Essays on entrepreneurship, worker mobility and firm performance

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Chapter 4

Productivity Spillovers of High-productivity Firms through Worker Mobility

4.1 Introduction

Labor mobility has been considered as one of the major sources of knowledge diffusion (see, e.g. Almeida and Kogut (1999); Guarino and Tedeschi (2006); Kim and Marschke (2005); Stoyanov and Zubanov (2012)). Knowledge transfers across firms through labor mobility can generate positive productivity spillovers. When workers move from more to less productive firms, the receiving firm can move closer to the best practice by exploiting the knowledge the workers bring along. There are two mechanisms how labor mobility can increase productivity. Knowledge transfer from new employees to incumbent workers leads to a higher quality of human capital in the receiving firm, thereby increasing its productivity. Alternatively, labor mobility increases the likelihood of a good match between the tasks at hand and workers' skills. The allocation of workers to the 'right' job will increase firm efficiency and labor productivity. Therefore, labor mobility is expected to have a positive impact on the productivity of enterprises.

When workers move from one firm to another they bring obtained knowledge and experience to the receiving firm. Several studies, such as Almeida and Kogut (1999); Oettl and Agrawal (2008) and Görg and Strobl (2005), confirm that knowledge flows follow workers as they move to a new enterprise. In a recent study, Stoyanov and Zubanov (2012) examine how the productivity gains are distributed between the hiring firms, the incumbent employees and the new employees. They find that the receiving firms benefit most from labor mobility. This is consistent with the findings of Balsvik (2011), who shows that the private returns to switching workplace are smaller than the productivity effect at the plant level.

This chapter provides new empirical evidence on the effects of worker mobility by building on previous efforts in this area. I examine the hypothesis that hiring workers from high-productivity firms increases the productivity of hiring firms. This hypothesis was first tested by Stoyanov and Zubanov (2012) for Denmark. In this study I apply a similar approach as Stoyanov and Zubanov (2012) for the Dutch manufacturing sector, using an employer-employee dataset which is matched with the administrative records of firms in the manufacturing sector. These data allow me to study the labor flows across firms during 1999 to 2013. My results suggest that enterprises that hired workers from high-productivity firms experience an increase in their productivity after one year. I find no significant effect associated with workers coming from less productive firms. Furthermore, I find that hiring workers within the same sector diffuses more knowledge and skills than hiring workers from other sectors.

This study contributes to the literature by explicitly considering the role of worker mobility in the knowledge spillover from high-productivity firms to receiving enterprises. As knowledge broadly defined includes different components such as experience and education, I distinguish between these two components and estimate the effect of experience while controlling for workers' education level. To the best of my knowledge, this study is the first to analyze knowledge spillovers through labor mobility for the case of the Netherlands.

The structure of this chapter is as follows. Section 4.2 discusses the theoretical underpinnings of the relationship between worker mobility and firm productivity. I also develop my hypotheses here and lay the groundwork for the econometric specification introduced in Section 4.3. This section also presents the data. Section 4.5 offers the empirical results, while Section 4.6 concludes.

4.2 Literature review

A vast literature studies the productivity effects of knowledge transfer across firms and industries. Arrow (1962) is one of the first to introduce the theory of learning-by-doing. However, it was Romer (1986) who explained the actual mechanism of knowledge transmission across establishments and individuals. He suggests that knowledge spillovers from private research will improve public knowledge and therefore intensify growth.

A common proxy for knowledge is patents or patent citations. Griliches (1992) and

Jaffe et al. (1993) study the diffusion of knowledge among firms using each other's patents. Given that knowledge is not only embedded in patents and is partly tacit, worker mobility can be considered as the most effective channel for knowledge spillovers. More precisely, Almeida and Kogut (1999) suggest that the combination of a high rate of mobility and skilled workers together accounts for knowledge spillovers. A number of studies confirm this view: employing workers with valuable experience positively impacts the hiring firm's productivity.

There are two lines of research explaining knowledge diffusion. The first strand of literature primarily focuses on R&D (research and development) workers as a source of knowledge spillovers. In particular, Cooper (2001) and Gersbach and Schmutzler (2003) propose theoretical models of labor mobility as a channel of R&D spillover. Cooper (2001) presents a two-period model of a competitive industry were employees may capitalize on knowledge acquired on the job by moving to rival enterprises. Gersbach and Schmutzler (2003) develop a new approach to endogenizing technological spillovers by analyzing a game in which firms can first invest in R&D and then compete in the labor market for their trained workers. They show that technological spillovers is coincide with total industry profit. They argue innovation incentives for endogenous spillovers are usually stronger than exogenous spillovers.

