Spillover from the same or related industry is more likely to generate imitation. Only spillover from non-competitors can stimulate novel innovation. The paper addresses a key issue involving the patterns of diffusion of new technologies by using a unique Swedish employer-employee dataset. Our findings do not just contribute the literature, but produce policy implications as well.

One might have issue with the question of endogeneity, either due to labor selection and reverse causality. A labor selection problem arises if mobile workers are better educated or selected on some unobservable characteristics. An economic shock to the firm might lead to an increase in innovation and labor input. First, we did not observe mobile workers have education that is more extensive and experience compare to stayers in the non-MNEs. Second, we found that the distribution of workers coming from non-MNEs and MNEs are similar. The difference weight between the two types labor should not correlate with the error term. We also use one-year lagged labor input to avoid the simultaneous bias.

We believe that the methodology employed in this paper offers a way to analyze the existence of the different types of spillover that are much discussed in the growth, productivity, and industrial organization literature, but are rarely subjected to rigorous empirical testing.

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Appendix: Individual Wage Equation

One way to measure the human capital is through the individual fixed effect. With the matched employer-employee data for Sweden firms, I estimate the fixed effect by individual wage regression. If labor market are competitive, wage depend on worker's marginal productivity. Individual fixed effect calculated through wage equation can capture some unobservable individual characteristic. We use the fixed effects panel regression by adding individual fixed effects as the following equation,

$$\begin{aligned} w_{i,t} = \alpha + \beta_1 X_{i,t} + \beta_2 F_{j,t} + \beta_3 D_{ownership,j,t} + \beta_4 D_{industry,j,t} \\ + \beta_5 D_{time,t} + \beta_6 D_{region,j,t} + f_i + e_{i,t} \end{aligned} \tag{7}$$

Where $w_{i,t}$ is the logarithm of annual salary wage of person i in year t. $X_{i,t}$ is a vector of observable individual characteristic variables and $F_{j,t}$ is a vector of firm j's observable characteristic variables. $D_{ownership,j,t}$ is the ownership structure dummies of three types firms: non-MNEs, DMNEs and FDMNEs. $D_{industry,j,t}$ is the industry dummies according to first digit of SIC2007 (21 sectors). $D_{time,t}$ is the year dummies from 2001 to 2010. $D_{region,j,t}$ is the regional dummies using FA-regions separations. f_i is the individual fixed effect for person i. $e_{i,t}$ 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.

