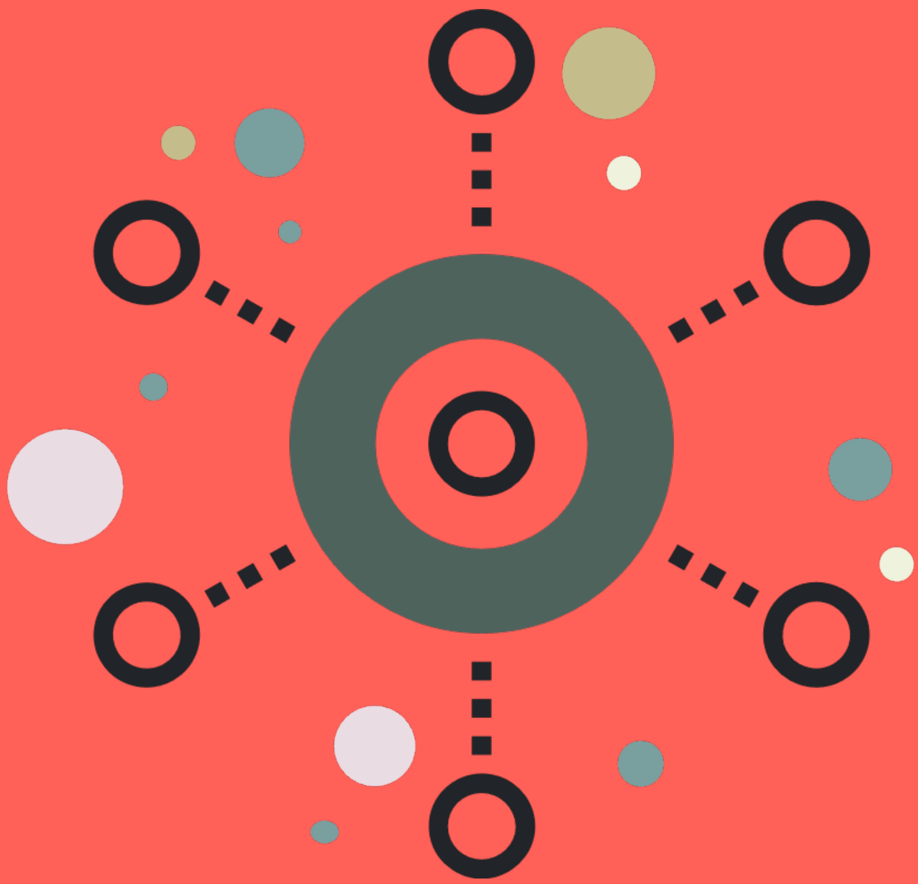

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Productivity effects of knowledge transfers through inter-firm labour mobility

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Productivity effects of knowledge transfers through inter-firm labour mobility[1]

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Abstract

A matched employer–employee dataset combined with modern matching methods and a *difference-in-differences* (DiD) estimator are used to examine whether firms that have recruited workers from knowledge-intensive firms (KIFs) obtain higher productivity and/or employment in comparison to firms that only have recruited workers from other firms. We find statistically significant differences between the treatment and control groups in both total factor productivity (TFP) and employment, i.e., recruitments from KIFs actually impacts both TFP and employment. For TFP, however, it appears that an initial knowledge level is required for firms to generate economic value from KIF recruitment. The effects are similar in magnitude across the groups of recruited workers (education, occupation, and experience), i.e., the effects cannot be explained by heterogeneity among recruited workers. We conclude that labour mobility is an important mechanism for the transfer of knowledge and ideas and that this process may result in productivity improvements in recipient firms.

Keywords: Firm productivity, inter-firm labour mobility, knowledge transfers

JEL: D24, J24, J60, O33

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1. Introduction

The incentives for firms to accumulate knowledge and skills are quite explicit (Teixeira, 2002). Less is known about the effects of knowledge diffusion across firms. While there are many plausible mechanisms for inter-firm transfers of knowledge, there is growing recognition of the mobility of skilled labour as an essential mechanism enabling productivity improvement, which is the central driver of both firm growth and economic growth (Griliches, 1992, 1979). The rationale is that labour mobility results in knowledge diffusion from technologically superior firms, which expand the opportunities identified in the process of finding new avenues of production. Certainly, technological upgrading requires higher levels of skill, knowledge and organisation in almost every function. However, the empirical evidence on the effects of inter-firm transfers of knowledge through labour mobility at the firm level is incomplete. In particular, there is uncertainty about the importance of this mechanism and the size of its effects when they stem from human capital acquired from knowledge-intensive firms (KIFs).

This study examines whether firms that have recruited workers from KIFs obtain higher productivity and/or employment in comparison to those that recruited from less knowledge-intensive firms (hereafter, non-KIFs). The paper consists of three novelties. First, we use a matched employer–employee dataset to employ a new procedure, originally developed by Andersson et al. (2019), to identify the KIFs in the economy from which our treatment group firms, but not the control group, have recruited skilled workers. Second, we apply modern matching methods and a *difference-in-differences* (DiD) estimator to identify inter-firm differences in productivity and employment. Third, we control for heterogeneity among recruited workers, i.e., we only compare recruited individuals with similar backgrounds (education, occupation and work experience).

The paper is organised as follows. Section 2 reviews related research. Section 3 describes the data and research design. The model results are presented in Section 4, where we also discuss robustness. Section 5 concludes the paper and discusses future research.

2. Previous research

Moen (2005) argues that inter-firm transfers of knowledge embodied in people should be analysed from the role and importance of human capital, which is central to the productivity of individuals and the competitiveness of firms and can even serve as a pre-condition for economic performance (Becker, 1993, 1962; Howell and Wolff, 1991). The term human capital is a widely used concept with varying definitions; it typically refers to some form of acquired formal education but may also encompass a wider set of skills, abilities to perform given tasks, or mastery of various techniques. Firms invest in human capital because they expect to derive higher future profits from productivity improvements. The research on the relationship between human capital and firm performance is clearly biased towards human capital and shows that labour quality explains inter-firm differences in productivity (Griliches and Regev, 1995). Of course, firms may adopt different strategies to upgrade its human capital. For instance, firms can choose to invest in in-house competence or to acquire knowledge and skills through recruitment from other firms. While both strategies may enable firms to access higher productivity trajectories, labour mobility in itself may enhance firm performance when workers are hired from firms that have already enacted innovations. It may also improve knowledge matching and spur networks (Hoisl, 2007).