The second strand of literature focuses on multinationals' R&D investment and knowledge transfer across countries. For instance, Fosfuri et al. (2001) analyze a model where a multinational invests in training of local managers to compete with domestic firms. According to their model, technological spillovers arise when such managers migrate to a domestic firm. Glass and Saggi (2002) reach a comparable conclusion based on their model of inter-firm knowledge diffusion through worker mobility. Finally, Dasgupta (2012) studies a dynamic general equilibrium model with perfect mobility of workers among countries, in which the long-term dynamic learning process plays a crucial role.

The number of empirical studies attempting to identify the mechanisms behind R&D spillovers via labor mobility is rather limited. Kaiser et al. (2015), using Danish data, show that hiring R&D workers is positively associated with the receiving firms' innovation and patent applications. A similar conclusion was drawn by Maliranta et al. (2009) for Finnish firms. Kim and Marschke (2005) show theoretically and empirically that the departure of scientists reduces firms' R&D expenditure and hence firms use patenting to minimize the harm caused by departing scientists. Møen (2005) argues that R&D is also a learning process for employees involved. Using Norwegian machinery and equipment industry data, he finds that technical workers in R&D-intensive firms pay for the accumulation of knowledge on the job by receiving lower wages at the beginning of their careers in anticipation of future higher wages. His findings confirm the importance of the factor of experience in worker mobility as an important channel of knowledge spillovers within and across firms. Magnani (2006) replicates and extends Møen (2005)'s approach for US manufacturing sectors. Although his results provide some support for Møen's findings, he finds little evidence for low wages in US R&D intensive industries at early stages of employment. However, this weak support for Møen's finding could be driven by the use of aggregated data at two digit R&D industry level, as opposed to the firm level data used by Møen. Fallick et al. (2006) show that high mobility of labor in Silicon Valley's computer industry facilitates the reallocation of resources towards firms with the best innovations and hence increase their performance.

There is also literature focusing on the experience of mobile workers as a factor in knowledge spillovers and innovation. Thulin (2009) studies the effect of labor mobility on regional wage growth in Sweden and finds positive effects. Serafinelli (2013) examines the effect of worker inflows from high-paying enterprises on receiving firms' productivity in Italy and confirms a positive association. Song et al. (2003) suggest tat knowledge transfer through hiring engineers from US to non-US firms happens when hiring firms are less path dependent and are located in non-core technological areas and when the hired engineers possess technological expertise distant from that of the hiring firm. Rosenkopf and Almeida (2003) reinforce these findings for the US semiconductor industry by showing that the knowledge diffusion via labor mobility increases with the technological distance between firms. Rao and Drazin (2002) point out that young and/or poorly connected firms in the US tend to hire former employees of their large counterparts and industry veterans which boost their productivity. Mion and Opromolla (2014) find that hiring managers with export experience in previous firms causes a better export performance of the hiring enterprises. Finally, Power and Lundmark (2004) show that the high mobility of certain ICT specialists in the Stockholm region increases firm performance.

The study by Stoyanov and Zubanov (2012) comes closest to this study. Tracking the flows in Danish manufacturing firms, these authors find that the productivity gains associated with hiring from more productive firms are equivalent to 0.35 percent per year for an average firm. Moreover, Poole (2013) studied labor flows in the Brazilian manufacturing sector, and examines the wage impact for incumbent workers. She finds a positive effect on incumbent workers' wages, attributable to their increased productivity due to the hiring of workers with multinational expertise.

In this chapter, I extend the literature by building on the model proposed by Stoyanov and Zubanov (2012)) and using a unique dataset for the Netherlands. Based on the findings in the earlier literature, I expect to find a positive association between hiring workers from high-productivity firms and the hiring firms' productivity.

Hypothesis: *Hiring workers from high-productivity firms increases the receiving firms' productivity.*

4.3 Data and Methodology

4.3.1 Data

The dataset used for this study is provided by Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS). The firm data come from the Business Register (ABR), which incorporates the whole population of firms and includes annual statistics on the number of employees, detailed industry codes of the establishment and its location. I merge the Business Register data with data from the Production Statistics surveys (PS-

Industry and PS-Service) as well as the SFGO[1] and SFKO[2] databases to extract balance sheet and revenue data, most notably turnover, value added, capital and the wage bill.

The worker data come from the Municipal Personal Records Database (GBA)[3] matched with the BAANKENMERENBUS and BAANSOMMENTAB surveys to link workers to their employers using the unique identification numbers for firms and persons. The data contains information on employment status, in particular, the employer, the type of contract, the number of days worked, the starting date of employment, and the annual wage received. Importantly, it also includes a dummy variable (Job) equal to one if a worker is hired for a new job, either in the same company or in a new firm. I define mobile workers as those employees with a new job in a new firm. Finally, the skill level of the labour force is made available via the source Educational Level (HOOGSTEOPLTAB) which utilizes the International Standard Classification of Education (ISCED) maintained by the United Nations.

