Productivity Gains from Worker Mobility and their Distribution between Workers and Firms

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Abstract

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JEL: D24; J31; J60

Keywords: productivity spillovers, worker mobility, wages, matched employer-employee data.

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1 Introduction

The importance of knowledge spillovers across firms as a factor affecting economic performance motivates a literature on the mechanisms facilitating these spillovers. One such mechanism operates through worker mobility between firms, whereby newly hired workers carry knowledge produced in their previous firms to their new firms. Our study develops a unified empirical framework to estimate the outcomes of this mechanism for firm productivity and worker compensation. We use matched employer-employee data from the universe of Danish manufacturing firms and workers to construct a measure of firms' exposure to spillovers through worker mobility. Starting with estimating the productivity gains from spillovers to the hiring firms, we then proceed to the corresponding wage gains enjoyed by the workers in those firms. Taking these two gains together, we estimate the total output gain for the economy and its distribution between the hiring firms, the workers who bring spillovers, and the rest of the workers.

Recent research on innovation has demonstrated that worker mobility plays an important role in research and development (R&D) spillovers and technology transfers, by finding a link between the movements of workers involved in R&D 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). A related theoretical literature on spillovers from foreign direct investment (FDI), including Fosfuri et al. (2001), Markussen (2001) and Glass and Saggi (2002), has argued that workers moving from more productive foreign firms to less productive domestic firms may facilitate productivity spillovers thanks to the access to superior technologies and business practices of their previous employers. This argument has been supported with direct empirical evidence in Gorg and Strobl (2005), Poole (2012) and Balsvik (2011), all of which studies have found significant productivity and wage differences between the firms depending on the shares of workers with a foreign-firm experience that they employed. Stoyanov and Zubanov (2012) have extended this empirical literature by linking worker mobility to productivity spillovers in all firms regardless of their domicile. They found, in particular, that lagging firms can improve their performance by hiring workers from more productive firms. Our results reinforce this finding by the application of a richer and more rigorous analytical framework.

The progress in identifying productivity gains to firms traceable to worker mobility notwithstanding, the possible wage gains to the workers who bring spillovers are studied less well. While the very term "spillovers" implies that hiring firms gain from worker mobility more than it costs to them, whether these gains are a pure externality or the outcome of a functioning market for knowledge is an important empirical question. If firms are aware of productivity gains from hiring certain workers, they will compete with each other in attracting these workers by offering part of the ensuing productivity gains as a wage premium to them. In fact, a perfectly competitive labor market with complete information would allocate all the gains to the workers. At the other extreme, the absence of a wage premium to moving workers with spillover potential will mean the absence of a market for their knowledge, implying that spillovers through worker mobility are indeed a pure externality. Competition among firms on the one hand, and various market imperfections on the other, will settle the wage premium to gains ratio somewhere between these two extremes, revealing the extent to which firms consider this knowledge in their hiring and R&D decisions.

The relatively thin literature on the consequences of spillovers through worker mobility for wages, including Pesola (2011), Balsvik (2011) and Poole (2012), has documented wage gains to workers moving from foreign to domestic firms. Of these studies, our method is closest to Balsvik's (2011) who has developed a unified analytical framework for estimating productivity and wage spillovers through worker mobility. Estimating the gains from spillovers to firms and workers jointly is important: doing so allows a comparison of the magnitudes of these gains, providing a direct answer to the question of our interest. Thus, Balsvik (2011) found that while new workers with foreign-firm experience are 20% more productive than similar workers without such experience, they receive a wage premium of only 1-3%. This finding implies that productivity gains from worker mobility are appropriated mostly by firms and are, therefore, largely an extrenality. Our results are consistent with hers.[1]

To outline our empirical method, we identify as workers who bring spillovers those coming from firms more productive than their receiving firm (we call such workers *spillover potentials*). Intuitively, assuming that differences in knowledge possessed by firms are reflected in productivity differences, workers hired from more productive firms will bring superior knowledge that will improve the performance of their new firms. By the same logic, and controlling for their personal characteristics, hiring workers from less productive firms should be neutral to performance. Our empirical results support both these intuitions. Our measure of firms' exposure to spillovers through worker mobility, which we call *productivity gap*, is the difference in the logarithms of total factor productivities (TFP) of the sending and receiving firms averaged across spillover potentials in each firm and year, times their share in the firm's workforce. To make this measure operational, we first recover TFP from a Cobb-Douglas production function estimated on our data, and then re-estimate the production function with the gap included, whereby we obtain the coefficient on the gap that measures the productivity gains to firms hiring spillover potentials. We calculate the corresponding wage premium to spillover potentials, as well as eventual wage gains to other workers, from the coefficients on the gap in the individual and firm-average wage equations, using a simple wage decomposition.

We find that firms gain in TFP after hiring spillover potentials. These gains, proportionate to the productivity gap, last several years after the hiring and, given the magnitude of the gap, are larger when spillover potentials come from the same industry group and increase with their skill group. We calculate that the TFP gains traceable to spillovers through worker mobility for the Danish manufacturing sector as a whole are 0.13% per year, or about a tenth of its annual TFP growth averaged over the sample period (1995-2007). Compared to other wise similar workers, spillover potentials receive a wage premium proportional to their individual productivity gap. This premium is 1.07% for an average spillover potential, which, given their small share in the total workforce (about 2%), amounts to just 0.023% of the total wage bill in the sector per year.

Spillover potentials are not the only workers who gain in wages. In fact, we find that the total sectoral wage bill increase linked to spillover potentials is 0.09% per year, implying that other workers gain 0.07% per year from the presence of spillover potentials in their firms.[2] Putting together the TFP and wage gains, we calculate the total contribution of worker mobility to the Danish manufacturing sector's output at 0.16% per year. Of this total output gain, 80% is retained by firms hiring spillover potentials, 15% goes to other workers, and only 5% accrues to spillover potentials themselves. Our finding that firms appropriate most of the gains from worker mobility suggests that knowledge transferred by spillover potentials is largely a positive externality enjoyed by firms without paying for it in full. Yet, this externality does not seem to go entirely unnoticed by firms, as spillover potentials receive higher wage premium than do other workers (1.07% vs. 0.07%).

Our study extends the literature on spillovers through worker mobility, which has so far concentrated on R&D workers or workers going from foreign to domestic firms, to the case of workers moving between any two firms. Our results for the productivity gains to firms and wage gains to spillover potentials, obtained for this more general case and applicable to the entire Danish manufacturing sector, are consistent with this literature. We therefore argue that the source of spillovers through mobility – private knowledge developed in the worker sending firms – is not confined to the relatively few pioneering firms, but is in fact to be found, in various quantities, in all firms. Similarly, the lack of an efficient market for the knowledge carried by spillover potentials seems to be a universal phenomenon. Yet, our finding that workers other than spillover potentials also benefit from spillovers, albeit very little, suggests that the productivity and *total* wage gains from spillovers are not so vastly different as one may think by looking at the wages of spillover potentials alone.

Our method, which has enabled us to produce some of the findings hitherto unreported, is another contribution to the literature. The method has three useful features. *First*, our measure of exposure to spillovers is applicable to any firm, regardless of its R&D intensity or domicile, allowing replication of our findings on large employer-employee data from industries or countries, which have now become increasingly available. *Second*, the analytical framework we employ in this study permits estimating productivity and wage gains from spillovers through worker mobility simultaneously, based on the same measure of exposure to spillovers. The high degree of unification achieved in our framework allows us to compare the gains from spillovers to firms not only with the wage gains to spillover potentials alone, but also with the wage gains to other workers. *Third*, extensions of our method, which we present in this paper, enable researchers to estimate gains from spillovers within the same and different industries, by spillover potentials' skill group, and over time. These extensions are useful as they help produce a richer empirical picture of spillovers through worker mobility.

The rest of the paper is organized as follows. Section 2 deals with the productivity gains to firms that hire spillover potentials, presenting the analytical framework for their estimation (Section 2.1), the data (Section 2.2) and the regression results (Section 2.3). In Section 3, we extend our analysis to the workers and calculate the total gains from worker mobility and their distribution between the firms, the spillover potentials and the rest of the workers. Section 4 presents three extensions of our main analysis: productivity and wage gains from worker mobility within and between industries (Section 4.1), the same by moving workers' skill level (Section 4.2), and the evolution of these gains in time (Section 4.3). Section 5 concludes with a summary of our findings.

2 Productivity gains from worker mobility to firms

In this section, we estimate the productivity gains to firms from hiring spillover potentials as compared to hiring none. Our starting point is the method featured in Balsvik (2011) which she applied to calculating the productivity advantage to domestic firms from hiring workers with recent experience at foreign-owned firms. Applying her method to a Cobb-Douglas production function with shares of workers with different types of past experience, she found that a 10% increase in the share of workers with foreign-firm experience was linked to about 1% increase in output by the domestic firms employing them – the result suggesting the presence of productivity spillovers from foreign to domestic firms through worker mobility. We extend and refine this method by allowing the productivity gains from hiring spillover potentials to vary depending on the technological distance between their previous and new firms, regardless of their domicile, and on the degree of knowledge transferability between the two firms.

2.1 Estimation issues

To estimate the productivity gains to firms, we begin by modeling firm i's output in year t, Y_{it}, as a Cobb-Douglas production function,

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m}, \tag{1}$$

where L denotes labor input, K and M are capital and materials inputs, A is the total factor productivity (TFP), and β_k, β_l and β_m are input elasticities. Labor input is heterogeneous as there are workers with and without spillover potential whose productivity may therefore differ. Hence, we specify L_{it} in efficiency units as follows:

$$\begin{aligned} L_{it} &= L_{it}^R + \delta_{it} \cdot L_{it}^S \\ &= (L_{it}^R + L_{it}^S)(1 - s_{it} + s_{it} \cdot \delta_{it}) \\ &= (L_{it}^R + L_{it}^S)(1 + s_{it} \cdot (\delta_{it} - 1)), \end{aligned} \tag{2}$$

where L^S is the labor input by spillover potentials in nominal units, s is their share in total workforce, L^R is the labor input by the rest of the workers employed in year t, also in nominal units, and $\delta_{it} \geq 1$ is the function that measures labor productivity advantage of spillover potentials (LPA) over the rest of the workers, which we specify later in this section.[3] From equation (2), the overall labor productivity gain due to the presence of spillover potentials (OLPG) and the resulting total factor productivity gain to the receiving firm (TFPG) are:

$$
\begin{aligned}
OLPG_{it} &= 1 + s_{it} \cdot (\delta_{it} - 1) \\
TFPG_{it} &= [1 + s_{it} \cdot (\delta_{it} - 1)]^{\beta_l}
\end{aligned}
\tag{3}
$$

Before specifying δ_{it}, spillover potentials have to be identified. The total workforce in the firm comprises the workers on the payroll as of the end of year t (November in our data) who fall into one of three groups: i) those who were hired earlier than in year $t-1$, ii) those hired in year t, and iii) those hired in year $t-1$. In identifying spillover potentials, we focus on the latter group. One reason for picking this group, rather than the new hires in year t, is lack of information in our data on the exact date in the year when the worker joined the firm. More importantly, the workers hired in t are unlikely to have spent enough time in their new firms to affect their productivity by means of the knowledge from their previous firms, since communicating and implementing this knowledge is likely to take longer than the average tenure of such workers in t (six months, assuming constant intensity of hiring throughout the year). In fact, as we show in our earlier work (Stoyanov and Zubanov, 2012), no productivity gains traceable to spillover potentials were detected in their new firms in the year of their hiring. We explore the spillover potential of the workers hired earlier than in year $t-1$, who might still reveal some knowledge from their previous firms, in an extension of our baseline empirical model in Section 4.3.

