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MT-DP – 2016/10

Productivity spillovers through labor flows:

The effect of productivity gap, foreign-owned firms, and skill-relatedness

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Abstract

What puts productivity spillovers into effect through worker mobility across firms? Productivity difference between the sending and receiving firms have been found to drive these spillovers; while an alternative explanation suggests that labor flows from foreign-owned companies provide productivity gains for the firm. We argue here that skill-relatedness across firms also matters because industry-specific skills are important for organizational learning and production. Hungarian employee-employer linked panel data from 2003-2011 imply that productivity gap rules out the effect of foreign spillovers. Furthermore, we find that flows from skill-related industries outperform the effect of flows from unrelated industries.

JEL: D22, J24, J60, M51

Keywords: skill-relatedness network, firm productivity, knowledge spillover, labor mobility, productivity gap, foreign ownership

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A munkaerő-áramlás átterjedési hatásai:

A termelékenységkülönbség, a külföldi tulajdon és a képességközelség szerepe

Csáfordi Zsolt – Lőrincz László – Lengyel Balázs – Kiss Károly Miklós

Összefoglaló

Mely tényezők által valósulnak meg a vállalatok közötti munkaerő-áramlás termelékenységre gyakorolt átterjedési hatásai? Korábbi kutatások a küldő és a fogadó vállalat közti termelékenységkülönbség döntő szerepére hívták fel a figyelmet, alternatív magyarázatok szerint pedig a külföldi tulajdonú cégektől érkező munkaerőnek döntő mértékű a hatása az átterjedési hatás nagyságára. Érvelésünk szerint a vállalatok képességközelsége (skill-relatedness) szintén számít e kérdésben, mivel a munkavállalók iparág-specifikus képességei fontosak a szervezeti tanulásban és termelésben. A magyarországi államigazgatási adatgyűjtés 2003–2011. évekre összefűzött panel adatai alapján a külföldi tulajdonú vállalatoktól érkező munkaerő hatása eltűnik, ha a termelékenységkülönbségre is kontrollálunk. Kutatásunk további eredménye, hogy a képességközelség szerint erősebben kapcsolódó iparágakból érkező munkavállalók hatása felülmúlja a kevésbé kapcsolódó iparágakból érkezők hatását.

JEL: D22, J24, J60, M51

Tárgyszavak: képességközelségi hálózat, vállalati termelékenység, tudásátterjedés, munkaerő-áramlás, termelékenységkülönbség, külföldi tulajdon

1. INTRODUCTION

Following Arrow (1962), worker mobility has long been considered a major source of knowledge flow across firms because the hiring firm benefits from the embodied knowledge and skills of incoming labor, which has a positive effect on wages and productivity in the target company (Almeida & Kogut, 1999; Zucker, Darby, & Torero, 2002; Palomeras & Melero, 2010; Stoyanov & Zubanov, 2014). The analysis of labor flows is still very important for research because the information retrieved from large datasets can help us to understand previously unexplored major mechanisms behind knowledge spillovers. In this paper, we focus on the joint effect of productivity gap and foreign spillovers and the effect of skill-relatedness.

According to a well-established statement, the incoming worker has stronger influence if she has been hired away from a more productive firm because her experience of a more efficient production might be directly implemented in the firm. Stoyanov & Zubanov (2012) demonstrates that a positive productivity gap between the sender and target companies has a positive and robust effect on productivity growth observed in the target company. In a closely related literature, labor mobility is frequently used to demonstrate the presence of productivity spillovers from foreign-owned or multinational enterprises (MNEs) to domestic companies and arguments state that MNEs train their workers better and the experience of previous MNE workers regarding production technologies, marketing and management processes provide extra gains for the hiring domestic firms. Görg & Strobl (2005) show that those domestic firms, of which owners worked for foreign-owned firms in the same industry, are more productive than other domestic firms. Balsvik (2011) finds that the private reward of moving from MNEs to non-multinational firms is far less than the productivity premium they cause at the hiring non-multinational firm. Poole (2013) identifies an increase in incumbent domestic workers' wages after hiring employees with some experience at a multinational establishment as an evidence of knowledge transfers from multinationals to domestic firms. Despite the well-developed literature shortly summarized above, the effects and the interactions of relative productivity, and foreign-domestic spillovers have not been looked at in a common framework, which will be the first aim of this paper.

Because labor cannot be considered homogenous – as it has been discussed from many aspects in the literature[1] – the skills of the of the moving worker matter for the extent of

[1] Labor was found to be specific to the firm (Becker, 1962, 1964; Mincer et al., 1974; Jovanovic, 1979a, 1979b; Flinn, 1986; Topel & Ward, 1992), to the occupation (Kambourov & Manovskii, 2009a, 2009b) or both to the firm and occupation (Miller, 1984; McCall, 1990; Pavan, 2011). Some argue that not firm or occupation specificities

knowledge spillovers the move bring forth. For example, the mobility of R&D personnel results in higher productivity growth than the mobility of non-R&D workers because the former bring more knowledge to the firm than the latter (Maliranta, Mohnen, & Rouvinen, 2009). Poole (2013) also finds that high-skilled workers transmit more information to their new firm than low-skilled workers. In this paper, we will take the industry-specific human capital approach (Neal, 1995; Parent, 2000; Sullivan, 2010) by arguing that similarity across industries in terms of dominant skills matter for knowledge spillovers transmitted by labor mobility. The rationale behind the expectation is that workers moving across industries use some of their previous experience in their new firm in a new industry, which might be more efficient if the skills of the employee are similar to the needed skills at the company (Neffke et al., 2016).

The skill-relatedness framework developed by Neffke & Henning (2013) and upgraded by Neffke et al. (2016) is used here to measure the similarity across industry-specific skills. Empirical findings suggest that a certain degree of relatedness is needed between the industry-specific skill base of the company and the new knowledge and skills transmitted to the company by worker mobility because new employees might understand and accomplish tasks easier when they have developed related skills previously and also because incumbent workers might absorb the new knowledge easier if the new knowledge is related to their extant knowledge (Boschma, Eriksson, & Lindgren, 2009; Timmermans & Boschma, 2014). However, the accumulated evidence is not exclusive at all; for example, inventing firms need to hire new inventors who possess expertise that are new to the firm in order to obtain productivity gains in innovation (Rosenkopf & Almeida, 2003; Song, Almeida, & Wu, 2003).

By looking at labor mobility across Hungarian firms in the 2003-2011 period, our paper aims to answer the following question: How do labor mobility from foreign firms, more productive firms, and skill-related industries contribute to productivity growth of firms?

We believe that the answer is especially important in catching-up economies where a significant share of new knowledge is imported to the country by MNEs or foreign-owned firms. Previous research in Hungary found spillover-effects from MNEs to domestic companies by looking at productivity dynamics of co-locating companies (Halpern & Muraközy, 2007); however, only highly productive domestic firms enjoy these positive externalities (Békés, Kleinert, & Toubal, 2009). We claim that labor mobility data enables us to untangle clearer spillover effects, which is important to make better policy recommendations.

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rather tasks have high importance (Nedelkoska & Neffke, n.d.; Poletaev & Robinson, 2008; Gathmann & Schönberg, 2010).

We contribute to the literature in two points. First, our analysis reveals that the effect of spillovers from foreign-owned firms disappears when productivity differences are introduced into the model. This implies that the knowledge spillovers from foreign firms to private domestic firms are only due to productivity effects on the firm level and workers coming from MNEs have no additional effect. The finding refines the outcome of several former studies that claimed the positive productivity effect of labor flows from foreign-owned firms to local ones; these papers commonly do not control for the magnitude of productivity difference between the receiving and sending companies. Second, we demonstrate that skill-relatedness between the sending and receiving firms exert an additional positive effect on productivity. The results suggest that the effect of labor mobility on firms' productivity is dominated by inflows from the same industry but inflows from skill-related industries also outperform the inflows from unrelated industries. These findings are robust against different skill-relatedness matrices. The evidence that skill-relatedness matters provides a novel contribution to the productivity spillover literature and might open up new questions for empirical research on labor mobility.

The structure of the paper is as follows. The structure of the data and main patterns of labor flows are presented in section 2. The baseline model of our labor mobility framework is introduced in Section 3, and results regarding the productivity gap and multinational spillovers are discussed in Section 4. Skill-relatedness measurement is introduced in Section 5, where we extend the empirical model and discuss results regarding industry-specific skills. The main conclusions are drawn in Section 6.

