

# Managerial knowledge spillovers and firm productivity\*

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## Abstract

The present paper brings together empirical findings suggesting, on the one hand, that heterogeneity in managerial knowledge is an important driver of differences in firm productivity, and on the other, that labour mobility plays a central role in the transmission of knowledge between firms. We test whether the mobility of managers leads to better firm performance by estimating a structural model of production and recovering firm-level productivity. We explore the characteristics of movers and sending firms that result in productivity gains for hiring firms, at both the aggregate and industry levels. Results suggest that hiring managers from other firms has strong positive effects on both firm survival and future productivity. Stronger effects are found when movers have relevant experience, advanced qualifications and come from firms with higher human capital. Furthermore, the effects decrease with the productivity level of the hiring firm, suggesting that managerial mobility helps laggard firms catch-up to more productive firms, and has a potential effect on reducing productivity dispersion.

**JEL Classification:** L2, J6, M1, D83, J24

**Keywords:** Firm productivity, Knowledge spillovers, Management, Labour mobility, Human capital

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# 1 Introduction

In the knowledge-based view of the firm put forward by Prescott and Visscher (1980), firms are characterised by organisational knowledge that allows them to combine their various inputs to produce output and effectively compete on the market. This production-relevant knowledge accumulates with output and is embedded in the workers of the firm. From the empirical perspective, the World Management Survey provides wide-ranging evidence of the importance of managerial capabilities for various measures of firm performance, from productivity to survival (Bloom and Van Reenen (2007), Bloom et al. (2016)). These authors have documented large heterogeneity in managerial quality across countries and industries, where very well managed firms coexist with very poorly managed ones.

The present paper seeks to understand how this managerial knowledge can be transmitted throughout the economy, and how laggard firms can learn from more advanced firms. In particular, we are interested in exploring whether the labour mobility of managers is a useful vector for the transmission of managerial knowledge between firms. Learning-by-Hiring has been shown to be instrumental for the transmission of knowledge, especially concerning technological knowledge (Parrotta and Pozzoli (2012)) or information relating to export markets (Mion and Oromolla (2014)).

The implementation of our research question is based on identifying firm-level productivity, and analysing how it responds to the mobility of managers. We explore whether hiring managers from other firms leads to higher productivity and which characteristics of movers and sending firms result in stronger effects. We compared this to the departure of managers to other firms, to the internal promotion of incumbent staff to managerial positions, and to non-managerial hires.

Our analysis uses the Finnish Linked Employer-Employee Data (FLEED), for the period 2003-2012, which allows us to identify all hires of managers and to link sending and hiring firms. We use the production data relating to turnover, labour, capital stock and intermediary inputs to estimate a structural model of production, following Akerberg et al. (2015). We depart from the literature on Learning-by-Hiring where spillovers are considered to be an additional input, and instead follow Doraszelski and Jaumandreu (2013) by including the spillover variables directly within the process of productivity, and by controlling for its impact on the probability of survival.

Our results broadly suggest that on average managerial hires have a positive effect on firm productivity, which is accentuated when managers have experience, advanced qualifications and come from firms with high human capital. We find that replacing half of a firm's managers with externally hired managers is associated with an increase in productivity of 2%, which can reach 4% for firms starting with low productivity. For these laggard firms, most managerial hires have beneficial effects, in particular hires from the frontier of the distribution, whereas firms at the frontier only gain from hiring well qualified managers coming from firms with important human capital.

The paper is structured as follows. Section 2 provides an overview of the different strands of literature on which this paper builds. Section 3 presents the data and provides reduced form evidence consistent with the presence of Learning-by-Hiring. Section 4 discusses the theoretical model and empirical strategy used to estimate firm-level productivity and the impact of managerial mobility thereon. Finally, Sections 5 and 6 present the results and conclude.

## 2 Literature review

The present analysis is firmly grounded in the knowledge-based theory of the firm of Prescott and Visscher (1980) and Grant (1996). The former argue that firm boundaries are determined by the accumulation and application of relevant knowledge to production. A firm is defined by its organisational capital, the information it has concerning the quality of its workforce, the appropriateness of the matches between employees and tasks, and the human capital of workers. The authors' model of the accumulation of such knowledge within firms explains observed patterns of firm size distributions and growth patterns. Grant (1996) emphasises a view of the firm as an 'institution for integrating knowledge' and argues that the organisational capital of firms mainly resides within the individuals working for them. To secure its competitive advantage, a firm must set up the relevant organisational practices for the distribution of decision-making authority in order to apply its knowledge most effectively.

From the empirical perspective, the presence, quality and impact of firms' organisational knowledge has been explored with the development of surveys relating to the implementation of various practices. Examples cover the development of learning organisations that create opportunities for employees to use and develop their competencies, flat hierarchies, the empowerment of workers, self-governing teams, and the use of temporary structures and lateral communications

as enabled by the adoption of ICTs (see, e.g. van Alstyne (1997); Birkinshaw and Hagstrom (2000); and Hales (2002)). In their comprehensive survey of the practices intended under organisational capital Black and Lynch (2005) argue, contrary to Prescott and Visscher (1980), that organisational capabilities do not accumulate as a by-product of production, but are the result of explicit investment decisions and implementation of practices, such as workforce training, employee voice and work design.

The seminal paper of Bloom and Van Reenen (2007) introduced the World Management Survey (WMS), which has become a benchmark for many subsequent analyses of the importance of management quality. The paper details the methodology of the survey, carried out in manufacturing firms in the United States, the United Kingdom, France and Germany. In particular, management quality is defined as adopting practices in four areas: operations management, monitoring individual performance, setting and enforcing targets, and using career incentives to attract and retain talent. The authors find that their constructed measure of management quality is positively associated with productivity, profitability, Tobin's Q, sales growth and survival, and that differences in competitive pressure and ownership structure explain the majority of the gap in management quality between the United States and the European countries. Furthermore, through a Randomised Control Trial, Bloom et al. (2013) show that the positive relationship between management quality and firm performance can be interpreted as a causal one.

Bloom et al. (2016) make both an empirical and theoretical contribution. The authors discuss the extension of the WMS to 11,000 firms across 34 countries and multiple industries including services, health care and education. They also develop a model of management as a technology. This model assumes that there is a monotonic relationship between management quality and firm performance, and that management quality is the result of an optimising decision process by firms who trade-off adjustment costs, depreciation and marginal product. They recover the adjustment costs and depreciation rate of managerial capital from the WMS panel data and find that these are higher than for physical capital. Finally, they replicate the results of Bloom and Van Reenen (2007), by showing that the management quality variable is strongly positively associated with measures of firm performance.

On par with other technological knowledge, managerial knowledge explains a significant part of performance. The present analysis seeks to build on these findings by exploring a particular avenue through which firms can acquire this productivity enhancing knowledge, namely labour

mobility. Indeed, a large literature has exploited linked employer-employee data to look at the transmission of knowledge through Learning-by-Hiring. The effect of hiring workers from other firms on the recipient firm's productivity has been explored by authors such as Stoyanov and Zubanov (2012) and Parrotta and Pozzoli (2012) for Denmark, Maliranta et al. (2009) for Finland and Stockinger and Wolf (2016) for Germany.

Stoyanov and Zubanov (2012) estimate the effect of the productivity gap between hiring and sending firms on the hiring firm's labour productivity. The authors find that hiring workers from more productive firms has an immediate positive effect of around 0.35%, and lasts for around 4 years. They also find that this effect is more pronounced when the workers are more educated or occupy managerial functions. Parrotta and Pozzoli (2012) find comparable results from estimating a structural model according to Akerberg et al. (2015), where they introduce Learning-By-Hiring as an additional input into production. The Learning-By-Hiring variable is based on the hiring of tertiary educated workers, who obtain at least a 5% wage increase from the move, resulting in a wage that is higher than both the one they had in the past 3 years and the average wage of the hiring firm, and who did not spend more than 3 months in unemployment. In addition, they test for the importance of the technological proximity of the sending and hiring firms using patent data. They find that the recruitment of knowledge carriers increases a firm's value-added by 1%-2%.

Estimating a structural model where hires from firms with "Spillover Potential" (SP) are included as additional inputs, Stockinger and Wolf (2016) find, on the contrary, that the evidence for the existence of spillovers strongly decreases when controlling for the selection of workers into firms. In particular, the authors rank firms according to their median wage, and individuals according to their rank in the firm's wage distribution, and define SP-hires as coming from firms better ranked in the wage distribution. In Finland, Maliranta et al. (2009) classify a firm's workforce according to their hiring status, age, former position, and current position, to explore their effect on various measures of firm performance. In particular, the authors look at the role of hires from employees in Research and Development (R&D) positions into similar R&D positions and into alternative non-R&D positions. They look at three types of dependent variables: growth in profitability, growth in labour productivity, and wage growth. Their main finding is that there seems to be no productivity spillovers when workers move from R&D positions into R&D positions, while there are spillovers when they move into non-R&D positions.

Following a different approach, authors such as Poole (2013) and Mion and Opromolla (2014)

have explored the distribution of potential spillover gains by looking at the effect of labour mobility on wages. Poole (2013) compares the effect of new hires with and without experience in foreign multinational enterprises (MNE) on individual wages of workers in Brazilian domestic firms. The author finds that a 10% point increase in the share of workers with experience in MNEs increases individual wages by 23\$ per year. She also finds that larger effects are found in knowledge-intensive industries and in less unionised industries. Finally, she finds that spillovers increase in the education level of both the MNE workers and domestic workers. In a similar vein, Mion and Opromolla (2014) estimate Mincerian wage regressions integrating mobility of managers and their past experience in exporting firms. They find that the only occupational category to witness a wage premium from export experience are managers. In a second step, the authors also model the firm's entry and continuation in export markets, as a function of hiring managers with export experience. They find no effect on entry into export markets, but a positive effect on continuation, suggesting that these spillovers affect the marginal costs of exporting more than its sunk costs.

At the intersection of these two strands of literature, the present paper seeks to provide evidence of the importance of managers for production, and especially of their mobility across firms as a source of knowledge transmission. The findings presented above suggest that both the characteristics of the movers, in particular their education level, and the characteristics of the sending firm, such as productivity, export status and human capital, are important to pin down the presence of spillovers.

### **3 The Finnish Linked Employer-Employee Data**

#### **3.1 The data**

The dataset used in the present analysis is the Finnish Linked Employer-Employee Data (FLEED). The Employee data cover all residents aged between 15 and 70 and contain both personal information such as age, gender, qualification, and family status, and professional information. Of particular importance is the firm identifier, recorded in the last calendar week of each year, registering the individual's main employer, as well as their occupation, recorded following the International Standard Classification of Occupations (ISCO). This latter piece of information allows us to easily identify which employees occupy managerial functions, interpreted in a broad sense to encompass middle managers and supervisors, as these are the individuals who are likely

to be directly involved in the implementation of high performance practices and to be repositories of managerial knowledge (Le Mouel and Squicciarini (2015)). This departs from the literature which focuses on top CEOs and their impact on the company strategy and corporate culture (Bertrand and Schoar (2003), Gabaix and Landier (2008)).<sup>1</sup> Information concerning the highest qualification obtained is used to control for the quality of human capital of both individuals and firms. We observe three levels of qualification: high school graduation, Higher Education (HE, covering vocational and bachelor degrees), and advanced HE (covering masters and doctoral degrees).

