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Worker Mobility and Productivity Spillovers

Abstract

Using linked employer-employee data from Finland, we examine the mobility of workers between establishments as a source of productivity-affecting knowledge spillovers. We find evidence that hiring workers from more productive establishments leads to higher productivity in the following year. For an average establishment, this productivity increase amounts to 0.45 percent in our most conservative estimate. The observed productivity gains hold for a variety of specifications, and changes in the receiving establishments' human capital stock are ruled out as an explanation.

Roope Ohlsbom
ETLA Economic Research
roope.ohlsbom@gmail.com

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Tiivistelmä

Työntekijöiden liikkuvuuden heijastusvaikutukset

Oletus yritysten työntekijöihin sitoutuneesta tuottavuuteen vaikuttavasta tiedosta on pitkään ollut osa alan tutkimuskirjallisuutta. Tämän tiedon laadun ja vaikutusten lisäksi sen leviäminen yritysten välillä on tärkeä tutkimuksen kohde. Usein esimerkiksi esitetään, että työntekijöiden liikkuvuus on potentiaalinen mekanismi yritysten välisille tiedon ja tuottavuuden heijastusvaikutuksille (spillover effects). Tässä tutkimuksessa tarkastellaan kyseistä hypoteesia seuraamalla työntekijöiden liikkeitä ja estimoimalla niiden yhteyttä toimipaikkojen tuottavuuteen suomalaisia yhdistettyjä työntekijä–työnantaja-aineistoja hyödyntäen.

Tulokset osoittavat, että työntekijöiden palkkaaminen tuottavammista toimipaikoista johtaa tuottavuuden kasvuun palkkaamista seuraavana vuonna. Varovaisimpana arviona tuottavuuslisäyksen suuruus on 0,45 prosenttia keskimääräiselle toimipaikalle. Havaittu yhteys tuottavuuden ja tuottavammista toimipaikoista palkkaamisen välillä säilyy useilla estimointispesifikaatioilla, eikä sitä voida selittää muutoksilla vastaanottavien toimipaikkojen inhimillisen pääoman määrissä.

M.Sc. (Economics and Business Administration) **Roope Ohlsbom** is a research assistant at ETLA Economic Research, an economist at the Federation of Finnish Enterprises and a doctoral candidate at Jyväskylä University School of Business and Economics.

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1 INTRODUCTION

The idea that a type of productivity-affecting knowledge is embedded in the workers of a firm has been posited and studied in a variety of ways in the economics literature[1]. In addition to the quality, dispersion and effects of this partly unmeasurable knowledge, an important subject of study are the mechanisms through which it can spill over across firms. Worker mobility is a plausible suggestion for such a mechanism, as demonstrated by Moen (2005), Kaiser, Kongsted, and Rønde (2008), Maliranta, Mohnen, and Rouvinen (2009) and Stoyanov and Zubanov (2012), among others[2]. The potential drivers of productivity are a central target of economic research, and spillovers through employee turnover are a prominent, albeit somewhat elusive, candidate.

Using a Finnish matched employer-employee data set, this article aims to isolate the spillover effects potentially associated with cross-firm worker movements. Due to the unique comprehensiveness of the data, we can filter out the productivity variance directly attributable to the changes in the human capital stock of the firms, hopefully leaving us with a measure of productivity spillovers. In addition to the existing literature, which finds evidence that moving workers enable productivity spillovers, Figure 1 provides further support for this postulate. As noted by Stoyanov and Zubanov (2012), worker mobility as a source of productivity spillovers should imply less productivity dispersion in industries with higher rates of average employee turnover from more to less productive establishments.

Figure 1 suggests that this is indeed the case in the Finnish data, as it is in the firm-level data from Danish manufacturing used by Stoyanov and Zubanov (2012). It shows the relationship between the 2013–2018 average industry-level turnover rate from more to less productive establishments and the normalized productivity variance for 88 industries at the 2-digit level of the Standard Industrial Classification. The pronounced negative

[1] For example, Prescott and Visscher (1980) posit employee and task characteristics as production relevant parts of firms' capital stock. See also Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Parente & Prescott (1994) and Jones (2005).

[2] See, for example, Moretti (2004), LeMouel (2018), Castillo, Garone, Maffioli, Rojo and Stucchi (2019) and Hlatshwayo, Kreuser, Newman and Rand (2019).

correlation is consistent with our assumption of worker mobility as a mechanism of productivity-affecting knowledge diffusion.

Furthermore, this negative correlation is much steeper when the turnover is from the top 25 percent to the bottom 25 percent of establishments, compared to the turnover from top to bottom 40 percent. This implies that the magnitude of the productivity difference between the sending and receiving establishments, or "productivity gap", is linked to how concentrated the productivity distributions are. Since spillovers are a likely cause of lower productivity dispersion, this suggests that spillovers depend on the size of the productivity gap. This paper thus follows Stoyanov and Zubanov (2012) in using this productivity gap as a measure of the receiving establishments' exposure to spillovers through worker mobility. It is the key explanatory variable in our examination of the link between a hiring establishment's productivity and the productivities of the sending establishments.