I started with a panel data set including all workers in the manufacturing and service sectors. I dropped all part time workers (defined as people with a work contract for less than 75% of a full-time equivalent) and those with very low wages or for whom no wage was reported. I also dropped employees with flexible hour contracts.[4] Next, I eliminated those workers who changed job more than once in a year.[5] Finally, I aggregated the data to the firm level. Unlike Stoyanov and Zubanov (2012)), the data used in this study covers all manufacturing and service firms, and therefore it covers not only workers moving within manufacturing but also those moving from service sectors to manufacturing sectors. The final sample is an unbalance matched employee-employment panel data set of the Dutch manufacturing sector covering the years 1999 to 2013.

[1] Statistiek financiën grote ondernemingen, in Dutch.

[2] Statistiek financiën kleine ondernemingen, in Dutch. As of 2000, SFGO and SFKO have been merged into a single data set called the NFO-statistics on finances of non-financial enterprises (NFO-statistiek financiën van niet-financiële ondernemingen in Dutch).

[3] Gemeentelijke basisadministratie persoonsgegevens in Dutch.

[4] Workers with flexible hours contract are reported as employees who have a contract but without a fixed number of working hours; firms use them whenever they are needed. For these jobs, wages can fluctuate heavily depending on the number of times they are called in.

[5] Workers who are reported as a new worker more than once during one year.

4.3.2 Methodological Approach

To examine whether and to what extent productivity growth is caused by movement of labor across firms, I closely follow the methodological approach of Stoyanov and Zubanov (2012). I identify the spillover based on the relationship between hiring workers from high-productivity firms and the labor productivity of the receiving firms. To study the receiving firms' productivity, I use the following dynamic model:

$$A_{it+1} = \gamma_1 A_{it} + \gamma_2 A_{it-1} + \gamma_3 A_{it-2} + \gamma_4 A_{it-3} + \alpha Gap_{it-1} + \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{it} + \tau_{st} + \varepsilon_{it} \quad (4.1)$$

In line with the literature (see, e.g Havranek and Irsova (2012)), firm productivity (A_{it}) is proxied by either the natural logarithm of turnover per employee or value added per employee. Both turnover and value added per employee are standard measurements of labor productivity, and by using two proxies I can assess the robustness of the results. I normalize each productivity measure by the applicable industry-year average respectively.[6] The normalization ensures that labor productivity of each firm is define relative to the average of productivity for a given industry per year. As productivity tends to be persistent, I add 4 lags of the outcome variable based on residual autocorrelation. I find empirically adding 4 lags of productivity reduces residuals autocorrelation to a negligible level. In addition, the lagged productivity levels help to absorb any productivity shock that drives the decision to hire new workers in the first place, which would otherwise be mistakenly identified as a spillover effect.

The main variable of interest, Gap_{it-1}, is the productivity gap between sending and receiving firms and it is calculated for each firm i hiring workers in year t as follows:

[6] Industry is defined at the 5-digit level of the NACE classification.

$$Gap_{it-1} = \left(\frac{\sum_{j=1}^{H_{it}} A^s_{jt-1} - A^r_{it-1}}{H_{it}}\right)\left(\frac{H_{it}}{N_{it}}\right)$$

Where A^s_{jt-1} and A^r_{it-1} are the normalized productivity levels of the sending and receiving firms in year $t-1$ (one year before hiring) and H_{it} and N_{it} are the number of new employees and total number of employees of the receiving firm, respectively. In words, the Gap variable is the difference in productivity between sending and receiving firms, averaged over all recruitments. It is positive whenever the receiving firm attracts new employees from more productive firms, zero whenever the firm does not hire any new workers (or in the knife-edge case of hiring from sending firms with exactly the same productivity level), and negative if the new workers come from less productive firms.

Furthermore, to account for other sources of productivity gains, I add a number of controls in equation 4.1, as in Stoyanov and Zubanov (2012). X_{it} is a vector of firms' characteristics, such as the number of employees, the number of newly hired workers relative to total employment and the natural logarithm of the capital labor ratio. Y_{it} is a vector of incumbent workers' characteristics and includes average skill, average age, percentage of female workers and the average number of years of work experience. Z_{it} is a vector of the same characteristics of newly hired workers. These variables control unobserved productivity shocks in the receiving firm. Finally, to account for unobserved industry-specific time-varying effects I include a full set of industry-time fixed effects τ_{st} based on 3 digit industries. ε is the disturbance terms. The inclusion of all control variables are in line with the Stoyanov and Zubanov (2012).