On the Employer side, the dataset covers all firms in the economy, and contains information on production variables, such as turnover, labour input in Full-Time Equivalent (FTE), capital stock, investment and expenditure on intermediary inputs. The unavailability of firm-level prices for either inputs or outputs restricts our ability to measure quantity productivity, and we will recover revenue productivity instead.<sup>2</sup> Small firms of less than 5 employees are dropped from the analysis because of their different production structures compared to larger firms. As seen in Table 1 they account for a negligible fraction of managerial recruitment in the economy, as many are in practice managed by their owners, and therefore their exclusion from the analysis should not bias our results. Firms in their first year of appearance are also dropped, to avoid the particular dynamics involved in firm creation, mergers, and acquisitions, as are firms in the Mining and Real Estate sectors. In total, the data cover around 30,000 firms per year, for the period 2003 to 2012.

### 3.2 Constructing the spillover variable

Our main variables of interest seek to measure the spillover potential that hiring firms are exposed to. We construct yearly flow matrices  $F_t$ , where element  $f_{ist}$  counts the numbers of workers transitioning from sending firm  $s$  in  $t-1$  to hiring firm  $i$  in  $t$ . We restrict our attention to firm-to-firm transition, and acknowledge that we cannot measure whether there were short unemployment periods or short employment spells in a third firm between 2 records, as these are measured in the last calendar week of the year. From the flow matrices, we count the number of hires that move into managerial or non-managerial positions, and the number of departing

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<sup>1</sup> An additional consideration to motivate our choice is the change in ISCO classification that took place in 2011. Using a broader definition of managers is less subject to measurement error in the transition year.

<sup>2</sup> All nominal production variables are deflated using industry-level price deflators from the OECD STAN database. Further details are provided in the Data Appendix.

managers and non-managers, and construct two vectors of variables. The first vector measures the spillover potential in hiring firm  $i$  coming from managerial hires,  $\mathbf{spill}_{it}$ , and the second captures other mobility measures in the firm,  $\mathbf{mobility}_{it}$ , which are included in all specifications of the model as controls.

In the baseline version of the model,  $\mathbf{spill}_{it}$  is constructed as the share of current managers that are newly hired, irrespective of profile and origin. The different specifications of the model correspond to the different splits of the managerial hire variable by characteristics of the mover or the sending firm. Firstly, the share of newly hired managers is split by managerial experience: we distinguish between managers who were already a manager in the sending firm, and call them experienced managers, from those who did not occupy managerial functions before the transition, which we refer to as external promotions. Secondly, we look at industry experience and identify managers who come from the same narrow 2-digit industry as the hiring firm (eg. Computer manufacturing), from other industries within the broad 1-digit industry (eg. Manufacturing), and those who come from outside the broad industry. Thirdly, we focus on the qualification of managers and classify managerial hires into three groups: up to high school qualification (noHE), Higher Education (HE) qualification and advanced Higher Education (advHE). Fourthly, we look at the human capital in the sending firms by calculating the average share of HE qualified and advanced HE qualified workers in the firms of origin of newly hired managers. Finally, we split the share of hired managers according to the productivity quartile of the sending firms (where productivity is recovered from the structural model).

The vector  $\mathbf{mobility}_{it}$  encompasses three control variables. The departure of managers to other firms in the previous period takes into account the disruptive effects of managerial mobility and gives an estimate of the costs in terms of lost productivity to the sending firms. Internal promotions, identified as employees who change their occupational status from non-managerial to managerial while remaining in the same firm, provide a benchmark for a baseline effect of having more managerial staff. Finally, the hiring of non-managerial workers serves as a control for the employment dynamics within the firm.

### 3.3 Descriptive statistics

Tables 1 and 3 summarise the patterns of labour mobility, by firm size and industry respectively. The first five columns show the yearly shares of firms that have experienced at least one mobility event (hire or departure of managers and non-managers and internal promotions). The subse-

quent columns report the share of managers in the total workforce, the survival rate and the number of firms. Table 1 shows that very micro firms (with less than 5 employees) differ from the rest of the firm population on the share of managers they employ, the fraction of managers hired externally and survival rates. For the firms included in our analysis, we observe a positive relationship between firm size and all mobility events. For example, the share of firms that hire a manager from outside is only 5.6% for micro firms and reaches 70% for large firms. This is associated with similar increases in the share of managerial departures, resulting in a very stable ratio of managers in total employment across firms of different sizes, from a minimum of 5.8% in large firms (more than 250 employees) to a maximum of 8.1% in medium small firms (20 to 49 employees). We also note that survival rates are very constant, at around 95.5%.

In Table 2 we compare the propensity of firms to hire managers from other firms compared to promoting internal staff, according to whether they experienced the departure of their managers in the previous period. Panel A shows the share of firms where at least one manager was hired or promoted in firms where no manager departed to another firm. Firms have a slightly higher tendency to internally promote managers than to hire them externally, with the exception of large firms. Panel B shows the case where firms did experience the departure of at least one manager, and paints a different picture. In these circumstances, the share of firms hiring external managers is around 10% points higher than that of firms replacing managers through internal promotion. We also observe twice as many firms engaging in hiring and promotions in years where they experienced the departure of managers compared to years where they did not. Results from this table highlight the importance of controlling for the departure and internal promotions of managers in our model.

Table 3 provides the same information as Table 1, broken down by 1 digit industry, the level at which the production function is estimated. We observe important heterogeneity in the share of managers in total employment, ranging from a low of 3.5% in the Logistics sector (Transport and Warehousing) and of 3.9% in the Construction sector to a high of 10.6% in the Hospitality (Hotels and Restaurants) and of 14.2% in IT services. This heterogeneity is reflected in the heterogeneity in mobility patterns: the sectors with the lowest mobility of managers are Logistics and Construction, and those with the highest mobility are IT services and Hospitality. Sectors with the highest survival rate are Utilities, Agriculture and Logistics, while those with the lowest survival rates are Hospitality, Administrative Activities and IT services.

Finally, Table 4 describes the average production variables, highest market share and pro-

portion of HE and advanced HE qualified workers by 1 digit industries. The sectors with the highest labour productivity are Utilities, Manufacturing and IT services. These are also the most concentrated sectors, where the largest firms have the highest market share (calculated as the share of sales of the 2 digit industry). Finally, IT services and Professional services stand out as the sectors with the highest human capital: the share of workers with advanced qualification is 18.9% and 19.5% respectively, and the share of workers with HE is 36.6% and 40.6% respectively. On the other end of the spectrum, Construction, Logistics and Hospitality have the lowest human capital: the share of workers with advanced HE is no larger than 1%, and the share of workers with HE is around 10%.

### 3.4 Reduced form evidence

We first present reduced form evidence of the relationship between managerial hiring and labour productivity, measured as value-added per Full-Time Equivalent. The transition matrix presented in Table 5 shows, for each quartile of the labour productivity distribution, the share of firms moving to other quartiles or out of the market. Firms are split according to their hiring status, with firms with no managerial hires displayed in Panel A, and firms with managerial hire displayed in Panel B. Managerial hiring seems to have a strong impact on firm survival, especially for firms in the bottom quartile of the distribution. Compared to an average exit rate of 4.5% at the economy level, the exit rate of firms in the bottom quartile who did not hire managers is 9.2%, whereas it is reduced to 2.5% for firms in the bottom quartile who did hire managers. We observe no clear pattern for the role of managerial hiring on the destination of surviving firms in the middle two quartiles. In both the bottom and top quartile however, hiring managers leads to a much higher share of firms who stay in their quartile of origin. This is particularly striking for firms in the top quartile: the share of firms who remain in the top quartile is 75.4% compared to 68.6% for firms with and without managerial hiring respectively.

Table 6 presents results of OLS regressions of log labour productivity on the  $\mathbf{spill}_{it-1}$  and  $\mathbf{mobility}_{it-1}$  variables, controlling for one lag of labour productivity and the probability of survival. Results suggest that managerial hiring is positively associated with labour productivity. In the baseline model, if a firm replaces half of its managers with externally hired managers, this is associated with an increase in labour productivity of 1% in the following period<sup>3</sup>. In

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<sup>3</sup> The variable of interest is measured as the share of managers that joined the firm in the previous period. The interpretation of the coefficient is such that if a firm replaces all of its managers with externally hired ones, it will observe a 2.1% increase in labour productivity. If it replaces only half of its managers with externally

the subsequent models, we find that managers with experience have a stronger effect than first-time managers, that industry experience in the narrow 2-digit industry has a weaker effect than experience outside that same industry, and that the size of the effect strongly depends on the qualification level of the managers. Furthermore, we find that the departure of managers has a strong disruptive effect on labour productivity: if a firm loses half of its managers it can expect a drop in labour productivity of 2.25%. The internal promotion of managers is associated with a 0.68% increase in labour productivity the year following the promotion, and firms who replace half of their employees observe a drop in labour productivity of 3.6%.

These reduced form results support the hypothesis that managerial hiring is a source of Learning-by-Hiring, which helps firms improve their future productivity. However, these results do not take into account the endogeneity in production decisions that affect productivity measurement, nor do they adequately control for the potential for selection of managers into firms. The following section presents the theoretical model and associated empirical strategy used to address these issues.

## 4 Methodology

### 4.1 Model

**Production function** We assume a translog revenue-generating function of the form

$$\begin{aligned}
 y_{it} &= f(l_{it}, k_{it}, m_{it}; \boldsymbol{\alpha}) + \omega_{it} + \epsilon_{it} \\
 &= \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \alpha_{ll} l_{it}^2 + \alpha_{kk} k_{it}^2 + \alpha_{mm} m_{it}^2 + \alpha_{lk} l_{it} k_{it} + \alpha_{lm} l_{it} m_{it} + \alpha_{km} k_{it} m_{it} + \omega_{it} + \epsilon_{it}
 \end{aligned}
 \tag{1}$$

where  $y_{it}$  is turnover,  $l_{it}$  is labour input,  $k_{it}$  is capital stock, and  $m_{it}$  is expenditure on intermediary inputs such as materials<sup>4</sup>.  $\omega_{it}$  is the firm-specific unobserved productivity that is the focus of our estimation, and  $\epsilon_{it}$  is an i.i.d shock that picks up measurement error in sales and unanticipated production shocks (e.g. machine breakdown, strikes etc...).

