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Worker mobility and productivity spillovers

An emerging market perspective

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SA-TIED Working Paper 88 | February 2020

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UNITED NATIONS UNIVERSITY
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WIDER Working Paper 2019/114

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December 2019

United Nations University World Institute for Development Economics Research
wider.unu.edu

Abstract: This paper uses matched employer-employee data from South Africa to examine the extent to which technology transfers between firms through the hiring of workers. Allowing for differential spillovers based on observable technology differences between sending and receiving firms, we find strong evidence for positive productivity spillovers through worker mobility. In contrast to previous studies set in more advanced economies, our results suggest that negative spillovers can occur. Firms that hire workers from less productive firms experience a decline in productivity in the following year compared with similar firms that do not hire any workers. This, we suggest, may be explained by the high skills deficit in the South African labour market, and an important mechanism for technology transfers in the future may be driven by investments in firm-level training initiatives.

Key words: technology transfers, worker mobility, employer-employee matched data, spillovers

JEL classification: D24, J24, J62, O33

Acknowledgements: We are grateful to UNU-WIDER, the National Treasury of South Africa, and the South African Revenue Service for facilitating and permitting the use of the data. We would like to thank Alejandra Ramos and Tara Mitchell for comments.

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This study has been prepared within the UNU-WIDER project Southern Africa—towards inclusive economic development (SA-TIED.

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ISSN 1798-7237 ISBN 978-92-9256-750-7

https://doi.org/10.35188/UNU-WIDER/2020/750-7

Typescript prepared by Merl Storr.

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The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland, Sweden, and the United Kingdom as well as earmarked contributions for specific projects from a variety of donors.

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1 Introduction

Technology spillovers between firms are an important source of growth.[1] One mechanism through which firms obtain knowledge about the technology in use in other firms is through worker mobility. Where large knowledge gaps exist between firms, the movement of workers from high-productivity firms to low-productivity firms has the potential to lead to productivity spillovers for the hiring firms. Some empirical studies have found evidence of such productivity gains for hiring firms through worker mobility (Castillo et al. 2016; Stoyanov and Zubanov 2012).[2] Separately identifying productivity spillovers from human capital effects, however, is challenging. Moreover, little is known empirically about the sources of technology that lead to such spillovers.

Using matched employer-employee data from South Africa, we examine the movement of workers between firms and capture productivity spillovers by linking the productivity of the receiving firms to the productivity of the firms that newly hired workers have come from (the sending firms). We build on previous studies by allowing for differential spillovers based on observable technology differences between sending and receiving firms. The literature on task-specific human capital by Gibbons and Waldman (2004) and Gathmann and Schönberg (2010) proposes that a portion of the human capital acquired on the job is specific to the tasks being performed, rather than being specific to the firm. Rather than just learning from physically superior technologies or machinery, workers can also learn about superior input sources, potential markets, management practices, or organizational design. This decomposition allows for the possibility that workers moving from firms with lower aggregate productivity may still bring productivity spillovers through knowledge about superior 'soft' technologies. By considering these factors, our approach allows a richer and more in-depth analysis of spillovers through worker mobility by identifying the sources of such spillovers.

The rich data requirements of this type of analysis have meant that empirical studies to date have focussed on a limited set of countries where matched employer-employee data are available, mostly in the developed world.[3] It is likely, however, that spillovers through worker mobility are even more likely in emerging market contexts, where the distribution of productivity is much wider (Asker et al. 2014; Bartelsman et al. 2013; Hsieh and Klenow 2009), and where distortions such as credit or knowledge constraints often prevent firms from accessing new technology, leaving them to rely on learning through other means (Bloom et al. 2010). In this paper, we use employer-employee matched data for South Africa, an emerging market economy, to explore whether there is evidence of productivity spillovers through worker mobility.

For knowledge spillovers through worker mobility to exist, a number of conditions must be met, and South Africa is a particularly interesting context for examining this issue, for a number of reasons. First, there needs to be a knowledge gap between the firm that the worker leaves and the hiring firm. In productive firms, workers are exposed to more sophisticated processes, practices,

[1] See Romer (1990) and Grossman and Helpman (1991) for seminal work on this topic.

[2] A related literature examines the impact of worker mobility from foreign to domestic firms on workers' wages and firm performance (Gorg and Strobl 2005; Poole 2013). There is also a literature exploring the impact of worker mobility on research and development (R&D) activity that also provides support for spillovers through worker mobility (Kaiser et al. 2008; Maliranta et al. 2009).

[3] One notable exception is Castillo et al. (2016), who use employer-employee matched panel data from Argentina and the introduction of an innovation support programme to track the mobility of workers exposed to the programme and how their knowledge diffuses to other firms. They find positive impacts on the productivity of non-participant firms from hiring workers previously exposed to the programme.

and training. This might include, for example, knowledge about high-quality input suppliers, knowledge about international markets, management techniques, supply chain relationships, or specific types of training. Where this knowledge is valuable to lower-productivity firms, they may be willing to pay a higher wage to hire these workers in the expectation that these workers will bring this knowledge to the new firm, leading to a positive knowledge externality on existing workers, and thereby productivity improvements. The larger the gap, the greater the potential productivity gain.[4]

Second, the high-productivity firm which the worker leaves cannot view the hiring firm as a competitive threat, otherwise it would try to retain the worker.[5] Both of these conditions are more likely to hold in an emerging market context, where dual-market economies are more likely to be present and within-sector productivity dispersion is greater.

Third, the inability of the high-productivity firm to write long-term contracts for its workers may prevent it from building workers' future learning at the firm into the wage compensation scheme. Heggedal et al. (2017) develop a model of spillovers through worker mobility where firms are either innovators that invest in technology or imitators that hire workers from the firm that has already innovated. They show that where firms cannot commit to long-term contracts with workers, productivity spillovers cannot be internalized. In an emerging market context, long-term labour contracts are much scarcer, particularly in relatively low-skilled sectors.