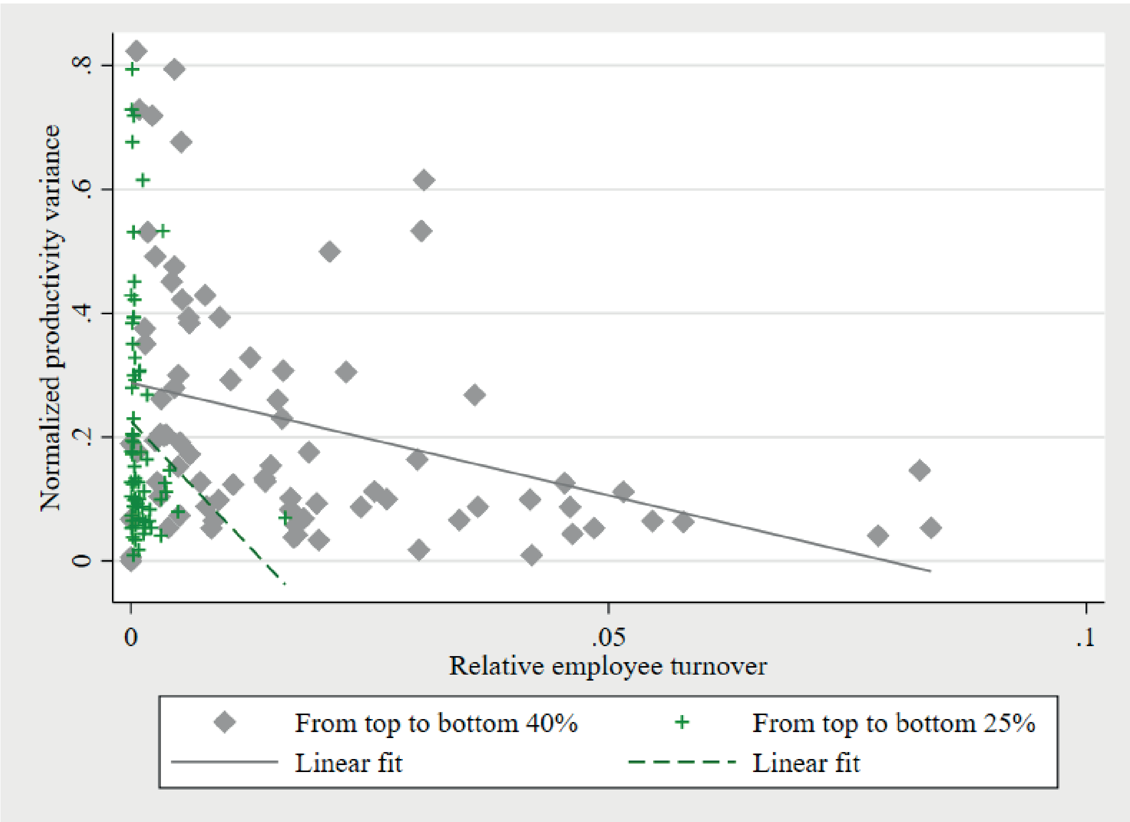

Figure 1 Industry-level average employee turnover and productivity variance.

However, we must also consider that if higher establishment-level human capital intensity increases productivity, employee turnover from higher to lower productivity establishments will affect productivity through this channel as well, not just through spillovers. We are essentially assuming that the total effect[3] of worker mobility on productivity is

[3] $Total\ effect\ of\ worker\ mobility\ on\ productivity = spillovers + effect\ of\ change\ in\ human\ capital\ stock$

the sum of the effects of spillovers from hiring (measured by the productivity gap) and the effects of the change in establishment-level average human capital. Therefore, to estimate the effect of knowledge spillovers on productivity using worker mobility, worker-specific human capital needs to be controlled for. For example, Stoyanov and Zubanov (2012) and Hlatshwayo et al. (2019) try to separate the sending firm's productivity and changes in firm-level human capital by constructing an estimate of the moving workers' human capital using a wage equation that enables the separation of the firm-wage component from individual worker-specific wages. Due to the comprehensive Finnish establishment-employee data set, we can isolate the human capital of the moving workers using their level of education and the R&D and ICT intensities of their sending establishments.

The main finding is that for an average establishment, hiring workers from the average more productive outside establishment is associated with at least 0.45% higher productivity in the following year. The productivity gap can therefore explain a relatively small but statistically significant part of observed establishment-level labour productivity. At the upper end of the estimates, using a fractional polynomial model, we find a 1.57% productivity gain in establishments hiring all new workers from more productive establishments. Section 2 outlines the empirical model and the key variables used in the estimations, section 3 compiles the results, extensions and robustness checks and section 4 concludes.

2 DATA AND EMPIRICAL MODEL

2.1 Sample and Data

The data includes all Finnish workers in the FOLK and FLEED (the Finnish Longitudinal Employer-Employee Data) matched employer-employee data modules of Statistics Finland. The data set covers the years 2011–2018. Only workers with a known employer establishment are used in the analysis. The employer-employee matches for a given year t are based on the longest employment relationship, with a minimum of six months. Therefore, since we are analysing the productivity of the receiving establishment in the year following the hiring of a worker, $t+1$, the new employees have always worked at the receiving establishments for at least 6 months before the productivity observation period starts. We can thus assume that the new hires have had time to potentially have an influence on the period $t+1$ productivity of the receiving establishment.

The total number of worker-year observations with a non-missing employer in the years 2011–2018 is 10.68 million, which can be divided into a little over 1.86 million new hires and 8.82 million stayers. The share of new hires is therefore 17.4% of all worker-year observations. Out of the 1.86 million new hires, we have employer productivity data for a little over 1.48 million. However, only workers moving across firms are included in the main analysis. Cross-firm movers make up approximately 1.44 million or 77.4% of all new hires in the data. Out of these 1.44 million new cross-firm hires, 1.17 million (81.5%) have non-missing productivity data for the receiving establishment.

Establishment-level variables used in the analysis, such as value added, gross value of production, R&D and ICT spending, number of employees, intermediate inputs and addition and depreciation of machinery are gathered from The Business Register database and enterprises' financial statement data maintained by Statistics Finland. Data for these variables covers the years 2011–2019.

The dependent variable in the main analysis is the labour productivity of the receiving establishment in the year following the hiring of new workers. Productivity is measured by the gross value of production divided by the number of employees. The independent variable of interest is the positive productivity gap between the sending and receiving establishments of newly hired workers, following the approach of Stoyanov and Zubanov (2012). It is calculated for establishment j hiring new workers i in year t as:

$$\overline{gap}_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} D_{i,t}(Y_{i,t-1}^{s} - Y_{j,t-1}^{r})}{H_{j,t}} \frac{H_{j,t}}{N_{j,t}}, \tag{1}$$

where $D_{i,t} = 1\ if\ \left(Y_{i,t-1}^{s} - Y_{i,t-1}^{r}\right) > 0$. $H_{j,t}/N_{j,t}$ denotes the share of new workers $H_{j,t}$ in the total employment $N_{j,t}$ of establishment j. $Y_{i,t-1}^{s}$ and $Y_{i,t-1}^{r}$ denote the labour productivities of the sending and receiving establishments of new worker i one year before the hiring takes place. For each hiring establishment j, the productivity gap therefore measures the difference between their own productivity and the productivity of the sending establishment, averaged across all new workers i and weighted by their share in total employment. The weighting of the average gap by the share of new workers should ensure that the gap variable captures the relative exposure of the receiving establishments to the influence of the new workers.

Furthermore, by weighting the productivity gap averaged across hired workers by their share, we are controlling for an establishment-level relative employee turnover-like measure in the estimations. This is important, since relative employee turnover is a potential confounder between the hiring gap and future productivity. As shown by Maliranta, Mohnen and Rouvinen (2009), employee turnover can have knowledge spillover effects, thereby indirectly affecting the productivity gap. It can also directly affect productivity if higher productivity workers tend to replace lower productivity employees more than vice versa. Not including the weighting could thus introduce a spurious association between the gap and the productivity of the receiving establishment.