Knowledge transfers through labour mobility have become the basis for a number of formal models (e.g., Fosfuri et al. 2001; Glass & Saggi 2002; Heggedal et al. 2017), but have also been examined in a number of empirical studies. Almeida and Kogut (1999) analysed the relationship between the mobility of engineers between firms and patent citations in the semiconductor industry and found that this mobility influences the local transfer of knowledge. Breschi and Lissoni (2009) drew similar conclusions. A starting point in several other studies is that foreign firms and/or multinationals are superior to rival firms because ownership advantages enable them to compete on international markets (Caves, 1974; Dunning, 1980). This suggests that employees can acquire skills and experiences at multinationals that are valuable to other firms, if transferred. For instance, Balsvik (2011) traced worker flows between plants in Norwegian manufacturing firms during the 1990s and found a positive correlation between the share of workers from multinationals in non-multinationals and the productivity of these (local) plants. Similar results were found by Masso and Vahter (2019) for Estonian firms using TFP as the outcome variable.

Poole (2013) used a matched establishment-worker database from Brazil and presented empirical results showing positive multinational wage spillovers through worker mobility in Brazil. When workers leave multinationals and are rehired at domestic establishments, the wages of domestic workers increase, suggesting a positive effect from multinationals through labour mobility. Poole also demonstrated heterogeneous impacts and argued that higher-skilled former multinational workers are better able to transfer information and that higher-skilled incumbent domestic workers are better able to absorb information. Highly educated workers earn a return on prior experience in foreign multinationals over and above the return on other previous experiences. Maliranta et al. (2009) employed an employer–employee panel with data from Finland to study whether the movement of workers across firms is a channel for the unintended diffusion of R&D-generated knowledge. They demonstrate that hiring workers previously in R&D to roles engaged in non-R&D activities boosts productivity and profitability, but this does not hold if the new role involves R&D. Braunerhjelm et al. (2020) use a Swedish matched employer–employee dataset pooled at the firm level to provide evidence that knowledge workers' mobility has a positive and strongly significant impact on firm innovation output measured by firm patent applications. They argue that the effect is statistically and economically significant for knowledge workers who have previously worked in a patenting firm (the learning-by-hiring effect). However, no effects were detected for inexperienced university graduates.

Taken together, for an effect to accrue from knowledge diffusion through labour mobility, we can expect to observe the following. First, a transferable firm-specific advantage should exist that serves as the basis of this effect. Second, a non-negligible quantity of job-switchers should exist that can transfer at least some of the firm-specific advantages across firms. Third, there must also be a measurable effect on the recruiting firms. Furthermore, some evidence suggests heterogeneous impacts indicating that skills and prior experiences influence the ability of firms and workers to absorb ideas developed by other firms. While the existing literature used various methodological approaches to examine the effects of labour mobility, none of them applied matching methods. Additionally, the assumption that an effect exists is largely based on the fact that multinationals are, by definition, technologically superior firms. Although this may be the case, this is a strong assumption, as a skilled labour force, and therefore, a high technology level, is not required to control economic activities in more than one country, suggesting that multinationals are a heterogeneous group of firms (see also Dunning and Lundan, 2008). Several aspects of this study distinguish it from the previous literature. First, we make use of an alternative delineation of technologically superior firms (i.e., the KIFs) from which we anticipate knowledge transfers that may result in productivity improvements. Second, we use a novel matching method to analyse differences in inter-firm productivity. Third, we control for the recruitment of workers with the same background. Our research design is described in the next chapter.

3. Research design

3.1 Data

A matched employer–employee dataset is utilised to trace inter-firm labour mobility. Our dataset is based on annual register data from Statistics Sweden and comprises information on basically all firms and individuals in Sweden over the period 2001-2017. Since the data include annual information on each individual's employer, we can trace whether a person has changed employers or not. A job-switcher is a person who has changed their employing firm between two consecutive years. A firm is defined as a registered company that may consist of one single business entity or, when relevant, an entire business group. Consequently, labour mobility within business groups is excluded. By combining information on each individual's employment path with very detailed information on business and workplace dynamics, we ensure that all observed labour mobility has involved a change in employing firm and is not the result of administrative changes, such as a new corporate identity. For empirical reasons, to be included in our dataset, a firm must have had at least 10 employees for at least 3 years. Firms with gaps in the time series are excluded. The matched employer–employee dataset implies that each included person is linked to at least one of the firms included in the dataset. Since the information on education, occupation, and so on is available at the individual level, we are able to extract very detailed information on the job-switchers' background (education, occupation, work experience), which we can use to identify the knowledge intensity of firms. Consequently, we are able to reduce heterogeneity among firms and persons recruited by firms in the treatment and control groups.

3.2 Knowledge-intensive firms (KIFs)

Conceptually, our focus on KIFs implies that firms are analysed through the lens of intellectual capital. Knowledge is key in creating new economic value. It then follows that KIFs are firms in which skilled workers are central to production. We define KIFs as firms in which the majority or even the entire workforce consists of skilled workers with some form of discipline-based knowledge, skill or qualification whose work involves creating new knowledge, solving complex problems, providing new solutions for clients or exploiting existing knowledge in new ways (March, 1991). Significant differences should, therefore, exist in the degree of knowledge intensity between KIFs and non-KIFs.