Fourth, it must be more cost-effective for the hiring firm to hire the trained worker than to invest in the technology upgrading of workers themselves. This is also more likely in an emerging market context, even for low-cost technologies, where small firms in particular are credit-constrained or face other barriers to knowledge accumulation.[6] Indeed, South Africa exhibits all of these characteristics.

We find strong evidence for productivity spillovers through worker mobility. In contrast to other studies set in more advanced economies, our results suggest that both positive and negative spillovers can occur. While there is evidence of productivity gains for firms that hire workers from firms that are more productive than they are, on average workers are more likely to move from low-productivity to high-productivity firms, which damages the average productivity of the receiving firm. This is likely due to the significant skills deficit in the South African labour market (see for example Schwab 2019). Further evidence for this is given by the fact that one of the channels through which technologies are transmitted to firms through workers is through training.

The rest of the paper is structured as follows. In section 2, we outline our conceptual framework and present our empirical approach. Section 3 describes the data and presents summary statistics. The results are presented in section 4, and section 5 concludes.

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[4] Using matched employer-employee data from Denmark, Stoyanov and Zubanov (2012) find evidence of productivity gains through worker mobility that increase with the size of the productivity gap.

[5] If the diffusion of this knowledge is detrimental to the high-productivity firm, then it will try to retain its workers by offering a higher wage, or by preventing them from being hired by competing firms. Indeed, in many sectors where this knowledge is particularly valuable, firms create barriers to prevent workers from working for competitors, such as non-compete clauses or paid leave during the period of notice.

[6] Papov (2013) finds for 25 transition economies that lack of access to credit leads to lower on-the-job training. It is also possible that smaller, less well-connected firms may not have the same level of access to government incentives for worker training or R&D as larger firms.

2 Conceptual framework and empirical approach

Technology spillovers through worker mobility occur when workers switch firms and carry with them 'productive knowledge' gained while working for a former employer. Let the technology of a firm in period $t+1$, A_{t+1}, be given by:

$$A_{j,t+1} = a_j + \sum_{\tau=0}^{T-1} \rho_\tau A_{j,t-\tau} + \delta\, g\big[H_{j,t}\big] + \boldsymbol{X}\beta + \epsilon_{j,t} \qquad [1]$$

where a_j is the firm's exogenous technology draw, and $\sum_{\tau=0}^{T-1} \rho_\tau A_{j,t-\tau}$ is a series of previous period productivity realizations. The firm's technology is also a function of the set of abilities of workers, $\mathrm{g}\big[\mathrm{H_{j,t}}\big]$, where $\mathrm{H}_{j,t} = \{h_{1,j,t}, h_{2,j,t}, \ldots, h_{L_j-1,j,t}, h_{L_j,j,t}\}$, and $L_{j,t}$ is the total number of workers in firm j at time t.[7] The function $g[H_t]$ reflects the rate of innovation due to higher human capital in the firm, and we assume that these innovations require one period to realize. $\boldsymbol{X}$ is a vector of characteristics or other observable factors that may affect productivity. Finally, the firm may experience some independent and identically distributed shock $\epsilon_{j,t}$ in every period.

To empirically identify spillovers, it is necessary to separate a firm's productivity from the human capital of its workers, in order to distinctly identify the productivity increase from receiving a worker from a highly productive firm from the increase in productivity due to hiring a worker that has a high level of human capital (Stoyanov and Zubanov 2012). We follow the literature in our decomposition of human capital into experience, tenure, general and sector transferable skills, and firm-specific skills. We assume that the value of a worker to a firm takes the form of a Mincerian function, shown in equation 2.[8]

$$h_{i,j,t} = \eta_i + \gamma\, \psi_{i,j,t-1} + X_{i,t}\kappa_1 + Z_{i,j,t}\kappa_2 + \varepsilon_{i,j,t} \qquad [2]$$

The worker's productivity in the current period is based on their pre-labour market ability η_i, the worker's relevant productive knowledge accumulated from previous employment $\psi_{i,j,t-1}$, a set of worker-specific characteristics $X_{i,t}$, and a set of worker-firm-specific factors $Z_{i,j,t}$.[9]

The human capital component of firm-level productivity can now be defined as $g\big[H_{j,t}\big]$, which is the arithmetic mean of worker ability.

$$g\big[H_{j,t}\big] = \frac{1}{L_{j,t}} \sum_{i=1}^{L_{j,t}} h_{i,j,t}$$

$$= \bar{\eta}_j + \gamma\, \Psi\big(\overline{\psi_{j,t}}\big) + \overline{X_{\iota,t}}\kappa_1 + \overline{Z_{\iota,J,t}}\kappa_2 + \overline{\varepsilon_{J,t}} \qquad [3]$$

where $\overline{\eta}$, $\overline{\mathrm{X}}_1$, $\overline{\mathrm{Z}}_J$, and $\overline{\varepsilon_J}$ are the mean of worker pre-labour market ability, worker characteristics, firm-specific characteristics, and errors, respectively. Ψ is the 'gap function', which is the weighted

[7] We estimate firm-level productivity as value added per worker. As labour is measured as the number of full-time equivalent workers, the human capital aggregate must be contained within the productivity measure, and so must be controlled for in identifying spillovers.

[8] This approach is similar to Stoyanov and Zubanov (2012), with the exception that we assume the worker's value to a firm (the wage) will include potential technological spillovers, which should be netted out of the estimate of human capital when used as a control variable to detect productivity spillovers.