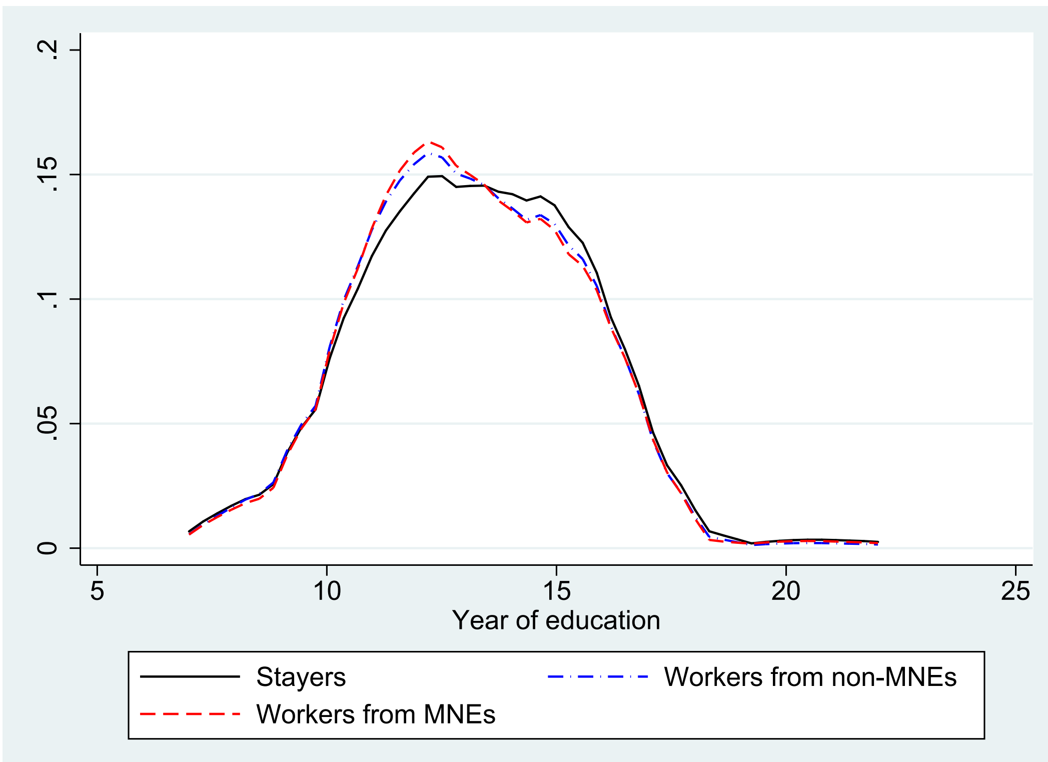

Figure 1: Distribution of Education (R&D Worker) in Non-MNEs

Figure 2: Distribution of Experience (R&D Worker) in Non-MNEs

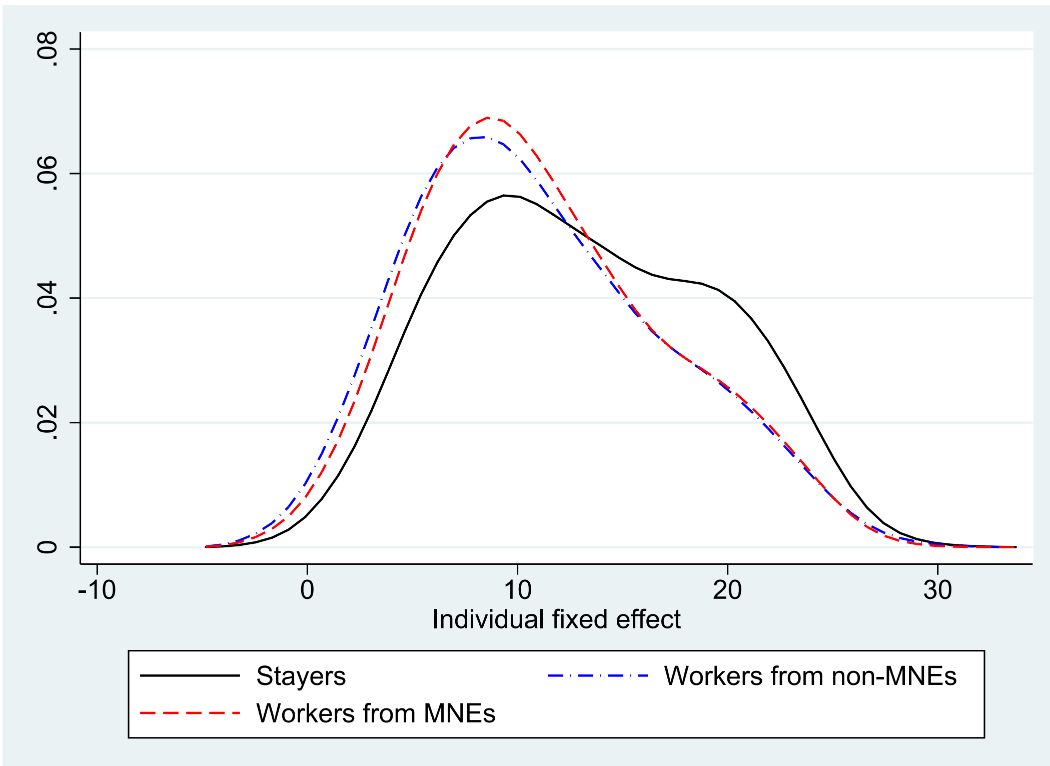

Figure 3: Distribution of Individual Fixed Effect (R&D Worker) in Non-MNEs

Table 1 Firm's definitions based on ownership structure

Firm's type by ownership structure	Abbreviations	Definitions
Non-multinational firms	non-MNEs	Swedish firm 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 R&D worker separations in non-MNEs period 2001-2010

	Non-MNEs			
	Stayers	From non-MNEs	From DMNEs	From FMNEs
Female	0.44	0.41	0.33	0.35
Swedish	0.83	0.80	0.81	0.8072
Age	44.63	40.83	39.96	40.19
Education	13.25	13.11	13.31	13.08
Experience	24.38	20.71	19.64	20.10
Individual fixed effect	13.11	11.02	10.68	10.58
Number of observation	1,631,258	162,825	51,564	56,120

R&D worker are workers holding a bachelor degree in natural, technical, agriculture, or health science and whose jobs are classified as professional, technicians, of associate professionals all involved in R&D.

Table 3 Non-MNEs firms in period 2001-2010

	Non-MNEs			
	Mean	S.D.	Min	Max
Imitation	0.09	4.61	0	1,050
Novel innovation	0.12	3.17	0	627
Dummy: firm had patenting history	0.02	0.15	0	1
Pre sample estimator (FE)	0.000001	0.00002	0	0.002
Share of workers with experience from Non-MNEs	0.09	0.26	0	1
Share of workers with experience from DMNEs	0.02	0.12	0	1
Share of workers with experience from FMNEs	0.02	0.11	0	1
Share of workers with experience from MNEs in the same industry	0.01	0.08	0	1
Share of workers with experience from MNEs in the relevant industry	0.02	0.11	0	1
Share of workers with experience from MNEs in other industry	0.07	0.22	0	1
R&D worker	2.63	26.14	1	2,453
Firm size	18.38	193.98	1	23,588
Physical asset	20,905,095	435,280,000	0	77,688,000,000
Firm age	6.92	6.24	1	25
Firm average education	7.34	6.24	0	21
Firm average experience	12.09	11.55	0	57
Firm average individual fixed effect	214.68	2,361.87	1	284,087
Number of firms	194,183			

All the firm have at least one R&D worker.

