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Does High Involvement Management Lead to Higher Pay?

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Abstract

Using nationally representative survey data for Finnish employees linked to register data on their wages and work histories we find wage effects of high involvement management (HIM) practices are generally positive and significant. However, employees with better wage and work histories are more likely to enter HIM jobs. The wage premium falls substantially having accounted for employees' work histories suggesting that existing studies' estimates are upwardly biased due to positive selection into HIM. Results using standard regression techniques are robust to propensity score matching and instrumental variables estimation. The premium also rises with the number of HIM practices and differs markedly across different types of HIM practice.

Key-words: wages; high involvement management; high performance work system; incentive pay; training; team working; information sharing

JEL-codes: J24; J31; J33; M12; M50; M52; M53; M54

1. Introduction

In recent decades many employers have introduced practices designed to maximise employees' sense of involvement with their work, and their commitment to the wider organization, in the expectation that this will improve their organization's performance. These "high involvement practices" include teams, problem-solving groups, information sharing, incentive pay, and supportive practices such as good training and associated recruitment methods. Collectively they constitute "high involvement management" (HIM). There is a sizeable literature exploring the links between these practices and firm performance (Bloom and Van Reenen, 2012) but less is known about the effects of HIM on employees' pay. If the practices make workers more productive we might expect this to lead to higher pay. However, HIM may be positively correlated with higher pay if high ability workers are matched to HIM workplaces. This may occur if, for example, firms require higher ability workers to maximise returns from their investment in HIM. Accordingly, if one is unable to control for worker sorting by ability, estimates of HIM's impact on employees' wages are likely to be upwardly biased.[1]

We contribute to the literature in two ways. First, we establish whether higher ability workers are more likely to use high involvement practices in their jobs. We do so by linking register data on Finnish workers' wage and work histories to a survey in which employees identify which, if any, high involvement practices they are exposed to in their jobs. Second, we calculate the wage returns to HIM practices in HIM jobs having controlled for worker sorting. We do so by conditioning on work and wage histories, and by matching HIM with non-HIM employees on the basis of their prior labour market experiences.

The remainder of the paper is structured as follows. Section Two reviews the theoretical and empirical literatures linking HIM to employees' wages. Section Three introduces our data. Section Four outlines the theoretical framework underpinning our investigation and the empirical strategy we adopt. Section Five reports our results and Section Six concludes.

2. Theoretical and empirical literatures

There are four reasons why one might expect HIM to improve labour productivity and thus employees' wages. First, learning to use high involvement practices entails building firm-specific human capital. This skill acquisition can entail on-the-job and off-the-job training resulting in higher labour productivity. This is why training is usually treated as a necessary pre-condition for the success of HIM (Appelbaum *et al.,* 2000). Second, increased job autonomy and the devolution of decision-making

[1] The term 'sorting' describes the process where job seekers and available jobs are matched in the labour market.

responsibilities to employees allows them to utilise their tacit knowledge of the labour and production processes to improve their productive capacity in a way that is not possible when they simply implement the job tasks allocated to them by managers and supervisors. The idea that HIM turns employees from 'passive' to 'active' participants in the production process is at the heart of HIM as conceived by the Harvard School (Beer *et al.,* 1984). Third, the shift to team-based production which often accompanies high involvement strategies can raise labour productivity where collaborators' labour inputs are complementary. Fourth, HIM can elicit greater employee effort via labour intensification (Ramsey *et al.,* 2000) or the motivational effects of higher job satisfaction or organizational commitment which may accompany job enrichment (Walton, 1985). Furthermore, there are usually greater incentives to increase effort under HIM because output is often linked to performance. One of the threats to HIM is the "1/N" problem whereby workers choose to free-ride on the efforts of their colleagues in the knowledge that this may only have a marginal impact on total team production. However, empirical studies have found that when team-based production is underpinned by group-based performance pay employees co-monitor one another's efforts to minimise the problem (Freeman *et al.,* 2010). Some of the above productivity-improving factors work through improving quality and innovation.

There are at least three other reasons to expect firms to raise their wages on adopting HIM which are less directly linked to increased worker productivity. The first is rent sharing. If labour productivity improvements exceed the costs of introducing and maintaining HIM, the firm will increase profits which it may share with employees – provided employees have sufficient bargaining power to extract a share of these additional rents.[2] HIM employers may also raise their wages above those offered in the market to reduce quit rates in order to ensure that they recoup the full value of their investments in HIM. In this case higher wages are paid for efficiency wage reasons. Finally, higher wages in HIM firms may reflect compensating wage differentials since workers may demand a wage premium to compensate for the disutility arising from the additional employee responsibilities that accompany high involvement practices. Since HIM can also be thought of as a mechanism by which firms share the risk of production with employees (via devolved responsibilities for decision-making and performance-based pay) this may also result in a compensating differential.

