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Recruiting for Small Business Growth: Micro-level Evidence

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Abstract

We examine the link between new employees in leading positions and subsequent productivity in small- and medium-sized (SME) enterprises. Managers and professionals are likely to possess important tacit knowledge. They are also in a position to influence the employing firm. Exploiting rich and comprehensive panel data for Sweden in the 2001-2010 period and employing semi-parametric and quasi-experimental estimation techniques, we find that newly recruited leading personnel have a positive and statistically significant impact on the productivity of the hiring SME. Interestingly, our results suggest that professionals with experience from international firms and enterprise groups contribute the most to total factor productivity. Overall, the findings suggest the importance of mobility of leading personnel for productivity-enhancing knowledge spillovers to SMEs.

JEL classification: D22, D24, D83, J24, J62

Key words: recruitment, knowledge spillovers, firm growth, productivity, SME

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1. Introduction

Mobility of labour is considered crucial for the transfer of knowledge between firms and, hence, for innovation and growth (Almeida and Kogut 1999; Cooper 2001; Fosfuri et al. 2001). Managers and professionals can be expected to play a key role as knowledge carriers. They are likely to accumulate tacit knowledge as well as being in influential positions in firms. For small- and medium-sized enterprises (SMEs), recruitment of such leading personnel may be particularly instrumental for productivity growth. In spite of this, the role of white-collar recruitment as a contributor to SME productivity is to a large extent an unexploited research area, motivating the present study.

The importance of tacit knowledge spillovers for firm performance has been highlighted in previous research (e.g., Moretti 2004b; Boschma et al. 2014; Boschma et al. 2009; Andersson et al. 2013). Individuals carry knowledge that is not easily codified but through interaction can be transferred to other individuals. Such knowledge can, for instance, be gathered through education and work experience.

A seminal contribution by Moretti (2004b) focused on knowledge spillovers between American plants using data for plants that were operational in both 1982 and 1992. He finds that a high educational attainment outside a plant is important for plant productivity. Highly educated individuals working in different industries but within the same city seem to share their knowledge, which in turn boosts firm performance. Moretti (2004a) finds that a high share of college educated individuals increases the wages of non-educated individuals within the same city, partly because the former group appears to make the latter more productive.

Some studies suggest that labour mobility does not uniformly cause positive knowledge externalities but that the effect depends on the matching between the employee and employer as well as workplace similarity (e.g., Boschma et al. 2014; Boschma et al.

2009). In this vein, Balsvik (2011) study how the mobility of workers from multinational enterprises (MNEs) to other firms in Norway affects productivity.[1] She finds evidence to suggest that bringing in experience from an international firm – through employment – makes the receiving firm more productive than does the employment of other workers.[2] Parrotta and Pozzoli (2012) exploit data for Denmark on the hiring of technicians and post-secondary educated workers and find that recruitment has a positive impact on firm productivity and yet does not negatively affect 'donating' firms.

A related literature investigates the impact of recruitment on foreign trade, expecting recruitment of persons with foreign market knowledge and contacts to facilitate foreign market entry and success. Some studies have examined the impact of hiring immigrants or expats on firm exports and conclude that such recruitment helps firms to overcome barriers to foreign trade (e.g., Hiller 2013; Hatzigeorgiou and Lodefalk 2016; Lodefalk 2016). The impact appears to be strongest for recruitment of skilled personnel to smaller firms, which arguably have less experience in internationalisation.

Another literature that is closely related to this paper studies the importance of managers for firms. Mion and Opromolla (2014) investigate the impact of manager mobility on export by Portuguese firms. They find that managers with previous experience in exporting to a foreign market are linked to increased likelihood that the new employer will also export to that market, a relation that does not exist for non-managers. Interestingly, they suggest that the effect of manager mobility for firm productivity would be an interesting topic for future research. More generally, there are several studies that point to the key role of management

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[1] Fosfuri et al. (2001) theoretically predict such spillovers. They also mention evidence that being employed by an MNE is associated with more job training.

[2] A related study is Javorcik and Poelhekke (2014), who study how Indonesian former foreign owned firms perform once they are divested, i.e., sold to local owners. By applying a difference-in-difference approach and comparing current and former foreign owned firms, they conclude that the ownership change leads to a drop in total factor productivity. These findings suggest that foreign parent firms continuously provide the local firms with important knowledge.

for firm decisions and performance (e.g., Bertrand and Schoar 2003; Bloom and Van Reenen 2010, 2007).[3]

We contribute to these studies by focusing specifically on the impact of recruitment of white-collar workers in leading positions on subsequent growth in SMEs. Newly recruited managers and other professionals – such as mathematicians, computer system designers, and economists – arguably possess tacit knowledge that is of importance for the new employer. Moreover, due to their leading position, they may find it easier to share and apply their knowledge than do other white- or blue-collar workers, such as associate professionals, clerks and manual labour. Our focus on SMEs is motivated by the expectation that recruited managers and professionals have a more instrumental role when entering a small- or medium-sized rather than a large firm and by the consideration that SMEs are important for net job creation (e.g., Henrekson and Johansson 2010).[4] In addition, we analyse whether and to what extent knowledge spillovers have heterogeneous or homogeneous impacts depending on the previous work experience of the recruit. For instance, it is plausible to think that a new manager with previous experience from a large, multinational firm who comes to a small, non-international firm may have a different impact than one who lacks that experience (see, e.g., Fosfuri et al. 2001).

Empirically, we exploit detailed and comprehensive employer-employee registers from Statistics Sweden that give us the opportunity to match workers with their past

[3] There is a relatively large literature on interfirm labour mobility and firm innovation, including patenting (for a brief overview, see, e.g., Parrotta and Pozzoli (2012)). For example, Braunerhjelm et al. (2014) analyse the movement of research and development personnel and the impact on firms' innovation ability, concluding that the former employer benefits in terms of an extended network and the latter in terms of new skills. However, focusing on the patenting/innovation impact of interfirm mobility is restrictive, both since such activities are highly concentrated among firms and since they arguably do not fully capture the growth impact of worker mobility.

