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Roope Ohlsbom

Management practices, human capital, and productivity

JYVÄSKYLÄ UNIVERSITY
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ABSTRACT

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This dissertation includes three articles concerning the field of economics of management practices and productivity. The first article analyses the variation in the management practices across countries and across regions within a country. The quantitative establishment-level management scores show that Finnish management practices are only slightly behind the US and on par with those in Germany. With the Finnish data, we then perform an Olley-Pakes decomposition of the management score using a moment-based estimation procedure. The decomposition shows no statistically significant differences in the unweighted average scores between Finnish regions, but reveal some significant differences in the employment weighted averages (i.e. aggregate scores) that can be attributed to the differences in the allocation of the labour force between establishments within regions.

The second article details how managerial human capital affects the relationship between productivity and quantitative management practices. The results imply that the productivity improvements associated with adopting more structured management practices vary with the levels of managerial human capital. Accounting for the interaction, a 10 percent increase in the management score is associated with an average of 7.1 percent higher labour productivity. Furthermore, management practices can account for more than 24 percent of the observed productivity dispersion. This is almost as much as information and communication technologies and more than both research and development and human capital.

The third article uses linked employer-employee data from Finland to examine the mobility of workers between establishments as a source of productivity-affecting knowledge spillovers. I find evidence that hiring workers from more productive establishments leads to higher productivity in the following year. For an average establishment, this productivity increase amounts to 0.45 percent in the most conservative estimate. The observed productivity gains hold for a variety of specifications, and changes in the receiving establishments' human capital stock are ruled out as an explanation.

Keywords: management practices, productivity, human capital, worker mobility

TIIVISTELMÄ

Ohlsbom, Roope
Johtamiskäytännöt, inhimillinen pääoma ja tuottavuus
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Väitöskirja sisältää kolme johtamiskäytäntöjen taloustiedettä ja tuottavuutta käsittelevää tutkimusartikkelia. Ensimmäisessä artikkelissa tarkastellaan johtamiskäytäntöjen vaihtelua maittain ja alueittain. Määrällisin menetelmin mitattujen johtamiskäytäntöpistemäärien perusteella Suomen teollisuuden johtamiskäytännöt vaikuttavat olevan vain vähän heikommat kuin Yhdysvalloissa ja samaa tasoa Saksan kanssa.

Suomen sisäisissä alueellisissa vertailuissa havaittiin vaihtelua työvoiman määrällä painotetuissa keskiarvoissa, mutta ei painottamattomissa keskiarvoissa. Erot työvoiman kohdentumisessa saattavat siis selittää alueellisia eroavuuksia Suomessa. Työvoiman kohdentumisen tarkempaan tutkimiseen hyödynnetään momenttiestimaattoreihin perustuvaa menetelmää, joka mahdollistaa keskivirheiden laskemisen ja tilastollisten hypoteesien testauksen Olley Pakes -hajotelman osille. Menetelmän avulla havaittiin viitteitä kilpailukyvyn kannalta relevantin allokaatiovaikutuksen alueellisista eroista.

Toisessa artikkelissa tutkitaan johtajien inhimillisen pääoman yhteyttä tuottavuuden ja johtamiskäytäntöjen väliseen suhteeseen. Tulosten perusteella strukturoitujen johtamiskäytäntöjen käyttöönottoon liittyvät tuottavuusparannukset riippuvat johtajien inhimillisen pääoman määrästä. Kun tämä interaktio on otettu huomioon, kymmenen prosenttia korkeampi johtamiskäytäntöpistemäärä on yhteydessä keskimäärin 7,1 prosenttia korkeampaan työn tuottavuuteen. Johtamiskäytännöt voivat selittää jopa 24 prosenttia havaitusta tuottavuusvaihtelusta, mikä on lähes yhtä suuri selitysosuus kuin tieto- ja viestintätekniikalla ja suurempi kuin tutkimus- ja kehittämistoiminnalla sekä inhimillisellä pääomalla.

Viimeinen artikkeli tarkastelee työntekijöiden liikkuvuudesta syntyneitä tuottavuuden heijastusvaikutuksia (spillover effects) hyödyntäen suomalaisia yhdistettyjä työntekijä-työnantaja-aineistoja. Tulokset osoittavat, että tuottavammista toimipaikoista työntekijöiden palkkaamista seuraa tuottavuuden kasvua palkkaamista seuraavana vuonna. Varovaisimpana arviona tuottavuuslisäyksen suuruus on 0,45 prosenttia keskimääräiselle toimipaikalle. Havaittu yhteys tuottavuuden ja tuottavammista toimipaikoista palkkaamisen välillä säilyy useilla estimointispesifikaatioilla, eikä sitä voida selittää muutoksilla vastaanottavien toimipaikkojen inhimillisen pääoman määrissä.

Avainsanat: johtamiskäytännöt, tuottavuus, inhimillinen pääoma, työntekijöiden liikkuvuus

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Espoo, 19.03.2023
Roope Ohlsbom

CONTENTS

1 INTRODUCTION

This dissertation includes three articles covering the economics of management practices, human capital and productivity. The overarching aim of this dissertation is a detailed analysis of the quality of floor-level management practices and their connection with firm and establishment-level outcomes. The first article is the first quantitative analysis of plant-level management practices using data gathered with the Finnish Management and Organizational Practices Survey (FMOP). It presents an indicative international comparison and a cross-regional comparison of the large areas of Finland. The latter utilizes an Olley-Pakes decomposition (Olley & Pakes 1996) and a moment-based estimation method (Hyytinen, Ilmakunnas & Maliranta 2016) to conduct statistical inference and hypothesis testing concerning the differences in the components of the management score. We find evidence that the differences in the allocation of employment between establishments may explain the regional disparities in the quality of management practices in Finland.

The second article utilizes data from the Finnish Management and Organizational Practices Survey to study the association between management practices and firm productivity, and to examine whether human capital intensity acts as a moderator variable for this relationship. The results point to a strong and positive relationship between management practices and labour productivity. We also find evidence that the marginal benefit of adopting more structured management practices is different for establishments with different levels of managerial human capital. Testing and accounting for this interaction is important for the reliable estimation of the management-productivity relationship.

The final paper posits another potential driver of productivity: spillovers through employee turnover. The idea that a type of productivity-affecting knowledge is embedded in the workers and managers of a firm is not a new one. In addition to the quality, dispersion and effects of this knowledge, an important subject of study are the mechanisms through which it can get transferred across firms. Worker mobility is a plausible suggestion for such a mechanism, as demonstrated by, for example, Moen (2005), Kaiser, Kongsted, and Rønde (2008), Maliranta, Mohnen, and Rouvinen (2009) and Stoyanov and Zubanov (2012).

The third article uses Finnish linked employer-employee data to provide evidence that the mobility of workers between establishments is a source of productivity-affecting spillovers. Hiring workers from more productive establishments leads to higher productivity in the following year. For an average establishment, this productivity increase amounts to 0.45 percent in the most conservative estimate. However, no link is found between the mobility of managers and the hiring establishments' productivity.

1.1 Motivation and literature

The potential drivers of productivity are a central focus point of economic research. Explanatory variables such as research and development (R&D), information and communication technologies (ICT) spending and worker skills, just to name a few, have been under intensive empirical scrutiny by economists for as long as there have been data to base studies on. However, more recently, a new piece of the productivity puzzle has been uncovered: management practices. In his survey of empirical research on productivity differences, Syverson (2011, 336) states that "perhaps no potential driver of productivity differences has seen a higher ratio of speculation to actual empirical study" when discussing the aptitudes of managers and the quality of management practices. At the forefront of amending this shortcoming is the Management and Organizational Practices Survey (MOPS), which is a quantitative survey tool that was developed by Nick Bloom, John Van Reenen and Erik Brynjolfsson together with the United States Census Bureau and the National Science Foundation (Bloom et al. 2019).

The large-scale quantitative measuring of management practices started with the World Management Survey (WMS), a much-cited research project developed by Nick Bloom and John Van Reenen (2007). The WMS was developed in collaboration with market leaders in management consultancy and has been extensively tested to make sure it captures meaningful information about floor-level management practices (Bloom & Van Reenen 2007). It is based on interviews with open-ended questions and uses a double-blind technique to minimize survey bias (Bloom, Lemos, Sadun, Scur & Van Reenen 2014). Based on the same theoretical framework as the WMS, the United States Census Bureau, together with researchers Nick Bloom, Erik Brynjolfsson and John Van Reenen, developed the original Management and Organizational Practices Survey (MOPS).

In their analysis of management practices and firm performance, Bloom et al. (2019) find that increasing the adoption of structured management practices measured by the MOPS from the tenth to the ninetieth percentile explained approximately 22% of the corresponding 90-10 productivity spread. As a contrast, R&D spending, ICT investment per worker and human capital account for 21.6%, 12% and 15.9% of the productivity spread, respectively (Bloom et al. 2019). This implies that the effect of management practices on the dispersion of productivity could be at least as significant as any of the other variables commonly regarded as important drivers of productivity variation.

Bloom et al. (2019) describe the magnitude of the management-productivity connection by a 26.2% increase in labour productivity for every upward change of one standard deviation in the management score. In other words, a 10 percentage point increase in the management score implies approximately 14.5% higher productivity. Other results include, but are not restricted to, the positive connections of management practices with establishment size, age, foreign ownership, skills of managers and the amount of exports (Bloom et al. 2019). All these correlations are found to hold in the US, as well as in Germany (Broszeit, Fritsch, Görg & Laible 2016) and Pakistan (Lemos, Choudhary, Van Reenen & Bloom 2016).

With these recent advances in collecting quantitative large-scale data on management practices, this important driver of productivity will hopefully start gaining even more attention from researchers and policy makers. Productivity drives economic growth, which is strongly correlated with other measures of well-being. Therefore, with every new uncovered driver of productivity, we can uncover more reasons behind the dispersion of economic and social welfare. To that end, this dissertation aims to contribute by providing a detailed analysis of the link between quantitative measures of management practices and firm performance.

The third article expands on idea of human capital,

1.2 Summary

1.2.1 Management practices and the allocation of employment

The goal of the first article is to use the Finnish Management and Organizational Practices Survey[1] (FMOP) data to examine the quality of management practices in the Finnish manufacturing sector. The FMOP questionnaire has a total of 35 questions, of which 16 concern management practices. In addition to the 16 management questions, the questionnaire has 13 questions on organizational practices and 6 background questions. The questions concern the year 2016, but most questions also have a recall component, where respondents are asked to give an answer regarding the circumstances five years earlier.

The responses for each question are normalized on a scale of 0 – 1 and the establishment-level management score is calculated as the unweighted average of the normalized responses. The answer options corresponding with the management practices that are considered to be the most structured are assigned a value of 1 and the least structured practices are assigned a value of 0. Bloom et al. (2019) define more structured management practices as "those that are more specific, formal, frequent or explicit" (Bloom et al. 2019, 28).

Based on an examination of simple unweighted averages, the Finnish management scores appear to be only slightly behind those of the US and approximately on par with those of Germany. This suggests that the management practices in Finnish manufacturing are on an internationally competitive, high-quality level.

The cross-regional comparison describes the differences in the quality of the management practices between the large areas of Finland. An Olley-Pakes (OP) decomposition is used to separate the components of the aggregate or employment weighted management score. Namely, aggregate productivity is divided into two terms: the unweighted average productivity and a covariance term of

1 The FMOP questionnaire can be found in appendix A of this introduction.

the productivity and firm size. The latter, which is also known as the allocation term, is essential because it describes how much of the input activity is allocated to more productive establishments or enterprises (Hyytinen et al. 2016).

To conduct the statistical inference and hypothesis testing of the cross-regional differences in these components, a moment-based estimation method is used. This method was introduced by Hyytinen, Ilmakunnas and Maliranta (2016). It allows for statistical inference and hypothesis testing of the magnitude of the OP components, therefore allowing for more statistically meaningful cross-regional comparisons of the allocation term.

The comparison shows no statistically significant differences in the unweighted management scores between the large areas of Finland. However, we find evidence for cross-regional differences in the aggregate (employment weighted) management scores, which implies that the allocation of employment between establishments plays a role in explaining regional differences in management practices. These results show that statistical inference concerning the allocation component of the decomposition is an integral part of any cross-regional, or cross-country, comparisons of management practices. What drives the regional variation of management practices and the allocation of employment in Finland is a subject for future research.

The results for the aggregate (employment weighted) differences between regions are robust to the inclusion of the educational level of employees and the productivity level of the establishments as control variables. However, due to the nature of the moment-based estimation procedure, we are unable to test whether the difference in the allocation term is robust to the inclusion of control variables.

The number of establishments in the data is relatively small, which may in part explain the apparent lack of statistically significant results. The partitioning into large areas was chosen partly because of the small sample size, yet the number of data points for each area remains relatively low. The measured cross-regional differences are also somewhat small in magnitude. This result would most likely be unaffected by an increased sample size. However, more robust results could be achieved by repeating the survey for a larger sample. Creating a time series of Finnish management practices using the FMOP methodology would also provide information on how the adoption of structured management practices evolves over time.

It is useful to note that management practices and, to some extent, even the allocation term, are potentially manipulable by policymakers and firms themselves. For example, making establishments more aware of their practices could affect their management scores, especially in below-average firms or areas. If the methods presented in this paper were used to analyse the management differences of cities and industries, in other countries or between countries, researchers might find results that are of major policy relevance for the purpose of improving productivity and economic competitiveness.

However, based on the results of the study, large productivity gains would be unlikely in Finland. The relatively slow productivity growth of post financial crisis Finland compared to many other countries is unlikely to be significantly accelerated by investing heavily in the already high-quality management practices. Instead, our analysis suggests that more attention should be paid to factors that reduce the mobility of the workforce and hampers competition between firms, both important elements of the (re)allocation of employment.

The first research article, presented in chapter 2, is co-authored with Professor Mika Maliranta. I have contributed to the article by preparing and scoring the original survey data, by combining the data with those of Statistics Finland, and by carrying out all the calculations and estimations presented in the article. I have written sections 2 and 3 of the article and most of sections 1 and 4 with some additions from Professor Maliranta.

1.2.2 Management practices, labour productivity, and human capital intensity

The second article contributes to the quantitative management practices literature by examining how human capital relates to the management-productivity association. Management practices are measured using the Finnish Management and Organizational Practices Survey (FMOP), which provides high quality quantitative data on establishment-level management practices. Other establishment-level variables used in the analysis, such as intermediate inputs, addition and depreciation of machinery and ICT spending are gathered from The Business Register database and enterprises' financial statement data maintained by Statistics Finland.

Employee level variables like years of education, degree and position within the organization are from the Finnish Longitudinal Employer-Employee Data (FLEED). Using the combined employer-employee data of Statistics Finland, we can partition human capital intensity into the separate contributions of the human capital of managers and non-managers.

The multivariable fractional polynomials interaction (MFPI[2]) approach (Royston & Sauerbrei 2004) enables a comparison of how well different models predict productivity from management practices and human capital in Finnish manufacturing establishments. The MFPI algorithm uses the Akaike's information criterion (AIC) to select the best-fitting fractional polynomial (FP) functions of the first and second degree. FP functions of varying complexity are then systematically examined to determine whether they describe the shape of the association between a regressor and the dependent variable better than a linear function. After the selection of the best-fitting functional form, a test for interactions between chosen regressors is performed. The MFPI approach can be generalized to account for continuous-by-continuous interactions using the same fractional polynomial methodology. This paper utilizes the generalized version, MFPIgen, to examine how human capital contributes to the management-productivity association.

2 MFPI combines the multivariable fractional polynomial (MFP) approach with a test for linear and nonlinear interactions between continuous regressors (Royston & Sauerbrei 2009).

The results point to a linear two-way interaction between management practices and the level of education of managers. To reliably estimate the association between firm performance and management practices, this interaction must be accounted for.

We find a strong and positive relationship between management practices and firm performance: a 10 percent increase in the FMOP management score is associated with 7.1 percent higher labour productivity. It is likely that the estimated model does not identify a causal effect, since there are plenty of plausible confounders, such as CEO effects, which are not controlled for. However, the associational results are significant both statistically and in magnitude, and robust to different specifications, measurement choices and data restrictions. The results therefore support the assumption that the FMOP management score is a meaningful measure[3] of firm characteristics.

Furthermore, the magnitude of the management-productivity relationship is large even when compared to other commonly studied drivers of productivity. Increasing the adoption of structured management practices from the tenth percentile to the ninetieth can account for up to 24 percent of the corresponding 90–10 productivity spread. The explanatory power of management is therefore close to as large as that of information and communication technologies (ICT), a little larger than human capital and more than 30 percent larger than research and development (R&D).

The analyses presented in the second article suggest that the marginal benefit of better management practices varies with establishments characteristics. Namely, the part of human capital attributable to managers is correlated with the rate of productivity improvements gained from better management. This should be noted when analysing management practices and firm performance. Since human capital is often measured from the characteristics of the entire workforce, and since most employees are not managers, human capital often ends up proxied by measures mostly comprised of non-manager characteristics.

The results direct policymakers' attention to increasing the adoption of structured management practices, especially in establishments and industries with already high human capital intensity. They also encourage complementing managerial improvements with policies that promote human capital formation.

The second article also demonstrates the importance and usefulness of comprehensive high quality census data. The Finnish data allows for the formation of information-rich data sets by further partitioning variables, like the dissection of manager and non-manager characteristics, with divisions by field of work and education, occupation, tenure and wage. As for future research, studying these aspects of firms' employees more closely would provide insight into the relationships between management, workforce quality, firm performance and even employee well-being.

[3] This is consistent with the findings of existing studies, such as Bloom et al. (2013) and Bloom et al. (2019), which provide evidence for management practices as a significant source of productivity dispersion.

1.2.3 Worker mobility and productivity spillovers

Several existing studies explore the mechanisms of productivity-affecting knowledge diffusion between firms[4]. A significant subset of studies on the topic suggests worker mobility as such a mechanism[5]. The third article contributes to this body of knowledge by using Finnish matched employer-employee data to isolate the spillover effects potentially associated with cross-firm worker movements. The mobility of managers and non-managers are analysed separately.

The dependent variable in the main analysis of the paper is the labour productivity of the receiving establishment in the year following the hiring of new workers. Productivity is measured by the gross value of production divided by the number of employees. The independent variable of interest is the positive productivity gap between the sending and receiving establishments of newly hired workers.

The data includes all Finnish workers in the FOLK and FLEED (the Finnish Longitudinal Employer-Employee Data) matched employer-employee data modules of Statistics Finland. The data set covers the years 2011–2018. Establishment-level variables used in the analysis, such as value added, gross value of production, R&D and ICT spending, number of employees, intermediate inputs and addition and depreciation of machinery are gathered from The Business Register database and enterprises' financial statement data maintained by Statistics Finland. Data for these variables covers the years 2011–2019.

Due to the comprehensiveness of the data, we can control for the productivity variance directly attributable to the changes in the human capital stock of the firms, among other possible confounders. This should leave us with a measure of productivity spillovers attributable solely to cross-firm worker mobility.

Firstly, we demonstrate that industries with higher rates of average employee turnover from more to less productive establishments exhibit less productivity dispersion. This is consistent with the assumption of worker mobility as a mechanism of productivity-affecting knowledge diffusion. Furthermore, the negative correlation between worker turnover and productivity dispersion is stronger when the productivity difference between sending and receiving firms is greater. The increasing negative correlation suggests that spillovers depend on the magnitude of the productivity difference between the sending and receiving firms. The article thus follows Stoyanov and Zubanov (2012) in using this productivity difference as the measure of the receiving firms' exposure to spillovers through worker mobility.

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4 See, for example, Prescott and Visscher (1980), Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Parente & Prescott (1994) and Jones (2005).

5 Moretti (2004), Moen (2005), Kaiser, Kongsted, and Rønde (2008), Maliranta, Mohnen, and Rouvinen (2009), Stoyanov and Zubanov (2012), LeMouel (2018), Castillo, Garone, Maffioli, Rojo and Stucchi (2019) and Hlatshwayo, Kreuser, Newman and Rand (2019).

Second, we isolate the human capital of the moving workers using their level of education and the R&D and ICT intensities of their sending establishments. This allows us to control for the effects on productivity of mobility-induced changes in human capital intensity. We find that hiring workers from the average more productive establishment is associated with at least 0.45 percent higher productivity in the following year. The productivity difference between sending and receiving firms can therefore explain a relatively small but statistically significant part of observed labour productivity. At the upper end of the estimates, allowing for non-linearity, we find a 1.57 percent average productivity gain in when hiring all workers from more productive establishments.

In addition to the estimates with the usual average productivity numbers, all regressions were run with employment weights to ensure that the qualitative conclusions hold for employment weighted productivity as well. Employment weighted regressions mitigate the impact of smaller establishments with extreme labour productivity numbers. They also account for the workforce allocated into higher productivity establishments, making the employment weighted results more relevant for cross-regional or cross-country comparisons, for example. Adding employment weights to the regressions does not change the statistical significance of or the conclusions drawn from the estimates.

The results also hold when only establishments with at least 5 employees are included and when establishments outside of the manufacturing sector are excluded. However, no association between the productivity gap and productivity is found when only looking at moving managers. The correlation between the gap and the receiving establishments' productivity also disappears when worker movements within firms are included in the analysis. This suggests that, at least in the aggregate, within-firm worker mobility is unlikely to induce productivity spillovers.

The analyses presented in the third article suggest that worker mobility can indeed induce productivity spillovers, even outside the direct effects of the altered workforce characteristics of the hiring establishments. Spillovers seem to occur even when the possible knowledge transfer via moving workers is accounted for. This does not necessarily imply much for an individual firm or establishment, especially considering the relatively small magnitude of the estimated spillovers.

However, the results can be interpreted to support a more flexible labour market and the provision of safety nets to mitigate the negative individual-level effects of employee turnover. Since worker mobility can induce growth-supporting productivity spillovers, and is partly driven by involuntary redundancies and periods of unemployment, we should ensure that these potential positive externalities do not come at the expense of the affected workers' welfare. Sufficient social security can support the acceptability and approval of high labour market flexibility and employee turnover rates.

Furthermore, the presented results imply that a cross-regional analysis of worker mobility and productivity can reveal interesting facts about how regional disparities in worker flows affect international competitiveness. The productivity gap measure can also be of use when calculating the costs associated with the concentration of the workforce in certain areas within countries. At the same time, supporting worker flows from more to less productive areas could potentially lead to decreased regional disparities in productivity.

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1.3 Appendix A: FMOP questionnaire

Osa A – Johtaminen

1 Mikä seuraavista kuvaa parhaiten toimipaikassa tehtyjä toimenpiteitä, kun tuotannossa havaittiin ongelma vuosina 2011 ja 2016?

Esimerkki: laadullisen vian löytäminen tuotteesta tai koneiston hajoaminen.

Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.

	2011	2016
Ongelma korjattiin, mutta muita toimenpiteitä ei tehty		
Ongelma korjattiin ja varmistettiin, ettei ongelmaa ilmene uudelleen		
Ongelma korjattiin ja varmistettiin, ettei ongelmaa ilmene uudelleen. Lisäksi meillä on jatkuvan kehittämisen prosessi tällaisten ongelmien ennakoimiseksi		
Mitään toimenpiteitä ei tehty		
Mitään ongelmaa ei havaittu		
Toimipaikan tietoja ei ole saatavilla vuodelta 2011		

2 Kuinka montaa suoritusmittaria toimipaikassa seurattiin vuosina 2011 ja 2016?

Esimerkiksi tuotannon, kustannusten, hävikin, laadun, varastojen, energian, poissaolojen ja toimitusaikojen mittarit.

Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.

	2011	2016
1-2 mittaria		
3-9 mittaria		
10 tai useampaa mittaria		
Ei ollenkaan suorituskykymittareita		

Jos suoritusmittareita ei ollut kumpanakaan vuonna, lomake hyppää kysymykseen 6.

3 Kuinka usein toimipaikan **johtajat seurasivat** suoritusmittareita vuosina 2011 ja 2016?

Johtajaksi tässä tulkitaan henkilö, jolla on sellaisia suoria alaisia, joita hän tapaa säännöllisesti, joiden rekrytoimiseen, työehtojen sopimiseen ja ylennyksien tekemiseen hän on osallistunut (esimerkiksi laitoksen johtaja, henkilöstöjohtaja tai laatupäällikkö).

***Merkitse kaikki sopivat vaihtoehdot** molempien vuosien sarakkeeseen.*

	2011	2016
Vuosittain		
Vuosineljänneksittäin		
Kuukausittain		
Viikoittain		
Päivittäin		
Tunneittain tai useammin		
Ei koskaan		

4 Kuinka usein **joku muu** kuin toimipaikan johtaja **seurasi** suoritusmittareita tässä toimipaikassa vuosina 2011 ja 2016?

Muilla kuin johtajilla viitataan tässä kaikkiin muihin toimipaikan työntekijöihin, joita ei voida määritellä johtajiksi edellisen kysymyksen määritelmän mukaisesti.