[2] Whether HIM employees have more or less bargaining power than 'like' employees that are not exposed to HIM is uncertain, *a priori*. Firms may become more reliant on incumbent workers if the firm-specific human capital required to organise HIM production is costly to acquire. Firms may thus face hold-up problems if HIM employees wish to challenge the firm's wage policy, a problem that may be particularly acute where HIM accompanies Just-in-Time production (JIT) in which inventory stocks are low and supply chains entail interdependence between firms (Wood and Bryson, 2009). On the other hand, if employees' acquisition of firm-specific HIM skills is at the expense of investment in transferable skills, the market value of those skills may limit the wages they can command outside the firm.

The seven mechanisms linking HIM to higher pay enumerated above start from the premise that employees in HIM firms will be paid higher wages than they would in 'like' firms without HIM, either because their labour productivity rises or because the employer raises the wage for other related reasons (rent sharing, efficiency wages, or compensating differentials). However, one must account for the possibility that worker sorting may induce a correlation between HIM and higher pay which is not causal. This may occur if unobservable differences between HIM and non-HIM workers are correlated with wages. High ability workers may sort into HIM if "good" workers have a lower disutility of effort (Lazear, 2000). Alternatively, if more able workers produce more output for the same level of effort, this will result in higher pay in workplaces offering the incentive contracts that often accompany HIM (Prendergast, 1999). If employers have a queue of workers to choose from when filling HIM job slots it is likely that they will choose the high ability workers with the skills and aptitude necessary to meet the challenges inherent in high involvement practices. Job candidates signal their ability to prospective employers through their work and earnings histories. These constitute a credible signal, because it is costly for a worker to acquire a "good" work history. We use the adjective "good" to refer to work histories exhibiting high and/or rising wages and stable employment with few unemployment spells. When histories are unobservable to the analyst – as is usually the case – estimated wage returns to exposure to HIM will be upwardly biased since the workers engaged in high involvement practices are drawn from the upper reaches of the ability spectrum and thus would receive higher wages even in the absence of HIM.

This characterisation of the job market, in which there are two sectors (HIM and non-HIM), worker heterogeneity characterised in terms of worker ability, and a 'double' selection process in which workers queue for jobs and employers pick workers from the queue, is akin to the model Abowd and Farber (1982) and Farber (1983) use to explain the distribution of worker talent in the union and non-union sectors of the economy. In their model workers in the lower part of the ability distribution queue for union jobs and union employers pick the best from that queue. Those in the upper part of the distribution take non-union jobs. As a consequence it is workers in the middle of the ability spectrum who are found in union jobs. In our setting, it is the high ability workers who queue for HIM jobs and, because HIM employers choose the best workers from the queue, it is those workers with the highest potential earnings who are found in HIM jobs.[3]

Empirical evidence in respect of HIM effects on wages is mixed. Some studies find a positive relationship (e.g. Appelbaum *et al.,* 2000; Hamilton *et al.,* 2003; Helper *et al.,* 1993; Forth and Millward,

[3] The queue for HIM jobs arises because the demand for HIM jobs exceeds its supply due to the fixed costs employers face in adopting HIM. These costs of switching to HIM create 'stickiness' such that HIM diffusion is patchy (Bryson *et al.,* 2007).

2004; Handel and Levine, 2006; Osterman, 2006); some find positive and negative effects (e.g. Handel and Gittleman, 2004); while others find no significant effects (e.g. Black *et al.,* 2004). Reviewing the studies using data through to the late 1990s Handel and Levine (2004) conclude that nationally representative surveys tend to find no effects of HIM on wages, whereas industry- or firm-specific studies tend to find larger positive effects. This difference may arise either because the latter are better able to control for measurement error associated with heterogeneity across firms or difficulties in capturing HIM practices. Alternatively, HIM effects may be heterogeneous across firms or industries and those firms and industries which have attracted researchers' attention may be those where HIM effects may be anticipated, thus making it difficult to extrapolate from these results to the population as a whole.

One Finnish study (Kalmi and Kauhanen, 2008) using the 2003 Quality of Working Life Survey (QWLS) which forms part of the data we use in this paper, found HIM effects on wages varied markedly across different types of HIM practice. However, their study, in common with the other studies to date, lacked longitudinal data on employees necessary to adequately account for worker selection into HIM when estimating HIM's effects on wages.[4] We overcome this problem by linking register data on Finnish workers' wage and work histories to a survey in which employees identify which, if any, high involvement practices they are exposed to in their jobs. We are thus able to calculate the wage returns to HIM practices in HIM jobs having controlled for worker sorting by conditioning on work and wage histories.