[4] SMEs have a less 'thick' intra-firm market in terms of services needed and a more limited pool of experience. An illustrative parallel may arguably be made to the relative importance of knowledge transfer from large and R&D-intensive to small and less R&D-intensive countries (Keller 2004). The SME focus also contributes to our understanding of heterogeneity in impacts of interfirm mobility across firms of different size. Moreover, SMEs would seem important for growth since there are indications that they create new innovative ideas and introduce new technology, which in later stages can be effectively adapted by larger firms due to economies of scale (Acs and Audretsch 2005; Daunfeldt et al. 2014).

and present employers in Sweden over the years 2001-2010. Importantly, our dataset contains detailed information on firms' employees, such as their previous workplaces and occupations, and on firm characteristics, such as firm size and affiliations. To provide results that are robust to endogeneity, we employ state-of-the-art algorithms for the estimation of total factor productivity, which is then regressed on recruiting variables while controlling for firm heterogeneity. As a robustness check, we adopt a combination of propensity score matching and a difference-in-difference estimator.

In a nutshell, we find that recruiting managers and professionals have a positive and statistically significant impact on the subsequent total factor productivity of the hiring firm. The within-firm association with productivity is almost twice as large as the one for recruitment of other workers. The impact of hiring leading personnel is the largest for professionals arriving from international firms and enterprise groups. The results seem to confirm our expectation that hiring leading personnel is associated with tacit knowledge spillovers that are instrumental for the subsequent growth of the SME. The results are robust to alternative specifications and estimators as well as endogeneity concerns.

The remainder of the paper is structured as follows. In Section 2 and 3, we elaborate on our conceptual and empirical framework. In Section 4, we present our data and descriptive statistics. Our econometric results are presented and discussed in Section 5 and the robustness analysis in Section 6. Finally, in Section 7, we offer concluding remarks.[5]

[5] Supplementary material is available in the online appendix.

2. Conceptual framework

Individuals gather knowledge, for example, through education, on-the-job training and communication, which may generate positive externalities that make their employer and other individuals and firms more productive (Moretti 2004b, 2004a; Becker 1964). They may, for example, learn about technology and its application, marketing, financing and management of firms in different situations. Part of that knowledge is tacit and therefore individually bound, and, arguably, this applies particularly to the knowledge acquired on the job (Polanyi 1962). Therefore, labour mobility becomes crucial for knowledge transfer between firms and, hence, for innovation and growth (Almeida and Kogut 1999; Cooper 2001; Fosfuri et al. 2001).[6] New workers may transfer knowledge to their colleagues about how to tackle specific problems by example or more generally through instruction and demonstration (Keller 2004).[7]

The movement of managers and professionals between firms is likely to be more strongly associated with knowledge transfer that promotes firm growth than is the movement of other workers.[8] Managers and professionals can be expected to have learnt from being in responsible positions at the donor firm; this is in terms of technologies, procedures, leadership and extended social networks. They arrive to a position where they likely can make their tacit knowledge count. They can transmit their ideas and hard won experience as well as extend the social networks of the recipient firm.[9] We also expect managers and professionals to more easily absorb the knowledge of the recipient firm than other workers, in part because of their experience from responsible positions and in part because they most likely are post-secondary graduates, which can be expected to be associated with general skills related to acquiring,

[6] The tacit knowledge we envisage is neither completely general nor specific in the terminology of Becker (1964) but rather somewhere in-between, enabling meaningful but incomplete transfer.

[7] Keller (2004) argues that despite recent technological advances, knowledge is most effectively transferred through face-to-face interaction, and recent research would seem to suggest that this is still the case (see, e.g., Denstadli et al. 2013; Gustafson 2012; Westermark 2013).

[8] Our conjecture is somewhat akin to the one of 'informed' and 'uninformed' staff in the model of Glass and Saggi (2002).

[9] The movement of managers and professionals may be beneficial for the new employer as well as the former employer through an extended social network. Hence, managers and professionals could work as links between employers (see, e.g., Braunerhjelm et al. 2014).

applying and transmitting knowledge. In combination, managers and professionals can therefore be expected to be in an advantageous position to identify and avail themselves of possibilities to make substantial contributions to the operations of the recipient firm, thus promoting growth.[10]

To frame our discussion on the impact of knowledge spillovers from the recruitment of managers and professionals on firm growth, we begin with a standard Cobb-Douglas production function. Consider the production function of a profit-maximising firm as:

$$Y_{it} = A_{it} K_{it}^{\beta} SL_{it}^{\gamma} UL_{it}^{\delta} \quad (1)$$

where Y_{it} is value-added in firm *i* at time *t*; A_{it} is total factor productivity (TFP); K_{it} is physical capital stock; SL_{it} and UL_{it} are skilled and unskilled labour, respectively; and the output elasticities are β, γ and δ.

TFP is, in turn, considered a function of the tacit knowledge of managers and professionals (MaP_{it}) as well as a vector $\boldsymbol{Z}_{it}$ of time-variant firm variables, which may or may not be observed, such as accumulated experience and networks of the firm.[11] More formally, we define:

$$A_{it} = f(MaP_{it}, \boldsymbol{Z}_{it}) \quad (2)$$

Equation (2) is our model of interest. We now turn to its estimation.

[10] Although a high level of labour mobility could lead to labour poaching, i.e., firms underinvest in their employees, the downsides are often assumed to be offset by the positive effect stemming from knowledge externalities (Boschma et al. 2009).

[11] It should be added that managers, professionals and other workers are included in the labour variables in eq. (1) according to their educational level. Strictly speaking, we therefore consider positive changes in MaP_{it} in eq. (2) to represent the spillover of tacit knowledge to the firm, i.e., an externality. However, for convenience, we will interchangeably use the terms recruitment of and knowledge spillovers from the hiring of managers and professionals, as well as the abbreviation MaP_{it}. We may add that one common way to try to indirectly measure technology is through its effects on productivity, in addition to measuring R&D expenses and patents (Keller 2004).

3. Empirical framework

To empirically estimate equation (2) and analyse the productivity effect of MaP_{it}, we need to obtain the TFP of the firm.