[9] Worker-specific factors may include age and general labour market experience, while worker-firm-specific factors may include tenure and firm-specific training.

average of the difference in productivity between the sending and receiving firms for new workers. This is described in equation 4, where M and L are the number of new and total workers in the receiving firm, respectively.

$$\Psi[\psi_{j,t}] = \frac{M_{j,t}}{L_{j,t}} \sum_{i=1}^{M_{j,t}} \frac{A^{s}_{j,t-1} - A^{r}_{j,t-1}}{M_{j,t}} \quad [4]$$

Combing equations 1 and 3, and defining the worker ability composite $u(\overline{H_{J,t}}) = \bar{\eta}_j + \overline{X_{\iota,t}}\kappa_1 + \overline{Z_{\iota,J,t}}\kappa_2$ (i.e. the mean of worker productivity not directly related to the productivity difference between receiving and sending firms), yields equation 5, which explicitly allows for technological spillovers to work through human capital.

$$A_{j,t+1} = a_j + \sum_{\tau=0}^{T-1} \rho_\tau A_{j,t-\tau} + \phi\Psi(\overline{\psi_{j,t}}) + \delta\, u(\overline{H_{J,t}}) + \bar{\epsilon}_{j,t} \quad [5]$$

In equation 5, the coefficient on the gap function, Ψ, determines the extent to which the relationship between receiving and sending firms' productivity affects the productivity of receiving firms.[10]

The key parameter of interest in equation 5 is ϕ, as it measures the impact of spillovers (the gap function) on productivity. A key source of endogeneity in estimating this parameter is the correlation between the sending firm's productivity and the other human capital components in $u(\overline{H_{J,t}})$. If it is the case that high-productivity firms generally have workers with higher human capital, a worker coming from a high-productivity firm to a low-productivity firm may increase the productivity through both the spillover and an increase in the average human capital in the new firm. Similarly to Stoyanov and Zubanov (2012), we control for this potential endogeneity by constructing a measure of human capital using the Abowd et al. (1999) wage equation, which allows us to separate firm-wage effects from individual effects. The first step in our empirical analysis is therefore to estimate the human capital component from the wage equation given in equation 2. We estimate equation 6 using the Cornelissen et al. (2008) implementation of the Abowd et al. (1999) high-dimensional fixed effects estimator. In this specification, we directly control for the impact of potential productivity spillovers on the wage offer.[11]

$$w_{i,j,t} = \eta_i + \gamma\, \psi_{i,j,t-1} + X_{i,t}\kappa_1 + Z_{i,j,t}\kappa_2 + \tau_t + \varepsilon_{i,j,t} \quad [6]$$

w_{ijt} is the log of the real wage of employee i; η_i is the worker-specific fixed effect; $\psi_{i,j,t-1}$is the difference in productivity between the sending and receiving firms; X_{it} is a vector of worker-specific characteristics, including tenure at the firm corresponding to the wage offer, age category, and an indicator of whether the worker is new to the firm; $Z_{i,j,t}$ are firm-specific characteristics, including sales, capital stock, and labour inputs; τ_t are time-specific fixed effects; ε_{ijt} is the error term.

[10] Note here that in Stoyanov and Zubanov (2012), the identification of human capital, and therefore the human capital aggregate $u(.)$, is based on a regression that excludes the possibility that firms may anticipate a productivity spillover. Where firms do anticipate spillovers, the exclusion of this term implies that a portion of $u(.)$ will be correlated with the spillover itself. Our approach limits the correlation between $u(.)$ and $\Psi(\div)$ to only the selection of high-ability workers in high-wage firms.

[11] This approach relies on the assumption of no assortative matching in the labour market (see Abowd et al. 1999).

Using these estimates, we construct an estimate of worker-specific human capital using equation 7.

$$\hat{h}_{ijt} = \hat{\eta}_i + \boldsymbol{X}_{it}\hat{\boldsymbol{\kappa}}_1 + \boldsymbol{Z}_{jt}\hat{\boldsymbol{\kappa}}_2 + \hat{\varepsilon}_{ijt} \quad [7]$$

This in turn is aggregated to the firm level to generate $u(\overline{H_{J,t}})$.

Within this framework, for technology to transfer between firms it must first transfer to the worker before it can transfer to the new firm. In this context, the traditional treatment of human capital as consisting of (i) a general transferable component, (ii) a transferable component at the sector level, and (iii) a firm-specific non-transferable component can be expanded to include (iv) productive information within each degree of transferability.[12] The transmission of productive knowledge from firm to worker can be understood in the context of task-specific human capital theory by, for example, Gibbons and Waldman (2004) and Gathmann and Schönberg (2010), who suggest that a portion of the human capital acquired through being employed is specific to the tasks being performed, rather than being specific to the firm. We assume that a portion of a firm's productivity is captured in the efficiency with which its workers perform these tasks, where the efficiency in doing these tasks may stem from physically superior technology or machinery, better information on input sources or potential markets, management practices, or organizational design.[13] The consequence of this assumption is that workers at a firm will gain human capital from performing tasks correlated with the set of productive characteristics of the firm. This approach has the additional implication that we can decompose productive spillovers into technology stemming from different activities of the firm.

We expand the shape of the gap function to allow for differential spillovers based on the observable technology difference between sending and receiving firms. As in Stoyanov and Zubanov (2012), we first allow for positive and negative spillovers to affect the firm. The intuition behind this asymmetry is that a firm, knowing that a worker comes from a less productive firm, will realize that the technology the worker embodies is inferior to its own. When considering the worker-embodied technology in the sense of Bloom et al.'s (2016) best-in-all-environments management technologies, for example, the firm will not expect the information on these technologies from lower-productivity companies to benefit the firm. As such, it may be relatively harmless for firms to hire workers with inferior technologies, particularly when we think of general technologies. If we disaggregate knowledge to encompass more specialized technologies, including soft technologies, this intuition may not hold. It may well be that a sending firm will have a lower productivity aggregate than the receiving firm; it may have better 'soft' technologies that are transmitted through worker mobility to the receiving firm.