While there is no formal model of knowledge spillovers through worker mobility on which to base our measure of spillover potentials' LPA, δ_{it}, the digest of the existing empirical literature presented in the introduction suggests two important characterizations for such measure. *First*, to the extent that it is the knowledge from their previous firms that makes spillover potentials relatively more productive, their LPA must be proportionate to the technological distance between their sending and receiving firms. Hence, assuming that better technology translates into higher productivity, we define spillover potentials as the workers hired in year $t-1$ *and* coming from more productive sending firms. *Second*, given the technological distance between the sending and receiving firms, spillover potentials' LPA 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. The following specification for δ_{it} combines both these characterizations:

$$\delta_{it} = \left(\prod_{j=1}^{N_{it}^S} \frac{A_{j,i,t-2}^S}{A_{i,t-2}} \right)^{\frac{\eta}{N_{it}^S}}, \tag{4}$$

where N_{it}^S is the number of spillover potentials 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 $0 \leq \eta < 1$ is a parameter measuring the degree of knowledge transferability. Year $t-2$ is chosen as the point in time to measure δ_{it} because this is the last full year during which spillover potentials were known to have been at their previous firms and to have had access to knowledge there. It is easy to see that, given our definition of spillover potentials, δ_{it} in (4) is guaranteed to be at or above 1, as postulated in equation (2), since $A_{j,i,t-2}^S/A_{i,t-2} \geq 1$, and that it increases with the productivity difference between sending and receiving firms and with the knowledge transferability parameter η.

Putting the expression for labor input in efficiency units (equation (2)) back into the production function (1) and taking logarithms, noting that $\ln(x+1) \approx x$ for x close to 0, gives

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_l (\delta_{it} - 1) s_{it}, \tag{5}$$

where y, a, k, l, m are the logarithms of output, TFP and the factor inputs. Further, putting the expression for δ_{it} from (4) into equation (5), we obtain

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_l \cdot \eta \cdot gap_{it} \cdot s_{it} \tag{6}$$

The term

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

which we call the *productivity gap*, reflects the technological distance between the sending and receiving firms averaged across the spillover potentials in firm i. Its coefficient in equation (6), $\beta_l \eta$, indicates the importance of both labor intensity of production technology and knowledge transferability between sending and receiving firms in shaping the magnitude of productivity gains to firms through worker mobility. Lastly, the gap's effect is moderated by the share of spillover potentials in the workforce, s_{it}, which affects the exposure of receiving firms to knowledge coming from spillover potentials: the more of them in the workforce, the higher the exposure and hence the larger the gain.[4]

We estimate equation (6) in two steps. At the *first* step, we estimate the production function equation:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it}, \tag{7}$$

which enables us to construct the productivity gap from the residual output u_{it} for every firm and year. The term u_{it} can be broken down to two mutually orthogonal components – the TFP term observed by the firm, $\tilde{a}_{it}$, and an unobserved random productivity shock e_{it}:

$$u_{it} = \tilde{a}_{it} + e_{it}$$

At the same time, from equation (6),

$$u_{it} = a_{it} + \beta_l \eta \frac{\sum_{j=1}^{N_{it}^S} \left(a_{j,t-2}^S - a_{i,t-2} \right)}{N_{it}^S} s_{it}$$

Thus, the effect of our main interest, $\beta_l \cdot \eta \cdot gap_{it} \cdot s_{it}$, is shared between $\tilde{a}_{it}$ and e_{it}: it is part of $\tilde{a}_{it}$ to the extent that firms observe spillovers in year t from workers hired in $t-1$.

It is important to distinguish between the residual output components $\tilde{a}_{it}$ and e_{it}, because $\tilde{a}_{it}$ being observable to the firm (but not to the econometrician) at the time when factor inputs are chosen may affect its decisions on their quantities, causing a bias in the input elasticities' ordinary least squares (OLS) estimates. To control for the possible simultaneity of productivity shocks and input factor choices, Olley and Pakes (1996), henceforth OP, devised a two-step estimation procedure. At the first step of it, labor and materials input elasticities are estimated from equation (7) where $\tilde{a}_{it}$ is approximated by a polynomial in capital and investments called a *control function* in the literature.[5] The assumptions that capital input is chosen in the previous year, upon observing the contemporaneous TFP, $\tilde{a}_{i,t-1}$, and that the process generating $\tilde{a}_{it}$ is first-order Markov, are used to derive moment conditions from which the capital input elasticity is computed at the second step.

Our implementation of the OP estimator differs from the original in that we allow for a second-order Markov process in TFP by specifying control functions for both $\tilde{a}_{i,t-1}$ and $\tilde{a}_{i,t-2}$. This extension is required because the residual output in period t depends implicitly on the TFP in period $t-2$ via the productivity gap. For the control functions for $\tilde{a}_{i,t-1}$ and $\tilde{a}_{i,t-2}$ to be separately identified, at least one more proxy variable for productivity is needed in addition to investments. Of the broad array of accounting data available to us, we construct four such proxies (all in logs): investment and divestment in buildings and land, and machinery and equipment. The reader is invited to consult the Appendix to this paper for further technical details.

One limitation of the OP estimator, pointed out in Ackerberg, Caves and Frazer (2006), is that the coefficients on labor and material inputs may not be identifiable because, if they are chosen at the same time with investments, these two inputs will be collinear with the control function. Therefore, our third, and preferred, estimation method for equation (7) relies on Wooldridge (2009) estimator, which strengthens parameter identification by bringing the moment conditions proposed by Levinsohn and Petrin (2003) together with the moment conditions on lagged materials and labor inputs in a unified general method of moments framework, producing what is known as the WLP estimator. We implement this estimator using the following moment conditions:

$$\mathrm{E}\left(e'_{it} \times \left[k_{it}\, k_{i,t-1}\, k_{i,t-2}\, l_{i,t-1}\, l_{i,t-2}\, m_{i,t-1}\, m_{i,t-2}\right]\right) = \mathbf{0}$$

Overidentification tests do not reveal any problems with this choice of moment conditions. Again, more details on our implementation of the WLP estimator is available in the Appendix.

Having estimated the factor input elasticities, we recover the residual output,

$$\hat{u}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}, \tag{8}$$

the share of spillover potentials in each firm and year, $\hat{s}_{it}$, which we derive from the condition $\hat{u}^S_{j,i,t-2} - \hat{u}_{i,t-2} > 0$ tested for each worker j hired by firm i in year $t-1$, and the gap:[6]

$$\widehat{gap}_{it} = \frac{\sum_{j=1}^{N^S_{i,t-1}} \hat{u}^S_{j,i,t-2} - \hat{u}_{i,t-2}}{N^S_{i,t-1}} \tag{9}$$

We will use the estimated $\hat{u}_{it}$, $\widehat{gap}_{it}$ and $\hat{s}_{it}$ at the next stage of the estimation procedure. Note that we measure the gap in terms of the residual output rather than its component $\tilde{a}_{it}$ alone. We do so to ensure that the gap as we measure it captures all potentially transferable knowledge that affects the firm's productivity, not only the part of it that the firm itself observes and reacts upon with its choice of inputs.

At the *second* step of our estimation procedure, we use the residual output, the share of spillover potentials, and the gap as defined above to estimate the coefficient $\beta_l \eta$ in equation (6). From this coefficient we will recover the knowledge transferability parameter η, the last element required for estimating spillover potentials' LPA as the function of the gap and the overall labor and total factor productivity gains linked to it (equations (3)). The first specification we employ to estimate $\beta_l\eta$ is the fully specified production function (6) with the gap, lags of residual output, estimated at the first step of the procedure, and additional controls included:

$$\begin{aligned} y_{it} = {} & a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \chi_1 controls_{it} \\ & + \theta_1 \widehat{gap}_{it} \hat{s}_{it} + \textstyle\sum_{p=1}^{2} \mu_{1p} \hat{u}_{i,t-p} + \phi_{kt} + \varepsilon_{1,it}, \end{aligned} \tag{10}$$

where ϕ_{kt} is the industry-year fixed effect, $\varepsilon_{1,it}$ is the random error term, and $\theta_1 = \beta_l\eta$. Two lags of residual output are included in order to capture autocorrelation in residual output, 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' residual output. Since equation (10) includes variables estimated at the first step, from equation (7), the standard errors of its coefficients are bootstrapped. The standard error of $\hat{\eta} = \hat{\theta}_1/\hat{\beta}_l$ is computed using delta method.

A potential problem with estimating the coefficient on the gap from equation (10) is that it may be underestimated to the extent that the gap is part of the TFP shock $\tilde{a}_{it}$ observed and acted upon by the firm. If this is the case, that part of the gap's effect will be captured by the control function in the OP and WLP estimators. An alternative, and arguably unbiased, estimate for the gap's coefficient is available from the direct regression of the estimated residual output on the gap and controls:

$$\begin{aligned}\hat{u}_{it} = & \chi_2 controls_{it} \\ & + \theta_2 \widehat{gap}_{it} \hat{s}_{it} + \textstyle\sum_{p=1}^{2} \mu_{2p} \hat{u}_{i,t-p} + \phi_{kt} + \varepsilon_{2,it}\end{aligned} \tag{11}$$

The estimates $\hat{\theta}_2$ and $\hat{\theta}_1$ will be equal if the effect of the gap sits entirely in the random shock component of the output, e_{it}, implying that the productivity advantage of spillover potentials does not influence the receiving firm's choice of factor inputs in the same year. Otherwise, $\hat{\theta}_1$ will be less than $\hat{\theta}_2$.