Table 4 Correlation matrix on firm level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	1.0000														
(2)	0.0156	1.0000													
(3)	0.0026	0.0031	1.0000												
(4)	0.0064	0.0153	0.0356	1.0000											
(5)	0.0050	0.0187	0.0258	0.7480	1.0000										
(6)	0.0041	0.0025	0.0252	0.6831	0.0261	1.0000									
(7)	0.0041	0.0233	0.0202	0.5029	0.3837	0.3352	1.0000								
(8)	0.0045	0.0189	0.0247	0.6757	0.4927	0.4755	0.7429	1.0000							
(9)	0.0054	0.0040	0.0278	0.7985	0.6047	0.5372	0.1947	0.1544	1.0000						
(10)	0.3950	0.0103	0.0279	0.0362	0.0281	0.0236	0.0276	0.0310	0.0264	1.0000					
(11)	0.1378	0.0132	0.0206	0.0280	0.0234	0.0165	0.0136	0.0188	0.0231	0.1735	1.0000				
(12)	0.3493	0.8029	0.0038	0.0177	0.0185	0.0062	0.0246	0.0215	0.0063	0.1931	0.0989	1.0000			
(13)	0.0075	0.0067	0.1344	0.1092	0.0817	0.0746	0.0554	0.0742	0.0867	0.0365	0.0380	0.0117	1.0000		
(14)	0.0044	0.0046	0.0792	0.0653	0.0477	0.0459	0.0321	0.0455	0.0508	0.0237	0.0397	0.0095	0.8405	1.0000	
(15)	0.2312	0.0147	0.0452	0.0643	0.0479	0.0442	0.0407	0.0524	0.0489	0.6199	0.2527	0.1299	0.0879	0.0730	1.0000

Variables: (1) Imitation; (2) Novel innovation; (3) Share of workers with experience from Non-MNEs; (4) Share of workers with experience from MNEs; (5) Share of workers with experience from DMNEs; (6) Share of workers with experience from FMNEs; (7) Share of workers with experience from MNEs in the same industry; (8) Share of workers with experience from MNEs in the relevant industry; (9) Share of workers with experience from MNEs in different industry; (10) R&D worker; (11) Physical asset; (12) Pre sample estimator (FE); (13) Firm average education; (14) Firm average experience; (15) Firm average individual fixed effect.

Table 5 Spillover for imitation

	Non-MNEs with no patent history				Non-MNEs with patent history			
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.742***		0.744***		0.590**		0.587**	
	(3.01)		(3.01)		(2.38)		(2.37)	
MNEs	2.012***				0.927***			
	(8.96)				(3.95)			
DMNES			2.263***				0.588	
			(9.07)				(1.63)	
FMNES			1.660***				1.113***	
			(4.37)				(3.72)	
Non-MNEs (lagged)		1.270***		1.271***		0.576*		0.581**
		(4.86)		(4.87)		(1.94)		(1.97)
MNEs (lagged)		2.046***				1.306***		
		(8.01)				(4.71)		
DMNES (lagged)				2.162***				0.812*
				(6.81)				(1.66)
FMNES (lagged)				1.889***				1.568***
				(4.47)				(4.88)
Log(R&D workers)	0.868***	0.873***	0.870***	0.873***	0.510***	0.493***	0.508***	0.487***
	(12.08)	(11.64)	(12.14)	(11.64)	(4.62)	(4.83)	(4.69)	(4.90)
Log(Physical asset)	0.0795**	0.0820**	0.0799**	0.0820**	0.0324	0.0496	0.0322	0.0521
	(2.45)	(2.41)	(2.45)	(2.42)	(0.88)	(1.17)	(0.87)	(1.22)
Log(FE)					0.524***	0.556***	0.521***	0.551***
					(4.54)	(4.81)	(4.55)	(4.80)
Observation	189871	148313	189871	148313	4312	3679	4312	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 6 Spillover for novel innovation

	Non-MNEs with no patent history				Non-MNEs with patent history			
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.895***		0.896***		0.547***		0.550***	
	(7.31)		(7.32)		(3.58)		(3.61)	
MNEs	0.929***				0.195			
	(6.34)				(0.94)			
DMNES			1.183***				0.546**	
			(6.86)				(2.55)	
FMNES			0.535**				-0.269	
			(2.16)				(-0.74)	
Non-MNEs (lagged)		1.124***		1.125***		0.494***		0.495***
		(8.29)		(8.30)		(2.72)		(2.72)
MNEs (lagged)		1.137***				0.513**		
		(6.46)				(2.22)		
DMNES (lagged)				1.220***				0.721***
				(5.44)				(2.94)
FMNES (lagged)				1.026***				0.264
				(3.92)				(0.68)
Log(R&D workers)	0.464***	0.466***	0.466***	0.466***	0.0819	0.0503	0.0868	0.0545
	(11.35)	(10.26)	(11.40)	(10.25)	(1.38)	(0.75)	(1.46)	(0.82)
Log(Physical asset)	0.0431***	0.0480***	0.0431***	0.0480***	0.0595**	0.0757**	0.0597**	0.0754**
	(3.44)	(3.31)	(3.44)	(3.31)	(2.36)	(2.28)	(2.36)	(2.28)
Log(FE)					0.413***	0.428***	0.418***	0.429***
					(6.88)	(6.54)	(6.97)	(6.59)
Observation	189871	148313	189871	148313	4312	3679	4312	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 7 Spillover for imitation controlling human capital

