

1. INTRODUCTION

It is commonly agreed that R&D generates positive externalities because of rent and/or knowledge spillovers (for reviews see, e.g., Griliches, 1992; Mohnen, 1996). Rent spillovers are most likely to occur via the trade of intermediate inputs and capital goods. Knowledge spillovers occur when information gets exchanged in a tacit or codified way when people meet, interact, trade, or cooperate. Knowledge spillovers are often captured by a measure of proximity between emitter and receiver on the grounds that knowledge spillovers are more likely to happen when the two parties are similar or physically close to each other.

There is a wealth of indirect econometric evidence pointing to the existence of R&D spillovers on the basis of statistically significant coefficients for (in some proximity space) relevant stocks of knowledge. The actual channels of spillover transmission have been discussed by many authors and incorporated in the innovation survey questionnaires, in the spirit of Levin (1988), but they are generally not modeled explicitly. There are some exceptions. Some studies attribute to technology suppliers or multinational enterprises the role of technology transmission (e.g. Arora, Fosfuri and Gambardella, 2001; and Görg and Strobl, 2005). Following Arrow's (1962, p. 615) lead, it is frequently suggested (see, e.g., Geroski, 1995; Stephan, 1996) that labor mobility – the movement of workers from one organization to another – is among the key transmission mechanisms of knowledge spillovers. Upon defining an agenda for future research (in the context of their critical survey of the literature on geographically localized knowledge spillovers), Breschi and Lissoni (2001, p. 1000) state that

“The first entry in the agenda is the labour market... A crucial mechanism through which knowledge diffuses locally is the mobility of technologists and scientists, either across firms, and between firms and academic institutions.”

This paper addresses the issue empirically by studying whether inter-firm labor mobility is a channel of knowledge spillovers that affect business performance. To this end a comprehensive longitudinal employer-employee panel dataset, available for research purposes at the Research Laboratory of Statistics Finland, is exploited.¹ A unique advantage of the dataset is that it enables to observe employees' inter-firm mobility and job assignments over time and also to trace their movements in and out of the employers' R&D functions. The productivity of hired R&D workers compared to existing R&D workers in a firm can be assessed and hence indirectly the presence of labor-mobility related knowledge spillovers among firms. To our knowledge, this is the first attempt to do so.

In our terminology knowledge spillovers occur when a firm's R&D project discloses new information that is useful to another firm in its R&D efforts, and the emitting firm is not fully compensated for the input. We make every effort to explicitly identify and isolate inter-firm labor mobility as one potential channel of knowledge spillovers. We devise a setting where the potential spillovers may also be internalized by the labor market, other factors possibly contributing to business performance are controlled for, and potential sources of bias are eliminated. Empirically we resort to long differences in studying firm-level profitability growth, and to an extent also productivity and average wage growth, with the shares of various types of hired, staying, and separating workers among the key variables of interest.

To anticipate our conclusions, we find that knowledge spillovers may be partly but are not fully internalized by the labor market. Thus, knowledge spillovers exist, albeit not necessarily of the most obvious type. Perhaps surprisingly, hiring workers from others' R&D labs to one's own does not seem to be a statistically significant spillover channel, even if we find weak support for it. Hiring workers previously in R&D to one's non-R&D activities, however,

clearly boosts both productivity and profitability. This is interpreted as evidence that these workers transmit knowledge that can be readily copied and implemented without much additional R&D effort. Our paper makes a contribution to the scarce microeconomic literature that explicitly studies how spillovers come about and how they are being transmitted.

Section 2 briefly reviews the previous literature on the topic. The model to be estimated is derived in Section 3. Section 4 discusses the employed data and its properties. Section 5 presents the baseline results, the robustness of which is discussed in Section 6. Section 7 concludes.

2. LITERATURE

A few game-theoretic models consider labor mobility as a channel of knowledge spillovers: In Cooper (2001) both the previous and the current employer of a job switcher utilize the same knowledge simultaneously. Due to the opposing effects of emitting and absorbing spillovers, an efficient labor mobility outcome can be reached. In Fosfuri and Rønde (2004) researchers are mobile within their geographical region. After a first generation they stay or move to a rival. Faced with the opposing spillover motives, firms choose to locate in the same region as others when the value of the second generation is high relative to the first (high benefits of hiring from rivals) and competition in the product market is soft (losing workers does not have severe end-market effects). In Kim and Marschke (2005) the threat of departing employees reduces R&D expenditures, as researchers are willing to accept lower wages in return on the knowledge, as well as raises the propensity to patent, as firms attempt to curb emitted spillovers.² In Franco and Filson (2006) former employees may use their previous employers' technology to establish rivals. Wages are adjusted downward to reflect this; in the Pareto-optimal competitive equilibrium mobility remains socially suboptimal. More

advanced parent firms are more likely to spawn spin-outs.³ Combes and Duranton (2006) study the intensity of competition in both the product and the labor markets. As competition intensifies, labor flows are reduced as firms raise the wages of their most strategic workers thereby increasing costs (wages) and lowering benefits (knowledge flows) of co-location.

All of the above game-theoretic models address aspects of firms' opposing motives for absorbing and emitting spillovers. Under reasonable assumptions and parameter values firms tend to make strategic choices that increase knowledge spillovers via labor mobility.⁴ Despite apparent incentive problems, spillovers are potentially internalized by the labor market.⁵ The effect of spillovers on wages is undetermined: on the one hand researchers are willing to accept lower wages in anticipation of future returns, but on the other hand the most strategic workers might be able to capitalize on their (implicit) threat to leave; high wages might also be used to absorb spillovers via hiring. Fosfuri and Rønde (2004) imply that high wages and high mobility might in fact co-exist. Spillovers via labor mobility as well as their internalization by the labor market might be conditional on the type of spilloverable knowledge and/or on firm and industry characteristics.

A few prior empirical studies explicitly consider labor mobility as a channel of knowledge spillovers: Almeida and Kogut (1999) study patent holders mobility and suggest that at least in the Silicon Valley knowledge is embedded in regional labor networks. Song, Almeida, and Wu (2003) show that hiring engineers from US to non-US firms is used for exploring technologically distant knowledge (as opposed to reinforcing existing expertise) as well as for tapping into geographically distant spillover sources. Rao and Drazin (2002) point out that younger and/or poorly connected firms are at a disadvantage when it comes to innovation in financial services. They observe that younger US firms tend to recruit industry veterans, poorly connected firms recruit from their larger counterparts, and that these strate-

gies boost firm performance. Power and Lundmark (2004) suggest that the observed high mobility of certain ICT specialists in the Stockholm region promotes industrial concentration and firm performance. Görg and Strobl (2005) find that domestic businesses in Ghana whose owners previously worked for multinational enterprises tend to be more productive than other domestic firms.⁶ Fallick, Fleischman, and Rebitzer (2006) show that the high mobility of employees in the computer industry facilitates the reallocation of resources. As compared to other locations in the US, mobility and related agglomeration economies seem to be more pronounced in California. Hoisl (2007) observes that inventors employed in larger German firms tend to be less mobile than those employed in smaller ones. While an increase in inventor productivity decreases the probability of switching jobs, mobility *per se* promotes subsequent productivity.

Møen (2005) is the closest counterpart to our work in the previous literature. Møen's key proposition is that R&D is also a learning process for those involved. To the extent that employees receive on-the-job training (or otherwise gather valuable knowledge), they are willing to pay for it in anticipation of higher wages in the future. Møen uses a Norwegian employer–employee panel to estimate various wage models with R&D-related experience profiles among the key variables of interest. He finds that technical employees in R&D-intensive firms have lower wages early in their careers and later earn returns on their implicit investment in the form of higher wages. "These findings suggest that the potential externalities associated with labor mobility, at least to some extent, are internalized in the labor market." (Møen, 2005, p. 83). Magnani (2006) replicates and extends Møen's investigation with a panel of US manufacturing workers. Magnani's results provide some support to Møen's findings: also in the US there seems to be a R&D-induced steepening of the wage profile; there is, however, little evidence for an earnings drop in R&D-intensive industries at early stages of

one's career. As pointed out by the author, the latter (non-)finding might be driven by the use of two-digit industry-level R&D, as opposed to the firm-level R&D data used by Møen.

The available empirical evidence suggests that labor mobility is indeed a channel of knowledge spillovers, although this overall observation has to be taken with a grain of salt, as most studies do not account for the possibility that spillovers might be internalized by the labor market; the studies that do, indeed find that at least some internalization takes place. Like the game-theoretic work, the empirical evidence also hints that spillovers via labor mobility might be conditional on the type of knowledge being transferred.

Møen (2005) and Magnani (2006) are able to show that some spillovers are internalized by the labor market but they are unable to say to what extent. In a sense we study the flipside of their research question: after explicitly allowing for knowledge spillovers to be internalized by wage offers upon switching jobs, do any (uninternalized) spillovers remain? We can go further into the existence of knowledge spillovers transmitted by labor mobility as – unlike Møen (2005) – we observe employees' inter-firm mobility *and* job assignments over time; thus we are able to explicitly trace movements in and out of employers' R&D functions.