In estimating LPA it is important to distinguish its two sources: human capital and exposure to knowledge. The interest of this paper is to identify the LPA as the function of exposure to knowledge, holding human capital fixed. This task can be accomplished by means of two mutually supportive additions to our estimation framework. *First*, we control for the possibility that spillover potentials may differ in human capital endowment from other workers by including in our regressions the observed (age, gender, experience, education and occupation) as well as unobserved human capital characteristics calculated separately for each worker group. We infer the worker's unobserved human capital by estimating the firm- and individual-specific components in his or her wage using the method developed in Abowd, Kramarz and Margolis (1999). Their method uses worker movements between firms as the source of variance to identify individual- and firm-specific components of wages, by running the following wage equation:

$$w_{jit} = \lambda + z_{jt}\omega + \xi_j + \psi_i + v_{jit}, \tag{12}$$

where w_{jit} denotes logarithm of the 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. Having estimated (12), we calculate for every worker a measure of his or her human capital as the wage net of the firm-specific effect and the general constant term:

$$h_{jit} = w_{jit} - \lambda - \psi_i,$$

which we then aggregate up to the firm level, producing

$$\bar{h}_{it} = \frac{1}{N_{it}} \sum_{i=1}^{N_{it}} (w_{jit} - \lambda - \psi_i)$$

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 entering our measure of the gap. The measure of spillover potentials' human capital is constructed from their wages in year $t-2$, the last full year when they were employed in their previous firms.

As a *second* extension to our estimation framework, aimed at identifying the gap's effect controlling for human capital, we look at the gaps formed by workers coming from more as well as less productive firms, labelled *positive* and *negative* gaps, respectively. 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 by contributing to the receiving firm's human capital stock, just as hiring worse-quality ones will deteriorate it. On the other hand, if the gap's coefficient reflects spillovers, there will be a significant positive effect only of the positive gap, formed by the spillover potentials as we have defined them; the knowledge embedded in workers with a negative gap, coming from technologically inferior firms, will just be neutral to the receiving firm's productivity. Thus, the presence of the human capital component in the estimated gap's effect can be gauged by the extent to which the positive and negative gaps' coefficients are equal.

Summing up, the equations we estimate are equations (10) and (11) with the positive and negative gaps entering separately:

$$\begin{aligned} y_{it} = {} & a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \chi_1 controls_{it} \\ & + \theta_1^{+} \widehat{gap}_{it}^{+} \hat{s}_{it}^{+} + \theta_1^{-} \widehat{gap}_{it}^{-} \hat{s}_{it}^{-} + \textstyle\sum_{p=1}^{2} \mu_{1p} \hat{u}_{i,t-p} + \phi_{kt} + \varepsilon_{1,it}, \end{aligned} \tag{13}$$

and

$$\begin{aligned} \hat{u}_{it} = {} & \chi_2 controls_{it} \\ & + \theta_2^{+} \widehat{gap}_{it}^{+} \hat{s}_{it}^{+} + \theta_2^{-} \widehat{gap}_{it}^{-} \hat{s}_{it}^{-} + \textstyle\sum_{p=1}^{2} \mu_{2p} \hat{u}_{i,t-p} + \phi_{kt} + \varepsilon_{2,it}, \end{aligned} \tag{14}$$

where

$$\begin{aligned} \widehat{gap}_{it}^{+} &= \frac{\sum_{j=1}^{N_{i,t-1}^{S+}} \left(\hat{u}_{j,t-2}^{S} - \hat{u}_{i,t-2} \right)}{N_{i,t-1}^{S+}}, \\ \widehat{gap}_{it}^{-} &= \frac{\sum_{j=1}^{N_{i,t-1}^{S-}} \left(\hat{u}_{j,t-2}^{S} - \hat{u}_{i,t-2} \right)}{N_{i,t-1}^{S-}}, \end{aligned} \tag{15}$$

$N_{i,t-1}^{S+}$, $N_{i,t-1}^{S-}$ are the numbers of workers coming from more and less productive firms, respectively, hired by receiving firm i in year $t-1$, and

$\hat{s}^+, \hat{s}^-$ are their respective shares in the total workforce of that firm.

2.2 Data

Our empirical analysis requires information on workers' current and previous employers, necessitating the use of matched employer-employee data. Such data are available from Statistics Denmark. The first dataset we use is the Integrated Database for Labor Market Research (IDA), covering the total population of individuals aged 15-65 residing in Denmark during the period from 1980 to 2007. Detailed information are available on individual socio-economic characteristics: age, gender, employment status, annual salary and income from other courses, 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, labor costs, purchases of materials and energy inputs, as well as detailed data on investments which we use at the first step of our estimation procedure. 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. An average firm produces 9.3 million ($=e^{9.137} \times 1,000$) Danish Kroner (1.65 million US$) worth of goods per year, employing 10.5 workers and DKK

1.7 billion and 3.4 million worth of capital and materials. Many firms had had an exposure to productivity gains through hiring spillover potentials, since for the duration of the sample period hiring such workers took place in about a third (24.3 thousand) of observations. Firms hiring spillover potentials are different from the rest of the sample in that they have larger size (28.8 vs. 10.5 workers), produce more output per worker, employ more skilled workers (75% mid-skilled or above vs. 63%), and pay higher wages (192.5 vs. 178.6 thousand DKK per year). Our statistical analysis will control for these differences to determine the part played by spillover potentials in their superior performance.

Our sample, counting 1.8 million worker-year observations and 72.6 thousand firm-year observations, is about a third of the universe of manufacturing firms and workers. However, it covers 87% and 86% of the sector's output and employment, respectively, because it includes disproportionately more larger-than-average firms which tend to provide more complete data and to stay alive longer. Therefore, what happens on 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 aged 41.6, earning 280.4 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 210.2 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 spillover potentials in total observations is only about 2%.[7] Zooming in on those rare 2%, an average spillover potential is younger (37.4 vs. 41.6), less experienced and less well-paid (257 vs. 280.4 thousand DKK per year) than the rest of the workers. A further analysis will establish whether they are paid a wage premium by their receiving firms compared to otherwise similar workers.

2.3 Results

Before we discuss regression results for equations (13) and (14), reported in Tables 3 and 4 respectively, let us briefly review the estimates for input elasticities, $\widehat{\beta}_k, \widehat{\beta}_l, \widehat{\beta}_m$, and the residual output, $\hat{u}$, obtained at the first stage of our estimation procedure from equation (7). Because these estimates are nearly identical to the input elasticities obtained at the second stage from equation (13), we rely on Table 3 to assist their presentation. The input elasticities are within the range of magnitudes reported in the literature but differ between the three estimators. The labor and capital input elasticities decrease as we control for TFP shocks affecting factor inputs in columns (4)-(9), while the materials input elasticity tends to increase. The returns to scale, around 0.95 as estimated by OLS (columns 1-3), decrease to 0.87 in OP (columns 4-6). Adding extra moment conditions in WLP (columns 7-9) raises the returns to scale to 0.93 due to changes in the coefficients on labor and materials, which coefficients are likely to be unstable in the OP framework because of the problems with their identifiability mentioned in Section 2.1. Although not all differences in the OLS, OP and WLP estimates render themselves to simple explanations, the three estimators produce very similar measures of residual output with pairwise correlations of 0.94-0.98, depending on the pair. The similarity of the residual output measures implies that our measures of the positive and negative gaps do not vary much with the production function estimator.

[Table 2 about here.]

Table 2 reports the descriptive statistics for three important variables obtained at the first stage of the estimation procedure, which we will use later in illustrating our main statistical results. These variables are: the positive gap ($\widehat{gap}_{it}^{+}$) for each of the estimators we have used, the share of spillover potentials as we have defined them (s_{it}^{+}), and the product of the gap and the share of spillover potentials ($\widehat{gap}_{it}^{+} s_{it}^{+}$). The averages are available at the firm and worker level. The averages at the worker level are representative of the entire workforce; therefore, we will use them in illustrating what spillovers through worker mobility mean for the workers (Section 3.2). The firm-level averages are reported in the simple and weighted forms, with weights proportionate to firms' shares in total output, to make them applicable to the representative firm. Since in this section we discuss results for firms, we concentrate on the weighted firm-level statistics in Table 2. Looking at these statistics, spillover potentials make up around 2% (depending on the estimator) of the representative firm's workforce, their gaps averaging at 0.25-0.29. The small share of spillover potentials in the representative firm will limit the productivity advantage that they deliver to it. In fact, the representative firm has gap times share, $\widehat{gap}_{it}^{+}s_{it}^{+}$, of only 0.0062-0.0070. In our preferred specification (WLP), the representative firm counts 1.88% of its workforce as spillover potentials, whose average gap is 0.2725, and has gap times share of 0.0064.

[Table 3 about here.]

Turning to the results in Table 3, obtained at the second stage of our estimation procedure, our main findings are a positive and statistically significant coefficient on the positive gap, and an insignificant one on the negative gap. The difference between the positive and negative gaps' coefficients suggests that human capital brought in by new workers cannot explain the effect of gap on productivity, since this explanation would imply equal coefficients on the two gaps. 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 additional controls. The first specification (columns 1, 4, 7) includes the Abowd, Kramarz and Margolis (1999) human capital measure (calculated separately for spillover potentials and the rest of the workers), industry-year fixed effects and two lags of residual output. 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 positive 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 positive gap's effect survives these controls. Since the negative gap's effect is small, both statistically and economically, we will concentrate on the results for the positive gap.

Using the regression coefficients in Table 3, we now calculate the logs of OLPG, TFPG and LPA as defined in Section 2.1 (equations (3) and (4)):

$$\ln OLPG_{it} = \hat{\eta} \cdot \widehat{gap}_{it}^{+} \cdot \hat{s}_{it}^{+}$$

$$\ln TFPG_{it} = \widehat{\beta}_l \cdot \hat{\eta} \cdot \widehat{gap}_{it}^{+} \cdot \hat{s}_{it}^{+}$$

$$\ln LPA_{it} = \hat{\eta} \cdot \widehat{gap}_{it}^{+}$$

It must be noted that the assumption underlying equation (2) and the latter calculation is that other workers do not become more productive by learning from spillover potentials, which process we cannot observe. Therefore, the LPA as defined above is in fact the upper boundary of spillover potentials' labor productivity advantage. Clearly, its lower boundary, based on the assumption that every worker learns from spillover potentials and becomes equally productive with them, is equal to the OLPG.