The coefficient α measures the average spillover effect from hiring new employees from more productive firms. To test whether hiring from more productive firms has different spillover effects compared to hiring from less productive firms, I calculate positive and negative productivity gaps separately for new employees hired from more or less productive sending enterprises:

$$Gap_{it-1}^{Positive} = \frac{\sum_{j=1}^{H_{it}} D_{jt}(A_{jt-1}^{s} - A_{it-1}^{r})}{H_{it}} \frac{H_{it}}{N_{it}}$$
$$Gap_{it-1}^{Negative} = \frac{\sum_{j=1}^{H_{it}} (1 - D_{jt})(A_{jt-1}^{s} - A_{it-1}^{r})}{H_{it}} \frac{H_{it}}{N_{it}}$$

where D_{jt} is an indicator variable equal to one if the sending firm is more productive than the receiving firm, and zero otherwise. The extended version of equation 4.1 becomes:

$$A_{it+1} = \gamma_1 A_{it} + \gamma_2 A_{it-1} + \gamma_3 A_{it-2} + \gamma_4 A_{it-3} + \alpha_1 Gap_{it-1}^{Positive} + \alpha_2 Gap_{it-1}^{Negative} + \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 Z_{it} + \tau_{st} + \varepsilon_{it} \quad (4.2)$$

Knowledge can be general or specific to a particular firm or industry. Moreover, workers are more likely to move in the same or related industry as they might have better job opportunities using prior obtained technological knowledge. Therefore, I differentiate between the gap calculated for workers moving within the same industry (two-digit NACE classification), and those moving between industries. This allows me to test whether, and to what extent, this knowledge can overcome technological barriers between different sectors and industries. In this case, the model will be as follows:

$$A_{it} = \gamma A_{it-1} + \alpha_1 Gap_{it-1}^{Diff} + \alpha_2 Gap_{it-1}^{Same} + \beta_1 X_{it} + \beta_2 Z_{it} + \tau_{st} + \varepsilon_{it} \quad (4.3)$$

where $Gapit - 1^{Diff}$ and $\alpha_2 Gapit - 1^{Same}$ are productivity gaps for workers moving within and between industries weighted by their share in the receiving firms employees and they are defined as:

$$Gap^{Same}_{it-1} = \frac{\sum_{j=1}^{H_{it}} (I^{same}_{jt})(A^{s}_{jt-1} - A^{r}_{it-1})}{N_{it}}$$
$$Gap^{Diff}_{it-1} = \frac{\sum_{j=1}^{H_{it}} (1 - I^{same}_{jt})(A^{s}_{jt-1} - A^{r}_{it-1})}{N_{it}}$$

I^{same}_{jt} is an indicator variable equal to one if worker n moves from firm j to firm i within the same industry and zero otherwise. This model is similar to that of Stoyanov and Zubanov (2012). Finally, I extend the equation 4.3 by differentiating hiring from more and less productive firms in the same or from different industries:

$$A_{it} = \gamma A_{it-1} + \alpha_1 GapPositive^{Diff}_{it-1} + \alpha_2 GapNegative^{Diff}_{it-1} + \alpha_3 GapPositive^{Same}_{it-1} + \alpha_4 GapNegative^{Same}_{it-1} + \beta_1 X_{it} + \beta_2 Z_{it} + \tau_{st} + \varepsilon_{it} \quad (4.4)$$

In addition, I estimate the above equations separately for large firms (i.e., number of employees $\geq$ 50) and small firms (number of employees $<$ 50). One reason why large firms might benefit more from knowledge spillovers is that hiring firms are relatively larger (58 employees) than non-hiring firms (about 6 employees). Moreover, larger firms are more likely to be run by better managers (Lucas (1978)). Better management can help facilitate the application of knowledge of newly hired employees resulting in higher levels of productivity. I also distinguish between young and old firms. In particular, start-ups are found to have a powerful impact on productivity and job creation. In particular, firms younger than 5 years are found to be job creators, while older firms might be job destroyers (Haltiwanger et al. (2013)), hence start-ups have a considerable share in hiring. Moreover, as start-ups and young firms are new, they are less likely to be affect by productivity shocks for their hiring choices.

4.4 Descriptive Analysis

Table 4.1 presents the descriptive statistics measured at the worker level. The results reported in this table cover the labor force of the manufacturing sector in the Netherlands between 1999 and 2013.[7] As one can see from Table 4.1, the average hiring rate is 13.8 %, while 2.9 % of the new employees have been hired from more productive firms. The average age of the job stayer (existing workers) is 40.5 years; about 28% of them are female. The majority of stayers are middle skilled and the rest is almost equally divided between low- and high-skilled workers.[8] In comparison, new workers are on average 32 years old and about 8 years younger than stayers, and they are more likely to belong to the mid-skilled group of workers. This could be due to the young age of this group and the chance of obtaining higher education during study. Since, about 20% of the workers in the sample is aged between 18 and 25, some of these newly hired workers may not be job changers but may have recently entered the labor force. This can affect their reported education and skill levels.[9] Stayers on average have approximately 7 years of work experience (two years above the average job experience of the sample) while newly hired workers on average have 2 years of experience. However, workers who are coming from more productive firms have on average about 4 years of job experience and only 21 % are female. The average yearly wage of the stayer is about 14% higher than that of newly hired employees. This can partly be due to age of the new hires (and hence less job experience). Additionally, employees hired from more productive firms receive on average 3% more than stayers and their wages are 6 % higher than the average wage paid in the manufacturing sector. This wage premium is consistent with that reported by Stoyanov and Zubanov (2012) for the Danish workforce, and the hypothesis that firms try to attract workers from more productive firms by offering higher wages.