These technologies may include factors such as knowledge of export markets, information on quality imports, research and development (R&D) knowledge, or worker training. Furthermore, these technologies may be transmitted at different rates and be more difficult to evaluate in terms

[12] Acemoglu and Pischke (1998), Becker (1962), and Blundell et al. (1999) focus on the role of training, separating it into a firm-specific or non-transferable component, and a general or transferable component. Neal (1995) and Dustman and Meghir (2005) explicitly refer to transferable and non-transferable skills in their treatment of human capital.

[13] This interpretation of the firm's technology shares roots with the 'management as a technology' literature by Bloom et al. (2016), as well as the broader management literature. As examples of this interpretation, see Liebeskind (1996) for a discussion of strategic behaviour by firms to maintain their knowledge monopolies, Brynjolfsson et al. (2002) for a discussion of the complementarities between computers and organizational capital, and Garicano (2000) for a discussion of knowledge hierarchies as a theory of the firm.

of quality. We expand the gap function in equation 4 to take these into account, where P indicates the type of soft technology, and s_p is the importance of the spillover to the firm:

$$\Psi[\psi_{j,t}] = \frac{M_{j,t}}{L_{j,t}} \sum_{i=1}^{M_{j,t}} \frac{\psi_j(A_{j,t-1}^s, A_{j,t-1}^r) + \sum_{p=1}^{P} s_p \psi_{j,p}\left(P_{j,t-1}^s, P_{j,t-1}^r\right)}{M_{j,t}} \quad [8]$$

s_p can be interpreted as the strength of the source of the spillover in the same context as the rate of innovation creation in endogenous growth models. In distinguishing separate factors in this way, we may also identify the ease of evaluation of potential productivity-enhancing mechanisms. Where a specific innovation's potential is easily identifiable, it is expected that the coefficient on the positive spillover, s_p^+, will be significant, whereas its negative counterpart, s_p^-, should be insignificant, as the firm will easily identify damaging information. Furthermore, information sets where it is important that the worker has working knowledge (such as R&D) may be more costly to the firm's productivity, meaning that $s_{p,R\&D}^-$ is likely to be more negative than simple productive knowledge from using a computer, for example. We consider a number of different sources of spillovers in our empirical analysis, including exports and imports, R&D expenditure, and training expenditure.

3 Data

We use tax administrative data collected by the South African Revenue Service for the period 2009 to 2014.[14] Specifically, we match the South African corporate income tax data, which are collected annually and are based on self-reported corporate income tax returns, to the pay-as-you-earn tax data records. This implies that we have information on each worker in each firm, and we can map their mobility between firms from year to year. This allows us to identify workers that switch between firms, and so we can isolate the human capital of the workers, and the productivity and associated characteristics of the firms that they switch from (the sending firms) and the firms that they switch to (the receiving firms).

Table 1 presents the proportion of firms in the panel that have a worker switch out of the firm and the proportion of workers that switch jobs in each year. It is clear that there is a significant amount of worker mobility in our sample, with over 60 per cent of the sample of firms having a worker that switched to another firm, and over 15 per cent of workers switching firms over the course of our sample period.

Table 1: Worker mobility

Year	No. of firms	% firms with switcher	No. of worker observations	% workers that switch
2011	21,231	26.24%	430,711	3.05%
2012	23,882	28.05%	482,542	3.29%
2013	24,627	29.42%	498,138	3.36%
2014	23,115	27.91%	485,343	3.06%
Total	92,855	27.97%	1,896,734	3.19%

Source: authors' calculations based on data from South African administrative database.

[14] For a full description of the data set and how it is compiled, see Kreuser and Newman (2018).

Our main outcome variable of interest is firm-level productivity, which we measure as output per worker.[15] Output is measured using the firm's value added, which we compute as total sales minus the cost of sales. Labour inputs are measured as the total number of workers in the firm weighted by the number of days worked. Wages are measured as the daily wage rate deflated using the aggregate inflation rate. Summary statistics are presented in Table A1 in the Appendix.

Table 2: Worker transition matrix by productivity decile of sending and receiving firms

	Productivity deciles of receiving firms									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Productivity deciles of sending firms										
1st	**23.6%**	19.1%	11.2%	9.0%	9.8%	9.3%	6.8%	4.9%	4.6%	1.7%
2nd	21.2%	**16.6%**	11.7%	10.8%	10.7%	8.6%	7.4%	6.4%	4.4%	2.2%
3rd	15.4%	14.0%	**13.6%**	12.1%	10.5%	9.8%	9.5%	6.9%	5.4%	2.8%
4th	14.5%	12.2%	15.1%	**12.4%**	11.7%	11.3%	8.8%	7.7%	4.6%	1.8%
5th	11.3%	10.7%	11.0%	11.7%	**13.0%**	13.6%	10.4%	9.8%	6.2%	2.3%
6th	10.2%	9.7%	10.3%	10.4%	11.0%	**12.4%**	13.3%	11.9%	7.3%	3.6%
7th	7.9%	8.7%	9.3%	11.7%	10.4%	11.8%	**13.9%**	14.1%	8.8%	3.3%
8th	7.3%	6.4%	6.7%	10.2%	11.0%	13.3%	13.2%	**14.6%**	12.2%	5.1%
9th	12.8%	5.8%	6.6%	6.1%	7.7%	8.4%	12.9%	13.9%	**15.4%**	10.4%
10th	6.9%	4.6%	5.8%	4.4%	7.2%	11.3%	9.2%	12.8%	18.5%	**19.2%**

Source: authors' calculations based on data from South African administrative database.