	Non-MNEs with no patent history							
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.159	0.668***	0.787***	-0.107				
	(0.72)	(2.70)	(3.13)	(-0.43)				
MNEs	1.542***	1.947***	2.055***	1.453***				
	(7.26)	(9.02)	(9.15)	(6.09)				
Non-MNEs (lagged)					0.740***	1.225***	1.334***	0.436
					(2.75)	(4.60)	(4.90)	(1.36)
MNEs (lagged)					1.621***	2.007***	2.106***	1.487***
					(6.45)	(7.98)	(8.06)	(5.49)
Log(R&D workers)	0.711***	0.852***	0.912***	1.186***	0.685***	0.860***	0.948***	1.058***
	(9.60)	(11.34)	(9.38)	(6.24)	(8.88)	(11.03)	(9.51)	(5.46)
Log(Physical asset)	0.0803*	0.0699**	0.0899**	0.218***	0.119**	0.0749**	0.100**	0.257***
	(1.67)	(2.27)	(2.48)	(3.06)	(2.28)	(2.22)	(2.37)	(3.44)
Log(Firm average education)	4.459**			4.802***	6.547***			6.305***
	(2.07)			(4.83)	(3.15)			(4.66)
Log(Firm average experience)		0.125		-1.802***		0.101		-1.941***
		(1.35)		(-7.79)		(0.98)		(-7.40)
Log(Firm average individual fixed effect)			-0.0461	-0.509***			-0.0785	-0.439**
			(-0.84)	(-2.67)			(-1.26)	(-2.02)
Observation	189871	189871	189871	189871	148313	148313	148313	148313

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 8 Spillover for imitation controlling human capital

	Non-MNEs with patent history							
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.413	0.588**	0.623**	0.283				
	(1.64)	(2.36)	(2.47)	(1.06)				
MNEs	0.847***	0.924***	0.958***	0.833***				
	(3.60)	(3.91)	(4.18)	(3.80)				
Non-MNEs (lagged)					0.375	0.576*	0.579*	0.217
					(1.26)	(1.94)	(1.94)	(0.70)
MNEs (lagged)					1.135***	1.302***	1.337***	1.019***
					(4.06)	(4.71)	(4.83)	(3.30)
Log(R&D workers)	0.463***	0.510***	0.637***	0.772***	0.405***	0.492***	0.615***	0.662***
	(4.02)	(4.58)	(4.54)	(3.84)	(3.69)	(4.80)	(5.08)	(3.24)
Log(Physical asset)	0.0376	0.0313	0.0656	0.119*	0.0851	0.0483	0.0845	0.174**
	(0.86)	(0.81)	(1.42)	(1.67)	(1.49)	(1.11)	(1.62)	(2.05)
Log(Firm average education)	1.507*			1.806***	2.428***			2.256***
	(1.92)			(5.13)	(2.62)			(4.93)
Log(Firm average experience)		0.0202		-0.575*		0.0296		-0.723*
		(0.16)		(-1.77)		(0.24)		(-1.84)
Log(Firm average individual fixed effect)			-0.153*	-0.404**			-0.155**	-0.371*
			(-1.77)	(-2.12)			(-2.03)	(-1.80)
Log(FE)	0.516***	0.523***	0.535***	0.578***	0.533***	0.554***	0.563***	0.591***
	(4.44)	(4.45)	(4.65)	(4.73)	(4.60)	(4.73)	(4.92)	(4.75)
Observation	4312	4312	4312	4312	3679	3679	3679	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 9 Spillover for novel innovation controlling human capital

	Non-MNEs with no patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.490***	0.784***	0.810***	0.343***				
	(4.04)	(6.21)	(6.31)	(2.77)				
MNEs	0.563***	0.831***	0.842***	0.490***				
	(3.84)	(5.58)	(5.48)	(3.26)				
Non-MNEs (lagged)					0.824***	1.058***	1.081***	0.726***
					(6.24)	(7.69)	(7.84)	(5.41)
MNEs (lagged)					0.871***	1.080***	1.093***	0.846***
					(4.98)	(6.16)	(6.12)	(4.77)
Log(R&D workers)	0.319***	0.426***	0.382***	0.504***	0.329***	0.437***	0.413***	0.504***
	(6.67)	(9.56)	(6.91)	(6.89)	(6.31)	(8.92)	(6.77)	(6.42)
Log(Physical asset)	0.00680	0.0301**	0.0285**	0.0641***	0.0137	0.0372**	0.0371**	0.0876***
	(0.56)	(2.32)	(2.13)	(3.70)	(0.98)	(2.50)	(2.37)	(3.86)
Log(Firm average education)	0.637***			2.276***	0.679***			2.392***
	(8.65)			(18.05)	(7.02)			(15.17)
Log(Firm average experience)		0.142***		-1.269***		0.117**		-1.290***
		(3.44)		(-12.69)		(2.49)		(-11.17)
Log(Firm average individual fixed effect)			0.0722***	-0.257***			0.0491*	-0.288***
			(2.70)	(-4.46)			(1.68)	(-4.43)
Observation	189871	189871	189871	189871	148313	148313	148313	148313

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 10 Spillover for novel innovation controlling human capital