To empirically identify KIFs, we employ a method suggested by Andersson et al. (2019), which was originally developed to analyse the cause and effects of large knowledge-intensive investments.[2] Their method provides a multidimensional view of the role of knowledge in production, including research and development work, and measures the knowledge intensity of each firm relative to all other firms in the economy. Recruiting skilled workers from relatively KIFs should thus be fruitful for firms aiming to find new productive trajectories: KIFs are not only the most knowledge-intensive and technologically advanced firms in the economy but they also should be more likely to invest substantial effort to provide more training and stronger learning environments than other firms. In practice, their method implies that firms are classified by business orientation and by the composition of employees in terms of education and occupation. Table 1 presents the variables used to classify firms.Table 1 Variables to classify firms by knowledge intensity

Variable	Description
Knowledge and technology intensive industry	The firm is active in high-tech manufacturing or knowledge-intensive services (Eurostat definition*)
Long university education	Share of employees with ≥3 years university or college education
Research education	Share of employees with research education
STEM education (extended definition)	Share of employees with an education in a selection of areas in science, technology, engineering, mathematics, plus media and design
Professional (core functions)	Share of employees in professions (selected ISCO codes in category 2) directly associated with knowledge-intensive activities: physicists, chemists, mathematicians and statisticians, computing professionals, engineers, architects, specialists in biology, agriculture and forestry
Technician (support functions)	Share of employees in support functions (selected ISCO codes in category 3) directly associated with knowledge-intensive activities: engineers and technicians, computer technicians and data operators, biomedical analysts

* Eurostat definition of high-tech industry and knowledge-intensive services: https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm

The classification procedure is made in two steps. First, firms are classified by business sector (1 if the firm produces knowledge-intensive services or technologically advanced

[2] Large knowledge-intensive investments (LKI) is not an established term in economic research and there is no integrated research literature on the topic. However, the LKI concept provides a foundation for analysing firm activities characterized by large and continuous investments in intangible assets and/or giving rise to such investments in up- or downstream activities. A typical LKI consists of an investment involving the recruitment of qualified workers (Andersson et al., 2019).

industrial products, 0 otherwise). Firms are then classified according to their workforce composition based on two conditions: (i) if the share of employees in a firm with a specific feature, such as university education, diverges by 1 standard deviation from the mean (liberal condition); and (ii) if the share of employees with the same specific feature diverges by more than 2 standard deviations from the mean (conservative condition). For example, firms are classified as follows: 1 if the share of employees having ≥3 years of university education is at least 1 standard deviation above the mean, 0 otherwise; and 1 if the share of employees having ≥3 years of university education is at least 2 standard deviations above the mean, 0 otherwise. In total, 11 indicators are obtained that jointly reflect the knowledge intensity of a firm, meaning that firms can obtain between 0 and 11 conditions (hereinafter, LKI points). Consequently, there are 12 categories in total, and KIFs are simply those firms that exhibit higher knowledge intensity than their competitors in the rest of the economy.

Table 2 provides an overview of the knowledge intensity in Swedish firms in 2017[3]. Firms have a skewed distribution over the 12 categories (representing the number of achieved LKI points). Of the total 28 300 firms, only 79 firms achieved 11 LKI points. These are the most KIFs, in which approximately 75 percent of the employees had at least 3 years of university education and 23 percent had a research education. We can also see that the majority had a STEM-oriented education and/or occupation, indicating that these firms should have a strong orientation towards research and development, produce high-tech industrial goods and/or knowledge-intensive services. STEM knowledge and critical thinking are typical in such complex products (Lo Turco and Maggioni, 2020).

Overall, the more knowledge intensive a firm is, the more it features a composition of workers with a relatively long and advanced STEM education, including research competence. KIFs also pay relatively high wages and are to a large extent multinational and engaged in international trade, i.e., participate in global value chains. Almost 60 percent of the total 28 300 firms did not meet any of the 11 conditions, thus being the least KIFs in the economy. In these firms, very few employees have a post-secondary education and/or a STEM-oriented education. The (average) wage is much lower than that in in KIFs.

In this paper, KIFs are empirically defined as firms that meet at least 8 out of 11 conditions. Non-KIFs are firms that meet 0-7 conditions. Of course, there is no contradiction between claiming the distinctiveness of KIFs and assuming a general increase in the relevance and level of knowledge as long as there is a significant difference between KIFs and non-KIFs. Although the employed method is a simplification in terms of capturing the role of knowledge in production, it nevertheless presents a fine-grained view on how KIFs are distinguished from other firms. KIFs are not only relatively knowledge intensive but also consist of human capital resources who are usually considered strong providers of technology- and knowledge-driven growth as well as productivity. Therefore, KIFs are not only the most knowledge-intensive firms in the economy but should also be the firms at the technological frontier with knowledge capital that may spur innovation, future ventures and economic growth.

[3] The distribution of firms across the 12 categories is similar over the period 2001-2017

Table 2 Firms by knowledge intensity 2017 (Category = number of achieved LKI points, denoting knowledge intensity)

		Firms				Average	Education level				STEM-	STEM	Average
		Number	Share	MNE	IT	employment	Short	Medium	Long	Research	education	occupation	wage
	Category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
KIF	11	79	0,3%	47%	95%	48	7%	18%	74%	23%	87,1%	73%	550 890
KIF	10	97	0,3%	53%	97%	233	13%	22%	65%	18%	71,2%	62%	566 263
KIF	9	215	0,7%	34%	89%	127	10%	29%	61%	6%	77,7%	70%	526 964
KIF	8	244	0,9%	42%	90%	198	15%	33%	52%	3%	71,3%	64%	525 677
	7	361	1,3%	38%	86%	125	22%	39%	39%	2%	67,6%	61%	517 077
	6	364	1,3%	34%	85%	78	29%	36%	35%	2%	59,7%	55%	521 452
	5	507	1,8%	29%	79%	54	30%	30%	40%	4%	49,5%	39%	496 626
	4	542	1,9%	26%	77%	204	31%	28%	41%	3%	44,8%	27%	500 755
	3	1 328	4,6%	20%	59%	83	32%	21%	47%	0,7%	26,2%	11%	464 069
	2	2 396	8,3%	15%	61%	59	60%	19%	20%	0,3%	44,1%	7%	379 856
	1	5 522	19,2%	14%	57%	77	71%	20%	9%	0,1%	30,2%	3%	347 447
	0	17 048	59,4%	9%	58%	58	83%	13%	4%	0,0%	17,6%	1%	316 231
	Total	28 703	100,0%	30%	78%	112	34%	26%	41%	5%	54%	39%	476 109

Note: (1) Number of firms by category; (2) Category share of total firms; Share of firms (3) that are part of multinational enterprise (Swedish-owned/foreign-owned); (4) with international trade; (5) Average number of employees; Share of employees with (6) primary or secondary education; (7) post-secondary education (higher vocational studies) or <3 years of university; (8) at least 3 years of university education; (9) research education; (10) selected STEM educations, see Table 1; (11); selected STEM occupations, see; (12) Average wage in SEK

3.3 Inter-firm labour mobility from KIFs

For knowledge transfers to arise through labour mobility, there should exist a nontrivial number of job-switchers. Table 3 summarizes all inter-firm labour mobility in Sweden over the period 2001-2017. Firms are grouped by LKI points, which is important because our treatment group consists of firms that have recruited workers from KIFs (meeting 8-11 conditions), while the control group consists of firms that recruited workers from non-KIFs (0-7 conditions). In total, we can observe approximately 86 000 job-switches from KIFs (Category 8-11), of which 35 percent moved to other KIFs, 37 percent to firms with intermediate knowledge intensity (Category 3-7) and 28 percent to firms with low knowledge intensity (Category 0-2). This indicates that there is potential for knowledge transfers from KIFs to firms at different technological levels.

Table 3 Inter-firm labour mobility by aggregate categories (LKI points) and total, 2001-2017

From / To	KIF Cat.8-11	Absolute Cat. 3-7	Cat. 0-2	KIF Cat. 8-11	Share Cat. 3-7	Cat. 0-2
Cat. 8-11	30 038	31 929	33 301	35%	13%	2%
Cat. 3-7	31 987	85 190	161 054	37%	34%	8%
Cat. 0-2	24 577	132 548	1 732 437	28%	53%	90%
Total	86 602	249 667	1 926 792	86 602	249 667	1 926 792

Among the job-switchers from KIFs, 8 percent had at least 1 year of experience as managers in a KIF; 88 percent had at least 1 year of experience from work as a professional or specialist in a KIF; 79 percent had at least 1 year of experience from STEM-related work in a KIF; 65 percent had both STEM education and at least 1 year of experience from STEM-related work. These features are important to emphasise for two reasons. First, the observed labour mobility flows from KIFs largely consist of skilled workers that should be more likely to influence the recruiting firms than other workers. Second, to understand how job-switchers from KIFs impact recruiting firms, we need to consider whether the effect depends on the type of knowledge or skills that the job-switchers possess rather than from what firms they have been recruited from.

3.4 Outcome variables: Productivity and employment growth

To understand how job-switchers from KIFs impact recruiting firms, we use two outcome variables: productivity and employment growth. Productivity can be measured using different methods. The simplest and probably the most common measure is labour productivity, i.e., value added per employee or hours worked, which is easy to compute and only requires information on value added and employment. However, labour productivity is a partial measure of productivity because it ignores substitution between capital and labour (Brynjolfsson & Hitt 2003). In contrast, TFP considers all factors of production and can be measured by parametric methods, e.g., the Solow residual (Solow 1957) and stochastic frontier analysis (SFA) (Aigner et al., 1977; Pieri et al., 2018), or non-parametric methods such as the Malmquist index (Caves et al., 1982; Mattsson et al., 2018). Non-parametric methods have the limitation of interpreting all deviation from the production frontier as inefficiency, which generates a high degree of sensitivity to outliers. SFA methods focus on efficiency, i.e., distance from the frontier, and endogeneity is to a large extent ignored (an exception in SFA is Shee & Stefanou, 2015).[4] In this study, we use the TFP measure suggested by Levinsohn & Petrin (2003), which handles endogeneity using an intermediate input, i.e., material.[5] The second outcome variable is the number of full-time (annual) employees.

3.5 Matching procedure to identify comparative groups

Ideally, individuals who have worked for KIFs are a random sample of all individuals, and the firms that have recruited from KIFs are randomly distributed among all firms. However, this is not the case, since firms themselves choose what knowledge to recruit. There is also potential that a positively selected sample of highly productive individuals work for KIFs. Against this background, we need to rely on a quasi-experimental research design. Matching methods make treatment and control groups more comparable, so that a potential correlation in the evaluation parameter estimates is more likely to be causal (Cobb-Clark and Crossley, 2003).

Matching is used to identify a comparable control group of firms that closely matches firms in our treatment group. There are several matching techniques available in the causal inference literature, e.g., propensity score matching[6] (Rosenbaum and Rubin, 1985), coarsened exact matching (CEM) (Blackwell et al., 2009), and the Mahalanobis distance (Mahalanobis, 1936; Rubin, 1980). CEM has the advantage over other matching methods of being non-parametric, being more transparent, dealing with common support by construction and reducing the sensitivity to measurement error (Iacus et al., 2012). However, CEM may result in many lost observations when matching is exact. In contrast, matching can become imprecise if less strict restrictions are applied, resulting in greater dissimilarities between firms and thus less comparable treatment and control groups.

Given this background and the specific features of our dataset, we concluded that a three-step matching procedure, summarized in Table 4, is the preferred approach to generate comparable groups in terms of observable characteristics while at the same time keeping a sufficient number of observations. The period of interest is *t*-3 to *t*+3, where t represents the first year the treated firms hire from a KIF.[7]

[4] SFA also has limitations in regard to producing firm specific measures of TFP (Mattsson et al., 2020).

[5] Robustness tests have been conducted with labour productivity.

[6] See, e.g., King and Nielsen (2019) for arguments for not using propensity score matching

[7] Note that period *t* can be in different calendar years, because the first year of recruitment can be different. Therefore, the control firms are also matched by year.

Table 4 Summary of matching variables

Matching method	Variable	Description
Step 1: Coarsened exact matching (CEM)	Pre-treatment periods	Number of pre-treatment periods (1-3)
	Year (t-1)	Calendar year (2001-2016)
	Industry (t-1)	Firm industry (NACE-code, two-digit level, 88 sectors in total)
	Knowledge intensity (t-1)	Firms classification by knowledge intensity[1] (KI) in three groups: Low, Medium, High
	Long university education (t-1)	Share of employees with long university education (≥3 years), separated in three groups[2]: Low, Medium, High
Step 2: Matching by maximum acceptable difference	Firm size (t-1)	Maximum acceptable difference in employees between treated and control firms
	TFP (t-1)	Maximum acceptable difference in TFP between treated and control firms
	Change in employment	Maximum acceptable difference in employment change between treated and control firms during the pre-treatment period
Step 3: Matching by Mahalanobis distance	When the outcome variable is (1) TFP change, (2) Employment change	Mahalanobis distance used to rank neighbours based on pre-treatment using (1) TFP change or (2) employment change

1 The classification of firms by knowledge intensity is based on the KI index explained in Table 1 (Section 3.2) and results in the following groups: Low KI (0-2 points), Medium KI (3-7 points) and High KI (8-11 points)
2 The education groups are (1) below 1 standard deviation from the mean; (2) within ±1 standard deviation from the mean; (3) above 1 standard deviation from the mean

The three-step matching procedure can be described as follows. In Step 1, we make an exact match between treatment and control firms in terms of the number of pre-treatment years, industrial sector, knowledge intensity and education level. Matching on number of pre-treatment periods (i.e., t-1, t-2, t-3) is vital because new and incumbent firms are likely to develop differently. This implies that firms in the treatment group that appear in, say, t-2 are only matched with firms in the control group that appeared in period t-2. Because industries may take different development paths due to changes in macroeconomic conditions, international trade and so on; we match firms by industrial sector (NACE) at the two-digit level (88 sectors in total) and calendar year is used to control for business cycles. To obtain further similarities, firms are classified into three groups based on (i) their knowledge intensity (LKI index explained in Table 1, Section 3.2) and (ii) share of employees with long university education (≥3 years). This is important, as differences in knowledge composition and technological level may result in differences in productivity growth.

Step 2 aims to further increase the similarity between the matched firms obtained in Step 1, as substantial differences were observed on important variables in some matched pairs. This is done by controlling for firm size (employment), TFP in t-1, and employment change during the pre-treatment period. It is important to control for these factors, as firms with different initial size, performance and employment change may diverge in the post-treatment period for reasons other than our treatment indicator, i.e., recruitment from KIFs. To control for firm size, we perform matching by maximum acceptable differences in the number of employees depending on the size of the treatment firm[8]. We control for divergent performance, in terms of TFP, such that the control firms cannot diverge more than two standard deviations from their treated pair[9]. For employment change, we require that the absolute change in employees are within a specific interval, i.e., firms that do not fulfil the condition, , $|\Delta L_T - \Delta L_C| \leq 20$ are excluded, where L_T and L_C are the pre-treatment change in the number of employees for treated and control firms, respectively.

Together, Steps 1 and 2 result in analytically meaningful groups (strata), i.e., comparative groups with similar treated and control firms. Each firm within a stratum is, by construction, inside the common support, i.e., it fulfils all of the matching requirements in Steps 1 and 2. However, some of these strata consist of many observations. Because no distinction is made regarding whether a control firm is more or less similar within these strata, we introduce a third step that further improves the comparability. In Step 3, we rank firms based on their Mahalanobis distance. When TFP is the outcome variable, the most similar control firms within each stratum are identified as those with the smallest distance for the difference in TFP growth between treated and control during the pre-treatment period. When employment is the outcome variable, the same procedure is used with the change in the number of employees[10]. Finally, the comparison group consists of the five firms with the smallest distance within each stratum[11]. Jointly, these steps result in parallel pre-treatment trends for the outcome variables in our dataset.

Our matching procedure results in a treatment group with firms that have recruited workers from KIFs but that may also have recruited from less knowledge-intense firms and a control group with firms that have recruited workers with the same or similar background but not from KIFs. Recruitments from KIFs are made in period *t* but may also occur during the post-period, while recruitments from other firms can occur in any period.

3.6 Matching results: Comparison of the treatment and control groups

Table 5 shows substantial differences between the treatment and control groups before the matching procedure. For example, the average treatment firm has 218 employees, while the average firm in the control group has 31 employees. Considerable differences can also be observed for TFP, education level, and capital-labour ratio. After matching, firms in the treatment and control groups are much more similar. For instance, the average treatment firm has 35 employees, and the average firm in the control group has

[8] The limits are set so the difference cannot be more than 20 employees if the treated firm has fewer than 50 employees, not more than 40 if the treated firm has between 50 and 100, not more than 60 if the treated firm is between 100 and 250 and not more than 100 if the treated firm has more than 250 employees.

[9] The standard deviation for TFP is calculated sector and year specific.

[10] For firms that are present during all pre-treatment years, matching is performed on the difference between *t*-1 and *t*-3. For firms present during 2 pre-treatment years, matching is performed on the difference between *t*-1 and *t*-2. For firms where t-1 is the first year, the level is used.

[11] We exclude groups of treated and control firms where fewer than 5 firms remain before Step 3. Additionally, there are different firms chosen as control groups when TFP is the outcome or employment is the outcome, as the distances are calculated differently.

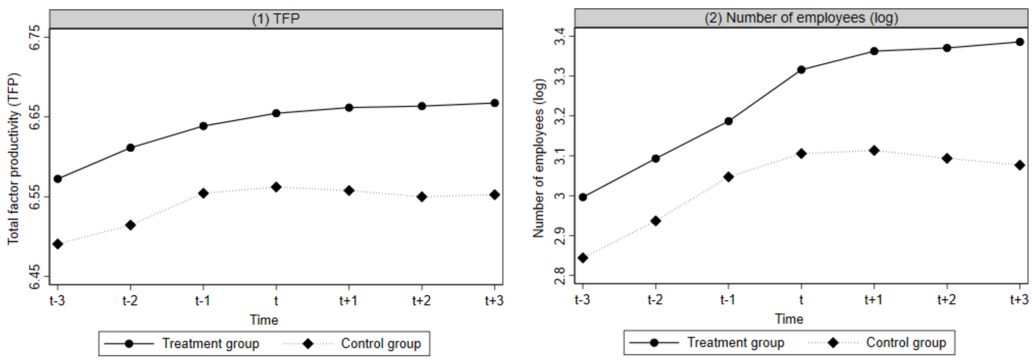
29 employees. This indicates that our matching procedure is successful in creating comparable treatment and control groups.

Table 5 Descriptive statistics of the treated and control groups before and after matching, *t*-1

Variable	Before matching		After matching	
	Treated	Control	Treated	Control
Log(TFP)	6.773	6.415	6.639	6.554
	(0.549)	(0.436)	(0.436)	(0.405)
Firm size (employees)	218.1	31.10	34.53	28.66
	(1160.3)	(54.09)	(32.57)	(28.08)
Share of employees with long education	0.192	0.0638	0.147	0.126
	(0.206)	(0.127)	(0.177)	(0.176)
Capital-labour ratio	4.818	4.994	4.828	4.801
	(1.862)	(1.624)	(1.678)	(1.612)
Observations	5900	180356	2932	14660

Of course, minor differences between the groups should remain, but as pointed out by Iacus et al. (2012, p. 23), "…no magical method will be able to fix this basic data inadequacy...". The most crucial element in creating comparative groups is a parallel pre-treatment trend in the outcome variables (in this study, TFP and employees). Figure 1 shows that similar development among the firms in the compared groups is achieved, i.e., parallel trends in the pre-treatment period. This means that the assumption of DiD is fulfilled, so our model results have the potential to be interpreted as an effect.

Figure 1 Development of TFP and employees for the total number of recruitments



3.7 Estimation method and interpretation of model results

We use a DiD panel method with fixed effects that eliminates time-invariant differences. The employed model is described in equation 1:

$$(1)\quad y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 time_t + \beta_3 DiD_t + \beta_j \mathbf{X}_{it} + \varepsilon_{it},$$

where y_{it} represents the outcome variables, i.e., TFP and employees (log-values) for firm i in period t. *Treated* is a dummy variable that equals 1 if a firm recruited from a KIF and 0 otherwise. *Time* is a dummy variable denoting periods t-3 to t+3, where t-1 is the period of reference. *DiD* is the interaction between the treated dummy variable and the time dummy variables, which is the coefficient of interest, i.e., the DiD estimator. For example, the estimate of t+2 is interpreted as the difference between treated and control at time period t+2 in comparison to the difference at t-1. $\mathbf{X}_{it}$ is a vector of control variables comprising the number of employees (log-values), capital-labour ratio (log values), the share of employees with long education, and calendar year fixed effects. ε_{it} is the error term.

The regression model generates estimates of the effects of recruitment from KIFs, i.e., firms in the treatment group are compared with firms in the control group that recruited during the same year. Because it is likely that firms chose to recruit workers with different skills, it is important to control for heterogeneity among the recruited workers. This implies that we avoid potential issues occurring from comparisons between recruitment in general and the recruitment of workers with very different skills, such as engineers and receptionists. Therefore, comparisons are made between firms that recruited workers with the same background (education, occupation, and work experience). This means, for example, that DiD estimates show whether recruiting workers with management experience results in differences for the recruiting firms depending on whether the worker is recruited from a KIF. In effect, equation 1 generates DiD estimates for TFP and employees with regard to recruitment in total and individuals with the following backgrounds: workers with at least 1 year of experience in management-related work; professional work; professional work in STEM-related occupations; and professional work in STEM-related occupations where the worker also has a STEM education. We control for these backgrounds because they reflect skilled workers that are central to production and creating new economic value. The implication of this approach is that we are examining whether the estimated treatment effect of knowledge transfers arises through labour mobility from KIFs. In other words, observed differences between the treatment and control groups are more likely to be caused by workers recruited from KIFs and not by differences in the backgrounds of the recruited workers.

However, selection bias may exist, which could challenge the interpretation of our results. More specifically, selection may cause non-random imbalances among the compared groups through the distribution of factors influencing the outcome variables. Of course, recruitment is not a random process, as firms choose which individuals to recruit and individuals may choose which firms to be recruited by. A problem exists if individuals recruited from KIFs have better initial abilities in comparison to individuals recruited from other firms, i.e., the observed effect is not a consequence of new knowledge, learning and work experience gained at KIFs but instead individual effects (selection). Firms in the treatment group may also be more successful at recruiting individuals with better initial abilities, although their observed backgrounds (education, occupation and work experience) are the same or similar to those recruited by firms in the control group. On the other hand, it is not obvious why there would be significant differences in the abilities of recruited employees between the compared groups. It is unlikely that the recruiting firms know whether the firms they recruit from are, by definition, KIFs, which is why we do not consider selection into treatment as critical. In addition, we are unable to control for initial abilities due to data restrictions.

Interpreting the results as causal is problematic if relevant variables are missing in our matching procedure. One potentially important, unobservable, and omitted factor at the firm level is firms´ strategic plans, i.e., how firms plan to improve competitiveness to achieve further growth and gain new market share. Such strategies are likely to involve recruiting the employees needed to achieve firm goals. Nevertheless, it should be noted that our treatment group and the matched control group have similar pre-treatment trends in the outcome variables for a period of three years prior to recruitment.

4. Model results

Model 1 in Table 6 presents DiD estimates when total recruited employees from KIFs are accounted for, and the control group consists of the matched group of firms recruiting from firms other than KIFs. We can see that the DiD estimates for TFP are approximately 2 percent during the post-treatment period, suggesting that a statistically significant difference exists between the treatment and control groups. Models 2-5 present the DiD estimates for treated and control firms recruiting individuals with the same or similar backgrounds: workers with at least 1 year of experience in management-related work (Model 2); professional work (Model 3); professional work in STEM-related occupations (Model 4); and professional work in STEM-related occupations where the workers also have a STEM education (Model 5). While the effect in magnitude is similar across most of the model specifications, the significance of the results is only valid for one post-treatment year for managers (Model 2) and for three post-treatment years for professional workers (Model 3). This suggests that there is a partially positive effect that accrues from the recruitments from KIFs, i.e., knowledge transfer through labour mobility influences the TFP of the recipient firms. However, we can also see that the results are not statistically significant when firms recruiting of STEM workers are compared (Models 4 and 5).

A potential problem is observed for Models 1 and 3. The pre-treatment trend that appears parallel for total recruitment in Figure 1 is significant at the 10 percent level in the pre-treatment period, i.e., there is a non-parallel pre-treatment trend according to the (pre-treatment) estimates. A non-parallel pre-treatment trend is problematic if there are the firms in the treatment group, in relation to their matched controls, with a non-parallel pre-treatment that creates differences in the post-treatment period. In other words, if their development is different during the pre-treatment period, it is not possible to claim that the post-treatment estimates are an effect of the treatment, i.e., recruitment from KIF.

Table 6 DiD estimates on TFP for the different categories of recruitment

Outcome variable: Log(TFP)	(1) Total	(2) Managers	(3) Professionals	(4) STEM O	(5) STEM EO
t-3	-0.007	-0.002	-0.016*	-0.008	-0.014
	(0.008)	(0.018)	(0.009)	(0.010)	(0.011)
t-2	0.011*	0.021	0.003	0.008	0.004
	(0.006)	(0.015)	(0.007)	(0.008)	(0.011)
t	0.009	-0.004	0.007	0.007	0.005
	(0.006)	(0.015)	(0.007)	(0.009)	(0.011)
t+1	0.016**	0.037*	0.015*	0.011	0.014
	(0.008)	(0.022)	(0.009)	(0.011)	(0.013)
t+2	0.022***	0.032	0.023**	0.015	0.013
	(0.008)	(0.022)	(0.009)	(0.012)	(0.014)
t+3	0.022**	0.035	0.021*	0.005	0.017
	(0.010)	(0.027)	(0.011)	(0.014)	(0.016)
Observations	105,566	14,344	74,037	46,452	31,385
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As a control for robustness and heterogeneity among the recruiting firms, we compare firms that were relatively knowledge intensive in the pre-treatment period[12]. Table 7 includes estimates for firms that fulfil at least 6 of 11 criteria (LKI points, see Table 1) and present non-significant pre-treatment periods, implying that the assumption of parallel pre-treatment periods is fulfilled for this sample. A positive effect is observed, and although it is not reported here, the effect appears to increase with the level of firms′ knowledge intensity, i.e., when increasing from low to relatively higher levels[13].

We can also observe significant results across the different model specifications. In comparison to Table 6, the effects are substantially larger in terms of magnitude and significance level. In other words, firms with higher initial knowledge intensity are more successful in generating economic value from KIF recruitment. In contrast, firms with a maximum of 5 LKI points are non-significant across specifications (see Table A1). This suggests that some degree of knowledge intensity is required to benefit from recruiting individuals from KIFs.

[12] Figures for TFP trends over time for the sample with at least 6 LKI points are reported in Figure A1 in the Appendix.

[13] It is not possible to obtain estimates for higher levels of knowledge intensity, as there are too few observations.

Table 7 DiD estimates on TFP for the different categories of recruitment among firms with at least 6 LKI points during the pre-treatment period

Outcome variable: Log(TFP)	(1) Total	(2) Manager	(3) Specialist	(4) STEM O	(5) STEM EO
t-3	-0.021	0.010	-0.009	-0.018	-0.011
	(0.021)	(0.027)	(0.021)	(0.020)	(0.021)
t-2	0.008	0.034	0.008	-0.010	-0.017
	(0.022)	(0.023)	(0.024)	(0.028)	(0.033)
t	0.016	-0.001	0.000	-0.007	0.004
	(0.017)	(0.023)	(0.018)	(0.016)	(0.019)
t+1	0.036**	0.111***	0.048**	0.019	0.047**
	(0.018)	(0.037)	(0.020)	(0.020)	(0.023)
t+2	0.081***	0.045	0.086***	0.068***	0.086***
	(0.020)	(0.029)	(0.022)	(0.024)	(0.026)
t+3	0.081***	0.075***	0.068**	0.067**	0.124***
	(0.027)	(0.028)	(0.029)	(0.032)	(0.034)
Observations	7,646	3,751	6,326	5,685	5,367
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 reports corresponding DiD estimates when the number of employees is the outcome variable. There is a positive effect from workers recruited from KIFs, significant at the 1 percent level for most post-treatment periods and 5 percent for the other periods. The pre-treatment periods, i.e., *t*-3 and *t*-2, are non-significant, meaning that the parallel trend assumption holds. The effect is similar across the specifications and increases over time, meaning that the results are robust regardless of the backgrounds of the recruited workers. This suggests that the effect on employment of recruiting from KIFs is not dependent on workers' backgrounds.

Table 8 DiD estimates of the number of employees for the different categories of recruitment

Outcome variable: log(number of employees)	(1) Total	(2) Manager	(3) Specialist	(4) STEM O	(5) STEM EO
t-3	0.008	-0.016	-0.003	-0.006	-0.021
	(0.008)	(0.023)	(0.010)	(0.012)	(0.013)
t-2	0.004	-0.000	-0.000	-0.005	-0.005
	(0.005)	(0.015)	(0.006)	(0.007)	(0.009)
t	0.047***	0.034**	0.039***	0.022***	0.023**
	(0.006)	(0.015)	(0.007)	(0.008)	(0.010)
t+1	0.080***	0.059**	0.067***	0.052***	0.051***
	(0.009)	(0.026)	(0.011)	(0.014)	(0.017)
t+2	0.099***	0.082**	0.091***	0.079***	0.077***
	(0.011)	(0.034)	(0.014)	(0.018)	(0.022)
t+3	0.121***	0.117***	0.112***	0.102***	0.106***
	(0.013)	(0.042)	(0.017)	(0.021)	(0.026)
Observations	105,472	14,393	73,963	46,426	31,310
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In summary, our results show that there are effects on both TFP and employment arising through inter-firm labour mobility from KIFs. The observed effects cannot be explained by heterogeneity among the recruited workers. The effect on TFP tends to increase with the level of knowledge intensity among the recruiting firms, which indicates that the question of knowledge transfers through labour mobility cannot be separated from the question of absorption capacity.

5. Conclusions

We examined whether firms that have recruited workers from knowledge-intensive firms (KIFs) obtain higher productivity and/or employment in comparison to firms that have recruited workers from other firms (non-KIFs). This study is premised on the background that inter-firm labour mobility is an essential mechanism for knowledge transfers. For this examination, we used a matched employer–employee panel with Swedish data and modern matching methods. We compared firms that have recruited skilled workers from KIFs (treatment group) with firms that have recruited workers with similar backgrounds (education, occupation and experience) from less KIFs (control group). The matching procedure used reduces imbalances between the compared groups, which, in turn, implies that the estimated effects are more likely to depend on the recruited labour than on other factors. To the best of our knowledge, our approach is unique to the empirical literature on knowledge diffusion and implies that differences between the compared groups cannot be explained by observed heterogeneity among the recruited workers.

Our results show statistically significant differences between the treatment and control groups, i.e., recruitments from KIFs actually impacts both TFP and employment. For TFP, however, the effects are linked to the level of knowledge intensity among recruiting firms and only accrue to firms with relatively high knowledge intensity in the pre-treatment period. It appears that an initial knowledge level is required for firms to generate economic value from KIF recruitment. The effects are similar in magnitude across the groups of recruited workers (education, occupation, and experience). We conclude that labour mobility is an important mechanism for the transfer of knowledge and ideas and that this process may result in productivity improvements in recipient firms. Overall, this suggests that firms can choose to innovate or emulate others by recruiting workers from firms that have already innovated.

Our study has two types of policy implications. First, the identification of KIFs presents a novel approach to delineate an adequate source of knowledge diffusion that enables productivity improvements. Practitioners who wish to enhance the effects from future ventures in the knowledge economy should therefore consider how their knowledge investments promotion schemes are designed. Second, labour market conditions including rigid regulations and other factors that potentially reduce the propensity of workers to change employers should be carefully evaluated. Clearly, if the goal is to foster productivity through labour mobility, but the policy tool actually inhibits this, then a rethink of policy is required. However, knowledge transfer may not be systematic or coordinated in nature, which challenges the opportunities to address this mechanism through direct and indirect means. Nevertheless, practitioners should consider a flexible labour market as a strategically important factor to enhance competitiveness of an economy.

A possible avenue in future research is to extend our analysis to examine whether the identified effects can be regarded as knowledge externalities. In fact, our study can only suggest that the potential for spillovers through labour mobility does exist (for a more extensive discussion on labour mobility and knowledge externalities, see e.g., Moen, 2005). Furthermore, as human capital is a local resource unevenly distributed across space, it is likely that the effect from inter-firm transfers of knowledge has a strong spatial dimension. However, the literature on productivity-interregional human capital mobility is surprisingly thin. This is why further research is needed to understand whether promoting mobility of skilled labour across regions will spur productivity and foster local technology capacity. Last, the empirical literature that analyse the extent of as well as the drivers of mobility of skilled workers from knowledge intensive firms is scarce (see e.g., Andersson et al., 2020). Filling gaps in this literature should contribute to a more consistent view regarding the role and importance of inter-firm knowledge transfers through labour mobility.

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Appendix

Figure A1 Development of TFP for the different recruitment categories among firms that met at least 6 LKI conditions in the pre-treatment period

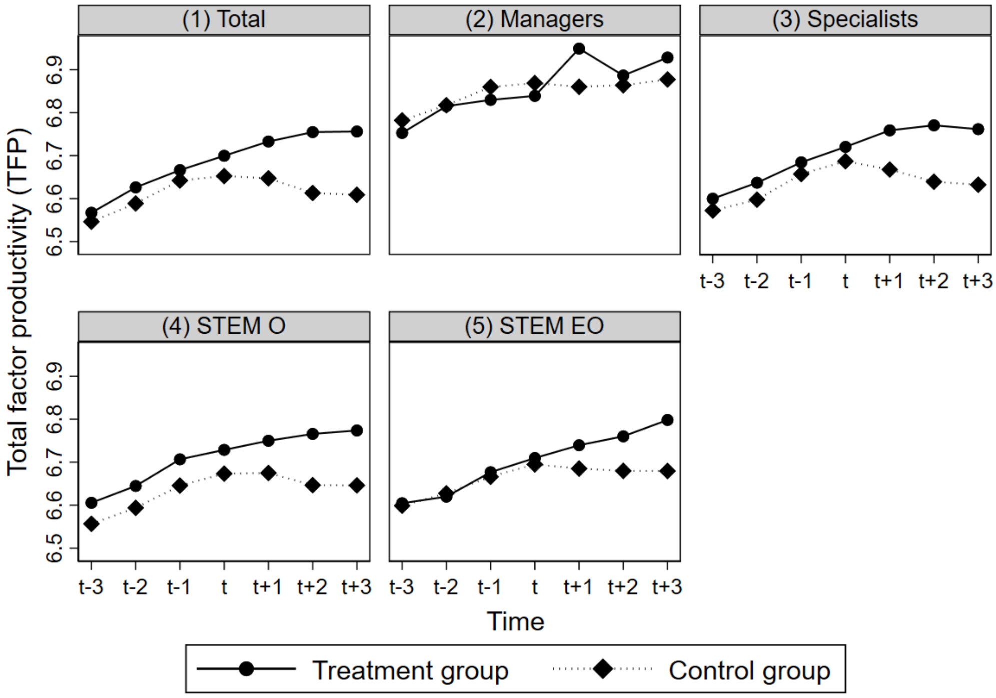

Table A1 DiD estimates on TFP for the different categories of recruitment among firms that met maximum 5 LKI points in the pre-treatment period

Outcome variable: Log(TFP)	(1) Total	(2) Manager	(3) Specialist	(4) STEM O	(5) STEM EO
t-3	-0.004	-0.005	-0.015	-0.003	-0.013
	(0.008)	(0.023)	(0.010)	(0.011)	(0.013)
t-2	0.011*	0.017	0.004	0.013	0.010
	(0.006)	(0.018)	(0.007)	(0.008)	(0.011)
t	0.007	-0.005	0.006	0.009	0.005
	(0.006)	(0.019)	(0.008)	(0.010)	(0.013)
t+1	0.011	0.008	0.008	0.008	0.004
	(0.008)	(0.026)	(0.010)	(0.012)	(0.016)
t+2	0.013	0.026	0.011	0.004	-0.008
	(0.009)	(0.029)	(0.010)	(0.014)	(0.016)
t+3	0.011	0.018	0.010	-0.010	-0.015
	(0.010)	(0.036)	(0.012)	(0.016)	(0.018)
Observations	97,920	10,593	67,711	40,767	26,018
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tillväxtanalys

Myndigheten för tillväxtpolitiska utvärderingar och analyser