3.1 Estimation of total factor productivity

TFP is commonly computed as the residual from equation (1), that is, $A_{it} = Y_{it}/K_{it}^{\beta}SL_{it}^{\gamma}UL_{it}^{\delta}$. Therefore, we first need to know the output elasticities. Conceptually, we might receive such estimates by applying ordinary least squares estimation to the log-linearised version of equation (1) while excluding A_{it} and assuming it to have zero mean in conditional expectation. However, a well-known problem in this regard is that firms are likely to simultaneously adjust their input choices to expected productivity shocks using more (less) inputs in the event of positive (negative) shocks (see, e.g., the overview in Van Beveren 2012). The simultaneity of input choices and productivity shocks, which are now in the error term, violates the basic exogeneity assumption of ordinary least squares estimation. It is likely to lead to biased estimates of the output elasticities and, in turn, a biased estimate of the firm's TFP.[12]

Researchers have suggested various parametric and semi-parametric techniques to address this problem. Parametric fixed effects estimators could be used to capture time-invariant parts of firm heterogeneity, but they have not performed well empirically, leading to questions about the underlying assumptions (Olley and Pakes 1996; Ackerberg et al. 2007; Levinsohn and Petrin 2003). Instead, Olley and Pakes (1996) and Levinsohn and Petrin (2003) have proposed structural approaches using semi-parametric estimators. The idea is to find a variable – for example, material inputs or capital investment – that is costless to adjust to anticipated but unobserved short-term productivity shocks, for example, expected breaks in production due to exchange of key machinery. The variable is then used as a proxy for

[12] Selection bias is another issue with OLS panel estimation of TFP when disallowing the entry and exit of firms.

unobserved productivity shocks. It is assumed to be a monotonous function of TFP and is conditioned on observables. TFP can then be inverted out.

Practically, in equation (1), TFP is replaced by the inverted out and non-parametric function of the proxy variable and observables. Having estimated the output elasticities of the production factors, the elasticity of the proxy variable can be retrieved from non-linear estimation of a variation of (1) under assumptions on firm dynamics in terms of productivity and the proxy variable. Finally, one computes TFP as the residual from the resulting production function.

However, more recently, there has been criticism that collinearity between labour and the proxy variables may complicate identification of the labour output elasticity parameter, again resulting in biased TFP-estimates (Ackerberg et al. 2015; Bond and Soderbom 2005). Ackerberg et al. (2015) instead extend the Olley and Pakes (1996)-estimator by only using the first-stage estimation to retrieve the residual in the estimation of equation (1). In the second stage, they estimate the unknown parameters and then finally compute TFP, as previously explained.

In this paper, we slightly extend the technique of Ackerberg et al. (2015) along the lines of Vandenberghe (2013). The latter considers the importance of controlling for firm heterogeneity in TFP-estimation to fulfil the underlying monotonicity assumption and to improve identification of the output parameters. In effect, this means that we control for time-invariant firm-specific effects in the first stage estimation. Then, we retrieve the estimated parameters and lastly estimate TFP. Finally, we arrive at our empirical version of equation (2) to analyse the role of MaP_{it} for firm growth.

In the first stage, we generate the predicted $\hat{y}_{it}$, with lower-case letters indicating natural logarithms, by estimating:

$$y_{it} = \alpha + \beta k_{it} + \gamma sl_{it} + \delta ul_{it} + \varphi_t(.) + v_i + \varepsilon_{it} \quad (3)$$

where φ_t is a second-order polynomial of the input variables and material, a polynomial that proxies for unobserved productivity shocks; v_i is unobserved time-invariant firm heterogeneity; and ε_{it} is an i.i.d. error term. In other words, we exploit contemporary information to obtain value added net of unanticipated shocks and measurement error. Next, we use non-linear optimisation to obtain the output elasticity estimates, given certain moment conditions.[13] The conditions follow from the assumptions that all input variables but not the proxy variable – materials – are determined in advance and cannot be as easily adjusted and that productivity follows a first-order Markov process. The latter means that current TFP is equal to its expectation conditional on TFP in t-1 plus an innovation or news component ξ_{it}, which is assumed to be mean independent of information known in the previous period. Specifically, we use the moments below to estimate the output elasticities:

$$E\left[\xi_{it}\middle|\begin{matrix}K_{it}\\ SL_{it-1}\\ UL_{it-1}\end{matrix}\right]=0 \qquad (4)$$

Having estimated the output elasticities while controlling for the simultaneity problem through semi-parametric technique, we are ready to proceed to the empirical specification of equation (2).

3.2 Empirical specification

Formally, we consider a firm's expected conditional total factor productivity as a function of the recruitment of managers and professionals as well as other covariates:

$$E[a_{it}|MaP_{it-n}, O_{it-n}, \boldsymbol{Z}_{it-n}, v_i] = \zeta_{MaP}MaP_{it-n} + \zeta_O O_{it-n} + \boldsymbol{\zeta}_Z\boldsymbol{Z}_{it-n} + \boldsymbol{\zeta}_I\boldsymbol{I}_{it-n} + v_i \qquad (5)$$

where i is the firm; t is the year; n is the lag dimension, which is one for recruitment variables and two for covariates; MaP_{it-n} represents employment of managers and professionals; O_{it-n}

[13] In this stage, we use robust and firm-clustered standard errors from 50 block bootstrap replications.

represents the employment of other workers; $\boldsymbol{Z}_{it-n}$ is a 1 x K1 vector of firm covariates (log of firm size, log of firm age, multinational affiliation and legal form); $\boldsymbol{I}_{it-n}$ is a 1 x K2 vector of fixed effects (industry, year, municipality); and v_i is again time-invariant firm heterogeneity. MaP_{it-n} and O_{it-n} enter the specification unlogged since far from all SMEs are likely to recruit new employees a particular year.

We include the employment of other workers, O_{it-n} to control for knowledge spillovers that otherwise may bias the results, even if such workers are expected to have substantially less influence on firm growth than managers and professionals. In the $\boldsymbol{Z}_{it-n}$ vector, we include variables that, if excluded, may cause omitted variable bias. In essence, we consider the variables to be related to the experience and social networks of the firm as well as the ambitions within the firm (see, e.g., Haltiwanger et al. 2013; Kogut and Zander 1993; Li and Yueh 2011; Baik et al. 2015).

Our empirical specification is dynamic in the sense that it has a lagged structure. Productivity is a function of knowledge spillovers through the recruitment of managers and professionals in the preceding year, conditioned on covariates previously established. We expect knowledge spillovers to follow only from repeated and intense interaction between the new recruit and the firm, as discussed in social network theory (Granovetter 1973). In short, it takes time for knowledge to be transferred and applied by the firm so that it may affect firm growth (Keller 2004).[14] Another motivation for the lagged structure is to reduce remaining endogeneity concerns.