	Non-MNEs with patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.420***	0.529***	0.541***	0.343**				
	(2.83)	(3.48)	(3.57)	(2.26)				
MNEs	0.110	0.175	0.188	0.126				
	(0.53)	(0.84)	(0.91)	(0.61)				
Non-MNEs (lagged)					0.371**	0.484***	0.492***	0.262
					(2.09)	(2.69)	(2.72)	(1.42)
MNEs (lagged)					0.418*	0.483**	0.505**	0.442*
					(1.81)	(2.10)	(2.16)	(1.85)
Log(R&D workers)	0.0341	0.0793	0.0666	0.0634	-0.000431	0.0482	0.0372	0.0419
	(0.57)	(1.34)	(0.97)	(0.82)	(-0.01)	(0.73)	(0.49)	(0.49)
Log(Physical asset)	0.0514*	0.0517**	0.0539*	0.0982**	0.0710**	0.0662*	0.0704*	0.124**
	(1.96)	(1.97)	(1.81)	(2.53)	(2.05)	(1.94)	(1.78)	(2.40)
Log(Firm average education)	0.694***			1.281***	0.742***			1.265***
	(4.36)			(7.07)	(3.89)			(5.85)
Log(Firm average experience)		0.111		-0.535***		0.143*		- 0.449***
		(1.62)		(-3.74)		(1.80)		(-2.62)
Log(Firm average individual fixed effect)			0.0217	-0.104			0.0193	-0.129
			(0.48)	(-1.36)			(0.37)	(-1.43)
Log(FE)	0.413***	0.411***	0.412***	0.430***	0.424***	0.424***	0.427***	0.440***
	(6.92)	(6.89)	(6.91)	(7.08)	(6.51)	(6.55)	(6.59)	(6.67)
Observation	4312	4312	4312	4312	3679	3679	3679	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 11 Different spillover source for imitation controlling human capital

Dependent variable: imitation	Non-MNEs with no patent history (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.718***	0.140	0.641***	0.758***				
	(2.93)	(0.64)	(2.61)	(3.04)				
MNEs in the same industry	-0.778	-0.565	-0.700	-0.834				
	(-0.96)	(-0.69)	(-0.86)	(-1.02)				
MNEs in the relevant industry	1.269**	0.928	1.195*	1.319**				
	(2.07)	(1.49)	(1.94)	(2.15)				
MNEs in other industry	2.175***	1.678***	2.105***	2.218***				
	(8.14)	(6.44)	(7.93)	(7.99)				
Non-MNEs (lagged)					1.257***	0.726***	1.209***	1.317***
					(4.81)	(2.68)	(4.54)	(4.84)
MNEs in the same industry (lagged)					-1.759*	-1.716	-1.735	-1.814*
					(-1.65)	(-1.61)	(-1.62)	(-1.70)
MNEs in the relevant industry (lagged)					1.687***	1.558**	1.654***	1.744***
					(2.67)	(2.39)	(2.61)	(2.79)
MNEs in other industry (lagged)					2.290***	1.775***	2.248***	2.344***
					(7.07)	(5.58)	(7.03)	(7.07)
Log(R&D workers)	0.877***	0.715***	0.859***	0.918***	0.879***	0.690***	0.865***	0.950***
	(11.94)	(9.46)	(11.15)	(9.04)	(11.75)	(8.96)	(11.12)	(9.60)
Log(Physical asset)	0.0786**	0.0794*	0.0685**	0.0885**	0.0807**	0.117**	0.0733**	0.0982**
	(2.43)	(1.65)	(2.22)	(2.42)	(2.39)	(2.24)	(2.19)	(2.34)
Log(Firm average education)		4.448**				6.538***		
		(2.06)				(3.13)		
Log(Firm average experience)			0.131				0.106	
			(1.39)				(1.03)	
Log(Firm average individual fixed effect)				-0.0429				-0.0745
				(-0.75)				(-1.21)
Observation	189871	189871	189871	189871	148313	148313	148313	148313

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 12 Different spillover source for imitation controlling human capital

	Non-MNEs with patent history							
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.562**	0.381	0.558**	0.598**				
	(2.29)	(1.53)	(2.26)	(2.40)				
MNEs in the same industry	1.379**	1.434**	1.400**	1.195*				
	(1.97)	(2.13)	(1.97)	(1.67)				
MNEs in the relevant industry	0.0638	-0.0103	0.0523	0.170				
	(0.10)	(-0.02)	(0.08)	(0.27)				
MNEs in other industry	0.0962	0.0288	0.0852	0.177				
	(0.29)	(0.09)	(0.26)	(0.52)				
Non-MNEs (lagged)					0.564*	0.360	0.565*	0.570*
					(1.92)	(1.22)	(1.93)	(1.92)
MNEs in the same industry (lagged)					-0.243	-0.320	-0.221	-0.351
					(-0.34)	(-0.43)	(-0.31)	(-0.49)
MNEs in the relevant industry (lagged)					1.693***	1.638***	1.685***	1.726***
					(3.02)	(2.92)	(3.00)	(3.08)
MNEs in other industry (lagged)					0.211	0.238	0.191	0.420
					(0.47)	(0.59)	(0.43)	(0.99)
Log(R&D workers)	0.493***	0.444***	0.492***	0.612***	0.475***	0.385***	0.473***	0.598***
	(4.67)	(4.09)	(4.63)	(4.41)	(4.47)	(3.34)	(4.44)	(4.49)
Log(Physical asset)	0.0345	0.0394	0.0325	0.0651	0.0524	0.0887	0.0503	0.0858
	(0.94)	(0.91)	(0.84)	(1.41)	(1.18)	(1.51)	(1.11)	(1.62)
Log(Firm average education)		1.507**				2.446***		
		(1.97)				(2.66)		
Log(Firm average experience)			0.0368				0.0494	
			(0.29)				(0.40)	
Log(Firm average individual fixed effect)				-0.143*				-0.151*
				(-1.65)				(-1.91)
Log(FE)	0.524***	0.513***	0.521***	0.534***	0.571***	0.542***	0.567***	0.577***
	(4.53)	(4.44)	(4.44)	(4.60)	(4.86)	(4.58)	(4.77)	(4.94)
Observation	4312	4312	4312	4312	3679	3679	3679	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 13 Different spillover source for novel innovation controlling human capital