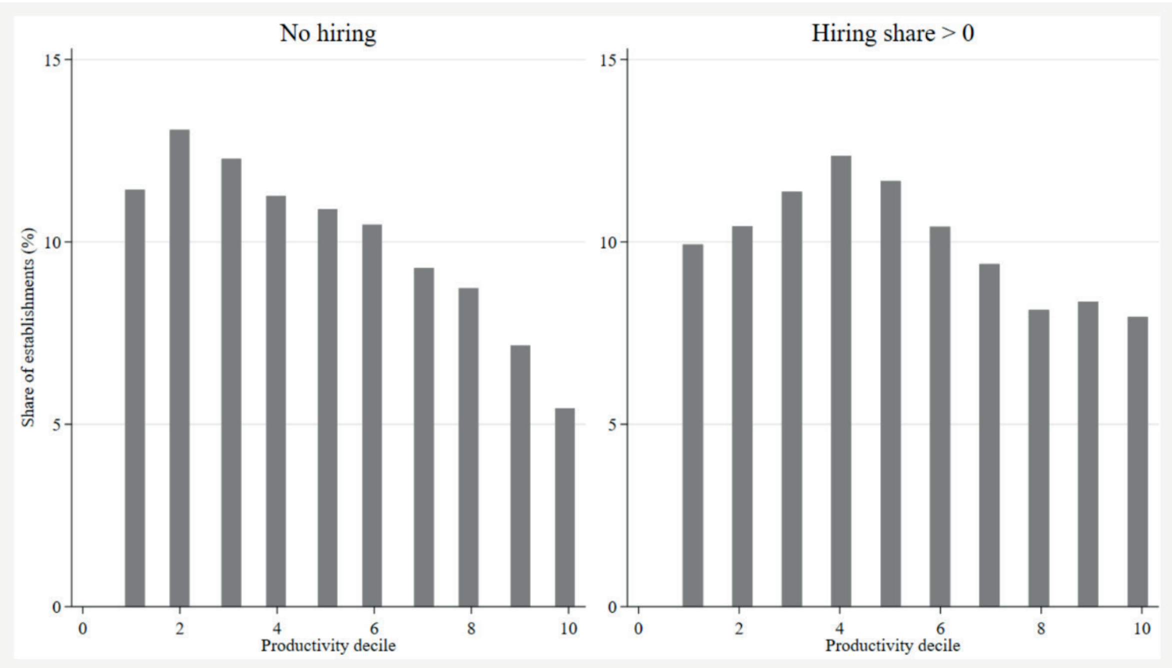

Figure 2 The distribution of the share of establishments in each productivity decile for non-hiring and hiring establishments.

Histograms of the shares of hiring and non-hiring establishments in each productivity decile are shown in Figure 2. The mass of the establishments that did not hire new workers is concentrated clearly more in the lower deciles of productivity compared to the establishments with a positive hiring share. It would therefore seem, based on the raw data alone, that more productive establishments are more likely to hire new workers. However, both hiring and productivity could be related to the size of the establishment, which is why Figure 3 shows the average number of employees in each productivity decile, along with the average positive productivity gaps between the senders and receivers of hired workers.

From Figure 3 we can see that any possible connection between positive productivity gaps in hiring and establishment productivity should not be confounded by establishment size: establishments in the higher productivity deciles are larger, but the gap decreases as size increases. Figure 3 also shows that both the positive hiring gap and the share of managers seem to increase with productivity deciles, more clearly so for the share of managers. This is expected, since establishments in higher size deciles have both higher shares of managers and higher productivity on average. For example, the mean share of managers in size decile 5 is 0.7%, whereas in size decile 8 it is 6.2%.

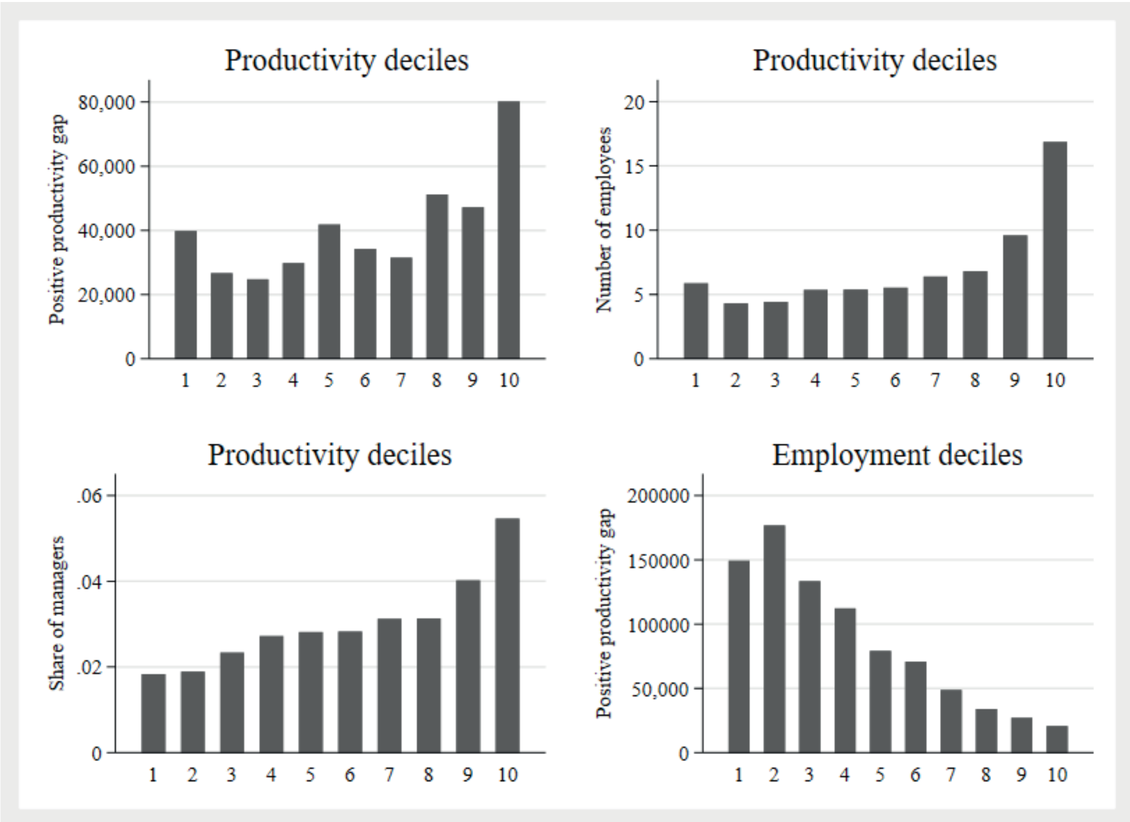

Figure 3 Comparisons of key variables by productivity and employment deciles.