In Table 2, we present a transition matrix for workers that switch jobs over the sample period, similar to that presented by Stoyanov and Zubanov (2012). It illustrates the productivity decile of the sending and receiving firms, and can be read as the probability that a worker from one decile will transition to a different decile in the next period. On average, more than 15 per cent of workers who move firms go to a firm within their own productivity decile, while around 40 per cent stay in the same decile or go to a neighbouring decile. These results appear to indicate that while there is significant movement of workers across the productivity distribution, a large proportion of workers will transition to a productivity decile close to the firm they came from.

Our core aim in this paper is to investigate whether there are productivity spillovers when workers move from one firm to another. Overall, Table 2 indicates significant movement within the productivity distribution, into both higher-productivity deciles and lower-productivity deciles. The extent to which the productivity gap is positive or negative is also likely to matter. Summary statistics for the average productivity gap are presented in Table 3. It appears that on average the gap between sending and receiving firms is negative, suggesting that firms are more likely to hire workers from low-productivity firms. This is in contrast to Stoyanov and Zubanov (2012), where the productivity gap is on average positive. However, their results are obtained in a country where skills deficits are considered to be limited. A likely explanation for the difference may therefore be

[15] We also do robustness checks using Ackerberg et al.'s (2015) approach, as described in Kreuser and Newman (2018). To estimate the production functions, capital is measured as the firm's fixed capital stock, calculated as the sum of the property, plant and equipment, and other fixed capital. All of our results are robust to the use of this measure of productivity. Results are available on request.

found in the lack of skilled labour in the South African context and the difficulty firms face in hiring qualified staff.

In our sample, however, there are firms that hire workers from higher-productivity firms, and so we decompose the productivity gap to detect both positive and negative spillovers. We also disaggregate the gap function into different types of soft technologies, which workers can still potentially bring with them to a new firm even if the sending form is of lower productivity. We consider a number of different types of soft technologies that might be transferred through worker mobility. We consider the R&D expenditure of the firms, the total level of expenditure on worker training, and the extent of exposure to foreign trade measured as total expenditure in imports and exports as captured in the customs data. All monetary values are deflated using industry-level deflators, and average values for firms in the sample are also presented in Table 3. Each of the gap functions is calculated by taking the previous period difference in the value of the relevant element between the receiving and the sending firm at the worker level, and aggregating this across all new workers entering the firm.

Table 3: Summary statistics

Variables	Mean	Standard deviation
Log productivity	12.406	0.749
$\Psi(A_{j,t-1})$	-0.002	0.038
$\Psi(A_{j,t-1}) > 0$	0.010	0.320
$\Psi(A_{j,t-1}) < 0$	0.023	0.490
$\Psi(Exp_{\{t-1\}}) > 0$	0.128	2.884
$\Psi(Exp_{\{t-1\}}) < 0$	0.101	3.903
$\Psi(Imp_{\{t-1\}}) > 0$	0.134	3.600
$\Psi(Imp_{\{t-1\}}) < 0$	0.097	3.376
$\Psi(Training_{\{t-1\}}) > 0$	0.052	0.793
$\Psi(Training_{\{t-1\}}) < 0$	0.031	1.184
$\Psi(RnD_{\{t-1\}}) < 0$	0.011	0.385
$\Psi(RnD_{\{t-1\}}) > 0$	0.015	0.274
Log of value of exports	4.574	6.516
Log of value of imports	4.750	6.857
Log of training expenditure	1.303	3.454
Log of R&D expenditure	0.238	1.651
Share of new entrants	0.028	0.071
Share of leavers	0.010	0.074
Log mean age of workers	3.605	0.115
Mean tenure of workers	3.290	0.766

Source: authors' calculations based on data from South African administrative database.

4 Results

To identify technology transfers through worker mobility, we estimate equation 5, which relates the productivity of firms to the gap function $\Psi(\overline{\psi_{j,t}})$, which is our measure of the average difference in the productivity of the receiving and sending firms for all new workers. In this equation, we include controls for the past productivity of the firm, the human capital of the workers in the firm, other observable characteristics of the workers in the firm (age and tenure), characteristics of the firm itself (size and worker turnover), and industry-year fixed effects. In order to estimate this equation, however, we first need to estimate a worker-specific control variable for human capital, which is unobservable. As discussed in section 2, worker human capital is estimated using equation 6. We estimate this equation using the Cornelissen et al. (2008) implementation of the Abowd et al. (1999) high-dimensional fixed effects estimator. We use the estimates from this regression to back out our worker-specific measure of human capital using equation 7. We then aggregate this measure into a human capital index, $u(\overline{H_{J,t}})$ for inclusion in the estimation of equation 5. The results for the wage regression are presented in Table A1 in the Appendix.

The results for worker-embodied technology spillovers are presented in Table 4. We focus on four main specifications. In column 1 we present a basic specification without controls for the human capital composite $u(\overline{H_{J,t}})$ and including only controls for past productivity and industry-year fixed effects. In column 2 we add the human capital composite. In column 3 we add controls for employee characteristics, namely the average age and tenure of workers in the firm. Finally, in column 4 we add firm-specific control variables.