3. Data

Our data are the Quality of Work Life Survey (QWLS) 2003 of Statistics Finland (SF). The initial sample for QWLS is derived from a monthly Labour Force Survey (LFS), where a random sample of the working age population is selected for a telephone interview. The 2003 QWLS was based on LFS respondents in October and November who were 15-64-year-old wage and salary earners with a normal weekly working time of at least five hours. 5270 individuals were selected for the QWLS sample and invited to participate in a personal face-to-face interview. Out of this sample, 4104 persons or around 78 per cent participated (Lehto and Sutela, 2005) in the interviews, which took place mostly in October-December 2003, with some taking place in the beginning of January 2004. Owing to missing

[4] Kalmi and Kauhanen (2008: 442) say "A potential shortcoming of the data is that they are cross-sectional. Panel data on individuals would allow unobservable time-invariant heterogeneity and selection issues to be addressed. However, panel data on individuals are rare, partly due to confidentiality issues. We are not aware of any research on the impact of High Performance Work System that uses panel data on individuals." In fact, there are some exceptions which are usually firm case studies focussing on incentive pay and financial participation, e.g. Renaud *et al.* (2004).

information on some variables for some workers, the sample size used in this study is 3779 observations.

In addition to the HIM practices the worker is exposed to in her employment (discussed below) the QWLS contains information on the type of job the employee does and the nature of the employer, together with employees' personal characteristics and work experience. SF supplements QWLS with information from the LFS on, for example, working time and labour market status, and information on annual earnings from tax registers and on education (level and field) from the register of degrees earned. Supplementary information on the industry and location of the employer is gathered from various other registers maintained by SF.

The QWLS data is a cross-section data set that includes only limited self-reported information on past labour market experience. However, we match the QWLS data to longitudinal register data. These are the Finnish Longitudinal Employer-Employee Data (FLEED). FLEED is constructed from a number of different registers on individuals and firms that are maintained by Statistics Finland. In particular, FLEED contains information from Employment Statistics, which records each employee's employer during the last week of each year. We match QWLS and FLEED using unique personal identifiers (i.e. ID codes for persons). We have followed the employees over the period 1990-2003. In each year, we can link information on the firm and establishment to each person.

In order to adequately capture key concepts in the HIM literature we extend the scope of HIM used previously by Kalmi and Kauhanen (2008) from four to seven items. We include indicators for both group (team) and organization based performance-related pay (PRP) using information on what kind of bonuses the person receives. Twice as many employees are paid organization based bonuses compared to team based PRP (14 per cent compared to 7 per cent). A dummy for training that captures continuous development of skills at work equals one if the employee has participated in employer-provided training during the past 12 months. We define self-managed teams as teams that select their own foremen and decide on the internal division of task responsibilities. A dummy variable for information sharing equals one if employees are informed about the changes at work at the planning stage rather than shortly before the change or at its implementation. A dummy variable for appraisal equals one if the respondent agrees with the statement that the remuneration system is based on appraisal of personal work performance made every year. Finally, we capture employees' job autonomy using information on the worker's ability to influence (either 'a lot' or 'quite a lot') at least five of the following aspects of work: task content; the order in which one does tasks; the pace of work; working methods; the division of tasks between employees; the choice of working partners; the schedules of projects, deliveries and services; and working hours.

If HIM practices are complementary (Milgrom and Roberts, 1995) it may be that productivity and thus wage effects are more clearly discernible when HIM practices are combined. Following Kalmi and Kauhanen (2008) we examine the joint effects of management practices with a High Performance Work System (HPWS) dummy variable which equals one if at least two of the seven HIM practices (team based PRP, organization based PRP, employer-provided training, self-managed teams, information sharing, appraisal and job autonomy) are present. In addition, we use several other variables. First, we construct a count variable for the number of HIM practices which runs from zero to 5 where 5 identifies employees exposed to 5 or 6 practices.[5] These specifications capture any additive effects of HIM which might arise if each HIM practice is distinct and complementary.

Second, we construct a set of dummy variables which identify specific combinations of HIM which are theoretically important. The aim of these interaction terms is to capture synergies between different HIM practices. Because there are a possible 197 HIM bundles[6] we focus on bundles that are common enough to support robust analysis. The Harvard school of HIM scholars viewed HIM as a transformatory process maximising worker discretion in the organization and execution of tasks. Firms were expected to benefit from a shift away from the narrow job specifications and rigid divisions of labour associated with Taylorism towards more challenging work (Walton, 1985). Job autonomy was at the core of this conception of HIM, often allied to team-working. The centrality of direct employee involvement in decision-making meant emphasis was placed on the degree to which teams were sel-directed or self-managed. Training, appraisal and information sharing are essentially support structures that are the basis for the skill and knowledge acquisition which offers workers opportunities for direct or indirect organizational involvement (Wall and Wood, 2005; Wood and Bryson, 2009). They are needed to ensure that employees are equipped to meet the challenge of job autonomy: autonomous workers need appropriate information to make informed decisions while the blurring of job boundaries means employees need training and feedback through appraisal to ensure the continuous development of their skills. Thus, bundles which combine these elements are essential for the analysis of HIM.

In Becker and Huselid's (1998) theory HIM will not succeed unless workers' control over tasks is accompanied by "return rights", that is, rights to appropriate some of the rents associated with taking on that control. Without return rights employees may be loathe to expend the additional efforts implied

[5] None of the employees in the data are exposed to all seven HIM practices.
[6] This is the number of all possible combinations of 1, 2, 3, 4, 5, 6, or 7 HIM practices.

by HIM practices. To foster the group effort implied by team working those incentives should be linked to organizational or team efforts, as opposed to individual effort. Thus, bundles incorporating group or organizational PRP deserve particular attention.