As shown in Table 4.2, the Dutch manufacturing firms with no hiring are small and

[7] The number of worker-year observations in the total sample is about 84.1 million, out of which about 7.4 million refer to the manufacturing sector.

[8] In this study, I define skilled worker as workers who have tertiary education, bachelor, master, doctoral or equivalent (see Appendix A for more details).

[9] I focus on job changers while controlling of new hired workers ratio.

Table 4.1. Summary Statistics for Workers

Variable	Sample	Stayer	New Hire	H More pro
Age	39.4	40.5	31.97	37.6
Low-skilled	29.6	29.9	29.4	26.2
Mid-Skilled	42.3	39.1	44.5	46.4
High-Skilled	28.1	31	26.1	27.4
Experience (year)	5.03	7.01	2.03	4.32
Female(manufacturing's labor)	26.4	27.6	25.5	21.3
Female(whole labor force)	40.5			
Labor hiring ratio (%)			13.8	2.9
ln(wage)	10.42	10.45	10.31	10.48
ln(value added)	3.90	3.96	3.87	3.95
ln(turnover)	4.92	4.97	4.89	4.94

Worker-year observation of Manufacturing is about 7,4 million.

have an average size of 6 employees who have a low wage premium. Hiring firms appear to be more productive than firms with no hiring. The value added and turnover per employee are higher for manufacturers hiring from more productive firms. Moreover, the yearly wage per employee offered by hiring firms is higher than those with no hiring. Firms with hiring from more productive firms offer higher wages than those hiring from less productive firms.

Table 4.2. Summary Statistics for Manufacturing Firms

Variable	Sample	No Hiring	Stayer	Hiring Superior	Hiring Inferior
ln(value added)	3.91	3.64	3.96	3.95	3.85
ln(turnover)	4.91	4.85	4.96	4.94	4.89
ln(wage)	10.41	10.32	10.45	10.46	10.39
Experience (year)	4.38	4.51	7.61	4.32	4.01
Firm size (labor)	29.5	5.7			

The number of firm-year observations for manufacturing is 232,377. Hiring firms on average have about 58.43 employees and sending firms have on average 45.47 employees.

One can see from Table 4.3 that Dutch manufacturing firms are in existence on average 10 years since their establishment and employ on average about 29 employees with an average age of 38, of which 33% are highly skilled workers and 26 percent are female.[10] The employees on average have 5.03 years of work experience in the same company while newly hired staff on average worked 2.03 years with their previous employer. Moreover, sending firms have about 45 employees on average. Hiring firms on average hired 5 new workers during the sample period, with an average age of 32, of which 28 % are female.

[10] The description and data sources of the variables and the pairwise correlation matrix of all variables is presented in Table 4.A.2 in Appendix A.

Table 4.3. Summary Statistics

Variable	Description	Mean	Std.	Min	Max
$Gap^{Turnover}$	Difference between sending and receiving firms' productivity	-0.168	0.979	-8.966	6.978
Gap^{Value}	Difference between sending and receiving firms' productivity	-0.234	0.818	-5.476	6.413
$Gap^{Turnover}$ *Positive*	Productivity gap if sending firm has higher productivity	.748	.633	0	7.05
$Gap^{Turnover}$ *Negative*	Productivity gap if sending firm has lower productivity	-.833	.639	-8.966	-.00002
Gap^{Value} *Positive*	Productivity gap if sending firm has higher productivity	.595	.512	0	6.414
Gap^{Value} *Negative*	Productivity gap if sending firm has lower productivity	-.753	.534	-5.645	-.0001
Size of sending firm	Average size of sending firm	45.47	245.59	1	35018
Labor	Total number of employee of firm i at time t	29.5	191.62	0	35018
Age firm	Years since a firm is established at time t	9.51	10.64	0	37
Hiring ratio	Total number of new workers divided by total number of employees at time t	0.233	0.276	0	1
Experience	Total number of years that an employee has work experience	5.034	4.121	0	49
Female	The proportion of female employees of firm i at time t	0.264	0.288	0	1
Skilled	The proportion of high-skilled employees of firm i at time t	0.329	0.213	0	1
Age	Average age of the workforce of firm i at time t	38.8	8.82	16	80
Age new	Average age of new workers hired in firm i at time t	31.97	9.93	16	80
Experience new	Total number of years that new workers hired worked in previous firm at time t	2.03	2.93	0	49
Female new	The proportion of female in new workers hired in firm i at time t	0.28	0.35	0	1

Note: All statistics reported in this table are based on the sample of 239,168 firm-year observations.