	Non-MNEs with no patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.892***	0.490***	0.781***	0.808***				
	(7.32)	(4.06)	(6.23)	(6.33)				
MNEs in the same industry	0.0562	0.243	0.120	0.118				
	(0.11)	(0.49)	(0.24)	(0.23)				
MNEs in the relevant industry	0.343	0.0266	0.252	0.255				
	(0.84)	(0.07)	(0.62)	(0.63)				
MNEs in other industry	1.115***	0.743***	1.015***	1.028***				
	(6.62)	(4.44)	(5.96)	(5.88)				
Non-MNEs (lagged)					1.121***	0.821***	1.054***	1.077***
					(8.27)	(6.22)	(7.67)	(7.82)
MNEs in the same industry (lagged)					-0.428	-0.356	-0.407	-0.403
					(-0.76)	(-0.65)	(-0.73)	(-0.72)
MNEs in the relevant industry (lagged)					0.951***	0.756**	0.907**	0.909**
					(2.61)	(2.10)	(2.49)	(2.49)
MNEs in other industry (lagged)					1.183***	0.912***	1.125***	1.141***
					(5.14)	(4.09)	(4.95)	(4.96)
Log(R&D workers)	0.467***	0.321***	0.428***	0.384***	0.467***	0.330***	0.438***	0.412***
	(11.39)	(6.69)	(9.58)	(6.91)	(10.32)	(6.35)	(8.98)	(6.80)
Log(Physical asset)	0.0431***	0.00685	0.0300**	0.0284**	0.0482***	0.0137	0.0373**	0.0370**
	(3.44)	(0.56)	(2.32)	(2.12)	(3.31)	(0.98)	(2.50)	(2.36)
Log(Firm average education)		0.637***				0.680***		
		(8.64)				(7.03)		
Log(Firm average experience)			0.142***				0.118**	
			(3.45)				(2.53)	
Log(Firm average individual fixed effect)				0.0726***				0.0503*
				(2.72)				(1.73)
Observation	189871	189871	189871	189871	148313	148313	148313	148313

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 14 Different spillover source for novel innovation controlling human capital

	Non-MNEs with patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.545***	0.419***	0.527***	0.539***				
	(3.57)	(2.82)	(3.47)	(3.56)				
MNEs in the same industry	-0.281	-0.147	-0.236	-0.268				
	(-0.49)	(-0.26)	(-0.41)	(-0.47)				
MNEs in the relevant industry	0.0259	-0.0964	-0.00969	0.0122				
	(0.07)	(-0.26)	(-0.03)	(0.03)				
MNEs in other industry	0.352	0.260	0.326	0.344				
	(1.32)	(0.99)	(1.22)	(1.30)				
Non-MNEs (lagged)					0.498***	0.376**	0.488***	0.496***
					(2.74)	(2.12)	(2.71)	(2.74)
MNEs in the same industry (lagged)					-0.795	-0.654	-0.738	-0.788
					(-1.27)	(-1.04)	(-1.18)	(-1.26)
MNEs in the relevant industry (lagged)					0.501	0.406	0.477	0.497
					(1.16)	(0.92)	(1.10)	(1.15)
MNEs in other industry (lagged)					0.793***	0.668**	0.739***	0.783***
					(2.96)	(2.52)	(2.72)	(2.87)
Log(R&D workers)	0.0855	0.0368	0.0826	0.0700	0.0611	0.00861	0.0579	0.0519
	(1.44)	(0.62)	(1.39)	(1.02)	(0.92)	(0.13)	(0.87)	(0.69)
Log(Physical asset)	0.0597**	0.0516**	0.0519**	0.0541*	0.0755**	0.0712**	0.0667**	0.0719*
	(2.36)	(1.96)	(1.97)	(1.80)	(2.30)	(2.07)	(1.96)	(1.82)
Log(Firm average education)		0.694***				0.740***		
		(4.36)				(3.84)		
Log(Firm average experience)			0.110				0.135*	
			(1.60)				(1.69)	
Log(Firm average individual fixed effect)				0.0218				0.0133
				(0.48)				(0.25)
Log(FE)	0.414***	0.414***	0.412***	0.413***	0.429***	0.425***	0.425***	0.428***
	(6.88)	(6.91)	(6.89)	(6.91)	(6.58)	(6.54)	(6.58)	(6.63)
Observation	4312	4312	4312	4312	3679	3679	3679	3679