The work history variables include the number of past job switches (defined as a change of establishment), past employment and unemployment months, a dummy variable for those who have ever worked in the manufacturing sector, an indicator for having worked in a large firm (firm with more than 300 employees), number of layoff episodes, past average earnings (1990-2001) and past earnings growth (average over periods 1999-2000 and 2000-2001). All of the above work history variables are linked to QWLS from the longitudinal register data. In addition, we use information in QWLS to form an indicator for persons who have been more than 10 years with the current employer and for those who have had more than three different professions over their working life. In sensitivity analyses, we also add controls for past socio-economic status (dummies for lower white-collar and upper white-collar employees in 2000, with blue-collars as the reference group) and control for two-digit occupational group.

The inclusion of a wage growth variable in models estimating the probability of being exposed to HIM practices is prompted by the possibility that workers may be able to signal their quality to employers not only through their past mean earnings, but also their recent wage profile. Indeed, employers may give particular weight to evidence of recent earnings growth. If job applicants are successful in signalling their quality to employers in this way one might anticipate a positive effect of recent wage growth on the propensity to enter HIM workplaces over and above the effect of average wages over one's prior work history. This is, in a sense, the opposite of the Ashenfelter dip apparent in the welfare evaluation literature whereby those entering welfare programmes have particularly poor earnings trajectories prior to programme entry relative to seemingly 'like' individuals who do not enter the programme (Ashenfelter, 1978). In the welfare evaluation literature failure to account for the 'dip' may upwardly bias estimates of programme effects on subsequent earnings since some of the wage recovery associated with regression to the mean might otherwise be attributed to the programme. In the case of HIM, failure to account for the upward trajectory of wages for those entering HIM jobs may downwardly bias estimates of HIM effects on subsequent earnings since reversion to mean wages subsequently implies a reduction in wage growth which would erroneously be attributed to HIM.

Turning to our dependent variable, earnings in 2003, we have two sources of data. The first is the log of annual earnings from the register data. Earnings include the base wage, overtime pay, bonuses, and wage supplements. The bonuses and wage supplements are determined at the establishment level, whereas collective (industry-level) bargaining sets a floor for the base pay. The second measure is the log of self-reported wages from the QWLS based on midpoints of monthly wage bands. We prefer the register measure since it is continuous and is less prone to reporting error. However, we test the sensitivity of our results to the self-reported wage measure and to the use of hourly earnings.

We control for the standard determinants of earnings, i.e. gender, age, marital status, educational level, union membership status, usual weekly hours worked, plant size, multi-plant firms, foreign ownership, public sector employer and industry (with fourteen dummy variables). To avoid omitted variables bias, all specifications include among the control variables an indicator for workers who are paid a piece rate.[7] All of these variables are based on the data on individuals in QWLS. Descriptive statistics for dependent and independent variables are presented in Appendix Table A1 with those for the HIM variables presented in Appendix Table A2.

4. Model and estimation

To formalize the arguments, consider the simple model used in Lemieux *et al.* (2009). Their emphasis is on the sorting of employees to fixed wage and PRP jobs, but the same arguments can be used also for other aspects of HIM. In their model the chief features that distinguish wage formation under PRP contracts from those under fixed wages are the fixed monitoring costs associated with PRP; higher returns to expected ability under PRP than fixed wages (explaining the sorting of high-ability workers into PRP contracts); and an error component linked to unobserved ability under PRP which is absent under fixed wages.

Production of individual i in job (firm) j is given by

$$y_{ij} = \gamma_{0j} + \gamma_{1j}e_{ij} \tag{1}$$

where γ_{0j} is output that is independent of effort, e_{ij} is effort and γ_{1j} is marginal product of effort. Assume that workers are paid the value of production, so $w_{ij} = y_{ij}$. Utility is given by $U_{ij} = w_{ij} - exp(e_{ij} - \alpha_i)$, where α_i is ability (or skills), which is normally distributed as $\alpha_i \sim N(\tilde{\alpha}_i, \sigma_i^2)$, conditionally on observed worker characteristics. Ability is revealed after the worker has taken up a job. To simplify the model, it can be assumed that the variance of ability is related to its mean by $\sigma_i^2 = \delta\tilde{\alpha}_i$, where $0<\delta<1$.

[7] The combination of team based PRP and organization based PRP with piece rates is very uncommon (less than 1 per cent of all workers).