2. DATA

We have access to the Hungarian administrative data integration database, which is an anonymized employer-employee linked panel dataset created by the matching of five administrative data sources, for years 2003-2011, developed by the databank of HAS CERS. The database contains a 50% random sample of the 15-74 aged population living in Hungary in 2003 and the involved employees are traced over the period. The most important demographic features of employees (gender, age, place of living in the year of entry), and information about their employment spells (months worked, ISCO-88 occupation code, monthly wage) as well as company characteristics (4-digit industry code according to NACE'08 classification, employment size, and specific rows of their balance sheets and financial statements including tangible assets, equity owned by private domestic, private foreign, and state owners, sales, pre-tax profits, material-type costs, personnel expenditures, wage bill) are known. All monetary variables are deflated by yearly industry-level producer price indices to get their real 2011 value.

The data is managed the Databank of Institute of Economics of Hungarian Academy of Sciences and can be accessed for scientific research upon individual request. For more details consult http://adatbank.krtk.mta.hu/adatbazisok___allamigazgatasi_adatok.

Data manipulation included two steps. First, we created yearly matrices from the monthly-based intercompany movements of employees. Details of the first step can be found in Appendix I. Second, we excluded those worker movements where spin-offs, mergers and acquisitions or reorganizations were suspected to be the reason for change in company ID instead of real labor movements. Following Neffke et al. (2016), we identified these spurious labor flows when (1) all employees of a firm with 5 or less employees moved to another firm with identical ID; (2) at least 80% of the employees of a firm with more than 5 employees moved to another firm with identical ID; (3) at least 100 employees "moved" between two firms within one year. Furthermore, we excluded firms with less than 2 employees, firms with extremely high productivity[2], and those firms that did not receive incoming workers from the private sector. This procedure resulted in 652,289 individual job switches and 70,771 firm-year combinations during the observed period.

Table 1

Number of observations on employees, job switches and firms

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2003-2011
Employees in the sample	1,916,163	1,924,358	1,919,602	1,925,337	2,046,954	2,056,555	1,987,377	1,967,692	1,991,074	17,735,112
Individual job switches	228,787	236,669	240,440	256,719	277,626	240,756	238,595	280,572	-	2,000,164
Analyzed job switches	76,118	78,821	80,592	88,929	98,606	83,132	66,861	79,230	-	652,289
Firms in the database	335,017	344,198	353,551	362,542	398,426	410,660	396,845	374,560	364,186	3,339,985
Firms with at least 2 employees	-	72,317	87,724	89,228	89,821	89,525	80,712	72,695	-	582,022
Analyzed firms with new hires	-	10,538	11,141	11,379	11,495	10,867	7,575	7,776	-	70,771

Note: No valid observations for analysis in 2003 and 2011 due to the use of lagged and lead variables.

3. THE PRODUCTIVITY GAP EFFECT

We measure firm productivity by the natural logarithm of value added per worker standardized with industry-year averages. To quantify productivity spillovers, we use the productivity gap between sending and receiving firms according to the formulation of Stoyanov & Zubanov (2012). Thus we calculate the average difference between the sending

[2] The threshold was set to labor productivity of HUF 50 million per worker. 0.8% of the cases were dropped according to this rule.

firms' and receiving firm's productivity, weighted by the number of incoming workers from sending firm i; and multiply this number by the share of new workers within the total employment at the receiving firm:

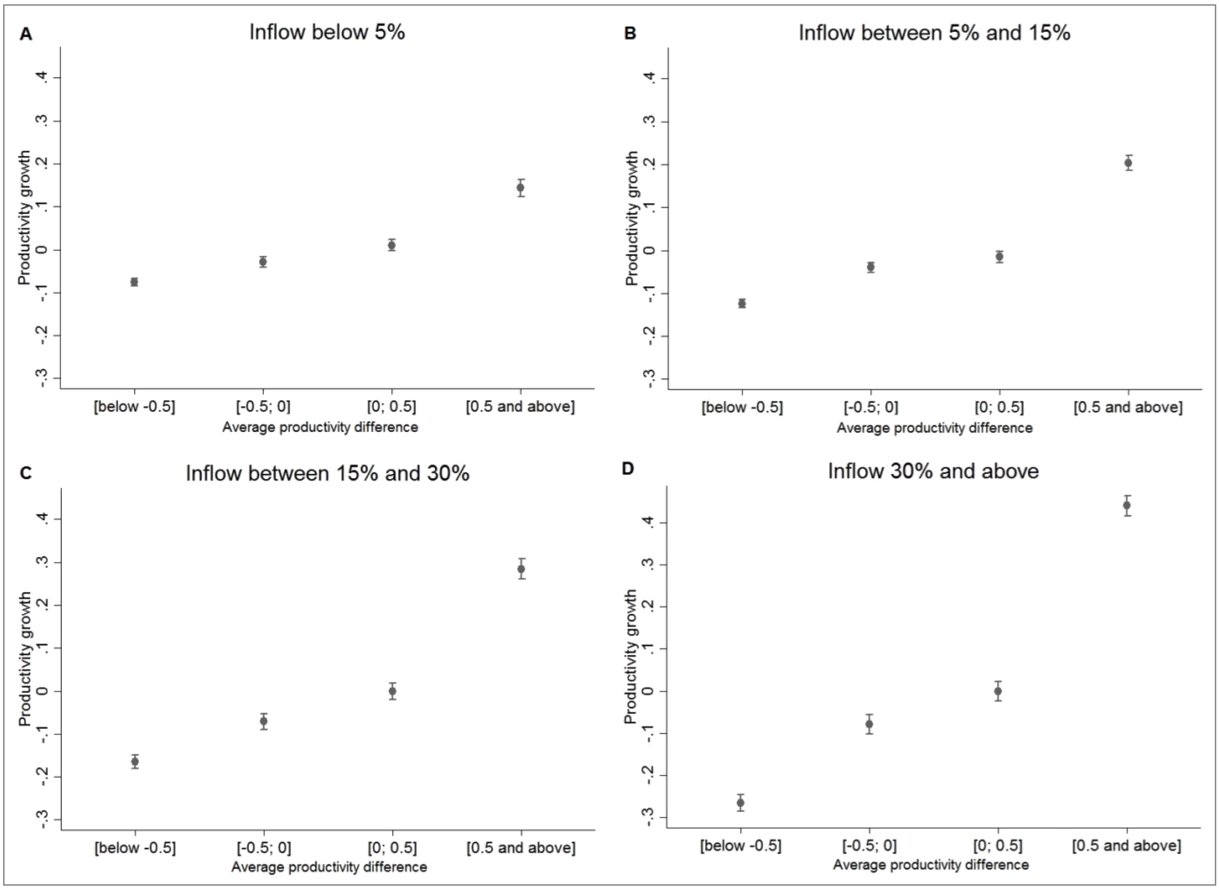
$$prodgap_{j,t} = \frac{\sum_{i=1}^{H_{j,t+1}}(A_{i,t}-A_{j,t})}{H_{j,t+1}} \cdot \frac{H_{j,t+1}}{N_{j,t+1}}, \qquad (1)$$

where $A_{i,t}$ and $A_{j,t}$ denote the logarithm of labor productivity standardized with industry-year averages of the sending firm i and the receiving firm j at time t, respectively, $H_{j,t+1}$ is the number of new workers in the receiving firm j, and $N_{j,t+1}$ is the total number of employees in the receiving firm j.

Figure 1 illustrates the connections between the yearly changes in productivity of the receiving firm on the basis of the average productivity difference between the receiving firm and the sending firms in a bivariate analysis. Average productivity difference has been transformed with the formula e^x-1, so that labor inflows arriving from at least 65% more productive firms take the value of 0.5 on the horizontal axis. Productivity growth is also transformed in a similar way. Subfigures are separated by the share of new workers within the employees of the receiving firm. One can observe that higher productivity difference is associated with higher productivity growth, which suggests that workers arriving from a more productive firm have higher positive effect on the productivity of the receiving firm. When labor inflows constitute a greater share of the workforce of the receiving firm, the effect of productivity difference is bigger. In the extreme case when labor inflows reach at least 30% of the number of employees in the receiving firm, a positive productivity difference of at least 65% is associated with a 50-55% increase in productivity of the receiving firm. The connection is also significant for the negative productivity difference, but the effect seems to be smaller.