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies

Table 15 Patent application in different industries

Industries	Patent application	Percentage
Agriculture, forestry and fishing	2,137	0.61%
Mining and quarrying	6,777	1.93%
Manufacturing	218,989	62.39%
Electricity, gas, steam and air conditioning supply	227	0.06%
Water supply; sewerage, waste management and remediation activities	87	0.02%
Construction	434	0.12%
Wholesale and retail trade; repair of motor vehicles and motorcycles	8,624	2.46%
Transportation and storage	33	0.01%
Accommodation and food service activities	13	0.00%
Information and communication	5,417	1.54%
Financial and insurance activities	65	0.02%
Real estate activities	149	0.04%
Professional, scientific and technical activities	51,904	14.79%
Administrative and support service activities	330	0.09%
Public administration and defence; compulsory social security	0	0.00%
Education	45	0.01%
Human health and social work activities	104	0.03%
Arts, entertainment and recreation	32	0.01%
Other service activities	71	0.02%
Activities of households as employers; undifferentiated goods- and sevices-producing activities of households for own use	0	0.00%
Activities of extraterritorial organisations and bodies	55,586	15.84%
Total	351,024	100%

Swedish Standard Industrial Classification 2007 is based on EU:s recommended standard NACE Rev.2. It is primary an activity classification. Production units as companies and local units are classified after the activity which is carried out. One company or a local unit can have several activities (SNI-codes).

Table 16 Different spillover source for imitation controlling human capital (three high-tech industries)

	Non-MNEs with no patent history							
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	1.015***	0.274	0.904***	1.067***				
	(4.24)	(1.23)	(3.78)	(4.36)				
MNEs in the same industry	-0.843	-0.747	-0.719	-0.915				
	(-0.88)	(-0.77)	(-0.75)	(-0.95)				
MNEs in the relevant industry	1.136*	0.890	1.039	1.190*				
	(1.78)	(1.38)	(1.63)	(1.88)				
MNEs in other industry	2.257***	1.678***	2.145***	2.316***				
	(6.37)	(4.96)	(6.04)	(6.28)				
Non-MNEs (lagged)					1.530***	0.750**	1.442***	1.603***
					(5.62)	(2.53)	(5.16)	(5.60)
MNEs in the same industry (lagged)					-1.792	-1.942	-1.748	-1.860
					(-1.35)	(-1.55)	(-1.33)	(-1.38)
MNEs in the relevant industry (lagged)					2.076***	2.052***	2.022***	2.137***
					(3.26)	(3.17)	(3.18)	(3.37)
MNEs in other industry (lagged)					2.377***	1.728***	2.285***	2.458***
					(5.48)	(4.08)	(5.28)	(5.41)
Log(R&D workers)	0.844***	0.688***	0.821***	0.893***	0.869***	0.726***	0.847***	0.949***
	(10.65)	(8.62)	(9.98)	(7.94)	(11.39)	(8.12)	(10.97)	(9.30)
Log(Physical asset)	0.0721**	0.107*	0.0581*	0.0833**	0.0640*	0.151**	0.0509	0.0822*
	(2.00)	(1.71)	(1.70)	(2.05)	(1.70)	(2.51)	(1.33)	(1.69)
Log(Firm average education)		7.301***				10.53***		
		(3.17)				(8.89)		
Log(Firm average experience)			0.177*				0.188*	
			(1.85)				(1.95)	
Log(Firm average individual fixed effect)				-0.0500				-0.0828
				(-0.83)				(-1.22)
Observation	75218	75218	75218	75218	57851	57851	57851	57851

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies. Firms belongs to the following industries: manufacturing, professional, scientific and technical activities, activities of extraterritorial organizations and bodies.

Table 17 Different spillover source for imitation controlling human capital (three high-tech industries)

	Non-MNEs with patent history							
Dependent variable: imitation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.533**	0.346	0.532**	0.575**				
	(2.07)	(1.32)	(2.07)	(2.20)				
MNEs in the same industry	1.260*	1.327*	1.266*	1.044				
	(1.80)	(1.90)	(1.77)	(1.45)				
MNEs in the relevant industry	0.147	0.0400	0.145	0.250				
	(0.24)	(0.07)	(0.23)	(0.41)				
MNEs in other industry	0.141	0.115	0.139	0.237				
	(0.37)	(0.30)	(0.36)	(0.60)				
Non-MNEs (lagged)					0.484	0.244	0.485	0.485
					(1.56)	(0.79)	(1.57)	(1.55)
MNEs in the same industry (lagged)					-0.215	-0.430	-0.202	-0.338
					(-0.29)	(-0.52)	(-0.27)	(-0.45)
MNEs in the relevant industry (lagged)					1.696***	1.678***	1.692***	1.716***
					(3.01)	(2.93)	(3.00)	(3.03)
MNEs in other industry (lagged)					0.294	0.504	0.282	0.581
					(0.57)	(1.04)	(0.54)	(1.24)
Log(R&D workers)	0.543***	0.492***	0.543***	0.692***	0.519***	0.422***	0.518***	0.666***
	(5.44)	(4.69)	(5.38)	(5.39)	(5.41)	(3.86)	(5.35)	(5.81)
Log(Physical asset)	0.0267	0.0319	0.0261	0.0628	0.0433	0.0838	0.0420	0.0799
	(0.74)	(0.74)	(0.70)	(1.32)	(1.02)	(1.41)	(0.97)	(1.50)
Log(Firm average education)		1.639				2.949**		
		(1.62)				(2.58)		
Log(Firm average experience)			0.00993				0.0299	
			(0.07)				(0.24)	
Log(Firm average individual fixed effect)				-0.175**				-0.176**
				(-1.97)				(-2.26)
Log(FE)	0.465***	0.460***	0.464***	0.474***	0.518***	0.495***	0.516***	0.522***
	(4.04)	(3.99)	(3.98)	(4.11)	(4.46)	(4.23)	(4.41)	(4.53)
Observation	3051	3051	3051	3051	2596	2596	2596	2596