Assume first that the distinction between HIM and non-HIM firms is in pay determination. As shown in Lemieux *et al.* (2009), in a fixed wage firm (which we interpret as a non-HIM firm) there is a contract with fixed wage and effort. The optimal, expected utility maximizing effort leads to wage (and output)

$$w_{ij}^{N} = \phi_j + \gamma_{1j}(\tilde{\alpha} - \sigma_i^2) = \phi_j + \gamma_{1j}(1 - \delta)\tilde{\alpha}_i \tag{2}$$

where $\phi_j = \gamma_{0j} + \gamma_{1j}log(\gamma_{1j})$. In a firm with PRP the wage varies with effort. The worker chooses his effort after observing the realization of ability α_i. To set up the system (e.g. monitoring), there are fixed costs that are deducted from the pay. Given optimal effort, the expected wage is

$$\tilde{w}_{ij}^{HIM} = \phi_j - \mu_j + \gamma_{1j}\tilde{\alpha}_i \tag{3}$$

where μ_j is the monitoring cost. The variance term cancels out in this case.

The worker will choose between the fixed wage and performance pay jobs, based on a comparison of the utilities. The utility comparison, in turn, involves comparison of expected wages. This implies that a worker will choose a job in a firm with HIM, if $\tilde{w}_{ij}^{HIM} > w_{ij}^{N}$, or $\gamma_{1j}\tilde{\alpha}_i - \mu_j > \gamma_{1j}(1-\delta)\tilde{\alpha}_i$. This can be stated as $\tilde{\alpha}_i > \mu_j/\gamma_{1j}\delta$. One important implication of the model is that higher ability workers will self-select into HIM firms, since they get a higher expected return to skills (the coefficient of $\tilde{\alpha}_j$ is higher in HIM firms than in non-HIM firms) and for them the inequality is more likely to hold. Higher marginal productivity of effort, higher variance of ability, and lower monitoring costs increase the likelihood of choosing a HIM job. The model also has the implication that the returns to observable human capital will be larger in HIM than non-HIM jobs, since the coefficient of $\tilde{\alpha}_i$ is higher.[8]

There are other aspects of HIM systems besides PRP. These can be illustrated with the same model. Working in an HIM firm may involve team work. This could be introduced into the model by making the assumption of higher productivity of effort γ_{1j} in team work than in non-team work. This would give an advantage to HIM jobs even in fixed-wage firms. However, it is possible that productivity gains

[8] This can be tested by including interactions of HIM with human capital (education) in the estimated model or, as we also do later, by doing the analysis separately for different education levels. The model has also four other predictions that are more difficult to test with our data. First, the wage intercept should be lower in PRP (HIM) jobs than non-PRP (non-HIM) jobs because the firm factors in the costs of monitoring in the PRP case. This can be tested by looking at intercept in models where HIM is interacted with human capital, although the inclusion of other variables makes the prediction less clear. Second, the returns to unobservable ability will be larger in PRP than non-PRP jobs. Third, the returns to observable job characteristics will be smaller in PRP than non-PRP jobs. This would require interacting many of our control variables with HIM. Fourth, the variance of the firm-specific component in wages is smaller in PRP than non-PRP jobs. Since we do not have a large number of observations per firm, we cannot test this.

are only possible if the team work is accompanied by appropriate training. Therefore only a bundle of team work and training would give higher wages. One might also anticipate that the combination of team work with group based PRP will lower monitoring costs as the team members will monitor each other's effort. This has the straightforward implication that if a firm uses the bundle of PRP and team work, the threshold for a worker to choose a job in such a firm will be lower, and the expected wage is higher than in a firm that uses just performance-based pay. These examples illustrate the value of using several HIM practices.

In the empirical analysis we run regressions of the following form:

$$lnW_i = X_i ß + \delta HIM_i + \varepsilon_i \qquad (4)$$

where X is a vector of observable characteristics of individuals and their employer with betas being coefficients to be estimated. HIM captures the indicator of HIM which, as noted above, varies across specifications. The parameter δ represents the average proportional difference in wages between HIM and non-HIM workers adjusted for worker and workplace characteristics. ε_{it} is a random component. In the theory presented above, the wage is related to mean $\tilde{\alpha}_i$ of the random ability, conditionally on observed worker characteristics. Further, there is selection of high-ability types to HIM firms. However, we do not observe $\tilde{\alpha}_i$, so it is part of the error term. We therefore test the sensitivity of results to the inclusion of a more extensive set of observable characteristics, the workers' work histories, in the X vector. The baseline specifications are estimated with OLS, but we also use propensity score matching and an instrumental variables (IV) approach in robustness checks.

5. Results

5.1. Baseline estimates

Before presenting estimates of HIM effects on employees' wages we explore the correlates of employees' exposure to HIM. Table 1a presents the marginal effects from probit equations for eight measures of HIM and Table 1b presents the marginal effects from a Poisson regression for the number of HIM practices and marginal effects from a probit model for more than one HIM practice. Column 1 of Table 1a estimates the probability of having any one of the seven HIM practices ('Any HIM') versus having none for the whole sample. Columns 2-8 use the same model specification but estimate the probability of exposure to each of the seven separate HIM practices, namely team based PRP, organization based PRP, training, self-managed teams, information sharing, appraisal and autonomy. The models in Columns 2-8 are run on subsets of the full sample to ensure those scoring zero on the dependent variable are not, in fact, exposed to another HIM practice. For example, the subsample for Column 2 is either subject to team based PRP or has no HIM practices at all. Robust standard errors are presented in parentheses. Column 1 of Table 1b estimates the count model for the number of HIM practices while Column 2 estimates the probability of having two or more HIM practices (what we term a "High Performance Work System" or HPWS) compared to the probability of having no HIM practices. The independent variables are jointly significant in all models, with pseudo R-squared between 0.08 and 0.30 in Table 1a (0.05 and 0.13 in Table 1b). The probit models in Table 1a seem to work best for organization and team based PRP, whereas the pseudo R-squared is lowest for autonomy and information sharing.