Starting with the most complete OLS specification (column 3), the positive gap's coefficient 0.244 implies that TFPG to receiving firm from hiring spillover potentials is 0.244 of their average gap times the corresponding share in the workforce. For instance, a firm hiring 10% of its workforce from 10% more productive firms will produce 0.244% ($= 0.244 \times 0.1 \times 0.1$) more output with the same inputs than a similar firm hiring no spillover potentials. Dividing the gap's coefficient by labor input elasticity, 0.423, renders the knowledge transferability parameter $\hat{\eta} = 0.576$. Given our assumption that it is the knowledge difference that underlies the sending–receiving firms' productivity gap, $\hat{\eta} = 0.576$ implies that a large share, nearly 60%, of this knowledge is transferable between firms despite technological and other barriers that may hinder this transfer (more on the role of common technology in spillovers through worker mobility in Section 4.1). The OLPG is thus 0.576 of the average gap times share, and the LPA of spillover potentials is 0.576 of the average gap. Applying these results to the representative firm (OLS-estimated gap 0.2531 and gap times share 0.0062, Table 2), the implied TFPG to this firm is 0.15% per year, linked to a 0.36% OLPG and LPA of 14.6%.

However, the OLS estimate for the gap's coefficient may be subject to two biases. The first is caused by the positive gap's correlation with the receiving firm's TFP shock, which is not controlled by the OLS estimator. The second is due to labor input's positive correlation with the same shock affecting the estimate of β_l, again not addressed in OLS. Applying the OP and WLP estimators that control for both these biases, we observe that, compared to the OLS, the positive gap's coefficient has reduced in magnitude and is now 0.15-0.17 in the most complete regression specifications (columns 6 and 9). Confirming our expectations, this decrease suggests that firms experiencing a positive TFP shock tend to hire from relatively more productive firms. Yet, controlling for this correlation, the implied TFPG to a firm hiring 10% of its workforce from 10% more productive firms is still a non-negligible 0.169% ($= 0.169 \times 0.1 \times 0.1$, based on the most complete specification estimated with our preferred WLP, column 9). The WLP estimation results also point out to OLS overestimating labor input elasticity, implying that firms' labor input is positively correlated with the TFP shock that they can observe. Accounting for this correlation produces a labor input elasticity estimate of 0.333 (column 9), lower that 0.423 produced by OLS. Applying WLP to the production function equation (13) produces somewhat lower implied effects for the representative firm: a TFPG of 0.11% per year linked to a 0.32% OLPG thanks to spillover potentials' LPA of 13.9%.

There may still be a downward bias in the gap's coefficient estimated from the production function equation (13) because part of the gap's effect may have been captured by the control function for TFP shocks. Indeed, turning to the estimation results for the residual output regression (equation (14)) in Table 4, which we estimate in the same specifications and with the same estimators, we observe somewhat larger coefficients on the positive gap: 0.197 in our preferred specification (column 9). Similarly to (13), the coefficient on the negative gap is small in magnitude and insignificant in all specifications, supporting our earlier conclusion that the observed gap's effect is unlikely to be explained by spillover potentials' human capital. The gap's coefficient 0.197 and the knowledge transferability parameter 0.592 imply that a receiving firms's TFPG is 0.197 of its gap times share, which is linked to hiring spillover potentials whose LPA over the rest of its workers is 0.592 of their average productivity gap.

[Table 4 about here.]

Applying these results to the representative firm gives the implied TFPG of 0.13% per year. This gain is linked to a 0.379% OLPG thanks to hiring spillover potentials who are, on average, 15% more productive than otherwise similar workers in that firm. By virtue of its representativeness of the whole manufacturing sector, we conclude that the sector as a whole grows by the same 0.13% per year, which is 10.1% 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 a tenth less than actually observed. Notice that the way we measure labor input implies that these gains are net of the possible wage gains accrued to the workers, which we turn to in the following section.

3 Wage gains linked to spillover potentials

We have shown that receiving firms enjoy productivity gains after hiring spillover potentials net of any extra wage costs, such as a wage premium that might have been paid to them. Such wage premium is possible as competition ensures that factor inputs are rewarded depending on their productivity. For instance, Balsvik (2011) finds that the wage paid by domestic firms to new workers with foreign-firm experience is up to 4% higher (depending on the tenure at the foreign firm) than the wage paid to otherwise similar new workers without such experience, and up to 7% higher compared to stayers. Estimating the wage premium paid to spillover potentials is the first task of this section.

[Figure 1 about here.]

Despite the fact that spillover potentials' average pay is lower than global average (Table 1), there are signs in the data suggesting that they earn more than similarly qualified other workers in their new firms. Figure 1 illustrates the dynamics of wages of the workers who changed firms in 2001 (the midpoint of our sample's time span) versus the workers who did not. To isolate wage differences having to do with the workers' observable characteristics, we plot the residuals from the wage equation with and without firm fixed effects. Looking at Figure 1's left panel (wage residuals without firm fixed effects), we observe spillover potentials' wages relative to those of otherwise similar workers in the entire labor force. Spillover potentials saw a drop in their wages in the last two years before the move, after which period their wages gradually recovered though never quite reaching the global average or the wages of other moving workers who are not spillover potentials. These dynamics, however, are likely to be influenced by the moving workers' destinations, since spillover potentials move to *less* productive firms, which pay lower wages on average, and other moving workers go to *more* productive firms paying more. Indeed, adding sending and receiving firms' fixed effects (Figure 1's right panel), we see that, relative to the average wage of similar workers at their new firms, spillover potentials receive a small premium.

The second task we attempt is to estimate wage gains to other workers linked to spillover potentials. The possibility for these gains arises from other workers' becoming more productive through learning from spillover potentials. Alternatively, even if their productivity stays the same, other workers may still profit by sharing in their firm's productivity gains through wage bargaining actuated by fairness-related comparisons (Smith, 1996), especially that the differences between spillover potentials and otherwise similar workers are typically not highly perceptible. Estimating gains to other workers will complete the calculation of the full gains from spillovers through worker mobility, as well as their distribution between the three parties: the firms, the spillover potentials themselves, and the other workers.

3.1 Estimation issues

To estimate the wage premium paid to spillover potentials, we run the wage equation specified at the individual worker level with the positive and negative productivity gaps in it:

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

where $\ln w_{jit}$ is log wage of worker j (not necessarily a spillover potential) in firm i in year t (one year after the job move, if any), v_{jit} is the random error term, and $\widehat{gap}_{jit}^{+}$ and $\widehat{gap}_{jit}^{-}$ are the positive and negative productivity gaps defined for each worker separately, as the residual output difference between the worker's previous and new firms in year $t-2$. Thus $\widehat{gap}^{+}_{jit} = 0$ for a worker coming from a less productive firm, $\widehat{gap}^{-}_{jit} = 0$ for a worker coming from a more productive firm, and $\widehat{gap}^{-}_{jit} = \widehat{gap}^{+}_{jit} = 0$ for a job stayer. We include the firm-year fixed effect ϕ_{it} to isolate firm-wide influences on wages, such as compensation policies or firm productivity level, that may be correlated with the individual gap. The inclusion of ϕ_{it} leads us to interpret the positive gap's coefficient γ^{+} as the fraction of the gap paid as the wage premium to spillover potential j in firm i in year t on top of the average wage in that firm and year.

The controls vector includes worker characteristics (firm characteristics are subsumed by the firm-year fixed effects): age, gender, education, skill group, experience, two dummy variables indicating whether a worker comes from a more or a less productive firm, Abowd, Kramarz and Margolis (1999) measure of human capital estimated from equation (12) separately for spillover potentials from more and less productive firms and the rest of the workforce, and dummy variables corresponding to the number of job transitions during the sample period. Standard errors in equation (16) are clustered at the firm level.

To calculate the effect of spillover potentials on other workers' wages, we first estimate the gap's effect on log *average* wage (denoted $\overline{\ln w_{it}}$) in the receiving firm i in year t, running the firm-level wage equation:

$$\begin{aligned}\overline{\ln w}_{it} = {} & \Gamma^{+}\widehat{gap}^{+}_{it}\hat{s}^{+}_{it} + \Gamma^{-}\widehat{gap}^{-}_{it}\hat{s}^{-}_{it} + \Phi_i + \tau_{kt} \\ & + \Xi \cdot controls_{it} + \sum_{p=1}^{2} \delta_p \hat{u}_{i,t-p} + V_{it}, \end{aligned} \tag{17}$$

where $\widehat{gap}^{+}_{it}$ and $\widehat{gap}^{-}_{it}$ are the positive and negative gaps at the firm level, as defined in equations (15), $\hat{s}_{it}^{+}$ and $\hat{s}_{it}^{+}$ are the shares of workers corresponding to the gaps, 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 V_{it} is the random error term. Equation (17) is analogous to the individual wage equation (16) except that it is specified at the firm level and includes firm fixed effects. It is important to note that we run equation (17) using weighted OLS, with weights proportionate to the firms' shares in total employment, as we wish to make inferences for the average worker in our sample.

Combining the estimates from equations (16) and (17), the total wage gain to spillover potential j in firm i and year t, linked to the knowledge he or she brings, is

$$\underbrace{\gamma^{+}\left[\widehat{gap}_{jit}^{+} - \widehat{gap}_{it}^{+}\hat{s}_{it}^{+}\right]}_{\substack{\text{premium on top}\\ \text{of average wage}}} + \underbrace{\Gamma^{+}\widehat{gap}_{it}^{+}\hat{s}_{it}^{+}}_{\substack{\text{average}\\ \text{wage gain}}} \tag{18}$$

We use (18) further to calculate the average wage gain to the workers other than spillover potentials. Assuming that this gain is proportionate to the gap times the share of spillover potentials in the workforce, the following decomposition of the average wage gain to all workers applies:

$$\underbrace{\Gamma^{+}\widehat{gap}_{it}^{+}\hat{s}_{it}^{+}}_{\substack{\text{average gains}\\ \text{per worker, all}}} = \hat{s}_{it}^{+} \cdot \underbrace{\left(\gamma^{+} \sum_{j=1}^{N_{i,t-1}^{S+}} \frac{1}{N_{i,t-1}^{S+}} \left[\widehat{gap}_{jit}^{+} - \widehat{gap}_{it}^{+}\hat{s}_{it}^{+} \right] + \Gamma^{+}\widehat{gap}_{it}^{+}\hat{s}_{it}^{+} \right)}_{\substack{\text{average gains}\\ \text{per worker,}\\ \text{spillover potentials}}}$$

$$+(1-\hat{s}_{it}^{+}) \cdot \underbrace{(x \cdot \widehat{gap}_{it}^{+}\hat{s}_{it}^{+})}_{\substack{\text{av. gains}\\ \text{p/worker,}\\ \text{the rest}}}, \tag{19}$$

where coefficient x measures the implied effect of a firm's exposure to spillovers, $\widehat{gap}_{it}^{+}\hat{s}_{it}^{+}$, on the wages of the rest of its workers. Because it involves the share of spillover potentials in the firm, varying by worker and year, it is convenient to apply this decomposition to the average worker whose data are reported in the "Workers" part of Table 2. Thanks to the average worker's representativeness, the results of this decomposition will also apply to the manufacturing sector's labor force as a whole, which will enable us to relate the gains to all the workers to the gains to all the firms in the sector that we estimated in Section 2.3. Drawing on our preferred productivity regression specification (WLP), the average worker is employed in the firm where $\hat{s}_{it}^{+} = 2.14\%$ of employees are spillover potentials whose average gap is $\left(N_{i,t-1}^{S+}\right)^{-1} \sum_{j=1}^{N_{i,t-1}^{S+}} \widehat{gap}_{jit}^{+} = 0.2456$, 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.