Table 1 lists employee-level descriptive statistics separately for stayers, new hires across firms and new hires from more productive establishments across firms. Workers moving between establishments within firms are not included. The main differences between stayers and new hires are found in the average wages and age: stayers have significantly higher wages and are also older than new hires.

This is unsurprising, since older workers tend have more experience on average, which is often directly translated into salaries. The difference in wages might also reflect the results of Møen (2005), who finds that at least in R&D intensive firms, hired scientists, engineers and workers with secondary technical education pay for future on-the-job knowledge by accepting lower wages early in their careers. The wage discount is also largest for the youngest workers in Møen's (2005) Norwegian data set. Therefore, the results from Norway coincide with the lower wages and the five to six years lower mean age of new hires in Table 1.

Table 1 Employee-level summary statistics.

Mean	Stayers	New hires	New hires from more productive establishments
Wage (€)	35 743	29 522	31 523
Age	41.8	36.6	35.8
Female (share)	0.42	0.43	0.40
Higher education (share)	0.26	0.29	0.26
Managers (share)	0.044	0.040	0.036
Medium-skilled workers (share)	0.64	0.68	0.71
High-skilled workers (share)	0.31	0.28	0.25
Observations	8 821 722	1 440 431	315 083

Notes: The means are calculated for all workers between the years 2013 and 2018. New hires only include workers who moved across firms, moves between establishments within a firm are not included. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). Managers are defined as employees belonging to the group "managers" in the Statistics Finland Classification of Occupations 2010. "Medium-skilled workers" include skill levels 1 and 2 and "high-skilled workers" skill levels 3 and 4 in the Incomes Register´s Classification of Occupations.

When comparing new hires from more productive establishments to all new hires, the former have a smaller share of managers, high-skilled workers and workers with higher education, but a somewhat higher mean wage. The average new hire from more productive establishments is also younger, so age does not explain the higher wages. The wage differential could therefore be indicative of, for example, high productivity workers asking for higher wages when transitioning between jobs or firms using higher wages to attract workers from more productive competitors.

Table 2 summarizes some establishment-level statistics. Out of the 1.57 million establishment-year observations, hiring took place in 491 751 or a little over 31.3 percent. As expected, the non-hiring establishments are significantly smaller than the hiring ones. For establishments with at least 5 employees, hiring took place in 55.7 percent of the subsample, whereas the share of establishments with a positive hiring share is only 21.2 percent in the subsample with less than 5 employees.

Table 2 also shows clear differences in the share of managers and wages between hiring and non-hiring establishments. This disparity is at least partly reflective of the size differential, since larger establishments also pay higher wages and have higher shares of managers on average: in establishments with at least 5 employees, the mean wage is 31124 euros and the share of managers is 5.8 percent, whereas in establishments with less than 5 employees the corresponding figures are 22937 euros and 1.3 percent. The hiring establishments are also more productive and have a significantly younger workforce on average. The average productivity of the hiring establishments is 17.4 percent higher compared to the non-hiring establishments.

Table 2 Establishment-level summary statistics

			Hiring share > 0		
Mean	All establishments	Hiring share = 0	Stayers	Hires from more productive	Hires from producti
Wage (€)	25 953	23 804	30 703	30 333	28 24
Age	43.8	45.4	40.3	36.4	35.2
Female (share)	0.39	0.38	0.43	0.38	0.40
Higher education (share)	0.20	0.18	0.22	0.25	0.22
Managers (share)	0.026	0.018	0.054	0.039	0.027
Medium-skilled workers (share)	0.72	0.73	0.69	0.72	0.75
High-skilled workers (share)	0.26	0.25	0.25	0.24	0.22
Labor productivity (€)	174 366	165 110		193 810	
Establishment size (employees)	5.9	2.8		12.9	
Observations	1 569 460	1 077 703		491 751	

Notes: The summary statistics are calculated at the establishment level, but new hires only include workers who moved across firms. Moves between establishments within the same firm are not included. For establishments with a positive hiring share, the means were first separately calculated for all stayers and new hires from more and less productive establishments before averaging across establishments. Higher education is defined as having completed at least a bachelor's degree or equivalent (15-16 years from the beginning of primary education). Managers are defined as employees belonging to the group “managers” in the Statistics Finland Classification of Occupations 2010. "Medium-skilled workers" include skill levels 1 and 2 and "high-skilled workers" skill levels 3 and 4 in the Incomes Register´s Classification of Occupations. Labor productivity is measured as the gross value of production/number of employees.

2.2 Empirical model and identification issues

The linear model estimated on the data is

$$Y_{j,t+1}^{r} = \beta \cdot \overline{gap}_{j,t} + \boldsymbol{X}_{j,t}\mu + \bar{\boldsymbol{Z}}_{j,t}^{1}\gamma_1 + \bar{\boldsymbol{Z}}_{j,t}^{2}\gamma_2 + f_j + \bar{\epsilon}_{j,t+1} \tag{2}$$

where $\overline{gap}_{j,t}$ is the positive productivity gap of establishment j, as defined in equation (1). $\bar{Z}_{j,t}^{1}$ and $\bar{Z}_{j,t}^{2}$ are vectors of averaged worker characteristics[4] and the measure for the human capital of new workers, respectively. $X_{j,t}$ is a vector of the receiving establishment’s characteristics, including capital stock, materials, employment and a constant. Industry-year fixed effects are denoted by f_i and $\bar{\epsilon}_j$ is a stochastic error term.

The measure of new workers’ human capital, $\bar{Z}_{j,t}^{2}$, consists of the level of education of the new workers and the ICT and R&D intensities of the sending establishments in

[4] wage, share of managers, level of education, dummies for medium-skilled and high-skilled workers, age.

year $t-1$. Its inclusion should help isolate the intangible productivity spillovers potentially resulting from worker mobility, instead of the direct effects of firms simply employing more workers with high human capital. The human capital of new workers also likely both affects the sending establishments' productivity and causes an unobserved shock to the receiving establishment's productivity, which is absorbed by the error term $\bar{\epsilon_j}$. It follows that controlling for the new worker's human capital is essential for consistently estimating the coefficient on the productivity gap, β.

Productivity in year t is not included in the regressions, since it is assumed to at least partly mediate the potential effect of the gap on future productivity. In other words, because the gap variable includes the year $t-1$ productivity of the receiving establishment, $Y_{j,t}^{r}$ is likely a mediator between the gap and our dependent variable $Y_{j,t+1}^{r}$. This mediation assumption is supported by the coefficient of the gap on $Y_{j,t+1}^{r}$ going to zero (0.0003 with $p = 0.84$) when productivity in year t is included as a regressor. Therefore, to estimate the total effect of the productivity gap on future productivity, we do not control for $Y_{j,t}^{r}$. Furthermore, $Y_{j,t}^{r}$ cannot be a confounding variable, since the productivity of the receiving establishment cannot affect the productivities of the sending and receiving establishments in year $t-1$. Two lags of the receiving establishment's productivity, $Y_{j,t-2}^{r}$ and $Y_{j,t-3}^{r}$ are added as a test of coefficient robustness[5].