3. MODEL

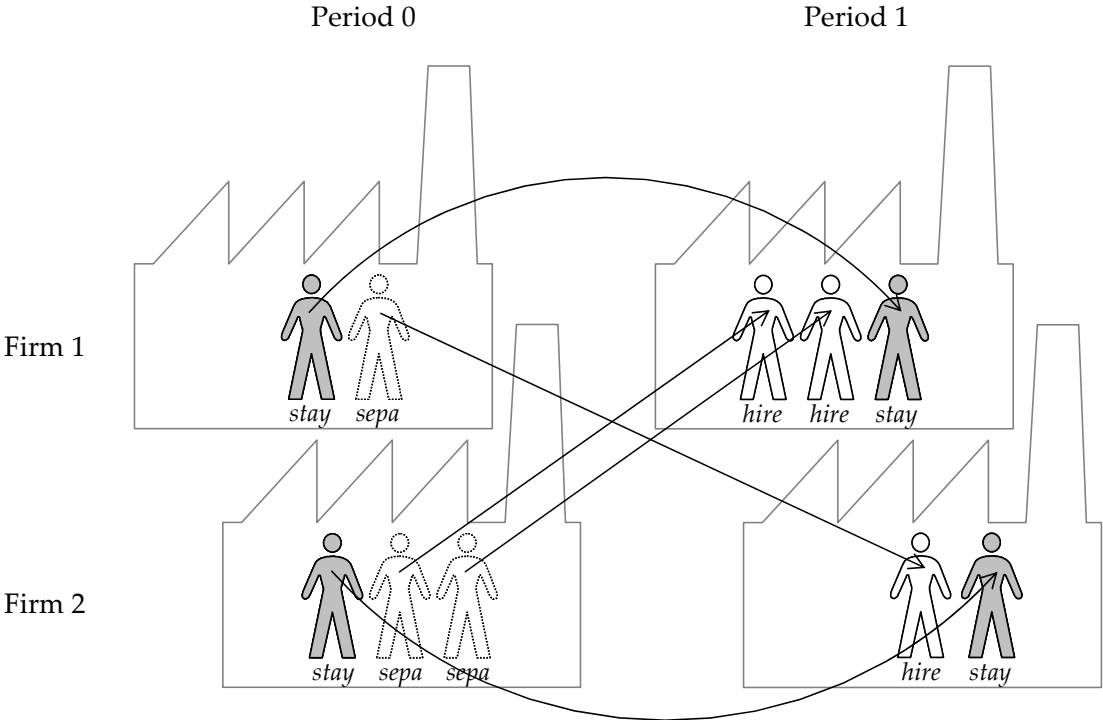
Detailed derivation of the employed model can be found in the Appendix. This section provides a brief overview as well as some intuition of the model.

Let us think of an employee using his/her skills and competences to provide a flow of services to an employer in exchange of a wage reflecting his/her personal productivity in the current period. Upon conducting his/her work, the employee accumulates knowledge on various aspects of the employer's business. As this knowledge is known in the current organization, it does not (yet) yield private returns to the employee.⁷

In the next period the employee can either stay in the current job or switch to a new one. As the knowledge the employee has acquired in the previous employer’s business is not necessarily known by the new employer, there might be some willingness to pay for it. Thus, upon switching jobs the employee might earn returns to the previous employer’s investment.⁸ To the extent that spillovers are internalized by the labor market, the new wage reflects both personal productivity and the value of knowledge carried over from the previous employer. The part of the spillover that remains uninternalized is revealed by the difference between the productivity gain the job switcher induces and the wage s/he receives, which is observed as a profitability gain at the firm level once other factors have been controlled for.⁹

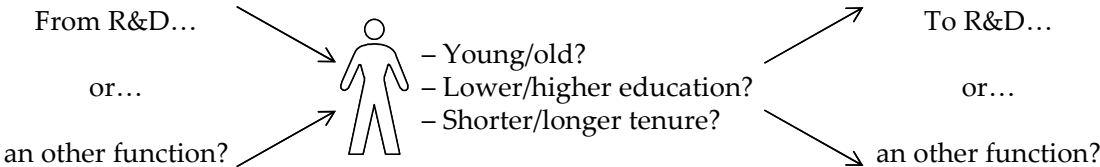
In order to estimate the knowledge spillovers not internalized by the labor market, the devised model studies how hiring, staying, and separating employees are reflected in changes of profitability, productivity, and wages. Figure 1 illustrates the model setup.

Figure 1. The model setup.



In order to address our research question, the worker flows illustrated in Figure 1 has to be separated by their type. Furthermore, as the regression analysis only reveals average effects of each flow, they have to be split by worker characteristics in order to define sufficiently homogenous groups. These refinements are illustrated in Figure 2 (see the following section for further discussion).

Figure 2. Model refinements with respect to the worker flow type and employee characteristics.



Equations (12), (13), and (19) in the Appendix define the three equations to be estimated. The dependent variable is the growth rate of wages, productivity, or profitability. The change in profitability is approximately equal to the difference between the change in productivity and the change in the average wage. Changes in the three dependent variables are explained by compositional changes in the type of workers, in particular in hired R&D workers. The key explanatory variables are employees’ hiring from, staying in, and separating from R&D and non-R&D business functions; each of these flows is split in three ways on the basis of each individual’s age, education, and job tenure (see Figure 2).

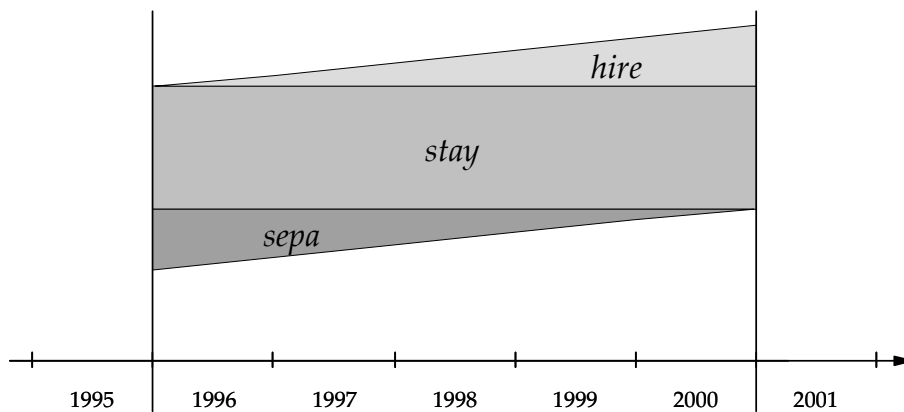
4. DATA

The data for this study is drawn from the *Finnish Longitudinal Employer–Employee Data* (FLEED) publicly available for research purposes (subject to terms and conditions of confidentiality) at *Statistics Finland’s* research laboratory. FLEED merges comprehensive taxation and other administrative records of all labor force members as well as all employ-

ers/enterprises subject to value added tax (VAT); it can be complemented by a range of additional information from both private and public sources.¹⁰

Figure 3 illustrates the empirical setup. The linked employees and their characteristics are observed at the end of the year 1995 and 2000. These two points in time are compared to determine the categories of staying, hiring and separating workers.¹¹

Figure 3. The empirical setup.



Hiring, staying, and separating are considered across five characteristics of the individuals in the respective categories (the composition of each group is determined by the symbols in the middle columns of Table 1):

- the age of the workers (either *Young* or *Old*, with those aged 35 years or less in the initial period being defined as *Young*),
- the educational level of the workers (either *Lower* or *Higher*, the latter group composed of all those having at least a bachelor's or equivalent degree),
- the tenure of the workers in the firm (either *Short* or *Long ten.*, those that in the initial period had been with the firm 5 years or less being defined as having *Short* tenure),
- the previous job assignment (having been employed elsewhere either in *R&D* or in *Other* (non-R&D) activities, as well as
- the current job assignment (being employed in the firm in *R&D* or *Other* activities).¹²

Table 1. Variable definitions.

	Young/Old	Lower/Higher ed.	Short/Long ten.	R&D/Oth., prev.	R&D/Oth., curr.	Description (<i>Hire</i> -variables are shares of end-year total employment; <i>Stay</i> -variables are shares of continued employment (start-year = end-year); <i>Sepa</i> -variables are shares of start-year employment)
Labor mobility variables						
<i>Hire, Young into Other</i>	Y	L	S	O	O	Hired young/low-ed., prev. & curr. in non-R&D
<i>Hire, Old into Other</i>	O	L	S	O	O	Hired old/low-ed., prev. & curr. in non-R&D
<i>Hire, Young/Ed. into Other</i>	Y	H	S	O	O	Hired young/hi-ed., prev. & curr. in non-R&D
<i>Hire, Old/Ed. into Other</i>	O	H	S	O	O	Hired old/hi-ed., prev. & curr. in non-R&D
<i>Hire, Young/R&D into Other</i>	Y	H	S	R	O	Hired young, prev. in R&D & curr. in non-R&D
<i>Hire, Old/R&D into Other</i>	O	H	S	R	O	Hired old, prev. in R&D & curr. in non-R&D
<i>Hire, Young/R&D into R&D</i>	Y	H	S	R	R	Hired young, prev. & curr. in R&D
<i>Hire, Old/R&D into R&D</i>	O	H	S	R	R	Hired old, prev. & curr. in R&D
<i>Hire, Young/Ed. into R&D</i>	Y	H	S	O	R	Hired young, prev. in non-R&D & curr. in R&D
<i>Hire, Old/Ed. into R&D</i>	O	H	S	O	R	Hired old, prev. in non-R&D & curr. in R&D
<i>Stay, Young in Other</i>	Y	L	S	O	O	Stayed young/low-ed. w. short ten. in non-R&D
<i>Stay, Old in Other</i>	O	L	S	O	O	Stayed old/low-ed. w. short ten. in non-R&D
<i>Stay, Old/Ten. in Other</i>	O	L	L	O	O	Stayed old/low-ed. w. long ten. in non-R&D
<i>Stay, Young/Ed. in Other</i>	Y	H	S	O	O	Stayed young/hi-ed. w. short ten. in non-R&D
<i>Stay, Old/Ed. in Other</i>	O	H	S	O	O	Stayed old/hi-ed. w. short ten. in non-R&D
<i>Stay, Old/Ed./Ten. in Other</i>	O	H	L	O	O	Stayed old/hi-ed. w. long ten. in non-R&D
<i>Stay, Young in R&D</i>	Y	H	S	R	R	Stayed young/hi-ed. w. short ten. in R&D
<i>Stay, Old in R&D</i>	O	H	S	R	R	Stayed old/hi-ed. w. short ten. in R&D
<i>Stay, Old/Ten. in R&D</i>	O	H	L	R	R	Stayed old/hi ed. with long tenure in R&D jobs
<i>Sepa, Young from Other</i>	Y	L	S	O		Sep. young/low-ed. w. short ten. in non-R&D
<i>Sepa, Old from Other</i>	O	L	S	O		Sep. old/low-ed. w. short ten. in non-R&D
<i>Sepa, Old/Ten. from Other</i>	O	L	L	O		Sep. old/low-ed. w. long ten. in non-R&D
<i>Sepa, Young/Ed. from Other</i>	Y	H	S	O		Sep. young/hi-ed. w. short ten. in non-R&D
<i>Sepa, Old/Ed. from Other</i>	O	H	S	O		Sep. old/hi-ed. w. short ten. in non-R&D
<i>Sepa, Old/Ed./Ten. from Other</i>	O	H	L	O		Sep. old/hi-ed. w. long ten. in non-R&D jobs
<i>Sepa, Young from R&D</i>	Y	H	S	R		Sep. young/hi-ed. with short ten. in R&D
<i>Sepa, Old from R&D</i>	O	H	S	R		Sep. old/hi-ed. w. short ten. in R&D
<i>Sepa, Old/Ten. from R&D</i>	O	H	L	R		Sep. old/hi-ed. w. long ten. in R&D
Other variables	Description					
<i>Labor productivity growth</i>	Start- & end-year diff. of value added / worker / its start- & end-year avg.					
<i>Average wage growth</i>	Start- & end-year diff. of average wage / its start- & end-year avg.					
<i>Profitability growth</i>	Start- & end-year diff. / its start- & end-year avg. (see the text)					
<i>Industry</i>	Dummies: two-digit NACE rev. 1 industries (41 in all)					
<i>Region</i>	Dummies: two-digit NUTS regions (20 in all)					
<i>Firm age</i>	Log of firm age					
<i>Multi-establishment</i>	The firm has multiple establishments					
<i>Foreign ownership</i>	Dummy: Foreign ownership ($\geq 20\%$) at the beginning/end period.					
<i>Initial labor productivity</i>	Log of initial period labor productivity level					
<i>Initial wage sum</i>	Log of initial average wage					
<i>Capital intensity growth</i>	Start- & end-year log-diff. of the (physical) capital/labor ratio					