Figure 1

Productivity growth and productivity gap by the extent of inflow



When exploring how different labor flows affect productivity of firms, we have to consider several alternative explanations. The first problem arises when firms invest into new combinations of inputs, which changes productivity of the firm as well. Therefore, the quantity of capital must be controlled for together with labor inflow and outflow. The second problem is the effect of exogenous demand and industry specific shocks on value added per worker because a positive demand shock may increase the value added per capita even if a firm does not employ new workers simply because sales are growing. To control for this effect, we will use industry-region-year fixed effects in the pooled OLS regression models. The third problem is the self-selection of workers, because the human capital of incoming workers might be correlated with the productivity of the sending firm, which might tangle our estimates on the effect of productivity gap between the sending and receiving firms. We may also assume endogenous connection between productivity growth and the quality of incoming workers, if a priori expectations on future firm productivity attract more productive workers to firms with better growth potential, which will result in a correlation between the human capital of incoming labor and the future productivity of the receiving firm. Hence, we need to separate the effect of knowledge spillover between firms and the effect of undesirable correlations of incoming labor force's human capital.

In order to remedy the problem of worker self-selection and to control for the objectionable correlations of the human capital of the moving workforce with the productivity levels of firms, we include the average human capital of the receiving firms for years t and t+1 in the productivity growth estimation. In calculating human capital, we follow the idea of Abowd, Kramarz, & Margolis (1999), and use the worker-specific component of the wage equation specified by

$$w_{m,j,t} = \alpha + z_{m,t}\beta + \theta_m + \varphi_j + \varepsilon_{m,j,t} \qquad (2)$$

where $w_{m,j,t}$ denotes the natural logarithm of wage of worker m working for firm j at time t, $z_{m,t}$ stands for the vectors of worker m's time-variant attributes (age, age-squared, 1-digit occupation code) at time t, θ_m represent their time-invariant personal characteristics, and φ_j is the firm fixed effect. The wage equation is estimated by panel regression with employee and employer fixed effects, for which multi-dimensional fixed-effects approach and Stata command reghdfe of Correia et al. (2015) is used.

The worker-specific component is calculated as:

$$HC_{m,t} = z_{m,t}\beta + \theta_m + \varepsilon_{m,j,t} \qquad (3)$$

for each worker. Worker-specific human capital is then averaged for each firm j:

$$HC_{j,t+1} = \frac{\sum_{i=1}^{N_{j,t+1}}(HC_{m,t})}{N_{j,t+1}}, \qquad (4)$$

where $N_{j,t+1}$ is the number of total employees in the receiving firm j, and $HC_{m,t}$ stands for the human capital of each employee at firm j measured at time t. For results of the wage equation estimation and a more detailed description of the calculation of human capital, see Appendix II.

We estimate the level of productivity of firm j at t+1 if the firm receives labor inflow at t using the following equation and include the lagged productivity of firm j to control for autocorrelation:

$$A_{j,t+1} = \alpha A_{j,t} + \beta_1 \cdot prodgap_{j,t} + \beta_2 \cdot HC_{j,t} + \beta_3 \cdot HC_{j,t+1} + \gamma \boldsymbol{X}_{j,t} + \delta \boldsymbol{D} + \varepsilon_{j,t} \qquad (5)$$

where $A_{j,t+1}$ and $A_{j,t}$ denote the natural logarithm of productivity of firm j standardized with industry average in the receiving firm at t+1 and t, respectively; $\boldsymbol{X}_{j,t}$ includes the characteristics of the receiving firm at t (firm size, total assets, share of outflows, employee fluctuation, share of workers without job in the previous year), and $\boldsymbol{D}$ denotes industry-region-year dummies.

Pooled OLS estimations with industry-region-year fixed effects confirm previous results of Stoyanov & Zubanov (2012); a positive and significant effect of productivity gap on subsequent productivity of the receiving firm (Table 2 Columns A-B). The coefficient of 0.163

means that a firm hiring 10% of its employees from 10% more productive firms at year t gains a productivity increase of 0.1 × 0.1 × 0.163 = 0.16% at t+1.

Following Stoyanov & Zubanov (2012), productivity gap can be decomposed to positive and negative productivity gap indicators when only those movements are taken into account that originate from more or less productive firms compared to the receiving one:

$$prodgap^{P}_{j,t} = \frac{\sum_{i=1}^{H_{j,t+1}} D_{i,t}(A_{i,t}-A_{j,t})}{H_{j,t+1}} \cdot \frac{H_{j,t+1}}{N_{j,t+1}} \quad (6)$$

$$prodgap^{N}_{j,t} = \frac{\sum_{i=1}^{H_{j,t+1}} (1-D_{i,t})(A_{i,t}-A_{j,t})}{H_{j,t+1}} \cdot \frac{H_{j,t+1}}{N_{j,t+1}} \quad (7)$$

where $D_{i,t} = 1$ if $A_{i,t} > A_{j,t}$, and zero otherwise. All other notations are identical with the ones in Equation 1. The above differentiation is useful if we assume that knowledge spillovers occur primarily when the incoming labor arrives from more productive firms. Equation 5 can be reformulated by decomposing the productivity gap into positive and negative gap:

$$A_{j,t+1} = \alpha A_{j,t} + \beta_1 \cdot prodgap^{P}_{j,t} + \beta_2 \cdot prodgap^{N}_{j,t} + \beta_3 \cdot HC_{j,t} + \beta_4 \cdot HC_{j,t+1} + \gamma \boldsymbol{X}_{j,t} + \delta \boldsymbol{D} + \varepsilon_{j,t} \quad (8)$$

where notations are identical with notations in Equation 5.

Our findings reveal the importance of positive productivity gap. Results are reported in Table 2 Columns C-D. One can see that hires from firms with higher productivity increases subsequent productivity of the firm with 0.31% (Column D). Although we found significant effect of the negative productivity gap in the bivariate analysis (see Figure 1), hires from firms with lower productivity do not have a significant influence on subsequent productivity in the multivariate specification.

Table 2

The effect of productivity gap

	Column A	Column B	Column C	Column D
Current productivity	0.682***	0.673***	0.690***	0.681***
	(0.006)	(0.006)	(0.006)	(0.006)
Productivity gap	0.172***	0.163***		
	(0.010)	(0.010)		
Positive productivity gap			0.327***	0.311***
			(0.018)	(0.018)
Negative productivity gap			0.013	0.011
			(0.015)	(0.015)
Human Capital		0.136***		0.130***
		(0.012)		(0.012)
Lag Human Capital		-0.003		-0.005
		(0.011)		(0.011)
Observations	70,771	70,771	70,771	70,771
R-squared	0.606	0.608	0.608	0.610

Notes: industry-region-year FE, firm-clustered robust standard errors in parentheses.

Additional controls are characteristics of receiving firm (total assets, ownership, size), and inflow-outflow measures (share of outflows, fluctuation, share of workers without job in the previous year).

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Equation 5 is estimated on different groups of firms to check the robustness of the estimated effects. Results are reported in Table 3. First, we relax the condition of having new hires, and include all firm-years to the model (Column A). Then we separate these by size (Columns B-C). Finally, we return to the original sample of firms having non-zero incoming workers, and analyze them by size (Columns D-E). The effect of the productivity gap becomes larger in big firms (0.32% in Column C, 0.35% in Column E). Possible explanations for this last phenomenon may lie in the effective HR processes and training in large firms; or, few incoming worker may spread new knowledge to more colleagues in large firms, which might be a new agenda for knowledge spillover studies.

Table 3

Robustness of the effect of productivity gap on different firm samples

	Column A	Column B	Column C	Column D	Column E
Lag productivity	0.583***	0.575***	0.751***	0.636***	0.761***
	(0.002)	(0.002)	(0.010)	(0.007)	(0.012)
Productivity gap	0.071***	0.068***	0.317***	0.130***	0.351***
	(0.009)	(0.009)	(0.053)	(0.010)	(0.053)
Estimation sample	All firms	All firms	All firms	Firms with new hires	
		N < 50	N >= 50	N < 50	N >= 50
Observations	582,022	551,533	30,489	50,766	20,005
R-squared	0.488	0.474	0.737	0.559	0.753

Notes: industry-region-year FE, firm-clustered robust standard errors in parentheses.

Additional controls are: Human Capital and Lag Human Capital, characteristics of receiving firm (total assets, ownership, size), general inflow-outflow measures (share of outflows, fluctuation, share of workers without job in the previous year, no new hires in Columns A-C).