4.5 Results

I start by estimating the base line model. Table 4.4 presents the regression results corresponding to equation 4.1 introduced in section 4.3.2. These estimations cover all Dutch manufacturing firms during 1999-2013, with the overall productivity gap and four lags of the receiving firm's productivity. As productivity tends to be persistent, I add 4 lags of the outcome variable in base model based on residual autocorrelation to control for productivity shocks in past years. Additionally, I apply robust standard error in estimation to control for serial autocorrelation as well. Columns 1 and 2 of Table 4.4 present the results of the baseline model without controls except for time-industry fixed effects, while columns 3 and 4 report the results if firm and incumbent worker characteristics are included. The last two columns present the results for the model including all controls as well as newly hired workers' characteristics. As shown in columns 1-6 of Table 4.4, the results reveal a positive significant association between receiving firm's productivity and their productivity gap. These results are robust using two different productivity measures. For instance, the coefficient on $Gap^{Turnover}$ as presented in column 1 (the model without controls), implies that firms hiring 10% of its new workers from firms that are 10% more productive will experience a 0.15% productivity gain one year after hiring. Similarly, the coefficient on Gap^{Value} suggests a 0.31 percent productivity gain a year after hiring.

As one can see from the table 4.4, the coefficient on the productivity gap variable remains positive and significant after adding control variables, although its size decreases. This means that the effect of the productivity gap between sending and receiving firms should not be analyzed independently of characteristics of receiving firms and new workers' characteristics, although the coefficients on these variables are mostly insignificant. These findings are in line with the results of Stoyanov and Zubanov (2012).

Furthermore, I extend the base model by distinguishing between positive and negative productivity gaps. With this model (equation 4.2), we can test whether the pro-

Table 4.4. Baseline Model

VARIABLES	1 Turnover	2 value added	3 Turnover	4 value added	5 Turnover	6 value added
$Gap^{Turnover}$	0.015***		0.012***		0.009***	
	(0.003)		(0.011)		(0.011)	
$Productivity_t^{Turnover}$	0.568***		0.536***		0.520***	
	(0.004)		(0.011)		(0.011)	
$Productivity_{t-1}^{Turnover}$	0.141***		0.102***		0.098***	
	(0.005)		(0.017)		(0.018)	
$Productivity_{t-2}^{Turnover}$	0.076***		0.067***		0.052***	
	(0.004)		(0.014)		(0.014)	
$Productivity_{t-3}^{Turnover}$	0.063***		0.053***		0.043***	
	(0.003)		(0.011)		(0.011)	
Gap^{Value}		0.031***		0.025***		0.014**
		(0.006)		(0.014)		(0.015)
$Productivity_t^{Value}$		0.536***		0.519***		0.515***
		(0.006)		(0.011)		(0.011)
$Productivity_{t-1}^{Value}$		0.176***		0.112***		0.098***
		(0.009)		(0.020)		(0.020)
$Productivity_{t-2}^{Value}$		0.089***		0.065***		0.057***
		(0.007)		(0.013)		(0.013)
$Productivity_{t-3}^{Value}$		0.042***		0.032***		0.031***
		(0.006)		(0.011)		(0.011)
Firm characteristics	No	No	Yes	Yes	Yes	Yes
Incumbent workers characteristics	No	No	Yes	Yes	Yes	Yes
New workers Ccharacteristics	No	No	No	No	Yes	Yes
Observations	82.045	35.711	73.643	31.104	73.634	31.091
R-squared	0.534	0.439	0.608	0.437	0.609	0.485

Note: All specifications include industry-year effects. Robust standard errors in parentheses.
Note: Dependent variable is $Productivity_{t+1}$
*** p<0.01, ** p<0.05, * p<0.1

ductivity spillover is driven by firms hiring from more-productive (positive gap) or less-productive (negative gap) firms. Columns 1 and 2 of Table 4.5 present the results for positive and negative productivity gaps for all firms using two different productivity measures. Columns 3 and 4 present the results for small firms (i.e. firms with less than 50 employees) and the last two columns show the results for large firms (i.e. firms having a number of employees higher or equal to 50). The results in column 1 show a positive significant association between a positive productivity gap and the receiving firm's productivity. This coefficient is larger than the coefficient on the overall gap (0.009) in Table 4.4. The estimate for the negative productivity gap is insignificant and negative, implying that hiring new workers from less productive firms has no effect on productivity. Similar results are obtained for the second measure of productivity.