As argued in Olley and Pakes (1996), reduced-form estimates of the production coefficients suffer from an endogeneity bias which stems from productivity being an observable state variable that firms take into account when making production decisions. Higher productivity firms are

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hired ones, it can expect  $2.1 \cdot 0.5 = 1.05\%$  increase in labour productivity

<sup>4</sup> All variables are in logs and corrected for the industry-year mean. Labour input is measured in Full-Time Equivalents

more likely to decide to produce more output and employ more inputs. This implies that the production coefficient of flexible inputs, like labour and materials, are going to be upward biased, while the sign of the bias on fixed inputs, like capital stock, is more difficult to determine *a priori*. We follow the approach pioneered by Olley and Pakes (1996) and further developed by Levinsohn and Petrin (2003) and Akerberg et al. (2015), which relies on the timing of input decisions to find a proxy for productivity. A flexible input of production, decided after current productivity has been observed by the firm, such as intermediary inputs or labour, will therefore contain information about productivity, and can be used as a proxy. In the present analysis, intermediary inputs are assumed to be flexible and decided in period  $t$ , taking state variables as given, while labour is considered to have some adjustment costs and to be decided in  $t - 1$ . The productive stock of capital is a fixed dynamic input that results from the accumulation and depreciation of investments.<sup>5</sup>

**Demand for intermediary inputs** The demand for intermediary inputs depends on the following state variables: labour and capital inputs, which have adjustment costs and are decided prior to intermediary inputs and the stock of human capital ( $\mathbf{HC}_{it}$ ) of incumbent workers measured as the average age, the share of men and the shares of high school graduates, HE graduates and advanced HE graduates. In addition, firm-level prices are part of the firm’s state space, but are unobserved in our dataset. The market share of the firm ( $s_{it}$ ) is included to control for general demand conditions and thus output prices, and firm-level average log wages ( $w_{it}$ ) control for all input prices, such as the prices of intermediary inputs. Finally, we allow the demand for intermediary inputs to depend on the arrival of new managers ( $\mathbf{spill}_{it}$ ) and other mobility patterns ( $\mathbf{mobility}_{it}$ ) in the current period, because these changes affect production decisions through the impact on the employment structure, the allocation and performance of tasks. By controlling for the contemporaneous effect of hires and departures, we ensure that the estimated effect on productivity picks up an effect beyond this additional manpower. The demand for intermediary inputs is thus given by

$$m_{it} = h_t(k_{it}, l_{it}, \omega_{it}, \mathbf{HC}_{it}, s_{it}, w_{it}, \mathbf{spill}_{it}, \mathbf{mobility}_{it}) \quad (2)$$

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<sup>5</sup> The use of fixed-effects estimation does not fully address the issue in the case of time-varying productivity. Furthermore, the Arellano-Bond first difference estimator is nested within our model, when we assume an AR(1) process for productivity. The full structural model allows for a more flexible law of motion.

We obtain an expression for productivity by inverting this equation following the proof set out in Levinsohn and Petrin (2003). We need to assume that productivity is the only unobservable that enters the demand for intermediary inputs and does so monotonically.

$$\omega_{it} = h_t^{-1}(k_{it}, l_{it}, m_{it}, \mathbf{HC}_{it}, s_{it}, w_{it}, \mathbf{spill}_{it}, \mathbf{mobility}_{it}) \quad (3)$$

**Law of motion of productivity** Following the literature, we assume that productivity follows a first-order Markov process and model managerial hires as an action that firms can undertake to directly affect their productivity process, in a similar fashion to how exporting or investing in R&D have been modelled (Olley and Pakes (1996), De Loecker and Warzynski (2012), Doraszelski and Jaumandreu (2013), Akerberg et al. (2015)). The law of motion of productivity takes the following form

$$\omega_{it} = g(\omega_{it-1}, P_{it-1}, \mathbf{spill}_{it-1}, \mathbf{mobility}_{it-1}) + \xi_{it} \quad (4)$$

where  $\xi_{it}$  is an i.i.d shock. The presence of these variables, lagged by one period, in the productivity process reflects our assumption that a firm's workforce, especially the managers, are repositories of production-relevant knowledge affecting firms' ability to successfully combine labour, capital and material inputs to obtain higher output. We can therefore test whether there is a Learning-by-Hiring effect that takes time and happens in addition to the immediate effect on sales arising from the performance of daily tasks, and included in the demand for intermediary inputs. Finally, the firm's probability of survival  $P_{it-1}$ , which is positively correlated with both firm productivity and the spillover and mobility variables, is included to capture the endogeneity between these variables.

## 4.2 Estimation strategy

Productivity  $\omega_{it}$  is recovered using a three-step estimation strategy. The first stage allows us to net out the effect of the shock to production  $\epsilon_{it}$  by controlling for productivity with the proxy variable. In the second stage, we estimate the probability of survival of the firm. Finally, the third stage allows us to identify the unbiased production coefficients<sup>6</sup>, and to recover the law of motion of productivity.

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<sup>6</sup> We have 9 production coefficients to estimate:  $\alpha_l, \alpha_k, \alpha_m, \alpha_{ll}, \alpha_{kk}, \alpha_{mm}, \alpha_{lk}, \alpha_{lm}, \alpha_{km}$ .

**Estimation of the first stage** In the first stage, we substitute  $\omega_{it}$  in the production function (1) by its expression in (3) to get the following expression

$$\begin{aligned} y_{it} &= f(l_{it}, k_{it}, m_{it}; \boldsymbol{\alpha}) + h_t^{-1}(k_{it}, l_{it}, m_{it}, \mathbf{HC}_{it}, s_{it}, w_{it}, \mathbf{w}_{it}, \mathbf{spill}_{it}, \mathbf{mobility}_{it}) + \sigma_t + \epsilon_{it} \\ &= \varphi_t(k_{it}, l_{it}, m_{it}, \mathbf{HC}_{it}, s_{it}, w_{it}, \mathbf{w}_{it}, \mathbf{spill}_{it}, \mathbf{mobility}_{it}) + \sigma_t + \epsilon_{it} \end{aligned} \quad (5)$$

where  $\sigma_t$  are time fixed effects. We estimate  $\varphi_t(\cdot)$  with a polynomial of order 3, and recover the fitted value  $\hat{\varphi}_t$ , which provides estimates of productivity  $\omega_{it}$  up to the production coefficients, which still need to be estimated. The expression for  $\omega_{it}$  on which the moment conditions are built in the third stage is

$$\hat{\omega}_{it} = \hat{\varphi}_t(k_{it}, l_{it}, m_{it}, \mathbf{HC}_{it}, s_{it}, w_{it}, \mathbf{w}_{it}, \mathbf{spill}_{it}, \mathbf{mobility}_{it}) - f(l_{it}, k_{it}, m_{it}; \boldsymbol{\alpha}) \quad (6)$$

**Estimation of the second stage** We run a probit model to predict the probability of survival of the firm, which depends on capital stock, a dummy for large firms above 250 employees,  $\mathbf{spill}_{it}$ ,  $\mathbf{mobility}_{it}$ , firm-level wages, the human capital of incumbent workers, and industry and time fixed effects. We also add the yearly industry shares of start-ups that were dropped in the data preparation stage to account for industry dynamics that likely affect the survival of incumbents. Predicted survival probabilities  $\hat{P}_{it}$  are included in the law of motion of productivity as described below.

**Estimation of the third stage** The unbiased production coefficients and  $\omega_{it}$  are recovered using GMM estimation. Our moment condition is built around  $\xi_{it}$ , the i.i.d shock of the law of motion of productivity, which is observed by firms in  $t$  and uncorrelated with past productivity

$$\begin{aligned} E[\xi_{it} \mid I_{it-1}] &= 0 \\ E[\hat{\omega}_{it} - g(\hat{\omega}_{it-1}, \hat{P}_{it-1}, \mathbf{spill}_{it-1}, \mathbf{mobility}_{it-1}) \mid I_{it-1}] &= 0 \end{aligned} \quad (7)$$

where  $\hat{\omega}_{it}$  and  $\hat{\omega}_{it-1}$  are obtained from Equation 6.

In practice, we assume two specifications for the law of motion of productivity (4). In the first specification  $\mathbf{spill}_{it-1}$  and  $\mathbf{mobility}_{it-1}$  enter linearly as such

$$\omega_{it} = \delta_1 \omega_{it-1} + \delta_2 \omega_{it-1}^2 + \delta_3 P_{it-1} + \delta_4 P_{it-1}^2 + \delta_5 \omega_{it-1} P_{it-1} + \gamma_1 \mathbf{spill}_{it-1} + \gamma_2 \mathbf{mobility}_{it-1} + \xi_{it} \quad (8)$$

and in the second specification, these variables are interacted with the firm’s productivity as such

$$\begin{aligned} \omega_{it} = & \delta_1\omega_{it-1} + \delta_2\omega_{it-1}^2 + \delta_3P_{it-1} + \delta_4P_{it-1}^2 + \delta_5\omega_{it-1}P_{it-1} \\ & + \gamma_1\mathbf{spill}_{it-1} + \gamma_2\omega_{it-1}\mathbf{spill}_{it-1} + \gamma_3\mathbf{mobility}_{it-1} + \gamma_4\omega_{it-1}\mathbf{mobility}_{it-1} + \xi_{it} \end{aligned} \quad (9)$$

This latter specification tests whether managerial hiring has heterogenous effects, and leads to estimating firm-specific marginal effects of hiring on productivity.

The instruments used to estimate the production coefficients are chosen in accordance with our the timing assumptions. We use the current value of capital because its value was determined one period ahead. The adjustments costs to labour arising from the rigidities in the Finnish labour market lead us to use both current and lagged values of the labour input. Finally our assumption regarding the static nature of intermediary inputs implies using its past values as instruments. However, we find that adding current value of expenditures on intermediary inputs drastically improves our ability to pin down the capital coefficient, which suggests that intermediary inputs might also have adjustments costs. We therefore use current and lagged values of both labour and intermediary inputs and their respective squared and interaction terms.<sup>7</sup>

### 4.3 Discussion of identification

The assumptions stated above embed our analysis in the framework of Akerberg et al. (2015) and allows us to argue that our production coefficients are identified. However, the identification of the law of motion of productivity, in particular of the spillover effects emerging from the mobility of managers requires further attention. The literature on sorting in the labour market argues for the presence of inherent selection in labour mobility, suggesting that ‘better’ managers are attracted and more likely to be hired by ‘better’ firms (Abowd et al. (1999)). Important motivations for this effect are better career and pay prospects offered by more productive firms. Our analysis seeks to account for potential sorting by controlling for observable characteristics of both the movers and the hiring firm. On the manager side, we split managerial hiring according to mover characteristics, as explained above. On the side of hiring firms, we control for the average wage paid by the firm and the human capital of its workforce. Furthermore,

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<sup>7</sup> The full list of instruments used is the following: constant term,  $k_{it}, l_{it}, m_{it}, l_{it-1}, m_{it-1}, k_{it}^2, l_{it}^2, m_{it}^2, l_{it-1}^2, m_{it-1}^2, l_{it}k_{it}, l_{it}m_{it}, k_{it}m_{it}, l_{it-1}k_{it}, l_{it-1}m_{it}, l_{it}m_{it-1}, l_{it-1}m_{it-1}, k_{it}m_{it-1}$ .

the structure of the model ensures that we also control for past productivity, which captures unobservable level differences between firms, and survival probability, which captures differences in firm dynamics, and thereby allows for unobserved managerial quality to be correlated with these factors. Bias can still arise if there is correlation between the unobserved managerial quality and the error term of the law of motion of productivity  $\xi_{it}$ , but this shock is assumed to be unpredictable by the hiring firms themselves.