R&D workers are defined as those in the group of “senior officials and employees in research and planning”.¹³ As shown in Table 1, this categorization leads us to consider a total of 28 hiring, staying, and separating shares.¹⁴

As the model derived in the Appendix suggests, the *hiring* variables are defined as shares of end-year total employment, the *staying* variables as shares of continued employment,¹⁵ and the *separating* variables as shares of start-year employment. The worker groups are mutually exclusive: thus, the *hiring* variables add up to the overall hiring rate, the *staying* variables add up to one, and the *separating* variables add up to the overall separation rate.

Four variables in Table 1 – namely *Hire, Young/R&D into Other; Hire, Old/R&D into Other; Hire, Young/R&D into R&D; and Hire, Old/R&D into R&D* – are the keys in answering the question whether inter-firm labor mobility is a channel of knowledge spillovers. To the extent that knowledge spillovers are internalized by the labor market, they are subtracted from the main dependent variable of profitability growth. If, however, there are labor mobility induced un-internalized spillovers from other firms’ R&D, they should show up in these four variables. The argument is that to the extent that wages do not fully reflect personal productivities of respective workers, acknowledging the fact that s/he comes from another firm’s R&D lab should capture the possible transfer of the knowledge accumulated via the stream of the other firm’s R&D investments. Thus, these variables should capture the equivalent of ‘stealing blueprints’ upon leaving for a new job, although it is by no means necessary (or common to our understanding) that such spillovers should take illegal or immoral forms.

Besides considering the issue separately for younger and older workers, also note that the personnel previously engaged in R&D is also split into those having new assignments in either R&D or other activities. While both of these groups can potentially spill over the R&D-generated knowledge of previous employers, arguably the transferred knowledge may be of

a different type: it seems plausible that a former R&D engineer is hired to non-R&D activities, because the spilloverable knowledge s/he possesses can be implemented so readily that it is unnecessary to funnel it through the receiving firm's R&D lab. Knowledge being channeled through the lab (by rather having a job assignment there) might be also relevant, but perhaps not as readily implementable upon being hired.

Firms' *outputs* and *inputs* are observed during the one-year periods immediately following the two points in time when employment and its characteristics are observed (cf. Figure 3). The growth rates in performance are then calculated by subtracting the performance levels in the two time periods (1996 and 2001) and then dividing them by their mid-year values, as discussed in the Appendix.¹⁶

Even if time-invariant firm effects are removed by construction from the dependent variables when considering growth rates, we include a fairly extensive set of controls in order to capture possible differences in dynamics across time. Industry dummies (NACE rev. 1 two-digit industries, 41 in all) account for the effects of idiosyncratic industry shocks; likewise a set of dummies controls for the possible regional effects (NUTS two-digit regions, 20 in all). The (log of) age of the firm is controlled for. A dummy captures the firm's exposure to foreign ownership. A dummy indicating that the firm has multiple establishments is also included. Changes in capital structure are controlled for by the log-difference of the start- and end-year physical capital intensity. In order to capture the possible catching-up or life cycle effects in productivity dynamics, the start-year levels of labor productivity and average wage are also included as controls.¹⁷

Observations are lost from our sample for various reasons. Our approach dictates that we must focus on those firms that appear in both the initial and the end year.¹⁸ In addition,

we have required that at least 10 persons can be linked to the firm in both years. Some observations are dropped from the analysis due to missing information.¹⁹

Before conducting the econometric analysis we leave out some potentially erroneous observations that might distort our results. First, we remove those observations where the number of linked employees differs by more than 10% from the number of employees in the company data, as this indicates that the linking of the individual and firm data is incomplete. Second, we remove some potentially influential outliers that we identified by using the method proposed by Hadi (1992, 1994).²⁰ In the baseline estimations we include firms that employ at least 20 persons. The main reason for leaving the smaller firms out is that the employment numbers of them are sometimes imputed on the basis of wages, which could badly distort the analysis in our setting. Finally we are left with an estimation sample of 1,339 firms (with some 200,000 employees) for our baseline estimation. The sample covers about one third of the corresponding population of firms and persons.

Table 2 presents descriptive statistics of the sample.²¹ In the course of the five-year window considered, new hires account for 34.6% (= sum of the *Hire* variables) of the end-of-window employment. Of these, 84.5% are lower educated (i.e., non-university) “production” (i.e., non-R&D) workers (*Hire, Young into Other* and *Hire, Old into Other*); new R&D hires were 6.1% of the total. 88.4% of the stayers were lower education production workers (the sum of *Stay, Young in Other, Stay, Old in Other, and Stay, Old/Ten. in Other*); also among stayers those in R&D accounted for 6.1% of the total. In the course of the five-year window, the separation rate (= sum of the *Sepa* variables; those departed between the two comparison points in proportion to the initial employment) is 40.2%, of which 88.2% are lower educated production and 5.2% R&D workers. Labor productivity (in nominal terms) grew at an average compound annual growth rate of about 10%, the average wage 13%, and profitability -1.2%.

Table 2. Descriptive statistics of the baseline estimation sample.

Variables	Unit	Mean	Percentiles				
			1 st	25 th	50 th	75 th	99 th
<i>Hire, Young into Other</i>	%	20.5	0.0	3.0	17.7	46.8	65.8
<i>Hire, Old into Other</i>	%	8.7	0.0	0.0	6.9	25.0	39.1
<i>Hire, Young/Ed. into Other</i>	%	2.2	0.0	0.0	0.4	9.5	19.4
<i>Hire, Old/Ed. into Other</i>	%	0.8	0.0	0.0	0.0	4.3	9.1
<i>Hire, Young/R&D into Other</i>	%	0.2	0.0	0.0	0.0	1.3	3.7
<i>Hire, Old/R&D into Other</i>	%	0.1	0.0	0.0	0.0	0.6	2.9
<i>Hire, Young/R&D into R&D</i>	%	0.4	0.0	0.0	0.0	2.9	5.4
<i>Hire, Old/R&D into R&D</i>	%	0.2	0.0	0.0	0.0	1.5	5.0
<i>Hire, Young/Ed. into R&D</i>	%	1.1	0.0	0.0	0.0	5.4	15.8
<i>Hire, Old/Ed. into R&D</i>	%	0.4	0.0	0.0	0.0	2.3	5.9
<i>Stay, Young in Other</i>	%	31.5	0.0	7.1	29.4	63.4	79.6
<i>Stay, Old in Other</i>	%	4.5	0.0	0.0	1.2	16.7	54.2
<i>Stay, Old/Ten. in Other</i>	%	52.4	0.0	12.9	56.1	80.0	89.5
<i>Stay, Young/Ed. in Other</i>	%	1.5	0.0	0.0	0.0	7.7	17.6
<i>Stay, Old/Ed. in Other</i>	%	0.2	0.0	0.0	0.0	0.9	6.8
<i>Stay, Old/Ed./Ten. in Other</i>	%	3.8	0.0	0.0	1.0	15.8	28.3
<i>Stay, Young in R&D</i>	%	2.1	0.0	0.0	0.0	10.0	31.3
<i>Stay, Old in R&D</i>	%	0.4	0.0	0.0	0.0	1.9	7.2
<i>Stay, Old/Ten. in R&D</i>	%	3.6	0.0	0.0	0.0	16.7	44.6
<i>Sepa, Young from Other</i>	%	17.1	0.0	2.5	14.3	41.3	65.2
<i>Sepa, Old from Other</i>	%	2.9	0.0	0.0	1.2	12.0	24.2
<i>Sepa, Old/Ten. from Other</i>	%	15.4	0.0	0.0	13.8	34.8	46.8
<i>Sepa, Young/Ed. from Other</i>	%	1.1	0.0	0.0	0.0	5.0	11.1
<i>Sepa, Old/Ed. from Other</i>	%	0.3	0.0	0.0	0.0	2.2	4.8
<i>Sepa, Old/Ed./Ten. from Other</i>	%	1.3	0.0	0.0	0.0	6.5	12.5
<i>Sepa, Young from R&D</i>	%	1.1	0.0	0.0	0.0	5.9	14.5
<i>Sepa, Old from R&D</i>	%	0.2	0.0	0.0	0.0	1.4	4.8
<i>Sepa, Old/Ten. from R&D</i>	%	0.7	0.0	0.0	0.0	4.2	8.5
<i>Labor productivity growth</i>	%	10.4	-84.1	-42.7	10.9	61.6	90.8
<i>Average wage growth</i>	%	13.4	-39.8	-19.5	15.5	36.2	55.5
<i>Profitability growth</i>	%	-1.2	-88.5	-44.1	-1.1	43.0	67.9
<i>Capital intensity growth</i>	%	5.9	-231.8	-102.8	5.2	119.8	211.2

The average productivity, i.e., value added per person, is 54,800 euros in 2001. The average wage level, i.e., wages per person, is 28,000 euros (2,350 euros per month).²² A comparison with the official statistics suggests that our sample is quite representative, as the average value added per person in these industries was 56,700 thousands euros in 2001 (Struc-

tural Business Statistics, Eurostat), and the average monthly earnings of the full-time workers in industry and services were 2,380 euros in 2001 (Gross Earnings Statistics, Eurostat).