3.2 Results

Table 5 presents estimation results for the individual wage equation (16) run with the gap values estimated previously with OLS, OP and WLP estimators. Consistent with our earlier results, the negative gap's coefficient, γ^-, is small and insignificant, implying no extra wage premium to the new workers who are not spillover potentials. The positive and significant coefficient on the positive gap, γ^+, implies that there is indeed a wage premium to spillover potentials proportionate to their corresponding 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, as 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 spillover potentials on top of the average wage in a given firm and year is 0.041 of their (positive) productivity gap. For the average spillover potential, whose gap is above the firm average by 0.24 (=0.2456, the average spillover potential's gap, minus 0.0053, the gap times share averaged at the worker level), this coefficient implies a wage premium of 0.98% on top of the contemporary average wage within his or her firm, controlling for other relevant characteristics. Relative to the sample average real wage growth, 4% per year, this premium is not insignificant. However, because spillover potentials make up only 2.14% of the workforce, their wage premium makes little difference to the total wage bill, increasing it by a mere 0.021% compared to the hypothetical case of no worker mobility across firms.

[Table 5 about here.]

The estimates from the firm-average wage equation (17) are presented in Table 6. The coefficient on the positive gap, Γ^+, is consistently positive and significant across the estimators and specifications, whereas the negative gap's coefficient is, as before, small and insignificant. Similarly to the individual wage equation (16) (Table 5), part of the link between the average positive gap and wages can be explained by worker characteristics. Still, the positive gap's coefficient in our most preferred and complete specification (column 9), $\Gamma^+ = 0.170$, implies that workers in a firm hiring 10% of its workforce from 10% more productive firms gain, on average, 0.17% ($= 0.170 \times 0.1 \times 0.1$) in wages per person per year compared to the counterfactual of having no spillover potentials at all. For the average worker in our sample, and hence for the manufacturing workforce as a whole, this wage gain stands at 0.09% per year, or 2.3% of the sector average real annual wage growth. Turning back to the spillover potentials part of the workforce, adding this average wage gain to spillover potentials' average wage premium, 0.98%, we obtain their full wage gain: 1.07% per year, paid in the year following the change of employer.

[Table 6 about here.]

Given the estimates for γ^+ and Γ^+ and the characteristics of the average worker in Table 2, the estimated coefficient x in (19) is 0.132, and the implied implied wage gain to workers other than spillover potentials is 0.07% per year. While this gain may seem negligible, it does imply a considerable redistribution of wage gains from spillover potentials to the rest of the workers. Indeed, if the average wage gains per worker (0.09% per year) were spillover potentials' only, then the average spillover potential's wage gain would have been 4.21% (= the average, 0.09%, divided by their share in the workforce, 2.14%) instead of the actual 1.07%.

Let us put together the estimated total gains from spillover potentials accrued to the firms in the manufacturing sector (Section 2.3) and to the workers (this section) to calculate the implied total output gains and their distribution between the three parties: the firms, the spillover potentials, and the rest of the workers. Recall from Section 2.3 that TFPG to the firms in the sector, net of the wage costs, are 0.13% per year. Adding to this figure the corresponding increase in the total wage costs times labor input elasticity, $0.09\% \times 0.333$, the total output gains become 0.16%. Most of these gains, roughly 80% (= 0.13%/0.16%), remains with the firms. Of the 20% that is left to workers, a quarter [8] accrues to spillover potentials, and the remainder goes to the rest. Thus, spillover potentials themselves receive only about 5% of the output gains that they bring to their receiving firms.

The low wage premium that spillover potentials earn relative to the productivity advantage they bring suggests the presence of information asymmetry, and possibly other frictions, in the labor market for them, preventing their labor productivity advantage being fully converted into a wage premium. Reaching out to the existing literature on the same topic, we calculate from Balsvik's (2011) findings that a wage premium for foreign-firm experience is 5-15% of the LPA thanks to this experience.[9] Though on the low side of the range of her estimates, our 5%

result is not inconsistent with hers, since the signal sent by a former foreign firm employee of his or her ability is more perceptible than the signal sent by an average spillover potential in our sample, and should therefore attract a larger wage premium. Hence, information asymmetry between spillover potentials and their new employers, which is larger in our general case than when a worker is known to have worked at a foreign firm before, can plausibly explain why spillover potentials' wage premium, relative to their labor productivity advantage, is low.

4 Extensions

4.1 Productivity and wage gains from worker mobility within and between industries

As the movement of workers is not confined by a particular industry, spillover potentials with the same productivity gap may bring varying productivity gains depending on the industry of their origin, since the knowledge they bring may have varying degree of transferability. Our analytical framework can be extended to differentiate between productivity gains through worker mobility within and between industries, by allowing the knowledge transferability parameter $0 \leq \eta < 1$ in equation (4) for our measure of firms' exposure to spillovers, δ_{it}, to vary depending on the spillover potential's industry of origin. In this section, we implement this extension by calculating the gaps $(\widehat{gap}^+_{it}, \widehat{gap}^-_{it})$ and corresponding worker shares $(\hat{s}^+_{it}, \hat{s}^-_{it})$ separately for the workers 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 7 about here.]

Table 7 lists the regression results for the residual output equation (14) and individual and firm average wage equations (16) and (17). The positive gap's estimate in column 6 is much larger for spillover potentials moving within the same industry (about 0.4) than for those moving between industries (0.09). 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. The negative gap's coefficient is small and insignificant regardless of the industry, reinforcing our earlier conclusion that human capital transfer 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 spillover potentials previously employed in the same and different industries, their individual wage gains, as a share of their gap, are nearly the same. The coefficient on the same-industry positive gap in the firm average wage regression (0.178, column 9) is close to its analogue in Table 6 (0.17) estimated for all spillover potentials. It is somewhat larger, though not significantly, than the same coefficient for spillover potentials coming from different industries (0.142). Taken together, the similarity of wage premiums to spillover potentials and dissimilarity of productivity gains to firms does not suggest a strong link between the two, reinforcing our previous conclusion that spillovers through worker mobility are largely a positive externality to hiring firms.

4.2 Productivity and wage gains by worker skill level

So far in our analysis we have used the measure of a firm's exposure to spillovers through worker mobility, $\eta \cdot gap_{it} \cdot s_{it}$, which assumes that, given the share of spillover potentials in the workforce (s_{it}), the productivity gains from spillovers increase with the productivity gap between the sending and receiving firms (gap_{it}), and with transferability of technology between sending and receiving firms (η). However, given these firm-level characteristics, productivity gains brought by spillover potentials, 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 spillover potentials 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 positive and negative gaps ($\widehat{gap}_{it}^{+}, \widehat{gap}_{it}^{-}$) and corresponding worker shares ($\hat{s}_{it}^{+}, \hat{s}_{it}^{-}$) for each skill group separately and reestimate equations (14), (16) and (17) with these newly defined variables.

The results, presented in Table 9, reveal considerable heterogeneity in the implied productivity gains to firms from hiring spillover potentials belonging to different skill groups. Consistent with our expectations, the labor productivity advantage (LPA, part of the coefficient θ_2^+) of spillover potentials in higher skill groups (highly-skilled and managers) is much larger than that of the lower skill groups, although even less skilled spillover potentials still contribute to the hiring firm's productivity. Spillover potentials' contribution to the average wages in their receiving firms (coefficient Γ^+) is proportional to their LPA; for instance, hiring a manager from a more productive firm increases everyone's wages more than hiring a less skilled worker from the same firm. However, spillover potentials' own wage premium (coefficient γ^+) as a share of their gap remains fairly stable and small, around 5%.

The total gains to firms and workers implied by the regression coefficients above depend on the shares of spillover potentials from different skill groups in the workforce. Calculating the implied gains for the representative firm and the average worker in the same way as earlier in sections 2.3 and 3.2 (bottom of Table 9), we find that, although managers have the highest LPA (0.3), the overall productivity gains enjoyed by firms from hiring them (TFPG=0.047%) are close to mid-skilled spillover potentials' (TFPG=0.054%), since managers are scarce. The wage gains follow the same pattern. It is also worth mentioning that the distribution of the total gains from spillover potentials between the firms, the spillover potentials themselves and the rest of the workers is fairly stable across the skill groups, with firms retaining around 80% of the total gains. Thus, the extent of the positive externality created by the movement of workers from more to less productive firms, which we have found in this study, does not seem to depend on spillover potentials' skill group.

4.3 The dynamics of spillover potentials' productivity advantage and wage premium

One possible explanation for observing that spillover potentials retain only a small portion of the gains they bring to their receiving firms in their first year of tenure is information asymmetry regarding their value. As their tenure progresses, therefore, one should see a closer link between their labor productivity advantage and wage premium. Another explanation is that their wage premium is deferred as the receiving firms try to ensure a continuation of their tenure. Such deferred compensation implies that the wage premium will continue to be paid in the years after joining the new firm, even though spillover potentials' productivity advantage is exhausted. However, spillover potentials' contribution to their new firm's productivity may last as well, for two reasons. First, since productivity follows an autoregressive process, the gap's effect one year after hiring, reported in Tables 3 and 4, will carry over to the following years through the autoregressive terms. Second, the gap may, in principle, have its own dynamics, unrelated to TFP shocks, influenced by the length of time it takes to transfer the knowledge from sending to receiving firms and to implement it, as well as by the gradual depreciation of that knowledge. In this section, we estimate the dynamics of the wage premium paid to spillover potentials and relate it to the dynamics of their contribution to productivity of their receiving firms.