## 5 Results

### 5.1 Structure of the Finnish economy

The production function is estimated at the 1 digit industry level, allowing for industry-specific production technologies. Average output elasticities of labour, capital and intermediary inputs are reported in Table 7. Sectors with the highest output elasticity of labour are Non-Market services, IT services, Administrative activities and Professional services, which have the highest share of qualified personnel. The sector with the highest output elasticity of intermediary inputs is the Trade sector, followed by Utilities and Hospitality. The recovered output elasticities of capital are very low overall, around 0.02 for most sectors with the exception of Non-Market services (0.07), Agriculture (0.10) and Utilities (0.29). The Utilities sector is the only sector with increasing returns to scale, at 1.22.

Table 8 shows the marginal effects of the various managerial hiring variables on survival probabilities, estimated from our second stage probit models.<sup>8</sup> Overall, managerial hiring increases survival probabilities by around 1 percentage point, from an average survival probability of 95.5%. We find a stronger effect on survival from inexperienced managers, managers coming from the same narrow industry or outside the broad 1 digit industry and better qualified managers. The characteristics of the sending firms, measured as either the share of qualified workers or the position in the productivity distribution do not seem to affect the probability of survival in a significant way. These results confirm the pattern observed in the transition matrix and emphasise the importance of controlling for survival probabilities in the law of motion of productivity, as explained in Olley and Pakes (1996).

Tables 9 and 10 summarise our core results and provide the coefficients recovered from the law of motion of productivity of Equations 8 and 9, according to mover and sender characteristics.

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<sup>8</sup> The full results of the probit estimations of survival probability are reported in Appendix Table A1.

These are coherent with results obtained from the reduced form estimations.

## 5.2 Mover Characteristics

The first column of Table 9 suggests that on average, replacing half of a firm’s managers with hires from another firm increases productivity by 2%. This effect is statistically significant and higher than the effect of replacing managers through internal promotions, which is associated with a 0.5% increase in productivity. Yet, both effects do not compensate for the loss in productivity associated with the departure of managers: if half of a firm’s managers depart to other firms, this is associated with a loss of productivity of 3.8%. When the  $\mathbf{spill}_{it-1}$  and  $\mathbf{mobility}_{it-1}$  variables are interacted with productivity, the point estimates of the average effects remain stable, and we observe a significantly negative relationship with productivity for all variables except internal promotions, as shown in the second column of Table 9. Figure 1 goes into the details of the relationship between managerial hiring and managerial departures and productivity, by plotting average marginal effects for these two variables by industry and quartile of productivity. The results suggest that in all quartiles except the bottom, the lost productivity resulting from managerial departures outweighs the gains from managerial hiring. We observe net gains only for firms in the bottom quartile of productivity in Agriculture, Utilities, Professional services and Non-market services.

The third and fourth column of Table 9 report the results of managerial experience. The effect on productivity of hiring managers who already occupied such positions in their previous firm is twice as high as hiring managers without managerial experience. However, the boost to productivity from experience decreases faster with productivity than the boost from inexperienced managers, as can be seen in Figure 2. We measure a disruptive effect of hiring experienced managers for firms in the frontier quartile of the productivity distribution in Utilities, IT services, Professional services and Non-market services. Finally, when comparing external promotions to internal promotions, we find a statistically significant positive difference in favour of the former, supporting the hypothesis that experience in other firms brings additional productivity-enhancing knowledge. Looking at industry experience, we find that firms can reap the highest benefit from hiring managers with experience in the same broad 1 digit industry. This positive difference is statistically significant for hires of managers from both the same narrow 2 digit industry or outside the broad sector.

Finally, comparing the effect of hiring managers with different qualification levels suggests

that even the arrival of managers with no higher education is associated with an increase in productivity. However, this effect is far outweighed by the arrival of more qualified managers. If a firm hires half of its managers with higher education, it will observe an increase in productivity of 1.9% and if these managers have advanced higher education the increase in productivity will be of 4.2%. While the point estimates of the interaction terms are not significant, we do observe a pattern in Figure 3, where the average marginal effects are plotted according to industry and productivity quartile. The return to higher education seems higher than that of the other qualification levels, but decreases sharply with productivity. For firms in the top quartile of the productivity distribution, the managers with advanced higher education have the strongest effect on productivity, and in the IT services, Professional services and Non-market services, these are the only managers to have a positive effect on productivity.

### 5.3 Sender Characteristics

The results displayed in Table 10 show that characteristics of the sending firms also matter for the ability of hiring firms to reap productivity benefits, controlling for the qualification of the moving managers. In the first two columns, we observe that hiring managers from firms with higher shares of employees with higher education and advanced higher education is associated with higher productivity. The results show that hiring managers from firms with a 10% points higher share of advanced higher education workers results in a productivity increase of 0.8%. This magnitude is relatively small, considering that the share of advanced higher educated workers is around 5% in all sectors outside IT and Professional services. However, this effect comes in addition to the boost associated with hiring managers who themselves have advanced higher education qualifications. The marginal effects shown in Figure 4 nevertheless suggest that firms in the bottom quartile of the distribution, across sectors, do observe an increase in productivity of at least 1% when they hire managers from firms with 10% points more workers with advanced higher education. The share of workers with first level higher education does not seem to play a large role in the ability of firms to experience Learning-by-Hiring.

The last two columns of Table 10 present results concerning the importance of the position of the sending firms in the productivity distribution, in particular, whether managers were hired from firms in the top or in the bottom productivity quartile. On average, hires from the bottom quartile of the productivity distribution have a disruptive effect on the productivity of the hiring firm, whereas hires from the frontier quartile have no significant effect. In Figure 5, we

see that managerial hires from the frontier have a positive effect in firms in the bottom quartile, especially in Agriculture, Utilities, Logistics, IT services, Professional services, Administrative activities and Non-Market services. In all sectors, the effect of hiring managers from the frontier becomes disruptive for firms that are themselves on the frontier. Figure 10 confirms that hiring managers from the bottom quartile has negative effects on productivity in all sectors and for all productivity quartiles, but it also suggests that this effect is dampened for the best performing firms.

## 6 Conclusion

Overall our results provide strong evidence of the presence of Learning-by-Hiring from managerial mobility. Firms seem to benefit most from hiring managers with experience and advanced qualifications, and who come from sending firms with high human capital, both in terms of higher survival probabilities and higher revenue productivity. We find heterogenous effects depending on the position of the hiring firm in the productivity distribution. At one extreme, laggard firms consistently seem to benefit from managerial hiring, in particular if the hired managers come from the best performing firms. At the other extreme, frontier firms only seem to witness productivity gains from hiring highly qualified managers, and managers who come from firms with high human capital. In particular, we find no evidence that firms already on the frontier benefit from hiring managers from their peers. Taken together, this suggests that managerial mobility can be a mechanism for laggard firms to catch-up in the productivity distribution, thereby reducing productivity dispersion.

However, we also find that these spillovers come at a cost, and that overall welfare effects are not straightforward to determine. Indeed, we consistently find that firms seem to experience a 3.5% drop in productivity when their managers are poached by other firms, and it is not clear whether internal promotions or hiring managers from other firms compensates this loss. Promotions of own staff and non-managerial hires are only associated with small increases in productivity if any.

The results shed light on one particular mechanism through which firms can acquire productivity-enhancing knowledge, which seems to be especially beneficial for firms that are falling behind. Frontier firms, on the contrary, need to look to sources other than improved management to reap productivity gains. Commonly studied factors associated with strong performance at the

frontier are investments in technological knowledge and innovation. Future research will look into the interplay of these investments with managerial learning.

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## A Tables and Figures

Table 1: Mobility by firm size

| Sizeclass  | Empl.   | % of firms with at least one |         |             |                  |                     | % Managers in Firm |          | N. Obs |
|------------|---------|------------------------------|---------|-------------|------------------|---------------------|--------------------|----------|--------|
|            |         | Hire                         | Depart. | Int. Promo. | Non-Manager Hire | Non-Manager Depart. | Tot. Empl.         | Survival |        |
| Very Micro | 0-4     | 1.2                          | 1.2     | 1.2         | 48.9             | 28.8                | 2.4                | 84.3     | 993588 |
| Micro      | 5-9     | 5.6                          | 5.7     | 6.3         | 76.2             | 63.6                | 6.9                | 96.3     | 152518 |
| Small      | 10-19   | 10.4                         | 11.1    | 11.4        | 87.6             | 77.1                | 7.4                | 96.4     | 81569  |
| Med. Small | 20-49   | 20.5                         | 21.4    | 21.4        | 94.1             | 85.3                | 8.1                | 96.2     | 48662  |
| Medium     | 50-99   | 35.0                         | 35.1    | 33.8        | 97.5             | 88.6                | 7.5                | 95.6     | 14187  |
| Med. Large | 100-249 | 46.9                         | 46.6    | 42.7        | 98.7             | 89.5                | 6.2                | 95.1     | 8315   |
| Large      | 250+    | 70.0                         | 67.2    | 61.7        | 99.7             | 89.7                | 5.8                | 95.9     | 5743   |

Table 2: Mobility by firm size and departure of managers

| Panel A: Firm where no manager left |         |                                 |            |  |        |
|-------------------------------------|---------|---------------------------------|------------|--|--------|
| Sizeclass                           | Empl.   | % of firms at least one Manager |            |  | N. Obs |
|                                     |         | Hire                            | Int. Prom. |  |        |
| Very Micro                          | 0-4     | 0.8                             | 1.0        |  | 866991 |
| Micro                               | 5-9     | 3.7                             | 5.4        |  | 141877 |
| Small                               | 10-19   | 6.8                             | 9.5        |  | 71895  |
| Med. Small                          | 20-49   | 13.0                            | 16.7       |  | 38034  |
| Medium                              | 50-99   | 22.5                            | 26.5       |  | 9176   |
| Med. Large                          | 100-249 | 29.7                            | 32.0       |  | 4436   |
| Large                               | 250+    | 42.5                            | 40.9       |  | 1884   |

| Panel B: Firms where at least 1 Manager left |         |                                 |            |  |        |
|--|---------|---------------------------------|------------|--|--------|
| Sizeclass                                    | Empl.   | % of firms at least one Manager |            |  | N. Obs |
|  |         | Hire                            | Int. Prom. |  |        |
| Very Micro                                   | 0-4     | 37.6                            | 19.8       |  | 10048  |
| Micro  | 5-9     | 36.1                            | 22.1       |  | 8615   |
| Small  | 10-19   | 39.7                            | 27.2       |  | 9021   |
| Med. Small                                   | 20-49   | 48.1                            | 38.3       |  | 10383  |
| Medium                                       | 50-99   | 58.1                            | 47.4       |  | 4960   |
| Med. Large                                   | 100-249 | 66.6                            | 54.9       |  | 3864   |
| Large  | 250+    | 83.4                            | 71.8       |  | 3855   |

