

The distribution of the gains from spillovers through worker mobility between workers and firms

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Abstract

Knowledge spillovers through worker mobility between firms, found in previous research, imply that knowledge production within firms creates a positive externality to the hiring firms and their workers. We calculate the shares in the gains from spillovers retained by these parties using matched employer-employee data from Danish manufacturing. We find that around two-thirds of the total output gain (0.1% per year) is netted by the firms as extra profit, about a quarter goes to the incumbent workers as extra wages, while the workers who bring spillovers receive no more than 8% of it. This gains distribution, which favors the hiring firms, is similar for different types of moving workers, and is stable over time.

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1 Introduction

Theories of knowledge spillovers across firms have often relied on inter-firm worker mobility as a mechanism facilitating such spillovers (Fosfuri et al., 2001; Markussen, 2001; Glass and Saggi, 2002; Dasgupta, 2012). Several recent empirical studies, including Gorg and Strobl (2005), Markusen and Trofimenko (2009), Balsvik (2011), Parrotta and Pozzoli (2012) and Stoyanov and Zubanov (2012), have documented the workings of this mechanism, linking firm productivity gains to hiring workers from technologically superior firms.¹ Since the latter receive no compensation from the firms that hire their workers, the existence of knowledge spillovers through worker mobility implies a positive externality. The ambition of our study is to determine how much of this externality ends up as extra profit to the hiring firms, and how much is transferred as extra wages to the workers they employ.

The findings from previous empirical studies, most of which focussed on the movements of workers from foreign- to domestic-owned firms, suggest that part of the ensuing output gains is indeed remitted to the workers. In particular, domestic firms pay a wage premium to new hires with foreign-firm experience over the wages of otherwise similar workers without such experience (Pesola, 2011; Balsvik, 2011). Incumbent workers benefit as well, seeing their wages grow in step with the share of ex-foreign firm employees in their firms (Poole, 2013). Hiring foreign specialists by domestic firms is also linked to wage increases in those firms, estimated at 4.5 – 6.2% depending on skill level (Markussen and Trofimenko, 2009).

Despite the gains to the firms and to the workers being available from the above studies, there has been no attempt to compare those gains. Our study is the first such attempt. We estimate the gains from worker mobility to the hiring firms and their workers using a specially designed empirical framework, and for all firms in an economy regardless of their domicile. Doing so requires a measure of a receiving firm’s exposure to spillovers through

¹A related literature on patent citations, historically the first to discuss knowledge spillovers, found a link between the movements of R&D workers and citations by their new employers of the patents granted to their previous employers (Almeida and Kogut, 1999; Song, Almeida and Wu, 2003; Oettel and Agrawal, 2008; Singh and Agrawal, 2011).

worker mobility that is more flexible than foreign vs. domestic ownership of the sending firm. The lack of such measure in the previous literature forced researchers to narrow down the study scope, to assume that all foreign-owned firms are equally good sources of knowledge spillovers, and to ignore domestic firms as a source of potentially useful knowledge. Our method, which we outline below, relaxes these limitations.

We estimate output gains from worker mobility and their distribution between the parties by tracking inter-firm movements of spillover potentials (SPs), whom we identify as the workers with a positive gap between their previous and new firms' total factor productivity (TFP) levels. This characterization is consistent with the theories behind spillovers through worker mobility (for example, Dasgupta, 2012) that treat the exposure to superior knowledge, which is manifested in higher productivity, as the source of spillovers. Assuming that output gains through mobility come entirely from SPs' higher labor productivity, aided by their exposure to knowledge in their previous firms, we obtain an equation linking a hiring firm's output gains from SPs to their average productivity gap and share in the labor force. We next derive a decomposition of the total output gains into the wage gains to SPs and non-SPs, and the profit gains to the hiring firms, which we estimate using linked worker-firm data from the Danish manufacturing sector.

To preview our findings, the total output gain linked to SPs is 0.1% in the year after hiring, or just under a tenth of the annual productivity growth averaged over the sample period. Compared to otherwise similar non-SPs, SPs receive a wage premium of 1.17% per year on average. Non-SPs benefit too, though their average wage gain is a lot less, 0.09% per year. With SPs making up only about 2% of all the workers, the total wage gain from spillovers through mobility is 0.11% per year. Applying our gains decomposition to the above estimates, we calculate that the hiring firms net 57-76%, and non-SPs between 20% and 35%, of the total output gain, whereas SPs retain at most 8%. Put differently, firms receive a profit of around two dollars per each dollar spent on hiring SPs. This distribution of the output gains between the parties, which reveals abnormally high rents to the firms, is

robust to alternative estimation approaches and is stable over time.

On the qualitative side, our findings suggest that knowledge acquisition through hiring SPs may be a lucrative alternative to buying patents or in-house R&D, and is all the more attractive because it does not require significant cash outlays or technical expertise. It is, however, hard to pinpoint labor market imperfections that would explain the high rents to the hiring firms that we find. The one that we find most plausible and consistent with the (limited) empirical evidence so far, is poor observability of moving workers' spillover potential, which leads to a lack of competitive market for SPs. Further research should examine this explanation more rigorously.

In the remainder of this paper, Section 2 presents the conceptual framework for our study, which is followed by a discussion of the relevant estimation issues in Section 3. Section 4 presents our data together with some descriptive statistics. The baseline results – output and wage gains from SPs, and their distribution – are reported in Section 5. Section 6 contains a number of extensions corroborating our baseline results, and Section 5 concludes.

2 Conceptual framework

In this section, we define the key concepts that we use in our analysis. We also present a framework that relates firm output gains to hiring SPs and decomposes these gains into the wage and profit gains. Although one could estimate the wage and profit gains from SPs directly, without linking them to output, the advantage of our output gains decomposition is in the keeping of negative profit observations in the sample, which would have been lost if profit gains were estimated directly.

2.1 Output gains from spillover potentials

Suppose firm i 's output in year t , Y_{it} , is a Cobb-Douglas function of labor (L), capital (K), materials (M) and the total factor productivity (TFP, A):

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m}$$

As in Stoyanov and Zubanov (2012), we define spillover potentials (SPs) as workers hired from firms with a higher TFP than that of their current employer. Assuming that the gains from SPs come solely in the form of their higher labor productivity, we capture the labor productivity difference between SPs and non-SPs by specifying labor input in efficiency units:

$$\begin{aligned}
L_{it} &= L_{it}^{nSP} + \delta_{it} \cdot L_{it}^{SP} \\
&= (L_{it}^{nSP} + L_{it}^{SP})(1 - s_{it} + s_{it} \cdot \delta_{it}) \\
&= \tilde{L}_{it}(1 + s_{it} \cdot (\delta_{it} - 1)),
\end{aligned} \tag{1}$$

where $\tilde{L} = L^{SP} + L^{nSP}$ is the total labor input in nominal units² (the sum of headcounts), s is SPs' share in total workforce, and $\delta \geq 1$ is the measure of SPs' labor productivity advantage (LPA) over the rest of the workers, more on which in section 3.1.1.³ Putting the expression for labor input in equation (1) back into the production function gives

$$Y_{it} = A_{it} K_{it}^{\beta_k} M_{it}^{\beta_m} \tilde{L}_{it}^{\beta_l} G_{it}, \tag{2}$$

where

$$G_{it} = [1 + s_{it} \cdot (\delta_{it} - 1)]^{\beta_l} \tag{3}$$

is the factor by which hiring SPs ($s > 0$ and $\delta > 1$) increases firm i 's output as compared to hiring no SPs ($s = 0$ or $\delta = 1$). This output gain comes from SPs increasing the overall labor productivity by a factor $1 + s_{it} \cdot (\delta_{it} - 1)$ (see equation (1)).

²Depending on whether SPs are observable to the firm or not, the firm's choice variable can be either the numbers of SPs and other workers separately, or the total labor input. Our estimation approach can handle both cases.

³Although, for simplicity of exposition, in equation (1) we abstract from other factors affecting efficiency units of labor, such as human capital, we do control for many such factors in our statistical analysis.

2.2 Output gains distribution between firms and workers

To derive a decomposition of the total output gain from SPs into the gains retained by the hiring firms and their workers, consider first a firm without SPs, which earns a profit (subscripts skipped for brevity)

$$\pi_0 = AK^{\beta_k} M^{\beta_m} \tilde{L}^{\beta_l} - w_0 \tilde{L} - r_0 K_0 - h_0 M_0, \quad (4)$$

where w_0 , r_0 and h_0 are respective input prices. Suppose L^{SP} workers quit and are replaced by the same number of SPs. Hiring SPs will increase output because they are more productive, but there may also be extra costs due to higher input prices, labor in particular. Indeed, the wages of both worker types are likely to be affected, as SPs may receive a premium reflecting the knowledge they bring (Balsvik, 2011), and non-SPs may benefit by learning from SPs (Poole, 2013) or through wage bargaining actuated by fairness concerns (Smith, 1995). The profit after hiring SPs is

$$\pi_1 = AK^{\beta_k} M^{\beta_m} \tilde{L}^{\beta_l} G - w_1^{SP} L^{SP} - w_1^{nSP} L^{nSP} - r_1 K_1 - h_1 M_1, \quad (5)$$

where G is defined in (3) and w_1^{SP} , w_1^{nSP} are new wages of SPs and non-SPs, respectively.

Assume that the suppliers of capital and materials do not benefit from SPs, that is, $r_1 = r_0$ and $h_1 = h_0$.⁴ Assume further that, even though the firm's profit increases with $G > 1$, factor inputs do not change, that is, $K_1 = K_0$ and $M_1 = M_0$. The latter assumption is undemanding for G close to 1, which it is in our data, since then the output increase from higher input volumes will be nearly compensated by the extra costs of production. With these assumptions, taking the difference between π_1 and π_0 we obtain

$$\frac{\pi_1 - \pi_0}{\pi_0} s_\pi = (G - 1) - \frac{(w_1^{SP} - w_0)}{w_0} \varphi s - \frac{(w_1^{nSP} - w_0)}{w_0} \varphi (1 - s), \quad (6)$$

⁴Our results in section 6.1 suggest that there are no recipients of the gains from SPs other than firms and workers, supporting this assumption.

where $\varphi = \frac{w_0 \tilde{L}}{AK^{\beta_k} M^{\beta_m} \tilde{L}^{\beta_l}}$ is the share of labor costs in the total output and s_π is the profit's share. The above equation implies that the profit gain from SPs is the total output gain, $G - 1$, net of the wage gains of SPs and non-SPs, all weighed by their respective shares in the total output. As we show in Appendix A, the decomposition in (6) remains valid in the presence of differences between SPs and non-SPs other than exposure to knowledge, as long as we control for them statistically in calculating both the output and wage gains.