As mentioned, we control for time-invariant firm heterogeneity. Estimation is therefore focussed on the within-firm variation of productivity. We consider this important to avoid, for example, differences in the ability of owners of firms to drive our results. In

[14] Alternatively, one may think of the recruitment as a strategic investment that takes time to pay off. Even if, e.g., technology may be instantly understood by the one exposed to it, as in the theoretical model of Glass and Saggi (2002), its application and its pay off may take time to materialise.

addition, we pay careful attention to other confounding factors at the industry and municipal level as well as across time by including corresponding fixed effects.

Returning to the issue of endogeneity, we cannot completely rule out that actual or anticipated firm growth results in the employment of managers and professionals rather than the reverse. Such selection into the hiring of managers and professionals may introduce an endogeneity bias in the estimation of equation (5). To test the robustness of the results from the lagged within-firm specification of equation (5), we employ a quasi-experimental model.

First, we generate a counterfactual by finding valid controls to 'treated' firms through the nearest neighbour (one-to-one) propensity score matching with replacement (Rosenbaum and Rubin 1983). We divide firms into those that hire managers and professionals ('treated') and those that instead hire other workers ('controls')[15]. Then, we match each treated firm with a control based on observable pre-treatment characteristics likely to affect assignment into treatment. If correctly implemented, the matching generates a control group that has the same likelihood of treatment as the group of treated firms, whereby treatment is as if randomly assigned. We therefore assume that the productivity outcome is independent of participation in the treatment (recruitment of influential versus less influential workers), conditional on the pre-treatment observables – the so-called conditional independence assumption (CIA).

Formally, the conditional expected treatment status, which equals the propensity score ρ, is:

$$E(D_i = 1|a_{it}, \boldsymbol{X}_{it}) = P(D_i = 1|\boldsymbol{X}_{it}) = f(\boldsymbol{X}_{it}) + IND_{it} + TREND_t \qquad (6)$$

[15] Using this definition of controls, we only compare firms that all decide to hire new personnel. Consequently, we expect to reduce heterogeneity, such as decisions to recruit, and we estimate the relative effect from hiring leading personnel.

where $D_i = \begin{matrix} 1, & \Delta MaP_i>0 \wedge \Delta O_i=0 \\ 0, & \Delta MaP_i=0 \wedge \Delta O_i>0 \end{matrix}$; $\boldsymbol{X}_{it}$ is a 1 x K vector of pre-hiring characteristics of the firm (including lagged firm size, value-added, age, share of managers and professionals, share of skilled workers, the average age of workers, and the squared values of selected variables); IND_{it} is a two-digit industry indicator variable; and $TREND_t$ is a common trend variable. Based on the resulting ρ, we assign each treated firm with a control using nearest neighbour (one-to-one) matching with replacement.[16] The productivity outcome is then independent of the type of recruited workers, assuming the CIA holds.

Second, we adopt a Difference-in-Difference (DiD) estimator to control for time-invariant unobservable firm heterogeneity and time-variant shocks that may affect treated firms and controls differently (Blundell et al. 2004; Heckman et al. 1997). We use the estimator to analyse the potentially differential growth impacts of recruitment of managers and professionals versus that of other workers in the post-recruitment period. After constructing the counterfactual and assuming that this controls for selection into recruitment of influential workers, we estimate the average effect λ_{ATE} on the treated firms, where

$$\lambda_{ATE} = E[E(a_{it'}|D_i = 1) - E(a_{it}|D_i = 0)] \tag{7}$$

Having described our methodology and arrived at our main empirical specification – equation (5) – as well as the robustness check – equation (7) – we now present our data, descriptive statistics and preliminary evidence.

4. Data and descriptive statistics

For our empirical analysis, we construct a matched employer-employee dataset that covers the time period 2001-2010 using four registers of Statistics Sweden. Merging information from the various registers is facilitated by the fact that all individuals, plants, firms and enterprise

[16] We also impose the common support condition in the matching to minimise potential matching bias; that is, we require that the probability of recruiting managers and professionals is strictly positive for all firms.

groups in Sweden have unique identifiers; thus, less reliable statistical matching methods are superfluous.

In most of our analysis, the Structural Business Statistics (*"Företagens ekonomi",* FEK) register is the point of departure. The FEK register contains the population of private non-financial Swedish firms with at least one employee, and is available over the 1998-2013 period.[17] The register includes information such as employment, value added and turnover. To this we merge information from the Firm and Plant Dynamics (*"Företagens och arbetställenas dynamik",* FAD) and the Enterprise Group Register ("Koncernregistret", KCR). FAD contains data on firm dynamics in terms of employment. It assigns each firm a numeric code based on whether the majority of a firm's personnel in a given year constitutes a majority or minority of the firm's workforce the forthcoming year. KCR contains data on firms that are part of an enterprise group, such as whether they are foreign owned.

Since we are interested in organic growth in productivity, we exploit information from FAD to only include firms where a majority of the workforce in year *t* is a majority in year *t*+1.[18] Put differently, we keep firms that are persisting in the sense that the personnel composition remains similar. The approach also helps us to control for confounding factors related to mergers or acquisitions.

Next, we merge the firm-level data with individual-level data from the Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA), which covers the universe of Swedish residents who are at least 16 years old. Information

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[17] The excluded organisations are sole proprietorships without employees, financial industry firms, and a limited number of other categories (housing cooperatives, international organisations and public administration). Exploiting the LISA database, which is subsequently described, we note that none of the excluded organisations that are privately held have a strong tendency to hire leading personnel, while publicly held organisations – which are generally of large size – do ('Appendix' Table A1). The latter are, nevertheless, excluded both for conceptual and practical reasons since our focus is on profit-driven private firms and we lack information on key variables, e.g., value added, for the excluded organisations.

[18] The FAD codes are based on different combinations of two conditions: (A) $\left(\frac{G_i}{EMP_{it'}}\right) > 0.5$; and (B) $\left(\frac{G_i}{EMP_{it}}\right) > 0.5$, where $G_i = EMP_{it'} \cap EMP_{it}$, and EMP_{i*} is employment in time *t* or *t'*. In this study, we consider a firm as remaining iff. both (A) and (B) hold.

such as individuals' educational background and age is included. By combining the firm- and individual-level data, we are able to match information about the workers with their respective workplaces. For instance, we are able to observe how many workers within a firm have a certain type of education, workers' age, and importantly for our purposes, their previous workplace.