Contrasting the results in columns 3 and 5, I find no significant effect for small firms while the positive gap is positive and significant for large firms. This means for small firms hiring from less or more productive firms after one year has no influence on productivity level of firms. In general, hiring for large firms is associated with productivity gains as long as at least some new workers come from more productive firms. In the last column of Table 4.5 in which productivity is measured based on firms' value added, the coefficient on the negative gap variable is found to be negative and significant, meaning that for large firms hiring from firms with lower added value decreases the value added of the receiving firm after one year. These results suggests that the main positive effect reported in Columns 5 and 6 of Table 4.4 are caused by large firms.

Table 4.5. Receiving Firm's Productivity and the Productivity Gap

VARIABLES	Turnover	value added	Turnover	value added	Turnover	value added
Positive gap turnover	0.011**		0.008		0.018***	
	(0.004)		(0.006)		(0.006)	
Negative gap turnover	-0.004		-0.005		-0.003	
	(0.005)		(0.006)		(0.008)	
Turnover	0.607***		0.579***		0.674***	
	(0.005)		(0.007)		(0.007)	
L.turnover	0.220***		0.213***		0.195***	
	(0.006)		(0.009)		(0.009)	
Positive gap value		0.011**		0.008		0.016**
		(0.007)		(0.011)		(0.009)
Negative gap value		-0.005		0.009		-0.020*
		(0.009)		(0.013)		(0.012)
Value		0.539***		0.545***		0.536***
		(0.007)		(0.011)		(0.008)
L.value		0.188***		0.201***		0.178***
		(0.009)		(0.017)		(0.011)
	All firms	All firms	Small firms	Small firms	Large firms	Large firms
			$N < 50$	$N < 50$	$N \geqslant 50$	$N \geqslant 50$
Observations	50.394	26.685	28.508	9.174	21.886	17.511
R-squared	0.508	0.403	0.414	0.374	0.634	0.430

Note: The gap calculated separately for more and less productivity sending firms. All specifications include industry-year effects and characteristics of firm, incumbent workers and new workers (X_{it}, Y_{it} and Z_{it}).
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

If knowledge transfer via mobility of labor can overcome technology differences between industries, then the estimated coefficient of Gap^{Same}_{it-1} and Gap^{Diff}_{it-1} in equation 4.3 should be equal. Yet Table 4.6 shows that the gaps' estimate is much higher for workers moving within the same industry than for those moving between industries. Worker mobility towards higher-added-value firms in another industry does not result in higher value added for the hiring firm. This finding is very similar to results reported by Stoyanov and Zubanov (2012) for Danish manufacturing. Further, I break down both within and between productivity gap into positive and negative parts. I find that only the coefficient on positive productivity gaps is significant, while the coefficient on negative gaps remains insignificant for both both productivity proxies.

Since the effect of hiring workers from more productive firms within the same sector is much higher than that for hiring from other sectors, one can conclude that knowledge brought into the receiving firm by new workers is mainly industry-specific. This implies that hiring within the same sector might bring more relevant new knowledge and skills than what can be brought by workers who were previously employed in other industries.

Table 4.6. Gap in the Same and Different Industry

VARIABLES	Turnover	Value added	Turnover	Value added
Turnover gap same	0.025***			
	(0.006)			
Turnover gap different	0.010**			
	(0.003)			
Value added gap same		0.017**		
		(0.008)		
Value added gap different		0.006		
		(0.005)		
Turnover positive same			0.034***	
			(0.006)	
Turnover negative same			0.006	
			(0.013)	
Turnover positive diff			0.021**	
			(0.008)	
Turnover negative diff			-0.013	
			(0.018)	
Value positive same				0.021**
				(0.008)
Value negative same				0.004
				(0.018)
Value positive diff				0.014*
				(0.010)
Value negative diff				-0.059*
				(0.034)
Observations	58380	35750	58380	35750
R-squared	0.538	0.441	0.546	0.457

Note: The gap calculated separately for more and less productivity sending firms. All specifications include industry-year effects and characteristics of firms and incumbent workers and new workers (X_{it}, Y_{it} and Z_{it}).
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusions

Labor mobility is considered to be an important channel of knowledge transfer. The goal of this chapter is to investigate the role of labor mobility in the diffusion of knowledge across enterprises and its impact on receiving firms' productivity. In the analysis, I differentiate between high- and low-productivity firms. In the estimations, I control for both incumbents' and new workers' productivity relevant characteristics. Therefore, I am confident that the identified labor inflow productivity effects stem from the sending firms' productivity position.

My analysis revealed that enterprises that employ new workers from more productive firms experience a productivity gain one year after hiring. However, I find no significant effects associated with workers coming from less productive firms. Furthermore, I find that hiring within the same sector knowledge and skills in contrast to hiring workers from other sectors. These results are consistent with the results of the spillover through labor mobility theory, according to which new employees bring knowledge and skills from their previous position. Moreover, my findings confirm the result reported by Stoyanov and Zubanov (2012)).