Table 3: Mobility by industry

|                   | % of firms with at least one |           |             |                  |                       | % Managers in |      | Firm Survival | N. Obs |
|-------------------|------------------------------|-----------|-------------|------------------|-----------------------|---------------|------|---------------|--------|
|                   | Hire                         | Departure | Int. Promo. | Non-Manager Hire | Non-Manager Departure | Tot. Empl.    |      |               |        |
| Agriculture       | 7.5                          | 8.7       | 7.1         | 81.8             | 67.2                  | 7.1           | 96.8 | 7,982         |        |
| Manufacturing     | 13.3                         | 15.2      | 16.9        | 81.1             | 72.2                  | 7.4           | 95.6 | 62,917        |        |
| Utilities         | 13.7                         | 12.8      | 13.6        | 81.5             | 64.6                  | 8.6           | 97.6 | 4,407         |        |
| Construction      | 5.5                          | 5.6       | 8.9         | 82.5             | 68.7                  | 3.9           | 94.8 | 54,222        |        |
| Trade             | 12.3                         | 14.2      | 13.2        | 82.1             | 68.9                  | 9.2           | 95.1 | 75,294        |        |
| Logistics         | 6.6                          | 6.9       | 7.8         | 85.6             | 72.3                  | 3.5           | 96.5 | 29,117        |        |
| Hospitality       | 18.6                         | 20.5      | 17.2        | 88.7             | 76.9                  | 10.6          | 93.9 | 18,983        |        |
| IT & Telcos       | 25.3                         | 25.2      | 22.7        | 85.3             | 69.7                  | 14.2          | 94.5 | 16,021        |        |
| Prof. Services    | 15.3                         | 15.0      | 14.6        | 83.0             | 67.0                  | 9.5           | 94.8 | 28,997        |        |
| Admin. Activities | 17.3                         | 16.8      | 13.4        | 89.9             | 76.3                  | 5.7           | 94.3 | 19,931        |        |
| Non-Mkt. Services | 9.8                          | 9.6       | 10.4        | 87.6             | 73.0                  | 4.9           | 94.9 | 25,103        |        |

Table 4: Average production variables, by industry

|                   | Sales | Capital Stock<br>in million € | Materials | Labour FTE | Labour Prod.<br>in €/FTE | Highest Mkt share | HE Workers % | Adv HE Workers |
|-------------------|-------|-------------------------------|-----------|------------|--------------------------|-------------------|--------------|----------------|
| Agriculture       | 3.82  | 2.91                          | 2.73      | 19.9       | 43,905                   | 49.4              | 14.9         | 1.6            |
| Manufacturing     | 25.30 | 8.65                          | 19.24     | 56.2       | 65,831                   | 85.7              | 16.8         | 3.5            |
| Utilities         | 21.66 | 33.90                         | 16.88     | 38.2       | 105,148                  | 51.6              | 22.7         | 4.6            |
| Construction      | 3.47  | 0.58                          | 2.41      | 20.7       | 47,755                   | 6.8               | 11.1         | 0.8            |
| Trade             | 14.47 | 1.90                          | 12.45     | 29.8       | 56,609                   | 6.0               | 23.6         | 4.4            |
| Logistics         | 5.51  | 3.39                          | 3.65      | 36.6       | 51,687                   | 10.8              | 9.6          | 1.0            |
| Hospitality       | 2.16  | 0.65                          | 1.43      | 22.2       | 30,799                   | 8.6               | 10.7         | 0.8            |
| IT & Telcos       | 9.83  | 7.64                          | 5.67      | 48.5       | 60,131                   | 36.6              | 30.0         | 18.9           |
| Prof. Services    | 3.20  | 1.75                          | 1.98      | 23.5       | 53,175                   | 40.6              | 36.2         | 19.5           |
| Admin. Activities | 3.33  | 1.71                          | 1.66      | 46.4       | 40,142                   | 6.6               | 14.1         | 2.8            |
| Non-Mkt. Services | 2.65  | 0.91                          | 1.34      | 23.7       | 39,643                   | 50.4              | 26.2         | 6.4            |

Table 5: Transition matrix between quartiles of labour productivity, by managerial hiring

| Panel A: Firms without a managerial hire  |      |                 |              |              |              |  |
|---|------|-----------------|--------------|--------------|--------------|--|
| Origin Quartile<br>of Labour Productivity | Exit | Destination     |              |              |              |  |
|   |      | Bottom Quartile | 2nd Quartile | 3rd Quartile | Top Quartile |  |
| Bottom Quartile                           | 9.2  | 57.3            | 22.6         | 7.2          | 3.8          |  |
| 2nd Quartile                              | 2.7  | 21.4            | 48.8         | 22.3         | 4.9          |  |
| 3rd Quartile                              | 2.6  | 7.1             | 22.0         | 49.8         | 18.5         |  |
| Top Quartile                              | 3.7  | 4.0             | 4.9          | 18.8         | 68.6         |  |

| Panel B: Firms with a managerial hire     |      |                 |              |              |              |  |
|---|------|-----------------|--------------|--------------|--------------|--|
| Origin Quartile<br>of Labour Productivity | Exit | Destination     |              |              |              |  |
|   |      | Bottom Quartile | 2nd Quartile | 3rd Quartile | Top Quartile |  |
| Bottom Quartile                           | 2.5  | 65.8            | 18.8         | 7.9          | 5.0          |  |
| 2nd Quartile                              | 1.5  | 22.0            | 47.6         | 23.0         | 5.9          |  |
| 3rd Quartile                              | 1.6  | 9.1             | 19.6         | 51.0         | 18.7         |  |
| Top Quartile                              | 1.8  | 3.9             | 3.7          | 15.2         | 75.4         |  |

Table 6: OLS regressions of Labour Productivity on spillover and mobility variables

| Dependent Variable      | (1)                     | (2)                     | (3)                     | (4)                     |
|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| Log Labour Productivity | Baseline                | Experience              | Ind. Origin             | Qualif.                 |
| Log Labour Productivity | 0.731***<br>(0.00163)   | 0.731***<br>(0.00163)   | 0.731***<br>(0.00163)   | 0.730***<br>(0.00163)   |
| Prob. Survival          | 0.0191***<br>(0.00130)  | 0.0191***<br>(0.00130)  | 0.0191***<br>(0.00130)  | 0.0187***<br>(0.00130)  |
| Man. Hire               | 0.0210***<br>(0.00450)  |                         |                         |                         |
| Exp Man. Hire           |                         | 0.0346***<br>(0.00802)  |                         |                         |
| Ext. Promotion          |                         | 0.0183***<br>(0.00582)  |                         |                         |
| Same det. Industry      |                         |                         | 0.0159**<br>(0.00754)   |                         |
| Same broad industry     |                         |                         | 0.0247***<br>(0.00944)  |                         |
| Diff broad industry     |                         |                         | 0.0231***<br>(0.00657)  |                         |
| No HE Man. Hire         |                         |                         |                         | -0.00359<br>(0.00656)   |
| HE Man. Hire            |                         |                         |                         | 0.0274***<br>(0.00716)  |
| Adv HE Man. Hire        |                         |                         |                         | 0.0767***<br>(0.0113)   |
| Int. Promotion          | 0.0136***<br>(0.00345)  | 0.0135***<br>(0.00345)  | 0.0137***<br>(0.00345)  | 0.0134***<br>(0.00345)  |
| Man. Departure          | -0.0450***<br>(0.00408) | -0.0450***<br>(0.00406) | -0.0451***<br>(0.00408) | -0.0443***<br>(0.00408) |
| Non-Man. Hire           | -0.0739***<br>(0.00422) | -0.0741***<br>(0.00421) | -0.0738***<br>(0.00422) | -0.0729***<br>(0.00422) |
| Observations            | 214,579                 | 214,579                 | 214,579                 | 214,579                 |
| R-squared               | 0.493                   | 0.493                   | 0.493                   | 0.493                   |

All independent variables are lagged one period. Standard error in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 7: Average output elasticities estimated in baseline model, by industry

|                   | $\theta_l$ | $\theta_k$ | $\theta_m$ | Observations |
|-------------------|------------|------------|------------|--------------|
| Agriculture       | 0.36       | 0.10       | 0.49       | 4,400        |
| Manufacturing     | 0.31       | 0.02       | 0.68       | 40,505       |
| Utilities         | 0.24       | 0.29       | 0.69       | 2,896        |
| Construction      | 0.34       | 0.03       | 0.63       | 33,043       |
| Trade             | 0.20       | 0.01       | 0.77       | 47,170       |
| Logistics         | 0.33       | 0.02       | 0.63       | 18,859       |
| Hospitality       | 0.29       | 0.02       | 0.68       | 11,240       |
| IT & Telcos       | 0.45       | 0.01       | 0.57       | 9,698        |
| Prof. Services    | 0.45       | 0.00       | 0.53       | 17,622       |
| Admin. Activities | 0.52       | -0.01      | 0.49       | 11,563       |
| Non-Mkt. Services | 0.46       | 0.07       | 0.42       | 14,683       |