Our method of estimating the dynamics of gap's effect on wages and firm productivity is based on regressing future wages and residual output on current values of the gap and other controls:

$$\hat{u}_{i,t+q} = \theta_q^+ \widehat{gap}_{it}^+ s_{it}^+ + \theta_q^- \widehat{gap}_{it}^- s_{it}^- \\ + \chi_q controls_{it} + \sum_{p=0}^{q+1} \mu_{p,q} \hat{u}_{i,t-2+p} + \phi_{kt} + \varepsilon_{i,t+q}, q \geq 1 \quad (20)$$

$$\ln w_{j,i,t+q} = \gamma_q^+ \widehat{gap}_{jit}^+ + \gamma_q^- \widehat{gap}_{jit}^- + \phi_{it} \\ + \xi_q \cdot controls_{jit} + v_{j,i,t+q}, \quad (21)$$

$$\overline{\ln w}_{i,t+q} = \Gamma_q^+ \widehat{gap}_{it}^+ s_{it}^+ + \Gamma_q^- \widehat{gap}_{it}^- s_{it}^- + \Phi_i + \tau_{kt} \\ + \Xi_q \cdot controls_{it} + \sum_{p=1}^{2} \delta_{p,q} \hat{u}_{i,t-p} + V_{i,t+q}, \quad (22)$$

where the notations are the same as in the residual output and wage equations (14), (16) and (17) presented earlier. An adaptation of the local projections method developed in Jordà (2005), this method is easy to implement and is robust to possible dynamic misspecifications in the underlying equations (14), (16) and (17). The coefficients γ_q^+ and Γ_q^+ estimate the effect of the positive gap on wages $q + 1$ years after joining the new firm, and the coefficients θ_q^+ and θ_q^- measure the effects of the positive and negative gaps-times-share on residual output. The full wage premium paid to spillover potentials is calculated for each q using equation (19).

[Table 8 about here.]

The results, reported in Table 8, show that productivity gains to hiring firms persist several years after hiring spillover potentials, reaching its peak in the third year and receding thereafter. In other words, spillover potentials continue to contribute to their new firm's productivity several years after being hired, implying that the total gains to firms from hiring spillover potentials, realized over several years, are larger than the gains one year after hiring estimated earlier in the paper. For illustration, doing the same calculations as in Section 2.3 with the gap times share for the representative firm (Table 2) shows that it a firm manages to hire spillover potentials at this rate for five consecutive years, its cumulative TFPG in the sixth year will be 0.7% – a large number, but of course not many firms will be so successful in their hiring.

The wage premium paid to spillover potentials and to incumbent workers persists for four years after hiring and then declines sharply in the fifth year. Relative to their LPA, average wage premium of spillover potentials remains low. In fact, the shares of the firms, the spillover potentials and the incumbent workers in the total output gain remain stable over the five year period. The stability of spillover potentials' wage premium relative to their LPA as time progresses does not support our suppositions that it is either deferred in order to retain them or raises gradually over time and information asymmetry is resolved. Rather, spillover potentials continue receive a stably low wage premium years after being hired.

5 Conclusion

The central ambition of this paper has been to estimate the gains from spillovers through worker mobility to the firms and to the workers, in order to determine the extent to which these gains are a pure, uncompensated externality. We began with calculating productivity gains to firms from hiring workers previously employed at more productive firms, whom we call spillover potentials. The theory based on which we have anticipated these gains is that such workers, thanks to their access to better, more efficient technology at their previous firms, can bring some of the knowledge developed there to their new employers. We have proposed an empirical method, the key element of which is the measure of firms' exposure to outside knowledge through hiring spillover potentials. Applying this method, we find that firms with a higher exposure to such knowledge enjoy larger productivity gains. These gains amount to 0.13% per year for the representative firm (and hence for the entire manufacturing sector), or a tenth of the sector's TFP growth, and persist for several years. We also find that productivity gains from spillover potentials are larger when they come from the same industry group and when they belong to a higher skill group, both of which findings add important characterizations to our main story without principally altering it.

In the remainder of our study, we have looked at the gains to workers traceable to spillovers through worker mobility, and at the distribution of the gains from hiring spillover potentials between the firms and the workers. Linking individual wages and productivity gap, we have found that spillover potentials gain in wages in proportion to their gap, the gain averaging at 1.07% in the first year after being hired. Furthermore, aided by a simple framework to estimate individual and average wage gains linked to spillover potentials, we have found that workers other than spillover potentials also gain in wages proportionate to their firm's exposure to outside knowledge as summarized in our measure of productivity gap. Turning to the distribution of the total gains between the firms and the workers, the workers' gains are, and remain so for up to five years after hiring, only about a fifth of the total, of which spillover potentials themselves retain only a quarter. We therefore conclude that worker mobility between more and less productive firms is largely a positive externality for the latter, helping their growth by giving cheap access to superior knowledge developed elsewhere.

6 Appendix - Modified Olley and Pakes (1996) and Wooldridge (2009) estimation procedures

Here we provide a detailed description of the estimation procedures, other than OLS, used for the construction of our TFP and productivity gap measures. Reconsider the production function equation (7):

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

where residual output u_{it} includes a component observable to the firm at time t, $\widetilde{a}_{it}$, and an unobservable productivity shock e_{it}:

$$u_{it} = \widetilde{a}_{it} + e_{it}$$

Factor inputs may be correlated with $\widetilde{a}_{it}$, causing a bias to their OLS estimates. We discuss two estimators dealing with this bias – the Olley and Pakes (1996) and Wooldridge (2009), also known as Wooldridge-Levinsohn-Petrin (WLP) estimator. Both estimators have been extensively discussed in the previous studies; however, their common versions assume a first-order Markov process in $\widetilde{a}_{it}$. This assumption is at odds with most of our empirical analysis, since our specification for spillover potentials' labor productivity advantage (equation (4)) implies that output in period t depends on $\widetilde{a}_{it-2}$ through the productivity gap term. The main purpose of this appendix is to explain how we modify these estimators to allow for a second-order Markov process in $\widetilde{a}_{it}$, which is more appropriate for our empirical analysis.

6.1 Modified Olley and Pakes (OP) procedure

The OP approach to deal with the bias to the factor inputs' estimates due to their correlation with $\widetilde{a}_{it}$ is to proxy $\widetilde{a}_{it}$ with other observables linked with it. A simple theory identifies such observables. Assuming the capital stock at time t is a deterministic function of capital stock and investments in the previous period,

$$k_{it} = \rho k_{i,t-1} + i_{i,t-1}, \tag{23}$$

where $0 < \rho < 1$ accounts for the depreciation of capital. Pakes (1994) showed that the investment function $i_{it} = f_{1t}(k_{it}, \widetilde{a}_{it})$ that solves the dynamic profit maximization problem is monotonically increasing in capital stock and productivity and thus can be inverted to express $\widetilde{a}_{it}$ as a function of observable capital and investments:

$$\widetilde{a}_{it} = g_t(k_{it}, i_{it})$$

In the first stage of the OP procedure, $g_t(k_{it}, i_{it})$ is substituted back into the production fucntion to control for $\widetilde{a}_{it}$. Since function $g_t(\cdot)$ is unknown, it is approximated with a third degree polinomial in k_{it} and i_{it}, called the *control function*. Adding the control function in the regression prevents the identification of β_k because k_{it} is collinear with it. However, the first stage does allow to identify β_l and β_m, and to obtain fitted values of the term $\widehat{\Phi}_{it} = \beta_k k_{it} + g_t(k_{it}, i_{it})$ that includes β_k. In order to identify β_k, the second stage of the OP estimator proceeds by assuming that $\widetilde{a}_{it}$

follows a first-order Markov process and thus can be decomposed into its conditional expectation as of time $(t-1)$ and the error term ξ_{it}:

$$\widetilde{a}_{it} = E\left[\widetilde{a}_{it}|\widetilde{a}_{it-1}\right] + \xi_{it} = f\left(\widetilde{a}_{it-1}\right) + \xi_{it}$$

Given the assumption on capital dynamics (equation (23)), the moment condition $E\left[k_{it}|\xi_{it}\right] = 0$ is used to identify β_k, where $f(\cdot)$ is approximated by a third degree polinomial and $\widetilde{a}_{i,t-1} = \widehat{\Phi}_{i,t-1} - \beta_k k_{i,t-1} = g_{t-1}\left(k_{i,t-1}, i_{i,t-1}\right)$.

Our definition of spillover potential's labor productivity advantage as a function of the sending–receiving firms' productivity distance two years prior implies that output in period t depends on $\widetilde{a}_{it-2}$ through the productivity gap term. Therefore, if the distribution of $\widetilde{a}_{it}$ depends on its realization in period $(t-2)$, the estimate of the gap's coefficient will be biased. For example, if $\widetilde{a}_{it}$ follows an AR(2) process, the coefficient $\beta_l\eta$ in equation (6) will have a negative bias when the second autoregression coefficient is positive, which is indeed the case in our data. To address this problem, we allow the productivity term $\widetilde{a}_{it}$ to follow a second-order Markov process, whereby productivity shocks observed one year prior would also matter for current investment and input factors decisions.

The assumption that $\widetilde{a}_{it}$ follows a second-order Markov process results in the optimum investment choice becoming a function of both $\widetilde{a}_{it}$ and $\widetilde{a}_{i,t-1}$:

$$i_{it} = f_{1t}\left(k_{it}, \widetilde{a}_{it}, \widetilde{a}_{it-1}\right)$$

The problem with this modification of the investment function is that the control function for $\widetilde{a}_{it}$ can no longer be constructed in the same way as in the classical version of OP because $\widetilde{a}_{it}$ and $\widetilde{a}_{i,t-1}$ cannot be separately identified with investments alone. There must be another control variable b_{it}, in addition to investments, that firms optimally choose in t given available information, for our estimation problem to be solved. If there are two control variables chosen optimally conditional on the state variables, then $b_{it} = f_{2t}\left(k_{it}, \widetilde{a}_{it}, \widetilde{a}_{it-1}\right)$, or $\binom{i_{it}}{b_{it}} = G_t\left(k_{it}, \widetilde{a}_{it}, \widetilde{a}_{it-1}\right)$, where $G_t = \left(f_{1t}, f_{2t}\right)$. Assuming that G is a bijection of $\left(\widetilde{a}_{it}, \widetilde{a}_{it-1}\right)$ to $\left(i_{it}, b_{it}\right)$, it can be inverted to obtain $\widetilde{a}_{it} = G_t^{-1}\left(k_{it}, i_{it}, b_{it}\right)$. Then the first stage of the OP proceeds as usual with the function $G_t^{-1}(\cdot)$ used to control for the productivity shock approximated by a third degree polynomial in k_{it}, i_{it}, and b_{it}. In that stage we obtain consistent estimates of β_l and β_m, as well as fitted values of $\left(G_t^{-1} + \beta_k k_{it-1}\right) = \widehat{F}_t$. In the second stage the coefficient on capital is estimated from

$$y_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_m} m_{it} = \beta_k k_{it} + \lambda\left(\widehat{F}_{t-1} - \beta_k k_{it-1}; \widehat{F}_{t-2} - \beta_k k_{it-2}\right) + e_{it} + \xi_{it},$$

where the function λ is approximated by a polynomial in its two arguments.