5. RESULTS

Table 3 presents White (1980) heteroscedasticity-consistent ordinary least squares (OLS) estimates of the model derived in Section 3. These are our baseline results that are estimated with weighting by firm size (the average of the initial and the last year's employment). A justification for using weighting comes from the fact that we are interested in the profitability and productivity effects of the employment flows. Unweighted estimation gives equal weight to large firms with low flow rates and small firms that have high flow rates but account for a small share of employment. Another justification for using employment weights is that the errors are likely to be heteroscedastic in a way that standard deviations are inversely proportional to firm size (Ilmakunnas and Maliranta, 2005). The left-most column shows the regression with the profitability growth as the dependent variable and thus provides our core set of results. The middle column shows a regression with the labor productivity growth as the dependent variable.²³ The right-most column shows a regression with the average wage growth as the dependent variable. Note that for many independent variables the left-most column is the difference between the middle and the right-most column, although the correspondence is just approximate.

We first briefly comment on the variables other than those related to labor mobility: As expected, growth of capital intensity increases productivity. The employees also seem to benefit from investments in the form of increased wages. The initial labor productivity level is negatively related to profitability and productivity growth indicating a catching-up or regression-towards-mean phenomenon (Friedman, 1992). Its relation to wage growth is, how-

ever, positive. One explanation for this finding is that the employees are rewarded for the employer's performance via profit-sharing and similar schemes. The average initial wage level is negatively associated with wage growth. Interestingly, its relationship with profitability growth is positive. Foreign-owned companies have higher growth rates of profitability, productivity and wage than domestically-owned ones, but only the coefficient for wage growth is statistically significant. Consistently with various firm's life-cycle models, older firms have lower productivity growth. However, the same holds true for wage growth, leaving the profitability growth effect statistically insignificant.

While the staying and separating variables are primarily controls, it is interesting to note that having a large fraction of staying young educated workers in non-R&D occupations boost productivity and profitability (the young low-educated workers is the reference group here). Furthermore, we find that the separation of certain sub-groups of the older workers has a significant positive effect on productivity and profitability growth, implying that these workers were less productive and profitable than the average worker of the firm.²⁴ We also find that a higher share of staying older workers has a negative effect on productivity growth (the result for older R&D workers is, however, statistically insignificant).²⁵

The most important and interesting finding can be read from the 5th and 6th rows of Table 3: we find that hiring R&D workers from other firms has a positive effect on productivity, when they are hired to non-R&D occupations. The estimates also indicate that these workers are very highly paid but, even so, these recruitments are profitable to the company. These findings apply to both young and old workers. On the other hand, no statistically significant effects can be found when workers are hired to R&D occupations, irrespective of the source of these flows.²⁶

Table 3. The baseline regression results.

	<i>Profitability</i>	<i>Productivity</i>	<i>Wage</i>
(1) <i>Hire, Young into Other</i>	-0.063 (0.106)	-0.087 (0.118)	-0.028 (0.060)
(2) <i>Hire, Old into Other</i>	-0.204 (0.177)	-0.367 ** (0.178)	-0.163 ** (0.068)
(3) <i>Hire, Young/Ed. into Other</i>	0.690 * (0.404)	0.929 ** (0.402)	0.410 ** (0.184)
(4) <i>Hire, Old/Ed. into Other</i>	-0.656 (0.701)	-0.392 (0.761)	0.516 (0.347)
(5) <i>Hire, Young/R&D into Other</i>	3.922 ** (1.888)	4.469 ** (2.122)	0.574 (0.847)
(6) <i>Hire, Old/R&D into Other</i>	4.498 ** (2.189)	5.236 ** (2.512)	1.295 (0.853)
(7) <i>Hire, Young/R&D into R&D</i>	-1.512 (1.369)	-0.709 (1.386)	0.674 (0.450)
(8) <i>Hire, Old/R&D into R&D</i>	1.946 (1.329)	1.687 (1.424)	-0.037 (0.586)
(9) <i>Hire, Young/Ed. into R&D</i>	-0.427 (0.547)	-0.533 (0.625)	0.154 (0.252)
(10) <i>Hire, Old/Ed. into R&D</i>	-0.303 (0.719)	-0.424 (0.784)	-0.190 (0.347)
(11) <i>Stay, Old in Other</i>	-0.111 (0.136)	-0.411 ** (0.164)	-0.266 *** (0.078)
(12) <i>Stay, Old/Ten. in Other</i>	0.026 (0.099)	-0.021 (0.102)	-0.114 ** (0.047)
(13) <i>Stay, Young/Ed. in Other</i>	0.721 ** (0.335)	0.924 *** (0.311)	0.260 (0.162)
(14) <i>Stay, Old/Ed. in Other</i>	0.763 (0.964)	0.994 (1.067)	0.132 (0.530)
(15) <i>Stay, Old/Ed./Ten. in Other</i>	-0.124 (0.256)	-0.008 (0.274)	0.207 * (0.108)
(16) <i>Stay, Young in R&D</i>	0.401 (0.327)	0.503 (0.361)	0.033 (0.148)
(17) <i>Stay, Old in R&D</i>	-0.577 (0.431)	-0.800 (0.552)	-0.246 (0.256)
(18) <i>Stay, Old/Ten. in R&D</i>	-0.148 (0.213)	0.174 (0.224)	0.279 *** (0.095)
(19) <i>Sepa, Young from Other</i>	-0.154 (0.134)	-0.397 ** (0.156)	-0.247 *** (0.064)
(20) <i>Sepa, Old from Other</i>	0.599 ** (0.281)	1.040 *** (0.361)	0.366 *** (0.136)
(21) <i>Sepa, Old/Ten. from Other</i>	0.268 * (0.155)	0.299 * (0.155)	0.070 (0.059)
(22) <i>Sepa, Young/Ed. from Other</i>	-1.032 (0.683)	-0.776 (0.776)	0.145 (0.320)
(23) <i>Sepa, Old/Ed. from Other</i>	1.848 (1.210)	1.851 (1.241)	-0.194 (0.605)
(24) <i>Sepa, Old/Ed./Ten. from Other</i>	-1.169 (0.880)	-0.689 (0.950)	0.304 (0.233)
(25) <i>Sepa, Young from R&D</i>	-0.116 (0.569)	0.055 (0.644)	0.158 (0.280)
(26) <i>Sepa, Old from R&D</i>	0.557 (1.143)	0.839 (1.316)	0.314 (0.565)
(27) <i>Sepa, Old/Ten. from R&D</i>	0.776 (0.849)	0.604 (0.809)	-0.197 (0.285)
(28) <i>Capital intensity growth</i>	0.022 (0.020)	0.041 ** (0.021)	0.019 *** (0.007)
(29) <i>Initial labor productivity</i>	-0.254 *** (0.048)	-0.219 *** (0.048)	0.052 *** (0.013)
(30) <i>Initial wage sum</i>	0.428 *** (0.096)	-0.095 (0.101)	-0.574 *** (0.037)
(31) <i>Foreign ownership</i>	0.034 (0.034)	0.042 (0.036)	0.024 * (0.014)
(32) <i>Firm age</i>	-0.002 (0.016)	-0.031 * (0.016)	-0.019 *** (0.007)
(33) <i>Multi-establishment</i>	-0.036 (0.024)	-0.021 (0.024)	0.009 (0.010)
<i>Also including industry (41 in all) and regional (20 in all) dummies.</i>			
Observations	1,339	1,339	1,339
R ²	0.50	0.52	0.67

Note: ***, **, and * indicate statistical significance at 1, 5, and 10 per cent levels. Concerns firms with at least 20 persons. Estimated with employment weights. Heteroscedasticity-consistent standard errors in parenthesis.