3 Estimation issues

Our research question boils down to estimating the components of equation (6) from the available data. In this section, we explain how we estimate the output gains ($G - 1$) and the wage gains by SPs $\left(\frac{(w_1^{SP} - w_0)}{w_0} \varphi s\right)$ and non-SPs $\left(\frac{(w_1^{nSP} - w_0)}{w_0} \varphi (1 - s)\right)$. The profit gains can be calculated from (6) as the output gains net of wage gains. Alternatively, they can be estimated directly from the data, which we do as a robustness check (section 6.1). Since the elements of (6) are firm- or worker-specific, we calculate them for the representative firm and worker.

3.1 Output gains

3.1.1 Definitions

The factor G in equation (3) measuring the output gains from SPs is determined by the share of SPs (s), SPs' labor productivity advantage (δ) and labor input elasticity (β_l). We estimate these parameters simultaneously, within the context of the previously assumed Cobb-Douglas production function (equations (2) and (3)). We follow the approach of Stoyanov and Zubanov (2012) and identify SPs in firm i and year t as the workers hired in year $t - 1$ from firms with a higher TFP than i in year $t - 2$, the last full year when those workers were in their previous firms and had access to knowledge there.⁵ Our specification of δ , also

⁵We exclude those hired in year t , because, not knowing the exact date of their joining the firm, we cannot be sure that they have spent enough time in their new firm to affect its productivity by applying knowledge from their previous firms. Indeed, no productivity gains traceable to SPs were detected in the year of their hiring. We will also explore the spillover potential of the workers hired before year $t - 1$, who might still

based on Stoyanov and Zubanov (2012), is

$$\delta_{it} = \left(\prod_{j=1}^{L_{it}^{SP}} \frac{A_{j,i,t-2}^S}{A_{i,t-2}} \right)^{\frac{\eta}{L_{it}^{SP}}}, \quad (7)$$

where L_{it}^{SP} is the number of SPs employed in firm i according to our definition above, $A_{j,i,t-2}^S$ is the TFP of worker j 's sending firm in year $t - 2$, and $0 \leq \eta < 1$.

This specification speaks to two theoretical predictions, both verified in empirical literature. *First*, to the extent that the previously acquired knowledge makes SPs more productive, their labor productivity advantage will be proportionate to the technological distance between their sending and receiving firms. *Second*, given the technological distance, δ should be proportionate to the degree of knowledge transferability from sending to receiving firms, which depends, in particular, on the commonality of technology used by the two firms. It is easy to see that δ increases with the technological distance and with the degree of knowledge transferability η , and that δ is guaranteed to be at or above 1, as postulated in equation (1), since for all SPs $A_{j,i,t-2}^S/A_{i,t-2} \geq 1$ by definition.

3.1.2 Estimation procedure

Incorporating our measure of exposure to spillovers in equation (7) in the original production function (2), we obtain the equation from which s , δ and β_l can be estimated as follows. Taking logarithms of both parts of (2) and noting that $\ln G_{it} = \ln [1 + s_{it} \cdot (\delta_{it} - 1)] \approx s_{it} \cdot (\delta_{it} - 1)$ for $s_{it} \cdot (\delta_{it} - 1)$ close to 0, gives

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_l (\delta_{it} - 1) s_{it}, \quad (8)$$

where y, a, k, l, m are the logarithms of output, TFP and the factor inputs in nominal units (that is, in headcount for labor input). Further noting that $(\delta - 1) \approx \ln \delta$ for δ close to 1 and

 reveal some knowledge from their previous firms, as an extension.

applying (7), we arrive at the baseline equation linking the firm's output and its exposure to spillovers:

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_l \cdot \eta \cdot gap_{it} \cdot s_{it} \quad (9)$$

where the term

$$gap_{it} = \frac{\sum_{j=1}^{L_{i,t-1}^{SP}} (a_{j,i,t-2}^S - a_{i,t-2})}{L_{i,t-1}^{SP}}$$

is the *productivity gap* reflecting the technological distance between the sending and receiving firms averaged across the SPs in firm i .

We estimate equation (9) in two steps. In the *first step*, we estimate the production function part of it:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it}, \quad (10)$$

from which we recover the TFP,

$$\hat{u}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}, \quad (11)$$

the share of SPs in each firm and year, derived from the condition $\hat{u}_{j,i,t-2}^S - \hat{u}_{i,t-2} > 0$ for each worker j hired by firm i in year $t - 1$, and the gap,⁶

$$\widehat{gap}_{it} = \frac{\sum_{j=1}^{L_{i,t-1}^{SP}} \hat{u}_{j,i,t-2}^S - \hat{u}_{i,t-2}}{L_{i,t-1}^{SP}} \quad (12)$$

In the *second step*, we obtain $\hat{\beta}_l$ and $\hat{\eta}$ by reestimating equation (9) with the gap and controls:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \theta \widehat{gap}_{it} \hat{s}_{it} + \text{controls}_{it} + e_{it}, \quad (13)$$

where e_{it} is the error term and $\theta = \beta_l \cdot \eta$. Collecting the estimates from both steps of the

⁶In constructing the gap measure, we will discard the top and bottom 1% of observations to remove likely outliers.

estimation procedure, we calculate the output gains from SPs as

$$G - 1 \approx \ln G = \hat{\theta} \cdot g\hat{a}p \cdot \hat{s} \quad (14)$$

The general estimation problem for the production function is to control for TFP shocks observable to the firm but not to the econometrician, which will bias the ordinary least squares (OLS) estimates of the regression coefficients. Another problem, specific to our study, is possible correlation between firms' hiring decisions (and hence the gap) and their observed TFP shocks. This problem will cause an upward bias to the gap's coefficient, as firms with a higher observed TFP shock may want, and can better afford, to hire workers from more productive firms. The importance of both problems goes beyond the production function estimation concerns. Thus, obtaining consistent estimates of factor input elasticities is required to produce a consistent estimate for the gap and hence to determine the output gains from spillovers through mobility. Furthermore, since the gap is present in the wage equations (15) and (16), which measure the gains from spillovers to SPs and non-SPs, consistent production function estimates are required to compute the distribution of the output gains between firms and workers. Several estimators proposed in the literature can address these problems, of which we apply two: OP, based on Olley and Pakes (1996), and WOP, its extension developed in Wooldridge (2009).

3.1.3 Controls

To account for sources of output gains from SPs other than the productivity gap, we add a number of controls in the second-stage production function equation (13), including the firm-year averages of SP and non-SP characteristics (see regression tables for details), firm characteristics, industry-year fixed effects, a firm-year average measure of human capital disaggregated by worker type, the gap constructed for workers from less productive firms, and two lags of TFP. The last three controls merit further explanation. The human capital measure we use is essentially the wage net of its firm-specific component. It was originally

proposed in Abowd, Kramarz and Margolis (1999), and further operationalized in Abowd, Creecy and Kramarz (2002) and Cornelissen (2008), whose method we follow. Its estimation relies on worker movements between firms as the source of variance to identify individual- and firm-specific components in the individual wage equation:

$$\ln w_{jit} = \lambda + z_{jt}\pi + \xi_j + \psi_i + v_{jit}, \quad (15)$$

where $\ln w_{jit}$ is the log wage of worker j employed in firm i in year t , z_{jt} is the vector of worker j 's observable characteristics, ψ_i is the firm fixed effect, ξ_j is the worker fixed effect, and v_{jit} is a random error term. In our specific application, a consistent estimation of (15) rests on the assumption of no correlation between the individual characteristics and the gap. This assumption is relatively undemanding given the scarcity of SPs in our sample and the small effect of the gap on wages.

Having estimated (15), we calculate for every worker the measure of his or her human capital as the wage net of the firm-specific effect and the error, which we then average at the firm level separately for SPs, movers from less productive firms, and stayers. Subtracting the firm-specific component ψ_i from the wage renders our measure of human capital free from firm-specific influences (such as compensation policies) which may also be correlated with sending firm's productivity and hence the gap. The measures of human capital in t are constructed from the wages in year $t - 2$, the last full year when SPs were in their previous firms.

The gap measure analogous to (12) but constructed for the workers coming from less productive firms, which we call *negative gap*, is used as an additional control for human capital in the gap's effect. To the extent that the gap's effect is driven by human capital, the coefficients on the positive and negative gaps will be equal, since better quality workers will improve performance just as worse quality ones will deteriorate it. On the other hand, if the gap's coefficient reflects spillovers, there will be a positive effect only of the positive

gap, while the knowledge carried by workers coming from technologically inferior firms (the negative gap), will be neutral to productivity.

Lastly, we include the first and second lags of TFP to capture autocorrelation in equation (13)'s residuals, which, if present, would bias the coefficient on the gap, because the gap is a function of the second lag of own and sending firms' TFP. This inclusion goes against the assumption of a first-order Markov process in TFP, which underlies the conventional OP and WOP estimators. We extend these estimators to allow for a second-order Markov in Appendix B, which extension requires an additional, and very strong, assumption. However, the estimation results from our extended OP and WOP estimators (available in the online appendix) are similar to the ones we report in the main body of our work.

3.2 Wage gains

To estimate the wage gains to SPs and non-SPs – the second and third terms in decomposition (6) – we first estimate the SPs' premium relative to the average wage of otherwise similar non-SPs in their receiving firms. We run the following individual wage equation:⁷

$$\begin{aligned} \ln w_{jit} = & \gamma \cdot \widehat{gap}_{jit} + \gamma^- \cdot \widehat{gap}_{jit}^- + \phi_{it} \\ & + \text{controls}_{jit} + v_{jit}, \end{aligned} \tag{16}$$

where \widehat{gap}_{jit} is the productivity gap, calculated for each worker separately as the TFP difference between their sending and receiving firms in year $t - 2$, and \widehat{gap}_{jit}^- is the negative gap as defined in section 3.1.3, also calculated at the worker level, and v_{jit} is the random error term. Hence, $\widehat{gap}_{jit} = 0$ for a worker coming from a less productive firm, $\widehat{gap}_{jit}^- = 0$ for an

⁷Note the difference between the wage equations (16), which measures the gap's effect on earnings, and (15), which measures human capital. Equation (15) includes worker fixed effects to control for time-invariant unobserved determinants of human capital but does not include the firm-year fixed effects ϕ_{it} . This difference reflects the different purposes served by these related equations. Worker fixed effects in (15) are necessary to obtain a complete measure of human capital, and firm-year fixed effects in (16) are required to control for firm-year determinants of wage which may be correlated with the gap. The worker and firm-year fixed effects cannot be included together in the same equation because they are not jointly identifiable. Hence, we run equations (15) and (16) separately.