In the specification outlined in equation (2), ability bias is another potential issue for identification. A bias would arise if higher ability workers tend to self-select into establishments with higher productivity. However, controlling for the factors related to this unobserved ability, like education levels and ICT and R&D experience from the sending firm, should remove the bias to the extent that our measure captures said worker ability. Furthermore, an opposite bias is also plausible: if firms try to hire workers with the highest perceived ability for their establishments with the lowest productivity, the sign of the bias would be reversed and the effects of worker mobility on productivity would be underestimated rather than overestimated. This is a likely scenario if firms tend to use outside hires to try and bring their least productive establishments up to speed with the rest of the firm.

[5] The coefficient of the gap goes from 0.01 ($p = 0.036$) to 0.003 ($p = 0.061$) when the lags are included in the baseline regression.

3 RESULTS

3.1 Receiving establishment's productivity and the gap

Table 3 estimates equation (2) separately for the overall productivity gap and the positive and negative gaps. Analogously to the positive productivity gap in equation (1), the overall productivity gap is calculated for establishment j hiring new workers i in year t as:

$$\overline{gap^{o}}_{j,t} = \frac{\sum_{i=1}^{H_{j,t}}(Y_{i,t-1}^{s} - Y_{j,t-1}^{r})}{H_{j,t}} \frac{H_{j,t}}{N_{j,t}}. \tag{3}$$

Table 3 Receiving establishment's productivity and the overall, positive and negative productivity gaps

Productivity (t+1)	(1)	(2)	(3)	(4)	(5)	(6)
Overall productivity gap	-0.00001	0.00001				
	(0.000)	(0.000)				
Positive productivity gap			0.010**	**0.008****		
			(0.005)	(0.004)		
Negative productivity gap					-0.00001	-0.00001
					(0.000)	(0.000)
Observations	221 711	221 711	124 886	124 886	148 321	148 321
Industry-year fixed effects		Yes		Yes		Yes
R^2	0.000	0.015	0.000	0.019	0.000	0.017

Notes: OLS coefficients with Huber–White standard errors in parentheses. Productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

Table 3 shows that the coefficients for the overall and negative productivity gaps are essentially zero. This is expected, since we assume there are no negative spillover effects caused by hiring workers from less productive establishments. Negative spillovers would imply negative learning[6] which, as noted by Stoyanov and Zubanov (2012), is unlikely. The results in columns 5 and 6 ($p = 0.382$ and $p = 0.389$) confirm the expectation that cross-firm hiring of new workers from less productive establishments is neutral to future

[6] A positive and significant coefficient on the negative productivity gap could conceivably also imply some other unexplained mechanism, but we will assume this is not the case. the assumption of no negative spillovers is also supported by the regression results presented in Table 3.

productivity. The zero coefficient on the overall productivity gap is also not surprising, since almost 67% of all the measured cross-firm productivity gaps between the sending and receiving establishments are negative. Following the results in table 3, the rest of the paper will focus exclusively on the positive productivity gap.

The results for the OLS linear regression of equation (2) are recorded in Table 4. Establishment characteristics, averages of worker characteristics (see Table 1) and the new workers' human capital variable are added as controls to the specification presented in column 4 of Table 3. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. Level of education is measured as the share of workers with a higher education, which is defined as having completed at least a bachelor's degree or equivalent (15-16 years from the beginning of primary education).

The coefficient on the productivity gap is between 0.022 and 0.025 in every specification of table 4, with p-values ranging from 0.007 in column 1 to 0.018 in column 4. Though statistically significant at the 95% confidence level, this positive relationship between the gap and the receiving firm's productivity is rather small in magnitude: for an average establishment, hiring every worker from establishments that are more productive by the mean positive gap of 36 878.73€ is associated with $811.33€$ $(= 0.022 \times 36878.73€)$ higher productivity one year after hiring. This is approximately 0.45 percent[7] of the productivity of an average establishment. This is consistent with the findings of Hlatshwayo et al. (2019), who report a 0.38 percent productivity gain from hiring new workers from more productive firms. The gap therefore explains only a relatively small portion of the observed productivity dispersion. Alternatively, increasing the positive productivity gap of all workers by one tenth of a standard deviation is associated with a 0.66 percent (1185.9€[8]) higher productivity in the following year.

[7] $811.33€/180318.90€ = 0.004499$

[8] $0.022 \times 539047€ = 11859€$, or 6.6% of the productivity of the average establishment.

Table 4 Receiving establishment's productivity and the positive productivity gap

Productivity (t+1)	(1)	(2)	(3)	(4)
Positive productivity gap	0.025***	0.024**	0.024**	0.022**
	(0.009)	(0.010)	(0.010)	(0.009)
ICT/worker of sender			2078*	3514***
			(1133)	(1035)
R&D of sender			4532***	1015*
			(588)	(615)
Share of new workers			16786***	6273
with a higher education			(12133)	(5064)
Establishment characteristics	Yes	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes	Yes
Human capital of new workers			Yes	Yes
Industry-year fixed effects	Yes	Yes		Yes
Observations	27 207	20 872	20 813	20 813
R^2	0.129	0.341	0.200	0.341

Notes: OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. ICT is measured as the log of information and communications technology planning and programming expenditure per employee. Following Bloom et al. (2019), R&D is measured as $\log(1 + R\&D\ intensity)$, where R&D intensity is total research and development expenditure per worker. Only observations with non-negative values of ICT and R&D expenditures are included. Missing values of ICT and R&D have been replaced by 2-digit level industry means. Labour productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $*\,p < 0.10,\ **\,p < 0.05,\ ***\,p < 0.01$.

Even though not very strong, the relationship between our gap measure and productivity is likely to capture productivity spillovers caused by inter-firm worker mobility, as intended. This is implied by the inclusion of new workers' human capital having almost no effect on the gap's coefficient. If the link between worker mobility and productivity was explained by the direct effects of firms employing more workers with high human capital, we would expect the positive correlation to weaken or even disappear when going from column 2 to 4 in Table 4. Therefore, the results support the assertion of the productivity gap as a reliable measure of establishments' exposure to spillovers from worker mobility.

In the estimations presented in Tables 3 and 4, worker mobility between establishments within the same firm is excluded. When including within-firm worker movements, no statistically significant correlation between the productivity gap and future productivity is found. Approximately 77.4% of the workers moving between establishments also switched firms. Considering how significant this share is, and assuming that there is more variation in characteristics across firms than in establishment characteristics within firms, excluding the within firm transfers will likely result in a more accurate reflection of productivity spillovers.