[INSERT TABLES 1a-1b ABOUT HERE]

Our primary interest is the role of the work history variables. They are jointly statistically significant in all ten models of Tables 1a-1b, as revealed by the F-test statistics. However, the direction of effects for particular work history variables and their statistical significance varies by type of HIM practice. As anticipated, past average earnings are positively associated with exposure to HIM practices. They are statistically significant for five of the eight HIM specifications in Table 1a, the exceptions being team based PRP, organization based PRP and autonomy. A one standard deviation increase in past average log earnings (i.e., an increase of 1.56) over the period 1990-2001 is associated with a 2.1 (=0.0136*1.56*100) percentage point increase in the probability of working in a HIM job in 2003 (Table 1a, Column 1). The relationship between rising past earnings and HIM exposure is more moderate: a one standard deviation increase in the rate of earnings increase averaged over the periods 1999-2000 and 2000-2001 is associated with a 0.5 (=0.010*0.50*100) percentage point increase in the probability of working in a HIM job in 2003. However, the effect is not significant. Earnings growth only has a statistically significant marginal effect for appraisal in Table 1a, but it is significant for both the total number of HIM practices and the HPWS measure in Table 1b. The finding is consistent with a 'reverse Ashenfelter dip' as discussed earlier.

The work history variables include a number of other markers of worker quality, notably the number of months spent in employment in one's work history, the number of months spent unemployed, and the number of layoffs experienced. The number of months spent unemployed is negatively associated with being in an HIM job in 2003. The effect is statistically significant in the case of organization based PRP, training and appraisal in Table 1a. It is also significant for the both measures in Table 1b. One possible interpretation of this correlation is that those employees who have experienced unemployment in the past are more risk averse because of their negative life experience. Dohmen and Falk (2010) have shown that risk takers sort into incentive schemes. Thus, they are more likely to be found in an HIM job. The number of layoff episodes is significantly negatively correlated with information sharing and autonomy, and for the number of HIM practices in Column 1 of Table 1b. We anticipated that being a stable employee, as indicated by number of months in employment, the number of employer switches and the number of switches in profession over one's working life, would also influence HIM exposure. However, this tended not to be the case. What did matter was tenure with the current employer. There is a significant positive association between working ten or more years in the current job and current exposure to HIM practices: the effect is statistically significant for receipt of organization based PRP, training, self-managed teams, information sharing, autonomy, and for the HPWS measure.

The literature suggests that HIM practices are most common in larger firms and were pioneered in manufacturing (Wood and Bryson, 2009), so we anticipated that experience in larger firms and in manufacturing might proxy past exposure to HIM and, thus, increase the probability that the employee has an HIM job in 2003. Large firm experience is indeed positively and significantly associated with receiving team based PRP, organization based PRP, training, appraisal, and the number of HIM practices and being in a HPWS job.[9] However, experience of employment in manufacturing is not statistically significant in any of the specifications.

These results confirm that employees' work histories are a significant predictor of subsequent entry to an HIM job. Although the effects do not all point in one direction, there are clear indications that it is more able workers – as indicated by past earnings, earnings growth, and 'good' work histories – who are more likely to be found in HIM jobs.[10] A further indication that this is the case is the strong positive association between being highly qualified (highly educated) and using HIM practices in one's job. Indeed, this is the most robust result in Tables 1a-1b and is apparent for all the HIM measures.

Table 2 presents the first set of estimates of the effects of HIM on earnings. There are eight panels, one for 'any HIM' and one for each of the seven separate HIM measures. The first column presents results

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[9] Current employment in a larger workplace and in a multi-establishment firm rather than a single-establishment firm were also positively associated with being exposed to HIM.

[10] One concern might be that in conditioning on the prior earnings of those who have been exposed to HIM for some time we underestimate the impact of HIM on earnings. To address this concern we reran the results we present but truncate the earnings histories at 1999, that is, some four years before our survey indicators of exposure to HIM. Results are insensitive to this alteration. This, coupled with the fact that HIM wage returns are not particularly heterogenous across tenure sub-groups (see later) lends credence to our main findings.

which condition on demographic and employer characteristics only. The second column also incorporates the work history variables.