SP, and $\widehat{gap}_{jit}^- = \widehat{gap}_{jit} = 0$ for a job stayer. The controls include worker characteristics (firm characteristics are subsumed by the firm-year fixed effects, ϕ_{it}): age, gender, education, skill group, experience, two dummy variables indicating whether a worker comes from a more or a less productive firm, the measure of human capital estimated from equation (15) separately for SPs, other movers and stayers, and dummy variables corresponding to the number of job transitions during the sample period. The firm-year fixed effect ϕ_{it} measures the mean log wage in the respective firm and year after controlling for individual worker characteristics. Because these characteristics include the gap, ϕ_{it} can be interpreted as the mean log wage of non-SPs (for whom $\widehat{gap} = 0$). Hence, coefficient γ measures the wage premium to SPs relative to otherwise similar non-SPs as the fraction of the gap.

We proceed to calculating the effect of SPs on the wages of otherwise similar non-SPs by running a firm-level wage regression with the estimated firm-year fixed effects $\hat{\phi}_{it}$ as the dependent variable:

$$\begin{aligned} \hat{\phi}_{it} = & \Gamma \widehat{gap}_{it} \hat{s}_{it} + \Gamma^- \widehat{gap}_{it}^- \hat{s}_{it}^- + \Phi_i + \tau_{kt} \\ & + \text{controls}_{it} + V_{it}, \end{aligned} \tag{17}$$

where $\widehat{gap}_{it}^- \hat{s}_{it}^-$ is the negative gap times the share of moving workers from less productive firms, Φ_i and τ_{kt} are firm and industry-year fixed effects, controls include firm and worker average characteristics (the same as in the individual wage equation (16)) and two lags of TFP (\hat{u}) estimated from the production function equation (10), and V_{it} is the random error term. Coefficient Γ measures the average wage gain to non-SPs' as the fraction of the gap times the share of SPs in a given firm and year.

Combining the estimates from individual- and firm-level wage equations (16) and (17),

we derive the wage gains to SPs and non-SPs as

$$\begin{aligned}\frac{(w_1^{nSP} - w_0)}{w_0} &= \hat{\Gamma} \cdot \widehat{gap}_{it} \hat{s}_{it} \\ \frac{(w_1^{SP} - w_0)}{w_0} &= \hat{\Gamma} \cdot \widehat{gap}_{it} \hat{s}_{it} + \hat{\gamma} \cdot \widehat{gap}_{jit},\end{aligned}\tag{18}$$

and the average wage gain as

$$\frac{(w_1^{SP} - w_0)}{w_0} s + \frac{(w_1^{nSP} - w_0)}{w_0} (1 - s) = (\hat{\gamma} + \hat{\Gamma}) \cdot \widehat{gap}_{it} \hat{s}_{it}\tag{19}$$

Because the above expressions for the wage gains involve the gap and the share of SPs in the firm, which vary by firm and year, it is convenient to calculate them for the average worker whose data are reported in the “Workers” part of Table 2. Drawing on our preferred production function estimator (WOP), the average worker is employed in the firm where $\hat{s}_{it} = 2.14\%$ of employees are SPs whose average gap is $(L_{i,t-1}^{SP})^{-1} \sum_{j=1}^{L_{i,t-1}^{SP}} \widehat{gap}_{jit} = 0.2456$, resulting in the gap times share $\widehat{gap}_{it} \hat{s}_{it} = 0.0053$. These statistics are different from their equivalents for the representative firm because firms’ shares in total output, though close, are not equal to their shares in total employment.

4 Data

To track workers’ movements between firms, we use matched employer-employee data obtained from Statistics Denmark for the years 1995-2007. The data on workers come from the Integrated Database for Labor Market Research (IDA), covering the total population of individuals aged 15-65 residing in Denmark. Detailed information is available on individual socio-economic characteristics: age, gender, employment status, annual salary and income from other sources, experience, level of education, and skill group. All working individuals are matched to firms where they were employed in the last week of November of each year. The firm data (FIDA) include: industry affiliation, book value of physical capital, sales, workforce size, wages, purchases of materials and energy inputs, as well as detailed data

on investments which we use in our production function estimation (section 3.1.2). FIDA covers the entire population of firms, of which those with 50 or more workers are surveyed annually, and the rest are surveyed less frequently with the observations in-between interpolated. In our analysis, we use the part of the matched IDA and FIDA data coming from the manufacturing sector.

[Table 1 about here.]

Table 1 lists descriptive statistics measured at the firm and worker level, calculated on the sample used in our regression analysis. Many firms had had an exposure to productivity gains through hiring SPs, which took place in about a third (30.7 thousand) of observations during the sample period. Firms hiring SPs are different from the rest of the sample in that they have larger size (27.4.8 vs. 10.0 workers), produce more output per worker, employ more skilled workers (75% mid-skilled or above vs. 63%), and pay higher wages (189 vs. 174 thousand DKK per year). Our statistical analysis will control for these differences to determine the part played by spillovers through worker mobility in those firms' superior performance.

Despite some missing data, firms in our sample represent 87% of the manufacturing sector's output and 86% of its workforce. Therefore, what happens in this sample will be representative of the Danish manufacturing sector as a whole. To be able to project our statistical findings to the sectoral level, we use the concept of representative firm (the last column in Table 1). The representative firm is different from the average firm in that the statistics for the representative firm are averages of the underlying firm-level data weighted by the respective firm's share in total output. Therefore, the representative firm is larger than average on output and factor input measures. Thanks to such weighting, the effects on the representative firm's output, calculated from our regression coefficients, will be the same for the manufacturing sector as a whole.

Turning to workers' data, an average worker is 41.3 years old, earning 277.1 thousand DKK per year, and is most likely to be a college-educated male working in a medium-skilled

occupation in a large firm (average 209.1 workers). The discrepancies in the averages at the firm and worker levels exist because larger firms, whose weight in total observations at the worker level is greater, produce and pay more. Applying to firm-level observations their weights in total employment levels off these differences; indeed, the worker-level averages are close to those for the representative firms, since firms' weights in total output are close to their weights in total employment. The average worker changes firms once every ten years (more frequently in smaller firms); however, the share of SPs in total observations is only about 2%.⁸

Zooming in on those rare 2%, an average SP is younger (37.0 vs. 41.3), less experienced and less well-paid (229.3 vs. 277.1 thousand DKK per year) than the rest of the workers. Yet, SPs earn more than otherwise similar non-SPs. Figure 1 plots log wages net of observables estimated from the wage equation (15) (left panel), and the same net of firm fixed effects (right panel), averaged for the workers who changed firms in 2000 (close to the midpoint of our sample's time span), and for those who did not. Figure 1's left panel shows that SPs earn more than other workers do prior to job change, but less than movers from less to more productive firms thereafter. These dynamics, however, are likely to be influenced by moving workers' destinations, since by definition SPs move to less productive firms, which pay relatively low wages, and other moving workers go to more productive, higher-wage firms. Indeed, looking at the wages net of observables and firm fixed effects (Figure 1's right panel), we see that, relative to movers from less to more productive firms, SPs receive a wage premium, which persists over time but is not statistically significant.

[Figure 1 about here.]

There are also signs in the data suggesting that the size of SPs' wage premium depends on the gap. Thus, disaggregating SPs into the first and the fourth quartile of the productivity gap (Figure 2) we observe that workers with the highest spillover potential (4th quartile)

⁸Another 2% are workers moving from less to more productive firms. The rest of the job changers are not included in our gap measures because they were either unemployed in the previous year, or come from non-manufacturing sending firms, or just enter the labor market.

receive a substantial wage premium relative to non-SPs, which is statistically significant and persists over time. On the other hand, the residual wage profile of SPs with the smallest gap (1st quartile) does not differ much from that of movers from less to more productive firms.

[Figure 2 about here.]

5 Baseline results

5.1 Output gains

As explained in section 3.1.2, we estimate the production function equation (9) in two steps: first, the part of it without the gap (equation (10)), and second, the original equation with the gap and controls added in it (equation (13)). Tables 2 and 3 report the results from the first and second steps, respectively. The three estimators – OLS, OP and WOP – produce very similar measures of TFP (\hat{u}) with pairwise correlations of 0.94 – 0.98, depending on the pair. This similarity implies that our measure of the gap, calculated from \hat{u} according to (12), will not vary much with the production function estimator.

[Table 2 about here.]

Turning to the estimates of our main interest, Table 2 reports descriptive statistics for the gap, the share of SPs, and the product of the two, calculated at the firm and worker level. The averages at the worker level are representative of the entire workforce; therefore, we will use them in calculating the wage gains from SPs (Section 5.2). We report unweighted and weighted firm-level averages, with weights proportionate to firms’ output shares, to make them applicable for this section’s analysis of SPs effect on the sectoral output. Looking at these statistics, SPs make up, on average, around 2% of the workforce, and their productivity gap averages at 0.23 – 0.31. The small share of SPs results in the small average gap times share, only 0.0062 – 0.0082, and limits the effect of SPs on output. In our preferred specification (WOP), the representative firm counts $\hat{s} = 0.0179$ of its workforce as SPs, whose average gap is $\widehat{gap} = 0.3064$, and has gap times share $\widehat{gap} \cdot \hat{s} = 0.0082$.

[Table 3 about here.]

The main results in Table 3 are a positive and significant coefficient on the positive gap, and a small and insignificant one on the negative gap. The difference between these coefficients implies that human capital brought in by new workers cannot explain the productivity effect of the gap, since otherwise the two coefficients would be equal. Since the negative gap’s effect is small, both statistically and economically, we will focus on the positive gap.

To help isolate factors other than knowledge spillovers that can operate through the gap, as well as to pinpoint their sources, we run three specifications of the production function equation with different sets of controls. The first specification (columns 1, 4, 7) includes the Abowd, Kramarz and Margolis (1999) human capital measure (calculated separately for SPs and others from equation (15)), industry-year fixed effects and two lags of TFP. The second specification (columns 2, 5, 8) includes the same controls plus firm characteristics: separations rate, and shares of new workers hired from more and less productive firms. Finally, the third, and most complete, specification (columns 3, 6, 9) includes the same plus other observable characteristics of the workers, averaged at the firm level: age, gender, experience, education and occupation group within the firm. Comparing the gap’s coefficients across these specifications, we see that its effect is mostly influenced by the observed characteristics of the workers, many of which are related to human capital. Yet, most of the gap’s effect survives these controls.