Since we are interested in recruitment to leading positions in firms, we exploit the occupational classification of workers, which is contained in LISA. Occupations are classified according to the Standard for Swedish Occupational Classification (SSYK, rev 1996), which corresponds to the International Standard Classification of Occupations (ISCO-88). SSYK ranks occupations into ten hierarchical main levels.[19] The levels are based on the skills required to perform a certain job and its complexity. The top two categories are 'Managers' (SSYK 1) and 'Professionals' (SSYK 2), and these are of our main interest. For instance, these categories include CEOs, mathematicians, engineers and economists. The SSYK variable entered the LISA database in 2001, which restricts our analysis to the time period 2001-2010.

Finally, we limit our analysis to small and medium sized firms for reasons already explained and remove extreme outliers. We define an SME as a firm with at most 249 employees during a particular year (OECD 2005). The resulting unbalanced panel dataset encompasses approximately 139,000 and 167,000 firms in the final and ending years 2001 and 2010, respectively ('Appendix' Table A2).[20]

[19] The ten main categories are: 1. Managers, senior officials and legislators; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators as well as assemblers; 9. Elementary occupations; and 0. Armed forces.

[20] In year 2010, there were approximately 215,000 firms in the matched dataset, with 214,000 being SMEs. After removing firms that likely have developed non-organically, there are approximately 172,000 firms. Removing extreme outliers, we have 167,167 SMEs. ('Appendix' Figure A1)

In Table 1, we provide a snapshot of our sample in 2010.[21] The average firm is a micro-enterprise, having just eight employees. Approximately two of them are employed as managers and professionals and six as other workers.[22] The median firm is even smaller, having three employees. The average firm is small also in terms of recruitment, although there is quite a lot of heterogeneity as captured by the standard deviation. The average firm approximately recruits 0.2 managers and professionals and one other worker.[23] Altogether, the firms in our sample recruited approximately 212,000 workers in 2010, with approximately 5 percent being managers, 11 percent professionals and 84 percent other workers ('Appendix' Table A4). On average, a firm is ten years old and does not belong to an enterprise group. Additionally, the results display that firms are very heterogeneous and that large firms substantially skew the distribution of firms in variables such as value added and physical capital stock.

[21] Presented is the total number of firms in our sample. Due to restrictions in the estimation of TFP, our analysis includes approximately 60,000 firms annually. For a definition of key variables, see 'Appendix' Table A3.
[22] The reason why the employees in the two categories do not exactly add up to the mean is that a small minority of workers have not been assigned an occupational code. However, reassuringly, further analysis reveals that there is no systematic pattern of missing information across the distribution of occupational codes and industries
[23] In our sample, limited liability firms hire most of the newly hired leading personnel; although the average number of hired managers and professionals is the highest in foreign owned firms; see 'Appendix' Table A1.

Table 1. Descriptive statistics. Year 2010.

	Mean	Median	Std. Dev.	Min.	Max.
No. of employees	8,15	3	18,56	1	249
Managers and professionals (MaP)	1,62	1	5,85	0	227
Other workers	6,05	2	15,02	0	240
Newly hired					
Managers	0,06	0	0,34	0	21
Professionals	0,15	0	1,05	0	81
Other workers	1,07	0	3,43	0	158
Newly hired MaP					
from large to small firm*	0,03	0	0,18	0	6
from small to small firm*	0,18	0	1,18	0	88
from enterprise group to stand-alone SME	0,03	0	0,30	0	35
from one to another enterprise group	0,08	0	0,66	0	55
within same enterprise group	0,01	0	0,31	0	62
from stand-alone firm to SME	0,03	0	0,27	0	25
from foreign trading firm to SME	0,09	0	0,67	0	63
from non-foreign trading firm to SME	0,11	0	0,66	0	51
from MNE to non-MNE affiliated firm	0,03	0	0,31	0	32
from and to non-MNE firm	0,11	0	0,70	0	80
Firm age	10,21	12	5,67	0	37
Enterprise group status	0,25	0	0,43	0	1
Multinational status	0,05	0	0,21	0	1
Value added	4 335	1 132	17 396	-739 877	2,15E+06
Physical capital stock	5 109	1 003	113 024	-221,8	2,19E+07

Notes: Data refer to the year 2010. Number of firms is 167,167. Monetary values are in 1,000 SEK (approximately 123 USD). * (Here, large and small refer to the 75th and 15th percentiles in the distribution of all firms, respectively, corresponding to cut-offs of 835 and 15 employees. Hence, small firm<16 employees; large firm>834 employees)

To understand recruitment patterns, we provide details on where newly recruited managers and professionals come from. We find that most of them are ‘donated’ by other SMEs rather than from large firms. The finding is contrary to what might be expected, as small firms could benefit from the expertise of large firms by hiring their leading personnel.

The result might be explained by the fact that most potential recruits work for SMEs.[24] Studying recruitment from an enterprise group perspective, we note that a substantial amount of leading personnel are recruited from and to firms that are affiliated with an enterprise group.[25] Turning to what category of workers firms of different sizes recruit, we find that micro-enterprises hire many managers relative to other SMEs, whereas the other SMEs hire relatively many professionals. An explanation might be that the very small firm needs to fill key management positions, whereas the larger SME recruits to complete the competence bloc of the firm (Johansson 2010).[26]

Having reviewed the descriptive statistics from our panel dataset, we also need to prepare for our subsequent robustness analysis by defining the cohorts for matching and DiD estimation. We define a cohort as a group of firms that is followed over a four-year window – 2002-2005 or 2006-2009 – since we would like to observe the firm one year before and two years after 'treatment'. The firms either recruit managers and professionals ('treated', $D_i = 1$) or other workers ('controls', $D_i = 0$) in year t+1, but they do not recruit at any other point in time within the window.[27] We only let a firm be treated once, but a firm can possibly be in the control group during both periods. Together, the two cohorts contain 94 treated and 70 control firms. The small number of firms is due to the mentioned restrictions in the matching procedure; both in terms of employment pattern and the within same industry requirement. The average firm does not hire in a particular year, and many firms are therefore excluded from the matching and DiD analysis. As for the characteristics of treated and controls, we note that the treated firms generally are somewhat older and have a somewhat larger workforce and value added ('Appendix' Table A6.)