Table 4: Productivity and worker-embodied technological spillovers—baseline specification

	(1)	(2)	(3)	(4)
$\Psi(A_{j,t-1})$	0.350***	0.300***	0.260***	0.280***
	(0.052)	(0.052)	(0.050)	(0.050)
$A_{j,t-1}$	0.850***	0.830***	0.830***	0.810***
	(0.003)	(0.003)	0.003)	(0.003)
$g(H_{j,t})$		0.004***	0.003**	0.036***
		(0.001)	(0.001)	(0.002)
Industry-year FE	Yes	Yes	Yes	Yes
Worker controls	No	No	Yes	Yes
Firm controls	No	No	No	Yes
Observations	60,197	50,815	50,815	51,623
R-squared	0.75	0.76	0.76	0.76

Note: The results for the full set of control variables are presented in Table A2 in the Appendix. In all regressions, productivity is measured as log value added per worker. $\Psi(A_{j,t-1})$ is the weighted productivity spillover constructed using equation 4. $g(H_{j,t})$ is the human capital composite measure constructed by aggregating the estimated human capital components from the wage equation as in equation 7. Worker controls include the log mean age of workers in the firm and the mean tenure of workers in the firm. Firm controls include the extent of worker turnover in the firm (new employees/total employees and leavers/total employees) and firm size controls which are a series of dummy variables constructed based on the weighted number of employees per firm. All regressions include industry-year fixed effects. Standard errors, in parentheses, are clustered at the firm level. *** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$.

Source: authors' calculations based on data from South African administrative database.

In all specifications, we find a positive coefficient on the productivity spillover term, indicating that the productivity difference between the sending and the receiving firm matters for the productivity of the receiving firm. It is clear from a comparison of the results between columns 1 and 2, which control for the human capital of workers, that the inclusion of this composite is important in the estimation of this effect: there is still evidence of productivity spillovers, but they are of lower magnitude. Including worker-specific characteristics in column 3 does not affect the magnitude of the effect, while the inclusion of firm-specific characteristics in column 4 leads to a slightly larger effect with a coefficient of 0.28. To interpret this coefficient, we consider the mean productivity gap between sending and receiving firms. With a mean gap of -0.002, this suggests that a hiring firm will experience a small productivity decline of 0.05 per cent in the year after hiring compared with an identical firm (based on the observed characteristics) that did not hire any workers.

Given that the aggregate productivity gap encompasses both positive and negative gaps, this aggregate result is difficult to interpret in isolation, particularly given the extent of worker mobility between different productivity deciles as seen in Table 2. We separate productivity spillovers into (i) spillovers from workers coming from higher-productivity firms than the receiving firms and (ii) spillovers from workers coming from lower-productivity firms than the receiving firms. The results are presented in Table 5, with columns 1 to 4 mirroring the specifications presented in Table 4. We find evidence for both positive and negative spillovers. To quantify the effect, the average positive productivity gap as illustrated in Table 3 is 0.01. With a coefficient of 0.38, this implies that on average firms that hire a worker from a firm with higher productivity will experience a productivity gain of 0.38 per cent compared with an identical firm that did not hire any workers. The magnitude of this effect is very similar to that found by Stoyanov and Zubanov (2012) for the case of Denmark. Conversely, with an average negative productivity gap of 0.023 and a coefficient of -0.21 on the negative spillover term, our results suggest that firms that hire a worker from a firm with lower productivity will experience a productivity loss of 0.48 per cent. This is in contrast to Stoyanov and Zubanov (2012), who only find evidence of positive spillovers, with negative spillovers having no effect. As mentioned above, our results suggest that in the South African case, hiring workers from low-productivity firms may well be detrimental to productivity, and is symptomatic of a labour force with a low skill level in general. This is in comparison with Denmark, where the average skill level of the labour force is substantially higher, meaning that there is less risk associated with hiring workers from low-productivity firms.

In the final part of our analysis, we decompose productivity spillovers into a number of different types of soft technologies that might be transferred through worker mobility. The results are presented in Table 6. For ease of illustration, we only present the results for the full specification including all controls. In each specification, we also include controls for the level and lag of each of the characteristic variables of interest. In column 1, we consider the extent to which firms that hire workers from firms that export and import more or less than the hiring firm experience productivity gains from the knowledge that these workers bring with them. We find some evidence that hiring workers from more export-intensive firms leads to a productivity gain. With an average gap in export intensity of 0.128 (see Table 3), the coefficient of 0.061 implies that, on average, hiring a worker from a firm that is more export-intensive leads to a productivity gain of 0.78 per cent relative to a firm that does not hire any workers. We find no evidence for positive spillovers from import-intensive firms. Moreover, it appears that there is no risk associated with hiring workers from less export-intensive and less import-intensive firms once the negative spillover from hiring workers from firms with inferior general technology ($\Psi(A_{j,t-1})$) is controlled for.

In column 2, we consider whether the level of training that workers received in their previous firms matters. We find evidence for both positive and negative spillovers from training. Where the firm hires a worker that spends more on training, it should expect on average an increase of 0.18 per cent (the sample average for the positive training gap is 0.052, and the coefficient on positive training gaps is 0.035). We also find evidence of a cost associated with hiring a worker from a company that invests less in training. The negative coefficient of -0.47 translates into a productivity loss of 0.15 per cent on average (the sample average for the positive training gap is 0.031). As mentioned above, in an economy with a significant skills deficit, firm-level training initiatives become particularly important. Our results suggest that they are important not only for the firms themselves, but also for the potential spillovers that they yield for firms that subsequently hire these workers, in terms of both positive spillovers and negative spillovers. In column 3 we consider R&D expenditure but find no evidence that gaps in R&D expenditure matter for labour mobility-induced productivity spillovers. Finally, in column 4 we combine all measures and find that the most important transmission factor is training; we also note that the results for the export gap do not hold up to the inclusion of all characteristics simultaneously.