Starting with the most complete OLS specification (Table 3’s column 3), the gap’s coefficient $\hat{\theta} = 0.25$ implies a receiving firm’s productivity gain from hiring SPs equal to 0.25 of its gap times SPs’ share in the workforce. For example, a firm hiring 10% of its workforce from 10% more productive firms will produce 0.25% ($= 0.25 \times 0.1 \times 0.1$) more output with the same inputs than a similar firm hiring no SPs. This OLS-based estimate of the productivity gain may be subject to bias due to the gap and labor input being correlated with the receiving firm’s TFP shock. Applying the OP and WOP estimators that control for this bias, we observe that, compared to the OLS, the positive gap’s coefficient has reduced in magnitude and is now around 0.12 in the most complete regression specifications (columns

6 and 9). This decrease suggests that firms experiencing a positive TFP shock tend to hire from relatively more productive firms. Still, even controlling for this correlation, the implied productivity gain to a firm hiring 10% of its workforce from 10% more productive firms is still a non-negligible 0.125% ($= 0.125 \times 0.1 \times 0.1$, based on the most complete specification estimated with our preferred WOP, column 9).

Based the estimates from our preferred WOP specification, the output gain from SPs to the representative firm is (recall equation (3))

$$G - 1 = \hat{\theta} \cdot \widehat{gap} \cdot \hat{s} = 0.125 \cdot 0.0082 = 0.1\%$$

Therefore, we conclude that the manufacturing sector as a whole grows by the same 0.1% per year, which is 8.2% of its annual TFP growth averaged over the sample period. It may thus be conjectured that, if there had been no spillovers through worker mobility in the Danish manufacturing sector, its TFP growth would have been just under a tenth less than actually observed.

Dividing the WOP gap's coefficient of 0.125 by labor input elasticity, 0.399, we obtain the knowledge transferability parameter $\hat{\eta} = \hat{\theta}/\hat{\beta}_l = 0.31$. Given our assumption that it is the knowledge gap that underlies the sending–receiving firms' productivity gap, $\hat{\eta} = 0.31$ implies that about a third of this knowledge is transferable between firms despite technological and other barriers that may hinder this transfer. We probe into the role of common technology in enabling spillovers through mobility in Section 6.2.

The estimate $\hat{\eta} = 0.31$ allows us to calculate SPs' log labor productivity advantage for the representative firm as $\hat{\eta} \cdot \widehat{gap} = 0.094$. This estimate implies that, controlling for other observable characteristics, an average SP is nearly 10% more productive than an average non-SP in that firm. It must be noted that the latter result is based on the assumption that non-SPs do not become more productive by learning from SPs, which process we cannot observe. Allowing for such learning, the log LPA as defined above becomes the upper boundary of

the true LPA. Its lower boundary, based on the contrary assumption that every worker learns from SPs and becomes equally productive with them, is 0. Whatever the productivity differences are between SPs and non-SPs, the overall labour productivity increase traceable to SPs is $\hat{\eta} \cdot \widehat{gap} \cdot \hat{s}_{it}$, or 0.25% for the representative firm.

5.2 Wage gains

Table 4 presents estimation results for the individual wage equation (16) run with the gap values estimated previously with OLS, OP and WOP estimators. Consistently with our earlier results, the negative gap's coefficient, γ^- , is small and insignificant, implying no significant wage premium (or penalty) to the new workers who are not SPs. The positive and significant coefficient on the gap, γ , implies that there is indeed a wage premium to SPs proportionate to the knowledge they bring as measured by their productivity gap. Comparing the estimates in specifications with and without controls, we conclude that a large part of this wage premium can be explained by the characteristics of the workers who receive it, since the coefficient on the positive gap goes down in magnitude as we add worker controls. In the end, with all controls included in our preferred specification (column 6), the wage premium to SPs on top of the average wage in a given firm and year is 0.035 of their gap. Hence, the average SP, whose gap is 0.31, earns an extra 1.09% per year on top of the average non-SP wage in his or her firm. Relative to the sample average real wage growth, 4% per year, this premium is not insignificant. However, given the small share of SPs in the workforce, their wage premium makes little difference to the total wage bill, increasing it by a mere 0.023% compared to the hypothetical case of no worker mobility across firms.

[Table 4 about here.]

The estimates from the firm-level wage equation (17) are presented in Table 5. Unlike that on the negative gap, the coefficient on the gap, Γ , is consistently positive and significant across the estimators and specifications, even though worker and firm characteristics explain a large part of the effect it measures. The gap's coefficient in our most preferred and complete

specification (column 9), $\Gamma = 0.124$, implies that non-SPs in a firm hiring 10% of its workforce from 10% more productive firms gain, on average, 0.12% ($= 0.124 \times 0.1 \times 0.1$) in wages per person per year compared to the counterfactual of hiring the same 10% but non-SPs. For the average non-SP in our sample this wage gain stands at 0.09% ($= 0.124 \times 0.0072$, average gap times share) per year. Adding this average wage gain to SPs' premium calculated above, we obtain their full wage gain: 1.17% per year, paid in the year following the change of employer. The average wage gain, calculated from equation (19), and thus the increase in the manufacturing sector's total wage bill linked to SPs, is 0.11% per year.

[Table 5 about here.]

Our calculations above point to a considerable redistribution of wage gains from SPs to the rest of the workers. Indeed, if all wage gains were SPs' only, then the average SP would have earned a 4.9% wage premium per year ($=$ the average wage gain, 0.11%, divided by SPs share in the workforce, 2.24%) instead of the actual 1.17%. Comparing this actual wage gain with the possible maximum of 4.9%, as well as the total wage gain of 0.11% with the total output gain of 0.1% (section 5.1) suggests that the gains from spillovers through worker mobility are not accrued to SPs alone but are in fact shared between the firms, the SPs and the other workers. We calculate these shares next.

5.3 Gains distribution

Given the output and wage gains, the share of labor costs in total output φ determines the gains distribution between firm and workers: the higher φ , the lower share in the total gain the firms will net. With no prior information about the value of φ , we use two alternative measures of it. One is the employment-weighted sample average share of wage costs in total output, 0.223. This value may be interpreted as the true φ 's lower boundary (and hence the firms' gains upper boundary), since it omits statutory contributions paid by the firms as well as implicit costs of employing labor, such as the costs of searching, hiring, training up and laying off workers. Our alternative measure is labor input elasticity estimated with WOP,

0.399 (Table 3), which, assuming a Cobb-Douglas production function as we do, would give the share of total labor costs in the profit-maximizing firm's output.

[Table 6 about here.]

Table 6 reports the shares in the total output gain of the firms, the SPs and non-SPs calculated from equation (6). The six sets of shares are based on our two alternative measures of φ applied to the the OLS, OP and WOP estimates of the gap, the share of SPs and output gains. The shares calculated with $\varphi = 0.223$ (columns 1-3) show that firms net at least 73% of the total output gain, and, with most of the remaining gains going to other workers, SPs receive between 2–4%. The firms' share in the total gain goes down as we do the calculations with φ equal to the WOP labor input elasticity. Yet, even under $\varphi = 0.399$ (columns 4-6), the firms' share in the total output gain is still more than a half, while the most generous estimate of the SPs' share is 8%. In fact, the firms retain more than half of the total gains for the values of φ up to 0.47, which is a lot higher than most of the labor input elasticity estimates found in the literature.

The above calculations, which suggest that firms retain most of the gains from SPs, permit two alternative interpretations. First, the hiring firms are unable to precisely identify the source of these gains due to uncertainty regarding the spillover potential of their workers, and therefore do not fully reward SPs for their contribution. Second, firms do observe the contribution of SPs but do not pay their competitive wage because of other labor market imperfections. We cannot identify these imperfections, but they must be truly large to sustain the abnormally high rents to the hiring firms implied by our results: \$2.3-\$4 return on each dollar invested in attracting SPs. On the other hand, we can support the first interpretation, based on uncertainty regarding workers' spillover potential, by applying the decomposition in (6) to the results in Balsvik (2011), whose data and method are comparable to ours, except for one difference, that the SPs in her study are the workers with foreign-firm experience hired by domestic firms. Because this experience, unlike the productivity gap, is a highly visible characteristic, their spillover potential should be better recognized and

rewarded. Indeed, their 5% wage premium over otherwise similar workers and the associated output gain of 0.27% imply that SPs retain 19% of that gain,⁹ which is higher than our estimated 4–8%. Hence, the uncertainty regarding spillover potential, which is larger in our general case than in the particular case of workers with foreign-firm experience, is a plausible explanation to why our estimated SPs’ wage premium is relatively low. However, because Balsvik’s (2011) results do not allow us to infer the wage gains to non-SPs and hence the net profit gains to the hiring firms, more research is needed to determine the full impact of spillover potential observability on the gains distribution.

6 Extensions

6.1 Direct estimation of profit gains

In the previous section, we estimated the distribution of the output gains from SPs assuming that profit gains to firms are the output gains net of the wage payments to the workers (recall equation (6)). As an alternative to this approach, we now estimate the profit gains directly from the data using an equation similar to the firm-level wage equation (17):

$$\ln \pi_{it} = \Pi \widehat{gap}_{it} \hat{s}_{it} + \Pi^- \widehat{gap}_{it}^- \hat{s}_{it}^- + \Phi_i + \tau_{kt} + \text{controls}_{it} + \psi_{it}, \quad (20)$$

where the list of controls is the same as in equation (17) and the term $\Pi \widehat{gap}_{it} \hat{s}_{it}$ measures the profit gain for a given firm and year:

$$\frac{\pi_1 - \pi_0}{\pi_0} \approx \Delta \ln \pi_{it} = \hat{\Pi} \cdot \widehat{gap}_{it} \hat{s}_{it}$$

The estimates of the key coefficient Π from equation (20), reported in Table 7, imply positive profit gains from hiring SPs, proportional to their average gap. Depending on specification, the positive gap is associated with a 0.85% to 2.12% increase in profit for the

⁹The total output gain was calculated as the elasticity of output with respect to SPs’ share, 0.1 (Table 8), times their sample average share, 2.7% in 2000. SPs’ share in the total output gain was calculated using the estimated labor input elasticity, 0.376 (Table 8), as $\frac{0.376 \times 0.027 \times 5}{0.27} = 18.8\%$.

representative firm. Converting the profit and wage gains into the output gains using their respective average shares in total output, we find that the estimates from equation (20) imply the share of firm profit in the total output gain of 61%, 81%, and 63% in the most complete OLS, OP, and WOP specifications (row b), which results are similar to those obtained from our baseline approach relying on equation (6).