***Merkitse kaikki sopivat vaihtoehdot** molempien vuosien sarakkeeseen.*

	2011	2016
Vuosittain		
Vuosineljänneksittäin		
Kuukausittain		
Viikoittain		
Päivittäin		
Tunneittain tai useammin		
Ei koskaan		

5	Mihin tuotannosta ja muista suoritusmittareista kertovat tiedot oli sijoitettu toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Kaikki tiedot olivat nähtävissä vain yhdessä ja samassa paikassa (esim. tuotantolinjan päässä) Tietoja oli nähtävissä useassa paikassa (esim. useassa kohtaa pitkin tuotantolinjaa) Toimipaikassa ei ollut nähtävillä kyseisiä tietoja
6	Mikä seuraavista kuvaa parhaiten tuotantotavoitteiden aikajännettä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Pääpaino oli lyhyen aikavälin tuotantotavoitteissa (alle yksi vuosi) Pääpaino oli pitkän aikavälin tuotantotavoitteissa (yli yksi vuosi) Sekä lyhyen että pitkän aikavälin tuotantotavoitteissa Ei tuotantotavoitteita *Jos tuotantotavoitteita ei ollut kumpanakaan vuonna, lomake hyppää kysymykseen 13a.*
7	Kuinka helppoa tai vaikeaa tavoitteiden saavuttaminen oli vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Mahdollista saavuttaa ilman suurempaa vaivannäköä Mahdollista saavuttaa pienellä vaivannäöllä Mahdollista saavuttaa normaalilla vaivannäöllä Mahdollista saavuttaa normaalia suuremmalla vaivannäöllä Mahdollista saavuttaa vain aivan poikkeuksellisella vaivannäöllä
8	Ketkä tiesivät tämän toimipaikan tuotantotavoitteista vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Vain ylimmät johtajat Useimmat johtajat ja osa tuotantotyöntekijöistä Useimmat johtajat ja useimmat tuotantotyöntekijät Kaikki johtajat ja kaikki tuotantotyöntekijät
9	Mihin **muiden kuin johtajien** tulospalkkiot perustuivat vuosina 2011 ja 2016? ***Merkitse kaikki sopivat vaihtoehdot*** *molempien vuosien sarakkeeseen.* 2011 | 2016 Työntekijöiden omaan suoritukseen, jota mitattiin tuotantotavoitteiden avulla Tiimien tai työvuorojen suoritukseen, jota mitattiin tuotantotavoitteiden avulla Toimipaikan suoritukseen, jota mitattiin tuotantotavoitteiden avulla Yrityksen suoritukseen, jota mitattiin tuotantotavoitteiden avulla Ei ollut tulospalkkiota *Jos tulospalkkiota ei ollut kumpanakaan vuonna, lomake hyppää kysymykseen 11.*

10	Jos tuotantotavoitteet saavutettiin, mikä osa **muista kuin johtajista** sai tulospalkkion tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 0 % 1 - 33 % 34 - 66 % 67 - 99 % 100 % Tuotantotavoitteita ei saavutettu
11	Mihin **johtajien** tulospalkkiot yleensä perustuivat vuosina 2011 ja 2016? ***Merkitse kaikki sopivat vaihtoehdot** molempien vuosien sarakkeeseen.* 2011 | 2016 Johtajien omaan suoritukseen, jota mitattiin tuotantotavoitteiden avulla Tiimin tai työvuoron suoritukseen, jota mitattiin tuotantotavoitteiden avulla Toimipaikan suoritukseen, jota mitattiin tuotantotavoitteiden avulla Yrityksen suoritukseen, jota mitattiin tuotantotavoitteiden avulla Ei tulospalkkioita *Jos tulospalkkioita ei ollut kumpanakaan vuonna, lomake hyppää kysymykseen 13a.*
12	Jos tuotantotavoitteet saavutettiin, mikä osa **johtajista** sai tulospalkkion tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 0 % 1 - 33 % 34 - 66 % 67 - 99 % 100 % Tuotantotavoitteita ei saavutettu
13a	Mikä oli ensisijainen tapa **muiden kuin johtajien** ylentämiseen tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Ylennykset perustuivat ainoastaan suoritukseen ja kyvykkyyteen Ylennykset perustuivat osittain suoritukseen ja kyvykkyyteen, ja osittain muihin tekijöihin (esimerkiksi tuttava- tai perhesuhteet) Ylennykset perustuivat pääosin muihin tekijöihin kuin suoritukseen tai kyvykkyyteen (esimerkiksi tuttava- tai perhesuhteet) Muita kuin johtajia ei yleensä ylennetä
13b	Mitkä alla olevista vaihtoehdoista olivat ensisijaiset kriteerit **muiden kuin johtajien** rekrytoimiseen muualta vuosina 2011 ja 2016? *Numeroi tärkeysjärjestyksessä molempina vuosina asteikolla 1-5.* *1 on tärkein, 2 toiseksi tärkein, … ja 5 vähiten tärkeä.* 2011 | 2016 Tehtävään liittyvä tietämys ja kyvyt Vuorovaikutus- ja neuvottelutaidot Tuttu sosiaalisten verkostojen kautta (työskennellyt aikaisemmin tässä yrityksessä/toimipaikassa, kollegojen tuttu, perhesuhteet tms.) Täsmällisyys ja luotettavuus annettujen tehtävien suorittamisessa Motivaatio suorittamisessa

14a	Mikä oli ensisijainen tapa **johtajien** ylentämiseen tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*	2011	2016
	Ylennykset perustuivat ainoastaan suoritukseen ja kyvykkyyteen		
	Ylennykset perustuivat osittain suoritukseen ja kyvykkyyteen, ja osittain muihin tekijöihin (esimerkiksi tuttava- tai perhesuhteet)		
	Ylennykset perustuivat pääosin muihin tekijöihin kuin suoritukseen tai kyvykkyyteen (esimerkiksi tuttava- tai perhesuhteet)		
	Johtajia ei yleensä ylennetä		
14b	Mitkä alla olevista vaihtoehdoista olivat ensisijaiset kriteerit **johtajien** rekrytoimiseen muualta vuosina 2011 ja 2016? *Numeroi tärkeysjärjestyksessä molempina vuosina asteikolla 1-5.* *1 on tärkein, 2 toiseksi tärkein, ... ja 5 vähiten tärkeä.*	2011	2016
	Tehtävään liittyvä tietämys ja kyvyt		
	Vuorovaikutus- ja neuvottelutaidot		
	Tuttu sosiaalisten verkostojen kautta (työskennellyt aikaisemmin tässä yrityksessä/toimipaikassa, kollegojen tuttu, perhesuhteet yms.)		
	Täsmällisyys ja luotettavuus annettujen tehtävien suorittamisessa		
	Motivaatio suorittamisessa		
15	Milloin alisuoriutuva **muu kuin johtaja** erotettiin tai siirrettiin uuteen tehtävään vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*	2011	2016
	Alle kuuden kuukauden jälkeen siitä, kun alisuoriutuminen havaittiin		
	Yli kuuden kuukauden kuluttua siitä, kun alisuoriutuminen havaittiin		
	Harvoin tai ei koskaan		
16	Milloin alisuoriutuva **johtaja** erotettiin tai siirrettiin uuteen tehtävään vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*	2011	2016
	Alle kuuden kuukauden jälkeen siitä, kun alisuoriutuminen havaittiin		
	Yli kuuden kuukauden kuluttua siitä, kun alisuoriutuminen havaittiin		
	Harvoin tai ei koskaan		

Osa B - Organisaatio

17	Sijaitsiko yrityksen pääkonttori samassa paikassa kuin toimipaikka vuosina 2011 ja 2016? *Mikäli kyseessä on yksitoimipaikkainen yritys, merkitse molempien vuosien sarakkeisiin "kyllä".*	2011	2016
	Kyllä		
	Ei		
	Jos kyllä molempina vuosina, lomake hyppää kysymykseen 24.		
18	Missä tehtiin päätökset **pysyvien kokoaikaisten työntekijöiden palkkaamisesta** vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*	2011	2016
	Vain tässä toimipaikassa		
	Vain pääkonttorissa		
	Sekä tässä toimipaikassa että pääkonttorissa		
	Muualla, missä? ______________________________		

19	Missä tehtiin päätökset **yli 10 % palkankorotuksien toteuttamisesta** vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Vain tässä toimipaikassa Vain pääkonttorissa Sekä tässä toimipaikassa että pääkonttorissa Muualla, missä? ______________________________
20	Missä tehtiin **uusia tuotteita** koskevat päätökset? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Vain tässä toimipaikassa Vain pääkonttorissa Sekä tässä toimipaikassa että pääkonttorissa Muualla, missä? ______________________________
21	Missä tehtiin **tuotteiden hinnoittelua** koskevat päätökset vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Vain tässä toimipaikassa Vain pääkonttorissa Sekä tässä toimipaikassa että pääkonttorissa Muualla, missä? ______________________________
22	Missä tehtiin tuotteiden **markkinointia** koskevat päätökset vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Vain tässä toimipaikassa Vain pääkonttorissa Sekä tässä toimipaikassa että pääkonttorissa Muualla, missä? ______________________________
23	Kuinka paljon euromääräisesti voitiin käyttää investointeihin tässä toimipaikassa ilman valtuutusta pääkonttorista vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.* 2011 | 2016 Alle 1000 € 1000 € - 9999 € 10 000 € - 99 999 € 100 000 € - 999 999 € 1 000 000 € tai enemmän
24	Kuinka moni toimipaikan henkilöstöstä on suoraan tämän toimipaikan johtajan alaisia (raportoivat johtajalle suoraan) vuosina 2011 ja 2016? Toimipaikan johtajan alaisia ovat sellaiset työntekijät, jotka ovat organisaatiossa seuraavalla alemmalla tasolla, tapaavat toimipaikan johtajaa säännöllisesti ja joiden rekrytoimiseen, palkkaukseen ja ylenemiseen toimipaikan johtaja on vaikuttanut. 2011 | 2016 Alaisten määrä (arviokin riittää)

25	Kuinka monta organisaatiotasoa tällä toimipaikalla on tuotantotasolta toimipaikan johtotasolle saakka laskettuna vuosina 2011 ja 2016? Esimerkki: toimipaikassa, jossa on tuotantotaso, tuotannon esimiehet sekä laitoksen johtaja, tasojen lukumäärä on 3.

	2011	2016
Tasojen määrä (arviokin riittää)		

26	Kuka jakoi työtehtäviä tuotantotyöntekijöille tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*

	2011	2016
Vain johtajat		
Pääosin johtajat		
Johtajat ja tuotantotyöntekijät yhdessä		
Pääosin tuotantotyöntekijät		
Vain tuotantotyöntekijät		
Joku muu, kuka? ______________________________		

27	Mikä seuraavista kuvaa parhaiten **tiedon saatavuutta** päätöksenteon tueksi tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*

	2011	2016
Tietoa ei ollut saatavilla		
Vähän tietoa oli saatavilla		
Kohtuullisesti tietoa oli saatavilla		
Paljon tietoa oli saatavilla		
Kaikki tarvittava tieto päätöksenteon tueksi oli saatavilla		

28	Mikä seuraavista kuvaa parhaiten **tiedon käyttöä** päätöksenteon tukena tässä toimipaikassa vuosina 2011 ja 2016? *Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.*

	2011	2016
Tietoa ei käytetty päätöksenteon tukena		
Päätöksenteko perustuu hieman käytettyyn tietoon		
Päätöksenteko perustuu kohtuullisesti käytettyyn tietoon		
Päätöksenteko perustuu vahvasti käytettyyn tietoon		
Päätöksenteko perustuu kokonaan käytettyyn tietoon		

29	Oppivatko **johtajat** tässä toimipaikassa käytännön johtamisesta miltään seuraavista? ***Merkitse kaikki sopivat vaihtoehdot** molempien vuosien sarakkeeseen.*

	2011	2016
Konsultit		
Kilpailijat		
Alihankkijat, tavarantoimittajat		
Asiakkaat		
Yhdistykset tai konferenssit		
Uudet työntekijät		
Pääkonttori		
Muut, mitkä? ______________________________		
Ei mikään ylläolevista		

Osa C – Taustatiedot

30 Millä organisaation tasolla työskentelit vuonna 2016?

- ☐ Toimitusjohtaja tai muu johtaja, esim. talousjohtaja
- ☐ Usean toimipaikan johtaja
- ☐ Yhden toimipaikan johtaja
- ☐ Jokin muu kuin johtaja
- ☐ Jokin muu, mikä? ____________________________

31 Minä vuonna aloitit työskentelyn tässä toimipaikassa? __________

32 Kuinka monta **johtajaa** tässä toimipaikassa työskenteli 31. joulukuuta 2011 ja työskentelee tällä hetkellä?

Johtajaksi tässä tulkitaan henkilö, jolla on sellaisia suoria alaisia, joita hän tapaa säännöllisesti, joiden rekrytoimiseen, työehtojen sopimiseen ja ylennyksien tekemiseen hän on osallistunut (esimerkiksi laitoksen johtaja, henkilöstöjohtaja tai laatupäällikkö).

	31.12.2011	tällä hetkellä
Johtajien lukumäärä tässä toimipaikassa (arviokin riittää)		

33 Kuinka monta osa-aikaista ja kokoaikaista **työntekijää** tässä toimipaikassa työskenteli 31. joulukuuta 2011 ja työskentelee tällä hetkellä?

	31.12.2011	tällä hetkellä
Muiden kuin johtajien lukumäärä tässä toimipaikassa (arviokin riittää)		

34 Kuinka suurella osalla **johtajista** tässä toimipaikassa oli vähintään alempi korkeakoulututkinto vuosina 2011 ja 2016?

Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.

	2011	2016
20 % tai vähemmän		
21 % - 40 %		
41 % - 60 %		
61 % - 80 %		
Enemmän kuin 80 %		

35 Kuinka suurella osalla **muista kuin johtajista** oli tässä toimipaikassa vähintään alempi korkeakoulututkinto vuosina 2011 ja 2016?

Merkitse yksi vaihtoehto molempien vuosien sarakkeeseen.

	2011	2016
0 %		
1 % - 10 %		
11 % - 20 %		
Enemmän kuin 20 %		

Paljon kiitoksia vastaamisesta!

2 MANAGEMENT PRACTICES AND ALLOCATION OF EMPLOYMENT: EVIDENCE FROM FINNISH MANUFACTURING

Roope Ohlsbom and Mika Maliranta

Abstract

We analyse variation in the management practices across countries and across regions within a country. For cross-country comparisons we use the Finnish Management and Organizational Practices Survey (FMOP) to calculate a management score for Finnish manufacturing that is compared to corresponding measures obtained from similar data in the US and Germany. Scores measured by unweighted averages of the establishments in these countries show that Finland is only slightly behind the US and on par with those of Germany. With the FMOP data, we then perform an Olley-Pakes decomposition of the management score using a moment-based estimation procedure. Our decomposition shows no statistically significant differences in the unweighted average scores between Finnish regions, but reveal some significant differences in the employment weighted averages (i.e. aggregate scores) that can be attributed to the differences in the allocation of the labour force between establishments within regions.

Keywords: management practices, management survey, MOPS, Olley-Pakes de-composition, competitiveness, allocation effect

JEL classification numbers: D22, L25, L60, M11, M50

2.1 Introduction

In the past decade, since the development of the quantitative survey tool known as the Management and Organizational Practices Survey (MOPS), management practices have gained a footing as a key driver of productivity differences. This paper contributes to the management practices literature by using the novel Finnish Management and Organizational Practices Survey (FMOP) to examine cross-regional and cross-country variations in management practices. Furthermore, we perform an Olley-Pakes micro-level decomposition that allows splitting the aggregate (i.e. employment weighted) management practice score into the contributions of the establishment-level component (unweighted average) and the allocation of employment between establishments (a covariance-like allocation term).

We perform this decomposition by applying a moment-based estimation method, proposed by Hyytinen and Maliranta (2016), that allows us to highlight the statistical, in addition to that of the economic, significance of the differences in the micro-level components of management practices found across regions. Using this method, we can examine the extent to which differences in the adoption of management practices are likely to explain observed regional dispersion in productivity.

Our results show that while no statistically or economically significant differences are found using simple unweighted average management scores, aggregate (employment weighted average) scores reveal some economically and statistically significant differences in the adoption of productivity-affecting management practices at the aggregate regional level. Furthermore, the disparities in the aggregate management scores arise from the allocation component, which exhibits economically and statistically significant variation across regions.

The results therefore imply that the productivity differences across Finnish large areas cannot be attributed to cross-regional differences in management practices. However, some of the regional productivity dispersion can be explained by the cross-regional differences in the allocation of employment between establishments with different levels of management practices. Our analysis also demonstrates that it is important to measure the contribution of the allocation of employment between establishments in explaining variations in management quality across regions, or countries, and that these estimates involve statistical uncertainty that has so far been largely ignored in the literature.

An indicative cross-country comparison using post-stratification weighted averages is presented, in addition to the descriptive statistics and a cross-regional analysis of Finnish management practices. Based on a rudimentary examination of averages, the Finnish management scores appear to be only slightly behind those of the US and approximately on par with those of Germany. This suggests that the management practices in Finnish manufacturing are on an internationally competitive, high quality level.

The domestic cross-regional analysis focuses specifically on the differences in the quality of the management practices between the large areas of Finland. An Olley-Pakes (OP) decomposition is used to decompose the aggregate (employment weighted) average management score into contributions of the unweighted average score, which gauges the management score at the plant-level, and a covariance-like allocation term that measures the role of the allocation of employment between management-heterogenous establishments.

The allocation term itself has gained notice in the productivity literature (Bartelsman, Haltiwanger and Scarpetta 2013) and more recently in the management literature (Bloom, Sadun and Van Reenen 2016). In productivity studies, the reallocation of resources has been shown to account for a large part of cross-country productivity differences[6]. However, these studies have not addressed the issue of estimating standard errors for the allocation component of the decomposition.

The covariance term also seems to be a useful measure of resource allocation, as argued for example by Bartelsman, Haltiwanger and Scarpetta (2013). They empirically show that differences in the Olley-Pakes covariance term of productivity account for a significant part of the observed cross-country productivity dispersion. Furthermore, by showing that the covariance between employment and productivity is an informative and robust measure for the impact of misallocation, Bartelsman et al. (2013) argue that employment is a natural choice for measuring the policy relevant allocation term. Therefore, following for example Bartelsman et al. (2013), Maliranta and Määttänen (2015) and Hyytinen et al. (2016) this paper uses the covariance between employment and management practices to measure resource allocation.

The evidence for management practices, as measured by survey tools derivative of the MOPS, as a key driver of productivity is convincing: previous studies have found repeated evidence on the significance of management practices in explaining productivity differences. Bloom et al. (2019) find that management practices are highly correlated with productivity and can account for as much as 22% of the cross-firm differences in labour productivity. As a comparison, the labour productivity differences that are explained by research and development, information and communications technology investment per worker and human capital are 21.6%, 12% and 15.9%, respectively. These factors have traditionally been considered to significantly explain the observed variation of productivity.

Jointly, with management practices included, all of the above can explain approximately 44% of the observed labour productivity differences, according to Bloom et al. (2019). Similar results are found with other measures of productivity. This implies that management practices, as measured by the MOPS management score, have a significant part in explaining firm productivity. The quantitative analysis of the differences in management practices can therefore reveal valuable information concerning the differences in productivity and economic

6 See for example Foster, Haltiwanger and Krizan (2001) for an overview.

competitiveness. Encouraging establishments to adopt better management practices on a large scale could potentially have tangible effects on the economy.

Yet, it is also important to consider the role of allocation of employment between establishments in explaining the competitive performance of the economy, or its regions. Because competition between establishments is one of the key drivers of the allocation of employment and output (Bloom and Van Reenen 2007; Syverson 2011), this insight emphasises the potentially important role of national competition policy in determining the international competitiveness of the economy.

The structure of the paper is organized as follows. Section 2 provides an overview of the FMOP survey instrument and data, the indicative international comparisons and the descriptive statistics of the FMOP data. A short description of the decomposition methods and the results from the moment-based estimation and hypothesis testing are presented in section 3. Section 4 concludes. All the analysis in this paper is descriptive, and without additional assumptions, no causal inferences can be made based on the calculations that are presented.

2.2 Data and international comparison

2.2.1 Data

With funding from the Strategic Research Council, the Finnish Management and Organizational Practices Survey (FMOP) was translated and adapted from its US counterpart (Bloom, Lemos, Sadun, Scur & Van Reenen 2016) to collect data on the quality of management practices in Finnish manufacturing establishments. The sample for the 2016 FMOP data collection consisted of 2509 Finnish manufacturing establishments with at least 4 employees. Firms employing less than 50 employees are excluded from the sample (see appendix A), but the small establishments that belong to firms of at least 50 employees are included. The final number of valid responses was 731, with a response rate of approximately 31% after accounting for overcoverage.

This is a relatively high response rate for a non-compulsory survey. In Germany, for example, where responding was not compulsory, the response rate was approximately 6% (Broszeit, Fritsch, Görg and Laible 2019). The Management and Expectations Survey, conducted in the United Kingdom by the Office for National Statistics, had a response rate of 38.7% (Awano et al. 2018). In the United States, where responding was mandatory by law, the response rates for the first and second waves of the survey were approximately 78% and 74%, respectively (Bloom et al. 2019). As an example of a high response rate for a non-compulsory survey, the first wave pilot Management Practices Survey (MPS) of 2015 in the UK achieved a response rate of 68% (Awano, Heffernan and Robinson 2017).

The analysis of total non-response that was conducted by Statistics Finland showed that the distribution of the respondents is skewed towards larger establishments, as measured by the number of personnel. Statistics Finland also conducted a post-stratification test to provide sample weights that correct for some of the non-response bias in the data. Additional restrictions[7] drop the final number of establishments that was used in the analysis down to 609.

The FMOP questionnaire has a total of 35 questions, of which 16 concern management practices. In addition to the 16 management questions, the questionnaire has 13 questions on organizational practices and 6 background questions. The questions concern the year 2016, but most of the questions also have a recall component, where respondents are asked to give an answer regarding the circumstances five years earlier.

The responses for each question are normalized on a scale of 0 – 1 and the establishment-level management score is calculated as the unweighted average of the normalized responses. The answer options corresponding with the management practices that are considered to be the most structured are assigned a value of 1 and the least structured practices are assigned a value of 0. Bloom et al. (2019) define more structured management practices as “those that are more specific, formal, frequent or explicit” (Bloom et al. 2019, 28).

The management questions can be divided into three sections: monitoring, targets and incentives. The monitoring section consists of questions 1 – 5 and they ask about the utilization and gathering of information and data in the monitoring of production. Questions 6 – 8 are about the setting of production targets and questions 9 – 16 ask about practices concerning bonuses and incentives, policies on recruitment and promotion and policies concerning the dismissal and reassignment of managers and non-managers. All the questions measure practical (often plant floor level) operating models and in-place practices, not personnel related factors such as managerial skills.

For parts of the empirical analysis, the control variables and regional subdivisions for the establishments in the FMOP data are acquired from the Establishments 2015 and 2016 data sets of the Finnish Business Register by Statistics Finland. Only data for the establishments that responded to the questionnaire were used. Consent to linkage with Statistics Finland establishment-level micro data was ensured for all respondents as a part of the FMOP survey. All handling of data has been conducted following disclosure avoidance procedures to ensure the confidentiality of the individual surveyed units.

2.2.2 International comparisons

The FMOP design meticulously follows the US Management and Organizational Practices Survey. The United States is a useful benchmark for international comparisons because its management practices have been recognized as the best in the world in studies that utilize the World Management Survey (WMS). Comparing the management scores between countries is challenging since the samples are constructed differently in each country.

[7] A more detailed description is provided in the appendix.

Studies have found a clear positive correlation between the size of establishments and the management score (Bloom et al. 2016; Awano, Heffernan and Robinson 2017; Bender, Bloom, Card, Van Reenen and Wolter 2018; Bloom et al. 2019; Broszeit, Fritsch, Görg and Laible 2019), which means that different size limits for the establishments that are included in each country's data will also affect the comparability of the management scores. In the case of Finnish manufacturing establishments, this relationship between establishment size and management practices can be seen in FIGURE 1 and FIGURE 2. FIGURE 2 also shows the additional role of firm size.

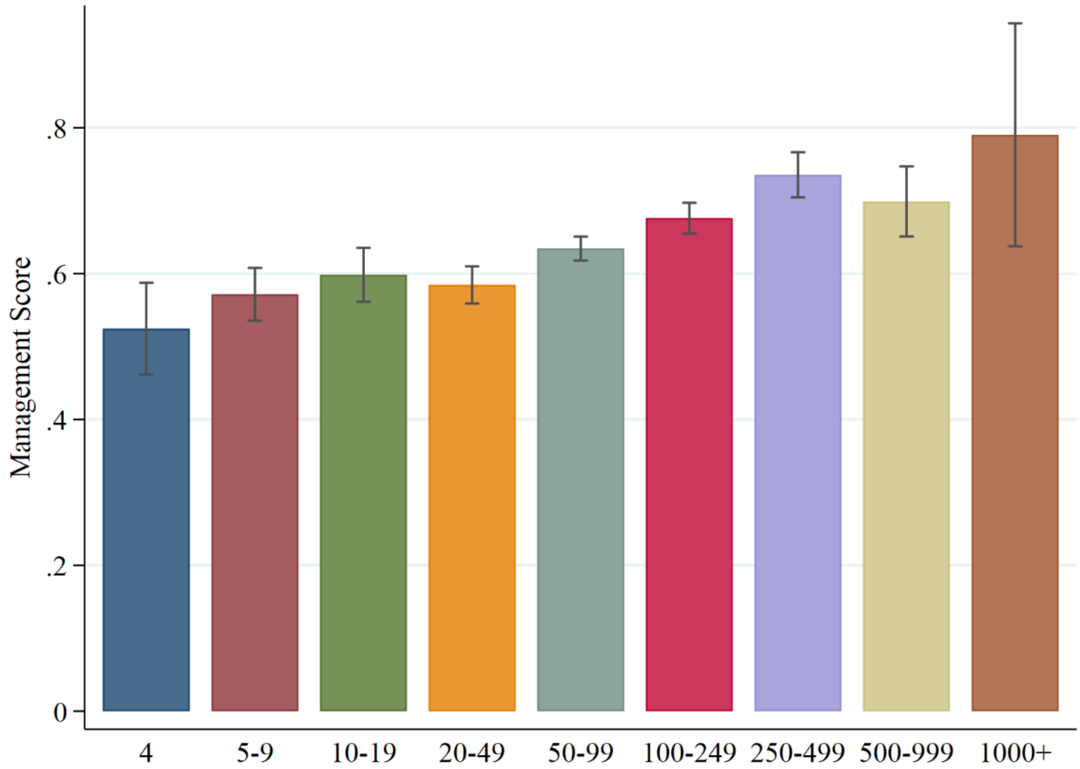

FIGURE 1 Unweighted average management scores by establishment size (number of employees) with confidence intervals.

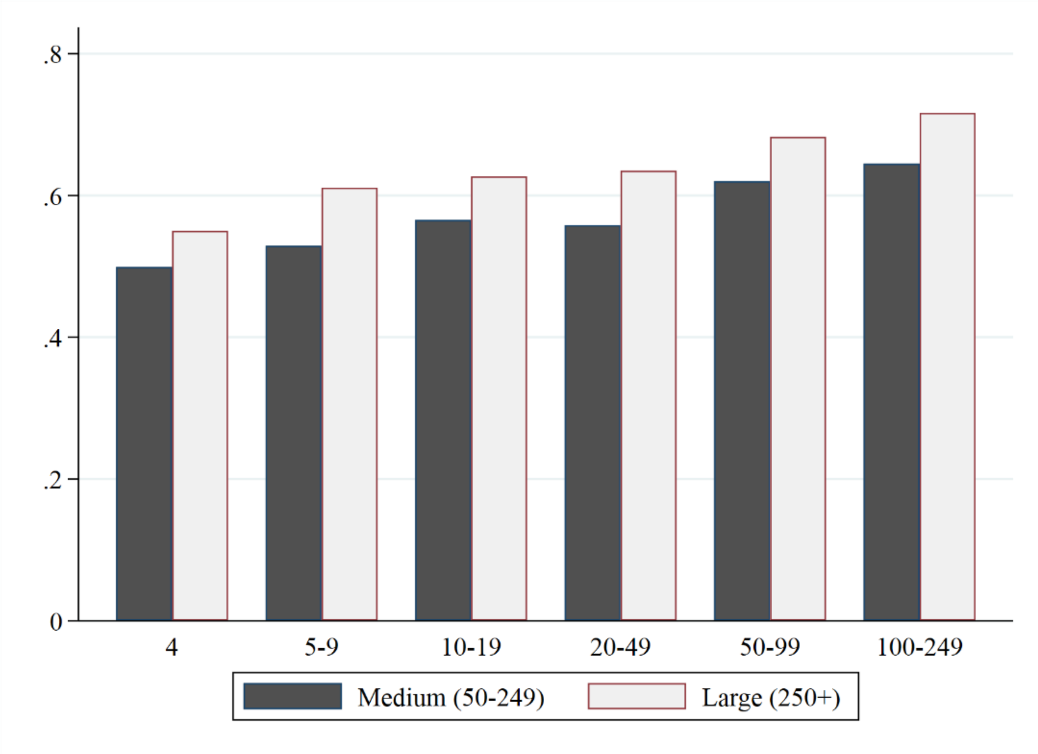

FIGURE 2 Unweighted average management scores by establishment size (number of employees) for medium and large enterprises.

FIGURE 3 is a simple comparison of the post-stratification weighted averages without using any imputed values. Because the establishments of small firms are missing from the FMOP data, the Finnish scores in the figure are slightly overestimated.

Another factor that might contribute to the overestimation of the Finnish scores compared to the US is the clearly the lower response rate. The FMOP had a response rate of 31%, whereas 78% of establishments responded in the US. The different reference years in each country also hinder their comparability, especially if the management scores vary over time. Comparisons utilizing the FMOP and the most recent US data have yet to be conducted.