[INSERT TABLE 2 ABOUT HERE]

Panel A presents the effect of being exposed to any of the seven HIM practices on employees' wages. If one conditions on demographic and current employer characteristics only, being in an HIM job is associated with a wage premium of around 19 per cent compared to a 'like' employee with similar characteristics who is not in an HIM job. Column two reveals that conditioning on work history variables leads to a reduction in the premium of about one-fifth, a reduction that is statistically significant at a 99 per cent confidence interval.[11]

A similar pattern of results is apparent in Panels B through H, although the wage returns are somewhat higher for organization based PRP and training than for the other HIM aspects. In general the difference in the estimated wage returns to these practices with and without controls for wage and work histories is statistically significant at a 99 per cent confidence interval except that in Panel B the significance level is 98 per cent.

Table 3 focuses on the number of HIM practices to which the employee is exposed. This is important because, as Appendix Table A2 shows, whereas 83 per cent of employees were exposed to at least one of the seven HIM practices, over half of all employees (56 per cent) were exposed to two or more HIM practices and were thus working in what we term a High Performance Work System. The results are striking: the wage returns to HIM rise steeply with the number of HIM practices to which the employee is exposed. In all cases the premium falls markedly with the introduction of the work history controls, but the difference in wage returns with and without work history controls rises monotonically with exposure to more HIM practices. Having conditioned on work histories, the wage premium for a single HIM practice is around 11 per cent; 12 per cent for two practices; 20 for three practices; and 28 per cent for four practices. The wage premium for five or more practices is even larger (Panel E), but the number of employees exposed to five or more practices is very small (Table A2). The wage premium for employees working in HPWS (Panel F) falls by around one-fifth having conditioned on work histories, but it remains sizeable and significant at around 17 per cent.

[11] To test the implication of the model that the returns to human capital are higher in HIM jobs, we also interacted the dummy for the highest education group with alternative indicators for HIM in an OLS estimation. The interaction was not statistically significant for any of the HIM variables.

[INSERT TABLE 3 ABOUT HERE]

Table 4 presents the wage premia associated with those theoretically important HIM bundles which are common enough in the sample to permit robust estimation. Fourteen of these 20 bundles include self-managed teams and/or job autonomy; five include team based PRP and five organization based PRP. In each case the association between the HIM bundle and wages is evaluated relative to comparators from among the sub-sample who were exposed to no HIM practices. The heterogeneity of the effects is striking. HIM premia range from 15 to 36 per cent before conditioning on work histories (Column 1) and no effect to 31 per cent having included work history controls (Column 2). As argued earlier in Section Three, self-managed teams and job autonomy are the central aspects of HIM. The bundles that are constructed around self-managed teams tend to produce somewhat higher wage premia than the ones based on job autonomy after controlling for work histories (cf. Panels A-C v. Panels D-F). Contrary to predictions of the Lemieux *et al.* (2009) model discussed above the combination of team based PRP and team-working is not associated with a particularly large wage premium (Panel K). Interestingly, this is also the only bundle in Table 4 that does not generate a statistically significant positive wage premium after controlling for work histories.

Combinations incorporating training produce larger wage premia, other things being equal. Thus, continuous development of skills at work increases considerably the wage returns to HIM. This pattern is consistent with the result in Table 2 (Panel D) that showed that employer-provided training alone is also able to produce particularly high wage returns. Also, wage returns to the bundles that include organization based PRP seem to be higher than the ones based on team based PRP (cf. Panels K-L v. Panels M-N and Panels O-P v. Panels R-S). Perhaps most notable of all is the finding that the wage premia in Table 4 are always lower with the controls for work history added. This confirms our main result regarding the role played by work history in selection of workers into HIM jobs.

[INSERT TABLE 4 ABOUT HERE]

5.2. Sensitivity analyses

We subject the results presented above to a number of sensitivity analyses including alterations to the conditioning *X*'s (changes to the work history,[12] adding two-digit occupational group controls and spousal education), the dependent variable (the residuals from a first stage wage equation, self-reported

[12] For a recent paper in the same spirit but with a different substantive focus (namely active labour market programme evaluation) see Lechner and Wunsch (2011).

earnings and hourly earnings), estimating the effects in different earnings quantiles, and employee sub-group analysis (full-time employees; high and low educated; long and short tenured; those to whom HIM has been introduced recently; those in small and large plants; private sector employees); and estimation methods. We use the HPWS measure in robustness checks because it is defined for the broad set of observations and its mean value is close to 0.5 (Appendix Table A2). We are therefore examining the robustness of the results in Panel F of Table 3. The estimates are reported in Appendix Table A3. The overriding impression is just how robust the results appear to be to these sensitivity checks. We comment briefly only the most interesting patterns.

The estimates in Panel A reveal that average past earnings is a particularly important contributor to the overall explanatory power of work history. The inclusion of additional controls in Panels B-D lowers the premium a little. For instance, Panel D incorporates spouse's education to capture otherwise unobserved worker ability via spousal assortative mating, the assumption being that more able workers are likely to have spouses with higher education. Consistent with this contention, its inclusion lowers the HIM wage premium, but not by much. There is some variance in the size of the wage premium depending on the precise wage measure used, but the differences are not large (Panels E-G).