On a separate note, the sum of the profit and wage gains relative to the total output gains, all of which now calculated independently of each other, is close to 1, showing a high degree of consistency between the two alternative approaches to calculating the gains distribution we have employed. The closeness of the sum of wage- and profit-to-output gain ratios to 1 also implies that there are no major recipients of the benefits from SPs other than the hiring firms and their workers, which supports the assumptions underlying our gains decomposition (6) in Section 2.2.

[Table 7 here.]

6.2 Output and wage gains from worker mobility within and between industries

Since not all technologies are equally applicable elsewhere, the gains from SPs may depend on the industry of their origin. To account for possible differences in the output gains from SPs moving within and between industries, we allow the knowledge transferability parameter $0 \leq \eta < 1$ in equation (7) to vary depending on an SP's industry of origin. We implement this extension by calculating the productivity gaps (\widehat{gap}_{it}) and workers shares (\hat{s}_{it}) separately for the SPs hired from within (high η) and outside (low η) each industry group, and by repeating the previous analysis for firms and workers with the newly specified measures. There are nine two-digit industries (NACE classification) in the manufacturing sector, and 55% of all job changes took place within the same industry.

[Table 8 about here.]

Table 8 lists the regression results for the production function equation (13) and indi-

vidual and firm average wage equations (16) and (17). The gap’s coefficient in column 6 is much larger for spillover potentials moving within the same industry (about 0.32) than for those moving between industries (0.1). The difference between these estimates reveals the importance of knowledge transferability in facilitating spillovers through worker mobility between firms: thanks to common production technology, knowledge is more transferable within than across industries, resulting in higher productivity gains for a given gap. As before, the sizeable difference between the positive and negative gaps’ coefficients, the latter being small and insignificant in all specifications, implies that human capital cannot explain our results.

Turning to the estimates for the individual wage equation (16) in columns 1-3, we see that, despite the difference in productivity gains brought in by SPs from the same and different industries, their individual wage gains as the share of the productivity gap they carry are nearly the same. The coefficient on the same-industry positive gap in the firm average wage regression (0.157, column 9) is not far from its analogue in Table 5 (0.124) estimated for all SPs or the same coefficient for SPs from different industries (0.097). Taken together, the similarity of wage premiums to SPs and dissimilarity of productivity gains to firms does not suggest a strong link between the two, which is perhaps not surprising given how little of the total output gain is given back to the SPs or other workers.

6.3 Output and wage gains by SPs’ skill group

So far in our analysis we have used the measure of a firm’s exposure to spillovers through worker mobility, $\eta \cdot \widehat{gap}_{it} \cdot \hat{s}_{it}$, which assumes that, given the share of SPs in the workforce, the gains from SPs increase with the gap and technology transferability between sending and receiving firms. However, holding these firm-level characteristics fixed, productivity gains brought by SPs, as well as their wages, may still vary depending on the attributes of those workers. One such attribute, on which we focus in this section, is skill group, since SPs in higher-skill groups will have better access to the knowledge of their previous firms than

those in lower-skill groups. Using the Statistics Denmark’s definitions of skill groups based on the International Standard Classification of Occupations, we classify all workers into one of the four skill groups: low-skilled, mid-skilled, high-skilled, and managers. Accordingly, we construct the gaps and corresponding worker shares for each skill group separately and reestimate the production function and wage equations (13), (16) and (17) with these newly defined variables.

[Table 9 about here.]

The results, presented in Table 9, reveal considerable differences in the estimated productivity gains to firms from hiring SPs belonging to different skill groups. Consistent with our expectations, the labor productivity advantage of SPs in higher skill groups (highly-skilled and managers) is much larger than that of the lower skill groups, although even the least skilled SPs still contribute to the hiring firm’s output. The output gains brought by different skill groups depend not only on their LPA but also on their shares in the workforce. For instance, although manager SPs are scarce, thanks to their high LPA (0.488) they bring higher total output gains (0.055%) than more abundant but less productive mid-skilled SPs (0.048%).

Turning to the effect on wages by skill group, we observe that SPs’ own wage premium (coefficient γ^+) increases with the skill group, peaking at 5.8% of their individual gap for managers, implying a 1.8% wage premium for the average manager SP. While higher than the average SP’s wage premium of 1.17%, it is still only a small fraction of the gap. SPs’ contribution to the average non-SP wages in their receiving firms (coefficient Γ^+) is proportional to their LPA and share in the workforce, with the manager and mid-skill SPs contributing the most. However, the total gains distribution, though varying somewhat in the shares accrued to SPs and non-SPs, features a stably large firms’ share across the skill groups.

6.4 The output and wage gains in the short- to medium run

While our analysis so far has been confined to SPs' effects on output and wages the next year, these effects may in fact last longer. For instance, the autoregressive process in TFP will propagate SPs' effect on output, which may be further shaped by the internal dynamics of knowledge implementation. There are also reasons for SPs' wage premium to last several years. First, as we have argued earlier (section 3.3), their premium may be affected by information asymmetry regarding their productivity. Presumably, the information asymmetry should decrease as their tenure progresses, and one should see a closer link between their labor productivity advantage and wage premium. Second, SPs' wage premium may be deferred as their new firms try to ensure that they stay long enough for the output gains they bring to be fully realized. Such deferred pay implies that a wage premium will continue to be paid to SPs in the years after joining, possibly even after their labor productivity advantage is exhausted.

To estimate the dynamics of gap's effect on wages and output, we rerun the production function and wage equations (13), (16) and (17) with future output and wages as dependent variables:

$$y_{i,t+q} = \beta_k k_{i,t+q} + \beta_l l_{i,t+q} + \beta_m m_{i,t+q} + \theta_q \widehat{gap}_{it} \hat{s}_{it} + \text{controls}_{it} + \sum_{p=1}^q \vartheta_p \widehat{gap}_{i,t+p} \hat{s}_{i,t+p}, q \geq 1 \quad (21)$$

$$\ln w_{j,i,t+q} = \gamma_q \widehat{gap}_{jit} + \gamma_q^- \widehat{gap}_{jit}^- + \phi_{i,t+q} + \text{controls}_{jit} + v_{j,i,t+q}, \quad (22)$$

$$\hat{\phi}_{i,t+q} = \Gamma_q \widehat{gap}_{it} s_{it} + \Gamma_q^- \widehat{gap}_{it}^- s_{it}^- + \Phi_{i(q)} + \tau_{k,t+q} + \text{controls}_{it} + \sum_{p=1}^q \Theta_p \widehat{gap}_{i,t+p} \hat{s}_{i,t+p} + V_{i,t+q}, \quad (23)$$

where the notations are the same as in the original equations (13), (16) and (17) presented

earlier. An adaptation of the local projections method developed in Jordà (2005) and extended in Teulings and Zubanov (2013), this easy-to-implement estimation procedure is robust to possible dynamic misspecifications in the underlying equations. The coefficients γ_q and Γ_q estimate the effects of the gap on SPs' wage premium and non-SPs' wages $q + 1$ years after joining the new firm, and the coefficient θ_q measures the effect of the gaps-times-share on output. The overall wage gain is calculated for each q using equation (19). The inclusion of the gaps times share in the years between t and $t + q$ in (21) and (23) controls for the effects of worker mobility between those dates on the outcome at $t + q$, which might otherwise have been attributed to the gap at t . The individual wage equation (22) has not been augmented in a similar way because the gap for a given worker remains the same during the whole tenure at a given firm.

[Table 10 about here.]

Table 10 reports the productivity and wage gains linked to SPs in a five-year period after hiring them. The results show that output gains from hiring a given cohort of SPs last several years, reaching a peak in the third year and receding thereafter. The dynamics of wage gains to SPs and non-SPs mimics that of output, so that the gains distribution remains fairly stable. The continuing positive effect of SPs results in the five-year total output gain linked to hiring them exceeding the year-after gain of 0.1% estimated earlier. Thus, calculations based on Table 10's results imply that the total output gain over the five-year period after hiring SPs becomes 0.94% of the baseline output. Over the same period, the average SP and non-SP will gain 5.6% and 0.5% of their respective baseline wages, implying the overall wage gain of 0.65%. Calculating the parties' shares in the total output gain over the five-year period using equation (6) with $\varphi = 0.223$, we obtain that firms net 80 – 85% of it, SPs 2.4 – 2.8%, and non-SPs 11 – 15%.

The stability of the gains distribution with time, and in particular the steadily low share of SPs in the total gain, does not support our deferred pay hypothesis for SPs. Our results do not seem to be consistent with the gradual reduction of information asymmetry over SPs'

value, either. However, the latter possibility cannot be rejected outright, since having to prove themselves again with a new employer undermines SPs' bargaining power over their wages. Exploring the factors affecting the dynamics of spillovers through mobility and their consequences for all parties involved should be a promising direction for further research.

7 Conclusion

The key question in our study has been to determine the distribution of output gains linked to spillovers through workers mobility between the hiring firms, the SPs, and the rest of the workers. We have found that the total output gain from SPs is 0.1% per year, of which the lion's share – at least two-thirds – is retained by the hiring firms, whereas the SPs themselves receive a paltry 8% at most. This finding implies that by far the biggest share of the positive externality from knowledge production enabled by the movement of workers between firms is retained by the hiring firms. Thus, to the extent that knowledge spillovers are important for economic growth, and inasmuch as worker mobility is a mechanism facilitating these spillovers, hiring new workers is instrumental for firms to gain cheap access to superior knowledge developed elsewhere.

We believe ours is the first study to show how output gains from knowledge spillovers through mobility are distributed between all the three parties involved. Another contribution to the relevant literatures is the unified empirical framework we have developed to measure spillovers through mobility, which can be applied to worker movements between any pair of firms regardless of their domicile. One useful feature of our framework, other than its generality, is that it is rich enough to support various extensions of our main research question, some of which we have implemented.

Appendix A - output gains distribution in the presence of skill differences between SPs and non-SPs

It is important to emphasize that output gains decomposition in (6) remains valid as long as we control for skill differences between SPs and non-SPs. Suppose that, apart from their labor productivity advantage due to access to better knowledge, SPs are more skilled than non-SPs by a factor ϕ and receive a wage premium μ as a result. Then the profit π_1 after hiring SPs becomes

$$\pi_1 = AK^{\beta_k} M^{\beta_m} \tilde{L}^{\beta_l} G\Phi - (w_1^{SP} + \mu) L^{SP} - w_1^{nSP} L^{nSP} - r_0 K - h_0 M,$$

where $\Phi = (1 + s(\phi - 1))^{\beta_l}$. Taking the difference between π_1 and π_0 and rearranging, we obtain

$$\frac{\pi_1 - \pi_0}{\pi_0} s_\pi = (G - 1) - \frac{(w_1^{SP} - w_0)}{w_0} \varphi s - \frac{(w_1^{nSP} - w_0)}{w_0} \varphi (1 - s) + \left\{ G(\Phi - 1) - \varphi s \frac{\mu}{w_0} \right\}$$

The term in the curly brackets represents output gains specifically from SPs' skills ($G(\Phi - 1)$) net of the extra costs paid by the firms to reward their skills ($\varphi s \frac{\mu}{w_0}$). Because the above term enters the gains decomposition linearly, controlling for SPs' skill in the production function and wage equations will fully isolate it, bringing back the original decomposition (6) of the gains from SPs net of the effect of their skill.