6. ROBUSTNESS

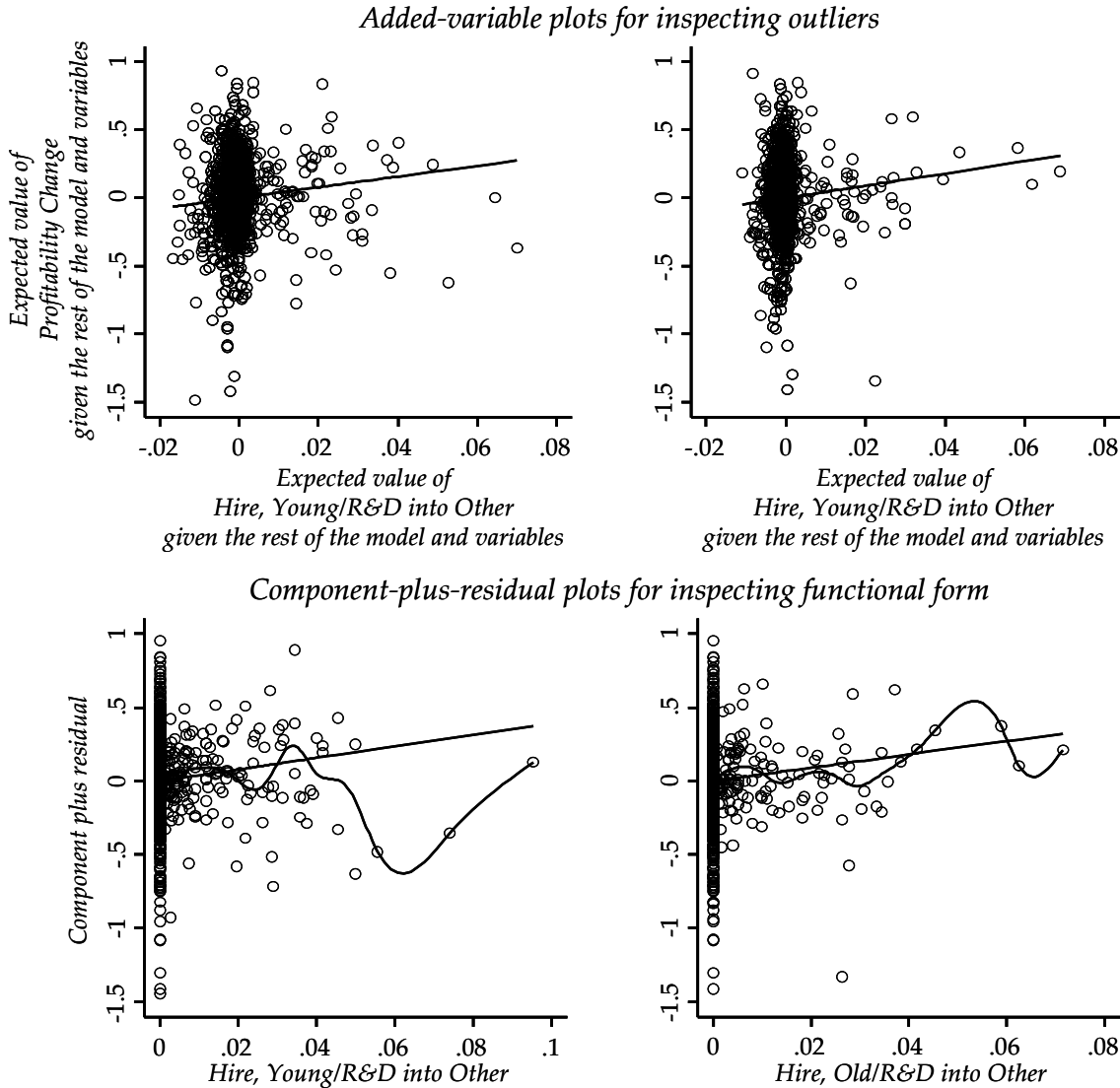
As a general remark, we wish to point out that the empirical setup employed in the previous section leads to conservative estimates, i.e., is more likely to lead to statistically insignificant results rather than the opposite. From the outset firm-specific effects are removed, and the setup is also quite robust to changes in firm structure.²⁷ In addition, we control for the possible presence of industry and regional shocks as well as for a host of other factors that could influence profitability and productivity growth.

In this section we perform five robustness checks: First, we examine whether the results in the previous section are pivoted by a few influential outliers. Second, we assess the functional form of the model. Third, we re-estimate the model with an adjusted sample as well as, fourth, with an alternative estimator. Fifth, we consider a parsimonious version of the model with redefined groups of hired and separating workers.

We draw the added-variable plots (also known as the partial-regression leverage or adjusted partial residual plots) for the dependent variable of *Profitability Change* and the explanatory variables of our greatest interest: *Hire*, *Young/R&D into Other* and *Hire and Old/R&D into Other*.²⁸ As can be seen in the upper pane of Figure 4, the positive coefficients of these variables are not driven by outliers; if anything, it seems that *Hire*, *Young/R&D into Other* is depressed downward by a few influential observations.²⁹

Similarly we also draw the component-plus-residual plots.³⁰ The lower pane of Figure 4 suggest that the linear specification does a good job in approximating the relationships at least over the relevant range from 0% to 4% for *Hire*, *Young/R&D into Other* and from 0% to 6% for *Hire*, *Old/R&D into Other*.

Figure 4. Exploring outliers and functional form.



The results in Table 4 consider the roles that the choices regarding the data and the estimator might play. First, we use a cut-off limit of 10 persons instead of the 20 persons cut-off point used in the baseline regressions in Section 5. With this adjustment our main finding that hiring former R&D workers to non-R&D occupations affects positively profitability remains statistically significant, albeit at a somewhat lower level, which we attribute to the fact that measurement accuracy is weaker among those additional 713 (= 2,052 – 1,339) firms employing 10–19 persons.³¹ Second, in order to study the possible effects of outliers, we estimate a median regression model; also these regressions confirm our core findings.

Table 4. OLS regressions with an alternative cut-off limit and median regressions.

	10 persons as the cut-off (weighted)			Median regression (unweighted)		
	<i>Profitability</i>	<i>Productivity</i>	<i>Wage</i>	<i>Profitability</i>	<i>Productivity</i>	<i>Wage</i>
(1) <i>Hire, Young into Other</i>	-0.043 (0.084)	-0.075 (0.095)	-0.040 (0.048)	-0.065 (0.044)	-0.287 *** (0.098)	-0.087 (0.053)
(2) <i>Hire, Old into Other</i>	-0.188 (0.149)	-0.342 ** (0.154)	-0.154 *** (0.059)	-0.170 *** (0.055)	-0.141 (0.124)	-0.162 ** (0.068)
(3) <i>Hire, Young/Ed. into Other</i>	0.464 (0.325)	0.651 ** (0.323)	0.361 ** (0.145)	0.366 ** (0.148)	1.108 *** (0.337)	0.338 * (0.186)
(4) <i>Hire, Old/Ed. into Other</i>	-0.089 (0.517)	0.311 (0.564)	0.573 ** (0.258)	-0.495 * (0.269)	-0.430 (0.617)	0.973 *** (0.336)
(5) <i>Hire, Young/R&D into Other</i>	2.571 * (1.441)	3.174 ** (1.592)	0.633 (0.616)	1.624 ** (0.643)	4.182 *** (1.437)	1.223 (0.776)
(6) <i>Hire, Old/R&D into Other</i>	2.885 * (1.702)	3.683 * (1.949)	1.340 ** (0.635)	1.753 ** (0.768)	3.677 ** (1.708)	0.807 (0.866)
(7) <i>Hire, Young/R&D into R&D</i>	-0.827 (0.972)	-0.154 (0.989)	0.539 * (0.324)	-0.420 (0.474)	-0.853 (1.048)	0.165 (0.568)
(8) <i>Hire, Old/R&D into R&D</i>	1.234 (0.871)	1.122 (0.957)	0.116 (0.410)	-0.031 (0.615)	1.315 (1.362)	0.038 (0.750)
(9) <i>Hire, Young/Ed. into R&D</i>	-0.384 (0.415)	-0.390 (0.480)	0.208 (0.198)	-0.160 (0.197)	0.035 (0.453)	0.146 (0.246)
(10) <i>Hire, Old/Ed. into R&D</i>	-0.339 (0.533)	-0.485 (0.601)	-0.167 (0.271)	-0.528 * (0.289)	-0.266 (0.655)	0.080 (0.414)
(11) <i>Stay, Old in Other</i>	-0.070 (0.101)	-0.280 ** (0.124)	-0.183 *** (0.057)	-0.048 (0.067)	-0.191 (0.152)	-0.036 (0.082)
(12) <i>Stay, Old/Ten. in Other</i>	0.030 (0.074)	0.006 (0.077)	-0.077 ** (0.036)	-0.113 *** (0.035)	-0.154 * (0.079)	-0.059 (0.043)
(13) <i>Stay, Young/Ed. in Other</i>	0.458 (0.278)	0.628 ** (0.263)	0.224 * (0.128)	0.136 (0.131)	0.115 (0.276)	0.073 (0.161)
(14) <i>Stay, Old/Ed. in Other</i>	0.972 (0.757)	1.290 (0.865)	0.275 (0.395)	-0.430 (0.368)	0.441 (0.822)	0.053 (0.430)
(15) <i>Stay, Old/Ed./Ten. in Other</i>	-0.045 (0.199)	0.095 (0.215)	0.209 ** (0.083)	-0.330 *** (0.080)	-0.302 (0.191)	0.084 (0.105)
(16) <i>Stay, Young in R&D</i>	0.264 (0.221)	0.356 (0.244)	0.044 (0.100)	0.153 (0.116)	0.026 (0.265)	0.069 (0.148)
(17) <i>Stay, Old in R&D</i>	-0.368 (0.306)	-0.516 (0.381)	-0.146 (0.186)	-1.078 *** (0.188)	-0.601 (0.434)	-0.182 (0.268)
(18) <i>Stay, Old/Ten. in R&D</i>	-0.039 (0.158)	0.241 (0.169)	0.257 *** (0.072)	-0.005 (0.090)	0.285 (0.210)	0.372 *** (0.112)
(19) <i>Sepa, Young from Other</i>	-0.100 (0.106)	-0.287 ** (0.127)	-0.190 *** (0.052)	-0.135 *** (0.047)	-0.159 (0.107)	-0.118 ** (0.057)
(20) <i>Sepa, Old from Other</i>	0.478 ** (0.242)	0.759 ** (0.328)	0.218 * (0.116)	0.348 *** (0.115)	0.229 (0.250)	0.013 (0.141)
(21) <i>Sepa, Old/Ten. from Other</i>	0.253 * (0.135)	0.274 ** (0.136)	0.051 (0.050)	0.213 *** (0.047)	0.201 * (0.106)	0.164 *** (0.057)
(22) <i>Sepa, Young/Ed. from Other</i>	-0.532 (0.529)	-0.292 (0.595)	0.179 (0.242)	-0.457 ** (0.214)	-0.928 * (0.500)	0.318 (0.264)
(23) <i>Sepa, Old/Ed. from Other</i>	1.077 (0.992)	1.134 (1.018)	-0.084 (0.491)	-0.073 (0.476)	0.541 (1.110)	0.088 (0.614)
(24) <i>Sepa, Old/Ed./Ten. from Other</i>	-1.045 (0.763)	-0.591 (0.824)	0.286 (0.199)	0.073 (0.219)	1.037 ** (0.493)	0.350 (0.267)
(25) <i>Sepa, Young from R&D</i>	-0.063 (0.394)	0.081 (0.450)	0.110 (0.201)	-0.570 ** (0.223)	-0.617 (0.516)	0.163 (0.275)
(26) <i>Sepa, Old from R&D</i>	0.551 (0.840)	0.746 (0.993)	0.205 (0.438)	1.767 *** (0.400)	1.278 (0.930)	0.607 (0.589)
(27) <i>Sepa, Old/Ten. from R&D</i>	0.502 (0.623)	0.459 (0.598)	-0.071 (0.218)	0.060 (0.300)	0.513 (0.701)	-0.389 (0.335)
(28) <i>Capital intensity growth</i>	0.022 (0.020)	0.041 ** (0.021)	0.019 *** (0.007)	0.022 (0.020)	0.041 ** (0.021)	0.019 *** (0.007)
(29) <i>Initial labor productivity</i>	-0.254 *** (0.048)	-0.219 *** (0.048)	0.052 *** (0.013)	-0.254 *** (0.048)	-0.219 *** (0.048)	0.052 *** (0.013)
(30) <i>Initial wage sum</i>	0.428 *** (0.096)	-0.095 (0.101)	-0.574 *** (0.037)	0.428 *** (0.096)	-0.095 (0.101)	-0.574 *** (0.037)
(31) <i>Foreign ownership</i>	0.034 (0.034)	0.042 (0.036)	0.024 * (0.014)	0.034 (0.034)	0.042 (0.036)	0.024 * (0.014)
(32) <i>Firm age</i>	-0.002 (0.016)	-0.031 * (0.016)	-0.019 *** (0.007)	-0.002 (0.016)	-0.031 * (0.016)	-0.019 *** (0.007)
(33) <i>Multi-establishment</i>	-0.036 (0.024)	-0.021 (0.024)	0.009 (0.010)	-0.036 (0.024)	-0.021 (0.024)	0.009 (0.010)
<i>Also including industry (41 in all) and regional (20 in all) dummies.</i>						
Observations	2,052	2,052	2,052	1,397	1,397	1,397
R ²	0.48	0.49	0.64	-	-	-