Table 5: Productivity and worker-embodied technological spillovers—asymmetric spillovers

	(1)	(2)	(3)	(4)
$\Psi(A_{j,t-1}) > 0$	0.190**	0.180**	0.260***	0.380***
	(0.080)	(0.078)	(0.080)	(0.092)
$\Psi(A_{j,t-1}) < 0$	-0.440***	-0.380***	-0.260***	-0.210***
	(0.062)	(0.062)	(0.060)	(0.063)
$A_{j,t-1}$	0.850***	0.830***	0.830***	0.810***
	(0.003)	(0.003)	(0.003)	(0.003)
$g(H_{j,t})$		0.004***	0.002*	0.035***
		(0.001)	(0.001)	(0.002)
Industry-year FE	Yes	Yes	Yes	Yes
Worker controls	No	No	Yes	Yes
Firm controls	No	No	No	Yes
Observations	60,197	51,623	51,623	51,623
R-squared	0.75	0.75	0.75	0.76

Note: The results for the full set of control variables are presented in Table A3 in the Appendix. In all regressions, productivity is measured as log value added per worker. $\Psi(A_{j,t-1}) > 0$ is the weighted productivity spillover as in equation 4 when workers come from more productive firms, and $\Psi(A_{j,t-1}) < 0$ is the weighted productivity spillover in equation 4 when workers come from less productive firms. $g(H_{j,t})$ is the human capital composite measure constructed by aggregating the estimated human capital components from the wage equation as in equation 7. Worker controls include the log mean age of workers in the firm and the mean tenure of workers in the firm. Firm controls include the extent of worker turnover in the firm (new employees/total employees and leavers/total employees) and firm size controls which are a series of dummy variables constructed based on the weighted number of employees per firm. All regressions include industry-year fixed effects. Standard errors, in parentheses, are clustered at the firm level. *** p < 0.1, ** p < 0.05, * p < 0.01.

Source: authors' calculations based on data from South African administrative database.

Table 6: Productivity and worker-embodied technological spillovers—disaggregated

	(1)	(2)	(3)	(4)
$\Psi(A_{j,t-1}) > 0$	0.29**	0.36***	0.37***	0.34***
	(0.14)	(0.094)	(0.093)	(0.11)
$\Psi(A_{j,t-1}) < 0$	-0.15*	-0.19***	-0.23***	-0.20***
	(0.080)	(0.065)	(0.065)	(0.067)
$\Psi(Exp_{\{t-1\}}) > 0$	0.061**			0.014
	(0.024)			(0.0091)
$\Psi(Exp_{\{t-1\}}) < 0$	0.012			-0.0067
	(0.026)			(0.013)
$\Psi(Imp_{\{t-1\}}) > 0$	-0.0010			-0.011
	(0.027)			(0.0079)
$\Psi(Imp_{\{t-1\}}) < 0$	-0.010			0.0088
	(0.027)			(0.0079)
$\Psi(Training_{\{t-1\}}) > 0$		0.035***		0.031**
		(0.013)		(0.014)
$\Psi(Training_{\{t-1\}}) < 0$		-0.047*		-0.047*
		(0.024)		(0.024)
$\Psi(RnD_{\{t-1\}}) < 0$			-0.043	0.0034
			(0.037)	(0.031)
$\Psi(RnD_{\{t-1\}}) > 0$			0.029	0.00081
			(0.023)	(0.021)
$A_{j,t-1}$	0.78***	0.81***	0.81***	0.78***
	(0.0037)	(0.0033)	(0.0033)	(0.0036)
$g(H_{j,t})$	0.031***	0.034***	0.035***	0.031***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Observations	49,195	49,195	49,195	49,195
R-squared	0.75	0.76	0.76	0.76

Note: This table is summary of results from the regression results presented in in Table A4 in the Appendix. In all regressions, productivity is measured as log value added per worker. $\Psi(A_{j,t-1}) > 0$ is the weighted productivity spillover as in equation 4 when workers come from more productive firms, and $\Psi(A_{j,t-1}) < 0$ is the weighted productivity spillover in equation 4 when workers come from less productive firms. Spillovers for each of the characteristic variables are measured in the same way. $g(H_{j,t})$ is the human capital composite measure constructed by aggregating the estimated human capital components from the wage equation as in equation 7. Worker controls (the log mean age of workers in the firm and the mean tenure of workers in the firm), firm controls (the extent of worker turnover in the firm (new employees/total employees and leavers/total employees) and firm size controls), and industry-year fixed effects are included in all regressions. The values of the relevant characteristic variable are also included in levels and lags in each specification. Standard errors, in parentheses, are clustered at the firm level. *** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$.

Source: authors' calculations based on data from South African administrative database.

5 Conclusion

This paper has examined the extent to which there are productivity spillovers through worker mobility. Using matched employer-employee data from South Africa, we find that the productivity difference between sending and receiving firms matters for the average firm-level productivity of the receiving firm. Controlling for human capital of workers, other worker-specific characteristics, and firm-specific characteristics, we find that hiring firms on average will experience a small productivity decline of 0.05 per cent in the year after hiring compared with an identical firm that did not hire any new workers. This average, however, hides important differences stemming from knowledge spillovers from workers coming from higher-productivity to lower-productivity firms as compared with spillovers from workers coming from lower-productivity to higher-productivity firms. We therefore decompose our results, and find that firms which hire workers from firms with higher productivity will experience a productivity gain of 0.38 per cent compared with identical firms not hiring new workers. However, the relatively large share of firms that hire a worker from a firm with lower productivity experience, on average, a loss in firm-level productivity of 0.48 per cent. The latter negative effect, which is not found in previous studies, signals that in the South African context it does not seem to be relatively harmless for firms to hire workers with 'inferior technologies'. The high skills deficit and the low level of general-purpose/soft-technology worker capabilities may well be driving this result.

Decomposing productivity spillovers into a number of different types of soft technologies, we do not find any evidence that differences in R&D expenditure or import/export intensity matter for labour mobility-induced productivity spillovers. However, we do find strong evidence that firm-level labour training initiatives matter. Our results therefore support that firm-level labour training initiatives are not only important for the firms themselves, but that they carry an externality that exists through improving general-purpose/soft-technology worker capabilities that eventually may reduce the current negative productivity effect of workers moving from low-productivity to high-productivity firms. An important mechanism for technology transfers in the future may therefore be driven by investments in firm-level training initiatives.