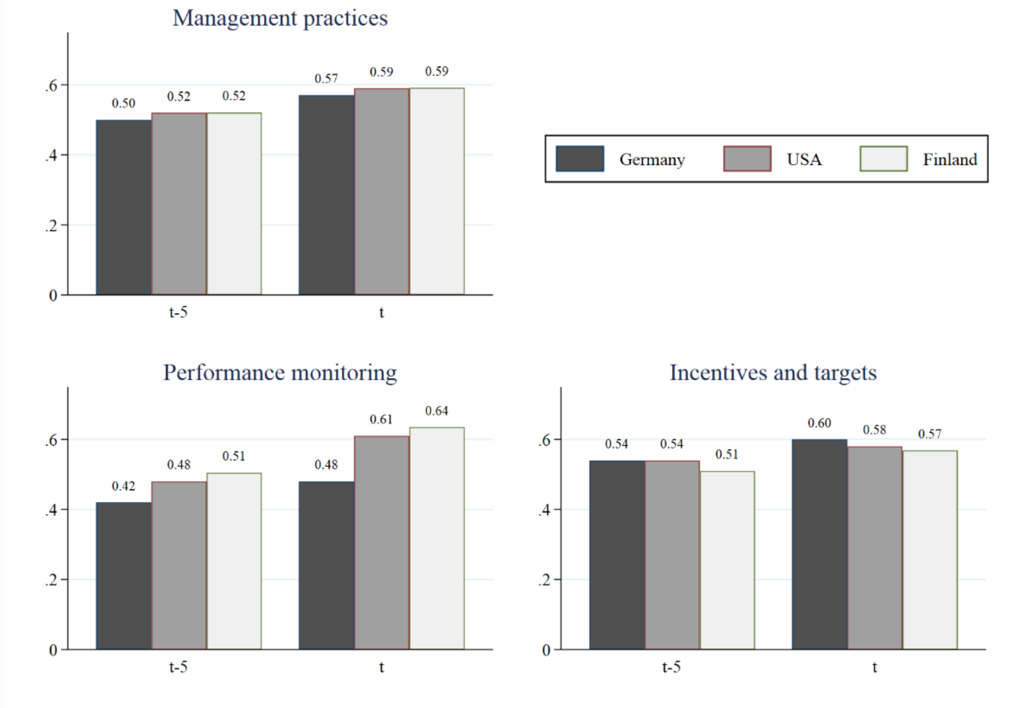

FIGURE 3 Comparison between Germany, the USA and Finland. Year t denotes 2010 for the US, 2013 for Germany and 2016 for Finland. The Finnish scores are weighted using industry-level post-stratification weights. Germany (Broszeit et al. 2019) and the USA (Bloom et al. 2013).

Finland also seems to have higher scores in performance monitoring than in incentives and targets when compared to Germany and the US. When incentives and targets are further divided into two categories, it is the incentives part that results in the lowest scores in the Finnish data. It is plausible that the low incentive scores are related to the relatively strict job market regulations and very high union membership rates in Finland.

The potential for effective monitoring is arguably related to digitalization, with the increasing use of digital systems in manufacturing establishments. To further examine this connection, we look at data from the annual Digibarometer published by Business Finland, the Ministry of Transport and Communications, the Technology Industries and Ecommerce Finland. Interestingly, Finland has indeed been ranked among the best three countries in the level of digitalization every year since 2014 (Ali-Yrkkö, Mattila, Pajarinen and Seppälä 2019). This could partly explain the high monitoring score of Finland compared to Germany and the US. In 2016, when the FMOP was conducted, Finland was number one in the Digibarometer, the US was ranked sixth and Germany placed fourteenth. Among other things, the Digital Barometer reflects the level and adoption of digitalised monitoring solutions, factors which are implicitly measured by the monitoring section of the FMOP questionnaire.

Evaluation of the different dimensions of the management score in Sweden, based on the World Management Survey (WMS), provides some further support for the conjecture that high monitoring scores may be related to the level of digitalization: Much like Finland in this paper, Sweden has a very high monitoring score in the WMS (Bloom, Genakos, Sadun and Van Reenen 2012). Sweden also ranks 4th in the Digibarometer for the years 2015 – 2017, higher than both Germany and the US (Ali-Yrkkö, Mattila, Pajarinen and Seppälä 2019).[8]

To mitigate the effect of different establishment size limits, comparing employment weighted (aggregate) averages instead of simple average scores would be useful. However, we do not have estimates of the strength of the allocation of workforce from other countries based on a survey following the MOPS methodology. The World Management Survey (WMS) based international comparisons in Bloom et al. (2016), and our own calculations in Maliranta and Ohlsbom (2017), suggest that the reallocation of workforce is stronger in the USA compared to Finland. Furthermore, Bloom et al. (2016) note that the reallocation is stronger in the United States than in the other 33 countries in their comparison, including countries like Japan, Sweden, Germany, Singapore and others. However, the WMS scores and the MOPS scores are not directly comparable, so we can not estimate how much stronger reallocation is in the US compared to Finland.

2.2.3 Descriptive statistics

With a standard deviation of 0.13, the dispersion of the management practices of Finnish manufacturing establishments is evident. As described by Maliranta and Ohlsbom (2017), approximately 7% of establishments have a management score higher than 0.8, whereas establishments with a score of less than 0.4 make up a little over 5% of the data. Furthermore, FIGURE 4 shows that the distribution is skewed slightly to the left, which means that the mass of the establishments is concentrated on the right side of the distribution. A rudimentary examination of the data shows that a considerable part of this dispersion is related to differences in establishment size. This aspect of the dispersion is analysed more carefully in Maliranta and Ohlsbom (2017), where we find a positive correlation between establishment size, firm size and management scores.

[8] We thank an anonymous referee for suggesting a consideration of the potential role of digitalization in the monitoring dimension of management.

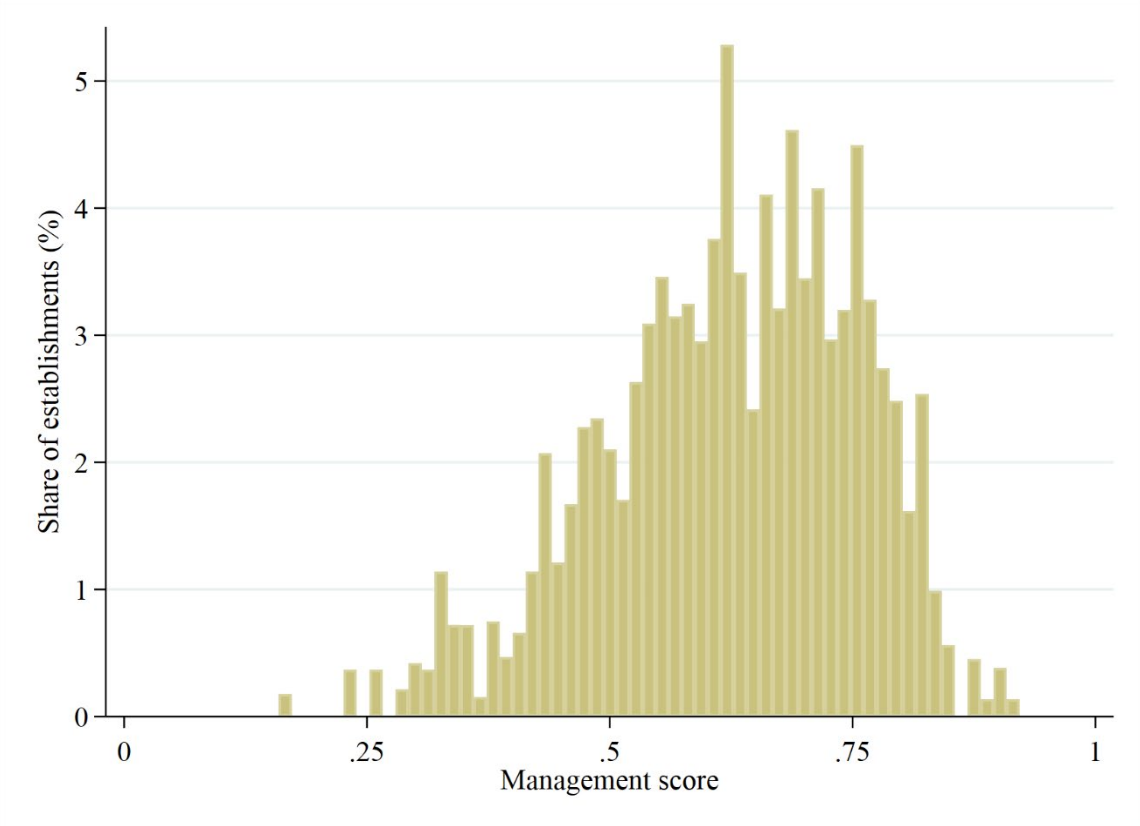

FIGURE 4 Distribution of the unweighted management scores.

The empirical analysis in the following section is focused on the possible role of cross-regional differences in the dispersion of management practices. The subdivision of large areas[9] was chosen to ensure that the individual areas have enough establishments in the data. Helsinki-Uusimaa is used as a baseline since it has the highest employment weighted (aggregate) and unweighted average management scores (0.71 and 0.64, respectively). FIGURE shows a map of the large areas of Finland.

[9] Level 2 of the subdivisions in the Nomenclature of Territorial Units for Statistics (NUTS) codes of Finland.

FIGURE 5 The large areas (NUTS 2) of Finland. Source: Statistics Finland municipality-based statistical units. Contains data from the National Land Survey of Finland Background map series Database.

The economic and demographic differences between the large areas are visible in TABLE 1.

TABLE 1 Descriptive statistics for the large areas of Finland.

Statistic	Helsinki-Uusimaa	Southern Finland	Western Finland	Northern & Eastern Finland
Population density (per km²)	180.1	36.8	23.7	6.4
Gross value added at basic prices (million EUR)	73,186	34,760	41,582	36,605
Share of manufacturing in gross value added	15.7%	24.9%	24.2%	21.0%
GDP per capita (EUR)	52,141	34,788	34,980	32,754
Employment (1000 persons)	876	496	606	539
Standard deviation of employment	30.2	16.7	16.4	17.5
Job vacancies	12,300	5,500	7,800	7,800
Economic dependency ratio	116.5	152.2	150.2	162.9
Share of population with higher education	12.8%	6.5%	7.0%	6.0%
Share of persons living in rural areas	8.1%	24.5%	40.4%	46.2%
Number of establishments	111,302	82,456	101,502	76,117
Turnover of establishments per employee (1000 EUR)	346	255	251	238
Excess job reallocation rate	15.2%	14.1%	14.0%	14.7%
Worker inflow rate	17.6%	15.3%	15.3%	16.3%
Worker outflow rate	21.8%	19.4%	18.8%	19.5%

Sources: Official Statistics of Finland (OSF): National Accounts and Enterprises. Source of excess job reallocation and worker flow rates: own calculations from linked employer-employee data of Statistics Finland. The job reallocation and worker flow rates are measured as averages of the rates in the years 2010 – 2014. The economic dependency ratio is calculated by dividing the sum of the number of unemployed and the number of inactive persons, or the non-employed population, by the number of employed and multiplying by one hundred. Higher education is defined as having a master's degree or equivalent level or a doctoral degree or equivalent level.

Population density and economic activity, measured by figures such as value added, GDP per capita and number of establishments, are the highest in Helsinki-Uusimaa by a relatively large margin. The higher density of production and housing might contribute to greater resource (re)allocation between establishments within Helsinki-Uusimaa. Furthermore, Helsinki-Uusimaa is by far the least rural of the large areas, with an 8.1% share of people living in rural areas, whereas the share is 24.5% in Southern Finland and more than 40% in both Western Finland and Northern & Eastern Finland.

The last three rows in TABLE 1 describe job reallocation and worker flows in each of the large areas, providing us with complementary dynamic measures of allocation. Measuring these job and worker flows is based on the measures of the job creation rate (JC) and the job destruction rate (JD), which are calculated as $JC_t = \sum_i \Delta E_{it}^{+}/((\sum_i E_{it} + \sum_i E_{i,t-1})/2)$ and $JD_t = |\sum_i \Delta E_{it}^{-}|/\left((\sum_i E_{it} + \sum_i E_{i,t-1})/2\right)$, respectively. Here, employment of firm i in year t is denoted by E_{it} and the plus and minus superscripts denote positive and negative changes in employment. The difference of the job creation and job destruction measures is called the net rate of change of employment (NET): $NET_t = JC_t - JD_t$ and the sum of these measures provides the (gross) job reallocation rate (JR): $JR_t = JC_t + JD_t$. (Davis and Haltiwanger 1998.)

Subtracting the absolute value of the net rate of employment from the gross job reallocation rate results in the excess job reallocation rate (EJR): $EJR_t = JR_t - |NET_t|$, which is included in TABLE 1. It is a simultaneous measure of the economy's job creation and job destruction (Ilmakunnas and Maliranta 2003).

To calculate worker inflow, the number of employees who have started working at an establishment i during year t, and have not left by the end of year t, denoted by H_{it}, is summed over all establishments. Dividing the value of worker inflow by the average of employment in periods t and $t-1$ results in the worker inflow rate (WIF), also known as the hiring rate: $WIF_t = 100 \sum_i \Delta H_{it}/\left((E_{it} + E_{i,t-1})/2\right)$. Similarly, worker outflow is $\sum_i S_{it}$, where S_{it} is the number of employees who started working in establishment i during year t, but have left by the end of year t. Again, the worker outflow rate (WOF) or separation rate is calculated by dividing the worker outflow by the average employment in periods t and $t-1$. (Ilmakunnas and Maliranta 2003.)

Differences in these worker flow measures highlight the importance of the allocation term, which is analysed in section 3, when performing cross-regional comparisons. Each of these statistics measures the highest in Helsinki-Uusimaa and the lowest in Western Finland and Southern Finland, the two of which have very similar labour market flow rates. All the flow rates of Northern & Eastern Finland are lower than those of Helsinki-Uusimaa but higher than those of the other large areas. These differences in worker flow rates suggest that, especially when comparing Helsinki-Uusimaa to Southern and Western Finland, the allocation of employment should be considered when estimating regional differences in management practices.

TABLE 2 Descriptive statistics for the establishments in the FMOP data.

	Number of establishments	Total number of employees	Aggregate management score	Unweighted management score
Helsinki-Uusimaa	97	12 175	0.71	0.64
Southern Finland	146	14 090	0.67	0.63
Western Finland	209	24 646	0.68	0.62
Northern & Eastern Finland	149	15 461	0.70	0.63
Total	601	66371	0.69	0.63

Studies from other countries have found significant differences in the unweighted management scores between different geographical areas (i.e. Bloom et al. (2012); Bloom et al. (2013)). Based on TABLE 2, which provides descriptive statistics of the FMOP data, these differences are not as apparent between the Finnish large areas.

FIGURE 6 demonstrates that the differences in the unweighted average management scores of the Finnish large areas are quite small, especially in relation to the confidence intervals. The differences in the unweighted averages, which do not take the allocation of the workforce into consideration, are also not statistically significant. FIGURE 6 also includes the employment weighted, or aggregate, management scores, to which the related statistical inference is presented in section 3. The unweighted (by employment) scores in FIGURE 6 are weighted using post-stratification weights calculated from the entire population of manufacturing establishments. This means that they are in line with the scores used in the international comparison presented in section 2.2.2, but not with the unweighted scores in TABLE 2.

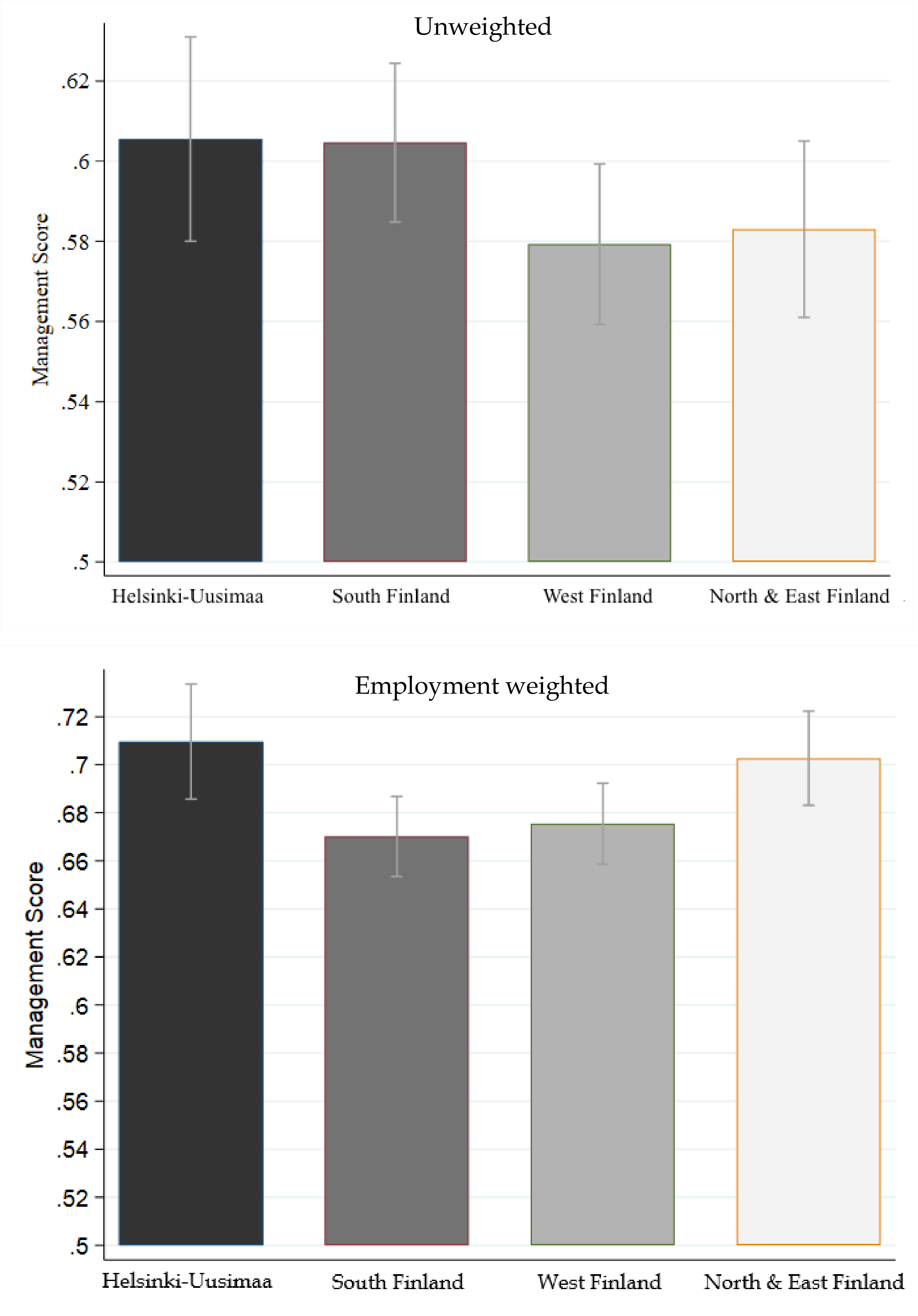

FIGURE 6 Unweighted and employment weighted average management scores for large areas with confidence intervals. Åland is omitted since it has only two establishments in the FMOP data. The unweighted (by employment) scores are weighted using post-stratification weights calculated from the entire population of manufacturing establishments.

2.3 Methods and results

2.3.1 Premise

The descriptive statistics that are presented in the previous section would suggest that there are no significant differences in the management practices of the large areas of Finland when measured using unweighted management scores. However, a simple inspection of the means gives no insight into the possible differences in the covariance-like allocation term. A decomposition of the aggregate management score could potentially reveal statistically significant cross-regional differences in the allocation term, despite there being none when considering only the unweighted averages. Since the allocation term describes the amount of workforce that is allocated to establishments with good management practices, it is an important measure in terms of economic and policy significance.

As pointed out by Hyytinen et al. (2016), a simple Olley-Pakes decomposition does not produce standard errors for the OP components or allow for any statistical inference regarding the policy relevant allocation term. They show, however, that this can be done by means of a procedure that is based on a generalized method of moments (GMM) estimation.

2.3.2 Methods

The empirical decomposition of the micro-level components of the levels of aggregate management practices in Finnish regions is performed using the method proposed by Olley and Pakes (1996). In the economics literature, these kinds of decompositions have often been used to analyse productivity levels. In the decomposition, aggregate productivity is divided into two terms: the unweighted average productivity and a covariance term of the productivity and firm size. The latter, which is also known as the allocation term, is essential because it describes how much of the input activity is allocated to more productive establishments or enterprises (Hyytinen et al. 2016).

A significant part of the growth and cross-country dispersion of productivity may be caused by the reallocation of resources from enterprises with low productivity to those with high productivity (Maliranta and Määttänen 2015). The covariance-like allocation term of the Olley-Pakes decomposition is a much-used measure for this reallocation since it is straightforward and has been theoretically and empirically shown to provide meaningful information. Bartelsman et al. (2013), for example, show that the allocation term, measured as the covariance between employment and productivity, is a robust indicator for the misallocation of resources and that it interacts strongly with frictions and policy-induced market distortions. Therefore, the allocation of resources with respect to management practices is measured as the covariance-like term between employment and the management score.

As with productivity, the qualities mentioned above make the Olley-Pakes covariance term essential in the analysis of cross-regional differences in management practices, especially in terms of how they relate to competitiveness. The aggregate (employment weighted) management score can be decomposed into the unweighted average score and the allocation effect, which is a covariance-like term for the management score and the size of the workforce in an establishment.

Here, the allocation term is economically significant because it measures how workforce is allocated between establishments with varying management scores. The larger the term, the larger share of the workforce is working under better managed establishments. This means that, in terms of competitiveness, the allocation term may play a crucial role when studying cross-regional differences.

Furthermore, comparing employment weighted (aggregate) averages instead of simple average scores would provide valuable insight into cross-country differences in management practices. Using employment weights decreases the impact of the smallest establishments on the results. This would help mitigate the comparability issues caused by each country's samples having different lower limits for establishment size.

To obtain the standard errors of the OP decomposition, a moment-based procedure, which was introduced by Hyytinen, Ilmakunnas and Maliranta (2016), is used. This method allows for statistical inference and hypothesis testing of the magnitude of the OP components, which in turn allows for more statistically meaningful cross-regional comparisons of the allocation term.

The procedure is based on a method of moments estimation, which is a way of motivating an ordinary least squares (OLS) estimator (Davidson 2001). Hyytinen et al. (2016) show how the components of the OP decomposition of aggregate labour productivity can be captured using a generalized method of moments (GMM) approach. This paper utilizes the same procedure for the aggregate management score in a cross-sectional setting. Following Olley and Pakes (1996), the decomposition is described by the expression

$$M_i = \bar{m} + \sum_{i=1}^{N} (s_i - \bar{s})\,(m_i - \bar{m}), \tag{1}$$

where m_i is the management score of establishment i.

s_i is the activity share of establishment i, as measured using labour input shares. $\bar{m}_i$ denotes the unweighted mean of the management scores, whereas the weighted or aggregate management score is $M_i = \sum_{i=1}^{N} s_i m_i$. The remaining term, $\sum_{i=1}^{N}(s_i - \bar{s})(m_i - \bar{m})$, is the policy relevant allocation term. It then follows from the population moments expression of the regression,

$$E[m_i|s_i] = E[m_i] + cov(m_i, s_i)var(s_i)^{-1}(s_i - E[s_i]), \tag{2}$$

that by scaling the labour input share measure s_i, a GMM estimation can capture the two components of the OP decomposition (Hyytinen et al. 2016).

2.3.3 Results from the moment-based approach

As mentioned in section 1, the following analysis is descriptive, and no causal results can be inferred without strong additional assumptions.

TABLE 3 shows the results of the moment-based estimation. Standard errors are calculated using the Huber-White estimator of variance. The left column shows the point estimates for all areas, whereas the right column shows the associated 95% confidence intervals. The first four rows of each column are for the unweighted average management score of each area. The second four rows show the results for the allocation term of each area, and at the bottom is the aggregate (employment weighted) average, which is the sum of the first two components.

The results in TABLE 3 show that the confidence intervals in the lower bound and upper bound columns for Northern & Eastern Finland, especially for the allocation term, are clearly wider than those for the other large areas. Furthermore, the allocation terms in the point estimate column for Helsinki-Uusimaa and Northern & Eastern Finland account for approximately 10% of the respective aggregate management scores ($9.9\% \approx 100 * \frac{0.07}{0.71}$ and $10\% = 100 * \frac{0.07}{0.70}$), whereas for Southern Finland and Western Finland, these ratios are 6% and 7%, respectively. The differences in the unweighted average scores, as mentioned in subsection 2.3, are not statistically significant between any two large areas.

The statistical tests that were performed using the moment-based procedure show that the differences in allocation terms are also not statistically significant at conventional significance levels, except for the difference in the allocation terms between Helsinki-Uusimaa and Southern Finland in the point estimate column of TABLE 3 ($0.03 = 0.07 - 0.04$). The Wald test statistic, testing the null hypothesis that there is no difference between the allocation terms of Helsinki-Uusimaa and Southern Finland, is 2.76 ($p = 0.096$). The difference is therefore statistically significant at the 10% significance level. The difference in the allocation terms accounts for approximately ¾ or 75% of the difference in the aggregate management scores between these two areas.

TABLE 3 Weighted and unweighted average management scores and allocation terms for the large areas with confidence intervals. Standard errors are calculated using the Huber-White estimator of variance.

	Point estimate	95% confidence interval	
		Lower bound	Upper bound
Unweighted average management score			
Helsinki-Uusimaa	0.64	0.61	0.66
Southern Finland	0.63	0.61	0.65
Western Finland	0.62	0.61	0.64
Northern & Eastern Finland	0.63	0.61	0.65
Allocation term			
Helsinki-Uusimaa	0.07	0.04	0.11
Southern Finland	0.04	0.01	0.06
Western Finland	0.05	0.03	0.08
Northern & Eastern Finland	0.07	0.02	0.12
Aggregate average management score			
Helsinki-Uusimaa	0.71	0.67	0.75
Southern Finland	0.67	0.65	0.69
Western Finland	0.68	0.65	0.70
Northern & Eastern Finland	0.70	0.66	0.75

Based on results from other countries, more cross-regional variations in the management practices of Finnish manufacturing establishments were expected. The lack of large cross-regional variations suggests that intervening on the management practices of Finnish establishments is unlikely to be among the most important tools in compressing regional disparities in Finland. The allocation component of the management score almost entirely accounts for the little variations that were found.

This suggests that policies focusing on issues related to competition between establishments and the mobility of labour within regions would likely be more effective than trying to directly improve management practices. Labour mobility is necessary for the reallocation of employment, but also works as a channel of knowledge spillovers between firms (Maliranta, Mohnen and Rouvinen 2009). Competition may drive workforce towards best-managed establishments and affect the adoption of management practices by increasing firms' incentives to invest in them (Bloom and Van Reenen 2007; Bloom, Propper, Seiler and Van Reenen 2015).

Examining the relationship between some measures of competition, such as the Herfindahl–Hirschman Index (HHI) or concentration ratios, and the reallocation of employment could be an interesting supplement to the analysis. However, the choice of unit of observation (establishment or firm), level of industry classification and geographic regions to define the relevant market renders the commonly used measures of competition highly ambiguous in this context. We have therefore not included calculations involving these types of measures.

The results from the moment-based approach show that statistical inference concerning the allocation component of the decomposition is essential for credible analysis of cross-regional differences in management practices. Cross-country comparisons of the Olley-Pakes components of the management score would therefore provide new insights into the differences in the allocation of resources, management practices and the aggregate productivity of countries. This would complement existing and upcoming analyses of global competitiveness.

Furthermore, the aggregate (i.e. employment weighted) management score is more robust to different establishment size lower limits in the compared samples. Therefore, it allows for not only more relevant, but also more reliable comparisons in the presence of such differences in size cut-offs. However, uniform establishment size cut-off limits for samples, in addition to the statistical method used in this paper, are needed to reliably compare the covariance-like allocation terms between countries or regions.

Standard errors for the allocation component can be estimated using the moment-based estimation method presented in part 3.2. However, a downside to the moment-based estimation procedure is the inability to include control variables in the estimation. An OLS estimation of a linear regression model is therefore presented to support the robustness of the results.

2.3.4 OLS estimation results

The GMM estimation procedure, proposed by Hyytinen et al. (2016), unfortunately does not allow for measuring the allocation component when the regression models include control variables, such as industry fixed effects. However, the allocation term can also be computed by performing a standard OLS estimation with and without employment weights and taking the differences of the parameter estimates of these two estimations. Unlike the GMM estimation procedure, this does not provide us with the standard errors for the allocation component.

Estimating the regression models with and without employment weights, while including control variables, can nevertheless provide evidence on the regional differences in the aggregate management practice quality levels, and at least an impression of the role of the allocation of employment between establishments. The results of the OLS regression can be found in Table 4, where the other large areas are compared to Helsinki-Uusimaa. Standard errors are again calculated using the Huber-White estimator of variance.