Note: ***, **, and * : statistical significance at 1, 5, and 10 per cent levels.

As we use detailed classifications of hired, staying, and separated workers in our analysis, some groups become rather small. Thus one might be concerned that correlations between the numerous explanatory variables induce biases. To examine this possibility we define a parsimonious model with only the key workers groups and minimum control variables. As can be seen in Table 5, the results of our main interest remain basically intact indicating that a large number of explanatory variables is not a problem in the context of our analysis.

Table 5. A parsimonious version of the model.

	<i>Profitability</i>	<i>Productivity</i>	<i>Wage</i>
<i>Hire, Young/R&D into Other</i>	4.468 ** (1.893)	6.648 *** (2.175)	2.515 *** (0.829)
<i>Hire, Old/R&D into Other</i>	3.971 * (2.121)	5.864 ** (2.441)	2.585 *** (0.962)
<i>Hire, other</i>	-0.172 ** (0.072)	-0.234 *** (0.081)	-0.049 (0.034)
<i>Sep., Young from R&D</i>	-0.130 (0.471)	0.598 (0.542)	0.841 *** (0.241)
<i>Sep., Old from R&D</i>	0.396 (0.641)	0.911 (0.663)	0.471 * (0.268)
<i>Sep, other</i>	0.105 (0.093)	0.078 (0.105)	-0.025 (0.038)
<i>Capital intensity growth</i>	0.024 (0.020)	0.041 * (0.021)	0.019 ** (0.007)
<i>Initial labor productivity</i>	-0.254 *** (0.048)	-0.213 *** (0.048)	0.061 *** (0.015)
<i>Initial wage level</i>	0.419 *** (0.080)	-0.055 (0.090)	-0.513 *** (0.039)
<i>Foreign-owned</i>	0.026 (0.035)	0.043 (0.037)	0.032 ** (0.014)
<i>Firm age</i>	-0.004 (0.016)	-0.023 (0.017)	-0.011 (0.007)
<i>Multi-plant firm</i>	-0.027 (0.024)	-0.016 (0.025)	0.006 (0.010)
Observations	1,339	1,339	1,339
R ²	0.48	0.49	0.63

Note: ***, **, and * indicate statistical significance at 1, 5, and 10 per cent levels. Concerns firms with at least 20 persons. Ordinary least squares estimates with employment weights. Heteroscedasticity-consistent standard errors in parenthesis.

7. CONCLUSION

This paper has used unique linked employer-employee firm- and individual-level data to test for the existence of labor flows as a source of knowledge spillovers. While there exists a large number of econometric studies that estimate and conclude to the existence of spillovers, most of them are unable to dissociate knowledge from rent spillovers, and very few come to grips with the channels of knowledge spillovers.³² We have tried to isolate one particular channel and to test whether that channel does indeed carry signs of knowledge spillovers; more precisely, we have tested whether productivity growth in our representative sample of Finnish firms was correlated with the hiring of workers that had worked in R&D departments in their previous employment, and whether or not any additional productivity performance due to the hiring of these workers was not captured by higher wages, i.e., resulted in higher profitability.

There is quite strong evidence of firm-to-firm knowledge spillovers but not of the most obvious type. Hiring workers from other R&D labs to one's own does not seem to be a statistically significant spillover channel, even if we do find weak support for it.³³ Hiring workers previously engaged in R&D to one's non-R&D activities, however, clearly boosts both productivity and profitability. This is interpreted as evidence that these workers transmit knowledge that can be readily copied and implemented without much additional R&D effort. Our findings also suggest that knowledge spillovers associated with R&D and channeled through inter-firm labor mobility may be partly, but are not fully, internalized by the labor market. Thus, inter-firm labor mobility is indeed found to be a channel of knowledge spillovers.

Our results, as well as those of Song, Almeida, and Wu (2003), suggest that spillovers are conditional on the type of knowledge. Like Møen (2005) and Magnani (2006), we find that some (but not all) spillovers are internalized by the labor market. It is worthwhile to take these observations into account in future research.

As the above-discussed game-theoretic literature as well as ours and others' empirical observations suggests, firms might have something to gain in exposing themselves to spillovers, e.g., by locating in certain regions. Recruiting is indeed among the channels to absorb certain types of spillovers, even if paying high wages might be necessary for inducing them. At least in the shorter run the effect of losing workers to other firms does not seem to be too severe. While generating knowledge is costly, having it might curb the firm's wage bill as learning about it might attract researchers. Furthermore, Hoisl's (2007) findings suggest that mobility *per se* may boost inventor productivity.

The apparent incentive problem in knowledge generation is perhaps the most commonly cited motivation for science, technology, and innovation policy. Our findings cast doubt to its validity for several reasons: First, not all spillovers relate to knowledge transmission; rent or pecuniary spillovers also exist and may actually dominate the knowledge spillovers. Second, incentive problems might only apply to certain types of knowledge. Third, the market might have already internalized the spillovers. Both theoretical models as well as empirical evidence from the Californian "real experiment" of having non-compete agreements unenforceable suggests that policymakers should make an effort to promote labor mobility and associated spillovers.

To the best of our knowledge, this is one of the first econometric papers that isolates and estimates the performance effects of R&D-related knowledge spillovers transmitted through inter-firm labor mobility. Even if we study a specific type and transmission channel

of spillovers, it should not be taken as an indication that we see other types and channels any less important. Our analysis was conducted at the level of the firm; an interesting avenue for further research would be to study the transmission of knowledge at the level of the employee. One could, e.g., study the identified transmitters as a group in greater detail by studying their productivities and wages over time in the spirit of Møen (2005) and Magnani (2006).

APPENDIX: DERIVATION OF THE MODEL

Our model employs a variant of a micro-level productivity decomposition method (cf. Ilmakunnas and Maliranta, 2005, 2007).³⁴ With linked employer–employee data it is possible to study the profitability, productivity, and wage effects of hired, staying, and separating workers by their type. Ilmakunnas and Maliranta (2005, 2007) focus on the role of age. The proposed extension tracks the nature of the employees’ job assignments – whether in R&D or non-R&D tasks – before and after a job change.