We implement the above procedure using four control variables that are optimally chosen by firms in each time period. These include: expenditure on construction and acquisition of buildings and land; purchases of machinery and equipment; total sales of buildings and land; and total disposal of machinery and equipment. While the first two will reflect a firm's response to positive productivity shocks, the latter two will reveal the firm's adjustments to negative shocks.

6.2 Modified Wooldridge procedure

The OP method has been criticized recently for a possible identification problem with $\widehat{\beta_l}$ and $\widehat{\beta_m}$ in the first stage. If labor and materials are chosen optimally and simultaneously with other control variables, they will also be functions of the observables at time t: $l_{it} = l_1(k_{it}, a_{it}, a_{it-1})$, $m_{it} = m_1(k_{it}, a_{it}, a_{it-1})$. Thus, variable inputs will be collinear to polynomial approximations of the control function and coefficients β_l and β_m will not be identifiable in the first stage. Wooldridge (2009) proposed a modification of the OP procedure which relaxes the strict exogeneity assumption of the variable inputs. With $\widetilde{a}_{it}$ following a first-order Markov process, it can be expressed as

$$\widetilde{a}_{it} = f(\widetilde{a}_{it-1}) + \xi_{it} = f[g_t(k_{it-1}, i_{it-1})] + \xi_{it} \tag{24}$$

Substituting (24) back into production function, one obtains

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + f[g_t(k_{it-1}, i_{it-1})] + \xi_{it} + e_{it} \tag{25}$$

Since l_{it} and m_{it} are correlated with ξ_{it}, while $E[\xi_{it}|l_{it-1}, m_{it-1}] = 0$, l_{it-1} and m_{it-1} are used as instruments for l_{it} and m_{it}. As with the OP, unknown function $f[g_t(\cdot)]$ is approximated with a third degree polynomial in k_{it-1} and i_{it-1} .

Allowing the productivity shock $\widetilde{a}_{it}$ to follow a second-order Markov process, equations (24) and (25) become

$$\begin{aligned}\widetilde{a}_{it} &= f\left(\widetilde{a}_{it-1}, \widetilde{a}_{it-2}\right) + \xi_{it} \\ &= f\left[g_t\left(k_{it-1}, i_{it-1}, b_{it-1}\right), g_{t-1}\left(k_{it-2}, i_{it-2}, b_{it-2}\right)\right] + \xi_{it}\end{aligned}$$

$$\begin{aligned}y_{it} &= \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} \\ &\quad + f\left[g_t\left(k_{it-1}, i_{it-1}, b_{it-1}\right), g_{t-1}\left(k_{it-2}, i_{it-2}, b_{it-2}\right)\right] + \xi_{it} + e_{it} \quad (26)\end{aligned}$$

Equation (26) again can be estimated by GMM approximating $f\left[g_t\left(\cdot\right), g_{t-1}\left(\cdot\right)\right]$ with polynomials in its arguments and the following moment conditions used to identify the factor inputs' coefficients:

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

Notes

[1]This said, the wages relative to productivity gains seem to vary depending on the worker. Thus, in a related study, Markusen and Trofimenko (2009) focussed on a particular group of workers, foreign experts, showing on Colombian data that recruiting one by a domestic firm raises its value added per worker and average wage by 11% each. Contrary to Balsvik's (2011) and our results, their findings imply that productivity gains from new workers are distributed proportionally between the firms and the workers.

[2]Although we cannot identify the source of this wage gain, learning from spillover potentials or a positive wage externality unrelated to productivity can be offered as possible explanations.

[3]Although, for simplicity of exposition, in equation (2) we abstract from other factors affecting efficiency units of labor, such as human capital, we do control for many such factors in our empirical analysis.

[4]Our specification of spillover potentials' LPA assumes that the exposure to knowledge from spillover potentials is linear in their share in the workforce. While we realize that this assumption may be restrictive, especially in the presence of learning by other workers, we choose to proceed with it for its simplicity and consistency with the specification for labor input in efficiency units in equation (2). Allowing for s_{it} to enter (6) nonlinearly as a robustness check (available on request) does not change our main results.

[5]Levinsohn and Petrin (2003) proposed, as an alternative to OP, to proxy TFP with a polynomial in capital and materials inputs. The

advantage of their approach is its efficiency, since materials input is not as lumpy as investments which contain many zeros in real data. It has, however, identification issues as we explain below.

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

[7]Another 2% are workers moving from less to more productive firms. For the rest of the job changers, information on sending firms is not available. The reasons include: non-manufacturing sending firms, long spells of unemployment, or entry on the labor market.

[8]The total wage gains by spillover potentials, 1.07%, multiplied by their share in the workforce, 0.0214, increases the total wage bill by 0.023%, which is a quarter of the average wage increase linked to spillover potentials, 0.09%.

[9]This ratio was calculated by dividing the wage premium to new workers with MNE experience net of the wage premium to moving workers without such experience (1% for those with a tenure at the previous firm between 1 and 3 years, 3% for those with a longer tenure) by the labor productivity difference between such workers, 20%.

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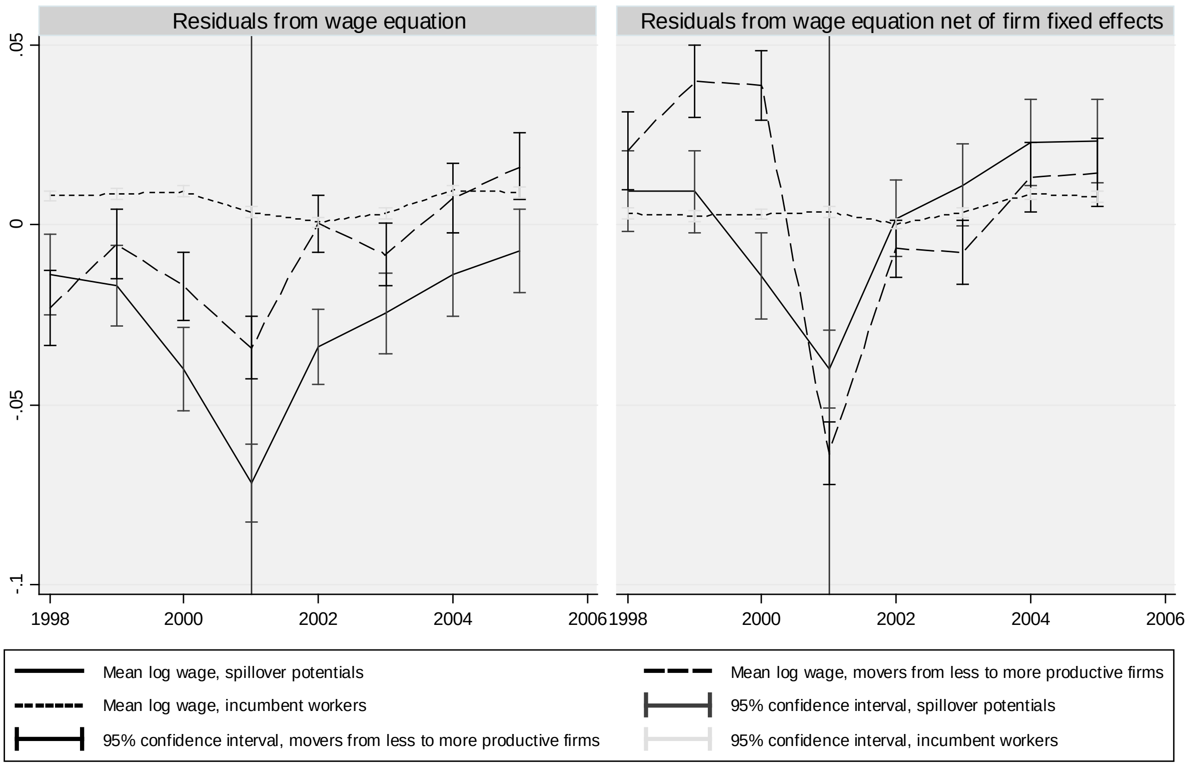
Figure 1. Wage profile of spillover potentials relative to other workers



Notes: On this figure all job changes are as of 2001.

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

	Workers		**Firms**		
	All workers	Spillover potentials	All firms	Firms that hire spillover potentials	Represen-tative firm
Log wage	12.544	12.457	12.093	12.168	12.352
Log human capital	0.106	0.049	0.025	0.011	0.016
High school (share)	0.341	0.312	0.385	0.395	0.378
College (share)	0.602	0.633	0.578	0.567	0.562
University (share)	0.057	0.056	0.036	0.038	0.06
Low skilled (share)	0.154	0.125	0.374	0.252	0.184
Mid skilled (share)	0.606	0.640	0.502	0.593	0.595
High skilled (share)	0.133	0.128	0.064	0.084	0.124
Managers (share)	0.107	0.108	0.060	0.072	0.097
Age	41.6	37.43	40.25	38.51	39.94
Log Experience	9.669	9.433	9.293	9.281	9.45
Male (share)	0.701	0.755	0.700	0.719	0.693
Separation rate	0.099	0.125	0.132	0.159	0.095
Hiring rate	0.092	0.194	0.081	0.156	0.091
Log employment	5.348	4.57	2.348	3.359	5.314
Log output	12.443	11.539	9.137	10.191	12.381
Log capital stock	10.833	9.920	7.439	8.520	10.774
Log material input	11.506	10.697	8.136	9.268	11.451
Number of obs.	1,816,843	38,838	72,586	24,337	72,586

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			WLP	
	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.
Gap positive	0.3007	0.2531	0.3102	0.4209	0.2927	0.3822	0.3701	0.2725	0.3692
Share of spillover potentials	0.0280	0.0213	0.0607	0.0276	0.0183	0.0580	0.0268	0.0188	0.0579
(Gap positive)*share	0.0077	0.0062	0.0193	0.0116	0.0070	0.0290	0.0097	0.0064	0.0257
					WORKERS				
		OLS			OP			WLP	
	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.	Simple mean	Weighted mean	Std. dev.
Gap positive	0.2257		0.2357	0.2811		0.2470	0.2456		0.2331
Share of spillover potentials	0.0261			0.0209			0.0214		
(Gap positive)*share	0.0059		0.0524	0.0059		0.0538	0.0053		0.0492