Additionally, my results suggest that hiring by large firms is associated with productivity gains as long as at least some new workers come from more productive firms, even if the average productivity gap across all new hirings is negative. However, for small firms my results suggest that hiring has no influence on the productivity level of the receiving firms, no matter whether they hire new employees from less or more productive firms.

While the empirical results generally support the worker mobility theory and confirm the results of previous empirical studies, I have left a number of issues unaddressed. First, this study ignores the occupation of moving workers and their job position in sending firms due to data limitation. It has been argued that knowledge diffusion via worker mobility and ability of workers in application of new knowledge can be dependent on workers' occupation (Song et al. (2003). Therefore, future research can exploit knowledge transfers via job switchers taking the occupation in firms for which they worked previously into account. Second, this study ignores the effect of departing workers on sending firms' productivity. This can be the subject of a new study.

4.A Data Description

Table 4.A.1 reports the main variables used in this study including their sources. In Section 4.4 I referred to 3 educational classes, low-skilled, mid-skilled and high-skilled labor. This classification is based on the International Standard Classification of Education (ISCED). Low-skilled workers have education codes 0,1 and 2, namely people with lower secondary education or lower certificate. The mid-skilled workers have upper secondary or post secondary education (education codes 3 and 4). Finally, high-skilled workers have eduction code 5 (short-cycle tertiary education, bachelor or master) or education code 6 (people with doctoral or equivalent certificate). In this study, with skilled worker I refer to highly skilled workers, i.e. employees education code of 5 or 6.

Table 4.A.1. Variables: Description and data sources

VARIABLES	DESCRIPTION	DATA SOURCE
$A^{Turnover}$	Total turnover divided by total employment at time t normalized by the applicable industry-year average	Production Statistics, SFGO, NFO, SFKO
$A^{ValueAdded}$	Valued added divided by total employment at time t normalized by the applicable industry-year average	Production Statistics, SFGO, SFKO,
ln(Wage)	Logarithm of total industry wage bill divided by total employment in industry i at time t	Production Statistics
ln(Labor)	Logarithm of total number of employees in firm i at time t	Business Register
Capital	Capital of firm i divided by total number of employee of i at time t	SFGO, SFKO, NFO
Firm Age	The number of the years since a firm is established	Business Register
Age	Average age of workforce in firm i at time t	GBA
Female	Proportion of female employees in firm i at time t	GBA
Skill	The proportion of high-skilled employees who have a college education	Educational Level

International Standard Classification of Education (ISCED) forms the basis for the variable SKILLit. Namely, employees with educational level 5 or 6 based on ISCED codes are considered as the highly-skilled workforce. Programes classified at ISCED level 5 include, for example: (higher) technical education, community college education, technician or advanced/higher vocational training, associate degree. Likewise, programs classified at ISCED level 6 cover, for example: bachelor's programs, license, or first university cycle.

An examination of the Pearson correlation matrix in Table 4.A.2 suggests that pairwise correlations between independent variables used in equations (1 through 4) fall bellow .5, suggesting that no major multicollinearity problem exists in the analysis.

Table 4.A.2. Pairwise Correlation

	A^T	A^V	Gap^T	Gap^V	Age Firm	ln(labor)	Hiring	Exp	Female	Skill	Age	Age new	Skill new	Exp new
$A^{Turnover}$	1													
A^{Value}	0.746	1												
$Gap^{turnover}$	-0.527	-0.358	1											
Gap^{Value}	-0.359	-0.480	0.687	1										
Age firm	0.003	-0.010	0.005	-0.075	1									
ln(labor)	0.021	-0.054	-0.038	-0.021	0.194	1								
Hiring	0.004	0.022	0.039	0.01	-0.145	-0.189	1							
Experience	-0.002	0.020	-0.022	-0.004	0.126	0.36	-0.425	1						
Female	-0.010	-0.039	0.005	0.019	0.036	-0.09	0.057	-0.12	1					
Skill	0.097	0.086	-0.064	-0.052	0.051	0.101	-0.027	0.015	0.045	1				
Age	-0.066	0.030	-0.010	0.023	-0.034	0.006	-0.288	0.401	-0.068	0.079	1			
Age new	-0.013	0.013	0.010	0.033	-0.119	-0.035	0.059	0.034	-0.039	0.064	0.652	1		
Skill new	-0.053	0.010	-0.026	0.001	-0.039	-0.336	-0.499	0.21	0.005	0.212	0.275	0.069	1	
Experience new	0.020	0.036	0.031	0.043	-0.06	0.001	-0.003	0.045	-0.068	0.012	0.226	0.347	-0.027	1