Table 8: Marginal effects of managerial hiring on survival probabilities

|                     | Marginal<br>Effect | Standard<br>Error | t-stat | p-value |
|---------------------|--------------------|-------------------|--------|---------|
| Man. Hire           | 0.0105             | 0.0018            | 5.75   | 0.000   |
| Exp. Man Hire       | 0.0093             | 0.0032            | 2.92   | 0.004   |
| Ext. Promotion      | 0.0135             | 0.0025            | 5.42   | 0.000   |
| Same det. Industry  | 0.0105             | 0.0031            | 3.42   | 0.001   |
| Same broad industry | 0.0063             | 0.0036            | 1.75   | 0.081   |
| Diff broad industry | 0.0130             | 0.0029            | 4.5    | 0.000   |
| No HE Man. Hire     | 0.0078             | 0.0027            | 2.92   | 0.003   |
| HE Man. Hire        | 0.0126             | 0.0030            | 4.14   | 0.000   |
| Adv HE Man. Hire    | 0.0135             | 0.0046            | 2.94   | 0.003   |
| Share HE Sender     | 0.0132             | 0.0050            | 2.63   | 0.009   |
| Share advHE Sender  | 0.0059             | 0.0081            | 0.72   | 0.469   |
| HE Man. Hire        | 0.0083             | 0.0033            | 2.54   | 0.011   |
| Adv HE Man. Hire    | 0.0076             | 0.0049            | 1.56   | 0.119   |
| Q1 $\omega$ Sender  | 0.0083             | 0.0048            | 1.74   | 0.081   |
| Q2 $\omega$ Sender  | 0.0022             | 0.0054            | 0.4    | 0.689   |
| Q3 $\omega$ Sender  | 0.0020             | 0.0056            | 0.35   | 0.725   |
| Q4 $\omega$ Sender  | 0.0042             | 0.0050            | 0.84   | 0.399   |
| HE Man. Hire        | 0.0111             | 0.0038            | 2.89   | 0.004   |
| Adv HE Man. Hire    | 0.0121             | 0.0053            | 2.28   | 0.023   |

Table 9: Law of motion of productivity, by mover characteristics

| Dep. variable<br>$\omega$  | Baseline                |                         | Experience              |                         | Industry of origin      |                         | Qualification           |                         |
|----------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
|                            | (1)                     | (2)                     | (3)                     | (4)                     | (5)                     | (6)                     | (7)                     | (8)                     |
| Man. Hire                  | 0.0405***<br>(0.00194)  | 0.0336***<br>(0.00336)  |                         |                         |                         |                         |                         |                         |
| Exp Man. Hire              |                         |                         | 0.0634***<br>(0.00446)  | 0.0409***<br>(0.0107)   |                         |                         |                         |                         |
| Ext. Promotion             |                         |                         | 0.0289***<br>(0.00241)  | 0.0231***<br>(0.00339)  |                         |                         |                         |                         |
| Same det. ind.             |                         |                         |                         |                         | 0.0338***<br>(0.00388)  | 0.0183***<br>(0.00664)  |                         |                         |
| Same broad ind.            |                         |                         |                         |                         | 0.0489***<br>(0.00415)  | 0.0448***<br>(0.00741)  |                         |                         |
| Diff broad ind.            |                         |                         |                         |                         | 0.0385***<br>(0.00293)  | 0.0336***<br>(0.00341)  |                         |                         |
| No HE Man. Hire            |                         |                         |                         |                         |                         |                         | 0.0198***<br>(0.00270)  | 0.0156***<br>(0.00398)  |
| HE Man. Hire               |                         |                         |                         |                         |                         |                         | 0.0377***<br>(0.00308)  | 0.0287***<br>(0.00664)  |
| Adv HE Man. Hire           |                         |                         |                         |                         |                         |                         | 0.0849***<br>(0.00702)  | 0.0740***<br>(0.00769)  |
| Man. Hire* $\omega$        |                         | -0.0637**<br>(0.0325)   |                         |                         |                         |                         |                         |                         |
| Exp Man. Hire* $\omega$    |                         |                         |                         | -0.190*<br>(0.0978)     |                         |                         |                         |                         |
| Ext. Promotion* $\omega$   |                         |                         |                         | -0.0582**<br>(0.0287)   |                         |                         |                         |                         |
| Same det. ind.* $\omega$   |                         |                         |                         |                         |                         | -0.200**<br>(0.0932)    |                         |                         |
| Same broad ind.* $\omega$  |                         |                         |                         |                         |                         | -0.0478<br>(0.0559)     |                         |                         |
| Diff broad ind.* $\omega$  |                         |                         |                         |                         |                         | -0.0332<br>(0.0236)     |                         |                         |
| No HE Man. Hire* $\omega$  |                         |                         |                         |                         |                         |                         |                         | -0.0438<br>(0.0352)     |
| HE Man. Hire* $\omega$     |                         |                         |                         |                         |                         |                         |                         | -0.0942<br>(0.0776)     |
| Adv HE Man. Hire* $\omega$ |                         |                         |                         |                         |                         |                         |                         | -0.0574<br>(0.0416)     |
| Int. Promotion             | 0.0113***<br>(0.00121)  | 0.00999***<br>(0.00190) | 0.0117***<br>(0.00135)  | 0.0100***<br>(0.00175)  | 0.0103***<br>(0.00138)  | 0.00913***<br>(0.00191) | 0.0105***<br>(0.00132)  | 0.00973***<br>(0.00186) |
| Man. Departure             | -0.0756***<br>(0.00196) | -0.0799***<br>(0.00277) | -0.0740***<br>(0.00202) | -0.0789***<br>(0.00266) | -0.0765***<br>(0.00198) | -0.0813***<br>(0.00267) | -0.0766***<br>(0.00218) | -0.0811***<br>(0.00267) |
| Non-Man. Hire              | 0.0119***<br>(0.00219)  | -0.00305<br>(0.00345)   | 0.0130***<br>(0.00199)  | -0.00110<br>(0.00317)   | 0.0123***<br>(0.00219)  | -0.00209<br>(0.00318)   | 0.00871***<br>(0.00242) | -0.00420<br>(0.00362)   |
| Int. Promotion* $\omega$   |                         | -0.0151<br>(0.0207)     |                         | -0.0209<br>(0.0170)     |                         | -0.0143<br>(0.0168)     |                         | -0.00972<br>(0.0193)    |
| Man. Departure* $\omega$   |                         | -0.0542*<br>(0.0289)    |                         | -0.0607*<br>(0.0314)    |                         | -0.0574**<br>(0.0253)   |                         | -0.0517*<br>(0.0270)    |
| Non-Man. Hire* $\omega$    |                         | -0.171***<br>(0.0293)   |                         | -0.162***<br>(0.0239)   |                         | -0.172***<br>(0.0244)   |                         | -0.143***<br>(0.0327)   |
| Observations               | 211,679                 | 211,679                 | 211,679                 | 211,679                 | 211,679                 | 211,679                 | 211,679                 | 211,679                 |
| R-squared                  | 0.748                   | 0.750                   | 0.766                   | 0.769                   | 0.755                   | 0.757                   | 0.708                   | 0.710                   |

All independent variables are lagged one period. All models include a polynomial of order 2 in lagged productivity and survival probability, unreported. Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 10: Law of motion of productivity, by sender characteristics

| Dependent variable<br>$\omega$ | Human Capital           |                         | $\omega$ Quartiles      |                         |
|--------------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
|                                | (1)                     | (2)                     | (3)                     | (4)                     |
| Share HE Sender                | 0.0126**<br>(0.00570)   | 0.0219***<br>(0.00645)  |                         |                         |
| Share advHE Sender             | 0.0879***<br>(0.0117)   | 0.0733***<br>(0.0109)   |                         |                         |
| Sender in Laggard Quartile     |                         |                         | -0.0317***<br>(0.00612) | -0.0212**<br>(0.00906)  |
| Sender in Frontier Quartile    |                         |                         | -0.000558<br>(0.00742)  | -0.00870<br>(0.00886)   |
| Share HE Sender* $\omega$      |                         | 0.0266<br>(0.0879)      |                         |                         |
| Share advHE Sender* $\omega$   |                         | -0.194<br>(0.124)       |                         |                         |
| Laggard* $\omega$              |                         |                         |                         | 0.0922<br>(0.0747)      |
| Frontier* $\omega$             |                         |                         |                         | -0.215<br>(0.165)       |
| HE Man. Hire                   | 0.0297***<br>(0.00380)  | 0.00984<br>(0.0102)     | 0.0302***<br>(0.00416)  | 0.0160**<br>(0.00765)   |
| Adv HE Man. Hire               | 0.0670***<br>(0.00656)  | 0.0575***<br>(0.00748)  | 0.0863***<br>(0.00767)  | 0.0761***<br>(0.00967)  |
| Int. Promotion                 | 0.0120***<br>(0.00130)  | 0.00725***<br>(0.00191) | 0.0110***<br>(0.00141)  | 0.00561***<br>(0.00216) |
| Man. Departure                 | -0.0721***<br>(0.00198) | -0.0792***<br>(0.00352) | -0.0717***<br>(0.00219) | -0.0783***<br>(0.00278) |
| Non-Man. Hire                  | 0.00939***<br>(0.00207) | -0.0184***<br>(0.00308) | 0.00977***<br>(0.00233) | -0.0129***<br>(0.00452) |
| HE Man. Hire* $\omega$         |                         | -0.209*<br>(0.118)      |                         | -0.147*<br>(0.0809)     |
| Adv HE Man. Hire* $\omega$     |                         | -0.0515<br>(0.0582)     |                         | -0.0784<br>(0.0642)     |
| Int. Promotion* $\omega$       |                         | -0.0644***<br>(0.0231)  |                         | -0.0793***<br>(0.0295)  |
| Man. Departure* $\omega$       |                         | -0.0797**<br>(0.0369)   |                         | -0.0737**<br>(0.0297)   |
| Non-Man. Hire* $\omega$        |                         | -0.292***<br>(0.0257)   |                         | -0.235***<br>(0.0410)   |
| Observations                   | 186,435                 | 186,435                 | 160,767                 | 160,767                 |
| R-squared                      | 0.683                   | 0.688                   | 0.734                   | 0.739                   |

All independent variables are lagged one period. All models include a polynomial of order 2 in lagged productivity and survival probability, unreported. Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure 1: Marginal effect of managerial hiring and departures, by productivity quartile of origin and industry