Notes: Summary statistics is calculated for the time period 1995-2007. TFP, positive gaps and shares 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 production function with productivity gaps

	(1) OLS	(2) OLS	(3) OLS	(4) OP	(5) OP	(6) OP	(7) WLP	(8) WLP	(9) WLP
Labor (β_l)	0.420**	0.420**	0.423**	0.417**	0.420**	0.416**	0.330**	0.330**	0.333**
	(0.003)	(0.003)	(0.003)	(0.010)	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)
Materials (β_m)	0.474**	0.474**	0.471**	0.438**	0.439**	0.437**	0.579**	0.579**	0.579**
	(0.003)	(0.003)	(0.003)	(0.010)	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)
Capital (β_k)	0.053**	0.053**	0.054**	0.020**	0.020**	0.021**	0.018**	0.018**	0.018**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gap positive (θ_1^+)	0.205**	0.279**	0.244**	0.214**	0.211**	0.148**	0.205**	0.194**	0.169**
	(0.040)	(0.059)	(0.049)	(0.031)	(0.043)	(0.043)	(0.037)	(0.054)	(0.053)
Gap negative (θ_1^-)	0.093	0.119	0.156	-0.043	-0.031	-0.003	0.011	0.023	-0.045
	(0.079)	(0.119)	(0.123)	(0.062)	(0.078)	(0.052)	(0.129)	(0.124)	(0.124)
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	0.983	0.983	0.983	0.091	0.102	0.975
N	105,478	105,478	105,478	71,464	71,464	71,464	72,574	72,574	72,574
Gap positive/L	0.488**	0.663**	0.576**	0.513**	0.505**	0.356**	0.621**	0.588**	0.509**
	(0.095)	(0.141)	(0.116)	(0.075)	(0.103)	(0.105)	(0.112)	(0.164)	(0.159)
Gap negative/L	0.221	0.284	0.369	-0.103	-0.073	-0.007	0.029	0.070	-0.135
	(0.182)	(0.283)	(0.291)	(0.142)	(0.177)	(0.136)	(0.394)	(0.369)	(0.372)

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 TFP equation with productivity gaps

	(1) OLS	(2) OLS	(3) OLS	(4) OP	(5) OP	(6) OP	(7) WLP	(8) WLP	(9) WLP
Gap positive (θ_2^+)	0.165**	0.311**	0.271**	0.241**	0.248**	0.198**	0.206**	0.237**	0.197**
	(0.043)	(0.054)	(0.060)	(0.029)	(0.046)	(0.045)	(0.034)	(0.055)	(0.052)
Gap negative (θ_2^-)	-0.100	-0.075	-0.042	-0.074	0.075	0.058	0.140	0.102	0.060
	(0.091)	(0.135)	(0.139)	(0.140)	(0.135)	(0.136)	(0.148)	(0.141)	(0.141)
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	0.363	0.364	0.365	0.490	0.490	0.494	0.667	0.402	0.405
N	105,427	105,427	105,427	71,433	71,433	71,433	72,611	72,611	72,611
Labor elasticity	0.420	0.420	0.423	0.417	0.420	0.416	0.330	0.330	0.333
	(0.001)	(0.001)	(0.001)	(0.010)	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)
Gap positive/L	0.393**	0.740**	0.641**	0.578**	0.590**	0.476**	0.624**	0.718**	0.592**
	(0.110)	(0.145)	(0.155)	(0.102)	(0.145)	(0.144)	(0.135)	(0.203)	(0.203)
Gap negative/L	-0.238	-0.179	-0.099	-0.177	0.179	0.139	0.424	0.309	0.180
	(0.259)	(0.424)	(0.426)	(0.386)	(0.633)	(0.641)	(0.471)	(0.470)	(0.845)

Notes: The dependent variable is the log of firm's TFP. * significant at 5%, ** significant at 1%. Standard errors in parentheses are obtained by bootstrap. 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). 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 TFP shocks in years (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 5. Estimation results for the individual wage equation with productivity gaps

	(1) OLS	(2) OLS	(3) OP	(4) OP	(5) WLP	(6) WLP
Gap positive (γ^{+})	0.029**	0.035**	0.066**	0.030**	0.060**	0.041**
	(0.009)	(0.008)	(0.013)	(0.009)	(0.015)	(0.009)
Gap negative (γ^{-})	0.016	0.008	0.017	0.010	0.019	0.010
	(0.009)	(0.006)	(0.012)	(0.009)	(0.012)	(0.011)
	Wage premium relative to labor productivity advantage					
	0.039	0.054	0.112	0.063	0.084	0.069
Controls for new and incumbent worker characteristics	NO	YES	NO	YES	NO	YES
R2	0.484	0.662	0.507	0.656	0.508	0.657
N	2,821,996	2,372,697	2,047,672	1,813,356	2,051,518	1,816,843

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 6. Estimation results for the firm-average wage equation with productivity gaps

	(1) OLS	(2) OLS	(3) OLS	(4) OP	(5) OP	(6) OP	(7) WLP	(8) WLP	(9) WLP
Gap positive (Γ^{+})	0.213**	0.206**	0.116**	0.356**	0.293**	0.168**	0.374**	0.277**	0.170**
	(0.070)	(0.063)	(0.038)	(0.057)	(0.061)	(0.052)	(0.056)	(0.063)	(0.054)
Gap negative (Γ^{-})	0.172	0.091	0.026	0.011	0.035	-0.024	0.064	0.087	0.029
	(0.093)	(0.074)	(0.025)	(0.051)	(0.049)	(0.042)	(0.063)	(0.060)	(0.054)
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	0.604	0.614	0.669	0.662	0.663	0.693	0.659	0.662	0.692
N	105,427	105,427	105,427	71,433	71,433	71,433	72,611	72,611	72,611
Share of spillover potentials	0.0213	0.0213	0.0213	0.0183	0.0183	0.0183	0.0188	0.0188	0.0188
Average (gap positive)*share	0.0062	0.0062	0.0062	0.0070	0.0070	0.0070	0.0064	0.0064	0.0064
Implied coefficient *x* in equation (19)	0.183	0.176	0.080	0.289	0.226	0.137	0.313	0.216	0.128
Average effect on wage of incumbent workers	0.0011	0.0011	0.0005	0.0020	0.0016	0.0010	0.0020	0.0014	0.00082
Average effect on wage of spillover potentials	0.0098	0.0097	0.0109	0.0277	0.0273	0.0127	0.0228	0.0222	0.01505
Effect on average wage	0.0013	0.0013	0.0007	0.0025	0.0021	0.0012	0.0024	0.0018	0.00109

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 7. Productivity and wage gains from worker mobility within and between industry groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Individual wage equation			TFP equation			Firm wage equation		
	OLS	OP	WLP	OLS	OP	WLP	OLS	OP	WLP
Gap positive, same industry	0.020**	0.034**	0.036**	0.490**	0.380**	0.405**	0.130**	0.186**	0.178**
	(0.008)	(0.011)	(0.011)	(0.101)	(0.090)	(0.119)	(0.061)	(0.065)	(0.065)
Gap positive, diff. industry	0.035**	0.040**	0.039**	0.129*	0.090*	0.084	0.068	0.136	0.142
	(0.009)	(0.010)	(0.010)	(0.065)	(0.050)	(0.055)	(0.062)	(0.219)	(0.177)
Gap negative, same industry	0.023**	0.021*	0.024*	0.143	0.135	0.117	0.046	0.033	0.071
	(0.009)	(0.013)	(0.013)	(0.193)	(0.117)	(0.116)	(0.059)	(0.049)	(0.065)
Gap negative, diff. industry	-0.009	0.001	0.003	-0.227	-0.072	0.023	0.004	-0.067	0.004
	(0.009)	(0.011)	(0.011)	(0.184)	(0.140)	(0.114)	(0.152)	(0.062	(0.070)
R2	0.671	0.665	0.665	0.365	0.494	0.405	0.669	0.693	0.692
N	2,374,181	1,815,753	1,819,330	105,380	71,412	72,586	105,380	71,412	72,586

Notes: The dependent variable is the log of individual worker's wage in columns (1)-(3), firm's TFP in columns (4)-(6), and the log of firm-year average wage 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 8. Productivity and wage gains from worker mobility in the years after hiring.

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
θ_2^+	0.198	0.208	0.264	0.239	0.158
γ^+	0.042	0.051	0.047	0.045	0.021
Γ^+	0.184	0.214	0.253	0.224	0.122
OLPG	0.00363	0.00381	0.00484	0.00438	0.00289
TFPG	0.00121	0.00127	0.00161	0.00146	0.00096
LPA	0.13438	0.14117	0.17917	0.16220	0.10723
Average gain per worker, overall	0.00064	0.00075	0.00089	0.00078	0.00043
Average gain per worker, spillover potentials	0.00982	0.01189	0.01116	0.01062	0.00502
Average gain per worker, other workers	0.00049	0.00057	0.00072	0.00062	0.00035
Share of gain retained by the firm	84.92%	83.57%	84.52%	84.81%	87.14%
Share of gain retained by spillover potentials	3.68%	4.17%	3.12%	3.29%	2.42%
Share of gain retained by other workers	11.40%	12.25%	12.36%	11.90%	10.44%

Notes: Time period covered in 1995-2007. TFP measure used to define spillover potentials was constructed from the Cobb-Douglas production function estimated by one-step GMM estimator by Wooldridge (2009).

Table 9. Productivity and wage gains from mobility of workers with different skills

Spillover potentials by skill group:	(1) Low skill	(2) Mid skill	(3) High skill	(4) Manager
θ_2^+	0.163	0.148	0.389	0.569
γ^+	0.026	0.036	0.035	0.063
Γ^+	0.127	0.162	0.394	0.531
OLPG	0.00050	0.00162	0.00105	0.00140
TFPG	0.00017	0.00054	0.00035	0.00047
LPA	0.07147	0.10858	0.21813	0.30228
Average gain per worker, overall	0.00009	0.00053	0.00028	0.00035
Average gain per worker, spillover potentials	0.00676	0.00885	0.00943	0.01856
Average gain per worker, other workers	0.00009	0.00041	0.00026	0.00031
Share of gain retained by the firm	84.86%	75.50%	78.84%	79.83%
Share of gain retained by spillover potentials	3.19%	5.69%	1.91%	2.43%
Share of gain retained by other workers	11.95%	18.81%	19.25%	17.74%
Share in labor force	0.28%	1.37%	0.27%	0.23%

Notes: Time period covered in 1995-2007. TFP measure used to define spillover potentials was constructed from the Cobb-Douglas production function estimated by one-step GMM estimator by Wooldridge (2009).

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