Furthermore, the disappearance of the significant correlation when including within-firm movers implies that worker mobility from more productive establishments to less productive ones within firms is less likely to induce productivity spillovers in the receiving establishments, compared to cross-firm worker mobility. An analysis of manager mobility and a fractional polynomial model are described as extensions in the following section.

3.2 Extensions and robustness checks

The first extension is an analysis of manager mobility. The share of managers in the subsample of establishments with less than 5 employees is 1.3%, whereas managers comprise an average of 5.8% of total workers in establishments with at least 5 employees. Therefore, the analysis only includes the latter. The control variables in the manager mobility regressions are the same as in Table 4, except the mean education level of new managers replaces the level of education of new workers. The share of managers with a higher education is 44.1% in the full subsample of establishments with at least 5 employees, whereas the corresponding share is 48.7% for newly hired managers.

Table 5 Receiving establishment's productivity and the overall, positive and negative productivity gaps for hired managers

Productivity (t+1)	(1)	(2)	(3)	(4)	(5)	(6)
Overall productivity gap for managers	-0.023 (0.017)	-0.021 (0.015)				
Positive productivity gap for managers			0.0004 (0.0001)	**0.0003*** (0.0002)		
Negative productivity gap for managers					-0.058 (0.057)	-0.053 (0.051)
Observations	13 521	13 521	7 491	7 491	6 934	6 934
Industry-year fixed effects		Yes		Yes		Yes
R^2	0.017	0.113	0.0001	0.150	0.044	0.164

Notes: OLS coefficients with Huber–White standard errors in parentheses. Managers are defined as employees belonging to the group "managers" in the Statis-tics Finland Classification of Occupations 2010. Productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$.

The results of Table 3 hold here as well: the coefficients for the overall and negative manager productivity gaps are essentially zero. The coefficient on the positive productivity gap is again positive, but unlike with all workers, it is extremely small and only statistically significant at the 90% confidence level. Furthermore, as evidenced by Table 6, the correlation between productivity and the positive productivity gap measured for moving managers is essentially zero in all specifications. No definitive conclusions can be drawn from these results, but it seems plausible that the mechanisms governing the hiring of managers differ from those governing the hiring of other workers in some significant ways.

Table 6 Receiving establishment's productivity and the positive manager productivity gap

Productivity (t+1)	(1)	(2)	(3)
Positive productivity gap (managers)	-0.0005*	-0.0005	-0.0005
	(0.0003)	(0.0003)	(0.0003)
ICT/worker of sender			1327
			(3571)
R&D of sender			-1037
			(2170)
Share of new managers			8162
with a higher education			(7802)
Establishment characteristics	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes
Human capital of new workers			Yes
Industry-year fixed effects	Yes	Yes	Yes
Observations	1 810	1 398	1 398
R^2	0.429	0.470	0.471

Notes: OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. ICT is measured as the log of information and communications technology planning and programming expenditure per employee. Following Bloom et al. (2019), R&D is measured as $\log(1 + R\&D\ intensity)$, where R&D intensity is total research and development expenditure per worker. Only observations with non-negative values of ICT and R&D expenditures are included. Missing values of ICT and R&D have been replaced by 2-digit level industry means. Labour productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$.

The regressions of future productivity on the productivity gap measure are not meant to accurately describe the absolute magnitude of productivity spillovers through worker mobility. Rather, they demonstrate that hiring and employee turnover are a plausible source of productivity variation. Going from all workers to only managers, the differences in the results highlight the uncertainty involved with these types of studies. This uncertainty must be considered in any study involving worker mobility; the mobility-affecting incentives of both the moving workers and the hiring firms are much too complex to reliably parse with any simple regression analyses.

3.2.1 Fractional polynomial model

The multivariable fractional polynomial (MFP) provides a systematic, fully data-driven way of selecting the best-fitting functional form for a statistical model (Royston & Sauerbrei 2009). The approach uses backward elimination to select which variables are included in the model and combines this with a systematic fractional polynomial function selection procedure to determine a functional form for the included predictors. In the first step of the MFP algorithm, the best-fitting fractional polynomial (FP) functions of the first and second degree are selected based on the Akaike's information criterion (AIC)[9]. In the second step, MFP systematically examines whether FP functions of varying complexity describe the shape of the association between a regressor and the dependent variable better than a linear function.

Table 7 reports the results[10] from estimating the full fractional polynomial (FP) model built by the MFP backfitting model-selection algorithm. All variables are centered around the mean and modelled as fractional polynomials with powers chosen by the algorithm. The coefficient in column 1 implies that for an average establishment, hiring all its workers from the average more productive outside establishment is associated with a 2.15 percent[11] higher productivity in the year after hiring. Adding average worker characteristics and the measure of new workers' human capital as controls lowers the observed association to 1.57 percent. Alternatively, increasing the positive productivity gap of all workers by one tenth of a standard deviation is associated with a 2.45 percent (4415.45€) higher productivity in the following year.

The positive association implied by the fractional polynomial model is significantly stronger compared to the original specifications, results of which are shown in Table 4. It is therefore not unjustifiable to treat the coefficients estimated from equation (2) as a somewhat conservative lower bound for the association between the productivity gap and the future productivity of the receiving establishment.

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[9] $Model\ deviance - 2 * (maximized\ log\ likelihood\ for\ the\ model\ being\ tested)$.

[10] The coefficients on the control variables are omitted for conciseness and are available on request from the authors.

[11] $244454.7 \times \{[(36878.73€/10000000)^{0.5}] - 0.0448603721\} = 3878.88€\ and\ 3878.88€/180318.9€ = 0.021511.$

Table 7 Fractional polynomial model

Productivity (t+1)	(1)	(2)	(3)
FP(Positive productivity gap)	244454.7***	194396.2***	190179.0***
	(55182)	(44837)	(64916)
Establishment characteristics	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes
Human capital of new workers			Yes
Observations	27 207	20 872	20 813
R^2	0.082	0.262	0.263

Notes: $FP(Positive\ productivity\ gap) = \hat{X}^{0.5} - 0.0448603721$, where $\hat{X} = \overline{gap}/10000000$. The division of the gap variable before centering on the mean is applied automatically to improve the scaling of the regression coefficient for FP(Positive productivity gap). OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. $*\,p < 0.10$, $**\,p < 0.05$, $***\,p < 0.01$.