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies. Firms belongs to the following industries: manufacturing, professional, scientific and technical activities, activities of extraterritorial organizations

Table 18 Different spillover source for novel innovation controlling human capital (three high-tech industries)

	Non-MNEs with no patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.984***	0.554***	0.862***	0.892***				
	(7.04)	(4.01)	(5.99)	(6.07)				
MNEs in the same industry	0.291	0.526	0.375	0.361				
	(0.52)	(0.97)	(0.67)	(0.64)				
MNEs in the relevant industry	0.419	0.106	0.325	0.330				
	(0.94)	(0.24)	(0.73)	(0.74)				
MNEs in other industry	1.192***	0.789***	1.079***	1.097***				
	(5.79)	(3.88)	(5.18)	(5.15)				
Non-MNEs (lagged)					1.238***	0.915***	1.164***	1.187***
					(8.11)	(6.21)	(7.50)	(7.64)
MNEs in the same industry (lagged)					-0.447	-0.376	-0.420	-0.415
					(-0.72)	(-0.63)	(-0.68)	(-0.67)
MNEs in the relevant industry (lagged)					1.263***	1.074***	1.218***	1.216***
					(3.46)	(3.00)	(3.35)	(3.32)
MNEs in other industry (lagged)					1.136***	0.841***	1.069***	1.086***
					(3.97)	(3.05)	(3.78)	(3.80)
Log(R&D workers)	0.462***	0.309***	0.421***	0.374***	0.465***	0.322***	0.435***	0.404***
	(10.15)	(5.88)	(8.56)	(6.11)	(9.43)	(5.69)	(8.16)	(6.08)
Log(Physical asset)	0.0419***	0.00366	0.0273*	0.0260	0.0511***	0.0147	0.0387**	0.0380**
	(2.78)	(0.25)	(1.78)	(1.62)	(2.91)	(0.87)	(2.20)	(2.03)
Log(Firm average education)		0.692***				0.743***		
		(7.24)				(6.03)		
Log(Firm average experience)			0.157***				0.131**	
			(3.33)				(2.55)	
Log(Firm average individual fixed effect)				0.0780**				0.0578*
				(2.47)				(1.72)
Observation	75218	75218	75218	75218	57851	57851	57851	57851

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies. Firms belongs to the following industries: manufacturing, professional, scientific and technical activities, activities of extraterritorial organizations and bodies.

Table 19 Different spillover source for novel innovation controlling human capital (three high-tech industries)

	Non-MNEs with patent history							
Dependent variable: novel innovation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of workers with experience from								
Non-MNEs	0.645***	0.527***	0.632***	0.643***				
	(4.03)	(3.33)	(3.97)	(4.03)				
MNEs in the same industry	-0.201	-0.0643	-0.157	-0.197				
	(-0.33)	(-0.11)	(-0.26)	(-0.32)				
MNEs in the relevant industry	0.192	0.0750	0.163	0.188				
	(0.50)	(0.19)	(0.42)	(0.49)				
MNEs in other industry	0.167	0.0967	0.144	0.165				
	(0.53)	(0.31)	(0.45)	(0.52)				
Non-MNEs (lagged)					0.362*	0.243	0.355*	0.362*
					(1.68)	(1.16)	(1.66)	(1.69)
MNEs in the same industry (lagged)					-0.807	-0.673	-0.759	-0.805
					(-1.22)	(-1.01)	(-1.15)	(-1.21)
MNEs in the relevant industry (lagged)					0.496	0.412	0.480	0.495
					(1.15)	(0.95)	(1.11)	(1.15)
MNEs in other industry (lagged)					0.899***	0.778***	0.853***	0.895***
					(3.11)	(2.70)	(2.88)	(3.02)
Log(R&D workers)	0.106	0.0565	0.103	0.101	0.0829	0.0289	0.0794	0.0790
	(1.63)	(0.86)	(1.58)	(1.38)	(1.12)	(0.39)	(1.08)	(0.97)
Log(Physical asset)	0.0449*	0.0374	0.0384	0.0433	0.0595*	0.0557	0.0527	0.0581
	(1.70)	(1.37)	(1.39)	(1.38)	(1.66)	(1.51)	(1.41)	(1.35)
Log(Firm average education)		0.626***				0.662***		
		(3.70)				(3.21)		
Log(Firm average experience)			0.0962				0.107	
			(1.27)				(1.23)	
Log(Firm average individual fixed effect)				0.00652				0.00548
				(0.14)				(0.10)
Log(FE)	0.349***	0.350***	0.348***	0.349***	0.349***	0.346***	0.346***	0.349***
	(5.67)	(5.69)	(5.67)	(5.68)	(5.38)	(5.32)	(5.36)	(5.40)
Observation	3051	3051	3051	3051	2596	2596	2596	2596

Note: *** denotes 0.1% significance; ** denotes 1% significance; * denotes 5% significance. Estimation is by constant dispersion Negative Binomial Regression with robust standard errors. The number of R&D workers, Physical asset, firm average education, firm average experience and average individual fixed effect are the logarithm of the real number plus one. All regressions include year and industry and region dummies. Firms belongs to the following industries: manufacturing, professional, scientific and technical activities, activities of extraterritorial organizations and bodies.