[24] In addition, larger firms may be more well positioned than smaller firms to recruit leading personnel and also be regarded as more attractive employers.
[25] That the sums of mean recruitment from firms with different affiliations do not add up to the total is due to the fact that donors may be organisations for which the affiliation variables are missing, e.g., municipalities or government agencies, which account for a large share of employment in Sweden.
[26] Descriptive statistics for TFP are available in 'Appendix' Table A5.

To ensure that firms within each like-for-like pair have a similar probability of recruiting leading personnel, thereby avoiding biased results, their pre-treatment characteristics should be similar. To reduce heterogeneity further, we only allow matched pairs within the same industry and year. We evaluate the matching by performing balancing tests on the matching variables. The mean of the variables should not differ significantly between treated and controls, and the standardised percentage bias should be small. As a rule of thumb, an average bias of less than |5 %| is preferable (Rosenbaum and Rubin 1983). The results are presented in 'Appendix' Table A6. We conclude that the matching performs reasonably well overall. The *t*-tests testing the null hypothesis of equal means are not rejected for 10 out of 12 matching variables at conventional levels of statistical significance. The average bias decreases from approximately 31 % before the matching procedure to 16 % for our matched sample. Hence, our matching does not perform as well in terms of the bias measure.[28] However, in general, we are able to construct a matched sample of treated and controls that have similar means in most of the pre-treatment characteristics.

5. Econometric results

We now turn to our econometric results from the estimation of equation (5), which are displayed in Table 2. We start out by presenting OLS results in Column 1 as a point of reference.[29] As expected, productivity is positively associated with firm size and age as well as multinational enterprise affiliation. The result for leading personnel confirms our expectation that the recruitment of managers and professionals is positively associated with productivity. Since recruits enter the specification in numbers, the resulting regression

[28] We are aware that using a small sample of firms in the matching procedure makes the analysis sensitive to outliers, where a single firm could have a large effect on both the average balance and bias. We also emphasize reasoning when evaluating matching performance. Consider, for instance, firm size, with an average of 3.4 and 3.1 employees for the treated and controls, respectively, but with an average bias of size 14.3 %, above the five percent threshold.
[29] The results for specifications where we sequentially introduce the covariates are available in 'Appendix' Table A7.

coefficient is a semi-elasticity. The result suggests that hiring another manager or professional is linked to approximately 2.7 percent higher productivity in the subsequent year, all else equal.

Table 2. Benchmark estimation results

	(1)	(2)	(3)	(4)
	OLS		Within-firm estimation	
Managers and professionals$_{t-1}$	0.0265***	0.00221***	0.00217***	0.00216***
	(0.00135)	(0.000764)	(0.000764)	(0.000758)
Others$_{t-1}$	-0.0129***	0.00145***	0.00147***	0.00123***
	(0.000367)	(0.000323)	(0.000323)	(0.000323)
Firm size (log)$_{t-2}$	0.212***	0.0623***	0.0624***	0.0668***
	(0.00199)	(0.00585)	(0.00585)	(0.00584)
Firm age	0.00194***	0.0110***	0.0110***	0.0257
	(0.000337)	(0.000698)	(0.000699)	(0.0166)
Multinational enterprise (0,1)	0.211***	-0.0411***	-0.0412***	-0.0409***
	(0.00719)	(0.0108)	(0.0108)	(0.0108)
Obs.	360,415	360,415	360,415	360,415
Adjusted R^2	0.12	0.68	0.68	0.68
Firm FE		y	y	y
Industry			y	y
Year				y

Notes: The response variable is total factor productivity (log). In Column 1, we present OLS estimation results, and, in Columns 2-4 within-firm estimation results, with robust and firm-clustered standard errors in parantheses. The legal form of the firm is controlled for throughout. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results discussed may be biased due to heterogeneity at several levels. In Columns (2)-(4), we therefore gradually introduce specific effects at the firm, industry and year level. When we control for unobserved time-invariant firm heterogeneity (Column 2), the association between hiring leading personnel and productivity is reduced to a tenth of its previous size while still being economically and statistically significant. Recruiting other workers is less strongly linked to productivity growth. Adding further specific effects only marginally affects the results (Columns 3-4). Our benchmark within-firm estimation results are displayed in Column (4). The semi-elasticity for leading personnel is 0.00216. In other words, we find that hiring an additional manager or professional is on average associated with a 0.2 percent increase of the productivity of the hiring SME. Reassuringly, our result for leading personnel is qualitatively in line with, although substantially more conservative than, the results for technicians and graduate workers in the firm-level study of Parrotta and Pozzoli (2012) using a panel of Danish firms.[30]

Next, we re-estimate equation (5) but separate the recruitment of managers and professionals to consider potential heterogeneity in impacts. We do not have any strong á priori expectations. On the one hand, managers are in charge of the daily business while being directed by the owner or a board of directors. Therefore, they may be more strongly related to firm productivity than professionals. On the other hand, managers range from chief executive officers to division managers and lower-level operations managers, while professionals, for example, include scientists with doctoral degrees who are likely instrumental in research and development that may underpin the future of a firm and who may bring in technological knowledge from their former employer.[31] Ultimately, the issue is therefore an empirical one. In Table 3, we display the empirical results. We find that managers have no statistically significant association with firm productivity, whereas the association for professionals is stronger than for the group of both managers and professionals. We interpret the results as suggesting that SMEs primarily need to complete their competence blocs for growth, including bringing in technological knowledge, rather than fill positions in the daily management of the firm.

[30] We may add that their study, *i.a*., differs from ours in that their employment variables single out technicians (part of SSYK 3), which in our study are included in the group of other workers, and workers with at least a bachelor's degree, irrespective of their occupational classification. Since our group of managers and professionals (SSYK 1 & 2) is more narrowly defined and, e.g., pays attention to the fact that there is a considerable mismatch between education and jobs for many workers, such as immigrants, we would have expected the hiring impact to be comparatively larger in our study. We conclude that the quantitative difference in the results is likely to be due, at least partly, to differences in our modelling approaches.
[31] SSYK classifies all personnel who are responsible for other workers, their wages or budget as managers.