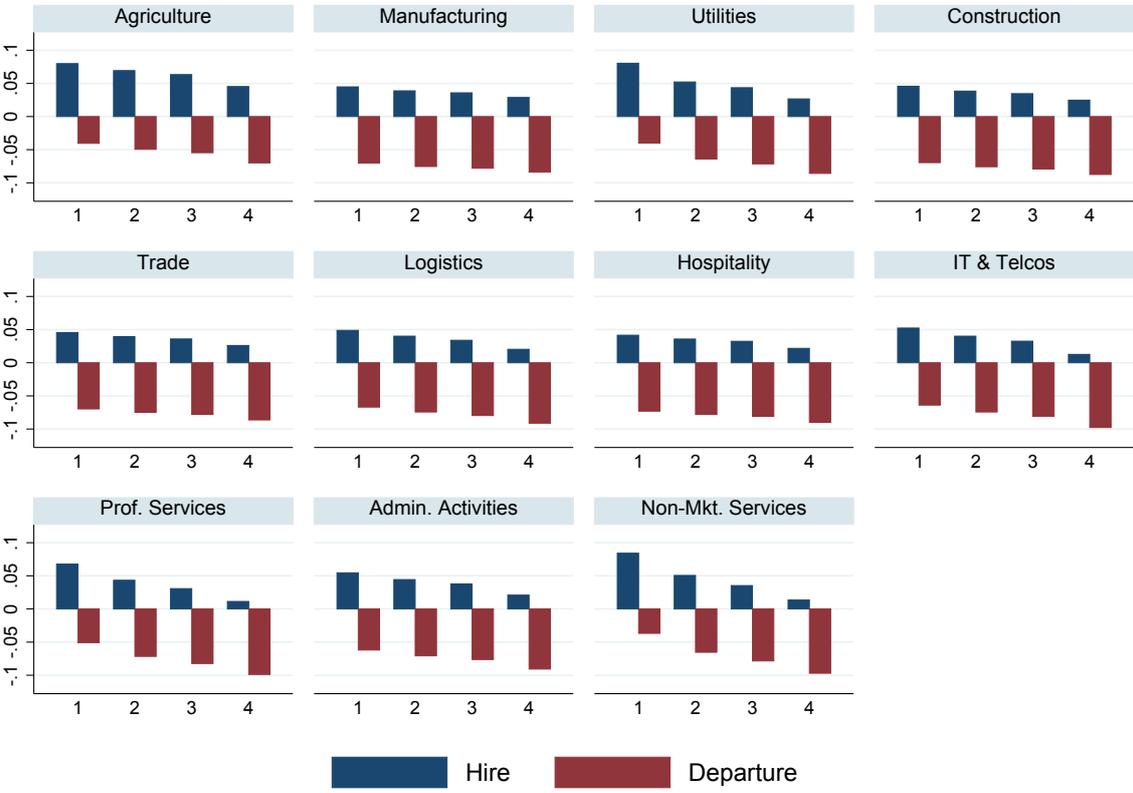


Figure 2: Marginal effect of managerial hiring, by experience of movers productivity quartile of origin and industry

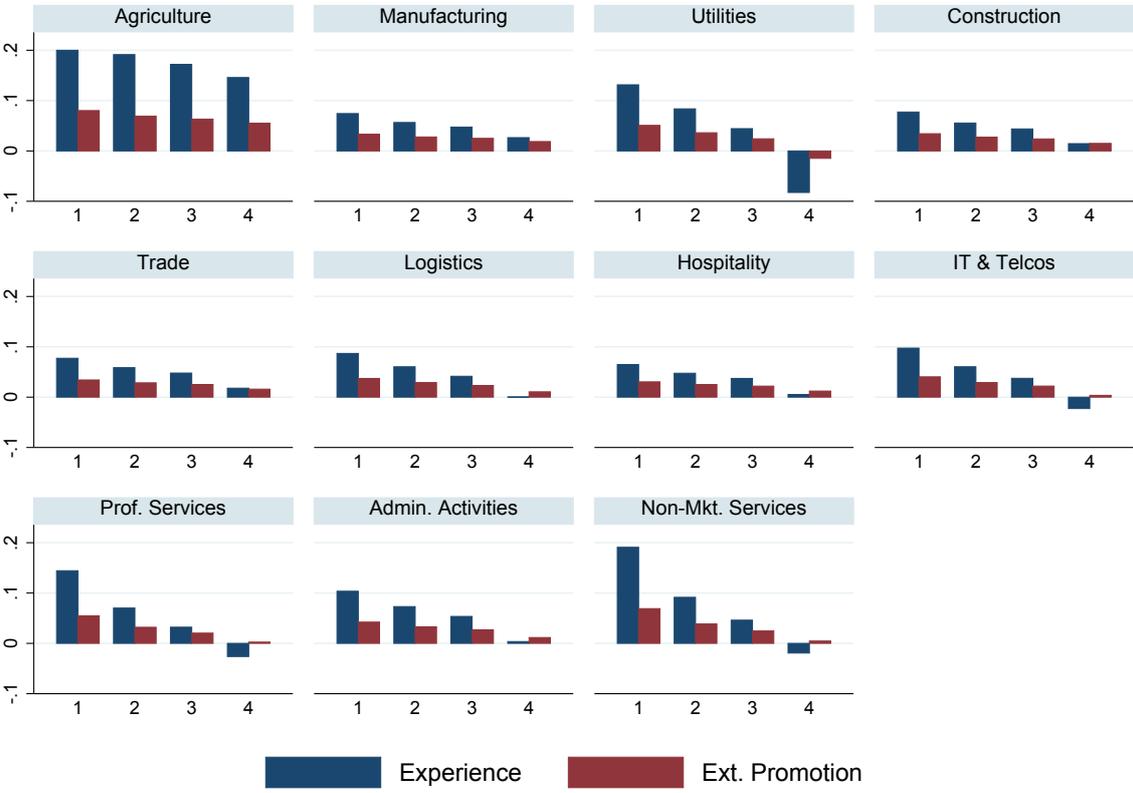


Figure 3: Marginal effect of managerial hiring, by qualification of movers, productivity quartile of origin and industry

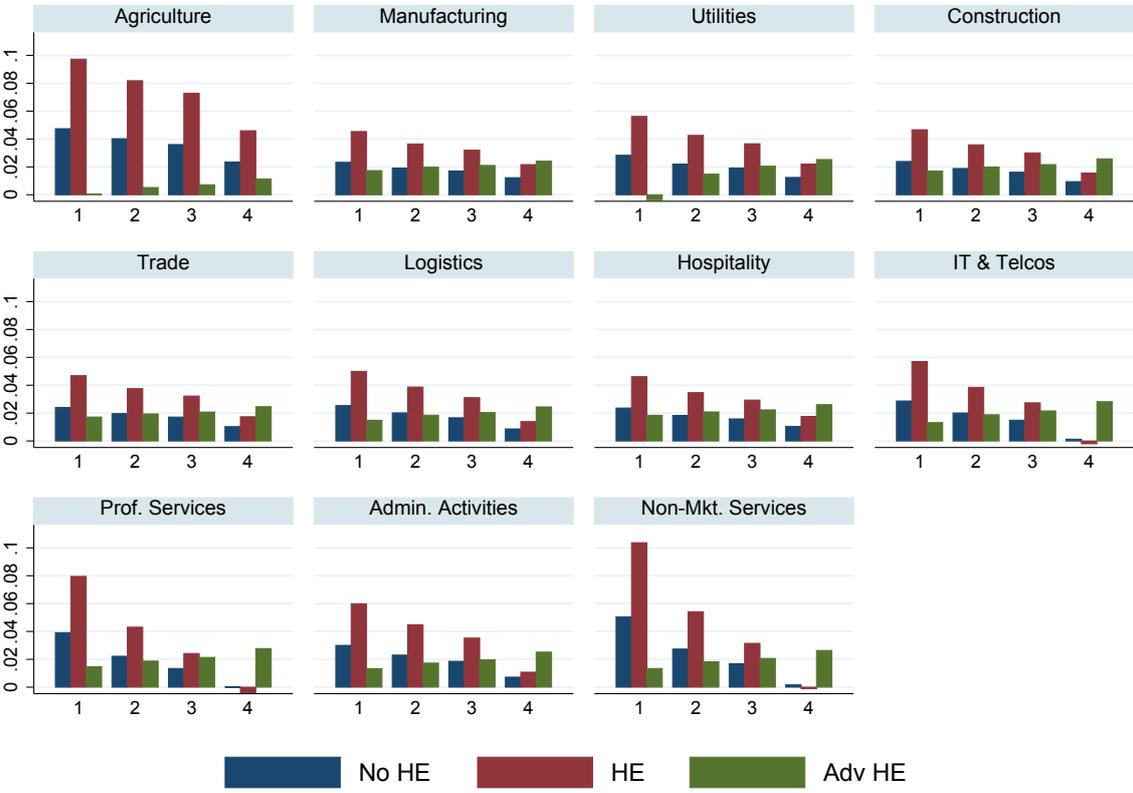
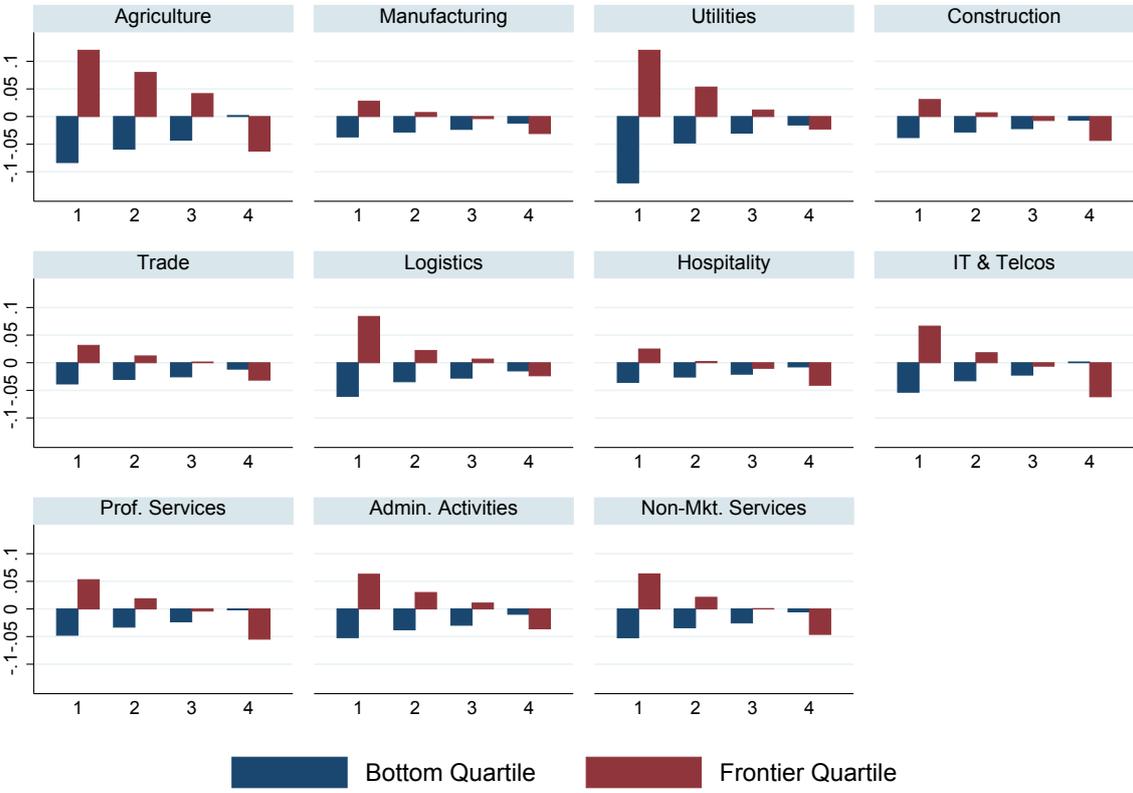


Figure 4: Marginal effect of managerial hiring, by human capital of sender, productivity quartile of origin and industry



Figure 5: Marginal effect of managerial hiring, by productivity quartile of sender, productivity quartile of origin and industry