Appendix B - Extending the OP and WOP estimators to allow for a second-order Markov process in TFP

Recall the production function equation (10):

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + u_{it}$$

where residual output u_{it} consists of two mutually orthogonal components: ω_{it} , which is observed to the firm at t , and ϵ_{it} , an unobserved productivity shock. The correlation of factor inputs with ω_{it} causes bias to their OLS estimates. The OP and WOP estimators control for this correlation by proxying ω_{it} with a polynomial function of a selection of relevant variables. The conventional versions of these estimators assume a first-order Markov process in ω_{it} , which is inconsistent with our production function specification with *two* lags of TFP included as controls, both of which are significant. However, the OP and WOP estimators can be extended to allow for a second-order Markov subject to an additional assumption as we show below.

The OP estimator

The OP estimator proxies ω_{it} with observables, such as capital and investments. Assuming capital stock (k) at t is a deterministic function of itself and investment (i) at $t - 1$,

$$k_{it} = (1 - \rho)k_{i,t-1} + i_{i,t-1}, \tag{24}$$

where $0 < \rho < 1$ accounts for depreciation, the firm will use investment as a tool to build up the optimal capital stock given ω_{it} . Pakes (1994) showed that the investment function $i_{it} = f(k_{it}, \omega_{it})$ that solves the dynamic profit maximization problem given (24) is monotonically increasing in both its arguments, and can thus be inverted for ω_{it} :

$$\omega_{it} = g(k_{it}, i_{it})$$

Since the functional form of $g(\cdot)$ is unknown, it is approximated with a third degree polynomial in k_{it} and i_{it} , called the *control function*.

In the first stage of the OP procedure, labor and materials input elasticities, β_l and β_m , are estimated from the production function equation with the added control function. Because the control function $g(\cdot)$ is collinear with $\beta_k k_{it}$, capital input elasticity β_k is estimated in the second stage, where the fitted values

$$\widehat{\Phi}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\epsilon}_{it} = \beta_k k_{it} + \omega_{it}$$

and the assumption that ω_{it} follows a first-order Markov process are used to identify it. The latter assumption allows ω_{it} to be expressed as the sum of its conditional expectation as of $(t-1)$ and the error term ξ_{it} orthogonal to it:

$$\omega_{it} = \mathbf{E}[\omega_{it} | \omega_{it-1}] + \xi_{it} = \lambda(\omega_{it-1}) + \xi_{it} = \lambda\left(\widehat{\Phi}_{i,t-1} - \beta_k k_{i,t-1}\right) + \xi_{it},$$

where $\lambda(\cdot)$ is an unknown function approximated by a third degree polynomial. β_k is then estimated from the regression

$$\widehat{\Phi}_{it} = \beta_k k_{it} + \lambda\left(\widehat{\Phi}_{i,t-1} - \beta_k k_{i,t-1}\right) + \xi_{it}$$

Our definition of SPs' labor productivity advantage as a function of the sending-receiving TFP gap two years back implies that output in period t may depend on $\omega_{i,t-2}$. A correlation between ω_{it} and $\omega_{i,t-2}$ will result in a bias to the estimated gap's coefficient. For example, if ω_{it} follows an AR(2) process with positive autoregression coefficients, which is indeed the case in our data, this bias will be downward. To address this problem, we estimate the

production function equation with ω_{it} following second-order Markov process:

$$\omega_{it} = \text{E}[\omega_{it}|\omega_{it-1}, \omega_{it-2}] + \xi_{it} = \lambda(\omega_{it-1}, \omega_{it-2}) + \xi_{it} \quad (25)$$

Akerberg et al. (2007) show that if ω_{it} follows a second-order Markov process the optimum investment choice is a function of both ω_{it} and $\omega_{i,t-1}$, that is,

$$i_{it} = f_1(k_{it}, \omega_{it}, \omega_{it-1})$$

The problem with this modification of the investment function is that the control function for ω_{it} can no longer be constructed in the same way as in the benchmark OP because ω_{it} and $\omega_{i,t-1}$ cannot be both identified with capital and investment alone.¹⁰ There must be at least one variable in addition to investments that firms optimally choose at t for the identification of ω_{it} and $\omega_{i,t-1}$ to become possible. Suppose there is such a variable, denoted b_{it} . Then, by analogy with investment, it can be expressed as $b_{it} = f_2(k_{it}, \omega_{it}, \omega_{it-1})$, or more compactly,

$$\begin{pmatrix} i_{it} \\ b_{it} \end{pmatrix} = G(k_{it}, \omega_{it}, \omega_{it-1}),$$

where G is a function mapping each observation $(k_{it}, \omega_{it}, \omega_{it-1})$ into a unique pair i_{it} and b_{it} . Assuming that G is a bijection of $(\omega_{it}, \omega_{it-1})$ into (i_{it}, b_{it}) , it can be inverted to obtain

$$\begin{pmatrix} \omega_{it} \\ \omega_{it-1} \end{pmatrix} = G^{-1}(k_{it}, i_{it}, b_{it})$$

The first stage of the modified OP estimator proceeds as usual, with the function $G^{-1}(\cdot)$, approximated as a third-degree polynomial in k_{it} , i_{it} , and b_{it} , used to control for the productivity shocks observed to the firm. Consistent estimates of β_l and β_m , as well as fitted

¹⁰Indeed, the control functions for ω_{it} and $\omega_{i,t-1}$ in terms of capital and investments will be collinear with each other.

values

$$\widehat{F}_{it} = \widehat{\omega}_{it} + \beta_k k_{it}$$

are obtained at this stage the usual way. Substituting the expression for ω_{it} from (25), the coefficient on capital is estimated in the second stage from the regression

$$\widehat{F}_{it} = \beta_k k_{it} + \lambda \left(\widehat{F}_{t-1} - \beta_k k_{i,t-1}, \widehat{F}_{t-2} - \beta_k k_{i,t-2} \right) + \xi_{it},$$

where the function $\lambda(\cdot, \cdot)$ is approximated by a third-degree polynomial in its two arguments.

The bijection assumption required to proxy the residual ω_{it} is strong, implying, for example, that if a pair of shocks $(\omega_{it}, \omega_{it-1}) = (4, 5)$ generates a pair of investments $(i_{it}, b_{it}) = (2, 1)$, the pair $(\omega_{it}, \omega_{it-1}) = (5, 4)$ will not have generated $(i_{it}, b_{it}) = (2, 1)$.¹¹ At present, there is neither a theoretical nor intuitive motivation for this assumption. Therefore, while the possibility to extend the OP estimator to the case of a second-order Markov in ω_{it} exist, one should be cautious in choosing this extension.

The WOP estimator

Akerberg, Caves and Frazer (2006) argued that a potential weakness of the OP estimator is identifiability of labor and materials elasticities in the first stage. If labor and materials, like investment, are chosen depending on capital and TFP shock at t , these inputs will be collinear with the control function and β_l and β_m will not be identifiable. Wooldridge (2009) proposed a GMM framework that enables the OP procedure to complete in one stage by specifying the moment conditions for all factor inputs at once. With ω_{it} following a first-order Markov process, and hence expressible as

$$\omega_{it} = \lambda(\omega_{it-1}) + \xi_{it} = \lambda(k_{it-1}, i_{it-1}) + \xi_{it},$$

¹¹We are grateful to an anonymous referee for bringing up this point.

the original production function regression can be rewritten as

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \lambda(k_{it-1}, i_{it-1}) + \xi_{it} + e_{it}$$

and estimated using GMM with the moment conditions

$$\mathbb{E}[\xi_{it} + e_{it} | l_{it-1}, m_{it-1}, k_{it}, k_{it-1}, i_{it-1}] = 0$$

As with the OP estimator, the unknown function $\lambda(\cdot)$ is approximated with a third degree polynomial in k_{it-1} and i_{it-1} .

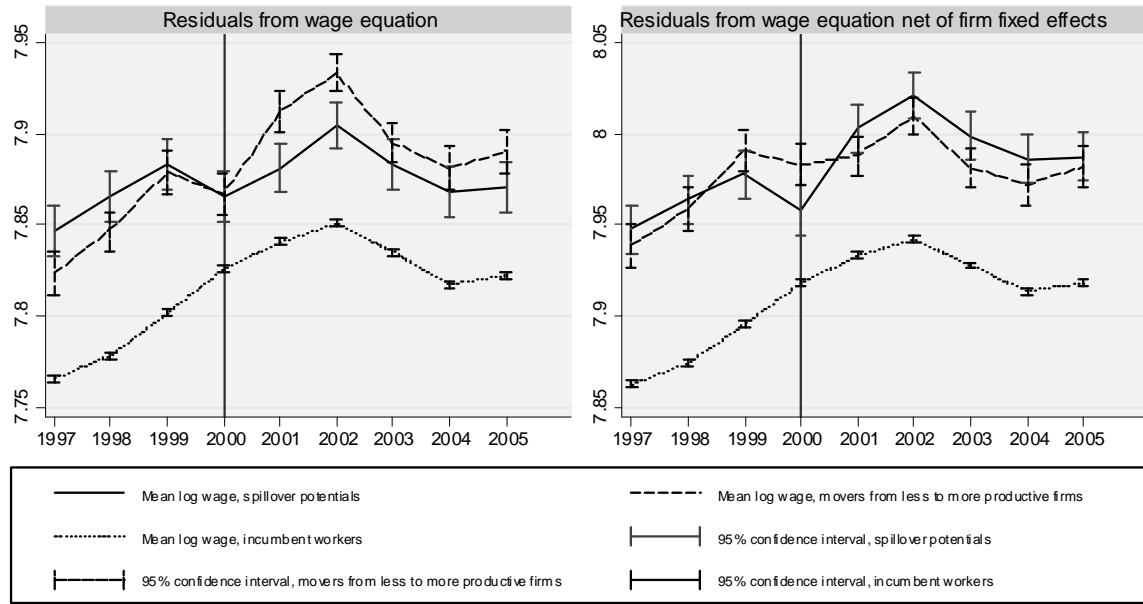
By analogy with the OP estimator, rewriting the production function equation with ω_{it} following a second-order Markov process is straightforward:

$$\begin{aligned} y_{it} = & \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} \\ & + \lambda(k_{it-1}, i_{it-1}, b_{it-1}, k_{it-2}, i_{it-2}, b_{it-2}) + \xi_{it} + e_{it} \end{aligned} \quad (26)$$