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Appendix

Table A1: Wage regression results using Abowd et al.'s (1999) estimator

Variables	
Switcher	0.065***
	(0.003)
Tenure	-0.023***
	(0.002)
Age 3	-0.086***
	(0.008)
Age 4	-0.055***
	(0.007)
Age 5	-0.035***
	(0.006)
Age 6	-0.018***
	(0.005)
Age 7	-0.006
	(0.004)
Age 8	-0.006**
	(0.042)
Output	0.064***
	(0.001)
Lag difference in output	0.006
	(0.002)
Capital	0.001
	(0.001)
Lag difference in capital	0.004***
	(0.001)
Labour	-0.019***
	(0.002)
Lag difference in labour	-0.007***
	(0.002)
Year 20	0.087***
	(0.003)
Year	0.130***
	(0.004)
Year	0.170***
	(0.005)
Year	0.207***
	(0.007)

Note: Standard errors, in parentheses, are clustered at the firm level. *** p < 0.1, ** p < 0.05, * p < 0.01.

Source: authors' calculations based on data from South African administrative database.

Table A2: Productivity and worker-embodied technological spillovers—baseline specification: control variables for Table 4

	Table 4, column (3)	Table 4, column (4)
Log mean age	0.030**	0.016
	(0.015)	(0.015)
Mean tenure	0.048***	0.049***
	(0.003)	(0.003)
Proportion new entrants		0.070*
		(0.043)
Proportion leavers		0.110**
		(0.057)
Size 2		-0.094***
		(0.009)
Size 3		-0.160***
		(0.009)
Size 4		-0.200***
		(0.010)
Size 5		-0.230***
		(0.011)
Size 6		-0.280***
		(0.012)
Size 7		-0.360***
		(0.020)
Size 8		-0.520***
		(0.067)
Constant	1.84***	2.010***
	(0.065)	(0.066)

Note: Standard errors, in parentheses, are clustered at the firm level. *** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$.

Source: authors' calculations based on data from South African administrative database.

Table A3: Productivity and worker-embodied technological spillovers—asymmetric spillovers: control variables for Table 5

	Table 5, column (3)	Table 5, column (4)
Log mean age	0.030**	0.016
	(0.015)	(0.015)
Mean tenure	0.0480***	0.049***
	(0.003)	(0.003)
Proportion new entrants		0.044
		(0.047)
Proportion leavers		0.110**
		(0.057)
Size 2		-0.094***
		(0.009)
Size 3		-0.160***
		(0.009)
Size 4		-0.200***
		(0.010)
Size 5		-0.230***
		(0.011)
Size 6		-0.280***
		(0.012)
Size 7		-0.360***
		(0.021)
Size 8		-0.530***
		(0.007)
Constant	1.84***	2.010***
	(0.065)	(0.066)

Note: Standard errors, in parentheses, are clustered at the firm level. *** p < 0.1, ** p < 0.05, * p < 0.01.

Source: authors' calculations based on data from South African administrative database.

Table A4: Productivity and worker-embodied technological spillovers—disaggregated: control variables for Table 6

	Table 6, column (1)	Table 6, column (2)	Table 6, column (3)	Table 6, column (4)
Log mean age	-0.0041	0.015	0.014	0.002
	(0.015)	(0.015)	(0.015)	(0.015)
Mean tenure	0.040***	0.048***	0.048***	0.041***
	(0.003)	(0.003)	(0.003)	(0.003)
Proportion new entrants	0.006	0.036	0.045	0.034
	(0.049)	(0.047)	(0.047)	(0.047)
Proportion leavers	0.110*	0.099*	0.110*	0.097*
	(0.056)	(0.056)	(0.056)	(0.056)
Size 2	-0.099***	-0.097***	-0.094***	-0.100***
	(0.009)	(0.009)	(0.009)	(0.009)
Size 3	-0.180***	-0.170***	-0.160***	-0.180***
	(0.009)	(0.009)	(0.009)	(0.009)
Size 4	-0.230***	-0.220***	-0.200***	-0.240***
	(0.010)	(0.010)	(0.010)	(0.010)
Size 5	-0.280***	-0.270***	-0.240***	-0.290***
	(0.011)	(0.011)	(0.011)	(0.011)
Size 6	-0.360***	-0.320***	-0.290***	-0.370***
	(0.013)	(0.013)	(0.013)	(0.013)
Size 7	-0.440***	-0.420***	-0.370***	-0.480***
	(0.024)	(0.021)	(0.021)	(0.022)
Size 8	-0.640***	-0.570***	-0.530***	-0.640***
	(0.064)	(0.067)	(0.069)	(0.071)
Log exports	0.004***			0.004***
	(0.001)			(0.001)
Log imports	0.007***			0.008***
	(0.001)			(0.001)
L.Log exports	0.0004			0.0001
	(0.001)			(0.001)
L.Log imports	-0.003***			-0.004***
	(0.001)			(0.001)
Log training exp		0.010***		0.009***
		(0.001)		(0.001)
L.Log training exp		0.002***		0.002**
		(0.001)		(0.001)
Log R&D exp			0.005***	0.003**
			(0.002)	(0.002)
L.Log R&D exp			0.003**	0.001
			(0.001)	(0.001)
Constant	2.490***	2.150***	2.040***	2.490***
	(0.071)	(0.067)	(0.066)	(0.069)

Note: Standard errors, in parentheses, are clustered at the firm level. *** p < 0.1, ** p < 0.05, * p < 0.01.

Source: authors’ calculations based on data from South African administrative database.