Adding employee education (average years of schooling) as a control variable in columns 5 – 8 shows that the education level of employees might have a positive relationship with the management quality in Helsinki-Uusimaa, but the inclusion of this factor does not dramatically change the results for regional differences. Productivity (log(revenue) / number of employees) is, as expected, also positively correlated with the management score, as seen in columns 9 – 16.

Qualitatively similar conclusions concerning regional differences are obtained from the regressions that include both education and productivity effects, presented in columns 13 – 16 of Table 4. Helsinki-Uusimaa has an aggregate score that is between 0.05 and 0.06 higher than Southern Finland ($p < 0.05$), with and without industry fixed effects. This difference could be considered somewhat economically significant in magnitude since the management scores are normalized on a scale of 0 – 1. Without industry fixed effects, Helsinki-Uusimaa's aggregate score is approximately 0.04 higher than Western Finland ($p < 0.10$). However, the statistical significance of the latter difference disappears when industry fixed effects are included.

With industry fixed effects included, the regional differences become larger by a small margin in every regression, with and without the control variables, but the conclusions remain unchanged. Furthermore, columns 4, 10, 12, 14 and 16 of Table 4 provide evidence that the aggregate (employment weighted) management quality is greater in Helsinki-Uusimaa than in Southern Finland.

The moment-based estimation in part 3.3 shows that the allocation terms are statistically significantly different between Helsinki-Uusimaa and Southern Finland, but the unweighted scores are not. The latter conclusion is supported by the OLS estimation, which unfortunately cannot be used to estimate the former. Since the moment-based estimation procedure does not allow control variables, the OLS estimation results are more credible when examining differences in the aggregate scores. However, since OLS does not allow for statistical inference or hypothesis testing concerning the allocation component, we must rely on the moment-based estimation for the allocation terms.

The OLS results suggest that if we were able to include control variables in the GMM estimation, we would find a statistically significant difference in the aggregate scores of Helsinki-Uusimaa and Southern Finland, like we did for the allocation term. Combining the GMM and OLS results indicates that the difference in the aggregate scores can be attributed to differences in the allocative efficiency of the regions, not differences in the quality of management practices at the establishment level.

TABLE 4 OLS regression results

Management score	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Employment weighted		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Southern Finland	-0.005	-0.040	-0.010	-0.046*	-0.014	-0.036	-0.019	-0.043	-0.006	-0.052**	-0.009	-0.057**	-0.014	-0.055**	-0.018	-0.058**
	(0.016)	(0.024)	(0.017)	(0.025)	(0.018)	(0.026)	(0.018)	(0.027)	(0.017)	(0.021)	(0.017)	(0.024)	(0.018)	(0.023)	(0.018)	(0.025)
Western Finland	-0.013	-0.034	-0.013	-0.036	-0.020	-0.032	-0.020	-0.032	-0.010	-0.039	-0.010	-0.041*	-0.017	-0.040*	-0.017	-0.041
	(0.016)	(0.025)	(0.016)	(0.026)	(0.018)	(0.026)	(0.017)	(0.028)	(0.016)	(0.022)	(0.016)	(0.025)	(0.018)	(0.024)	(0.017)	(0.026)
Northern & Eastern Finland	-0.007	-0.007	-0.014	-0.019	-0.005	-0.001	-0.013	-0.014	-0.004	-0.008	-0.010	-0.018	-0.001	-0.010	-0.009	-0.020
	(0.017)	(0.032)	(0.017)	(0.028)	(0.019)	(0.033)	(0.019)	(0.030)	(0.017)	(0.030)	(0.017)	(0.027)	(0.019)	(0.031)	(0.019)	(0.029)
Employee education					0.017***	0.005	0.017***	0.005					0.014***	-0.004	0.012**	-0.006
					(0.005)	(0.008)	(0.006)	(0.008)					(0.005)	(0.008)	(0.006)	(0.008)
Productivity (log)									0.030***	0.046***	0.027***	0.043***	0.033***	0.047***	0.029***	0.044***
									(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.010)
Observations	601	601	601	601	517	517	517	517	601	601	601	601	517	517	517	517
Industry Fixed Effects			Yes	Yes			Yes	Yes			Yes	Yes			Yes	Yes
R^2	0.001	0.019	0.039	0.056	0.022	0.020	0.061	0.061	0.044	0.103	0.070	0.123	0.073	0.101	0.0982	0.1243
Prob > F	0.872	0.287	0.003	0.050	0.011	0.395	0.000	0.074	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The coefficient for each large region shows the difference in the mean of the management score compared to Helsinki-Uusimaa. Productivity (log) is measured as log(revenue/number of employees). Employee education is measured as the employees' average years of schooling for each establishment. The industry fixed effects were calculated at the 2-digit level of the Standard Industrial Classification; manufacturing (10-33) was divided into seven subindustries: 10-15, 16-18, 19-23, 24-25, 26-27, 28-30 and 31-33. Prob > F is the p-value of the F-test and standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.3.5 Validity of the results

As mentioned in section 2, the data are skewed towards larger establishments and establishment size seems to be positively correlated with the management score. This means that the sample means that are calculated from the data are likely to be too high compared to the population means, unless post-stratification weights are used to correct for this non-response bias. The post-stratification weights used in the international comparisons are calculated from the entire population of manufacturing establishments, so they should be relatively effective in correcting for the non-response bias.

It is unlikely that there are systematic differences in the amount of bias between the large areas. Therefore, non-response bias should not significantly affect the main conclusions presented in this paper. If the bias were bigger in one large area than in another, the unweighted management score of the large area with greater non-response bias would be overestimated. However, employment weighted measures are much less affected by this type of bias, since the biggest measurement issues stem from missing small, rather than big, establishments. This implies that the allocation terms would be underestimated in the large areas with worse non-response bias.

Furthermore, the number of establishments in the data is relatively small, which might partly explain the apparent lack of statistically significant results. The partitioning into large areas was chosen partly because of the small sample size, yet the number of data points for each area remains relatively low. The measured cross-regional differences are also somewhat small in magnitude, which is a result that most likely would not be affected by a larger sample size.

However, more robust results could be achieved by repeating the survey for a larger sample, which should also contain the establishments that were included in the 2016 FMOP data. Combining more comprehensive data on management practices with the exceptionally rich microdata of Statistics Finland would allow for more potent robustness tests and further analysis. Creating a time series of Finnish management practices using the FMOP methodology would also enable researchers to study how the adoption of structured management practices evolves over time.

The FMOP, like any large-scale survey, almost certainly suffers from survey noise, but there should be no systematic differences in the amount or type of survey noise between the large areas. Therefore, it is unlikely to interfere with the comparisons. Some rudimentary descriptive analysis was also conducted using Finnish regions (NUTS 3) instead of large areas. The results suggest that the apparent statistical non-significance of the cross-regional differences in the unweighted management scores is likely preserved for this geographical division. However, for some of the regions, the number of establishments in the data is extremely small. FIGURE shows the unweighted average management scores for each region.

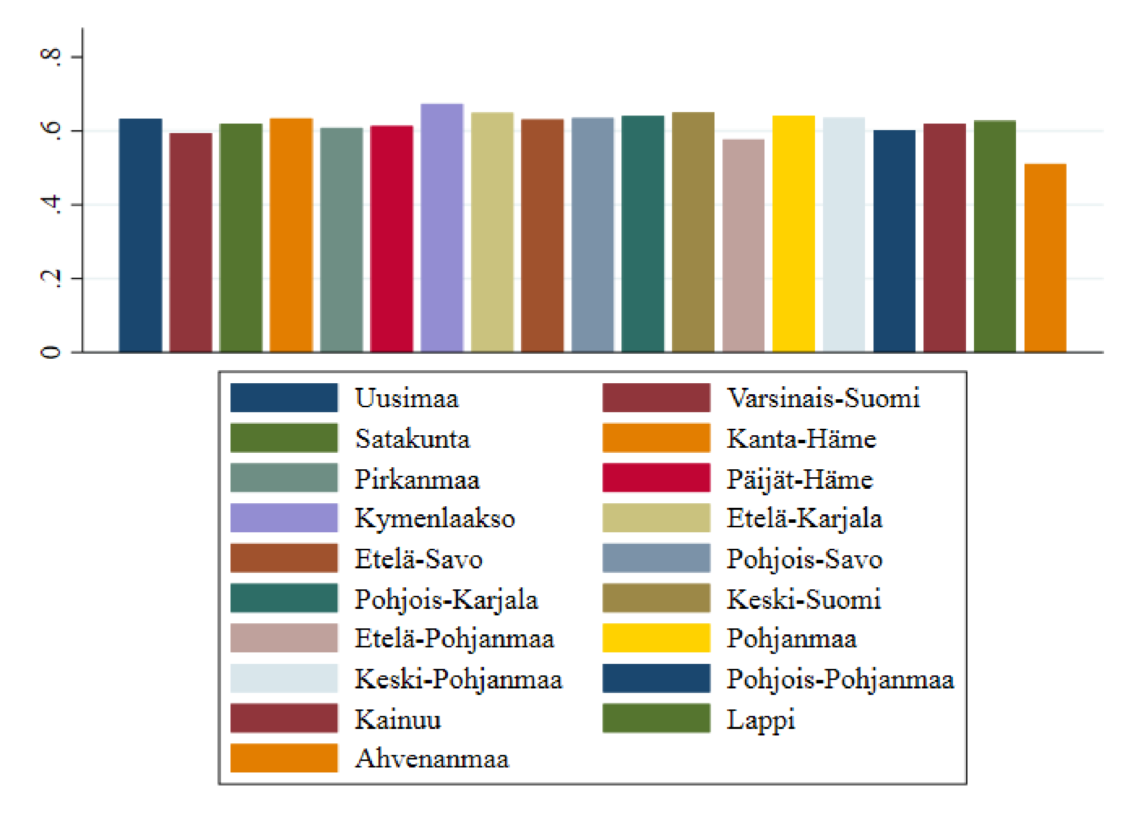

FIGURE 7 Unweighted average management scores by region.

We have also conducted the OLS and the moment-based estimations in log-units, which returned similar results. Furthermore, the analysis was conducted with and without mining and utilities, industries that are included in manufacturing[10] in the Finnish sample but were not included in the United States MOPS. The exclusion of these industries did not change the conclusions presented in the paper, but it does restrict the data by an additional 98 observations. All the analyses in sections 2 and 3 are descriptive, and without additional assumptions, no causal inferences can be made based on the calculations that are presented.

2.4 Conclusions

An examination of Finnish manufacturing establishments, using data from the Finnish Management and Organizational Practices Survey, showed no statistically significant cross-regional differences in the unweighted management scores when comparing the large areas of Finland. An Olley-Pakes decomposition is utilized to split the aggregate (employment weighted) management score into an unweighted average component and a covariance-like allocation term.

[10] Establishments were classified as manufacturing if they belong to industries 05-39 in the Standard Industrial Classification TOL 2008 (Statistics Finland 2017)

Examining the regional differences in the OP components using a moment-based estimation procedure, presented in Hyytinen et al. (2016), provides us with standard errors for the estimates of the allocation term, which is novel in the literature.

Our analyses advice researchers and policy-makers to direct their attention to the dynamics of competition and the mobility of the labour force between firms. We find suggestive indications of small to moderate regional variations in the allocation component of the management scores of Finnish manufacturing establishments. This points to the allocation of employment between establishments within regions as an explanation for the regional differences in management practices. What drives this variation in Finland is a subject for future research. However, Bloom et al. (2019) conclude that two key drivers for the differences in the management practices in the United States are the business environment and learning spillovers.

An OLS estimation is performed to support the conclusions drawn from the moment-based estimation procedure. The results for the aggregate (employment weighted) differences between regions are robust to the inclusion of the educational level of employees and the productivity level of the establishments as control variables. However, with currently known methods, we are unable to test whether the difference in the allocation term is robust to the inclusion of control variables.

The results suggest that the regional variations in the aggregate score are related to differences in the allocative efficiency within the regions, not to differences in the quality of management practices at the level of establishments. This shows that statistical inference concerning the allocation component of the decomposition is an integral part of any cross-regional, or cross-country, comparisons of management practices. The literature has so far largely ignored this aspect of the uncertainty concerning the measurement of management practices.

Many countries have found large differences in the quality of management practices between establishments, firms, industries and geographical areas (Bender et al. 2018; Bloom et al. 2016; Bloom et al. 2019). Since management practices are also closely related to firm productivity (Bloom et al. 2019), and therefore economic competitiveness, understanding the variations in management practices should clearly be of major policy interest. In particular, the share of the workforce that is allocated to establishments with different levels of management practices is a policy relevant piece of the productivity puzzle. The results presented in this paper highlight the importance of workforce allocation, and the uncertainty regarding its estimates, when measuring management practices.

Despite the varied economic and demographic features of the Finnish large areas, and in contrast with the international results, we find surprisingly little cross-regional variations in the quality of management practices in Finland. This, and the already internationally competitive level of Finnish management, implies that investing in the improvement of management practices is unlikely to be the most effective tool in compressing regional disparities, for example.

Instead, our analysis suggests that more attention should be paid to factors that are reducing the mobility of the workforce and hampering competition between firms, both important elements of (re)allocation of employment. Besides being a mechanism of reallocation, the mobility of the labour force works as a channel of knowledge spillovers between firms (Maliranta et al. 2009). Competition may increase firms' incentives to invest in their management practices (Bloom and Van Reenen 2007; Bloom et al. 2015) and drive workforce towards best-managed firms through a process involving creative destruction, with the result of improved competitiveness at the level of the economy or its regions.

Our cross-regional analysis highlights the uncertainty in international comparisons when they are performed without the use of micro-level decomposition methods and standard errors for the covariance-like allocation term. We suggest that if the methods outlined in this paper were used to analyse the management differences of cities and industries, in other countries or between countries, researchers might find results that are of major policy relevance for the purpose of improving productivity and economic competitiveness.

For example, combining these results with an analysis of the direct link between management practices and productivity could enable a researcher to determine the largest regional productivity differences attributable to differences in the adoption of management practices. Results describing said link between management practices and productivity are presented in the second article of this dissertation. Another target for a future study could be the link between establishments entering and exiting the market and the changes in the regional distributions of management practices[11]. This would require repeating the FMOP survey to create a time series of Finnish management practices.

Data availability

All data are controlled by Statistics Finland and can be accessed by contacting Statistics Finland's research services and completing an application for licence to use the statistical data. See https://www.tilastokeskus.fi/tup/mikroaineistot/index_en.html.

11 The authors would like to thank the preliminary examiners of this dissertation for these suggestions for future research.

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2.6 Appendix A: data description

2.6.1 Sampling frame

The enterprise-level sampling frame for the 2016 FMOP is based on the total sample of Statistics Finland's Financial statements inquiry for enterprises (TILKES). The TILKES concerns all enterprises that employ over 50 people, as well as enterprises whose turnover is more EUR 40 million or whose balance sheet exceeds EUR 300 million. The inquiry also includes 10-50 employee enterprises, which have been drawn by random sampling, some enterprises with less than 10 employees and all enterprises owned by municipalities. The inquiry includes approximately 6000 enterprises in total. The FMOP sampling frame consists mainly of the over 4-employee manufacturing establishments in over 50-employee enterprises included in the TILKES inquiry. (Statistics Finland 2017.)

2.6.2 Sample

The sample for the 2016 FMOP data collection consisted of 2509 manufacturing establishments with at least 4 employees that were extracted from the manufacturing and non-manufacturing enterprises included in the TILKES based sampling frame. Establishments were classified as manufacturing if they belong to industries 05-39 in the Standard Industrial Classification TOL 2008 (Statistics Finland 2017). A manufacturing establishment with at least 4 employees was picked from the sampling frame if it belonged to an enterprise with more than 50 employees, with an over EUR 40 million turnover or a balance sheet of more than EUR 300 million. The main rule in the sample selection was the number of personnel, but the sample includes 38 units that belong to enterprises with less than 50 employees, due to the other conditions. Because the establishments for the sample were chosen by nonprobability sampling, most of the results can only be generalised to the subset of manufacturing establishments which have at least 4 employees and are a part of an enterprise with at least one of the following qualities: more than 50 employees, a turnover of more than EUR 40 million or a balance sheet that exceeds EUR 300 million. (Statistics Finland 2017.)

2.6.3 Data collection

The first step of data collection was to find a respondent for each establishment in the sample. Telephone interviews were conducted to find plant managers to send the questionnaire to. 10% of the original sample was lost at this phase due to over-coverage and unwillingness to answer. The survey was conducted as an internet questionnaire, the description, instructions and link for which were sent out as an email to the target respondents. Responding was voluntary, and three follow-ups were sent to establishments that could not be reached or did not respond. Over-coverage and establishments that were explicitly unwilling to answer were dropped after each follow-up.

2.6.4 Questionnaire content

To ensure comparability between results, the FMOP questionnaire was replicated from the United States 2010 MOPS[12] as closely as possible. The questionnaire has a total of 35 questions, 16 of which concern management practices. In addition to the 16 management questions, the questionnaire has 13 questions on organizational practices and 6 background questions. The questionnaire concerns the past year (2016), but most of the questions also have a recall component, where respondents are asked to give an answer regarding the circumstances five years earlier (2011). The questions are in Finnish and have been translated to correspond with the questions of the US MOPS. The complete FMOP questionnaire can be found at the end of this document

2.6.5 Data

The final number of responses was 731, with a response rate of approximately 31% after accounting for over-coverage. According to the feedback from the establishments, the voluntary nature of the survey was a major negative factor in the willingness to respond. This can also be seen when comparing the 31% response rate of the FMOP to the 78% response rate of the original 2010 MOPS in the United States, where the survey was mandatory. Technical issues also affected the response rate, as the survey was conducted solely through internet collection. Analysis of total non-response conducted by Statistics Finland showed that the distribution of respondents was skewed towards larger establishments, as measured by the number of personnel. Statistics Finland conducted a post-stratification to provide sample weights that correct for non-response bias. The over-coverage of 146 establishments was also taken into account when constructing the sample weights.

2.6.6 Data restrictions

The industries in the FMOP sample, 05-39 in the Standard Industrial Classification, include mining and utilities (in addition to manufacturing), which were not included in the United States MOPS sample. Therefore, the FMOP analysis is conducted with and without the two additional industries, and removing the industries restricts the data by 98 observations. Furthermore, in accordance with the United States 2015 MOPS, only establishments that gave a valid response to questions 1, 2, 6, 13, 14, 15 and 16 are included in the analysis. This means that an additional 69 establishments, or about 9.4% of the data, are dropped due to item non-response. Item non-response was more severe in the 2011 recall questions. However, the included establishments were chosen based solely on the responses for 2016. There are no establishments in the data that gave valid responses to the required questions for 2011 but failed to do so for 2016. Item non-response does

12 Available at https://www.census.gov/programs-surveys/mops/technical-documentation/questionnaires.html.

not distort the management scores, which are calculated as the unweighted average of the responses, but it would cause bias in estimates regarding individual questions.

2.6.7 Scoring

The responses for each question are normalized on a scale of 0 – 1 and the establishment-level management score is calculated as the unweighted average of the normalized responses. The answer options corresponding with management practices that are considered the most structured are assigned a value of 1 and the least structured practices are assigned a value of 0. Bloom et al. (2019) define more structured management practices as "those that are more specific, formal, frequent or explicit" (Bloom et al. 2019, 28).

The management questions can be divided into three sections: monitoring, targets and incentives. The monitoring section consists of questions 1 – 5 and they ask about the utilization and gathering of information and data in the monitoring of production. Questions 6 – 8 are about the setting of production targets and questions 9 – 16 ask about practices concerning bonuses and incentives, policies on recruitment and promotion as well as policies concerning the dismissal and reassignment of managers and non-managers.

3 MANAGEMENT PRACTICES, LABOUR PRODUCTIVITY, AND HUMAN CAPITAL INTENSITY[13]

Abstract

Combining quantitative management practices data with the Finnish Longitudinal Employer-Employee Data, we demonstrate how managerial human capital affects the relationship between productivity and management practices. To do this, we must account for the educational background of managers and workers separately. We find evidence that the productivity improvements associated with adopting more structured management practices vary with the levels of managerial human capital. Accounting for the interaction, a 10 percent increase in the management score is associated with an average of 7.1 percent higher labour productivity. Furthermore, management practices can account for more than 24 percent of the observed productivity dispersion. This is almost as much as information and communication technologies and more than both research and development and human capital.

Key Words: management practices, management survey, FMOP, productivity, human capital, education

JEL: J21, J24, J63, M11, M54

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13 Preliminary results presented in the International Management Surveys Workshop December 11, 2019 at the United States Census Bureau .

3.1 Introduction

The discovery of significant and persistent heterogeneity in productivity across firms and establishments, even within narrowly defined industries, has spurred a wealth of related research (Syverson 2004). Such explanatory variables as research and development (R&D), information and communication technologies (ICT) spending, worker skills and, more recently, management practices have been a central part of uncovering more pieces of the productivity puzzle. This article contributes to the existing literature by demonstrating how managerial human capital affects the relationship between productivity and management practices. Using a uniquely comprehensive combined employer-employee data set, we can isolate the contribution of managerial human capital without the need for rough proxies[14].

The idea of management as a driver of productivity is an old one (for example, Walker (1887)), but as Chad Syverson (2011, 336) puts it in his survey of productivity studies: "Perhaps no potential driver of productivity differences has seen a higher ratio of speculation to actual empirical study." The main reason has been the lack of adequate large-scale data on management. Fortunately, this is no longer the case. The Finnish Management and Organizational Practices survey (FMOP) provides high quality quantitative data on establishment-level management practices. Furthermore, the comprehensive information on occupations in the combined employer-employee data of Statistics Finland enables an especially useful partition of human capital intensity: we can examine the education levels of managers and non-managers separately. The partition provides a measure of managerial human capital and allows for assessing the importance of managerial and non-managerial abilities and their interactions with other key variables in our models.

Using the multivariable fractional polynomials interaction (MFPI) approach (Royston & Sauerbrei 2008), a comparison of how well different models predict productivity from management practices and human capital in Finnish manufacturing establishments reveals a linear two-way interaction between the education of managers and management practices. Testing and accounting for this interaction is important for reliable estimation of the relationship between management practices and firm performance. No statistically significant interaction is found between management practices and the education of non-managers.

Accounting for the linear interaction between management and manager education, a 10 percent increase in the FMOP management score is found to be associated with an average of 7.1 percent higher labour productivity. The relationship between management and productivity is significant both statistically and in magnitude: increasing the adoption of structured management practices from the tenth percentile to the ninetieth can account for up to 24 percent of the

14 For example, Bender et al. (2018) use an estimate of employee earnings capacity as a proxy for human capital and the workers in the upper quartile of the pay distribution as a proxy for managers.

corresponding 90–10 productivity gap. This is close to as much as information and communication technologies (ICT), a little more than human capital and more than 30 percent more than research and development (R&D). These measures of the 90–10 spreads are not very robust, since they are sensitive to, for example, scaling and measurement issues. However, they are not meant to accurately describe the absolute importance of the included factors in explaining productivity variation, but rather demonstrate the relative importance of accounting for management.

3.2 Measuring management practices

Based on the same theoretical framework as the World Management Survey (Bloom & Van Reenen 2007), the United States Census Bureau, together with researchers Nick Bloom, Erik Brynjolfsson and John Van Reenen, developed the original Management and Organizational Practices Survey (MOPS). Studies utilizing these methods find large dispersion in the use of structural management practices across establishments, both between and within firms (Bloom et al. 2019). The survey tool has since been translated and adapted to collect data on the quality of management practices in Finnish manufacturing establishments. This paper uses said data, together with enterprises' financial statement data and the combined employer-employee data of Statistics Finland, to study the association between management practices and productivity and examine whether human capital intensity acts as a moderator variable for this relationship.

Following Dessein and Prat (2019), the different approaches to studying the role of management can be roughly divided into three perspectives: contingency theory (CT), the organization-centric empirical approach (OC) and the leadership-centric approach (LC). By merging the quantitative FMOP management practices data with data on manager skills, this paper aims to combine the OC and LC perspectives of management and draw from both approaches to produce empirical results concerning management and firm performance. In short, the findings suggest that the marginal benefit of adopting more structured management practices is different for establishments with different levels of managerial human capital.

Whereas OC looks at the connection between floor-level management practices and differences in firm performance, the leadership-centric empirical approach uses characteristics or skills of individual managers to explain said differences. Many LC studies focus on CEOs[15] and have found a link between CEO variables and firm performance. Lazear, Shaw and Stanton (2015) and Hoffman and Tadelis (2017) find similar evidence for middle managers instead of CEOs. It

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15 Examples of this approach producing evidence for a link between CEO variables and firm performance include Johnson, Magee, Nagarajan and Newman (1985), Bertrand and Schoar (2003), Bennedsen, Nielsen, Perez-Gonzalez and Wolfenzon (2007), Kaplan, Klebanov and Sorensen (2012) and Bandiera, Hansen, Prat and Sadun (2020).

is plausible that the organization-centric empirical approach and the leadership-centric empirical approach are intrinsically linked, as suggested by Dessein and Prat (2019), since it is unlikely that the effects of management practices and the characteristics of individual managers on firm performance are orthogonal. The results presented in this paper support this proposition.

In CT, management is modelled as another production factor that profit-maximizing firms optimize[16]. Management can represent management practices or the skills of managers or both. If the production optimization problem has more than one solution, CT predicts that ex-ante identical firms can differ in the adoption of management practices and managerial ability without any correlation to differences in performance. This implication of the contingency theory is not supported by the results presented in this paper. However, if the optimization problem has a unique solution, similar management should be observed in similar firms.

Starting from the Ichniowski, Shaw and Prennushi (1997) study on the association between HR management practices and performance in steel finishing lines, the organization-centric empirical approach (OC) has been a key part of the economics of management. The management survey tools by Bloom and Van Reenen (2007) and subsequent studies are a continuation and extension of this approach. Studies utilizing these surveys have found significant variation in management practices within and between countries and industries (Bloom and Van Reenen 2007; Bloom et al. 2014).

In their comparison of management practices and other more commonly studied drivers of firm performance in US manufacturing, Bloom et al. (2019) find that increasing the adoption of structured management practices from the tenth to ninetieth percentile explained approximately 22% of the corresponding 90-10 productivity spread. As a contrast, R&D spending, ICT investment per worker and worker skills (share of all employees with a college degree) account for 21.6%, 12% and 15.9% of the productivity gap, respectively (Bloom et al. 2019).

Since Bloom et al. (2019) use the education level of all employees as the measure of human capital, there is no way to distinguish how much of this quantity is driven by managers or non-managers. This presumably leads to human capital being mostly proxied by non-manager education, since most employees are not managers[17]. However, the results presented in this paper suggest that accounting for the part of human capital that can be attributed specifically to managers is more important for the reliable estimation of the relationship between productivity and management practices.

The findings of this study, and of Bloom et al. (2019), imply that ex-ante similar firms can and will adopt different management practices, and that these differences are correlated with differences in performance. This contradicts the predictions of contingency theory, unless the effects of adopting management

16 For example, Lucas (1978) outlined a model in which productive factors are optimally allocated over a distribution of managers with varying ability to maximize output.

17 As shown in Table 5, approximately 4 percent of the employees in the FMOP sample are managers.

practices for firms that are seemingly similar differ significantly in some unobservable ways. The results also suggest that the impact of structured management practices on between-firm productivity dispersion might potentially be at least as significant as any of the variables that have traditionally been regarded as some of the most important drivers of said variation (see, for example, Syverson 2011). The association between management practices and firm performance remains statistically and economically significant when detailed employee characteristics (Bender, Bloom, Card, Van Reenen and Wolter 2018) and firm fixed effects (Bloom, Sadun and Van Reenen 2016; Bloom et al. 2019) are accounted for. Similar associational results have been found in other countries, such as Germany (Broszeit, Fritsch, Görg & Laible 2016) and Pakistan (Lemos, Choudhary, Van Reenen & Bloom 2016).

There is also evidence that the relationship between management practices and productivity is a causal one: Bloom, Eifert, Mahajan, McKenzie and Roberts (2013) present experimental evidence concerning management practices and firm performance in large Indian textile firms. The randomized controlled trial involved 17 firms and their 28 establishments. On average, the use of the management practices the treated establishments were consulted to adopt increased from 25.6% to 63.4%, with the changes being persistent at least for the next year, whereas the control plants increased their usage of the same management practices by only 12 percentage points (Bloom et al. 2013).

The randomized management consulting raised plant output by an average of 9.4% ($p < 0.05$) and total factor productivity (TFP)[18] by 16.6% ($p < 0.1$). The increase in TFP resulted from rising output and the decrease of capital and mending labour, the latter of which was due to a decrease in quality defects (Bloom et al. 2013). The study provides relatively strong evidence for a causal effect of structured management practices on productivity, at least in the context of the manufacturing sector in developing countries.

3.3 Data and methods

3.3.1 Sample and Data

The 2016 Finnish Management and Organizational Practices Survey (FMOP) sample consists of 2509 Finnish manufacturing establishments with more than 3 employees. Only establishments belonging to firms that employ at least 50 employees were included in the sample. The final number of responses is 731, with a response rate of approximately 31% after accounting for over-coverage. An additional 69 establishments are dropped from the data when using the 2015 US MOPS inclusion criterion: a valid response to questions 1, 2, 6, 13, 14, 15 and 16 is required for inclusion in the final data. Using the 2010 US MOPS criterion of at

18 $TFP \equiv log(value\ added) - 0.42 * log(capital) - 0.58 * log(labour)$, where the factor weights are cost shares, capital is physical capital and labour is production hours.

least 10 non-missing responses instead increases the number of valid respondents but does not have a qualitative effect on the estimated results.

The FMOP questionnaire was translated and adapted for use in Finnish manufacturing establishments from the US MOPS methodology. The questionnaire consists of 35 questions, 16 of which are about management practices. 13 questions concern organizational practices and the remaining 6 are background questions. The responses are normalized on a scale of 0 – 1 and the management score is calculated as the unweighted average of the normalized responses. The answer options corresponding with the management practices that are the most structured are assigned a value of 1 and the least structured practices are assigned a value of 0. Bloom et al. (2019) define more structured management practices as "those that are more specific, formal, frequent or explicit" (Bloom et al. 2019, 28).

Since the original management and organizational practices survey was designed for manufacturing establishments, which does not include mining and utilities, all analyses were conducted both with and without mining and utilities. Excluding these industries removes 391 establishments from the total FMOP sample and 80 establishments from the set of valid FMOP respondents. The exclusion of these industries had no discernible effects on the magnitude or significance of the results. The reported figures are from the analyses with all sample industries included.

To limit the impact of outliers, only establishments with at least 10 employees are included in the reported regressions. If instead all establishments with at least 5 employees are included, the number of observations in the FMOP data is increased by 57. This slightly increases some point estimates and decreases others but does not affect statistical significance or any qualitative conclusions drawn from the regressions.

Other variables used in the analysis, such as intermediate inputs, addition and depreciation of machinery and ICT spending are gathered from The Business Register database and enterprises' financial statement data maintained by Statistics Finland. Employee level variables like years of education, degree and position within the organization are from the Finnish Longitudinal Employer-Employee Data (FLEED), also compiled and maintained by Statistics Finland.

3.3.2 Descriptive statistics

The management score has a sample mean of 0.62 and is close to normally distributed, as seen from the histogram in Figure 1. Approximately 10 percent of establishments have a management score higher than 0.8, and establishments with a score of under 0.4 make up a little under 10 percent of the data. Furthermore, Figure 1 shows that the distribution is skewed slightly to the left; compared to normally distributed data with the same mean and standard deviation, a bit more of the mass is concentrated to values higher than the mean.

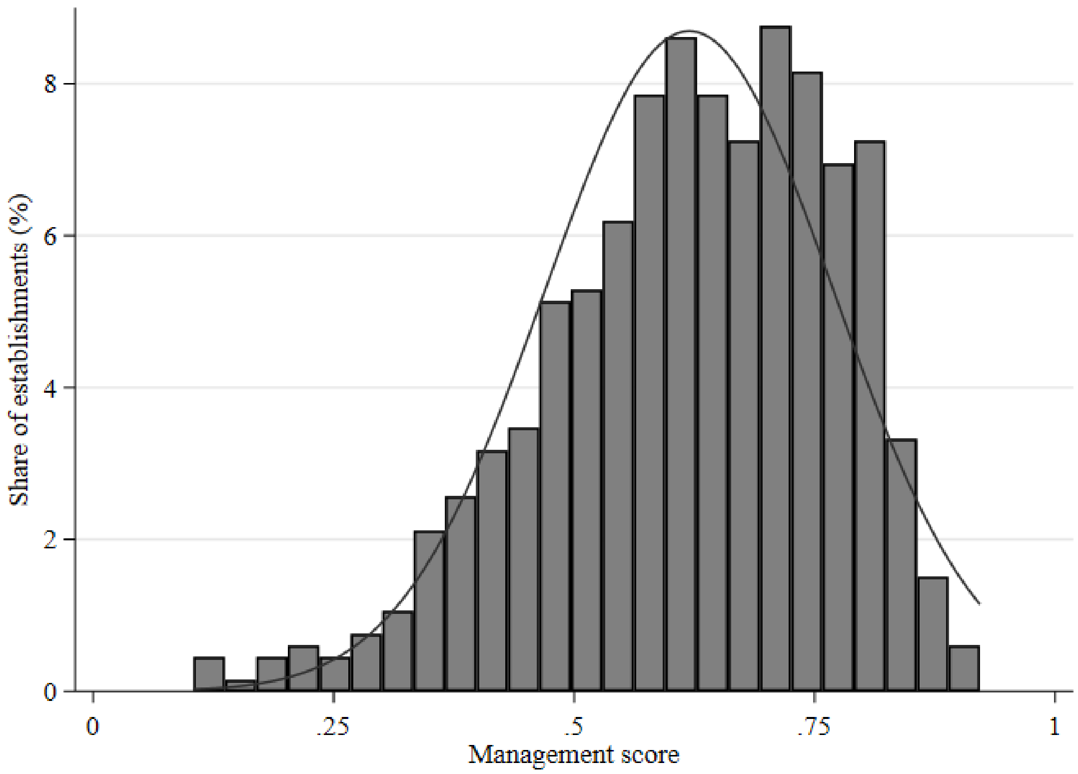

Figure 1 The distribution of the unweighted management score with an overlaid normal density with the same mean and standard deviation as the data.

Table 5 shows the mean of labour productivity, share of managers and non-managers with a higher education and the average years of education for the Finnish Management and Organizational practices survey sample, grouped by whether the establishment was a valid FMOP respondent or not. Managers and non-managers are defined as employees belonging and not belonging to the group "managers" in the Classification of Occupations 2010 [19] (Statistics Finland 2021). Higher education is defined as having completed at least a bachelor's degree or equivalent, which averages to 15–16 years from the beginning of primary education.

On average, the respondents and the non-respondents of the FMOP sample are similar in their characteristics with regards to productivity, employee education and employment. The difference in labour productivity between the respondents and non-respondents of the FMOP sample is not statistically significant ($p = 0.51$). The same is true for the differences in the share of managers with higher education and the gross value of production (not shown in Table 5). There is a statistically significant but small difference in the share of non-managers with higher education: the share is 0.024 smaller among the 662 establishments that gave a valid response. The sample standard deviation of non-manager education

19 The Classification of Occupations 2010 is based on the International Standard Classification of Occupations ISCO-08, which is under the responsibility of the International Labour Organization (ILO) and confirmed by the United Nations.

is 0.217, so the difference is approximately 11 percent of a standard deviation. Likewise, a statistically significant difference that is small in magnitude is found in the number of employees (not included in the table): on average, the respondents have 24 or 15.8 percent of a standard deviation more employees than the non-respondents. The sample mean of the number of employees for the total sample, the respondents and the non-respondents is 81, 98 and 74, respectively.

Table 5 Average productivity and education for respondents and non-respondents.

Mean *(Std. Dev.)*	Number of establishments	Labour productivity (€)	Share of managers	Share of managers with higher education	Share of non-managers with higher education	Years of education (all employees)
FMOP respondents	662	508 177	0.04	0.71	0.20	12.8
		(1 611 872)	*(0.06)*	*(0.36)*	*(0.18)*	*(1.23)*
FMOP non-respondents	1847	453 383	0.04	0.71	0.22	12.9
		(2 405 861)	*(0.08)*	*(0.37)*	*(0.23)*	*(1.41)*
Total FMOP sample	2509	468 097	0.04	0.71	0.21	12.9
		(2 220 516)	*(0.08)*	*(0.36)*	*(0.22)*	*(1.37)*

Notes: Productivity is measured as the gross value of production/number of employees. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). Standard deviations in parentheses.

Figure 2 shows the number of employees, labour productivity and output growth of the FMOP establishments by management score deciles. The average number of employees and labour productivity both increase the higher the establishment's management score bin. The fourth figure shows labour productivity by employment deciles to demonstrate that, unlike with the management score deciles, productivity does not seem to increase with the number of employees. See appendix A for additional descriptive figures.

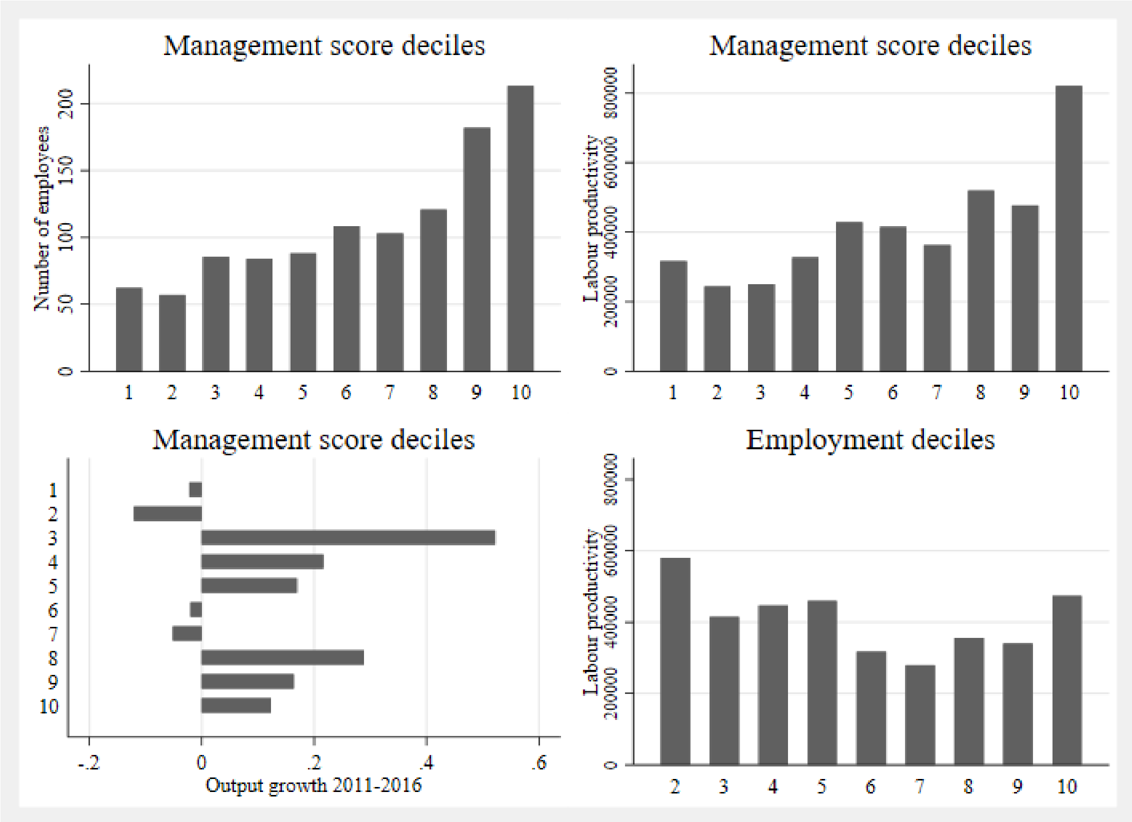

Figure 2 Comparisons of key variables by management score and employment deciles

3.3.3 Methods

The multivariable fractional polynomial (MFP) approach provides a systematic, fully data-driven way of selecting the best-fitting functional form for a statistical model (Royston & Sauerbrei 2009). The approach uses backward elimination to select which variables are included in the model. It also combines this with a systematic fractional polynomial function selection procedure to determine a functional form for continuous predictors. Royston and Sauerbrei (2004) propose an extension of MFP called multivariable fractional polynomials interaction (MFPI), which provides a test of possible nonlinear interactions between a binary independent variable of interest and continuous regressors.

In the first step of the MFPI algorithm, the best-fitting fractional polynomial (FP) functions of the first and second degree are selected based on the Akaike's information criterion (AIC)[20]. In the second step, MFPI systematically examines whether FP functions of varying complexity describe the shape of the association between a regressor and the dependent variable better than a linear function. After the selection of the best-fitting functional form, a test for interactions between chosen regressors is performed:

20 $Model\ deviance - 2 * (maximized\ log\ likelihood\ for\ the\ interaction\ model)$.

For a binary regressor of interest x_i[21], the contribution of a control variable z on the estimated association between x_i and the dependent variable y can be written as $\hat{f}(z) = \hat{f}_1(z) - \hat{f}_0(z)$, where $\hat{f}_i(z)$ are the estimated functions for the association between z and y for each $x_i, i \in \{0,1\}$. The MFPI algorithm compares a model with different functions (and thus different coefficients) of z for x_1 and x_2 with a model that has the same function (and thus the same coefficient) for z in both x_i. This comparison acts as the test for an interaction term between z and x_i (Royston & Sauerbrei 2009).

Royston and Sauerbrei (2008) also describe an extension of MFPI, MFPIgen, that generalizes the approach to continuous-by-continuous interactions using the same fractional polynomial methodology. This paper utilizes said generalized version of MFPI to examine how human capital contributes to the management-productivity association. Consistent with the recommendations of Royston & Sauerbrei (2008), graphical checks are presented to support the MFPIgen method results.

The baseline linear model that is estimated on the data is

$$ln\left(\frac{Y_i}{L_i}\right) = \alpha + \beta M_i + \gamma ln\left(\frac{I_i}{L_i}\right) + \mu ln\left(\frac{K_i}{L_i}\right) + (\gamma + \mu + \eta - 1)\, ln(L_i) + \delta H_i + \phi X_i + f_i + \epsilon_i, \qquad (1)$$

where Y_i/L_i denotes the labour productivity of establishment i, M_i is the FMOP management score, I_i denotes intermediate inputs (minus energy), K_i is capital stock, L_i are labour inputs (number of employees) and H_i is human capital. Y_i denotes the gross value of production. The right-hand side also includes industry dummies f_i and a stochastic error term ε_i. The model is derived from a standard production function, where the management score, human capital and employee turnover are included in natural exponential function form.

Employee education is measured as the share of employees with a higher education. Due to data restrictions, the sum of the addition and depreciation of machinery is used as a proxy for net capital stock K_i.

Relative employee turnover is denoted by X_i. It is a labour market flow measure and is added as an additional control variable. The overall labour market flow activity of an establishment is a potential confounder since employee turnover can have knowledge spillover effects (Maliranta, Mohnen & Rouvinen 2009) that improve management practices. Employee turnover can also affect productivity if higher productivity workers tend to replace lower productivity employees.

Relative employee turnover is measured as employee turnover divided by the average number of employed. Employee turnover equals the sum of worker inflow and worker outflow during the year. The model is estimated using OLS linear regression and, as a robustness check, generalized linear model (GLM) estimation to allow for a non-normal error distribution.

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21 $x_i = i$ for $i \in \{0,1\}$.

3.4 Results

3.4.1 Tests of interactions

The generalized multivariable fractional polynomials interaction (MFPIgen) approach aims to identify linear and nonlinear interactions between continuous regressors. Applying this approach to a model of productivity as a function of the management score and the two education variables reveals a statistically significant linear interaction between the management score and the share of managers with a higher education[22].

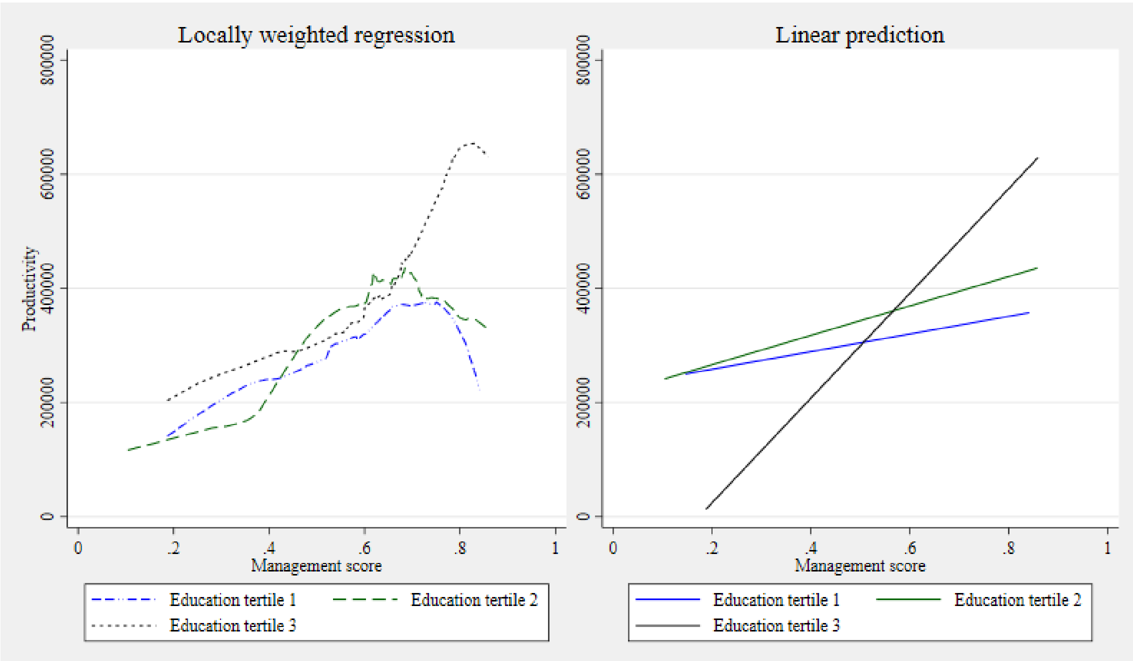

Figure 3 Manager education as a moderator variable. The education tertiles are tertiles of the share of managers with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). The locally weighted regression on the left uses the tri-cube weight function.

Figure 3[23] shows graphically how the association between management practices and productivity varies with the average level of manager education. Both the locally weighted regressions and the linear predictions in tertiles 1 and 2 of the

22 $p = 0.007$ when productivity is in levels or $p = 0.014$ when productivity is in logs

23 For ease of interpretation, the bottom and top 10 observations of the management score distribution have been cut from the figures. Including them has very little effect on the right-hand side linear prediction lines but improves the legibility of the locally weighted regression curves. Due to the low number of observations at the very tails of the distribution, the confidence intervals would also be very wide. No establishments have been cut from the regressions in Table 2. The figures with all establishments included are available upon request from the author.

education level of managers are very similar, and the statistically significant difference in the slopes is mainly driven by tertile 3. For education tertile 3, the management-productivity association is monotonically increasing, except at the very upper tail of the management score distribution. In the estimated regression models, both the management score and the education variable are modelled as continuous variables, as opposed to percentile bins, so the interaction term accounts for the whole distribution of the education variable.

No interaction is found between management practices and the education of non-managers ($p = 0.52$). Figure 4 demonstrates this graphically. The slopes of the linear predictions by tertiles of non-manager education are relatively close to each other, and even the locally weighted regression curves have similar shapes.

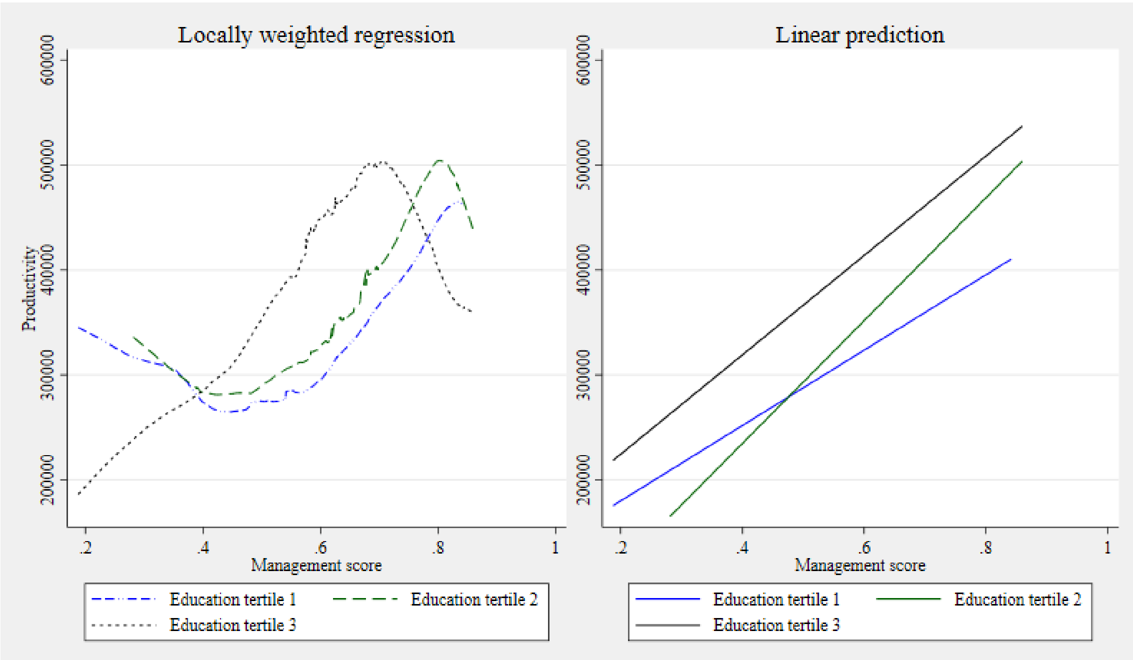

Figure 4 No statistically significant interaction found with non-manager education. The education tertiles are tertiles of the share of non-managers with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). The locally weighted regression on the left uses the tri-cube weight function.

The results of an OLS linear regression of (the log of) productivity on the management score by manager and non-manager education tertiles are reported in Table 2. The linear predictions in Figures 3 and 4 are a graphical representation of the estimates[24]. For reference, the coefficient of the management score in the simple baseline regression of the log of productivity on the management score in column 1 of Table 3 is 1.264. Table A 10 in appendix B shows the same regressions as Table 6 but with non-manager education as a control when the regression is

24 In the figures, labour productivity is in levels. In the regressions, the dependent variable is the natural logarithm of labour productivity.

divided into manager tertiles and vice versa. Like Figure 3, Table 6 further demonstrates the significant differences in the slope the management-productivity association for different values of manager education. This, together with the MFPIgen results, implies a need for an interaction term between the management score and manager education for a credible estimate of the correlation between management practices and productivity.

Table 6 Management-productivity association by education tertiles.

log(labour productivity) in	Manager education tertile			Non-manager education tertile		
	1	2	3	1	2	3
Management score	0.873**	0.902**	2.127***	1.004***	1.273***	1.348*
	(0.427)	(0.382)	(0.697)	(0.379)	(0.345)	(0.729)
Observations	129	97	204	175	207	185
Prob > F	0.043	0.020	0.003	0.009	0.000	0.066

Notes: Manager (and non-manager) education is calculated as the share of managers (and non-managers) with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education, including tertiary education).

3.4.2 Management practices and productivity

Start with the linear model of equation (1). Based on the MFPIgen results presented in subsection 3.1, we partition human capital H_i into manager and non-manager education, respectively denoted as H_i^m and H_i^n. The education variables are measured as the share of managers and non-managers with a higher (tertiary) education. An interaction term[25] for management practices and manager education is then added to equation (1) to get the following model:

$$\begin{aligned} ln(y_i) = \alpha + \beta M_i + \gamma ln(i_i) + \mu ln(k_i) + (\gamma + \mu + \eta - 1)\, ln(L_i) + \delta^m H_i^m \\ + \xi M_i H_i^m + \delta^n H_i^n + \phi X_i + f_i + \epsilon_i. \end{aligned} \tag{2}$$

The small letters denote variables divided by labour inputs L_i. Note that in this specification, the estimate for β, denoted $\hat{\beta}$, uniquely describes the association between management practices and productivity only when $H_i^m = 0$. This holds only for 63 establishments out of the 662 valid FMOP respondents. Otherwise, the association is described by $\hat{\beta} + \hat{\xi} H_i^m$[26]. The management score is never zero, so δ^{m} has no interpretation by itself.

25 Adding manager education as a control in a linear regression would only account for the change in the intercept. An interaction term also corrects for the change in the slope of the regression line. The changes in the slope are demonstrated in Figure 3.

26 $\ln(y_i) = \alpha + M_i(\beta + \mu H_i^m) + \gamma \ln(i_i) + \mu \ln(k_i) + (\gamma + \mu + \eta - 1)\ln(L_i) + \delta^m H_i^m + \delta^n H_i^n + \phi X_i + f_i + \epsilon_i$

Furthermore, since the null hypothesis of not including the individual education variables in the linear model cannot be rejected[27] in the MFP test of inclusion of covariates, H_i^m and H_i^n are only included as a robustness check in column 3 of Table 7, with no notable effects on the results. Excluding H_i^m and H_i^n results in the following specification:

$$\begin{aligned}\ln(y_i) = \alpha + \beta M_i + \gamma \ln(i_i) + \mu \ln(k_i) + (\gamma + \mu + \eta - 1)\ln(L_i) + \xi M_i H_i^m \\ + \phi X_i + f_i + \epsilon_i,\end{aligned} \tag{3}$$

which is estimated in column 5. The overall labour market flow activity X_i can be measured either by the employee turnover or the relative employee turnover (turnover/employment) of establishments. Replacing the former as the control in the regressions of columns 5 and 6 has no qualitative effects on the standard errors. However, most of the regression coefficients are more conservative when using relative employee turnover, so those are reported in Table 7.

[27] The fractional polynomial fitting algorithm converges after 2 cycles with a p-value of 0.55 for manager and 0.65 for non-manager education. The average years of education of all employees is excluded from the model with a p-value of 0.98.

Table 7 Establishment management scores and labour productivity

log(labour productivity)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Management score	**1.264*****	**0.823*****	0.877***	**0.733*****	**0.683*****	0.753***	0.866**
	(0.292)	(0.200)	(0.220)	(0.239)	(0.236)	(0.238)	(0.426)
log(materials/worker)		0.250***	0.264***	0.253***	0.249***	0.260***	
		(0.034)	(0.041)	(0.043)	(0.043)	(0.041)	
log(capital stock/worker)		0.102***	0.092***	0.093***	0.091***	0.090***	
		(0.019)	(0.023)	(0.023)	(0.023)	(0.023)	
log(employment)		-0.030	-0.061	-0.036	-0.043	-0.070	
		(0.032)	(0.045)	(0.043)	(0.043)	(0.044)	
Manager education			0.061				
			(0.088)				
Non-manager education			0.690***			0.697***	
			(0.238)			(0.236)	
Management score				0.179	0.167	0.105	0.380**
x manager education				(0.145)	(0.144)	(0.145)	(0.161)
Relative employee turnover					-0.193*	-0.202*	
					(0.100)	(0.105)	
Observations	569	432	333	333	333	333	430
Industry dummies		Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.186	0.469	0.460	0.446	0.450	0.465	0.191

Notes: OLS coefficients with Huber–White standard errors in parentheses. Labour productivity is measured as the gross value of production divided by the number of employees. Employee education is measured as the share of employees with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education, including tertiary education). Employee turnover equals the sum of worker inflow and worker outflow during the year and is an establishment's aggregate labour market flow activity measure. Relative employee turnover is measured as employee turnover divided by the average number of employed. Materials are intermediate inputs without energy. Due to data restrictions, the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The industry dummies are at the 2-digit level of the Standard Industrial Classification; mining (05–09), manufacturing (10–33) and utilities (35) were divided into nine subindustries: 05–09, 10–15, 16–18, 19–23, 24–25, 26–27, 28–30, 31–33 and 35. Prob > F (the p-value of the F-test) is less than 0.001 in every column. $*\,p < 0.10$, $**\,p < 0.05$, $***\,p < 0.01$.

Running a baseline regression of labour productivity on the establishment management score without any controls or industry dummies, the highly statistically significant coefficient is 1.264 ($p < 0.001$). In this specification, a 0.1 (or 10 percentage point) increase in the management score is therefore associated with a

13.5%[28] increase in labour productivity. As seen from columns 2 and 4, with intermediate inputs, capital, labour and industry dummies included, adding the interaction term decreases the management score coefficient from 0.823 to 0.733. Repeating the regression in column 2 with the same 333 observations available in the regression of column 4 confirms that the change in the management coefficient is not due to the dropped observations[29]; the coefficients and their statistical significances remain virtually unchanged. Including employee turnover further decreases the coefficient to 0.683.

This management practices coefficient is reported in Column 5, which shows the estimation results for the full specification from equation (4), with intermediate inputs, capital, labour, relative employee turnover, industry dummies and the management-education interaction term. Since the coefficient on the interaction term ($\hat{\xi} = 0.167$) in column 5 is not statistically significantly different from zero, we can think of the association[30] between management practices and productivity as being described by the coefficient on management practices ($\hat{\beta} = 0.683$).

The management score coefficient of 0.683 implies that a 0.1 (or 10%) increase in the management score is associated with an average of 7.1% higher labour productivity. The standard deviation of the management score is 0.15 and its sample mean is 0.62. Therefore, a higher management score of one standard deviation implies an average increase of 10.8%[31] in labour productivity.

For further reference, a replication of the labour productivity estimations in Table 1 of Bloom et al. (2019) is presented in Table A 11 in appendix B. For better comparability with the results of Bloom et al. (2019), who use the share of all employees with a college degree, the separate manager and non-manager education variables are replaced with the share of all employees (managers and non-managers) with a higher education. With the US data, the coefficient on management practices drops from 1.351 to 0.209 when capital stock, materials, labour, employee education and industry dummies are added to the baseline regression of labour productivity on the management score (Bloom et al. 2019). With the Finnish data, the corresponding change in the management coefficient is from 1.264 to 0.843, as shown in Table A 11.

As referenced in the introduction, there is strong empirical evidence and credible theoretical arguments that suggest management practices affect productivity. Nevertheless, the presented OLS management coefficients most likely do not accurately describe a causal effect, since there are plenty of possible omitted factors, such as CEO effects, which could confound the relationship between

28 $e^{0.1264} - 1 \approx 0.1347$

29 The number of observations drops from 432 in column 2 to 333 in column 4 due to missing data on manager education. Estimating the specification of column 4 while restricting the observations to the 333 in the regression of column 2, the coefficient of management is 0.863 (p < 0.001) instead of the 0.823 reported in Table 3.

30 The association is described by $\hat{\beta} + \hat{\xi} H_i^m$, but since the coefficient of the interaction term, $\hat{\xi}$, is statistically indistinguishable from zero, we can simply look at $\hat{\beta} = 0.683$.

31 $e^{0.683*0.15} \approx 1.108$

management and productivity. A type of ability bias is another potential issue for identification: a bias would arise if highly educated managers tend to self-select into establishments with higher productivity. Controlling for establishment-level employee turnover does not necessarily address this type of sorting. Such self-selection would make manager education a partial mediator between the management score and labor productivity, assuming manager education also directly affects productivity. Controlling for manager education would then lead to an underestimation of the potential effect of management practices on productivity.

However, the associational results are significant both statistically and in magnitude, and robust to different specifications, measurement choices and data restrictions. At the very least, the results show that the FMOP management score is a meaningful measure of firm characteristics. This is consistent with the findings of earlier studies, such as Bloom et al. (2013) and Bloom et al. (2019), which show that management practices play a significant role in explaining productivity differences.

Next, the magnitude of the management-productivity association is compared to ICT, R&D and skills, all factors that have traditionally been regarded as some of the most important drivers of productivity variation (e.g., Syverson 2011).

3.4.3 Comparison with other drivers of productivity

To assess the magnitude of the association between management and productivity, Table 8 reports the OLS estimates from a regression of log(labour productivity) on four key drivers of productivity differences. Namely, the management score, research and development expenditures (R&D) per employee, information and communication technologies spending (ICT) per employee and human capital (measured as worker skills[32], proxied by the share of all employees with a higher education). The main question is: how large a share can the spread of these variables explain of the spread in productivity?

Akin to Bloom et al. (2019), the focus of the comparison is on the share of the 90–10 productivity spread explained by the different factors. The share of 90–10 spread explained by each variable is reported in the second row from the bottom and is calculated by multiplying each column's variable’s 90–10 percentile difference by its coefficient, then dividing by the 90–10 spread of labour productivity. The 90–10 percentile difference, or 90–10 spread, of a variable is calculated as the difference between the ninetieth percentile and the tenth percentile of the distribution.

32 For robustness, two alternative measures of worker skills were used: the share of employees with a higher education and average years of education. The specifications in columns 4 and 6 use the former.

Table 8 Comparison of factors explaining productivity differences.

log(labour productivity)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Management score	1.208***					0.875***	0.907**
	(0.294)					(0.301)	(0.367)
ICT/worker		0.152***				0.072**	0.073*
		(0.016)				(0.032)	(0.039)
R&D			0.044***			0.051***	0.056***
			(0.006)			(0.010)	(0.012)
Skills (share of all employees with a higher education)				0.723***		0.071	
				(0.097)		(0.214)	
Share of managers with a higher education					0.287***		0.111
					(0.067)		(0.113)
Share of non-managers with a higher education					0.508***		-0.060
					(0.116)		(0.234)
Observations	556	1946	1946	1946	1384	556	422
Industry dummies						Yes	Yes
Share of 90–10 gap explained	0.240	0.257	0.178	0.209	0.288	0.523	0.571
$\sqrt{(R^2)}$	0.223	0.276	0.167	0.182	0.204	0.493	0.491

Notes: OLS coefficients with Huber–White standard errors in parentheses. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education, including tertiary education). ICT is measured as the log of information and communications technology planning and programming expenditure per employee. Following Bloom et al. (2019), R&D is measured as $log(1 + R\&D\ intensity)$, where R&D intensity is total research and development expenditure per worker. Only observations with non-negative values of ICT and R&D expenditures are included. Missing values of right-hand side variables have been replaced by 2-digit level industry means. The share of 90–10 gap explained is measured as the regression coefficient on the column's variable times its 90–10 percentile difference, divided by the 90–10 difference of labour productivity. The 90–10 percentile difference, or the "90–10 spread", is calculated as the difference between the ninetieth percentile and the tenth percentile of each variable. In column 5, the reported number is the share of the 90–10 gap explained jointly by the education variables. The corresponding number for non-manager education is 0.142. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

According to this measure, increasing the management score from the tenth percentile to the ninetieth can account for 24% of the corresponding productivity spread. This is consistent with the 22% found in the US manufacturing sector by Bloom et al. (2019). Compared to the 25.7%, 17.8% and 20.9% of ICT, R&D and skills, the conclusion is that management practices can account for as much of the 90–10 productivity gap as other important, more commonly studied drivers of productivity. Jointly[33] these factors can explain up to 52% of the 90–10 productivity gap, as shown in column 6 of Table 8. Columns 6 and 7 also demonstrate that even when other important factors are accounted for, the management score retains a strong association with labour productivity. These results are supported by the measured contribution of each variable to the standard deviation of the log of labour productivity, represented in the table by the square root of the R^2 in each regression: 22.3% for management practices, 27.6% for ICT, 16.7% for R&D and 18.2% for skills.

Column 5 splits the skills variable into the share of managers and non-managers with a higher education. The partition suggests that about 28.8 percent of the 90–10 productivity gap can be explained jointly by the two education variables. Column 7 repeats the regression in column 6 with the partitioned education variables in the place of skills, with near-identical results. In both specifications with all variables included, the role of education practically disappears. This is driven by management practices, since the coefficients on both skills and the education variables become indistinguishable from zero when the management score is added to the regressions in columns 4 and 5, without adding any of the other factors. In all these instances, the role of management practices remains statistically significant and large.

Measuring R&D at the establishment-level can be problematic with multi-plant firms, but the 17.8 percent share of the 90–10 productivity gap explained by the 90–10 R&D spread in Table 8 is consistent with the results of Bloom et al. (2019). In their firm-level analysis, they report 21.6% as both the share of the 90–10 productivity spread explained by R&D and the contribution of R&D to the standard deviation of log(labour productivity). This is also consistent with the 16.7% contribution of R&D to the standard deviation of labour productivity in the Finnish data, shown in the bottom row of Table 8.

Furthermore, compared to the 12 percent in Bloom et al. (2019), the 20.9 percent (or 28.8 percent jointly for the separate education variables) share of the 90–10 gap explained by skills is high but commensurate. The difference could be relatively high because the US analysis is at the firm level[34], or due to differences in the measuring and scaling of variables. The 18.2 percent contribution of skills to the standard deviation of labour productivity in the Finnish data is relatively close to the firm level equivalent of 14.2 percent from US manufacturing. However, these measures are not meant to accurately describe the absolute importance of the included factors in explaining productivity variation, but rather demonstrate the relative importance of accounting for management.

33 Calculated by $\left(\sum_k^4 \widehat{\beta_k} X_k\right)/y_{90-10}$, where $\hat{\beta}_k$ is the coefficient of factor k in column 7, X_k is the relative 90–10 percentile ratio of factor k and y_{90-10} is the relative 90–10 ratio of labour productivity.

34 The US variables have been weighted up to the firm level from establishment-level data using establishment's total value of shipments (Bloom et al. 2019).

3.4.4 Extensions and robustness checks

In addition to the reported estimates with normal unweighted average management scores, all regressions were run with employment weights to ensure that the qualitative conclusions hold for employment weighted (aggregate) management scores[35] as well. Employment weighted regressions mitigate the impact of smaller establishments with extreme labour productivity numbers. They also account for the workforce allocated into higher productivity establishments, making the employment weighted results more relevant in terms of competitiveness. Adding employment weights to the regressions does not change the statistical significance of or the conclusions drawn from the estimates. The coefficient of management practices in an employment weighted equivalent of the regression in column 7 of Table 7 is 0.604 ($p = 0.038$). The employment weighted regression is equivalent to fitting the model

$$\begin{aligned}\ln(y_i)\sqrt{L_i} = \alpha\sqrt{L_i} + \beta M_i\sqrt{L_i} + \gamma\ln(i_i)\sqrt{L_i} + \mu\ln(k_i)\sqrt{L_i} + \delta H_i\sqrt{L_i} \\ + \phi X_i\sqrt{L_i} + f_i\sqrt{L_i} + \epsilon_i\sqrt{L_i},\end{aligned} \tag{4}$$

where L_i is the number of employees in establishment i.

Furthermore, a generalized linear model (GLM) was fitted to allow for a non-normal error distribution. The gamma distribution was chosen for the estimation. The results from the main specifications of Table 7 are robust to the gamma GLM with both the identity link function ($X\beta = \mu$) and the canonical negative inverse link function ($X\beta = -\mu^{-1}$). In the full specification with materials, capital, labour, relative turnover, industry dummies and the interaction term, the GLM coefficients of the management score on log(productivity) are 0.652 ($p = 0.004$) and 0.815 ($p = 0.002$)[36], respectively for the two link functions. For reference, the corresponding coefficient of management in the main OLS regression in column 7 of Table 3 is 0.683.

The multivariable fractional polynomial (MFP) approach also tests for the inclusion and functional form of model variables. It combines backward elimination with an FP function selection procedure to select the MFP model that best fits the data / predicts the dependent variable from the regressors. Applying this approach to the full specification in equation (1), the management score, materials and capital are included in the model at the 99% confidence level ($p < 0.001$). Employee turnover is included at the 95% level ($p = 0.012$). Overall human capital, measured as the share of all employees with a higher education (human

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35 Olley-Pakes decomposition (Olley & Pakes 1996) of the FMOP management score: Employment weighted (aggregate) management score = unweighted score + covariance term.

36 The 0.815 is the result of calculating the average marginal (partial) linear prediction of the management score on labour productivity from the negative inverse link function GLM coefficient of -0.0045. This produces an estimate of the multiplier of M_i that is more comparable to the OLS coefficients in Table 3.

capital intensity) and alternatively as the average years of education of all employees, is not included in the model with the best fit ($p = 0.995$).

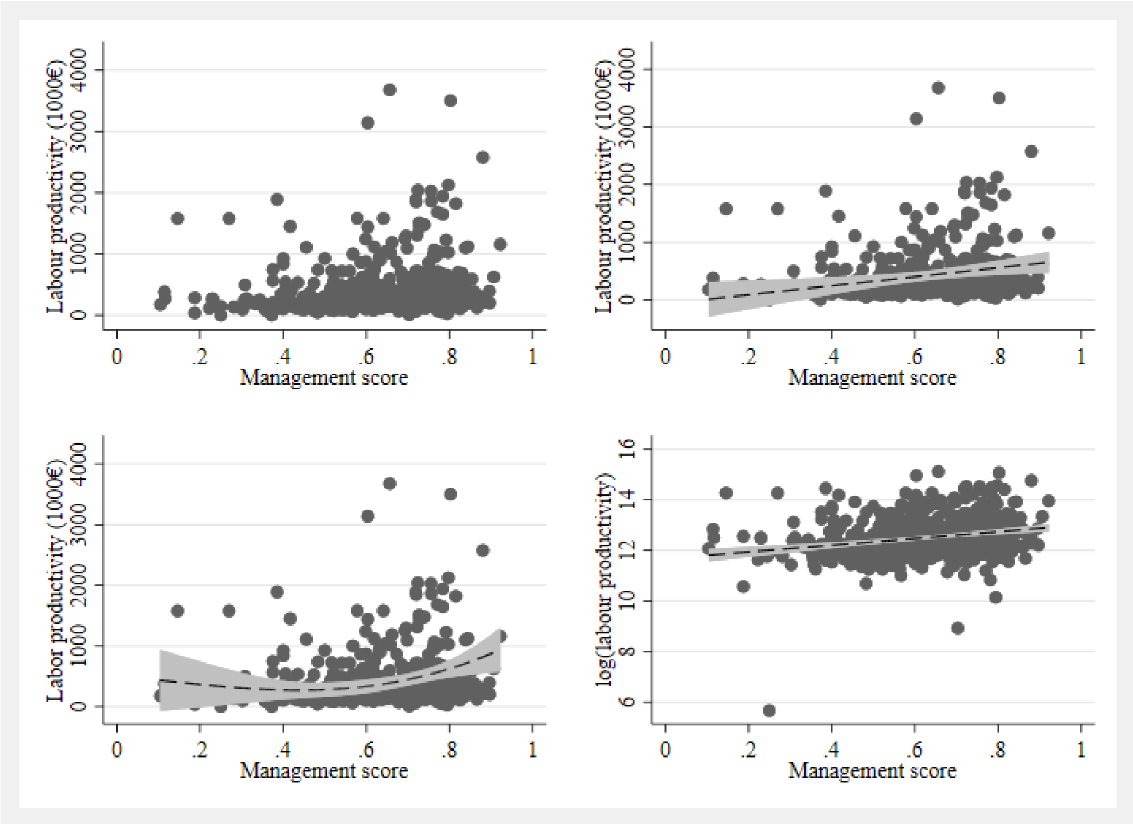

Figure 5 The linear prediction fits the data at least as well as the fractional polynomial fit in panel 3.

No statistically significant nonlinearity is found between the management practices and productivity, so a linear model was chosen for estimation. This is visualized in the scatter plots of Figure 5. The test for the functional forms of the other covariates concludes that the included variables fit the data best when kept linear[37]. The only exception is intermediate inputs, for which the best fit would be a fractional polynomial model with powers (2, 2), denoted in vector notation as $\ln(i_i)^{(2,2)\prime}\boldsymbol{\gamma} = \gamma_0 + \gamma_1 \ln(i_i)^{(2)} + \gamma_2 \ln(i_i)^{(2)} \ln[\ln(i_i)]$, where $i_i \equiv I_i/L_i$. However, modelling inputs with the FP functional form does not change any conclusions drawn from the results.

When human capital is partitioned into the education levels of managers and non-managers (see equation 3), the results of the model selection procedure remain unchanged: all other variables are included and linear, intermediate inputs is included as a fractional polynomial with powers (2,2) and the education variables are excluded from the model ($p = 0.55$ and $p = 0.65$ for manager and

37 Cannot reject the null of including management, capital and employee turnover as linear covariates at the 99% confidence level: $p = 0.29, p = 0.03$ and $p = 0.08$, respectively.

non-manager education). Regressions with employee education, both as years of education and as the share of employees with a higher education, were still run as a robustness check, with unchanged results. The estimation results of the full fractional polynomial model with mean-centered variables and nonlinear intermediate inputs are presented in the following.

Table 5 reports the results from estimating the full fractional polynomial (FP) model with non-linear intermediate inputs and mean centered variables, built by the MFP backfitting model-selection algorithm. As is evident from comparing the coefficients in Table 9 to Table 7, the main results from estimating the linear model of equation 4 coincide with the results from the estimation of the FP model. The regression coefficients of the management score in the full specification of the FP model without and with industry dummies are 0.812 and 0.611, respectively. When estimating the linear model of equation 4, the corresponding coefficients are 0.871 and 0.683.

All the other FP-transformed variables are only centered around the mean, but intermediate inputs is modelled as a fractional polynomial with powers (2, 2), denoted in vector notation as

$$\ln\left(\frac{I_i}{L_i}\right)^{(2,2)'}\boldsymbol{\gamma} = \gamma_0 + \gamma_1 \ln\left(\frac{I_i}{L_i}\right)^{(2)} + \gamma_2 \ln\left(\frac{I_i}{L_i}\right)^{(2)} \ln\left[\ln\left(\frac{I_i}{L_i}\right)\right]. \tag{5}$$

Employment is automatically excluded as a covariate by the MFP hypothesis test of model fit. Including it does not significantly change the results. The interaction term included as a control in the estimation of the FP model in columns 3 and 4 uses the original variables, since the MFP approach does not allow interactions.

Table 9 Fractional polynomial model

log(labour productivity)	(1)	(2)	(3)	(4)
FP(management score)	0.800***	**0.682*****	0.812***	**0.611*****
	(0.170)	(0.169)	(0.227)	(0.210)
FP(materials/worker)	-0.190***	-0.188***	-0.207***	-0.213***
	(0.032)	(0.035)	(0.037)	(0.039)
FP_2(materials/worker)	0.074***	0.074***	0.081***	0.083***
	(0.012)	(0.013)	(0.013)	(0.014)
FP(capital stock/worker)	0.116***	0.093***	0.111***	0.080***
	(0.0191)	(0.0185)	(0.0226)	(0.0219)
FP(relative employee turnover)	-0.235***	-0.187**	-0.202**	-0.195**
	(0.076)	(0.072)	(0.097)	(0.095)
Management score x manager education			-0.009	0.128
			(0.149)	(0.134)
Observations	431	431	333	333
Industry dummies		Yes		Yes
R^2	0.436	0.531	0.529	0.530

Notes: $FP(management\ score) = M_i - 0.628$, $FP(materials/worker) = \ln(I_i/L_i)^2 - 90.137$, $FP_2(materials/worker) = \ln(I_i/L_i)^2 \ln[\ln(I_i/L_i)] - 202.868$. $FP(capital\ stock/worker) = \ln(K_i/L_i) - 8.268$ and $FP(relative\ employee\ turnover) = X_i - 0.336$. OLS coefficients with Huber–White standard errors in parentheses.

All regressions were also performed with and without one outlier with extremely high labour productivity. Including the outlier amplifies the management-productivity association but does not change the statistical significance of any estimates. The reported analysis excludes the outlier to avoid overstating any estimates.

According to Bloom et al. (2019), random measurement error in the management score accounts for approximately 51 percent of the observed variation in the adoption of management practices in the US data. Therefore, due to regression dilution bias, the reported regression slopes might be biased towards zero. This is because the measurement error is in a right-hand side variable. Due to the high-quality Finnish business register and financial statement data maintained by Statistics Finland, it is likely that the random error in the left-hand side variable of the regression equation (labour productivity) is much less severe.

All relevant results are robust to the use of the average years of education instead of the share of employees with a higher education as the measure of worker skills. All regressions were also run with a measure of productivity using value added at factor cost instead of gross value of production as the dividend. Materials are excluded in these specifications since they are implicitly included in the value added variable. This exercise supports the results, since both the significance and the magnitude of most reported coefficients remain largely unchanged. The most notable difference is the management score coefficients in columns 4 and 5 of Table 3 being reduced from 0.73 and 0.68 to 0.54 and 0.45, respectively. These differences can likely be attributed to differences in the two alternative measures of output: value added at factor cost includes materials, external services and other business expenses, of which only materials is included as a covariate in the specifications with gross value of production as the output measure.

Furthermore, in addition to the reported results, all analysis was performed with mining and utilities excluded. This was done because the original MOPS, on which the Finnish version is closely based, was designed for use in "manufacturing" establishments, which does not include mining and utilities. However, the FMOP survey sample also contains these two industries. The results presented in this paper are robust to the exclusion of mining and utilities.

3.5 Conclusions

Advances in the tools for collecting quantitative large-scale data on management have made management practices as a potential driver of productivity an increasingly prominent target of research. This study complements the literature by examining how managerial human capital contributes to the management-productivity association. Using the multivariable fractional polynomials interaction (MFPI) approach (Royston & Sauerbrei 2008), a linear two-way interaction between management practices and the education of managers is found. Testing and accounting for this interaction is important for reliable estimation of the relationship between management practices and firm performance.

In a regression with intermediate inputs, capital, labour inputs, and industry dummies, a 0.1 (or 10 percentage point) increase in the management score is associated with an average of 8.6 percent higher labour productivity. Adding the interaction term between management practices and manager education as a control decreases the association to 7.1 percent. The magnitude of the management-productivity relationship is large when compared to other commonly studied drivers of productivity. Increasing the management score from the tenth percentile to the ninetieth percentile can account for 24 percent of the corresponding productivity spread. This finding is consistent with the 22 percent reported for the US manufacturing sector by Bloom et al. (2019). Compared to the 25.7 percent, 17.8 percent and 20.9 percent of ICT, R&D and skills (12, 21.6 and 16 percent in the US), the conclusion is that management practices is a key variable in explaining productivity dispersion.

The analyses presented in this paper suggest that the marginal benefit of adopting more structured management practices is different for establishments with different characteristics. Namely, the part of human capital that can be attributed to managers is correlated with the rate of possible productivity improvements associated with better management practices. This is important, because human capital is often measured through the education levels or other characteristics of the entire workforce. Therefore, since most employees are not managers[38], human capital is mostly proxied by averages to which most of the weight comes from non-manager characteristics.

It is plausible that the set of establishments both with a high average level of manager education and a strong management-productivity association simply partakes in the type of manufacturing that highly benefits from or requires both. Another possibility is that human capital directly affects the relationship between management practices and productivity. Based on the available data alone, without making additional untestable assumptions, we cannot determine which is true.

Nevertheless, the results direct policymakers' attention to increasing the adoption of structured management practices, especially in establishments and industries with already high human capital intensity. They also encourage complementing managerial improvements with policies that promote human capital formation[39]. This study demonstrates the importance and usefulness of comprehensive high quality census data that allows the formation of information-rich data sets by further partitioning variables. The Finnish data enables a highly rigorous dissection of manager and non-manager characteristics, with divisions by field of work and education, occupation, tenure and wage, for example. Studying these aspects of firms' employees more closely would provide insight into the relationships between management, workforce quality, firm performance and even employee well-being[40].

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38 As shown in Table 5, approximately 4 percent of the employees in the FMOP sample are managers.

39 See, for example, Heckman (2000) for an overview of sources of human capital formation with policy recommendations.

40 See, for example, Böckerman, Ilmakunnas and Johansson (2011), Böckerman (2015) and Peutere, Saloniemi, Böckerman, Aho, Nätti and Nummi (2020).

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3.7 Appendix A: figures

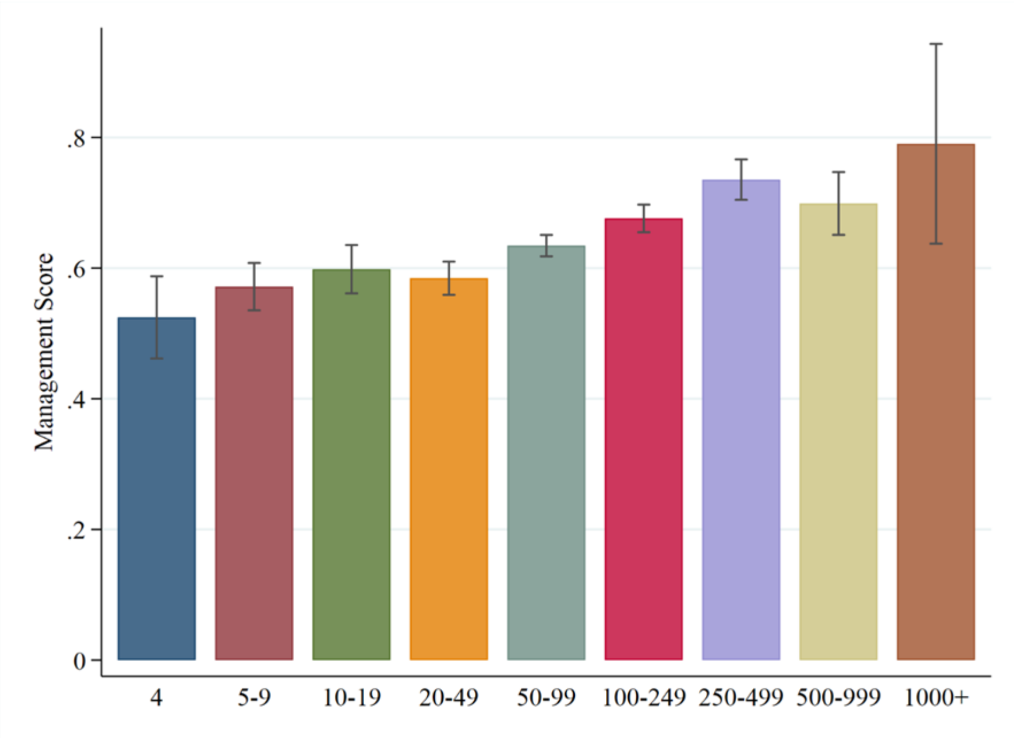

Figure A.6 Unweighted average management score by establishment size (number of employees) with confidence intervals.

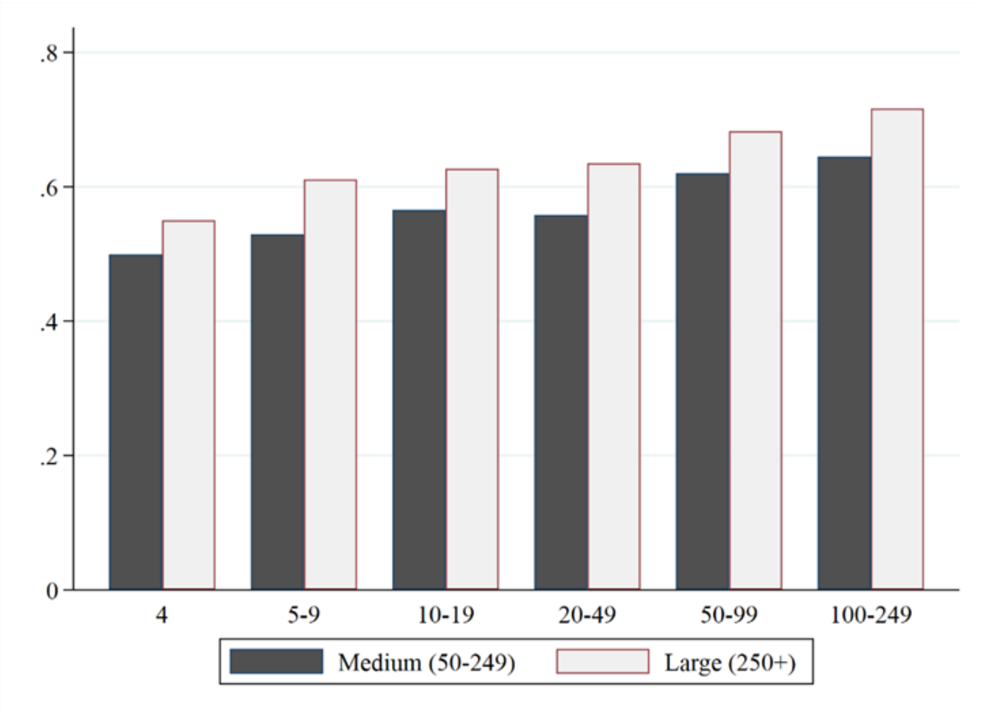

Figure A.7 Unweighted average management score by establishment size (number of employees) in medium and large enterprises.