With function λ approximated with a third-degree polynomial its arguments, equation (26) is estimated with nonlinear GMM with the following moment conditions:

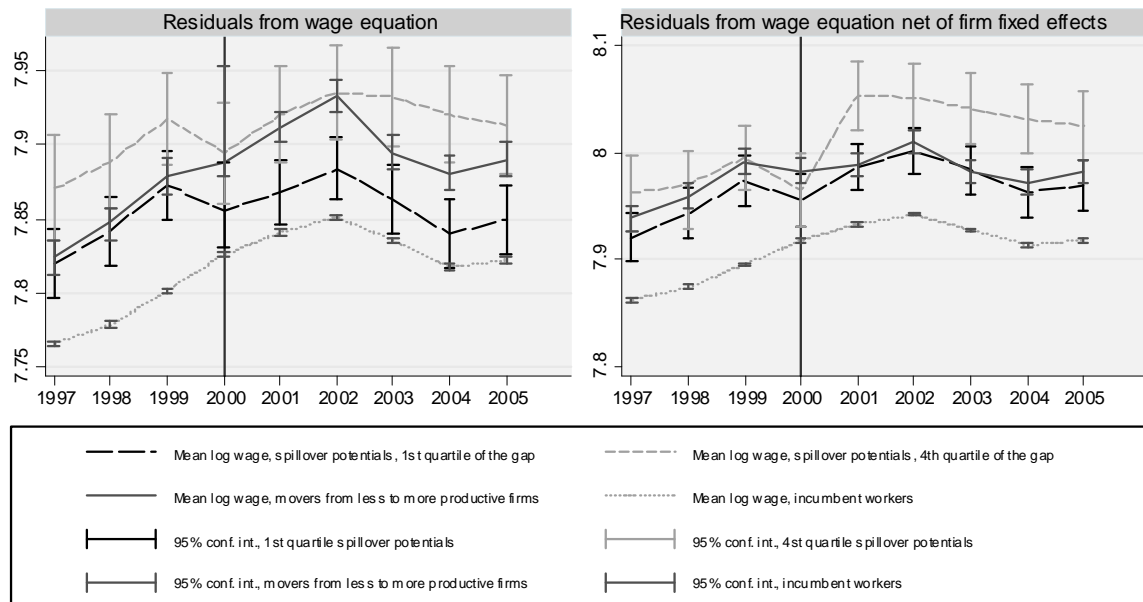
$$\mathbb{E}[\xi_{it} + e_{it} | l_{it-1}, m_{it-1}, k_{it}, k_{it-1}, i_{it-1}, b_{it-1}, k_{it-2}, i_{it-2}, b_{it-2}] = 0.$$

Figure 1. Wage profile of spillover potentials relative to other workers



Note: On this figure all job changes are as of 2000.

Figure 2. Wage profile of spillover potentials for the first and fourth quartiles of the gap



Note: On this figure all job changes are as of 2000.

Table 1. Mean values for selected firms' and workers' characteristics

	Workers		Firms		
	All workers	Spillover potentials	All firms	Firms that hire spillover potentials	Representative firm
Log wage	12.532	12.434	12.065	12.149	12.331
Log human capital	12.603	12.549	12.446	12.473	12.525
High school (share)	0.343	0.315	0.388	0.397	0.382
College (share)	0.601	0.631	0.575	0.566	0.559
University (share)	0.056	0.055	0.037	0.037	0.059
Low skilled (share)	0.151	0.122	0.372	0.252	0.182
Mid skilled (share)	0.61	0.649	0.503	0.594	0.599
High skilled (share)	0.132	0.125	0.064	0.082	0.122
Managers (share)	0.107	0.105	0.061	0.071	0.096
Age	41.34	37.03	39.87	38.15	39.63
Log Experience	9.655	9.391	9.264	9.257	9.43
Male (share)	0.703	0.764	0.699	0.721	0.695
Separation rate	0.167	0.194	0.132	0.159	0.165
Hiring rate	0.092	0.198	0.082	0.153	0.09
Log employment	5.343	4.374	2.305	3.311	5.307
Log output	12.428	11.298	9.075	10.114	12.359
Log capital stock	10.809	9.728	7.371	8.463	10.742
Log material input	11.499	10.402	8.074	9.155	11.437
Number of obs.	2,071,148	46,391	87,589	30,660	87,589

Notes: Summary statistics is calculated for the time period 1995-2007. Representative firm is defined as the average manufacturing industry output weighted by firms' share in total output.

Table 2. Summary statistics for productivity gap and share of spillover potentials

	FIRMS								
	OLS			OP			WOP		
	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.
Gap	0.3007	0.2531	0.3102	0.4323	0.2853	0.3891	0.4978	0.3064	0.4719
Share of spillover potentials	0.0280	0.0213	0.0607	0.0285	0.0182	0.0600	0.0283	0.0179	0.0582
Gap times share	0.0077	0.0062	0.0193	0.0122	0.0072	0.0304	0.0167	0.0082	0.0383
	WORKERS								
	OLS			OP			WOP		
	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.
Gap	0.2257		0.2357	0.2970		0.2559	0.3100		0.3340
Share of spillover potentials	0.0261			0.0223			0.0224		
Gap times share	0.0059		0.0524	0.0066		0.0581	0.0072		0.0786

Notes: Summary statistics is calculated for the time period 1995-2007. Measures of TFP, gap and share of spillover potentials were constructed from the production function estimated by OLS in columns (1)-(3), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (4)-(6), and one-step GMM estimator by Wooldridge (2009) in columns (7)-(9). Weighted means are constructed as the average across firms weighed by their shares in total industry output.

Table 3. Estimation results for the production function (9)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OP	OP	OP	WOP	WOP	WOP
Labor (β_l)	0.420** (0.003)	0.420** (0.003)	0.423** (0.003)	0.417** (0.003)	0.417** (0.003)	0.417** (0.004)	0.394** (0.003)	0.396** (0.002)	0.399** (0.002)
Materials (β_m)	0.474** (0.003)	0.474** (0.003)	0.471** (0.003)	0.444** (0.003)	0.444** (0.006)	0.442** (0.004)	0.351** (0.003)	0.349** (0.004)	0.348** (0.003)
Capital (β_k)	0.053** (0.001)	0.053** (0.001)	0.054** (0.001)	0.020** (0.001)	0.020** (0.001)	0.021** (0.001)	0.032** (0.001)	0.032** (0.001)	0.031** (0.001)
Gap (θ)	0.229** (0.049)	0.276** (0.059)	0.250** (0.059)	0.220** (0.037)	0.172** (0.041)	0.122** (0.037)	0.230** (0.018)	0.167** (0.028)	0.125** (0.031)
Gap negative	0.088 (0.090)	0.112 (0.123)	0.149 (0.121)	-0.028 (0.062)	-0.086 (0.063)	-0.038 (0.054)	-0.036 (0.076)	-0.072 (0.074)	-0.044 (0.065)
Controls for firm characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Controls for new and incumbent worker characteristics	NO	NO	YES	NO	NO	YES	NO	NO	YES
R2	0.980	0.980	0.980	0.981	0.981	0.981	0.975	0.975	0.975
N	105,478	105,478	105,478	88,271	88,271	88,271	87,617	87,617	87,617
Gap/ β_l	0.545** (0.115)	0.657** (0.140)	0.591** (0.139)	0.527** (0.084)	0.487** (0.103)	0.336** (0.105)	0.584** (0.048)	0.422** (0.070)	0.314** (0.077)

Notes: The dependent variable is the log of firm's output. * significant at 5%, ** significant at 1%. Standard errors in parentheses are obtained by bootstrap. The estimation method for production function is OLS in columns (1)-(3), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (4)-(6), and one-step GMM estimator by Wooldridge (2009) in columns (7)-(9). The time period covered is 1995-2007. All specifications include Abowd, Kramarz and Margolis (1999) measure of human capital calculated separately for the workers hired from more and less productive firms, as well as for the incumbent workers, industry-year fixed effects, and estimated productivity shocks in periods (t-1) to (t-2) as additional controls. Firm characteristics include separation rates and shares of new workers from less and more productive firms in total employment. Worker observable characteristics include gender, age, experience, education, and occupation.

Table 4. Estimation results for the individual wage equation (13)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OP	OP	WOP	WOP
Gap (γ)	0.058** (0.009)	0.033** (0.007)	0.047** (0.007)	0.027** (0.008)	0.049** (0.010)	0.035** (0.005)
Gap negative (γ^-)	0.021 (0.013)	0.010 (0.007)	0.006 (0.011)	0.009 (0.011)	0.007 (0.009)	0.006 (0.010)
Wage premium relative to labor productivity advantage						
	0.079	0.050	0.119	0.096	0.107	0.103
Controls for new and incumbent worker characteristics	NO	YES	NO	YES	NO	YES
R2	0.281	0.518	0.282	0.515	0.282	0.515
N	2,823,582	2,373,172	2,399,464	2,073,325	2,399,355	2,073,249

Notes: The dependent variable is the log of worker's wage. * significant at 5%, ** significant at 1%. The TFP is estimated by OLS in columns (1)-(2), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (3)-(4), and one-step GMM estimator by Wooldridge (2009) in columns (5)-(6). Standard errors in parentheses are clustered by firm. The time period covered is 1995-2007. All specifications include firm-year fixed effects, dummy variables for job changers coming from more and less productive firms, Abowd, Kramarz and Margolis (1999) measure of human capital calculated separately for the workers hired from more and less productive firms, as well as for the incumbent workers, and dummy variables for the number of job transitions during the sample period. Worker observable characteristics include gender, age, experience, education, and occupation.