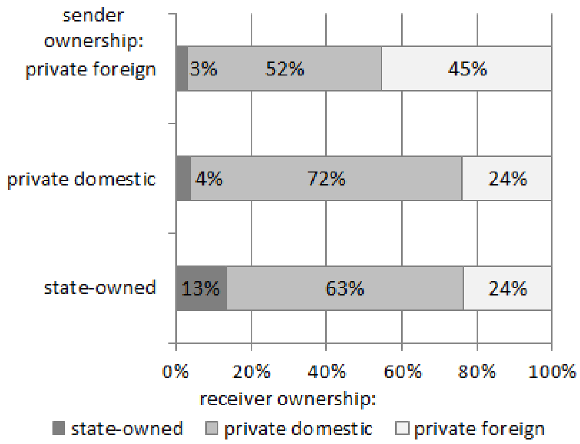
*** p<0.001, ** p<0.01, * p<0.05

4. IS THERE AN ADDITIONAL FOREIGN-DOMESTIC SPILLOVER EFFECT?

We define a company foreign-owned if at least 50% of the registered capital belongs to foreign private owners, the company is state-owned if at least 50% of the registered capital belongs to public entities, and the company is private domestic if at least 50% of the registered capital belongs to private domestic owners. Figure 2 illustrates that similarity between the sending and receiving firm in terms of ownership categories increases the probability of job switch. The probability that an employee will go to a foreign-owned company is almost two times higher when the sending firm was foreign-owned as compared to other types of sending firms. Also, the higher share of workers from private domestic firms will go to private domestic firms as compared to the moves from other firm categories. Finally, employees leaving state-owned companies are more likely to move to state-owned companies than employees leaving other types of firms. However, the majority of employees leaving firms from all ownership categories will end up in private domestic companies, because most of the firms are in this category.

Figure 2

Job switches by firm ownership



Labor flows from foreign-owned firms are usually considered as major source of knowledge spillovers because these firms are more productive and can provide their employees with better trainings (Görg & Strobl, 2005; Balsvik, 2011; Poole, 2013). However, the real source of spillovers is still not clear and we aim to see, whether there are additional effects of foreign spillovers besides the effect of productivity gap because foreign firms are typically more productive than domestic firms. In order to observe these in the data, we calculate the share of workers arriving from private domestic and foreign-owned companies, and analyze their effects in the regression models, first without, and then with the productivity gap:

$$A_{j,t+1} = \alpha A_{j,t} + \beta_1 \cdot \frac{H_{j,t+1}^{PD}}{N_{j,t+1}} + \beta_2 \cdot \frac{H_{j,t+1}^{F}}{N_{j,t+1}} + \beta_3 \cdot HC_{j,t} + \beta_4 \cdot HC_{j,t+1} + \beta_5 \cdot prodgap_{j,t} + \gamma \boldsymbol{X}_{j,t} + \delta \boldsymbol{D} + \varepsilon_{j,t}$$

(9)

where $H_{j,t+1}^{PD}$ denotes the number of new arrivals to firm j from private domestic companies at time t+1, $H_{j,t+1}^{F}$ denotes the number of hires coming from foreign owned companies at time t+1, and $HC_{j,t}$ denote human capital of firm j at time t. $\boldsymbol{X}_{j,t}$ stands for the characteristics of the receiving firm at t (firm size, total assets, general inflow-outflow measures), and D for the industry-region-year dummies.

Table 4

The effect of ownership and relative productivity of sending firms on subsequent productivity

	Column A	Column B	Column C
Lag productivity	0.646***	0.638***	0.673***
	(0.006)	(0.006)	(0.006)
Productivity gap			0.161***
			(0.010)
Human capital		0.146***	0.135***
		(0.012)	(0.012)
Lag human capital		-0.003	-0.004
		(0.011)	(0.010)
From private domestic	0.110***	0.102***	0.096***
	(0.020)	(0.020)	(0.019)
From private foreign	0.193***	0.164***	0.079**
	(0.027)	(0.027)	(0.027)
Observations	70,764	70,764	70,764
R-squared	0.602	0.604	0.608

Notes: industry-region-year FE, firm-clustered robust standard errors in parentheses.

Additional controls are: characteristics of receiving firm (total assets, ownership, size), general inflow-outflow measures (share of outflows, fluctuation, share of workers with no job in the previous year). The reference category of ownership type of incoming workers contains state-owned companies and those companies where none of the ownership type reaches 50%.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 4 illustrates the effect of ownership of the sending firms. In the first step, only the ownership variables are entered (Column A). We see significant differences between the reference category, private domestic companies and foreign owned ones. The results are consistent with the idea of knowledge transfer from foreign to local companies because the point estimate of foreign effect is significantly higher than the point estimate of the domestic effect. In the next model, human capital controls are included (Column B), which somewhat moderates this effect but the difference between foreign and domestic point estimates are still significant. Finally, productivity gap and ownership of the sending firms are considered jointly (Column C) and the difference between local private companies and foreign owned ones diminishes. This result suggests that the knowledge transfer from foreign companies to private domestic ones are only due to productivity effects.

5. SKILL-RELATEDNESS AND EFFECT OF INTER-INDUSTRY LABOR FLOWS

We argue that new employees might understand and accomplish tasks easier when their previously developed skills are related to the skills needed in the target company and consequently, skill-relatedness between the sending and the receiving firm can increase the effect of labor mobility. Boschma, Eriksson, & Lindgren (2009) have found that relatedness matters for productivity gains in case of non-local labor flows to the firm; however, a systematic comparison of productivity-gap, foreign spillovers, and skill-relatedness is still missing.

The idea that a certain degree of technological similarity is needed for inter-industry spillovers has been present in the literature for decades. Scholars quantify inter-industry relatedness by using both output-based approaches[3] and input-based approaches. The input-based approaches assume industries related if they use the same inputs in their production process, thus these resource-based relatedness indices focus on the origin of economies of scope. Various inputs are used for measurement; for example, Engelsman & van Raan (1991) and Breschi, Lissoni, & Malerba (2003) use patents that are filed in different industries, Fan & Lang (2000) used value-chain linkages retrieved from input-output tables, while Farjoun (1994, 1998); Chang (1996) and Chang & Singh (1999) concentrated on the similarities of human capital by looking at the occupational profiles of industries.

In this paper, we use the skill-relatedness approach developed by Neffke & Henning (2013) and further developed by Neffke et al. (2016). The basic idea is that skill-relatedness of industries measures the extent to which the same human capital can be employed in different industries by comparing labor flows between industries p and q to an expected level of flows between p and q that is based on random mobility distribution and is only affected by the total number of labor flows to and from the industries. The method builds on the assumption that labor mobility between pairs of industries is more common if the necessary skills applied in the industries are related, therefore skill-relatedness can be inferred from comparing actual labor movements to movements expected based on external characteristics of the industries. For example, if a skilled worker finds alternative employment in another

[3] In output-based analyses (Teece et al., 1994; Porter, 2003; Hidalgo, 2005; Lien & Klein, 2008; Bryce & Winter, 2009; Neffke, Henning, & Boschma, 2011; Neffke, Henning, & Boschma, 2012) the relatedness is measured by the co-occurred products that are produced in the single economic entities (plants, firms, regions, nations etc.).

industry, the production processes of the old and new industries apply similar skills, thus labor-flow indicates the degree of compatibility of skills between the industries.