A firm’s labor force consists of different worker groups $j = 1, \dots, M$. The firm’s output (value added) in period 1 is defined as the sum of the outputs of the worker groups (defined by, e.g., age, education, and/or employee tenure):

$$Y_1 = \sum_j Y_{1j}. \quad (1)$$

The firm’s labor productivity is the labor share weighted average of the groups’ labor productivities:

$$\frac{Y_1}{L_1} = \sum_j \frac{L_{1j}}{L_1} \frac{Y_{1j}}{L_{1j}}. \quad (2)$$

Each worker group can further be divided into two subgroups: workers who were employed by the firm at the previous period 0, i.e., staying workers (*stay*), and those who were not, i.e., hired workers (*hire*). Thus, the firm’s labor productivity becomes

$$\frac{Y_1}{L_1} = \sum_j \frac{L_{1j,stay}}{L_1} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}}. \quad (3)$$

Because the labor shares must add up to one

$$\sum_j \frac{L_{1j,stay}}{L_1} + \sum_j \frac{L_{1j,hire}}{L_1} = 1, \quad (4)$$

we can do the following manipulation (where $Y_{1,stay} = \sum_j Y_{1j,stay}$ and $L_{1,stay} = \sum_j L_{1j,stay}$)

$$\begin{aligned}
& \sum_j \frac{L_{1j,stay}}{L_1} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \left(\frac{1}{\sum_j L_{1j,stay}} \right) \sum_j L_{1j,stay} \left(\frac{1}{L_1} \right) \sum_j L_{1j,stay} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j \frac{L_{1j,stay}}{\sum_j L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} \sum_j \frac{L_{1j,stay}}{L_1} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} \left(1 - \sum \frac{L_{1j,hire}}{L_1} \right) + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} - \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} \sum \frac{L_{1j,hire}}{L_1} + \sum_j \frac{L_{1j,hire}}{L_1} \frac{Y_{1j,hire}}{L_{1j,hire}} \\
&= \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum \frac{L_{1j,hire}}{L_1} \left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} \right) \\
&= \sum_j \frac{L_{1j,stay}}{\sum_{1j} L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \frac{Y_{1,stay}}{L_{1,stay}} \right) \tag{5}
\end{aligned}$$

to re-write equation (3) as

$$\frac{Y_1}{L_1} = \sum_j \frac{L_{1j,stay}}{\sum_j L_{1j,stay}} \frac{Y_{1j,stay}}{L_{1j,stay}} + \sum_j \frac{L_{1j,hire}}{L_1} \left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \frac{Y_{1,stay}}{L_{1,stay}} \right). \tag{6}$$

In period 0 we have to separate out the workers who will remain with the firm in period 1 and those who will not, i.e., the separating workers (*sepa*). Noting that

$$\sum_j \frac{L_{0j,stay}}{L_0} + \sum_j \frac{L_{0j,hire}}{L_0} = 1 \tag{7}$$

the firm's labor productivity in period 0 is

$$\frac{Y_0}{L_0} = \sum_j \frac{L_{0j,stay}}{\sum_j L_{0j,stay}} \frac{Y_{0j,stay}}{L_{0j,stay}} + \sum_j \frac{L_{0j,sepa}}{L_0} \left(\frac{Y_{0j,sepa}}{L_{0j,sepa}} - \frac{Y_{0,stay}}{L_{0,stay}} \right). \tag{8}$$

By definition the staying workers in period 0 and in period 1 are the same individuals. Assuming that they are in the same group, we have:

$$L_{0j,stay} = L_{1j,stay}. \tag{9}$$

The difference of period 0 and 1 productivity levels is

$$\Delta \frac{Y}{L} = \frac{Y_1}{L_1} - \frac{Y_0}{L_0} \quad (10)$$

Slight manipulation yields

$$\begin{aligned} \frac{Y_1}{L_1} - \frac{Y_0}{L_0} = & \\ & \sum_j \frac{L_{0j,stay}}{\sum_j L_{0j,stay}} \left(\frac{Y_{1j,stay}}{L_{1j,stay}} - \frac{Y_{0j,stay}}{L_{0j,stay}} \right) + \\ & \sum_j \frac{L_{1j,hire}}{L_1} \left(\frac{Y_{1j,hire}}{L_{1j,hire}} - \frac{Y_{1,stay}}{L_{1,stay}} \right) + \\ & \sum_j \frac{L_{0j,sepa}}{L_0} \left(\frac{Y_{0,stay}}{L_{0,stay}} - \frac{Y_{0j,sepa}}{L_{0j,sepa}} \right) \end{aligned} \quad (11)$$

The first term on the right-hand side of Equation (11) captures the firm's labor productivity change attributable to the staying workers. It is the labor share weighted average of the productivity changes across worker groups. It may be interpreted as productivity growth due to the accumulation of human capital through experience. These workers may have such human capital that enables them to adopt or come up with more productive techniques, i.e., these workers may have dynamic long-run effects on the firm's productivity.³⁵

The second term on the right-hand side of Equation (11) captures the firm's labor productivity change attributable to hiring new workers. Hiring workers in group j boosts productivity, if the hires have on average a higher productivity level than the stayers in period 1. New hires may be more productive, e.g., due to skills, competences, and knowledge acquired in previous employment. Hiring-related adjustment costs are implicitly included, i.e., the new hires relative productivity is net of adjustment costs.

Finally, the third term on the right-hand side of Equation (11) captures the firm's labor productivity change attributable to separating workers. Separating workers in group j

boosts productivity, if they have a lower productivity level than the average stayer in period 0.

We parameterize the productivity differences of hired, separated, and staying workers assuming them to be constant within worker groups. Other differences across firms are captured by the variables contained in vector \mathbf{Z} . The remaining unexplained deviations ε are considered white noise.

Besides labor productivity, a similar decomposition can be used for the firm's average wage level by simply substituting W for Y . Thus, the following equations can be specified:

$$\frac{\Delta(Y/L)}{(Y/L)} = \alpha_{(Y/L)} + \sum_j \beta_{(Y/L),j,hire} HR_j + \sum_j \beta_{(Y/L),j,sepa} SR_j + \sum_j^{M-1} \chi_{(Y/L),j,stay} STAYSH_j + \delta' \mathbf{Z}_j + \varepsilon, (12)$$

$$\frac{\Delta(W/L)}{(W/L)} = \alpha_{(W/L)} + \sum_j \beta_{(W/L),j,hire} HR_j + \sum_j \beta_{(W/L),j,sepa} SR_j + \sum_j^{M-1} \chi_{(W/L),j,stay} STAYSH_j + \delta' \mathbf{Z}_j + \varepsilon, (13)$$

where $\overline{(Y/L)} = 0.5[(Y_0/L_0) + (Y_1/L_1)]$ and $\overline{(W/L)} = 0.5[(W_0/L_0) + (W_1/L_1)]$ are the average

productivity and wage levels, $HR_j = \frac{L_{1j,hire}}{L_1}$ and $SR_j = \frac{L_{0j,sepa}}{L_0}$ are the hiring and separating

rates, and $STAYSH_j = \frac{L_{0j,stay}}{\sum_j L_{0j,stay}}$ is the share of staying workers.

The labor productivity effects of hiring and separating workers in group j is thus

$$\beta_{(Y/L),j,hire} = \frac{(Y/L)_{1,j,hire} - (Y/L)_{1,stay}}{(Y/L)} \text{ and} (14)$$

$$\beta_{(Y/L),j,sepa} = \frac{(Y/L)_{0,stay} - (Y/L)_{0,j,sepa}}{(Y/L)}. (15)$$

The labor productivity growth effects of staying workers in group j is

$$\chi_{(Y/L),j,stay} = \frac{(Y/L)_{1,j,stay} - (Y/L)_{0,j,stay}}{(Y/L)} (16)$$

Intercepts $\alpha_{(Y/L)}$ and $\alpha_{(W/L)}$ indicate the growth rates of labor productivity and wages, respectively, in the reference group of stayers. Thus, $\chi_{(Y/L),j,stay}$ indicates the growth rate difference between group j and the reference group.

Firms are ultimately interested in profitability, which for the present purposes is defined as follows (see Ilmakunnas and Maliranta, 2007):

$$\Pi = 1 + \frac{OPM}{W(1+a)} = \frac{Y}{W(1+a)} = \frac{Y/L}{(1+a)(W/L)}, \quad (17)$$

where OPM denotes the operating margin $OPM = Y - W(1+a)$, where a is the ratio of payroll taxes to wages assumed to be constant over time and across worker groups.³⁶ The growth rate of profitability is thus approximated by the difference between the growth rates of productivity and wages, i.e.

$$\frac{\Delta\Pi}{\bar{\Pi}} \approx \frac{\Delta(Y/L)}{(Y/L)} - \frac{\Delta(W/L)}{(W/L)}, \quad (18)$$

where $\bar{\Pi} = 0.5[\Pi_0 + \Pi_1]$. We then obtain the profitability equation

$$\frac{\Delta\Pi}{\bar{\Pi}} = \alpha_{\Pi} + \sum_j \beta_{\Pi,j,hire} HR_j + \sum_j \beta_{\Pi,j,sepa} SR_j + \sum_j^{M-1} \chi_{\Pi,j,stay} STAYSH_j + \delta' \mathbf{Z}_j + \varepsilon, \quad (19)$$

where, on the basis of (14), the following approximations hold

$$\beta_{\Pi,j,hire} \approx \beta_{(Y/L),j,hire} - \beta_{(W/L),j,hire} \quad \text{and} \quad (20)$$

$$\beta_{\Pi,j,sepa} \approx \beta_{(Y/L),j,sepa} - \beta_{(W/L),j,sepa}. \quad (21)$$

Since

$$\beta_{(Y/L),j,hire} = \frac{(Y/L)_{1,j,hire} - (Y/L)_{1,stay}}{(Y/L)} \approx \ln \frac{(Y/L)_{1,j,hire}}{(Y/L)_{1,stay}} \quad (22)$$

and

$$\beta_{(W/L),j,hire} = \frac{(W/L)_{1,j,hire} - (W/L)_{1,stay}}{(W/L)} \approx \ln \frac{(W/L)_{1,j,hire}}{(W/L)_{1,stay}}, \quad (23)$$

we can write

$$\begin{aligned} \beta_{\Pi,j,hire} &\approx \ln \frac{(Y/L)_{1,j,hire}}{(Y/L)_{1,stay}} - \ln \frac{(W/L)_{1,j,hire}}{(W/L)_{1,stay}} = \ln \frac{(Y/W)_{1,j,hire}}{(Y/W)_{1,stay}}, \\ \Leftrightarrow \beta_{\Pi,j,hire} &\approx \ln \frac{\Pi_{1,j,hire}}{\Pi_{1,stay}}, \end{aligned} \quad (24)$$

which shows that the parameter of the hiring variable for the worker group j in the profit equation (14) can be interpreted as a measure of the profitability level of the hired group j workers relative to all stayers in period 1.

Analogously, we obtain that

$$\beta_{\Pi,j,sepa} \approx \ln \frac{\Pi_{0,j,sepa}}{\Pi_{0,stay}}, \quad (25)$$

which provides us a measure of the relative profitability level of the separated group j workers before they leave.