Table 3. Estimation results for managers and professionals, separately

	(1)
Managers$_{t-1}$	-0.00190
	(0.00304)
Professionals$_{t-1}$	0.00288***
	(0.000898)
Others$_{t-1}$	0.00135***
	(0.000334)
Firm size (log)$_{t-2}$	0.0666***
	(0.00584)
Firm age	0.0257
	(0.0166)
Multinational enterprise (0,1)	-0.0407***
	(0.0108)
Obs.	360,415
Adjusted R^2	0.68

Notes: The response variable is total factor productivity (log). Results are from within-firm estimation. We control for firm, industry and year specific effects as well as for the legal form of the firm. In parantheses are robust and firm clustered standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01

We also would like to investigate the extent to which the background of the new recruit matters for the receiving SME. As discussed in the introductory section, previous evidence suggests that recruits from, for example, exporting or multinational firms are instrumental for non-exporting or standalone firms. We therefore use the categories that we included in the descriptive statistics also in our econometric analysis, with the results displayed in Table 4. We first consider the case where a recruit to a leading position is 'donated' by a firm of an enterprise group (Columns 1-3). Interestingly, only professionals from enterprise groups and entering stand-alone SMEs are associated with a statistically significant change in productivity. Those entering affiliated firms or firms of other enterprise groups are not linked to productivity impacts. As regards managers, the only statistically significant link is for entry into firms of another enterprise group, but the link is slightly negative. A similar result for managers is found for those arriving from multinational enterprises to SMEs that have no such affiliation, as displayed in Column (4).

Table 4. Estimation results discerning the background of newly hired

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	From enterprise group to stand-alone firm	From other firm in the enterprise group	From other enterprise group to the firm of another enterprise group	From an MNE	From a large firm	From a foreign-trading firm to a non-trader	From a non-foreign trading firm to a non-trader
$Managers_{t-1}$	-0.00904	0.00472	-0.0112**	-0.0143*	0.00118	-0.00434	0.0104
	(0.00974)	(0.00615)	(0.00440)	(0.00732)	(0.00515)	(0.0121)	(0.00937)
$Professionals_{t-1}$	0.0151*	0.00132	0.00218	0.00963***	0.00340*	0.0113***	0.00508*
	(0.00858)	(0.00138)	(0.00306)	(0.00249)	(0.00175)	(0.00297)	(0.00361)
$Others_{t-1}$	0.00139***	0.00129***	0.00150***	0.00142***	0.00136***	0.00323***	0.00311***
	(0.000320)	(0.000318)	(0.000325)	(0.000321)	(0.000321)	(0.000825)	(0.000793)
Obs.	360,415	360,415	360,415	360,415	360,415	253,313	253,313
Adjusted R^2	0.68	0.68	0.68	0.68	0.68	0.66	0.66

Notes: The response variable is total factor productivity (log). Results are from within-firm estimation. We control for firm, industry and year specific effects as well as for the legal form of the firm. In parantheses are robust and firm clustered standard errors. For brevity, other covariate estimates are not reported. * p < 0.10, ** p < 0.05, *** p < 0.01

In Columns (4)-(7), we also note that professionals arriving from multinationals, enterprise groups and foreign-trading firms are substantially more strongly associated with subsequent productivity growth than they are in the benchmark results.[32] This result is in line with our expectations that professionals that arrive from firms with substantial resources can contribute a great deal to the SME that employs them, for example, by promoting innovation and marketing. Hiring an additional professional from a firm that participates in foreign trade or from an MNE is associated with a 1 percent increase in the recruiting firm's productivity. As regards the result for professionals arriving from foreign traders in non-trading SMEs, the finding is well in tune with the literature on heterogeneous export behaviour of firms, where exporting firms are 'the best' firms within their industries (see, e.g., Bernard et al. 1995).[33]

[32] In a related study, using data for Norway, Balsvik (2011) finds that newly hired workers from MNEs have a stronger impact on firm productivity than workers hired from elsewhere.
[33] In additional analysis, we note that key individual characteristics hardly differ between recruits from foreign trading and multinational firms versus other recruits ('Appendix' Table A8).

6. Robustness analysis

How robust are our results to endogeneity and specification issues? We test this by first employing our DiD matching estimator that provides a like-for-like comparison of difference-in-difference treatment effects. In Table 5 and Figure 1, we present our results from estimating equation (7).[34] The average treatment effect on the treated is 0.16 one year after treatment, suggesting that treated firms' productivity growth is 16 percent higher across the time period one year prior to one year after recruitment than is the productivity growth of control firms'. Two years after hiring, treated firms have even more productivity growth (27 percent) compared with control firms' productivity growth. These findings qualitatively confirm our benchmark result; this reassures us that our main findings are not driven by endogeneity, such as selection into recruitment, or macroeconomic shocks.[35]

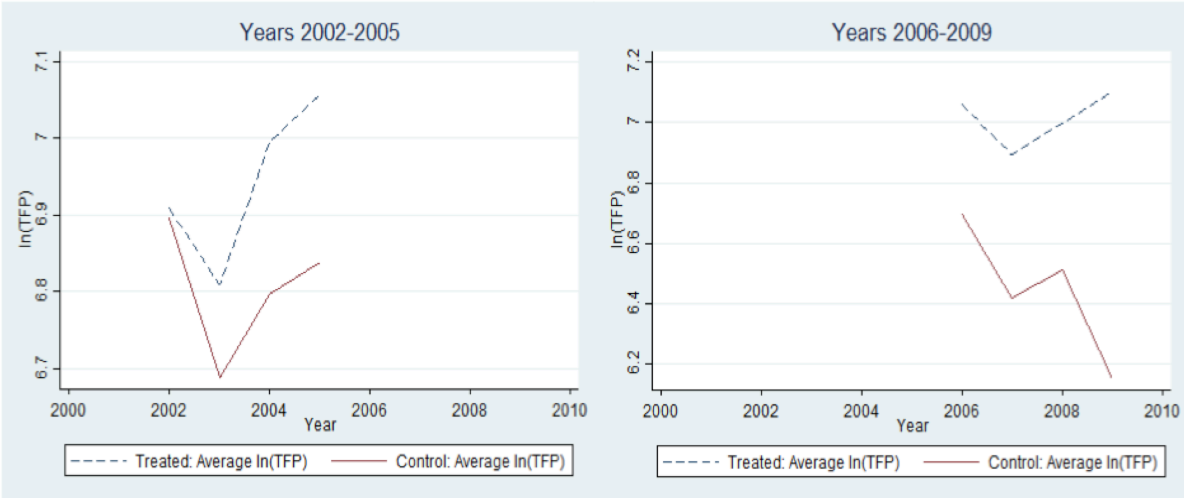
Table 5. DiD matching estimator results

	(1) *t*+1	(2) *t*+2
Managers and professionals	0.163** (0.073)	0.265** (0.106)

Notes: Presented are the average treatment effects on the treated from the DiD matching estimations, using nearest neighbour matching with the common support assumption. The response variable is growth in total factor productivity (log). The number of treated firms (hiring managers and professionals) is 94, and the number of control firms (hiring other workers) is 70. In parantheses are robust and firm clustered standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[34] The corresponding probit results are available in 'Appendix' Table A9.
[35] One of the key assumptions of DiD is that the pre-treatment trends in the outcome variable (TFP) are parallel. Observing the graphs, it is noticeable that the pre-treatment trends are not identical but fairly similar, in particular during the second treatment period. The results are also qualitatively robust to matching on the lagged trend in TFP ('Appendix' Table A10 and Figure A2).