3.2.2 Robustness of the results

In addition to the reported estimates with normal unweighted average management scores, all regressions were run with employment weights to ensure that the qualitative conclusions hold for employment weighted productivity[12] as well. Employment weighted regressions mitigate the impact of smaller establishments with extreme labour productivity numbers. They also account for the workforce allocated into higher productivity establishments, making the employment weighted results more relevant for cross-regional or cross-country comparisons, for example. Adding employment weights to the regressions does not change the statistical significance of or the conclusions drawn from the estimates. The coefficient of the positive productivity gap in an employment weighted equivalent of the regression in column 4 of Table 4 is 0.021, as opposed to the 0.022 in the original unweighted specification. The employment weighted regression is equivalent to fitting the model

$$Y^r_{j,t+1}\sqrt{L_j} = \beta\overline{gap}_{j,t}\sqrt{L_j} + \sqrt{L_j}\cdot\boldsymbol{X}_{j,t}\mu + \sqrt{L_j}\cdot\overline{\boldsymbol{Z}}^1_{j,t}\gamma_1 + \sqrt{L_j}\cdot\overline{\boldsymbol{Z}}^2_{j,t}\gamma_2 + f_j\sqrt{L_j} + \bar{\epsilon}_{j,t+1}\sqrt{L_j}, \tag{4}$$

where L_j is the number of employees in establishment j.

The main analysis includes establishments of all sizes. Only including establishments with at least 5 employees slightly increases some point estimates and decreases

[12] Olley-Pakes decomposition (Olley & Pakes 1996) of productivity: Employment weighted average productivity = unweighted average productivity + a covariance-like term between activity shares and productivity.

others but does not affect the statistical significance of the coefficients or any qualitative conclusions drawn from the regressions. When excluding all other industries except manufacturing[13], the coefficients corresponding to those in columns 1, 2 and 4 of Table 4[14] are reduced to 0.018**, 0.014* and 0.013*. In the regressions with only manufacturing, the range of the number of observations also goes down to approximately 5100–6800 from the original 20800–27200.

[13] Industries 10–33 in the Standard Industrial Classification TOL 2008 (Statistics Finland 2017).
[14] The coefficients are 0.025***, 0.024** and 0.022** in columns 1, 2 and 4 of Tabe 4.

4 CONCLUSIONS

The main finding of this paper is that hiring workers from more productive establishments can explain a relatively small but statistically significant part of the future productivity of the receiving establishments. Namely, hiring every worker from outside establishments that are more productive by the mean positive productivity gap is associated with 811.33€ higher productivity one year after hiring. This is approximately 0.45% of the productivity of an average establishment. It is unlikely that these spillovers are explained by hiring-induced changes in the receiving establishments' human capital stock, since we control for the human capital of the hired workers.

These results hold when establishments with less than 5 employees are excluded and when only establishments in the manufacturing sector are included. However, no link between the gap and the hiring establishments' productivity is found for moving managers. The found association also disappears when worker movements within firms are included. This suggests that worker mobility from more to less productive establishments within firms is unlikely to induce productivity spillovers in the receiving establishments, at least in the aggregate. Furthermore, we do not find any evidence that the average worker characteristics[15] of the receiving establishments significantly influence the relationship between the productivity gap and the productivity of the receiving establishment.

The analyses presented in this paper suggest that worker mobility can indeed induce productivity spillovers, even outside the direct effects of the changing workforce characteristics of hiring establishments. This does not necessarily imply much for an individual firm or establishment, especially considering the relatively small magnitude of the estimated spillovers. It does, however, support labour market flexibility and the provision of safety nets to mitigate the negative individual-level effects of employee turnover. Since worker mobility can induce growth-supporting productivity spillovers, and it is partly driven by involuntary redundancies and periods of unemployment, we should ensure that these potential positive externalities do not come at the expense of the workers' welfare.

Furthermore, the results presented imply that a cross-regional analysis of worker mobility and productivity might reveal interesting facts about the effects on international competitiveness of the regional disparities[16] in worker flows. The productivity gap measure can be of use when calculating the costs associated with the concentration of the workforce in certain areas within countries. At the same time, policies supporting worker flows from more to less productive areas could potentially lead to a decrease in regional productivity dispersion.

[15] Share of managers, share of high and medium skilled workers, share of workers with higher education, age and wage. See Table 2.

[16] For statistics on regional labour mobility in Finland, see Poghosyan & Scott (2018).

BIBLIOGRAPHY

Aghion, P. & Howitt, P. 1992. A model of growth through creative destruction. Econometrica 60 (2), 323–351.

Bender, S., Bloom, N., Card, D., Van Reenen, J. & Wolter, S. 2018. Management Practices, Workforce Selection, and Productivity. Journal of Labor Eco-nomics 36 (S1), 371–409.

Castillo, V., Garone, L., Maffioli, A., Rojo, S. & Stucchi, R. 2019. Knowledge Spillovers through Labour Mobility: An Employer–Employee Analysis. The Journal of Development Studies 56 (3), 469–488. [Referred 30.5.2022]. DOI: 10.1080/00220388.2019.1605057.

Grossman, G. & Helpman, E. 1991. Quality ladders in the theory of growth. The Review of Economic Studies 58 (1), 43–61.

Hlatshwayo, A., Kreuser, C. F., Newman, C. & Rand, J. 2019. Worker mobility and productivity spillovers: An emerging market perspective. WIDER Working Paper Series wp-2019-114, World Institute for Development Economic Research (UNU-WIDER).

Jones, C. 2005. Growth and ideas. In Aghion, P. & Durlauf, S. Handbook of economic growth (Chapter 16, 1063–1111). Amsterdam: Elsevier.

Kaiser, U., Kongsted, H. & Rønde, T. 2008. Labor Mobility and Patenting Activity. University of Copenhagen, Department of Economics, Centre for Applied Microeconometrics (CAM) Working Paper no. 2008-07.

Le Mouel, M. 2018. Knowledge-Based Capital and Firm Productivity [Doctoral dissertation]. Chapter 4: Managerial knowledge spillovers and firm productivity. Technische Universität Berlin, School VII Economics and Management.

Maliranta, M., Mohnen, P. & Rouvinen, P. 2009. Is Inter-Firm Labor Mobility a Channel of Knowledge Spillovers? Evidence from a Linked Employer-Employee Panel. Industrial and Corporate Change 18 (6), 1161–1191.

Moen, J. 2005. Is Mobility of Technical Personnel a Source of R&D Spillovers? Journal of Labor Economics 23 (1), 81-114.

Moretti, E. 2004. Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions. American Economic Review 94 (3), 656–690.

Olley, G. S., Pakes, A. 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64 (6), 1263–1297.

Parente, S. & Prescott, E. 1994. Barriers to technology adoption and development. Journal of Political Economy 102 (2), 298–321.