There are three main sources of bias when analyzing firm performance and labor characteristics empirically. First, there may be unobservable firm heterogeneity both in productivity and wage levels, which is correlated with the firms' choice of labor input. For example, the firm vintage and worker cohorts tend to be tied together, with young workers being employed in firms that have new equipment and high productivity levels. Since we are using growth rates as the dependent variables, this is not an issue of great concern here. That is, if there is an unobserved firm-specific time-invariant component in the productivity or average wage level, it is eliminated in the rates of change. Our approach is related to the use of long differences (see, e.g., Griliches and Mairesse, 1998); we define the growth rates and labor

flows in a five-year window. We also control for some observable firm characteristics, included in Z .

Second, there is heterogeneity across workers. This would not be an issue if the firms randomly chose new employees from the pool of applicants or randomly picked up those who are laid off. It is, however, likely that firms attempt to hire the best and lay-off the poorest performers. The hiring and separating flows may therefore be unrepresentative with respect to the corresponding groups in the whole population. However, since the selection bias is likely to affect the productivity and wage growth rates in the same way (see Hellerstein and Neumark, 2007), the bias should be mitigated when examining their difference, i.e. the growth rate in profitability.³⁷

Third, the hiring and separation rates are based on the firms' decisions and are thus possibly correlated with the error term. This simultaneity problem may be most pronounced for inputs that are most adjustable (Marschak and Andrews, 1944). For example, positive technology shock may lead to the hiring of new, young workers, which then causes an overestimate of their productivity effect (cf. Levinsohn and Petrin, 2003; Olley and Pakes, 1996). Ilmakunnas and Maliranta (2007) used regional employment variables as instruments when studying the productivity effects by age groups. This robustness check did not challenge their main conclusions. Due to data constraints a similar instrumental variable approach is not feasible here.³⁸ From the point of view of this paper an important question is whether a positive shock increases a firm's propensity to hire R&D workers.³⁹

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ENDNOTES

¹ Please contact the Research Laboratory of the Business Structures Unit, Statistics Finland, FIN-00022, Finland, for accessing the data.

² The latter proposition is empirically confirmed.

³ The model's implications are found to hold in the rigid disk drive industry.

⁴ Labor mobility nevertheless tends to remain socially suboptimal.

⁵ Note that this does not necessarily mean that the socially optimal level of R&D is reached.

⁶ The more broadly-defined spillover effects of multinationals activities are reviewed in Dunning and Lundan (2008).

⁷ One may nevertheless expect the employer to compensate for any gains in personal productivity. As Combes and Duranton (2006) point out, wages of the most strategic workers might rise, as employers try to curb emitting spillovers to rivals.

⁸ One may think of this as being the equivalent of stealing blueprints upon departing the previous employer's R&D lab.

⁹ Each employee receives a wage in the current and in the next period; each provides a flow of services at the rate of his/her personal productivity in both periods; each has a personal profitability effect depending on the difference between his/her productivity and wage in each period. In each period employees' wages, productivities, and profitabilities aggregate to what is observed at the firm level.

¹⁰ FLEED has data on both firms and establishments. While in many contexts the establishment level is appealing for both theoretical and empirical reasons, in the current context it is not. In the case of a multi-establishment firm (in other cases the establishment and firm levels coincide), an establishment is rarely the relevant decision making unit when it comes to R&D. Furthermore, firm-level R&D efforts are often more concentrated than production and possible discoveries are spread through the firm, in which case plant-level investments in R&D and related performance effect may have a rather noisy connection. Thus our analysis progresses at the level of a firm.

¹¹ Assuming homogenous individuals and no time lags in their performance effects, one could think of all (or "average") hiring and separating as taking place in mid-1998.

¹² For both the stayers and separating workers the "maintained" job assignment (either in R&D or in Other (non-R&D) activities in the initial period) is indicated in the middle column of Table 1.

¹³ Code 32 in *Statistic Finland's* 1989 classification of socio-economic groups.

¹⁴ Those in R&D tasks are assumed to be highly educated or to have similar qualifications. The hires with no tenure at the firm are labeled as having a short tenure. Note that by including the hiring, staying, and separating variables we implicitly control for the level and changes in all the dimensions considered. Thus, for example, the firm's R&D intensity and changes in it are implicitly controlled for via the labor shares.

¹⁵ Note that the start- and end-year employment is the same for staying by definition, and that the shares add up to one; thus the comparison group *Stay, Young, in Other* is necessarily excluded from the regressions.

¹⁶ Thus, the measures may be considered as reflecting the growth rate in performance between 1996 and 2001 in comparison to the level of performance at the turn of 1998 and 1999. As kindly pointed out by an anonymous referee, the observation period coincides with the dot-com bubble. Note, however, that we control for firm age and industry effects. Furthermore, less than one-tenth of the sample are in the "new economy" -affiliated manufacturing and service industries.

¹⁷ This is a relatively standard practice in the growth literature. Note that by also including industry dummies this practice captures, among other things, the convergence of the firm and the industry levels of performance. These variables are included purely as controls – their coefficients should be interpreted with caution.

¹⁸ In practice this means that the firm must have been recorded in 1995, 1996, 2000, and 2001.

¹⁹ Banking and insurance is excluded, as value added is not available for the firms in the industry.

²⁰ The method is useful for detecting multiple outliers in multivariate data. Identification of outliers is made on the basis of four variables: 1) the growth rate of average wage calculated from the company data, 2) the productivity growth rate, 3) the growth rate of employment according to the company data, and 4) the growth rate of employment according to the Employment Statistics. In this way we found 73 outliers (out of 2,143 observations at this stage) that were excluded in the baseline estimations (but were nevertheless included in some robustness checks).

²¹ In order to protect the identities of the firms included in the data, we report the 1st and 99th percentile values rather than the more usual minimum and maximum values.

²² Productivity, wage, and profitability numbers used in the analysis originate from the Financial Statements Statistics.

²³ Note too, that labor productivity *per se* is not a function of wages unlike a somewhat popular misconception suggests.

²⁴ Young staying workers with university degrees have a more positive effect on productivity and profitability growth than young or old staying workers without university degrees. In this respect these results bear some resemblance with those of Maliranta (2003, chapter 6) who find evidence of the dynamic effect (or Nelson–Phelps effect) high education.

²⁵ The results concerning the staying and separated older workers are quite consistent with those by Ilmakunnas and Maliranta (2007).

²⁶ Note, however, that the *Hire, Old/R&D into R&D* type of workers has a positive and significant at 15% level coefficient on profitability growth.

²⁷ To be exact, the results are robust to changes in firm structure to the extent that they are reflected in the composition of a firm's employment, as these are completely characterized by hiring, staying, and separation. Also changes in capital intensity are accounted for. As the firm-effect is removed, the effects of time-invariant aspects of firm structure are naturally also removed. To the extent that changes in firm structure are not reflected in the above, they are reflected in the error term.

²⁸ We employ Stata's `avplot` command. Added-variable plots project multi-dimensional data to two-dimensional space. In the analogous two-dimensional case, the "outlierness" of an observation is determined by its influence on the fitted slope.

²⁹ We re-estimated the model after eliminating the 69 observations for which the value of on the horizontal axes is above 0.2. The core results come out even more strongly in this case.

³⁰ We employ Stata's `cprplot` command. Added-variable plots project multi-dimensional data to two-dimensional space but, unlike added-variable plots identifying outliers, they can be used to inspect functional form.

³¹ Increasing the cut-off to 50 persons has the reverse effect, even if the number of observations drops to 599. Using unweighted as opposed to weighted regression has a similar effect, which also suggests that there might be measurement issues at the small end.

³² Potential channels are assumed and used to construct indexes of R&D spillovers, giving more weight to outside R&D sources that correspond to large flows through a presumed channel of transmission (e.g., import of machineries, trade of intermediate inputs, extent of R&D collaborative research to name only a few).

³³ In the baseline regression this spillover channel is statistically significant at 15% level but, as it does not seem to be robust to changes in the data and empirical specification, we lean towards accepting the null hypothesis. A possible explanation for this (non-)finding is that the implicit average time-span of 2.5 years in our analysis is too short for a positive effect to occur in the firm's performance. For example, Ali-Yrkkö and Maliranta (2006) show with a panel data set of Finnish firms over the period 1996–2004 that an economically and statistically significant effect cannot be found earlier than three to five years after the R&D investments. Rouvinen (2002) finds support to such a lag with a cross-country industry-level panel.

³⁴ Also Maliranta (1997), Vainiomäki (1999), and Diewert and Fox (forthcoming) have proposed similar decompositions.

³⁵ The Nelson–Phelps (1966) effect.

³⁶ This measure of profitability may seem rather rough as capital costs are not taken into account. Note, however, that our empirical implementation removes time-invariant firm-effects, includes industry dummies, and – most importantly – controls for changes in firms’ capital intensities.

³⁷ As kindly pointed out by an anonymous referee, in virtually any econometric setting, including ours, some worker characteristics are unobserved and thus there remains unobserved heterogeneity across workers, which biases us against finding any statistically significant effects.

³⁸ Instrumental variables (IV) is an inefficient estimator that requires a large number of observations and a large set of appropriate instruments when the model includes many potentially endogenous variables. In a similar context Ilmakunnas and Maliranta (2007) have 16,389 observations in their estimations but we have only 1,339 observations in our baseline models, which substantially restricts our opportunities to use the IV-method. More importantly, Ilmakunnas and Maliranta have only 6 potentially endogenous hiring and separation variables; in our analysis the corresponding number is 19. Thus, due to data and coefficient dimensions as well as weak instruments, similar approach is not feasible here.

³⁹ It is worth noting, however, that while our explanatory variables include all hiring and separating flows, we are implicitly controlling for the net employment growth (jointly determined by hiring and separating flows) that is one of the apparent consequences of a technology shock. Moreover, our set of explanatory variables includes a wide array of factors, including detailed industry and regional dummies, which should eliminate any remaining bias.