If workers switch industries with probabilities that are proportional to the total outflow of the industry of origin and the total inflow into the destination industry, the ratio of observed to expected flows is given by:

$$R_{pq} = \frac{F_{pq}F_{..}}{F_{p.}F_{.q}}, \quad (10)$$

where F_{pq} denotes the observed flow of workers from industry p to industry q, $F_{p.} = \sum_{p \neq q} F_{pq}$ is the number of workers leaving industry p, $F_{.q} = \sum_{p \neq q} F_{pq}$ is the number of workers joining industry q, and $F_{..} = \sum_{q \neq p} \sum_{p \neq q} F_{pq}$ is the total number of industry switchers. We assume that the skill relatedness of industries is symmetric, therefore we calculate this measure from the symmetrized labor flow network of 4-digit industries. Unlike Neffke et al. (2016), we used every worker's mobility to calculate the measure, and used the mobility network of high skilled workers for robustness checks only. R_{pq} values on the interval [0,1) correspond to lower-than-expected labor flows, whereas values above 1 indicate that observed labor flows exceed expected flows. As a consequence, the distribution of R_{pq} is strongly right-skewed. To obtain a more balanced distribution, we transform R_{pq} as follows:

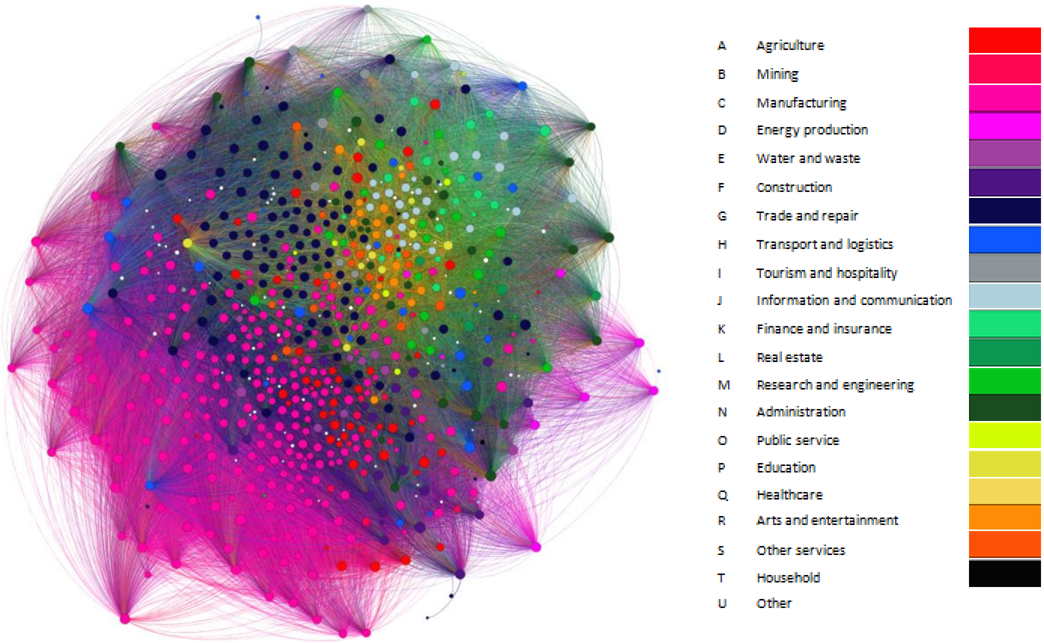
$$\bar{R}_{pq} = \frac{R_{pq}-1}{R_{pq}+1}, \quad (11)$$

which maps R_{pq} onto the interval $[-1,1)$ in a way that R_{pq} and $1/R_{pq}$ are mapped equidistant from zero at opposite sides. If $\bar{R}_{pq}$ equals zero, observed and expected flows are exactly equal. To avoid the effect of yearly fluctuations, and assuming that skill-relatedness do not change in the short run, we obtain the pooled skill relatedness measure by taking the average of the yearly $\bar{R}_{pq}$ between each *pq* industry pair, and pool it over the whole period. Taking this pooled $\bar{R}_{pq}$ as an indication of the relatedness among industries, we refer to this as the *skill relatedness (SR)* of industry p to industry q.

In Figure 3, the skill-relatedness network of four-digit industries is plotted using a spring algorithm, which brings related industries close to each other. It is visible from the network that there is a correlation between the official NACE classification and the skill-relatedness because industries of similar sectors tend to group together. However, one can observe a much more complex structure of industry relations of technological proximity than one can deduce from industry classification (Neffke, Henning, & Boschma, 2011).

Figure 3

Skill-relatedness network in Hungary, 2003-2012



Notes: Nodes are industries defined by 4-digit NACE codes and color-codes refer to sectors of 1-digit NACE codes. We included edges with weights $\overline{R_{ij}}$ >0. Natural logarithm of employment is used to depict the size of the industry, which is reflected by the size of the nodes. The position of the nodes is determined by the Force Atlas 2 algorithm in Gephi.

Similarly to Neffke et al. (2015), we find that the distribution of labor mobility across *SR* categories varies by occupation categories (Table 5). Majority of the moves occurs across unrelated industries (*SR*1 and *SR*2), but this is increasingly true for the low-skilled workers. On the contrary, managers and high-skilled workers are more likely to move across related industries or within the same industry than low-skilled workers. This suggests that low-skilled occupations are less industry-specific and the costs of changing the industry are low. Meanwhile the costs of an industry switch are the highest for managers, which infers that manager techniques might differ across industries and managers have to have a deep knowledge of their field to know how to set up firm structure, organize the activities, and allocate tasks within the firm.

Table 5

Job switches and skill-relatedness for different occupation segments, 2003-2011

Segment	different industry				Same industry	job switch	
	SR1	SR2	SR3	SR4		%	N
Managers	26,2%	20,5%	15,6%	17,8%	19,9%	100,0%	6 670
High-skilled	25,7%	21,0%	16,8%	20,0%	16,5%	100,0%	7 798
Mid-skilled high-wage	29,3%	20,6%	16,2%	17,5%	16,4%	100,0%	43 422
Mid-skilled low-wage	33,1%	21,2%	15,5%	15,2%	15,0%	100,0%	60 183
Low-skilled	39,5%	21,6%	13,1%	12,3%	13,5%	100,0%	18 657

Notes: N denotes the number of job switches of the occupation segment on average per year. ISCO-88 1-digit categories were used to identify occupation segments: 1 Managers, 2 High-skilled, 3-8 Mix of Mid-skilled High-earners and Mid-skilled Low-earners separated by industry median wage, 9 Low-skilled.

In the remaining of the analysis, we classify skill-relatedness into four categories (*SR*1: [-1;-0.5), *SR*2: [-0.5;0] *SR*3: [0;0.5), *SR*4:[0.5;1], where *SR*1 denotes the least related and *SR*4 the most related industries) and introduced an additional *SAME* category that indicates if $i \neq j \in p$.

Figure 4

Productivity growth and productivity gap by skill relatedness categories

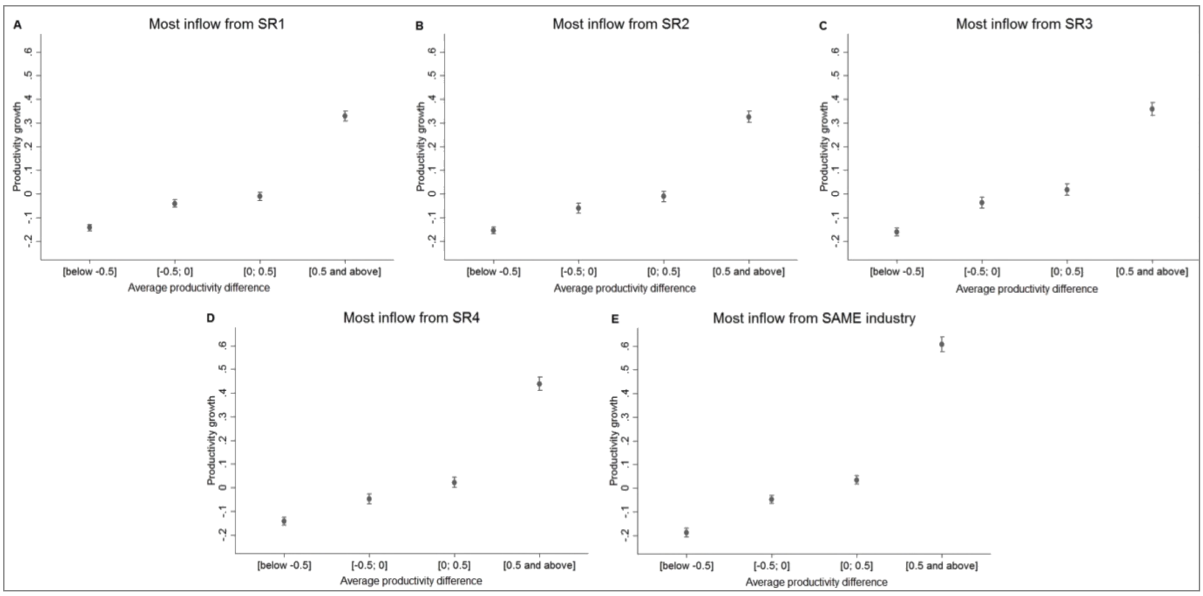


Figure 4 shows productivity growth in different categories of average productivity difference, separated by the skill relatedness (*SR)* categories from where the most inflow originates. The graphs confirm and extend our previous findings: the productivity gap has the most crucial positive effect in case of inflows coming from the same industry, then from $SR4$ industries, although the differences between other lower *SR* categories are insignificant. In case of inflows from the same industry, a positive productivity difference of at least 0.5[4] is associated with a 77-88% increase in productivity.

In order to include skill-relatedness into the estimation framework, we add two new variables to the equation: the number of workers arriving from the above SR categories and the interaction of skill-relatedness with the productivity gap. The final regression equation is specified by

$$A_{j,t+1} =$$

$$\alpha A_{j,t} + \beta_1 \cdot prodgap_{j,t} \sum_{k=2}^{4} \beta_k \frac{H_{j,t+1}^{SRk}}{N_{j,t+1}} + \beta_5 \cdot \frac{H_{j,t+1}^{SAME}}{N_{j,t+1}} + \sum_{k=2}^{4} \beta_{k+4} prodgap_{j,t}^{SRk} + \beta_9 prodgap_{j,t}^{SAME} + \beta_{10} \cdot$$

$$HC_{j,t} + \beta_{11} \cdot HC_{j,t+1} + \gamma \boldsymbol{X}_{j,t} + \delta \boldsymbol{D} + \varepsilon_{j,t}, \qquad (12)$$

where $H_{j,t+1}^{SRk}$ represents the number of new arrivals from firms with the respective skill-relatedness distance, $H_{j,t+1}^{SAME}$ the number of new workers at firm *j*, who did not change industry. The variable $prodgap_{j,t}^{SRk}$ denotes the productivity gap for only those workers, who arrived from firms with the specific skill-relatedness category specified above:

$$prodgap_{j,t}^{SRk} = \frac{\sum_{i=1}^{H_{j,t+1}} D_{i,t}(A_{i,t} - A_{j,t})}{H_{j,t+1}} \cdot \frac{H_{j,t+1}}{N_{j,t+1}}, \qquad (13)$$

where $D_{i,t}$ equals 1 if $SR(i,j)$ corresponds to the above specified ranges (*SR*1: [-1;-0.5), *SR*2: [-0.5;0] *SR*3: [0;0.5), *SR*4:[0.5;1]) and zero otherwise.

Table 6 contains the results of the estimation specified in Equation 13 in a step-wise manner. Each specification includes industry-region-year fixed effects, characteristics of receiving firm, average characteristics of sending firms and general inflow-outflow measures. First, only the share of incoming workers from different skill-relatedness categories are examined (Column A). The findings suggest that a higher share of inflows from industries that are more skill-related to the firm increases productivity stronger. Next, we control for human capital of the new arrivals (Column B), which only slightly moderates the previous finding, and the *SR* effects remain robust. In the third step, productivity gap is added, together with its interaction with the skill-relatedness measures (Column C). We find that the effect of productivity gap is positive and it is increased by hires from the same 4-digit industry only. Finally, models are completed with ownership variables (Column D); the effects of the skill

[4] Inflows arriving from on average 65% more productive firms (transformed with the formula $e^{0.5}$-1); productivity growth is also transformed.

relatedness and the productivity remain similar, and foreign spillovers do not have a significant effect.

Table 6

The effect of productivity gap and skill relatedness on subsequent productivity

	Column A	Column B	Column C	Column D
Lag productivity	0.647***	0.638***	0.673***	0.673***
	(0.006)	(0.006)	(0.006)	(0.006)
Human capital		0.146***	0.133***	0.133***
		(0.012)	(0.012)	(0.012)
Lag human capital		-0.003	-0.004	-0.004
		(0.011)	(0.010)	(0.010)
Share of SR2 inflows	0.032	0.022	0.021	-0.008
	(0.027)	(0.027)	(0.026)	(0.030)
Share of SR3 inflows	0.105***	0.090**	0.084**	0.054
	(0.028)	(0.028)	(0.027)	(0.031)
Share of SR4 inflows	0.131***	0.120***	0.118***	0.087**
	(0.025)	(0.025)	(0.024)	(0.029)
Share of same industry inflows	0.137***	0.121***	0.105***	0.072*
	(0.026)	(0.026)	(0.025)	(0.030)
Productivity gap			0.152***	0.148***
			(0.019)	(0.019)
PG of SR2 inflows			-0.026	-0.023
			(0.027)	(0.027)
PG of SR3 inflows			0.006	0.008
			(0.031)	(0.031)
PG of SR4 inflows			-0.004	-0.002
			(0.030)	(0.030)
PG of same industry inflows			0.120***	0.123***
			(0.033)	(0.033)
From private domestic				0.051
				(0.026)
From private foreign				0.052
				(0.030)
Observations	70,498	70,498	70,498	70,498
R-squared	0.603	0.606	0.609	0.609

Notes: Industry-region-year FE models. Firm ID-clustered robust standard errors in parentheses. *SR*1 [-1;-0.5] is used as baseline skill relatedness; further categories are *SR*2 [-0.5; 0], *SR*3 [0; 0.5]; *SR*4 [0.5;1]. Additional controls are characteristics of the receiving firm (total assets, ownership, size), and general inflow-outflow measures (share of outflows, fluctuation, share of workers without a job in previous year). *** $p<0.001$, ** $p<0.01$, * $p<0.05$

These findings support the idea that those workers who developed skills related to the profile of the target firm implement their experience easier, which has a boosting effect on productivity. Comparing this to Table 4 indicates, that by inclusion of the skill-relatedness measures, even the difference between inflows from state-owned and private domestic and foreign companies vanished.

In order to demonstrate the robustness of skill-relatedness effect on productivity spillovers, we present the results of two additional estimations in Appendix III. In the first estimation, we only look at the movements of managers, high-skilled employees, and middle-skilled high wage employees when analyzing productivity spillovers and also construct the skill-relatedness matrix from the above flows. This means that only those workers are counted in F_{pq}, $F_{p.}$, $F_{.q}$, and $F_{..}$ values in Equation 10 whose occupation is categorized as above, which is suggested by Neffke et al (2015). Results imply that flows from related industries and from the same industry outperforms flows from unrelated industries (Column A), even after controlling for productivity gap and its interactions (Column B). However, only the productivity gap and its interactions with the share of related flows remain significant when company ownership variables are introduced (Column C).

An additional robustness check utilizes the skill-relatedness matrix calculated from Swedish labor flow data. This last check is very important to demonstrate that our main finding still holds when the relatedness of industries are identified by exogenous data sources. Results reported in Appendix III file suggest that skill-related movements to the company and also the interaction of productivity-gap and skill-relatedness increases productivity.

6. CONCLUSION

This paper provides new evidence that knowledge spillovers transmitted by labor flows across companies are determined by productivity differences across the sending and receiving companies. Incoming labor increase firm productivity if new employees are coming from more productive firms. We also find that the above productivity gap overshadows the effect of foreign spillovers. This finding has important implications because it clears up the outcome of some former studies that claim a positive productivity effect of labor flow from multinational firms to domestic firms. Our results demonstrate that foreign spillovers in Hungary are solely due to productivity effects, so that flows from foreign firms are effective only if the foreign firm is more productive than the domestic firm. Furthermore, we show that skill-relatedness across industries matters because the incoming employees can exploit the skills they have acquired previously in a more effective way if their skills are related to the profile of the company. Increasing share of skill-related labor inflows leads to an increase in productivity.

Further research might go more into detail in what exactly the productivity differences lie, which really matter for spillovers through labor mobility. For example, is the training the multinationals or more productive firms provide to their employees important for knowledge spillovers? One might expect that the knowledge gained through longer periods of working at more productive firms matter more than narrowly defined trainings. Another underexplored but connected question concerns the role of organizational structure. New employees might exploit their skills better in an environment they are already used to and might perform better in a new organization with similar routines to what they are already familiar with. Finally, different versions of skill-relatedness measurements, such as occupation-based co-occurrence matrices might be applied to capture technological similarities across industries and future research shall go also to the firm level in doing so.