Poghosyan, T. & Scott, A. 2018. Regional Labor Mobility in Finland. IMF Work-ing Papers 2018 (525).

Prescott, E. & Visscher, M. 1980. Organizational capital. Journal of Political Economy 88 (3), 446–461.

Romer, P. M. 1990. Endogenous technological change. Journal of Political Economy 98 (5), S71–S102.

Royston, P. & Sauerbrei, W. 2009. Two techniques for investigating interactions between treatment and continuous covariates in clinical trials. The Stata Journal 9 (2), 230-251.

Statistics Finland. 2017. Standard Industrial Classification TOL 2008. Statistics Finland Data Collections. [Referred 20.5.2022]. Available at: http://stat.fi/meta/luokitukset/toimiala/001-2008/index.html.

Statistics Finland. 2021. Classification of Occupations 2010. Statistics Finland Data Collections. [Referred 10.5.2022]. Available at: https://www.stat.fi/en/luokitukset/ammatti/.

Stoyanov, A. & Zubanov, N. 2012. Productivity Spillovers Across Firms through Worker Mobility. American Economic Journal: Applied Economics 4, 168–198.

APPENDIX A: FIGURES

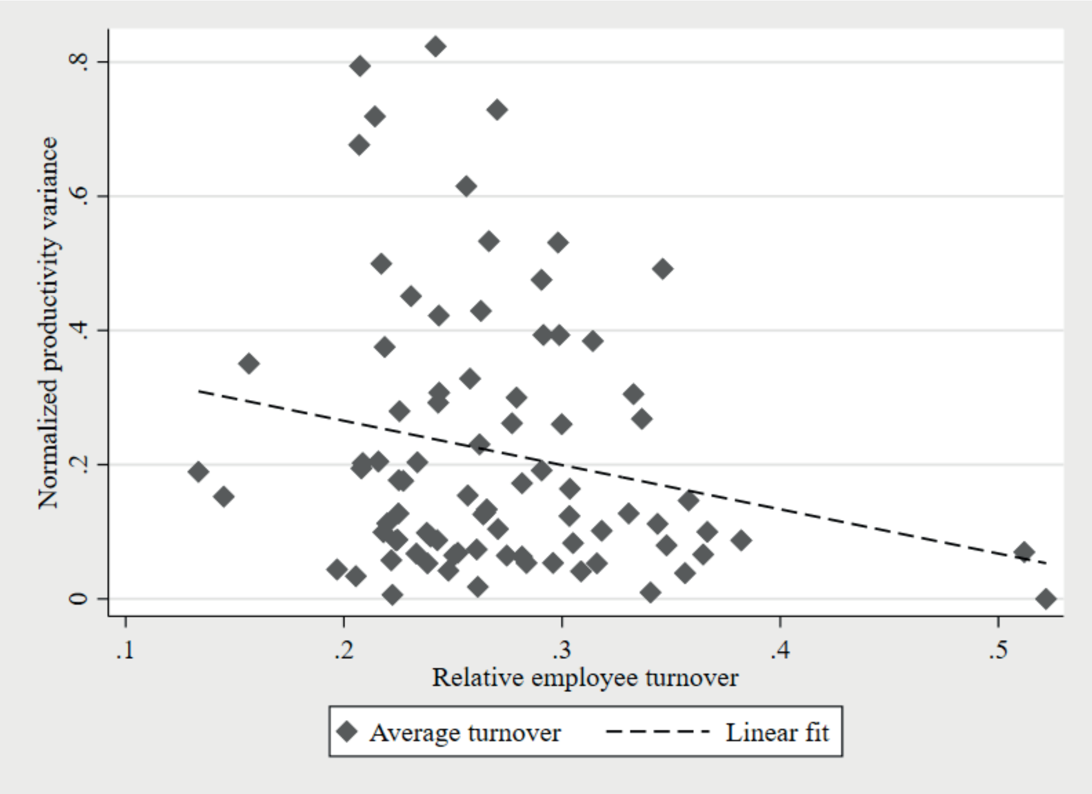

Figure A.4 Overall industry-level relative employee turnover and productivity variance.

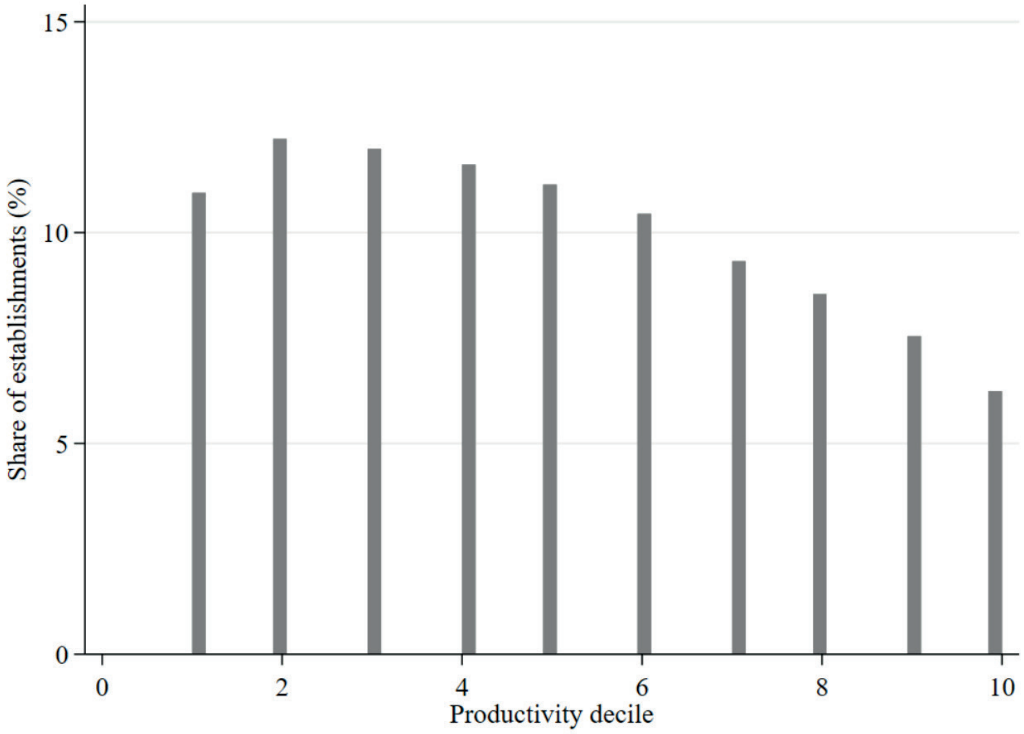

Figure A.5 The distribution of the share of establishments in each productivity decile.

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Publisher: Taloustieto Oy

Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki