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High-involvement management practices and the productivity of firms: Detecting industry heterogeneity

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Abstract
The aim of this article is to clarify the links between high-involvement management (HIM) practices, productivity and branches of industry. The data combine a representative survey (N = 787) of private-sector firms in Finland and register-based firm-level data on sales per employee in the year following the survey. The authors analysed the data using mixture regression and identified two clusters in the association between HIM and productivity. In one cluster, high-

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involvement management and productivity were positively associated, while in the other cluster, the association was negative. The association between the intensity of HIM utilisation and productivity is not always additive; the benefits of HIM were most prominent in industries where HIM was most seldom utilised. This paradox was most notable in the service sector.

Keywords
Employee participation, high-involvement management, mixture regression, performance, productivity

Introduction

Since around the mid-1990s, different articulations of high-performance paradigms have represented the modern style of organising work. In contrast to Fordist principles, these paradigms involve workers effectively using their skills, independently solving production problems, and simultaneously continuously developing their skills. The ultimate aim of these principles is a win-win situation that enhances not only workers' satisfaction but also productivity, and through this, strategic competitive advantages as well. Mainstream research literature confirms the positive link between participatory human resource practices and productivity (e.g. Combs et al., 2006; Jiang et al., 2012; Subramony, 2009). Still, the connection is far from unquestionable. By and large, the whole mechanism through which the high-performance principles enhance productivity is not clear cut or without contradictions (Chi and Lin, 2011; Guest et al., 2003). Moreover, according to a meta-analysis, differences in the various human resource management (HRM) practices explain the effects on performance less than the context in which they are carried out (Tzabbar et al., 2017).

The closer definition of these contexts alone has recently earned special attention in HRM research literature. The scope of the candidates to open the black box of the mechanism is wide. It extends from cross-national comparisons (Dastmalchian, 2020; Gilbert and Von Gilnow, 2015) and investigations based on company size (Arthur et al., 2019; Broszeit et al., 2019; Forth and Bryson, 2018; Wu et al., 2015) to studies where the mechanism has been brought closer to the shop floor level. Various dimensions of job quality, organisation culture and job satisfaction (Den Hartog and Vergurg, 2004; Garg, 2019; Lee et al., 2017; Wood and Ogbonnaya, 2018) – but also union density (Vazquez-Bustelo and Avella, 2019) and social capital (Jiang and Liu, 2015) – have been investigated as mediators between productivity and high-performance practices.

However, only a few studies have examined sectoral differences in the association in more detail (e.g. Appelbaum et al., 2000; Chi and Lin, 2011; DeVaro and Kurtulus, 2006). It is already known that the benefits seem to be stronger in manufacturing than in the service sector (Combs et al., 2006; Subramony, 2009). Still, more research is needed on this matter (e.g. Combs et al., 2006; Legge, 2006; Tzabbar et al., 2017). This article contributes to the debate regarding operational environments and the link between high-involvement management (HIM) and productivity by making the branch of industry the explicit focus. We are interested in learning to what degree the industry determines the benefits of HIM practices.

Empirically, the study reflects the situation in Finland, a country where explicit HIM principles are utilised commonly, although with variation in the intensity according to industry. In an environment like this, comparative analyses by industry are meaningful. The study is based on a sample of private-sector firms. A survey sent in 2012 to the employers of these firms was combined with register data on productivity a year following the survey. We used latent class – i.e. mixture regression – as the main approach to identify possible differences in the association between high-involvement management and productivity.

Theoretical background

High-performance management is usually defined as consisting of three main components: employees' opportunities to participate in the organisation, skill enhancement and incentives (Appelbaum et al., 2000). Each component may include a variety of human resource practices. High-involvement management, in turn, can be defined as a narrower concept referring specifically to employees' participation and decision-making in the organisation at large, beyond the aspects of one's core job (Lawler, 1986; Wood and De Menezes, 2011; Wood et al., 2012). It is a managerial orientation that 'encourages greater pro-activity, flexibility and collaboration' from workers (Wood and De Menezes, 2011: 1587). It emphasises working with others and the continuous development of work in the organisation.

These approaches emphasise the synergies between single human resource practices. Appelbaum et al. (2000) suggested that high-performance management practices improve productivity through two main mechanisms: by increasing the effectiveness of employees and by enabling organisational learning. The work organisation that gives employees autonomy in their work, opportunities to participate in decision-making and the option to engage in teamwork utilises its employees' skills efficiently and enables possibilities to learn from others. Training provides the skills needed for specific tasks and working within the organisation in general, while the purpose of incentives is to increase the employees' motivation and commitment (Appelbaum and Berg, 2001; Appelbaum et al., 2000). A meta-analysis showed that the three main bundles of high-performance practices – relating to skills, motivation and opportunities – were all positively related to employees' human capital and motivation, which, in turn, were related to lower voluntary turnover and better operational outcomes, and ultimately to better financial outcomes (Jiang et al., 2012). Evans and Davis (2005) further pointed out that different participatory human resource practices can relate to the effectiveness of a firm by improving the employees' relationships and the social structure in the organisation. For example, teamwork creates networks among employees, which in turn make work more flexible and effective. Teamwork, training and participation in decision-making improve the employees' shared knowledge of the organisation's goals and norms, which in turn is related to better performance (Evans and Davis, 2005). A review by Delarue et al. (2008) provides some evidence that teamwork could affect the performance of an organisation through these kinds of structural changes.

Another link between participatory practices and productivity relates to employees' well-being, either positively or negatively. The positive side emphasises the well-being effects of participation. Participation may reduce insecurity while increasing social contacts between employees in addition to perceived respect and trust, thus collectively improving the well-being of employees and making them more productive workers

(Wood et al., 2012). The negative perspective points out that increased participation may cause pressures and stress among employees; this may be due to better productivity at the expense of the employees' well-being or lowering the total positive effects on productivity (Godard, 2004; Ramsay et al., 2000; Wood et al., 2012).

It is also possible that participatory practices are unrelated to better performance. Cappelli and Neumark (2001) and Chi and Lin (2011) have suggested that the use of high-performance practices increases labour costs, thus reducing the overall benefits for the firm. Chi and Lin (2011) and Godard (2001) have also found that the very intensive use of participatory work practices may not be the most optimal. Chi and Lin's (2011) study showed that in high-technology manufacturing firms, the benefits of high-performance work systems decreased at very high levels.

Importantly, it is also possible that the effect of high-involvement or high-performance practices on productivity is different in different industries. According to contingent perspectives, the association could vary in different sectors as well as according to other structural and institutional factors (Godard, 2001, 2004; Peccei et al., 2013). However, only a few studies have analysed industry differences in the association (Chi and Lin, 2011; DeVaro and Kurtulus, 2006; Guest et al., 2003). Most prior studies on the topic have relied on the high-performance management concept, including questions related to employees' possibilities to participate in the organisation (empowerment), skill enhancement and incentives. A meta-analysis showed that all three bundles of high-performance practices (empowerment, skill-enhancement, incentives) were positively associated to firm performance (Subramony, 2009).

With respect to sectoral differences, the effect of high-performance practices on productivity seems to be stronger in manufacturing than in the service sector (Combs et al., 2006; Subramony, 2009). For sure, the different nature of the work explains the broad differences in results. Following Combs et al. (2006: 506–509), it is possible to specify at least four reasons why the association is stronger in manufacturing than in the service sector. First, the physical environment plays a more important role in manufacturing and demands that employees are sufficiently flexible to adapt to changes in the environment. Correspondingly, the service sector is less dependent on the employees' ability to respond to changes in the physical infrastructure. Second, the formal human resource systems may also play a more important role in improving the employees' often organisation-specific skills, knowledge and motivation in manufacturing. As Combs et al. (2006) have suggested, there are other potential sources for developing skills and motivation in the service sector. For example, direct interaction with customers may motivate employees to do their best. Third, it is also more difficult to manage the interaction with customers in the service sector when compared to the manufacturing sector. The fourth reason relates to human resource practices, their conceptualisation and measurement practices. As they are embedded in manufacturing, the special characteristics of the service sector have remained less visible in this context (Combs et al., 2006). In addition, Subramony (2009) notes that in manufacturing, the use of high-performance work systems may more often be related to some quality or flexibility programmes, which in combination lead to better productivity.

Differences in the association between participatory human resource practices and productivity might also relate to the complexity of tasks or the nature of production. Some studies suggest that the association between high-performance practices and productivity is stronger in more complex tasks. For example, Chi and Lin (2011) showed that high-performance work systems were related to better productivity in hi-tech manufacturing firms, but not in traditional manufacturing. Their measure of high-performance management included questions related to employees' skills (e.g. training, selective staffing), motivational incentives (e.g. performance appraisals, performance-related pay) and possibilities to participate in the organisation (autonomous teamwork, decision-making). Datta et al. (2005) showed that compared to other firms, the association between high-performance work systems – also including questions related to all three components – and productivity was stronger in industries with low capital intensity, high industry growth and high industry differentiation. Kintana et al. (2006) showed that the combination of high-performance work systems and advanced production technology was related to better performance only in technologically intensive industries. High-performance practices were measured with corresponding items as in the studies cited above. However, in their meta-analysis, Richter et al. (2011) did not receive support for the hypothesis that teamwork would be more beneficial in complex rather than simple tasks. Reflecting on service work, Batt (2002) found that the effect of high-involvement management on productivity was lower in call centres serving 'large business' customers with more complicated needs than in call centres with less complicated tasks. Her index of high-involvement management included questions related to the three components: employees' skills and training, work design (empowerment) and incentives. Batt (2002) concluded that as the work itself requires professional skills, the use of high-involvement practices did not help in competing with other firms; rather, it is simply a requirement for entering the market. Thus, the use of high-involvement practices might be so common in certain fields that it does not result in productivity differences between firms. Overall, based on previous studies, it could be expected that organisations employing a highly skilled workforce would benefit more from high-involvement management.

Finally, the differences in association between sectors or industries may be due to contextual and methodological reasons. Regarding the Finnish context, the profound restructuring and orientation to global markets in Finnish manufacturing (especially the paper industry and light electronics, e.g. Nokia) provided the boost to change cooperative hierarchies as well (Tainio and Lilja, 2003). This is in sharp contrast to the service sector, where such types of requests have for a long time simply not been made. In addition, the performance effects may only be seen after a certain threshold, i.e. when at least a certain proportion of employees are involved. These differences may be reflected in the samples in previous studies showing stronger associations in manufacturing. It is also possible to measure productivity more precisely in manufacturing than in the service sector, while studies on the service sector also typically have smaller sample sizes, thus increasing the standard errors for the estimates.

Aim of the study

The basic aim of this study is to investigate how the utilisation of HIM and its association with productivity varies by industry. Unlike in the many previous studies that have been based on samples from specific industry groups, the data in this study make it possible to compare the industries systematically. Earlier studies have paid attention particularly to the differences between manufacturing and services. Our design makes it possible to take a more detailed look at the inner diversity of these industries.

The data and design at hand enable a closer analysis of the intensity of HIM use. In general, HIM use varies by industry, while less is known about the additive effect of HIM. This study seeks to determine whether a greater intensity of HIM always contributes a greater positive effect on performance (e.g. Legge, 2006). It also aims to determine whether there are possible connections independent of the branch of industry.

The study is based on a representative survey of private-sector firms in Finland combined with register-based firm-level data on sales per employee. In the analysis, we control for the organisation size and employees' characteristics in firms in terms of age and education. First, larger organisations are more likely use certain human resource practices, such as teamwork, training and pay incentives or their specific combinations (Kauhanen, 2009; Wood et al., 2015). The size of the organisation may also affect the ways in which it benefits from high-involvement management (DeVaro and Kurtulus, 2006; Godard, 2001). Second, the education level of the employees may also affect the ways in which organisations have adopted high-involvement practices and how these practices are related to productivity. For example, a Finnish study showed that younger employees and employees with a higher socioeconomic status are more likely to participate in high-performance work systems, including teamwork, training and pay incentives (Kauhanen, 2009).

We use mixture regression to identify clusters in the sample with a differing association between high-involvement management and productivity. Regular regression analysis assumes that all cases come from the same population and have a similar association between independent variables and outcomes. With mixture regression, it is possible to relax this assumption (Ding, 2006; Grün and Leisch, 2008). This method has been previously used, for example, in research on market orientation and firm outcomes (Grewal et al., 2013) and strategic groups in the airline industry (Murthi et al., 2013), but not in studies related to high-involvement management and the performance of firms.

Mixture regression as an exploratory method fits this research problem well, as the number of industry groups is high. The statistical power would be too small to analyse the association within each industry separately. With mixture regression, it is possible to overcome these problems, as it summarises the possible differences in the association in separate clusters.

Based on previous studies cited in the previous section (e.g. Chi and Lin, 2011; Kintana et al., 2006), we expect to find at least one cluster with a positive association between high-involvement management and productivity and one cluster with no association. We also expect that, compared to the service sector, manufacturing firms will more commonly belong to the cluster with a positive association between high-involvement management and productivity.

Methods

Data

The study is based on a Finnish survey from 2012, which is part of the European Meadow concept (Measuring the Dynamics of Organisations and Work; Meadow Consortium, 2010). The survey sample represents Finnish public- and private-sector organisations. Representatives of both employers and employees were interviewed. This study is based on the employers' survey in the private sector linked with register-based firm-level data on productivity.

The sample of private-sector organisations was based on information obtained from Statistics Finland's Business Register for 2010. The sample was stratified based on industry, size and growth rate, and it excluded agriculture and forestry. Organisations were first divided into groups according to industry and number of employees. From each group, separate samples of firms with a high growth rate and other firms were chosen. Organisations were defined as high-growth firms if the number of employees grew by 15% or more on average in 2007–2010. In each organisation, an individual from the management was interviewed (e.g. chief executive, owner) in 2012 ($N = 1039$). The response rate among private-sector firms was 69.5%. The survey answers were linked with information from the Business Register and financial statement statistics. The survey data have been archived at the Finnish Social Science Data Archive (University of Tampere, 2012).

We restricted the analysis to organisations in which register data on sales per employee were available for the year following the survey: this resulted in 787 organisations meeting our criteria. There were some statistically significant differences among firms with and without register data on sales per employee (data not shown). In the final sample including the register data, some industry groups were overrepresented (mechanical and metal industries; mining, energy, and waste management; forest and chemical industries; other manufacturing; retail and logistics), while the group 'other services' was underrepresented (see the classification of industries below). Small firms were less commonly included in the final data that had information on sales per employee, whereas firms with higher sales per employee and high-growth firms were more commonly included.

Measures

Sales per employee. Sales per employee in 2013 (one year following the survey) was the dependent variable in the mixture regression. It is the only available measure of productivity for all private-sector firms in the registers. Information on sales is based on the structural business and financial statement statistics, and the number of employees is based on the Business Register. This information was obtained from Statistics Finland. As sales per employee had a highly skewed distribution, we used its natural logarithm in the regression analysis.

High-involvement management practices. The measure of high-involvement management was based on five questions in the employers' survey from 2012. In line with many previous studies based on high-involvement and high-performance approaches, we combined different practices into a single index (e.g. Datta et al., 2005; Guthrie, 2001; Kintana et al., 2006). It is assumed that the practices are mutually enforcing and more effective in combination than alone. As pointed out by Becker and Huselid (1998: 63–64), a single index is also flexible; it allows for different sets of practices to be emphasised in different firms or industries. The employers were first asked about decision-making power and the autonomy of the teams in the organisation with seven items.[1] The relative proportion of these characteristics was used as one indicator of high-involvement management. Those responding yes to any of the seven items were then asked: 'what percentage of employees at this company/organisation currently participates in such groups or teams?' The answers to this question were used as the second item in the HIM index. Employers were also asked three other questions showing the proportion of employees covered by each practice: 'Are any of the employees at this company/organisation currently involved in groups who meet regularly to think about improvements that could be made in this establishment and in its operations?' Those answering yes were asked, 'what percentage of employees at this company/organisation currently participates in such groups?' 'Approximately what percentage of your employees has a performance appraisal or evaluation interview at least once a year?' 'Approximately what percentage of employees has been given paid time-off from their work to undertake training in the past 12 months?' The reliability of these five items was 0.66 (Cronbach's alpha). The mean score of the five items was calculated so that the range of values varies between 0 and 100% among those with at least two valid values for the five items. There were very few missing values (3% at the most) in the items. The mean score was divided into quartiles to check for possible non-linear associations. The thresholds for equal size groups were, approximately 0–39% (1), 39–59% (2), 59–77% (3) and 77–100% (4).

Our measure of high-involvement management has some similarities with the measure used by Wood et al. (2012), as it includes questions relating to teamwork, employees' participation in the organisation's development, performance appraisal and training. These practices also include elements from the three main components of high-performance management used in previous studies. However, the employers' survey did not include questions on the use of pay incentives or employees' opportunities to control their own work (except for working time and remote work). One benefit of our measure is that four of the items show the share of employees participating in certain practices, not merely the presence of the practice.

Industry groups. The information on industry was based on the classification used by EU member states (Eurostat, 2008), which is compatible with the Standard Industrial Classification. We classified the two-digit information of industries into nine larger categories (see Appendix 1 for further details). These groups have similarities with the OECD (2016) classification: (1) Mechanical and metal industries; (2) Mining, energy and waste management; (3) Forest and chemical industries; (4) Electricity and electronics; (5) Other manufacturing; (6) Construction; (7) Retail and logistics; (8) Information-based services; and (9) Other services.

Size of organisation. The number of employees in the organisations was based on Business Register data for 2012, which show the average number of employees in that year. In the Business Register, the numbers indicate the employees working full-time and for the full year. Those working a half-day or for half the year represent 0.5 employees in the data. The number of employees working in the firms was divided into three groups (<50, 50–249, >249).

Employees' characteristics. The register data also included information on registered employees in the organisation. These numbers are based on Statistics Finland's employment register, in which all employees are linked to their employers. The numbers represent the situation in the organisations at the end of 2010, i.e. the situation at the time of forming the sample. We controlled for the share of employees over 50 years of age and the share of employees with tertiary education.

Empirical methods

We analysed the association between high-involvement management and sales per employee with linear mixture regression, using the Flexmix program in R (Grün and Leisch, 2008). This model allows different linear regression models for each identified sub-group. We first present the formal equation, and after that the practical implementation of the analysis. It is assumed that the marginal probability distribution of observations follows a mixture of K densities:

$$f(y|X) = \sum_{k=1}^{K} \pi_k(Z) f_k(y|X), \sum_{k=1}^{K} \pi_k = 1 \, with \, \pi_k > 0,$$

Where π_k is the probability of belonging to the sub-group k and $f_k(y|X)$ is the density for the kth sub-group giving the sub-group-specific model. In our application, X contains the categorical variables high-involvement management, size of organisation, share of employees over 50 years and share of employees with tertiary education, and covariate Z contains industry groups. Note that Z is not included in the actual regression model; instead it affects the relative proportions of the sub-groups. Here the multivariate normal distribution was applied, and therefore the density for the sub-group is

$$f_k(y|X) = (2\pi)^{-\frac{p}{2}} |\sum_k|^{-\frac{p}{2}} exp\left\{-\frac{1}{2}(y-\mu_k)' \sum_k^{-1}(y-\mu_k)\right\},$$

where μ_k are the mean estimates defined by the regression model and $\Sigma_k = \sigma_k^2 I$ is a covariance matrix within the kth sub-group. Thus, measurements are assumed independent within sub-group k, with the same variance σ_k^2. Within the kth sub-group, this corresponds to the ordinary linear regression set-up. The actual parameter estimates can then be obtained by maximising the log-likelihood over unknown parameters π_k, μ_k and σ_k^2, $k = 1,\ldots,K$ for each k separately.

In practice, after setting the basic regression model, the next step is to identify the number of clusters in the data. This is often done by testing the number of clusters from one up to some possible maximum number of clusters. As in mixture models in general, there are several criteria for choosing the best fitting model (Ding, 2006; Grün and Leisch, 2008). Information criteria include AIC, BIC and ICL values: the lower the value, the better the model. Entropy shows how well cases are classified into clusters with values ranging from 0 to 1. The higher the value, the better the class separation. It is also important that the algorithm converges properly to the maximum point, which was ensured by testing different (25) starting values. The 25 different starting values should ensure the convergence, since the actual model to be estimated is not complicated. Finally, a meaningful interpretation should also be found for each cluster.

In mixture regression, there are different ways to analyse the role of the predictors of clusters themselves. They can be possibly analysed afterwards after identifying the clusters (e.g. Silinskas et al., 2013) or they can be included in the joint model as predictors of membership proportions (e.g. Liu and Lu, 2012), as we have done in our model. The multinomial logistic regression model is then used to model these proportions either after fitting the mixture model or jointly with the regression model. We used the latter approach and analysed the effect of predictors on clusters by including them as 'concomitant' variables in the mixture model itself (Grün and Leisch, 2008). In mixture regression, the assignment of cases to clusters is based on posterior probabilities. Including significant concomitant variables in the model always changes the formation and size of clusters somewhat compared to a model without any covariates. It can also improve the classification of cases into clusters so that the class separation improves. As the last step of the analyses, we analysed the characteristics of the clusters using the chi-squared test and analyses of variance. For these analyses, the cases were classified into the most likely cluster based on the highest posterior probabilities. Using the most likely cluster as such is reasonable, as the average posterior probabilities turned out to be very high (see below).

Results

Descriptive statistics

Table 1 compares the distribution of the study variables between the nine industry groups, six of them representing different branches of manufacturing and three of them representing different types of services. The intensive use of high-involvement management was most common in the information-based services, 'other services' and the field of electricity and electronics. Correspondingly, the three industries most seldom belonging to that group were construction, retail and logistics, and forest and chemical industries. The level of education was highest (the share of employees with tertiary education) in the three industry groups where the intensive use of HIM was most common. There were also differences in the level of sales per employee among industry groups; the level was highest in mining, energy and waste management and forest and chemical industries, and lowest in information-based services and 'other services'.

Clusters in mixture regression

We performed the analysis in two steps. Firstly, we fitted a regression model for the entire data set. After that, we performed the so-called mixture regression analysis that allows analysis within the formed clusters.

In the whole sample, the two highest quartiles of high-involvement management were positively and statistically significantly associated with sales per employee in the following year when adjusted for the control variables including industry group (column one in Table 3). In addition, a high number of employees and a high level of education (the share of employees with tertiary education) were positively associated with productivity.

The results of the mixture regression suggested that there were sub-populations in the data with differences in this association. However, the outcome – sales per employee – included some extreme cases that seemed to affect the formation of clusters and

Table 1. Descriptive statistics of all variables according to the industry groups.

	n	High-involvement management (quartiles, %)				Number of employees (%)			Share of employees				Sales per employee (log)	
		Low			High	< 50	50–249	> 249	> 50 years old		With tertiary education		Mean	SD
									Mean	SD	Mean	SD		
Mechanical and metal industry	155	32.3	25.2	24.5	18.1	52.9	23.9	23.2	29.0	13.7	28.4	19.1	12.1	0.7
Mining, energy and waste management	41	22.0	17.1	36.6	24.4	41.5	39.0	19.5	32.6	16.0	37.9	28.1	13.0	1.1
Forest and chemical industries	79	26.6	26.6	29.1	17.7	38.0	27.8	34.2	28.5	11.9	29.2	13.3	12.6	0.8
Electricity and electronics	33	15.2	15.2	30.3	39.4	51.5	33.3	15.2	24.3	13.0	49.2	21.2	12.2	0.6
Other manufacturing	74	33.8	27.0	23.0	16.2	35.1	36.5	28.4	30.3	14.3	23.6	12.1	12.2	0.6
Construction	87	33.3	31.0	24.1	11.5	46.0	37.9	16.1	28.7	14.8	21.9	15.8	12.1	0.8
Retail and logistics	125	25.6	36.0	21.6	16.8	44.0	36.0	20.0	24.4	14.0	24.3	18.5	12.4	0.9
Information-based services	77	10.4	16.9	20.8	51.9	44.2	40.3	15.6	23.2	16.2	67.6	19.1	11.7	0.6
Other services	116	15.5	19.0	27.6	37.9	50.9	34.5	14.7	23.8	18.8	40.3	27.1	11.6	1.2
Total	787	25.0	25.3	25.3	24.4	45.7	33.3	21.0	27.0	15.2	33.6	23.7	12.1	0.9
p-value				< 0.001			0.041		< 0.001		< 0.001		< 0.001	

Note: Categorical variables were analysed with the chi-squared test and means with one-way ANOVA.

Table 2. Information criteria of the regression mixture models with one to four clusters.

Clusters	Log-likelihood	AIC	BIC	Entropy	ICL
1	−845.8198	1709.64	1751.457		1751.457
2	**−714.9991**	**1483.998**	**1609.451**	**0.78**	**1720.597**
3	−651.7906	1393.581	1602.669	0.65	1904.565
4	−630.7186	1387.437	1680.16	0.62	2133.903

regression slopes. Therefore, we removed 1% of the extreme values from both ends of the distribution. This left 770 cases, i.e. 17 cases were excluded.

We chose to continue the modelling with two clusters, as the model had the lowest ICL value (Table 2), although AIC improved up to four clusters and BIC improved up to three clusters. Entropy was higher in the two-cluster model (0.78), supporting the solution and showing better class separation. In addition, the average posterior probabilities for firms to be assigned to the most likely cluster were very high (0.92–0.94) and the groups formed were interpretably clear.

Table 3 and Figure 1 show the associations between high-involvement management and sales per employee in the two clusters. The majority of the firms were assigned to cluster 1 showing a positive association between HIM and productivity. In cluster 2, HIM and productivity were negatively associated. The second and the third quartiles of HIM in particular were negatively associated with productivity compared to the lowest level of HIM. Still, in both clusters, a higher number of employees and a larger share of employees with tertiary education were associated with higher productivity. According to this, the difference between the clusters seems to be embedded in the different role of HIM.

The characteristics of the clusters

As the last phase of the analysis, we cleared up the structure of the clusters. Table 4 shows how industry groups were assigned to the two clusters. All industry groups from the manufacturing sector as well as retail and logistics from the service sector were more commonly placed in cluster 1 (positive association between HIM and productivity). However, two industry groups from the service sector, namely information-based services and ‘other services’ were placed in cluster 2. Table 4 also shows that the firms in cluster 1 were larger (although the difference was not statistically significant) and had a smaller share of employees with tertiary education and a larger share of employees aged over 50 years old compared to the firms in cluster 2.

As shown in Table 1, the intensive use of high-involvement management was very common in the two service-sector fields assigned to cluster 2. The share of the highest quartile of HIM was 51.9% in the information-based services (it was 37.9% in ‘other services’). It is possible that the different categorisation of HIM could show positive associations also in these fields. Being aware of this, in an additional analysis, we categorised HIM into four groups within each industry and analysed the associations between HIM and productivity separately in each industry group in linear regression analyses (Table 5). In contrast to the main analyses, the intensive use of high-involvement

Table 3. Parameter estimates for linear regression in the whole sample and in the two clusters in the mixture analyses with sales per employee (logarithm) as the dependent variable.

	Total sample[a]		Cluster 1		Cluster 2	
	$N = 770$		$n = 586$		$n = 184$	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	11.5***	0.08	11.6***	0.08	11.3***	0.14
High-involvement management						
4 (highest quartile)	0.17*	0.05	0.24**	0.09	−0.16	0.12
3	0.18**	0.07	0.26***	0.07	−0.26*	0.13
2	−0.01	0.07	0.06	0.07	−0.35**	0.13
1 (lowest quartile; ref.)						
Number of employees						
< 50 (ref.)						
50–249	0.16**	0.05	0.12	0.06	0.21*	0.09
> 249	0.31***	0.06	0.29***	0.07	0.25*	0.12
Share of employees:						
with tertiary education	1.21***	0.13	1.60***	0.17	0.66***	0.17
> 50 years	0.06	0.16	0.14	0.20	−0.05	0.21

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[a]Industry was also controlled for in the analysis for the whole sample.

management was positively associated with productivity in information-based services also after adjusting for the control variables, but not in the field of ‘other services’. Thus, the results of these separate analyses suggest that using high-involvement management may be associated with better performance when compared to other firms in the same field. However, the smaller sample sizes in these separate analyses limit our ability to draw firm conclusions.

Discussion

The basic aim of this article was to analyse whether there are industry differences in the association between high-involvement management practices and the productivity of firms. This study was based on representative survey data from private-sector firms in Finland linked with register data on sales per employee. Mixture regression was first used to define clusters in the data with respect to this association. Two clusters were identified. In one cluster, the intensive use of high-involvement management and productivity were positively associated, while in the other cluster, the association was negative. Overall, the Bermuda Triangle between the branch of industry, productivity and high-involvement management practices turned out to be multifaceted. Two conclusions seem to be evident. Firstly, the relationship between productivity and HIM is not always additive (see Legge, 2006), i.e. the intensity in utilising HIM does not increase productivity equally in every context. Secondly, differences between manufacturing and

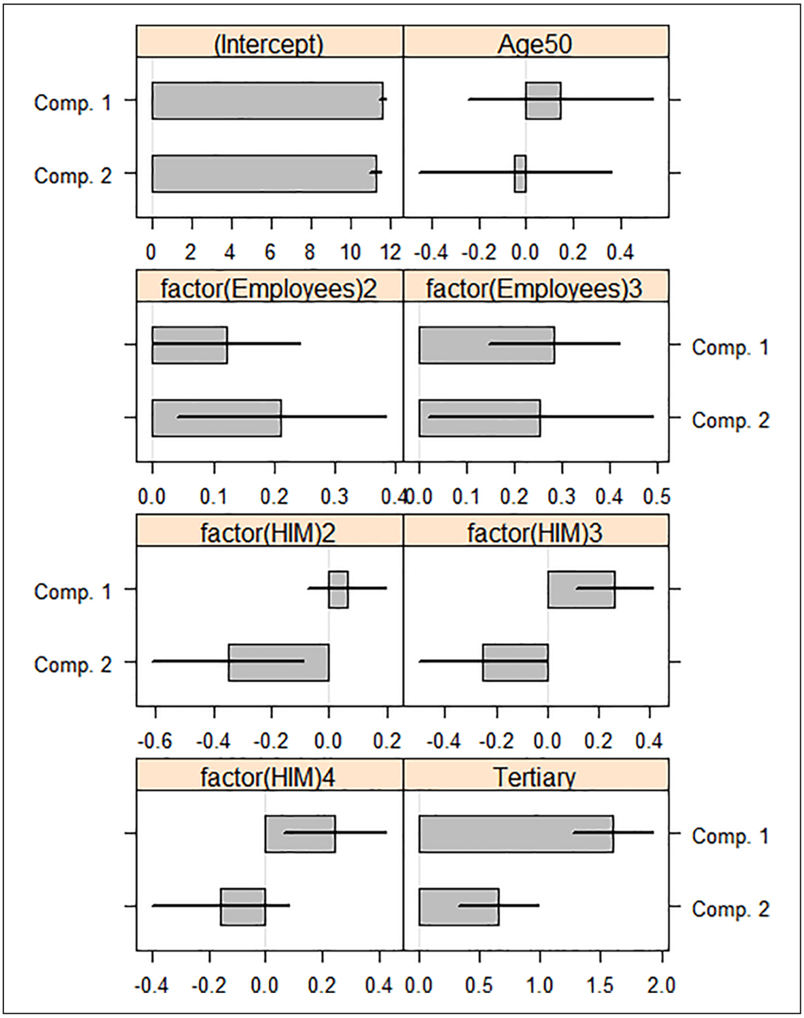

Figure 1. The coefficient estimates and their confidence intervals in the two clusters in the mixture analyses with sales per employee (logarithm) as the dependent variable.
Note: Age50 refers to the share of employees over 50 years old, and Tertiary refers to the share of employees with tertiary education. Employees 2 and 3 refer to categories 50–249 and >249, respectively, in comparison to <50. HIM 2, 3 and 4 refer to the three highest categories of high-involvement management in comparison to the lowest group (HIM 1). Comp. 1 and 2 refer to the two clusters, respectively.

services were seen in this analysis as well, although focusing on this basic division is not enough. The inner variations within the service sector are remarkable.

As expected, the variation in utilising HIM was notable. Conversely, the situation was equal when the focus was on the link between productivity and HIM. At the aggregate level, the logic seems to follow the standard reasoning: productivity increases together with HIM, and big units and a highly educated workforce enhance productivity as well.

Table 4. The distributions of industry groups and other variables among the two clusters.

	Cluster 1	Cluster 2	p-value
	Positive association, $n = 586$	Negative association, $n = 184$	
	% / mean	% / mean	
Industry groups (%)			
Mechanical and metal industry	24.1	7.1	< 0.001
Mining, energy and waste management	6.5	0.5	
Forest and chemical industries	13.0	0.0	
Electricity and electronics	4.6	3.3	
Other manufacturing	12.6	0.0	
Construction	14.5	0.5	
Retail and logistics	21.2	0.0	
Information-based services	0.7	39.1	
Other services	2.9	49.5	
Total	100	100	
Number of employees (%)			
< 50	44.7	50.5	0.079
50–249	32.4	34.2	
> 249	22.9	15.2	
Total	100	100	
Share of employees (mean):			
with tertiary education	28.3	50.2	< 0.001
> 50 years	27.9	24.2	0.004

Note: Categorical variables were analysed with the chi-squared test and means with one-way ANOVA.

Table 5. Association between high-involvement management and sales per employee (logarithm) separately for each industry group; linear regression.

	HIM in quartiles (divisions within industry groups)	Model 1			Model 2		
		B	SE	p-value	B	SE	p-value
Mechanical and metal industry ($n = 154$)	Intercept	11.80	0.10	0.000	11.61	0.13	0.000
	4 (high)	0.49	0.13	0.000	−0.01	0.13	0.958
	3	0.33	0.13	0.015	0.14	0.12	0.224
	2	0.20	0.13	0.134	0.05	0.12	0.678
	1 (low)						
Mining, energy and waste management ($n = 39$)	Intercept	12.06	0.23	0.000	11.40	0.25	0.000
	4 (high)	0.80	0.33	0.017	−0.05	0.37	0.903
	3	1.76	0.33	0.000	1.01	0.35	0.004
	2	0.73	0.32	0.021	−0.01	0.32	0.983
	1 (low)						

(Continued)

Table 5. (Continued)

	HIM in quartiles (divisions within industry groups)	Model 1			Model 2		
		B	SE	p-value	B	SE	p-value
Forest and chemical industries (n = 76)	Intercept	12.38	0.13	0.000	11.47	0.23	0.000
	4 (high)	0.27	0.19	0.157	0.00	0.17	0.982
	3	0.41	0.19	0.031	0.29	0.17	0.090
	2	−0.02	0.19	0.923	−0.11	0.17	0.526
	1 (low)						
Electricity and electronics (n = 33)	Intercept	12.01	0.19	0.000	11.91	0.56	0.000
	4 (high)	0.56	0.27	0.037	0.06	0.32	0.844
	3	−0.07	0.27	0.785	−0.26	0.25	0.309
	2	0.38	0.26	0.148	0.13	0.26	0.625
	1 (low)						
Other manufacturing (n = 74)	Intercept	12.12	0.12	0.000	12.16	0.22	0.000
	4 (high)	0.31	0.17	0.077	0.05	0.18	0.794
	3	0.18	0.17	0.297	−0.01	0.17	0.948
	2	−0.23	0.17	0.191	−0.33	0.17	0.047
	1 (low)						
Construction (n = 86)	Intercept	12.01	0.14	0.000	11.44	0.18	0.000
	4 (high)	−0.01	0.19	0.958	−0.24	0.17	0.154
	3	0.38	0.19	0.047	0.21	0.16	0.199
	2	−0.07	0.19	0.717	−0.21	0.16	0.190
	1 (low)						
Retail and logistics (n = 124)	Intercept	12.11	0.12	0.000	11.94	0.16	0.000
	4 (high)	0.66	0.17	0.000	0.36	0.16	0.029
	3	0.14	0.17	0.399	0.01	0.15	0.971
	2	0.17	0.17	0.326	0.18	0.15	0.245
	1 (low)						
Information-based services (n = 76)	Intercept	11.52	0.12	0.000	11.58	0.27	0.000
	4 (high)	0.40	0.18	0.022	0.39	0.19	0.035
	3	0.41	0.18	0.019	0.33	0.18	0.076
	2	0.20	0.18	0.251	0.20	0.18	0.265
	1 (low)						
Other services (n = 108)	Intercept	11.42	0.18	0.000	11.06	0.21	0.000
	4 (high)	0.22	0.25	0.376	−0.27	0.24	0.270
	3	0.49	0.25	0.052	0.07	0.24	0.780
	2	0.11	0.25	0.673	−0.03	0.23	0.913
	1 (low)						

Model 1: Without covariates.
Model 2: Adjusted for number of employees, share of employees with tertiary education, and >50 years old.

However, the mixture regression revealed the inner heterogeneity of the data. Following the analyses, it was possible to identify two separate clusters. Most of the cases (n = 586) followed the standard logic, but there was also a smaller group (n = 184) where the link was practically the opposite, i.e. the link between HIM and productivity was negative. However, the associations with the size of the unit and the general level of education and age of the workforce did not differ between the clusters. These uncommon results require further investigation.

The positioning of industry groups clarifies the situation. Overall, the manufacturing sector was quite uniformly assigned to the cluster with a positive association between the intensive use of high-involvement management and sales per employee. On the other hand, firms in retail and logistics were also exclusively placed in this cluster. By contrast, the situation in the two other service groups – information-based services and 'other services' – was totally different; they were nearly all assigned to the cluster with a negative association between high-involvement management and sales per employee.

The result is somewhat in line with previous meta-analyses showing that the association between high-performance or high-involvement practices and the firm's performance is stronger in industries in the manufacturing sector than in the service sector (Combs et al., 2006; Subramony, 2009). On the other hand, the results depict the inner heterogeneity of the service sector as well. In the light of these data, the use of high-involvement practices was most common in information-based services and 'other services'. Still, these industries were assigned to the cluster with a negative association between high-involvement and productivity. Compared with this, the position of the third service branch – retail and logistics – merits attention. Undoubtedly, it represents the low-skilled end of the service sector (e.g. the proportion of employees with tertiary level education), where the uses of HIM principles were clearly less common (Table 1). However, against expectations, the benefits of high-involvement practices in retail and logistics were the most significant in terms of productivity.

The paradoxical result perhaps indicates the saturation of the benefits of HIM practices. It is possible that involving employees is so common in the high-skilled end of the service sector that it does not cause any differences in productivity (cf. Batt, 2002). On the other hand, more specific measures of involvement could show positive associations with productivity in these fields.

Prior research has shown that it is more common for larger organisations to use organisational involvement (Wood et al., 2015), and they also benefit more from using teamwork (DeVaro and Kurtulus, 2006). The results of this study are in line with this finding, as large organisations were somewhat more common in cluster 1, with a positive association between high-involvement management and productivity. Based on previous studies, it could also be expected that firms with highly educated employees would benefit more from high-involvement management (Chi and Lin, 2011; Kintana et al., 2006). This assumption was not confirmed, as the share of highly educated employees was common in cluster 2, with a negative association between HIM and productivity.

One strength of this study is the representative data on Finnish private-sector firms and the high response rate. Other advantages include the facts that productivity could be measured with objective, register-based information, and that the measure of high-involvement management and productivity came from different sources. This is also the first study to apply latent class regression to this research topic. With this method, it was possible to identify clusters with differing associations in the data.

The study also has some limitations related to the study design and the available data. The association between high-involvement management and the firm's performance may somewhat depend on the ways in which the outcomes are measured. In this study, the performance of firms was measured as productivity based on register data, while in some previous studies the outcomes have also included profitability. For example, Guest et al. (2003) found that certain human resource practices correlated with profitability, but not with productivity. A previous Finnish study also found that in the manufacturing sector, job satisfaction was related to value added per employee, but not related to sales per employee (Böckerman and Ilmakunnas, 2012). Sales per employee is an imprecise measure of firm productivity compared to value added per hours worked, because sales and the number of employees are imprecise measures of output and labour input (Böckerman and Ilmakunnas, 2012). Thus, in this study, the associations between high-involvement management and the performance of firms may be underestimated. However, we have no specific reasons to expect that the bias is systematically larger in certain industry groups. On the other hand, sales per employee is the only available measure of firms' performance available for all sectors in the Finnish register data and in other countries.

Our measure of high-involvement management combined information on teamwork, employees' participation in organisational development and training, and performance appraisals. Most previous empirical studies on the topic have relied on the concept of high-performance management and considered, for example, pay incentives and employees' control over their jobs. It was not possible to take these elements into account in this study, and this limits comparisons to previous studies. The measure of HIM was based on the employers' survey representing the proportion of employees covered by each practice, which is more informative than information only on the presence of a single practice. Employees' perceptions would be needed to evaluate the implementation of these practices in firms. As only 0–2 employees were interviewed per firm, we did not utilise their answers in this study.

In this study, the link between HIM and productivity inside the service sector alone turned out to be important and worthy of further investigation. By and large, from this viewpoint Comb's note about the basic conceptualisation of HIM-related thinking is important: it is embedded in the world of manufacturing production and for this reason, it is not self-evident how sensitive these concepts and measures are in the analyses of current and different forms of service work.

Changes in the economic context might also explain the differences in the results between industries. The level of sales may have been increased or decreased considerably through a positive or negative shock in sales in the given year, while the average number of employees reacts only slowly to these changes. As a result, there might be a biased negative or positive association between high-involvement management and sales per employee, which is only caused by a sudden change in sales. The time examined in this study can be characterised as a tough recession, i.e. the fluctuations in the market were perhaps stronger than on average. Panel data would be needed to adjust for these differences in economic conditions.

Previous studies on high-involvement and high-performance management practices have also discussed and analysed the causal and possible reverse associations between management practices and productivity (e.g. Shin and Konrad, 2017). It has been already shown with these data that high-involvement practices do not predict better performance with a follow-up of one year (Böckerman et al., 2017), and thus the purpose of this study was not to detect causal associations.

In conclusion, based on the results of this study, the paradoxical relationship between the intensive utilisation of high-involvement practices and its association with productivity gives some grounds for speculation. The link was not additive: the competitive advantages seem to be located in areas where high-involvement practices are not used very widely. The result might indicate that HIM practices have their limitations in enhancing productivity; perhaps there is a saturation point after which the benefits no longer appear (e.g. in information-based services). Another interpretation is that in certain service-sector fields, the benefits of high involvement can be seen only after a certain threshold is achieved, i.e. when the practices cover a very high percentage of employees. The situation may also exemplify a variant of the 'benefits of backwardness' (e.g. Abramovitz, 1986): companies capitalise on high-involvement practices in environments where such practices are not so common (retail and logistics), where they can utilise already existing experience from other industries and use these advantages against the competition in their own field.

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Note

1. The exact survey question was: 'Are there working groups or teams in your organisation (working groups or teams can be formal or informal) (yes/no):

   a) that plan their daily or weekly work independently?
   b) that take responsibility for the quality of their work?
   c) that choose their members independently?
   d) that have direct connections with other teams in the organisation?
   e) that have direct connections outside the organisation (clients, subcontractors)?
   f) that develop their work continuously?
   g) that develop products or services?'

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Appendix 1

The classification of industries into larger categories. The two-digit numbers (based on NACE Rev.2) are compatible with the Standard Industrial Classification.

- *Mechanical and metal industries:* 24 manufacturers of basic metals; 25 manufacturers of fabricated metal products, except machinery and equipment; 28 manufacturers of machinery and equipment n.e.c.; 29 manufacturers of motor vehicles, trailers, and semi-trailers; 30 manufacturers of other transport equipment; 33 repairers and installers of machinery and equipment.
- *Mining, energy, and waste management:* B Mining and quarrying (05–09); D Electricity, gas, steam, and air conditioning supply (35); E Water supply – sewerage, waste management, and remediation activities (36–39).
- *Forest and chemical industries:* 16 manufacturers of wood and products of wood and cork, except furniture; manufacturers of articles of straw and plaiting materials; 17 manufacturers of paper and paper products; 19 manufacturers of coke and refined petroleum products; 20 manufacturers of chemicals and chemical products; 21 manufacturers of basic pharmaceutical products and pharmaceutical preparations; 22 manufacturers of rubber and plastic products.
- *Electricity and electronics:* 26 manufacturers of computer, electronic and optical products; 27 manufacturers of electrical equipment.
- *Other manufacturing:* 10 manufacturers of food products; 11 manufacturers of beverages; 12 manufacturers of tobacco products; 13 manufacturers of textiles; 14 manufacturers of wearing apparel; 15 manufacturers of leather and related products; 18 printers and reproducers of recorded media; 23 manufacturers of other non-metallic mineral products; 31 manufacturers of furniture; 32 other manufacturing businesses.

- *Construction:* F Construction (41–43).
- *Retail and logistics:* G Wholesale and retail trade, repair of motor vehicles and motorcycles (45–47); H Transportation and storage (49–53).
- *Information-based services:* J Information and communication (58–63); M Professional, scientific, and technical activities (69–75).
- *Other services:* I Accommodation and food service activities (55–56); K Financial and insurance activities (64–66); L Real estate activities (68); R Arts, entertainment, and recreation (90–93); S Other service activities (94–96); T Activities of households as employers, undifferentiated goods- and service-producing activities of households for own use (97–98); N Administrative and support service activities (77–82); O Public administration and defence, compulsory social security (84); Q Human health and social work activities (86–88); P Education (85).