## B Additional results

Table 1: Results of Probit estimations of survival

| Dependent Variable  | (1)                   | (2)                   | (3)                   | (4)                   | (5)                   | (7)                   |
|---------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Survival            | Baseline              | Exp.                  | Ind. Ori              | Qualif.               | HC                    | $\omega$ Quart.       |
| Man. Hire           | 0.196***<br>(0.0341)  |                       |                       |                       |                       |                       |
| Exp Man. Hire       |                       | 0.173***<br>(0.0593)  |                       |                       |                       |                       |
| Ext. Promotion      |                       | 0.253***<br>(0.0466)  |                       |                       |                       |                       |
| Same det. Industry  |                       |                       | 0.197***<br>(0.0575)  |                       |                       |                       |
| Same broad industry |                       |                       | 0.118*<br>(0.0678)    |                       |                       |                       |
| Diff broad industry |                       |                       | 0.242***<br>(0.0538)  |                       |                       |                       |
| HE Man. Hire        |                       |                       |                       | 0.237***<br>(0.0570)  | 0.155**<br>(0.0611)   | 0.0900***<br>(0.0347) |
| Adv HE Man. Hire    |                       |                       |                       | 0.253***<br>(0.0862)  | 0.143<br>(0.0916)     | 0.0394<br>(0.0396)    |
| Share HE Sender     |                       |                       |                       |                       | 0.247***<br>(0.0942)  |                       |
| Share advHE Sender  |                       |                       |                       |                       | 0.110<br>(0.152)      |                       |
| Q1 $\omega$ Sender  |                       |                       |                       |                       |                       | 0.0136<br>(0.0422)    |
| Q2 $\omega$ Sender  |                       |                       |                       |                       |                       | 0.0472<br>(0.0493)    |
| Q3 $\omega$ Sender  |                       |                       |                       |                       |                       | 0.0430<br>(0.0475)    |
| Q4 $\omega$ Sender  |                       |                       |                       |                       |                       | 0.109***<br>(0.0390)  |
| Man Departure       | -0.493***<br>(0.0157) | -0.495***<br>(0.0157) | -0.493***<br>(0.0157) | -0.490***<br>(0.0156) | -0.495***<br>(0.0157) | -0.513***<br>(0.0158) |
| Non-Man. Departure  | -0.494***<br>(0.0173) | -0.493***<br>(0.0173) | -0.494***<br>(0.0173) | -0.494***<br>(0.0173) | -0.492***<br>(0.0173) | -0.480***<br>(0.0182) |
| Int. Prom           | 0.151***<br>(0.0189)  | 0.150***<br>(0.0189)  | 0.151***<br>(0.0189)  | 0.150***<br>(0.0189)  | 0.144***<br>(0.0190)  | 0.120***<br>(0.0190)  |
| Non-Man. Hire       | 0.505***<br>(0.0135)  | 0.505***<br>(0.0135)  | 0.505***<br>(0.0135)  | 0.506***<br>(0.0135)  | 0.505***<br>(0.0135)  | 0.503***<br>(0.0142)  |
| Observations        | 253,744               | 253,744               | 253,744               | 253,744               | 253,744               | 227,135               |

Standard error in parentheses. All models include the following controls: Log Labour, Log Capital, Log wages, industry share of startups, mean age, share of males, share of high school, higher education and advanced higher education graduates, and industry and time fixed effects. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## C Markup estimations

Throughout the analysis, turnover is used as the measure of output, rather than physical output. This is driven by lack of data on firm-specific prices, and means that we measure revenue productivity rather than output productivity. Observed increases in revenue productivity can be driven by both quantity effects (increases in the efficiency with which firms produce physical units) and price effects (eg. the ability of firms to charge higher prices for the same units). In order to offer some interpretation concerning the relative importance of quantity or price effects of managerial mobility on revenue productivity, we follow De Loecker and Warzynski (2012) and estimate markups. Building on the assumption that materials are static inputs and adding cost-minimisation, firm level markups  $\mu_{it}$  can be recovered according to

$$\mu_{it} = \theta_{mit} \cdot \left( \frac{M_{it}}{Y_{it}/\exp(\epsilon_{it})} \right)^{-1} \quad (10)$$

where  $Y_{it}$  and  $M_{it}$  are the turnover and material expenditures in levels.<sup>9</sup> Observed turnover  $Y_{it}$  needs to be corrected for unforeseen shocks to production  $\epsilon_{it}$ . The translog assumption for the production function provides firm-specific output elasticities of intermediary inputs  $\theta_{mit}$  according to

$$\theta_{mit} = \alpha_m + 2\alpha_{mm}m_{it} + \alpha_{lm}l_{it} + \alpha_{km}k_{it} \quad (11)$$

This is an improvement on the Cobb-Douglas production function, which yields an average output elasticity that would be applied homogeneously to all firms. In a final stage we regress logged markups on hiring behaviour, labour and capital inputs to control for size and input intensity, and time and industry fixed effects, according to the following equation

$$\ln(\mu_{it}) = \lambda_s \mathbf{spill}_{it-1} + \lambda_m \mathbf{mobility}_{it-1} + \lambda_l l_{it} + \lambda_k k_{it} + \sigma_t + \sigma_i + \epsilon_{it} \quad (12)$$

Results presented in Table 2 give a mixed overview of whether the observed effects of managerial hiring on revenue productivity are driven by changes in prices and increases in market power. Odd columns report regressions where the dependent variable are the firm-specific mark-ups calculated following De Loecker and Warzynski (2012), and even columns report regressions where the dependent variable is the market share of the firm in its 2 digit industry. It appears

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<sup>9</sup> See De Loecker and Warzynski (2012) for the full derivation of this expression from the firm's first order conditions.

that managerial hiring has a negative impact on markups, but a positive impact on market-shares.

Table 2: Regression results of managerial hires on markups and market-shares

| Dependent variable: | Baseline                |                        | Experience              |                        | Industry of Origin      |                        | Qualification           |                        |
|---------------------|-------------------------|------------------------|-------------------------|------------------------|-------------------------|------------------------|-------------------------|------------------------|
|                     | <i>Log</i> $\mu$        | Log Mkt Share          |
| Man. Hire           | -0.0184***<br>(0.00410) | 0.126***<br>(0.00747)  |                         |                        |                         |                        |                         |                        |
| Exp Man. Hire       |                         |                        | -0.0325***<br>(0.00731) | 0.202***<br>(0.0129)   |                         |                        |                         |                        |
| Ext. Promotion      |                         |                        | -0.0123***<br>(0.00449) | 0.0794***<br>(0.00977) |                         |                        |                         |                        |
| Same det. Industry  |                         |                        |                         |                        | -0.0392***<br>(0.00549) | 0.232***<br>(0.0121)   |                         |                        |
| Same broad industry |                         |                        |                         |                        | 0.0257**<br>(0.0101)    | 0.0915***<br>(0.0157)  |                         |                        |
| Diff broad industry |                         |                        |                         |                        | -0.0230***<br>(0.00570) | 0.0561***<br>(0.0109)  |                         |                        |
| HE Man. Hire        |                         |                        |                         |                        |                         |                        | -0.0307***<br>(0.00586) | 0.184***<br>(0.0118)   |
| Adv HE Man. Hire    |                         |                        |                         |                        |                         |                        | -0.100***<br>(0.0104)   | 0.298***<br>(0.0183)   |
| Int. Promotion      | -0.0193***<br>(0.00244) | 0.0733***<br>(0.00617) | -0.0192***<br>(0.00294) | 0.0732***<br>(0.00617) | -0.0194***<br>(0.00273) | 0.0731***<br>(0.00617) | -0.0197***<br>(0.00258) | 0.0733***<br>(0.00617) |
| Man. Departure      | -0.0768***<br>(0.00336) | 0.00816<br>(0.00702)   | -0.0771***<br>(0.00370) | 0.0129*<br>(0.00699)   | -0.0777***<br>(0.00360) | 0.00978<br>(0.00702)   | -0.0760***<br>(0.00361) | 0.0118*<br>(0.00702)   |
| Non-Man. Hire       | 0.0203***<br>(0.00560)  | -0.266***<br>(0.00694) | 0.0203***<br>(0.00549)  | -0.266***<br>(0.00694) | 0.0193***<br>(0.00552)  | -0.269***<br>(0.00695) | 0.0204***<br>(0.00570)  | -0.264***<br>(0.00694) |
| Log Labour          | 0.0195***<br>(0.00185)  | 0.953***<br>(0.00160)  | 0.0199***<br>(0.00204)  | 0.953***<br>(0.00160)  | 0.0212***<br>(0.00177)  | 0.952***<br>(0.00160)  | 0.0194***<br>(0.00194)  | 0.952***<br>(0.00160)  |
| Log Capital         | -0.0218***<br>(0.00120) | 0.141***<br>(0.00100)  | -0.0221***<br>(0.00142) | 0.141***<br>(0.00100)  | -0.0230***<br>(0.00133) | 0.141***<br>(0.00100)  | -0.0213***<br>(0.00147) | 0.140***<br>(0.00100)  |
| Constant            | 0.841***<br>(0.00679)   | -12.18***<br>(0.0160)  | 0.842***<br>(0.00674)   | -12.18***<br>(0.0160)  | 0.842***<br>(0.00648)   | -12.18***<br>(0.0160)  | 0.838***<br>(0.00617)   | -12.17***<br>(0.0160)  |
| Industry FE         | Yes                     | Yes                    | Yes                     | Yes                    | Yes                     | Yes                    | Yes                     | Yes                    |
| Time FE             | Yes                     | Yes                    | Yes                     | Yes                    | Yes                     | Yes                    | Yes                     | Yes                    |
| Observations        | 211,667                 | 261,609                | 211,667                 | 261,609                | 211,667                 | 261,609                | 211,667                 | 261,609                |
| R-squared           | 0.588                   | 0.843                  | 0.588                   | 0.843                  | 0.588                   | 0.843                  | 0.588                   | 0.843                  |

All independent variables relating to managerial hires and mobility are lagged one period. Standard error in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*

## D Data Appendix

The present appendix provides further details regarding the construction and cleaning of the database.

### D.1 Deflation

All nominal monetary values are converted into real 2005 euros by applying deflators from the OECD STAN database. Values in the manufacturing sector are kept as they are, while values in the services sector are adjusted using country-level PPPs for 2005, from the Eurostat-OECD PPP Programme.<sup>10</sup>

### D.2 Capital stock

The main measure of capital stock used in the analysis is built according to the PIM methodology. The initial value of capital stock is set to the capital stock reported by the firm in the initial year. The depreciation rate is also obtained from the STAN database, as consumption of fixed capital divided by the sum of consumption and net capital stock ( $CCFC/(CCFC+CAPN)$ ). We use the reported value of capital for the robustness checks, and the correlation between these two measures is 0.78.

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<sup>10</sup> For more information, see [www.oecd.org/std/ppp/manual](http://www.oecd.org/std/ppp/manual)