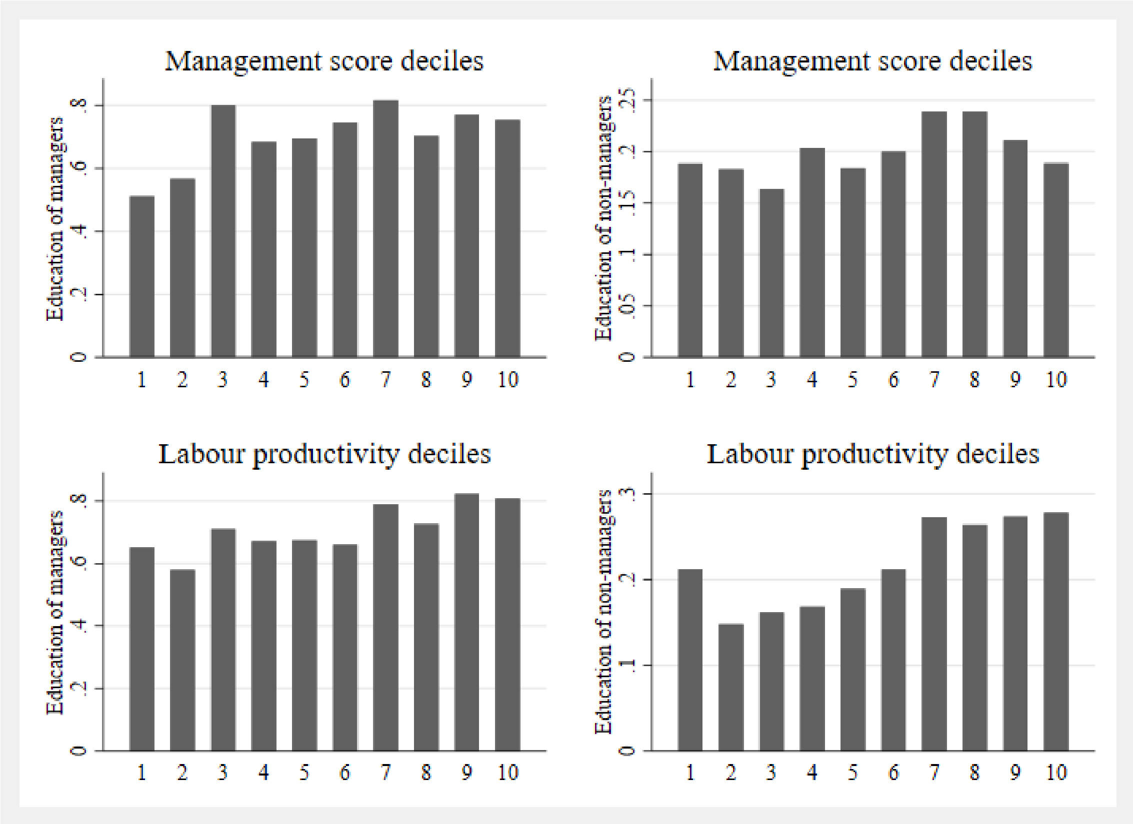

Figure A.8 Share of managers and non-managers with a higher education by management score and labor productivity deciles. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). Note that the scales of the y-axes are different for managers and non-managers.

3.8 Appendix B: Tables

Table A 10 Management-productivity association by manager (non-manager) education tertiles with non-manager (manager) education as a control.

log(labour productivity) in	Manager education tertile			Non-manager education tertile		
	1	2	3	1	2	3
Management score	0.750*	0.910**	2.136***	1.462***	1.364***	1.229
	(0.433)	(0.393)	(0.699)	(0.487)	(0.328)	(0.781)
Non-manager education	1.183	0.059	0.128			
	(0.758)	(0.352)	(0.315)			
Manager education				0.082	0.271*	-0.184
				(0.162)	(0.155)	(0.300)
Observations	129	97	204	99	165	166
Prob > F	0.018	0.070	0.010	0.009	0.000	0.290

Notes: Manager (and non-manager) education is calculated as the share of managers (and non-managers) with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education, including tertiary education).

Table A 11 Establishment management scores and labor productivity: replication of the labor productivity section of Table 1 — Plant Management Scores and Performance in Bloom et al. (2019).

log(labour productivity)	(1)	(2)	(3)	(4)	(5)
Management score	**1.264*****	0.948***	**0.823*****	0.953***	**0.843*****
	(0.292)	(0.201)	(0.200)	(0.202)	(0.200)
log(materials/worker)		0.250***	0.250***	0.248***	0.253***
		(0.034)	(0.034)	(0.034)	(0.032)
log(capital stock/worker)		0.129***	0.102***	0.128***	0.099***
		(0.020)	(0.019)	(0.020)	(0.023)
log(employment)		-0.044	-0.030	-0.052	-0.058*
		(0.031)	(0.032)	(0.032)	(0.034)
Skills (share of employees with a higher education)				0.181	0.583***
				(0.192)	(0.215)
Observations	569	432	432	431	431
Industry dummies			Yes		Yes
R^2	0.186	0.357	0.469	0.355	0.477

Notes: OLS coefficients with Huber–White standard errors in parentheses. Labor productivity is measured as the gross value of production divided by the number of employees. “Skills” is measured as the share of employees with a higher education. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education, including tertiary education). Employee turnover equals the sum of worker inflow and worker outflow during the year and is an establishment's aggregate labor market flow activity measure. Relative employee turnover is measured as employee turnover divided by the average number of employed. Materials are intermediate inputs without energy. Due to data restrictions, the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The industry dummies are at the 2-digit level of the Standard Industrial Classification; mining (05–09), manufacturing (10–33) and utilities (35) were divided into nine subindustries: 05–09, 10–15, 16–18, 19–23, 24–25, 26–27, 28–30, 31–33 and 35. Prob > F (the p-value of the F-test) is less than 0.001 in every column. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

4 WORKER MOBILITY AND PRODUCTIVITY SPILLOVERS

Abstract

Using linked employer-employee data from Finland, we examine the mobility of workers between establishments as a source of productivity-affecting knowledge spillovers. We find evidence that hiring workers from more productive establishments leads to higher productivity in the following year. For an average establishment, this productivity increase amounts to 0.45 percent in our most conservative estimate. The observed productivity gains hold for a variety of specifications, and changes in the receiving establishments' human capital stock are ruled out as an explanation.

Key Words: Worker mobility, Spillovers, Productivity, Human capital.

JEL: D22, D62, J21, J24, J62, L25

4.1 Introduction

The idea that a type of productivity-affecting knowledge is embedded in the workers of a firm has been posited and studied in a variety of ways in the economics literature[41]. In addition to the quality, dispersion and effects of this partly unmeasurable knowledge, an important subject of study are the mechanisms through which it can spill over across firms. Worker mobility is a plausible suggestion for such a mechanism, as demonstrated by Moen (2005), Kaiser, Kongsted, and Rønde (2008), Maliranta, Mohnen, and Rouvinen (2009) and Stoyanov and Zubanov (2012), among others[42]. The potential drivers of productivity are a central target of economic research, and spillovers through employee turnover are a prominent candidate.

Productivity spillovers from worker mobility are often linked to human capital and knowledge transfers, like the benefits from firms' R&D activities passing over to other firms along with the moving workers. This paper examines the hypothesis that firms hiring new workers could experience positive productivity spillovers even if the worker movements would not change the overall human capital composition of the hiring firms' human resources. Possible mechanisms include worker-level productivity boosts caused by the change of workplace or position and the assimilation and transfer of intangible conventions and practices. To capture these hypothesized intangible productivity spillovers, we need to control for the human capital of the moving workers, including exposure to the sending firms' R&D activities, as best we can.

Using a Finnish matched employer-employee data set, this article aims to isolate the potential intangible spillover effects associated purely with cross-firm worker movements themselves. Due to the unique comprehensiveness of the data, we can filter out the productivity variance directly attributable to knowledge transfers and the changes in the human capital stock of the firms. This should leave us with a measure of productivity spillovers unrelated to the direct effects of firms employing new workers with R&D knowledge or, more generally, increasing levels of human capital.

First, we examine whether moving workers enable productivity spillovers in general. In addition to the existing literature, Figure 1 provides further support for this claim. As noted by Stoyanov and Zubanov (2012), worker mobility as a source of productivity spillovers should imply less productivity dispersion in industries with higher rates of average employee turnover from more to less productive establishments.

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41 For example, Prescott and Visscher (1980) posit employee and task characteristics as production relevant parts of firms' capital stock. See also Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Parente & Prescott (1994) and Jones (2005).

42 See, for example, Moretti (2004), LeMouel (2018), Castillo, Garone, Maffioli, Rojo and Stucchi (2019) and Hlatshwayo, Kreuser, Newman and Rand (2019).

Figure 1 suggests that this is indeed the case in the Finnish data, as it is in the firm-level data from Danish manufacturing used by Stoyanov and Zubanov (2012). It shows the relationship between the 2013–2018 average industry-level turnover rate from more to less productive establishments and the normalized productivity variance for 88 industries at the 2-digit level of the Standard Industrial Classification. The pronounced negative correlation is consistent with our assumption of worker mobility as a mechanism of productivity-affecting knowledge diffusion.

Furthermore, this negative correlation is much steeper when the turnover is from the top 25 percent to the bottom 25 percent of establishments, compared to the turnover from top to bottom 40 percent. This implies that the magnitude of the productivity difference between the sending and receiving establishments, or "productivity gap", is linked to how concentrated the productivity distributions are. Since spillovers are a likely cause of lower productivity dispersion, this suggests that spillovers depend on the size of the productivity gap. This paper thus follows Stoyanov and Zubanov (2012) in using this productivity gap as a measure of the receiving establishments' exposure to spillovers through worker mobility. It is the key explanatory variable in our examination of the link between a hiring establishment's productivity and the productivities of the sending establishments.

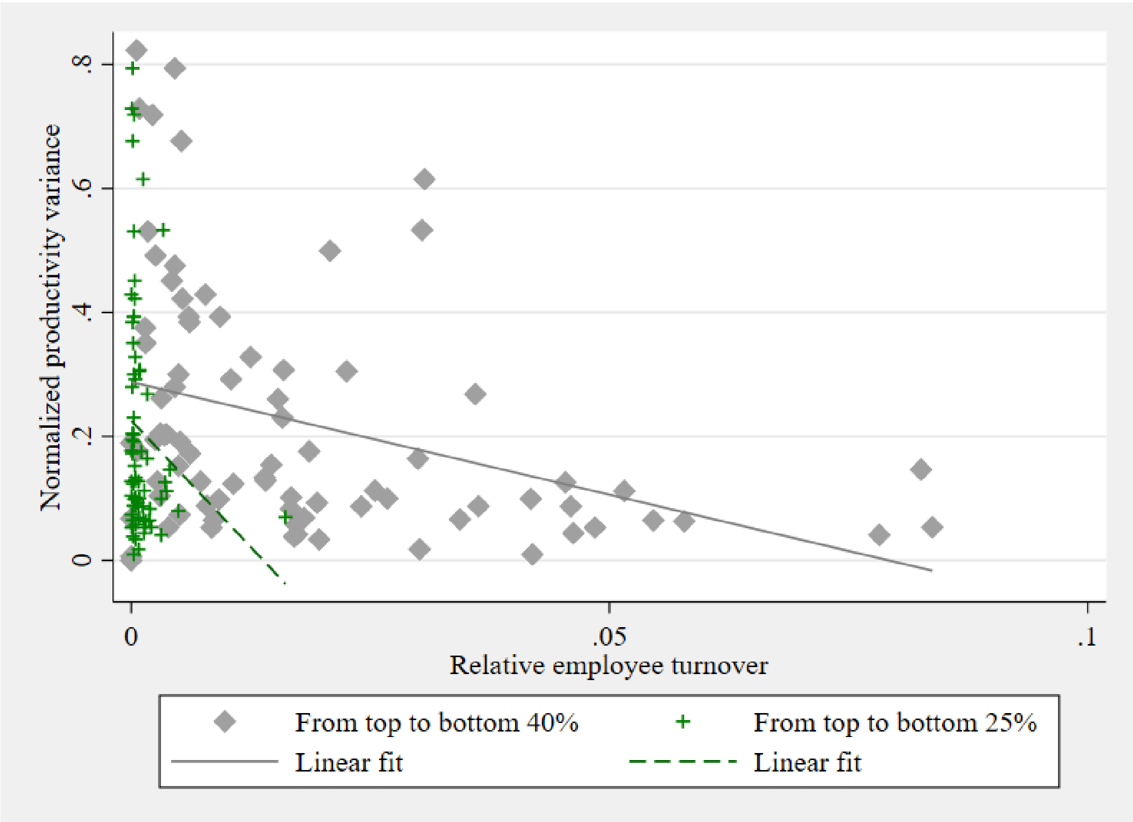

Figure 9 Industry-level average employee turnover and productivity variance.

However, we must also consider that if higher establishment-level human capital intensity increases productivity, employee turnover from higher to lower productivity establishments will affect productivity through this channel as well, not just through spillovers. We are essentially assuming that the total effect[43] of worker mobility on productivity is the sum of the effects of spillovers from hiring (measured by the productivity gap) and the effects of the change in establishment-level average human capital. Therefore, to estimate the effect of knowledge spillovers on productivity using worker mobility, worker-specific human capital needs to be controlled for.

For example, Stoyanov and Zubanov (2012) and Hlatshwayo et al. (2019) try to separate the sending firm's productivity and changes in firm-level human capital by constructing an estimate of the moving workers' human capital using a wage equation that enables the separation of the firm-wage component from individual worker-specific wages. Due to the comprehensive Finnish establishment-employee data set, we can isolate the human capital of the moving workers using their level of education and the R&D and ICT intensities of their sending establishments.

The main finding is that for an average establishment, hiring workers from the average more productive outside establishment is associated with at least 0.45% higher productivity in the following year. The productivity gap can therefore explain a relatively small but statistically significant part of observed establishment-level labour productivity. At the upper end of the estimates, using a fractional polynomial model, we find a 1.57% productivity gain in establishments hiring all new workers from more productive establishments. Section 2 outlines the empirical model and the key variables used in the estimations, section 3 compiles the results, extensions and robustness checks and section 4 concludes.

4.2 Data and empirical model

4.2.1 Sample and Data

The data includes all Finnish workers in the FOLK and FLEED (the Finnish Longitudinal Employer-Employee Data) matched employer-employee data modules of Statistics Finland. The data set covers the years 2011–2018. Only workers with a known employer establishment are used in the analysis. The employer-employee matches for a given year t are based on the longest employment relationship, with a minimum of six months. Therefore, since we are analysing the productivity of the receiving establishment in the year following the hiring of a worker, $t+1$, the new employees have always worked at the receiving establishments for at least 6 months before the productivity observation period starts. We can thus assume that the new hires have had time to potentially have an influence on the period $t+1$ productivity of the receiving establishment.

43 $Total\ effect\ of\ worker\ mobility\ on\ productivity = spillovers + effect\ of\ change\ in\ human\ capital\ stock$

The total number of worker-year observations with a non-missing employer in the years 2011–2018 is 10.68 million, which can be divided into a little over 1.86 million new hires and 8.82 million stayers. The share of new hires is therefore 17.4% of all worker-year observations. Out of the 1.86 million new hires, we have employer productivity data for a little over 1.48 million. However, only workers moving across firms are included in the main analysis. Cross-firm movers make up approximately 1.44 million or 77.4% of all new hires in the data. Out of these 1.44 million new cross-firm hires, 1.17 million (81.5%) have non-missing productivity data for the receiving establishment.

Establishment-level variables used in the analysis, such as value added, gross value of production, R&D and ICT spending, number of employees, intermediate inputs and addition and depreciation of machinery are gathered from The Business Register database and enterprises' financial statement data maintained by Statistics Finland. Data for these variables covers the years 2011–2019.

The dependent variable in the main analysis is the labour productivity of the receiving establishment in the year following the hiring of new workers. Productivity is measured by the gross value of production divided by the number of employees. The independent variable of interest is the positive productivity gap between the sending and receiving establishments of newly hired workers, following the approach of Stoyanov and Zubanov (2012). It is calculated for establishment j hiring new workers i in year t as:

$$\overline{gap}_{j,t} = \frac{\sum_{i=1}^{H_{j,t}} D_{i,t}(Y_{i,t-1}^{s} - Y_{j,t-1}^{r})}{H_{j,t}} \frac{H_{j,t}}{N_{j,t}}, \tag{1}$$

where $D_{i,t} = 1 \; if \; \left(Y_{i,t-1}^{s} - Y_{i,t-1}^{r}\right) > 0$. $H_{j,t}/N_{j,t}$ denotes the share of new workers $H_{j,t}$ in the total employment $N_{j,t}$ of establishment j. $Y_{i,t-1}^{s}$ and $Y_{i,t-1}^{r}$ denote the labour productivities of the sending and receiving establishments of new worker i one year before the hiring takes place. For each hiring establishment j, the productivity gap therefore measures the difference between their own productivity and the productivity of the sending establishment, averaged across all new workers i and weighted by their share in total employment. The weighting of the average gap by the share of new workers should ensure that the gap variable captures the relative exposure of the receiving establishments to the influence of the new workers.

Furthermore, by weighting the productivity gap averaged across hired workers by their share, we are controlling for an establishment-level relative employee turnover-like measure in the estimations. This is important, since relative employee turnover is a potential confounder between the hiring gap and future productivity. As shown by Maliranta, Mohnen and Rouvinen (2009), employee turnover can have knowledge spillover effects, thereby indirectly affecting the productivity gap. It can also directly affect productivity if higher productivity workers tend to replace lower productivity employees more than vice versa. Not including the weighting could thus introduce a spurious association between the gap and the productivity of the receiving establishment.

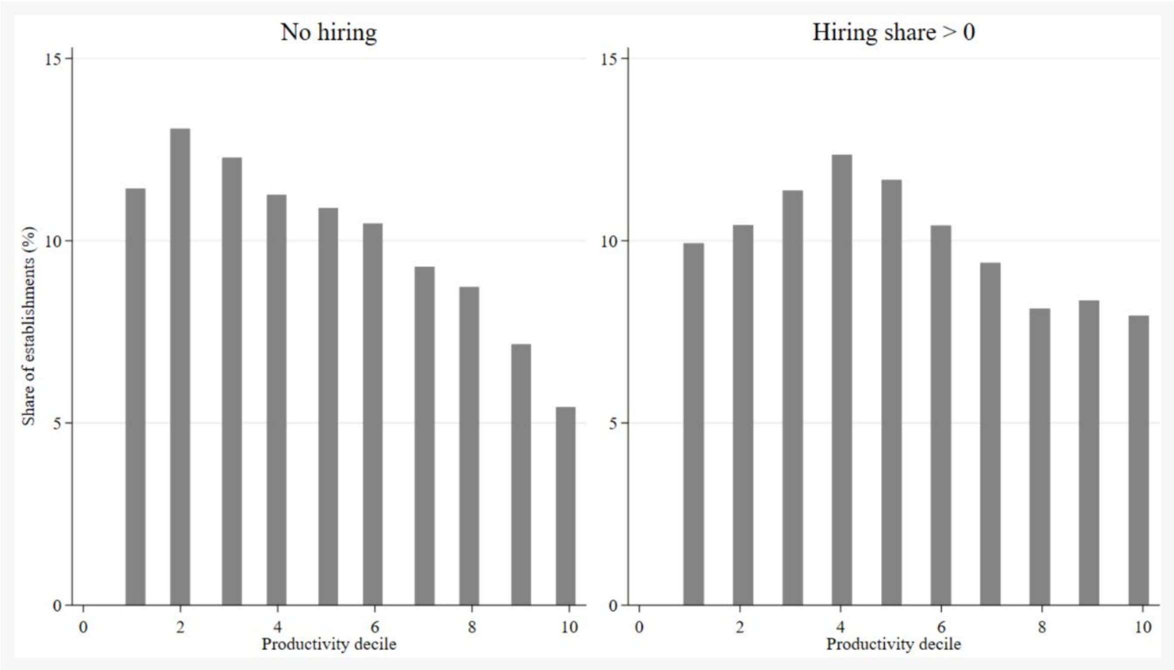

Figure 10 The distribution of the share of establishments in each productivity decile for non-hiring and hiring establishments.

Histograms of the shares of hiring and non-hiring establishments in each productivity decile are shown in Figure 2. The mass of the establishments that did not hire new workers is concentrated clearly more in the lower deciles of productivity compared to the establishments with a positive hiring share. It would therefore seem, based on the raw data alone, that more productive establishments are more likely to hire new workers. However, both hiring and productivity could be related to the size of the establishment, which is why Figure 3 shows the average number of employees in each productivity decile, along with the average positive productivity gaps between the senders and receivers of hired workers.

From Figure 3 we can see that any possible connection between positive productivity gaps in hiring and establishment productivity should not be confounded by establishment size: establishments in the higher productivity deciles are larger, but the gap decreases as size increases. Figure 3 also shows that both the positive hiring gap and the share of managers seem to increase with productivity deciles, more clearly so for the share of managers. This is expected, since establishments in higher size deciles have both higher shares of managers and higher productivity on average. For example, the mean share of managers in size decile 5 is 0.7%, whereas in size decile 8 it is 6.2%.

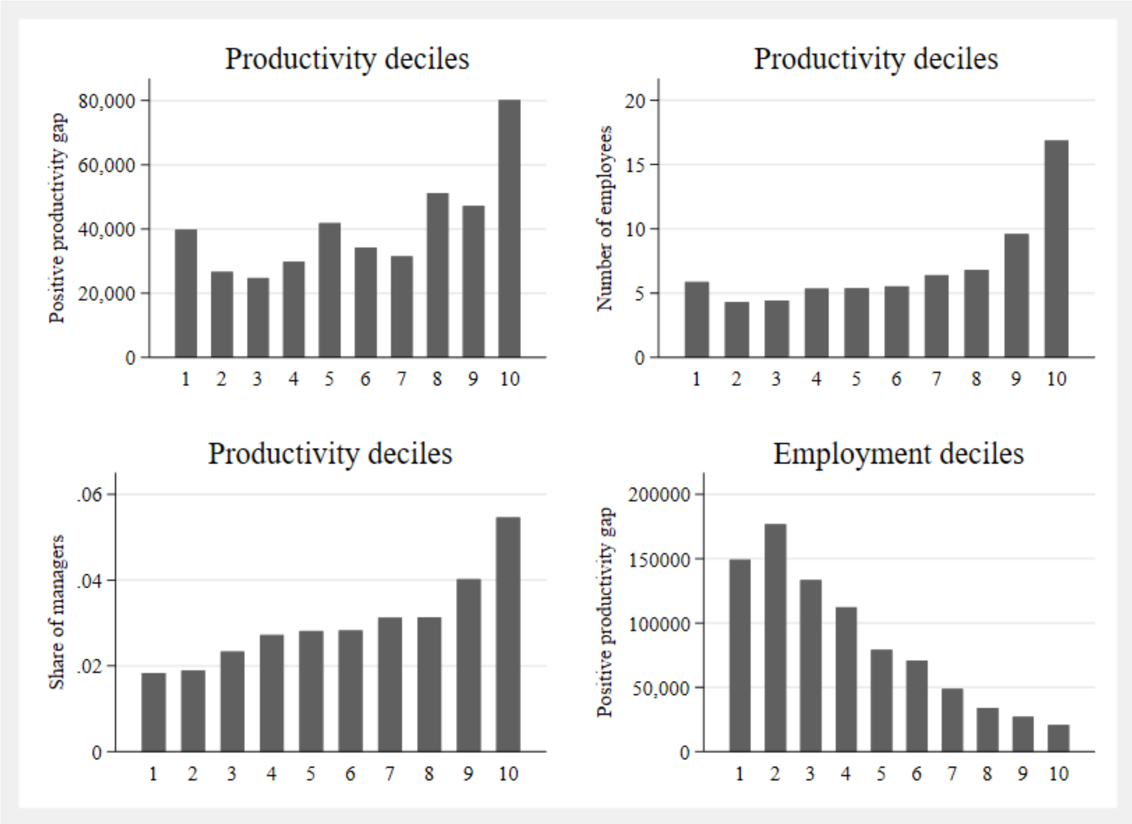

Figure 11 Comparisons of key variables by productivity and employment deciles.

Table 1 lists employee-level descriptive statistics separately for stayers, new hires across firms and new hires from more productive establishments across firms. Workers moving between establishments within firms are not included. The main differences between stayers and new hires are found in the average wages and age: stayers have significantly higher wages and are also older than new hires.

This is unsurprising, since older workers tend have more experience on average, which is often directly translated into salaries. The difference in wages might also reflect the results of Møen (2005), who finds that at least in R&D intensive firms, hired scientists, engineers and workers with secondary technical education pay for future on-the-job knowledge by accepting lower wages early in their careers. The wage discount is also largest for the youngest workers in Møen's (2005) Norwegian data set. Therefore, the results from Norway coincide with the lower wages and the five to six years lower mean age of new hires in Table 1.

Table 12 Employee-level summary statistics.

Mean	Stayers	New hires	New hires from more productive establishments
Wage (€)	35 743	29 522	31 523
Age	41.8	36.6	35.8
Female (share)	0.42	0.43	0.40
Higher education (share)	0.26	0.29	0.26
Managers (share)	0.044	0.040	0.036
Medium-skilled workers (share)	0.64	0.68	0.71
High-skilled workers (share)	0.31	0.28	0.25
Observations	8 821 722	1 440 431	315 083

Notes: The means are calculated for all workers between the years 2013 and 2018. New hires only include workers who moved across firms, moves between establishments within a firm are not included. Higher education is defined as having completed at least a bachelor's degree or equivalent (15–16 years from the beginning of primary education). Managers are defined as employees belonging to the group "managers" in the Statistics Finland Classification of Occupations 2010. "Medium-skilled workers" include skill levels 1 and 2 and "high-skilled workers" skill levels 3 and 4 in the Incomes Register´s Classification of Occupations.

When comparing new hires from more productive establishments to all new hires, the former have a smaller share of managers, high-skilled workers and workers with higher education, but a somewhat higher mean wage. The average new hire from more productive establishments is also younger, so age does not explain the higher wages. The wage differential could therefore be indicative of, for example, high productivity workers asking for higher wages when transitioning between jobs or firms using higher wages to attract workers from more productive competitors.

Table 2 summarizes some establishment-level statistics. Out of the 1.57 million establishment-year observations, hiring took place in 491 751 or a little over 31.3 percent. As expected, the non-hiring establishments are significantly smaller than the hiring ones. For establishments with at least 5 employees, hiring took place in 55.7 percent of the subsample, whereas the share of establishments with a positive hiring share is only 21.2 percent in the subsample with less than 5 employees.

Table 2 also shows clear differences in the share of managers and wages between hiring and non-hiring establishments. This disparity is at least partly reflective of the size differential, since larger establishments also pay higher wages and have higher shares of managers on average: in establishments with at least 5 employees, the mean wage is 31124 euros and the share of managers is 5.8 percent, whereas in establishments with less than 5 employees the corresponding figures are 22937 euros and 1.3 percent. The hiring establishments are also more productive and have a significantly younger workforce on average. The average productivity of the hiring establishments is 17.4 percent higher compared to the non-hiring establishments.