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APPENDIX

I. DETAILED DESCRIPTION OF DATA MANAGEMENT

We have access to the Hungarian administrative data integration database, which is an anonymized employer-employee linked panel dataset created by the matching of five administrative data sources, for years 2003-2011, developed by the databank of HAS CERS. The database contains a 50% random sample of the 15-74 aged population living in Hungary in 2003 and the involved employees are traced over the period. The most important demographic features of employees (gender, age, place of living in the year of entry), and information about their employment spells (months worked, ISCO-88 occupation code, monthly wage) as well as company characteristics (4-digit industry code according to NACE'08 classification, employment size, and specific rows of their balance sheets and financial statements including tangible assets, equity owned by private domestic, private foreign, and state owners, sales, pre-tax profits, material-type costs, personnel expenditures, wage bill) are known. All monetary variables are deflated by yearly industry-level producer price indices to get their real 2011 value.

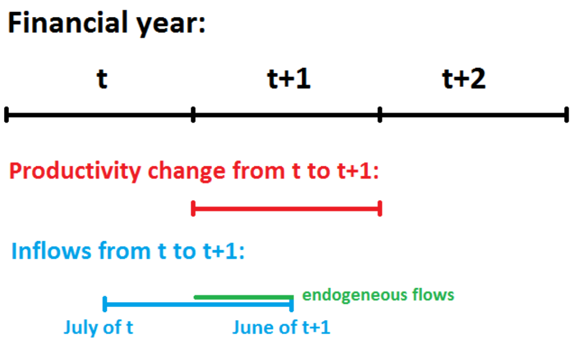
The data is managed the Databank of Institute of Economics of Hungarian Academy of Sciences and can be accessed for scientific research upon individual request. For more details consult http://adatbank.krtk.mta.hu/adatbazisok___allamigazgatasi_adatok.

The raw data contains employee-employer links on a monthly basis. We defined the main employer for every worker and for every year as the workplace where the worker spent the highest number of months in the given year and created yearly matrices of intercompany movements between these main employers. In particular, if an employee switches firm in the second half of year t or first half of year $t+1$, the receiving firm will be her employer in year $t+1$ and the sending firm will be her employer in year t.

However, our models assess the effect of labor mobility on firms' productivity on a yearly basis, which can lead to an endogenous connection between labor flows and productivity change (not discussed in the main text). The problem, illustrated in Figure I; productivity shocks (e.g. purchasing a machine) happening in the first half of year $t+1$ can affect the number of new hires in the first half of year $t+1$.

Figure I.

Periods of productivity change and labor mobility



The potential of reversed causality shortly summarized above might distort our analysis. In order to exclude the possibility of such endogeneity, we conduct the analysis only for those new hires that were observed in year t or in January in year t+1 the latest and exclude all the cases of labor mobility that happened between February and June.

A certain time period has to pass for the new employee to exert a significant effect on firm productivity. With new employees working for a short period and not controlling for months worked at the receiving firm, we would underestimate the effect of new hires on yearly productivity growth. Therefore, in the productivity spillover analysis, only those workers were considered as new hires, that stayed for at least 6 months with their new employer.

II. CALCULATION OF HUMAN CAPITAL

As described in the main text, human capital of each worker is calculated for each year spent in the private sector. The gaps in private sector employment at most 3 years are filled up by linear interpolation. In case of gaps of at least 4 years, or when the worker only worked in the public sector before getting a job in the private sector, human capital is calculated by a wage regression on the subsample of public sector workers. In addition to the multi-dimensional fixed-effects approach, as a robustness check, we also estimated a pooled OLS regression with age, age-squared, gender and skill-levels of workers. Results are presented in Table I.

Table I

Wage equations without and with employee fixed effects separately on private and public sector employees

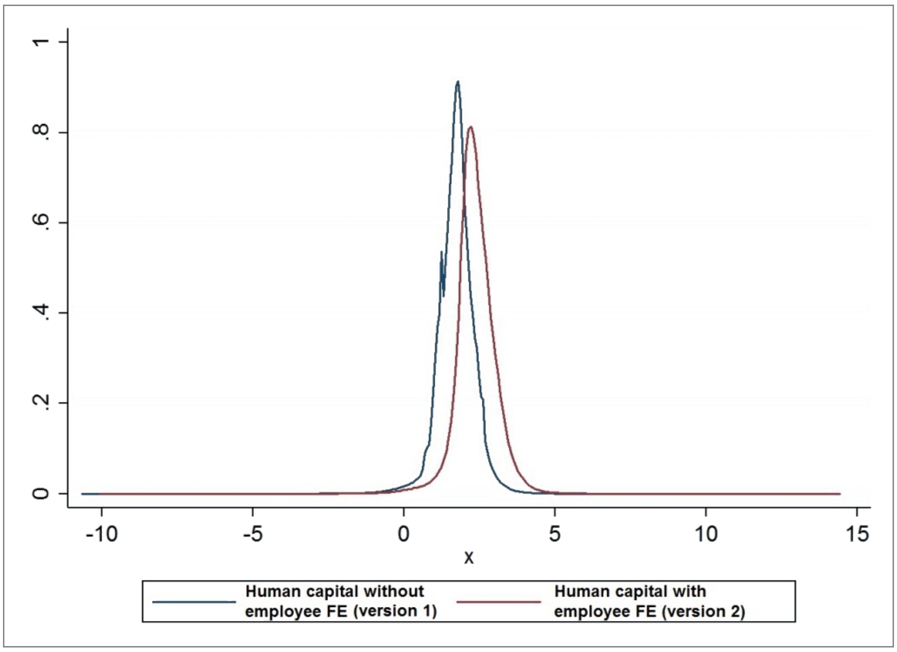
Method	Pooled OLS		Employee FE	
Sample of employees	Private sector	Public sector	Private sector	Public sector
Age	0.060***	0.039***	0.089	0.079
	(0.001)	(0.003)	(416.32)	(105.41)
Age-squared	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.182***	0.093***	-	-
	(0.004)	(0.009)		
Low skilled	0.155***	0.139***	-	-
	(0.007)	(0.033)		
Mid-skilled	0.009	-0.008	-	-
	(0.007)	(0.007)		
Managers	0.913***	1.128***	0.361***	0.624***
	(0.012)	(0.035)	(0.01)	(0.021)
Professionals	0.792***	0.790***	0.357***	0.524***
	(0.019)	(0.032)	(0.01)	(0.016)
Technicians and assistants	0.586***	0.536***	0.292***	0.349***
	(0.015)	(0.014)	(0.011)	(0.013)
Office administrators	0.475***	0.350***	0.241***	0.266***
	(0.022)	(0.015)	(0.014)	(0.012)
Commercial workers	0.387***	0.298***	0.241***	0.281***
	(0.022)	(0.011)	(0.012)	(0.019)
Agriculture and forestry	0.239***	0.121***	0.147***	0.130***
	(0.018)	(0.012)	(0.007)	(0.009)
Blue-collars in industry and construction	0.353***	0.267***	0.224***	0.226***
	(0.014)	(0.009)	(0.01)	(0.008)
Assemblers and machine operators	0.288***	0.279***	0.185***	0.213***
	(0.023)	(0.026)	(0.01)	(0.010)
Army	0.432***	0.844***	0.208***	0.629***
	(0.080)	(0.028)	(0.031)	(0.067)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	11,192,798	6,260,904	10,864,118	5,723,524
R-squared	0.687	0.759	0.843	0.849

Notes: Robust standard errors in parentheses. High-skilled: worked at least once in an occupation requiring tertiary education; Mid-skilled: worked at least once in an occupation requiring secondary education; Low-skilled: everybody else. The baseline occupation category is “Elementary occupations”. The baseline skill category is “High-skilled”. Employees present only in one year of the analysis do not have individual FE, therefore they are excluded from Columns C and D. *** p<0.001, ** p<0.01, * p<0.5

In Figure II, we can see the distribution of human capital calculated without and with employee fixed effects. Version 1 explains 69% of the variation of the log value of wage, whereas version 2 has an R-squared of 84%. Between the two versions of human capital, the correlation is 0.74. Since fixed effects can control for more individual-specific characteristics, version 2 can be a better approximation of the worker’s true human capital. Its closer-to-normal distribution makes it also more desirable for further analysis, therefore we continue with this measure.

Figure II.

Density plots of Human capital without employee FE (version 1) and with employee FE (version 2)



In Figure III and IV, we can see the distributions of human capital with employee fixed effects by gender and skill level. Looking at the curves, we can infer that there is no significant difference between the value of work-related abilities of men and women, although the variation is higher in case of women. There is a clear difference between the distributions of human capital by skill level, particularly for the advantage of high-skilled workers. These descriptive findings confirm our decision to use human capital calculated with worker fixed effects.