Table 5. Estimation results for the firm-average wage equation (13)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OP	OP	OP	WOP	WOP	WOP
Gap positive (Γ^+)	0.164** (0.082)	0.103* (0.055)	0.112* (0.058)	0.241** (0.066)	0.201** (0.067)	0.138* (0.066)	0.274** (0.064)	0.181** (0.058)	0.124* (0.054)
Gap negative (Γ^-)	0.114 (0.074)	0.074 (0.068)	0.065 (0.064)	0.065 (0.049)	0.062 (0.047)	0.054 (0.043)	0.069 (0.064)	0.074 (0.062)	0.042 (0.040)
Controls for firm characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Controls for new and incumbent worker characteristics	NO	NO	YES	NO	NO	YES	NO	NO	YES
R2	0.051	0.087	0.101	0.066	0.086	0.101	0.081	0.089	0.103
N	105,478	105,478	105,478	88,271	88,271	88,271	87,617	87,617	87,617
Average effect on wage of incumbent workers	0.0010	0.0006	0.0007	0.0016	0.0013	0.0009	0.0020	0.0013	0.0009
Average effect on wage of spillover potentials	0.0141	0.0137	0.0081	0.0155	0.0153	0.0089	0.0172	0.0165	0.0117
Effect on average wage	0.0013	0.0009	0.0009	0.0019	0.0016	0.0011	0.0023	0.0016	0.0011

Notes: The dependent variable is the firm-year average of log wage. * significant at 5%, ** significant at 1%. The TFP is estimated by OLS in columns (1)-(3), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (4)-(6), and one-step GMM estimator by Wooldridge (2009) in columns (7)-(9). Standard errors in parentheses are clustered by firms. Time period covered is 1995-2007. All specifications include Abowd, Kramarz and Margolis (1999) measure of human capital calculated separately for the workers hired from more and less productive firms, as well as for the incumbent workers, firm fixed effects, industry-year fixed effects, estimated productivity shocks in periods (t-1) to (t-2), dummy variables for job changers coming from more and less productive firms, and dummy variables for the number of job transitions during the sample period. Firms' characteristics include separation rate, shares of new workers from less and more productive firms in total employment, log of labor and capital in the hiring firm. Workers' observable characteristics include gender, age, experience, education, and occupation.

Table 6. Distribution of gains from spillovers between workers and firms

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OP	WOP	OLS	OP	WOP
Output gain	0.155%	0.088%	0.103%	0.155%	0.088%	0.103%
Share of output gain retained by the firm	88.21%	73.15%	76.14%	78.91%	51.96%	57.31%
Share of output gain going to SP	2.28%	3.73%	4.44%	4.08%	6.67%	7.94%
Share of output gain going to non-SP	9.51%	23.12%	19.42%	17.01%	41.37%	34.75%

Notes: The productivity gap is estimated by OLS in columns (1) and (4), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (2) and (5), and one-step GMM estimator by Wooldridge (2009) in columns (3) and (6). The share of gain going to SP is calculated as the ratio of additional costs to the representative firm associated with hiring SP instead of a NSP relative to output gain. The share of gain going to NSP is calculated as the ratio of an increase in wage of NSP for the representative firm associated with hiring SP relative to output gain. The rest of the output gain from hiring spillover potentials is assigned to the firm. In Columns (1)-(3) the share of labor in total costs is assigned to 0.223, which is the sample average share of salaries in total output. In Columns (4)-(6) the share of labor in total costs is assigned to 0.333, which is the elasticity output with respect to labor in the most complete WOP specification.

Table 7. Estimation results for firm's profit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OP	OP	OP	WOP	WOP	WOP
Gap positive (Π^+)	2.118**	1.741**	1.604**	1.374**	0.942**	0.845**	1.326**	0.980**	0.917**
	(0.663)	(0.447)	(0.453)	(0.457)	(0.304)	(0.284)	(0.422)	(0.338)	(0.336)
Gap negative (Π^-)	0.425	0.384	0.423	0.384	0.287	0.274	0.374	0.324	0.297
	(1.112)	(0.504)	(0.511)	(0.645)	(0.562)	(0.553)	(0.485)	(0.542)	(0.454)
Controls for firm characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Controls for new and incumbent worker characteristics	NO	NO	YES	NO	NO	YES	NO	NO	YES
R2	0.145	0.537	0.542	0.351	0.553	0.558	0.475	0.561	0.567
N	87,433	87,433	87,433	74,013	74,013	74,013	73,995	73,995	73,995
(a) effect on average profit	0.0203	0.0167	0.0154	0.0190	0.0130	0.0117	0.0154	0.0114	0.0106
(b) share of profit in TFP gain	0.8736	0.5958	0.6060	0.7328	0.6426	0.8127	0.4975	0.5064	0.6330
(c) share of SP in TFP gain	0.0430	0.0363	0.0228	0.0360	0.0460	0.0373	0.0338	0.0465	0.0444
(d) share of non-SP in TFP gain	0.1520	0.0792	0.0951	0.2239	0.2389	0.2312	0.2333	0.2122	0.1942
(e) the sum of three shares	1.0686	0.7113	0.7239	0.9927	0.9275	1.0812	0.7645	0.7651	0.8717

Notes: The dependent variable is the firm-year average of log wage in year (t+1). * significant at 5%, ** significant at 1%. The TFP is estimated by OLS in columns (1)-(3), two-step semi-parametric estimator by Olley and Pakes (1996) in columns (4)-(6), and one-step GMM estimator by Wooldridge (2009) in columns (7)-(9). Standard errors in parentheses are clustered by firms. Time period covered is 1995-2007. All specifications include Abowd, Kramarz and Margolis (1999) measure of human capital calculated separately for the workers hired from more and less productive firms, as well as for the incumbent workers, firm fixed effects, industry-year fixed effects, estimated productivity shocks in periods (t) and (t-1), dummy variables for job changers coming from more and less productive firms in period t, and dummy variables for the number of job transitions during the sample period. Firms' characteristics include separation rate, shares of new workers from less and more productive firms in total employment, log of labor and capital in the hiring firm. Workers' observable characteristics include gender, age, experience, education, and occupation.

Table 8. Output and wage gains from spillovers through worker mobility within and between industry groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Individual wage equation			Prod. function equation			Firm wage equation		
	OLS	OP	WOP	OLS	OP	WOP	OLS	OP	WOP
Gap, same industry	0.025** (0.009)	0.038** (0.012)	0.037** (0.010)	0.470** (0.101)	0.315** (0.098)	0.319** (0.108)	0.141* (0.063)	0.166* (0.072)	0.157** (0.064)
Gap, diff. industry	0.035** (0.009)	0.042** (0.010)	0.040** (0.011)	0.104 (0.070)	0.135 (0.064)	0.096 (0.065)	0.076 (0.066)	0.100 (0.058)	0.097 (0.054)
Gap negative, same industry	0.001 (0.010)	-0.006 (0.014)	-0.007 (0.011)	0.218* (0.106)	0.040 (0.059)	0.094 (0.114)	0.075 (0.065)	0.068 (0.063)	0.061 (0.065)
Gap negative, diff. industry	-0.012 (0.008)	-0.015 (0.011)	-0.009 (0.009)	-0.098 (0.090)	-0.082 (0.078)	-0.068 (0.087)	0.026 (0.094)	-0.014 (0.066)	-0.008 (0.071)
R2	0.521	0.514	0.515	0.980	0.981	0.975	0.103	0.103	0.105
N	2,377,525	2,073,325	2,073,249	105,437	88,271	87,617	105,437	88,271	87,617

Notes: The dependent variable is the log of individual worker's wage in columns (1)-(3), firm output in columns (4)-(6), and the firm-year fixed effect estimated from individual wage equation (12) in columns (7)-(9). TFP and productivity gaps were constructed from the Cobb-Douglas production function estimated by one-step GMM estimator by Wooldridge (2009). * significant at 5%, ** significant at 1%. Time period covered is 1995-2007. Specifications (1)-(3) include firm-year fixed effects, dummy variables for job changers coming from more and less productive firms, human capital measure calculated separately for the workers hired from more and less productive firms, as well as for the incumbent workers, dummy variables for the number of job transitions during the sample period, gender, age, experience, education, and occupation. Specifications (4)-(9) include industry-year fixed effects, estimated TFP shocks in years (t-1) to (t-2), separation rates and shares of new workers from less and more productive firms in total employment, and firm-year average of employees characteristics such as gender, age, experience, education, occupation, human capital measures of the workers hired from more and less productive firms and of the incumbent workers. Specifications (7)-(9) also include firm fixed effects.

Table 9. Output and wage gains by worker skill level

	(1)	(2)	(3)	(4)
Spillover potentials by skill group:	Low skill	Mid skill	High skill	Manager
θ	0.108 (0.094)	0.129 (0.074)	0.159 (0.061)	0.615 (0.184)
γ^+	0.020 (0.017)	0.034 (0.012)	0.036 (0.014)	0.058 (0.019)
Γ^+	0.081 (0.051)	0.124 (0.064)	0.225 (0.077)	0.426 (0.106)
Output gain (%)	0.011	0.048	0.016	0.055
LPA (%)	7.072	14.132	13.314	48.787
Average gain per worker, overall (%)	0.009	0.071	0.023	0.036
Average wage gain per worker, SPs (%)	0.671	1.103	1.100	1.813
Average wage gain per worker, non-SPs (%)	0.007	0.056	0.020	0.032
Share of gain retained by the firm (%)	81.2	66.8	67.4	85.5
Share of gain retained by spillover potentials (%)	3.7	7.1	4.2	1.6
Share of gain retained by other workers (%)	15.1	26.1	28.4	12.9
Share in labor force (%)	0.28	1.37	0.27	0.23

Notes: TFP measure used to define spillover potentials was constructed from the Cobb-Douglas production function estimated with WOP. Standard errors are in parentheses.

Table 10. Productivity and wage gains from worker mobility in the years after hiring.

	(1)	(2)	(3)	(4)	(5)
	Year 1	Year 2	Year 3	Year 4	Year 5
θ	0.173 (0.054)	0.184 (0.061)	0.206 (0.064)	0.190 (0.084)	0.122 (0.089)
γ^+	0.034 (0.007)	0.036 (0.009)	0.038 (0.012)	0.032 (0.014)	0.023 (0.015)
Γ^+	0.145 (0.064)	0.187 (0.068)	0.174 (0.070)	0.160 (0.071)	0.094 (0.874)
Output gain (%)	0.185	0.197	0.220	0.203	0.131
LPA (%)	26.066	27.724	31.039	28.628	18.382
Average gain per worker, overall (%)	0.124	0.154	0.146	0.133	0.081
Average wage gain per worker, SPs (%)	1.154	1.245	1.289	1.102	0.778
Average wage gain per worker, non-SPs (%)	0.100	0.129	0.120	0.110	0.065
Share of gain retained by the firm (%)	85.1	82.6	85.2	85.5	86.2
Share of gain retained by spillover potentials (%)	2.8	2.8	2.6	2.4	2.7
Share of gain retained by other workers (%)	12.1	14.6	12.1	12.1	11.1

Notes: TFP measure used to define spillover potentials was constructed from the Cobb-Douglas production function estimated with WOP. Standard errors are in parentheses.