Table 13 Establishment-level summary statistics

Mean	All establishments	Hiring share = 0	Hiring share > 0: Stayers	Hiring share > 0: Hires from more productive	Hiring share > 0: Hires from less productive
Wage (€)	25 953	23 804	30 703	30 333	28 249
Age	43.8	45.4	40.3	36.4	35.2
Female (share)	0.39	0.38	0.43	0.38	0.40
Higher education (share)	0.20	0.18	0.22	0.25	0.22
Managers (share)	0.026	0.018	0.054	0.039	0.027
Medium-skilled workers (share)	0.72	0.73	0.69	0.72	0.75
High-skilled workers (share)	0.26	0.25	0.25	0.24	0.22
Labor productivity (€)	174 366	165 110		193 810	
Establishment size (employees)	5.9	2.8		12.9	
Observations	1 569 460	1 077 703		491 751	

Notes: The summary statistics are calculated at the establishment level, but new hires only include workers who moved across firms. Moves between establishments within the same firm are not included. For establishments with a positive hiring share, the means were first separately calculated for all stayers and new hires from more and less productive establishments before averaging across establishments. Higher education is defined as having completed at least a bachelor's degree or equivalent (15-16 years from the beginning of primary education). Managers are defined as employees belonging to the group "managers" in the Statistics Finland Classification of Occupations 2010. "Medium-skilled workers" include skill levels 1 and 2 and "high-skilled workers" skill levels 3 and 4 in the Incomes Register´s Classification of Occupations. Labor productivity is measured as the gross value of production/number of employees.

4.2.2 Empirical model and identification issues

The linear model estimated on the data is

$$Y_{j,t+1}^{r} = \beta \cdot \overline{gap}_{j,t} + \boldsymbol{X}_{j,t}\mu + \overline{\boldsymbol{Z}}_{j,t}^{1}\gamma_1 + \overline{\boldsymbol{Z}}_{j,t}^{2}\gamma_2 + f_j + \bar{\epsilon}_{j,t+1} \qquad (2)$$

where $\overline{gap}_{j,t}$ is the positive productivity gap of establishment j, as defined in equation (1). $\bar{Z}_{j,t}^{1}$ and $\bar{Z}_{j,t}^{2}$ are vectors of averaged worker characteristics[44] and the measure for the human capital of new workers, respectively. $X_{j,t}$ is a vector of the receiving establishment's characteristics, including capital stock, materials, employment and a constant. Industry-year fixed effects are denoted by f_i and $\bar{\epsilon}_j$ is a stochastic error term.

The measure of new workers' human capital, $\bar{Z}_{j,t}^{2}$, consists of the level of education of the new workers and the ICT and R&D intensities of the sending establishments in year $t-1$. Its inclusion should help isolate the intangible productivity spillovers potentially resulting from worker mobility, instead of the direct effects of firms simply employing more workers with high human capital. The human capital of new workers also likely both affects the sending

[44] wage, share of managers, level of education, dummies for medium-skilled and high-skilled workers, age.

establishments' productivity and causes an unobserved shock to the receiving establishment's productivity, which is absorbed by the error term $\bar{\epsilon}_j$. It follows that controlling for the new worker's human capital is essential for consistently estimating the coefficient on the productivity gap, β.

Productivity in year t is not included in the regressions, since it is assumed to at least partly mediate the potential effect of the gap on future productivity. In other words, because the gap variable includes the year $t-1$ productivity of the receiving establishment, $Y_{j,t}^{r}$ is likely a mediator between the gap and our dependent variable $Y_{j,t+1}^{r}$. This mediation assumption is supported by the coefficient of the gap on $Y_{j,t+1}^{r}$ going to zero (0.0003 with $p = 0.84$) when productivity in year t is included as a regressor. Therefore, to estimate the total effect of the productivity gap on future productivity, we do not control for $Y_{j,t}^{r}$. Furthermore, $Y_{j,t}^{r}$ cannot be a confounding variable, since the productivity of the receiving establishment cannot affect the productivities of the sending and receiving establishments in year $t-1$. Two lags of the receiving establishment's productivity, $Y_{j,t-2}^{r}$ and $Y_{j,t-3}^{r}$ are added as a test of coefficient robustness[45].

In the specification outlined in equation (2), ability bias is another potential issue for identification. A bias would arise if higher ability workers tend to self-select into establishments with higher productivity. However, controlling for the factors related to this unobserved ability, like education levels and ICT and R&D experience from the sending firm, should remove the bias to the extent that our measure captures said worker ability. Furthermore, an opposite bias is also plausible: if firms try to hire workers with the highest perceived ability for their establishments with the lowest productivity, the sign of the bias would be reversed and the effects of worker mobility on productivity would be underestimated rather than overestimated. This is a likely scenario if firms tend to use outside hires to try and bring their least productive establishments up to speed with the rest of the firm.

4.3 Results

4.3.1 Receiving establishment's productivity and the gap

Table 3 estimates equation (2) separately for the overall productivity gap and the positive and negative gaps. Analogously to the positive productivity gap in equation (1), the overall productivity gap is calculated for establishment j hiring new workers i in year t as:

45 The coefficient of the gap goes from 0.01 ($p = 0.036$) to 0.003 ($p = 0.061$) when the lags are included in the baseline regression.

$$\overline{gap^o}_{j,t} = \frac{\sum_{i=1}^{H_{j,t}}(Y_{i,t-1}^s - Y_{j,t-1}^r)}{H_{j,t}} \frac{H_{j,t}}{N_{j,t}}. \tag{3}$$

Table 14 Receiving establishment's productivity and the overall, positive and negative productivity gaps

Productivity (t+1)	(1)	(2)	(3)	(4)	(5)	(6)
Overall productivity gap	-0.00001	0.00001				
	(0.000)	(0.000)				
Positive productivity gap			0.010**	**0.008****		
			(0.005)	(0.004)		
Negative productivity gap					-0.00001	-0.00001
					(0.000)	(0.000)
Observations	221 711	221 711	124 886	124 886	148 321	148 321
Industry-year fixed effects		Yes		Yes		Yes
R^2	0.000	0.015	0.000	0.019	0.000	0.017

Notes: OLS coefficients with Huber–White standard errors in parentheses. Productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

Table 3 shows that the coefficients for the overall and negative productivity gaps are essentially zero. This is expected, since we assume there are no negative spillover effects caused by hiring workers from less productive establishments. Negative spillovers would imply negative learning[46] which, as noted by Stoyanov and Zubanov (2012), is unlikely. The results in columns 5 and 6 ($p = 0.382$ and $p = 0.389$) confirm the expectation that cross-firm hiring of new workers from less productive establishments is neutral to future productivity. The zero coefficient on the overall productivity gap is also not surprising, since almost 67% of all the measured cross-firm productivity gaps between the sending and receiving establishments are negative. Following the results in table 3, the rest of the paper will focus exclusively on the positive productivity gap.

The results for the OLS linear regression of equation (2) are recorded in Table 4. Establishment characteristics, averages of worker characteristics (see Table

46 A positive and significant coefficient on the negative productivity gap could conceivably also imply some other unexplained mechanism, but we will assume this is not the case. the assumption of no negative spillovers is also supported by the regression results presented in Table 3.

1) and the new workers' human capital variable are added as controls to the specification presented in column 4 of Table 3. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. Level of education is measured as the share of workers with a higher education, which is defined as having completed at least a bachelor's degree or equivalent (15-16 years from the beginning of primary education).

The coefficient on the productivity gap is between 0.022 and 0.025 in every specification of table 4, with p-values ranging from 0.007 in column 1 to 0.018 in column 4. Though statistically significant at the 95% confidence level, this positive relationship between the gap and the receiving firm's productivity is rather small in magnitude: for an average establishment, hiring every worker from establishments that are more productive by the mean positive gap of 36 878.73€ is associated with 811.33€ ($= 0.022 \times 36878.73€$) higher productivity one year after hiring. This is approximately 0.45 percent[47] of the productivity of an average establishment. This is consistent with the findings of Hlatshwayo et al. (2019), who report a 0.38 percent productivity gain from hiring new workers from more productive firms. The gap therefore explains only a relatively small portion of the observed productivity dispersion. Alternatively, increasing the positive productivity gap of all workers by one tenth of a standard deviation is associated with a 0.66 percent (1185.9€[48]) higher productivity in the following year.

[47] $811.33€/180318.90€ = 0.004499$

[48] $0.022 \times 539047€ = 11859€$, or 6.6% of the productivity of the average establishment.

Table 15 Receiving establishment's productivity and the positive productivity gap

Productivity (t+1)	(1)	(2)	(3)	(4)
Positive productivity gap	0.025***	0.024**	0.024**	0.022**
	(0.009)	(0.010)	(0.010)	(0.009)
ICT/worker of sender			2078*	3514***
			(1133)	(1035)
R&D of sender			4532***	1015*
			(588)	(615)
Share of new workers			16786***	6273
with a higher education			(12133)	(5064)
Establishment characteristics	Yes	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes	Yes
Human capital of new workers			Yes	Yes
Industry-year fixed effects	Yes	Yes		Yes
Observations	27 207	20 872	20 813	20 813
R^2	0.129	0.341	0.200	0.341

Notes: OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. ICT is measured as the log of information and communications technology planning and programming expenditure per employee. Following Bloom et al. (2019), R&D is measured as $\log(1 + R\&D\ intensity)$, where R&D intensity is total research and development expenditure per worker. Only observations with non-negative values of ICT and R&D expenditures are included. Missing values of ICT and R&D have been replaced by 2-digit level industry means. Labour productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$.

Even though not very strong, the relationship between our gap measure and productivity is likely to capture productivity spillovers caused by inter-firm worker mobility, as intended. This is implied by the inclusion of new workers' human capital having almost no effect on the gap's coefficient. If the link between worker mobility and productivity was explained by the direct effects of firms employing more workers with high human capital, we would expect the positive correlation to weaken or even disappear when going from column 2 to 4 in Table 4. Therefore, the results support the assertion of the productivity gap as a reliable measure of establishments' exposure to spillovers from worker mobility.

In the estimations presented in Tables 3 and 4, worker mobility between establishments within the same firm is excluded. When including within-firm worker movements, no statistically significant correlation between the productivity gap and future productivity is found. Approximately 77.4% of the workers moving between establishments also switched firms. Considering how significant this share is, and assuming that there is more variation in characteristics across firms than in establishment characteristics within firms, excluding the within firm transfers will likely result in a more accurate reflection of productivity spillovers.

Furthermore, the disappearance of the significant correlation when including within-firm movers implies that worker mobility from more productive establishments to less productive ones within firms is less likely to induce productivity spillovers in the receiving establishments, compared to cross-firm worker mobility. An analysis of manager mobility and a fractional polynomial model are described as extensions in the following section.

4.3.2 Manager mobility

The first extension is an analysis of manager mobility. The share of managers in the subsample of establishments with less than 5 employees is 1.3%, whereas managers comprise an average of 5.8% of total workers in establishments with at least 5 employees. Therefore, the analysis only includes the latter. The control variables in the manager mobility regressions are the same as in Table 4, except the mean education level of new managers replaces the level of education of new workers. The share of managers with a higher education is 44.1% in the full subsample of establishments with at least 5 employees, whereas the corresponding share is 48.7% for newly hired managers.

Table 16 Receiving establishment's productivity and the overall, positive and negative productivity gaps for hired managers

Productivity (t+1)	(1)	(2)	(3)	(4)	(5)	(6)
Overall productivity gap	-0.023	-0.021				
for managers	(0.017)	(0.015)				
Positive productivity gap			0.0004	**0.0003***		
for managers			(0.0001)	(0.0002)		
Negative productivity gap					-0.058	-0.053
for managers					(0.057)	(0.051)
Observations	13 521	13 521	7 491	7 491	6 934	6 934
Industry-year fixed effects		Yes		Yes		Yes
R^2	0.017	0.113	0.0001	0.150	0.044	0.164

Notes: OLS coefficients with Huber–White standard errors in parentheses. Managers are defined as employees belonging to the group "managers" in the Statis-tics Finland Classification of Occupations 2010. Productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

The results of Table 3 hold here as well: the coefficients for the overall and negative manager productivity gaps are essentially zero. The coefficient on the positive productivity gap is again positive, but unlike with all workers, it is extremely small and only statistically significant at the 90% confidence level. Furthermore, as evidenced by Table 6, the correlation between productivity and the positive productivity gap measured for moving managers is essentially zero in all specifications. No definitive conclusions can be drawn from these results, but it seems plausible that the mechanisms governing the hiring of managers differ from those governing the hiring of other workers in some significant ways.

Table 17 Receiving establishment's productivity and the positive manager productivity gap

Productivity (t+1)	(1)	(2)	(3)
Positive productivity gap (managers)	-0.0005*	-0.0005	-0.0005
	(0.0003)	(0.0003)	(0.0003)
ICT/worker of sender			1327
			(3571)
R&D of sender			-1037
			(2170)
Share of new managers with a higher education			8162
			(7802)
Establishment characteristics	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes
Human capital of new workers			Yes
Industry-year fixed effects	Yes	Yes	Yes
Observations	1 810	1 398	1 398
R^2	0.429	0.470	0.471

Notes: OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. ICT is measured as the log of information and communications technology planning and programming expenditure per employee. Following Bloom et al. (2019), R&D is measured as $\log(1 + R\&D\ intensity)$, where R&D intensity is total research and development expenditure per worker. Only observations with non-negative values of ICT and R&D expenditures are included. Missing values of ICT and R&D have been replaced by 2-digit level industry means. Labour productivity is measured as the gross value of production/number of employees. The industry-year fixed effects are calculated at the 2-digit level of the Standard Industrial Classification. $*\,p < 0.10$, $**\,p < 0.05$, $***\,p < 0.01$.

The regressions of future productivity on the productivity gap measure are not meant to accurately describe the absolute magnitude of productivity spillovers through worker mobility. Rather, they demonstrate that hiring and employee turnover are a plausible source of productivity variation. Going from all workers to only managers, the differences in the results highlight the uncertainty involved with these types of studies. This uncertainty must be considered in any study involving worker mobility; the mobility-affecting incentives of both the moving workers and the hiring firms are much too complex to reliably parse with any simple regression analyses.

4.3.3 Fractional polynomial model

The multivariable fractional polynomial (MFP) provides a systematic, fully data-driven way of selecting the best-fitting functional form for a statistical model (Royston & Sauerbrei 2009). The approach uses backward elimination to select which variables are included in the model and combines this with a systematic fractional polynomial function selection procedure to determine a functional form for the included predictors. In the first step of the MFP algorithm, the best-fitting fractional polynomial (FP) functions of the first and second degree are selected based on the Akaike's information criterion (AIC)[49]. In the second step, MFP systematically examines whether FP functions of varying complexity describe the shape of the association between a regressor and the dependent variable better than a linear function.

Table 7 reports the results[50] from estimating the full fractional polynomial (FP) model built by the MFP backfitting model-selection algorithm. All variables are centered around the mean and modelled as fractional polynomials with powers chosen by the algorithm. The coefficient in column 1 implies that for an average establishment, hiring all its workers from the average more productive outside establishment is associated with a 2.15 percent[51] higher productivity in the year after hiring. Adding average worker characteristics and the measure of new workers' human capital as controls lowers the observed association to 1.57 percent. Alternatively, increasing the positive productivity gap of all workers by one tenth of a standard deviation is associated with a 2.45 percent (4415.45€) higher productivity in the following year.

The positive association implied by the fractional polynomial model is significantly stronger compared to the original specifications, results of which are shown in Table 4. It is therefore not unjustifiable to treat the coefficients estimated from equation (2) as a somewhat conservative lower bound for the association between the productivity gap and the future productivity of the receiving establishment.

49 $Model\ deviance -\ 2 * (maximized\ log\ likelihood\ for\ the\ model\ being\ tested)$.

50 The coefficients on the control variables are omitted for conciseness and are available on request from the authors.

51 $244454.7 \times \{[(36878.73€/10000000)^{0.5}] - 0.0448603721\} = 3878.88€\ and\ 3878.88€/180318.9€ = 0.021511$.

Table 18 Fractional polynomial model

Productivity (t+1)	(1)	(2)	(3)
FP(Positive productivity gap)	244454.7***	194396.2***	190179.0***
	(55182)	(44837)	(64916)
Establishment characteristics	Yes	Yes	Yes
Averages of worker characteristics		Yes	Yes
Human capital of new workers			Yes
Observations	27 207	20 872	20 813
R^2	0.082	0.262	0.263

Notes: $FP(Positive\ productivity\ gap) = \hat{X}^{0.5} - 0.0448603721$, where $\hat{X} = \overline{gap}/10000000$. The division of the gap variable before centering on the mean is applied automatically to improve the scaling of the regression coefficient for FP(Positive productivity gap). OLS coefficients with Huber–White standard errors in parentheses. For a list and summary statistics of the average worker characteristics, see Table 1 and Table 2. In addition to employment, establishment characteristics include materials and capital stock: materials are measured as intermediate inputs without energy, whereas the sum of the addition and depreciation of machinery is used as a proxy for net capital stock. The human capital of new workers is measured as the establishment average of their level of education and the ICT and R&D intensities of their sending establishments. $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$.

4.3.4 Robustness of the results

In addition to the reported estimates using the normal unweighted average productivity numbers, all regressions were run with employment weights to ensure that the qualitative conclusions hold for employment weighted productivity[52] as well. Employment weighted regressions mitigate the impact of smaller establishments with extreme labour productivity numbers. They also account for the workforce allocated into higher productivity establishments, making the employment weighted results more relevant for cross-regional or cross-country comparisons, for example. Adding employment weights to the regressions does not change the statistical significance of or the conclusions drawn from the estimates. The coefficient of the positive productivity gap in an employment weighted equivalent of the regression in column 4 of Table 4 is 0.021, as opposed to the 0.022 in the original unweighted specification. The employment weighted regression is equivalent to fitting the model

$$Y^r_{j,t+1}\sqrt{L_j} = \beta\overline{gap}_{j,t}\sqrt{L_j} + \sqrt{L_j}\cdot\boldsymbol{X}_{j,t}\mu + \sqrt{L_j}\cdot\overline{\boldsymbol{Z}}^1_{j,t}\gamma_1 + \sqrt{L_j}\cdot\overline{\boldsymbol{Z}}^2_{j,t}\gamma_2 + f_j\sqrt{L_j} + \bar{\epsilon}_{j,t+1}\sqrt{L_j}, \tag{4}$$

where L_j is the number of employees in establishment j.

52 Olley-Pakes decomposition (Olley & Pakes 1996) of productivity: Employment weighted average productivity = unweighted average productivity + a covariance-like term between activity shares and productivity.

The main analysis includes establishments of all sizes. Only including establishments with at least 5 employees slightly increases some point estimates and decreases others but does not affect the statistical significance of the coefficients or any qualitative conclusions drawn from the regressions. When excluding all other industries except manufacturing[53], the coefficients corresponding to those in columns 1, 2 and 4 of Table 4[54] are reduced to 0.018**, 0.014* and 0.013*. In the regressions with only manufacturing, the range of the number of observations also goes down to approximately 5100–6800 from the original 20800–27200.

The comprehensive Finnish employer-employee data could also be utilized to identify a subsample of workers involuntarily displaced due to the closing of establishments or mass layoffs[55]. The mobility of these workers could thus be considered exogenous; not prompted by their own decision-making or characteristics. The choice of receiving establishments they end up moving to would still be subject to selection bias, but leaving their previous employer would not. However, it is likely that the sending establishments would differ significantly from the average, which would need to be considered in the analysis. Nevertheless, examining the establishments that hire workers from this displaced subsample could at least provide evidence for or against the results presented in this paper.

4.4 Conclusions

The main finding of this paper is that hiring workers from more productive establishments can explain a relatively small but statistically significant part of the future productivity of the receiving establishments. Namely, hiring every worker from outside establishments that are more productive by the mean positive productivity gap is associated with 811.33€ higher productivity one year after hiring. This is approximately 0.45% of the productivity of an average establishment. It is unlikely that these spillovers are explained by hiring-induced changes in the receiving establishments' human capital stock, since we control for the human capital of the hired workers.

These results hold when establishments with less than 5 employees are excluded and when only establishments in the manufacturing sector are included. However, no link between the gap and the hiring establishments' productivity is found for moving managers. The found association also disappears when worker movements within firms are included. This suggests that worker mobility from more to less productive establishments within firms is unlikely to induce productivity spillovers in the receiving establishments, at least in the aggregate.

53 Industries 10–33 in the Standard Industrial Classification TOL 2008 (Statistics Finland 2017).

54 The coefficients are 0.025***, 0.024** and 0.022** in columns 1, 2 and 4 of Tabe 4.

55 The author would like to thank the preliminary examiners of this dissertation for this suggestion.

Furthermore, we do not find any evidence that the average worker characteristics[56] of the receiving establishments significantly influence the relationship between the productivity gap and the productivity of the receiving establishment.

The analyses presented in this paper suggest that worker mobility can indeed induce productivity spillovers, even outside the direct effects of the changing workforce characteristics of the hiring establishments. The mechanisms behind such spillovers are a topic for future research. Examples of potential explanations include worker-level productivity boosts caused by the change of workplace or position and the assimilation and transfer of intangible conventions and practices. The former could be analysed, for example, by looking at the persistence of the productivity changes linked to hiring workers to see if the spillover effects fade over time.

This does not necessarily imply much for an individual firm or establishment, especially considering the relatively small magnitude of the estimated spillovers. It does, however, support labour market flexibility and the provision of safety nets to mitigate the negative individual-level effects of employee turnover. Since worker mobility can induce growth-supporting productivity spillovers, and it is partly driven by involuntary redundancies and periods of unemployment, we should ensure that these potential positive externalities do not come at the expense of the workers' welfare.

Related to these implications, a future study should focus on the productivity of the sending establishments, to analyse the effects of firms losing workers[57]. This would provide further evidence for whether increased worker mobility is linked to higher national productivity. The comprehensive Finnish employer-employee data could also be utilized to identify a subsample of workers involuntarily displaced due to the closing of establishments or mass layoffs. The mobility of these workers could thus be considered exogenous to their own decision-making and characteristics. Examining establishments that hire workers from this subsample would provide a robustness check for the results presented in this paper.

Furthermore, the results presented imply that a cross-regional analysis of worker mobility and productivity might reveal interesting facts about the effects on international competitiveness of the regional disparities[58] in worker flows. The productivity gap measure can be of use when calculating the costs associated with the concentration of the workforce in certain areas within countries. At the same time, supporting worker flows from more to less productive areas could potentially lead to a decrease in regional productivity dispersion.

56 Share of managers, share of high and medium skilled workers, share of workers with higher education, age and wage. See Table 2.

57 The author would like to thank the preliminary examiners of this dissertation for this suggestion.

58 For statistics on regional labour mobility in Finland, see Poghosyan & Scott (2018).

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4.6 Appendix A: figures

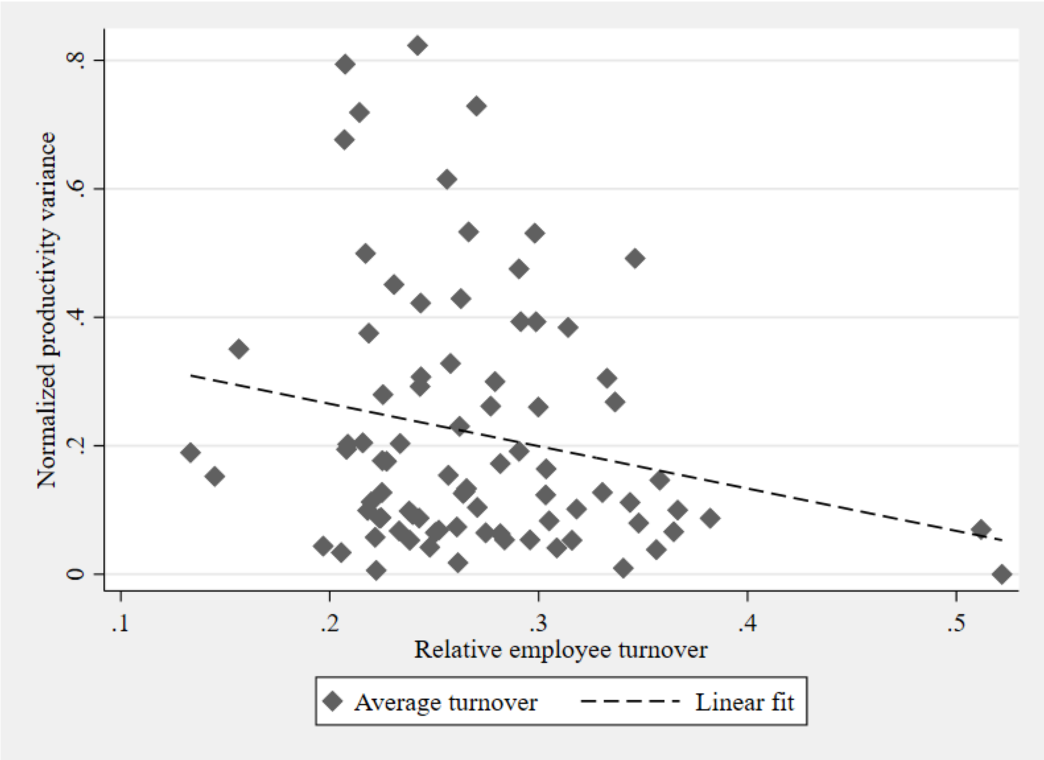

Figure A.12 Overall industry-level relative employee turnover and productivity variance.

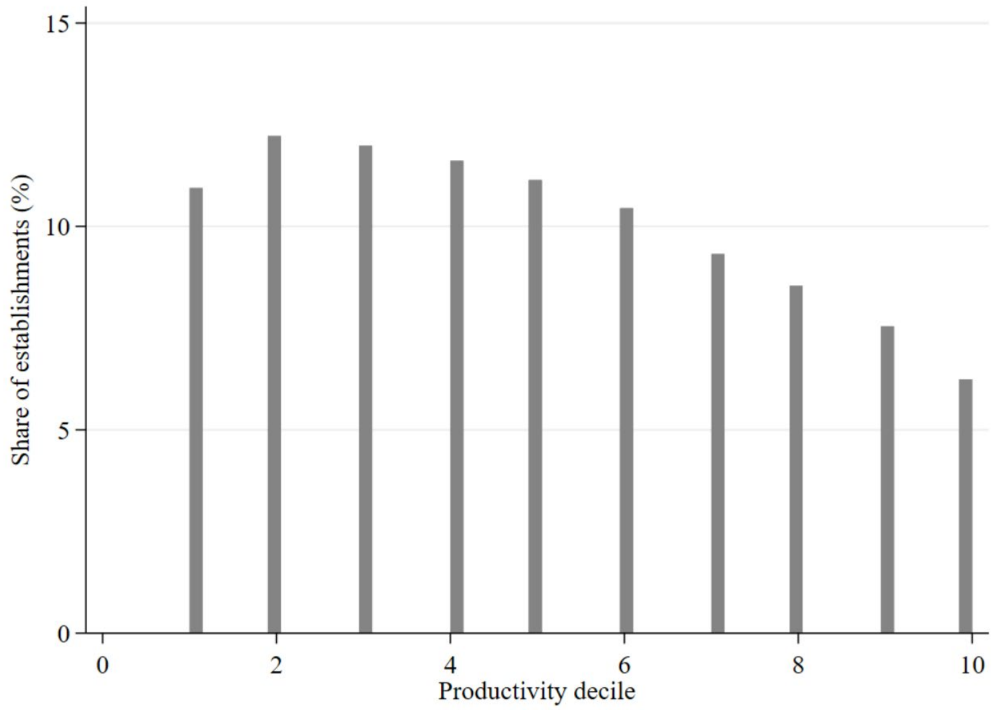

Figure A.13 The distribution of the share of establishments in each productivity decile.