Fig. 1 DiD matching estimator results – Average treatment on the treated



Notes: The figures present the average treatment effect on the treated from the DiD matching estimations, using nearest neighbour matching with the common support assumption. The response variable is growth in total factor productivity (log). The time periods are 2002-2005 and 2006-2009, where treament occurs in either 2003 or 2007. The total number of treated firms (hiring managers and professionals) is 94, and the total number of control firms (hiring other workers) is 70.

We now turn to the specification issues by presenting additional results in Table 6. In Columns (1)-(2), we have re-estimated equation (5) while including municipality and industry-year specific effects. Potentially, SMEs may be affected by both positive and negative factors in their local milieu, including, for example, access to a harbour or a university, and omitting these factors may bias our results. Likewise, the industry of an SME may experience shocks that radically change the competition for or demand of the SME, and this may also introduce omitted variable bias. Reassuringly, our results scarcely change at all after controlling for such unobserved heterogeneity.[36] In Column (3), we check whether dropping the linearity of our specification with respect to leading personnel alters our benchmark result. We find that adding the square of the variable does not qualitatively alter our key results. The semi-elasticity increases somewhat, and the squared term only displays a very small negative coefficient, suggesting a diminishing return to hiring managers and professionals that is of little economic importance.

[36] The results are also robust to, e.g., controlling for the foreign-trading status of the SMEs; and the employment of a partial adjustment model, in which the lagged value of the response variable is included as a covariate (Table A11, 'Appendix'). Using an estimation of total factor productivity from an OLS FE estimation does not qualitatively change the results, but results in inflated semi-elasticities.

Table 6. Robustness analysis

	(1) Municipality FE	(2) Industry*Year FE	(3) Non-linear link
Managers and professionals$_{t-1}$	0.00214***	0.00217***	0.00353***
	(0.000759)	(0.000758)	(0.00122)
Managers and professionals$^2_{t-1}$			-2.63e-05*
			(1.38e-05)
Others$_{t-1}$	0.00123***	0.00123***	0.00119***
	(0.000323)	(0.000323)	(0.000324)
Firm size (log)$_{t-2}$	0.0666***	0.0668***	0.0670***
	(0.00578)	(0.00585)	(0.00585)
Firm age	0.0256	0.0256	0.0258
	(0.0167)	(0.0166)	(0.0167)
Multinational enterprise (0,1)	-0.0422***	-0.0409***	-0.0410***
	(0.0109)	(0.0108)	(0.0108)
Obs.	360,415	360,415	360,415
Adjusted R^2	0.68	0.68	0.68

Notes: The response variable is total factor productivity (log). Results are from within-firm estimation. We control for firm, industry and year specific effects as well as for the legal form of the firm. In Column 1, we also include municipality specific effects, and in Column 2 industry*year specific effects. In parantheses are robust and firm clustered standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, we may add that additional results suggest that the recruitment of leading personnel has a negative contemporaneous impact on productivity, a positive but decreasing positive impact in the second and third year and a positive but statistically insignificant impact in the fourth year (‘Appendix Table A12’). The pattern is in line with our previous discussion that spillovers of tacit knowledge through the hiring of leading personnel may take time to pay off in terms of improved productivity.

7. Concluding remarks

The role of white-collar recruitment for SME productivity growth is largely an unexploited research area. The gap in research is at odds with the generally recognised importance of tacit knowledge spillovers for economic growth and with the prevalence of SMEs. Indeed, Mion and Opromolla (2014) highlight the effect of manager mobility for productivity as a topic for future research.

This paper contributes by exploiting comprehensive and very detailed employer-employee panel data in the 2001-2010 period to analyse the impact of recruiting managers and professionals on the productivity of small and medium-sized enterprises. We employ state-of-the-art algorithms for estimating total factor productivity, which, in turn, is regressed on recruiting variables while controlling for firm heterogeneity. We also adopt a quasi-experimental technique to test the robustness of our results. Importantly, we are able to analyse whether impacts differ depending on the matching between the donating and receiving firm.

We find evidence to suggest that the tacit knowledge carried by managers and professionals can be instrumental for the productivity of SMEs. Hiring an additional manager or professional is on average associated with a 0.2 percent increase in subsequent firm productivity. Interestingly, professionals generally contribute the most to firm productivity. The strongest impact – at least three times as large – comes from recruiting leading personnel from international firms and enterprise groups.

Our findings underline that mobility of senior personnel is key for the growth of SMEs. Managers and professionals can be expected to both have experience and the ability to absorb and relay tacit knowledge. For SMEs that generally have less experience and resources than large firms, such personnel might propel the firm in a new trajectory, in particular if the recruits are from better-endowed firms. As shown by the booming Swedish gaming industry, which is dominated by SMEs, being able to recruit key personnel from Sweden and internationally may be a necessary component of comparative advantage (Holm 2014).

However, SMEs are arguably unable to compete easily with the salaries of larger and more established firms due to their relative weak economic situation. Moving to an SME is also associated with downsides for other reasons. SMEs are often more prone to lay-offs or even exit from the market than more established firms are. Legislation that protects the labour force can make the leap to an SME even riskier since the potential recruit may lose job protection related to the length of employment at the current employer.

From an economic perspective, it therefore seems imperative to facilitate the mobility of leading personnel and their recruitment to SMEs. For example, policymakers may consider removing unnecessarily restrictive firing regulations, such that SMEs can keep newly recruited key personnel in the event of layoffs. Another proposal may be to enable SMEs to more easily match the salaries and job security of more established firms by offering favourably taxed employee stock options, which SMEs can use to attract managers and professionals.

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