Figure III.

Distribution of Human capital with employee FE by gender

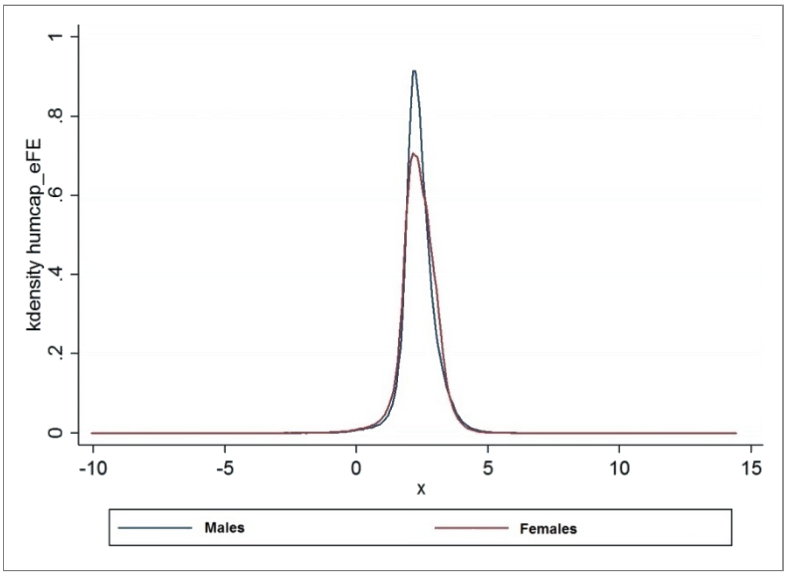
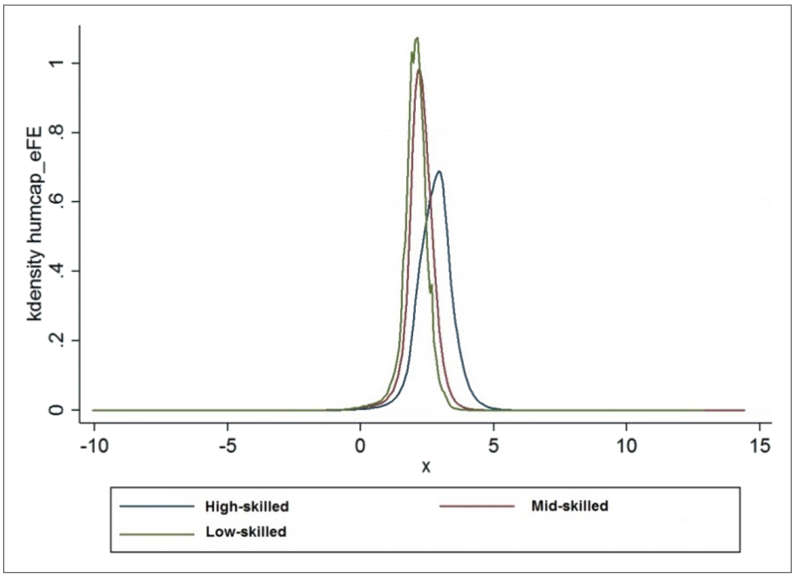


Figure IV.

Distribution of Human capital with employee FE by skill levels



High-skilled: worked at least once in an occupation requiring tertiary education; Mid-skilled: worked at least once in an occupation requiring secondary education; Low-skilled: everybody else.

III. ROBUSTNESS CHECK WITH ALTERNATIVE SKILL-RELATEDNESS MATRICES

In order to demonstrate the robustness of skill-relatedness effect on productivity spillovers, we present the results of two additional estimations. In the first estimation, we only look at the movements of managers, high-skilled employees, and middle-skilled high wage employees when analyzing productivity spillovers and also construct the skill-relatedness matrix from the above flows.

Results in Table II imply that flows from related industries and from the same industry outperforms flows from unrelated industries (Column A), even after controlling for productivity gap and its interactions (Column B). However, only the productivity gap and its interactions with the share of related flows remain significant when company ownership variables are introduced (Column C).

An additional robustness check utilizes the skill-relatedness matrix calculated from Swedish labor flow data. This last check is very important to demonstrate that our main finding still holds when the relatedness of industries are identified by exogenous data sources. The Swedish skill relatedness matrices were calculated for the years 2003-2010 similarly to the Hungarian ones. For this period, there were 32,301 industry pairs (out of 258,840 possible combinations), where both the Hungarian and the Swedish data indicated mobility. The correlation coefficient of the two skill-relatedness measure was 0.35 for these cases.

Results reported in Table III. suggest that skill-related movements to the company and also the interaction of productivity-gap and skill-relatedness increases productivity.

Table II.

Skill-relatedness and productivity spillovers; only high-skilled sample of movers

	Column A	Column B	Column C
Lag productivity	0.614***	0.646***	0.645***
	(0.006)	(0.006)	(0.006)
Human Capital	0.146***	0.133***	0.133***
	(0.014)	(0.014)	(0.014)
Lag of human capital	-0.002	-0.003	-0.004
	(0.012)	(0.012)	(0.012)
Share of SR2 inflows	0.005	-0.005	-0.029
	(0.030)	(0.030)	(0.031)
Share of SR3 inflows	0.078*	0.062*	0.037
	(0.031)	(0.030)	(0.031)
Share of SR4 inflows	0.085**	0.077**	0.055
	(0.029)	(0.028)	(0.029)
Share of same industry inflows	0.111***	0.093***	0.073*
	(0.029)	(0.028)	(0.029)
Productivity gap		0.063***	0.059***
		(0.012)	(0.011)
PG of SR2 inflows		0.032	0.035
		(0.025)	(0.025)
PG of SR3 inflows		0.076*	0.079**
		(0.030)	(0.029)
PG of SR4 inflows		0.079**	0.083**
		(0.028)	(0.028)
PG of same industry inflows		0.211***	0.214***
		(0.031)	(0.031)
From private domestic			0.035*
			(0.016)
From private foreign			0.043*
			(0.020)
Observations	54,791	54,791	54,791
R-squared	0.581	0.585	0.585

Notes: Industry-region-year FE models. Firm ID-clustered robust standard errors in parentheses. SR1 [-1;-0.5] is used as baseline skill relatedness; further categories are SR2: [-0.5; 0], SR3: [0; 0.5]; SR4: [0.5;1]. Additional controls are characteristics of receiving firm (total assets, ownership, size), general inflow-outflow measures (share of outflows, fluctuation, share of workers without a job in previous year).*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table III.

Skill-relatedness and productivity spillovers; Swedish skill-relatedness matrix

	Column A	Column B	Column C
Lag productivity	0.666***	0.678***	0.678***
	(0.008)	(0.008)	(0.008)
Human Capital	0.158***	0.149***	0.148***
	(0.019)	(0.019)	(0.018)
Lag of human capital	0.003	0.006	0.007
	(0.017)	(0.017)	(0.017)
Share of SR2 inflows	0.013	0.008	0.010
	(0.010)	(0.009)	(0.012)
Share of SR3 inflows	0.003	0.015	0.017
	(0.018)	(0.019)	(0.021)
Share of SR4 inflows	0.042*	0.045*	0.047*
	(0.019)	(0.019)	(0.021)
Share of same industry inflows	0.053	0.104	0.106
	(0.079)	(0.073)	(0.073)
Productivity gap		0.017	0.017
		(0.009)	(0.009)
PG of SR2 inflows		0.001	0.001
		(0.011)	(0.011)
PG of SR3 inflows		0.034*	0.034*
		(0.016)	(0.015)
PG of SR4 inflows		0.017	0.018
		(0.020)	(0.020)
PG of same industry inflows		0.302***	0.302***
		(0.076)	(0.076)
From private domestic			-0.005
			(0.011)
From private foreign			0.005
			(0.014)
Observations	31,549	31,549	31,549
R-squared	0.631	0.632	0.632

Notes: Industry-region-year FE models. Firm ID-clustered robust standard errors in parentheses. SR1 [-1;-0.5] is used as baseline skill relatedness; further categories are SR2: [-0.5; 0], SR3: [0; 0.5]; SR4: [0.5;1]. Additional controls are characteristics of receiving firm (total assets, ownership, size), general inflow-outflow measures (share of outflows, fluctuation, share of workers without a job in previous year). *** $p<0.001$, ** $p<0.01$, * $p<0.05$