There is little evidence of substantial heterogeneity in the returns to HIM across types of worker. For instance, the returns do not differ greatly across quantiles of the earnings distribution (Panels H to K), among those in employment continuously in 2003 (Panel L), by education (Panels M and N), or in the private sector (Panel T). It does seem, however, that the wage returns to HIM are bigger is small plants relative to large plants (Panels R and S).

Although we condition on extensive work and earnings histories we can not discount the possibility that the HIM wage premium may be driven by the unobservable wage enhancing attributes of those exposed to HIM practices. If this occurs because high-ability workers sort into jobs with HIM practices, one might expect the HIM premium to be larger among short-tenured workers, the assumption being that those with long-tenure were in post prior to the introduction of HIM. (The innovative work practices have gained popularity in Finland rapidly during the past 10 years.) The HIM wage premium is indeed larger among short-tenured employees (Panel P), but it remains large and significant even among those in post for at least 10 years (Panels O). The wage premium is also a little larger where HIM practices were introduced recently (Panel Q), which lends further support to the idea that the premium partly reflects worker sorting by ability, although it is also consistent with a literature which indicates that workplace innovations tend to have their largest effects early on and deplete over time (Bryson and Freeman, 2010: 209-210).

The seven HIM measures that we use are binary because of the limitations of the QWLS data. However, we can construct ordinal variables for two HIM measures, team working and appraisals. In the case of team working we add up the "scores" from the separate questions (the group selects its own leader, the group decides about its internal division of responsibilities, the group can self set the targets for its work, and tasks can be changed in the group, as required) to produce a scale from 16 to 0 where 16 is a fully autonomous team scoring the maximum 4 points on each item. The absolute level of wage estimates of these specifications are not comparable to the earlier ones. Thus, these results are not reported in Table A3. Importantly, the role played by work history was again confirmed. A similar measure can also be constructed for appraisal. The qualitative role of work history in reducing the estimates remained intact (not reported). To further assess the robustness of the results regarding the team work variable, we have estimated specifications for team work, irrespective of whether the team was self-managed. The exclusion of selecting own leader resulted in a reduction in the wage premium in most bundles, but the addition of work history variables pulled down the premium by roughly the same amount as in the case where selecting own leader is included (not reported).

Next we present results from alternative estimators (Table A4). An alternative to OLS to control for bias on observables is the semi-parametric statistical matching approach, propensity score matching (PSM) (Rosenbaum and Rubin, 1983; Heckman *et al.,* 1998), which compares wage outcomes for employees exposed to HIM with 'matched' non-HIM employees. We estimate the propensity to be exposed to the HPWS measure with a probit model incorporating the work history variables. This is the same as the model in Column 2 of Table 1b. PSM enables us to recover the average treatment effect for the treated (ATT) as well as the average treatment effect for the untreated (ATU). The weighted sum of the two is the average treatment effect (ATE), namely the impact that HIM would have on a randomly chosen employee. To obtain the effect of treatment-on-the-treated we use matching which operates by constructing counterfactuals from the non-participants. In Panel A of Table A4 we use a kernel estimator which identifies the counterfactual outcome as a weighted average of the outcomes for non-treated cases within the caliper where the weight given to non-treated cases is in proportion to the closeness of the comparator case to the treated case. In estimating the effects of treatment-on-the-untreated we adopt the identical approach when searching for comparators for the untreated among the treated. To be effective, matching should balance observable characteristics across the treatment and comparison groups in the region of common support. The quality of the match seems good; after matching there are no statistically significant differences between the groups (not reported). The ATT estimates in Panel A are a little higher than the ones obtained by using OLS (cf. Panel F of Table 3). However, again there is a significant reduction in the estimate after adding the work history variables to propensity score estimator. OLS conditional on common support produces very similar results as OLS (not reported) because we lose only a very small proportion (~1%) of all observations by imposing the common support condition in matching. It turns out that ATT and ATU are very similar (not reported). There is also striking similarity in the results for the other specifications used in Tables 2-4 with PSM compared to OLS (not reported). Bias-corrected matching using the method of Abadie *et al.* (2001, 2011) returns lower wage estimates than PSM without work history variables, but the effects are very similar when conditioning on work histories and our salient finding regarding the role of work history remains intact (Panel B).[13]

Finally, we present some IV estimates in Panels C and D of Table A4 for those who have less than 10 years' tenure. As noted above, these are the workers who may sort into HIM jobs and possess high ability that is unobservable to the analyst. Neither OLS nor PSM estimates can tackle worker sorting on unobservables. We use the lagged incidence of HIM in the same 2-digit industry cell in 1997 to instrument for exposure to HIM (the HPWS measure, more than 1 HIM aspects) in 2003. (1997 is the latest wave of QWLS before 2003.) The idea is that HIM is a technology which diffuses across time and space according to certain structural features of firms and their peers, e.g. via networks, or as an experience good, or through herding mentality. This affects the propensity of firms to deploy HIM. Having conditioned on the full set of current industry effects, there is no reason to suspect any effect of lagged industry HIM on current wages. The results in Panel C are based on four instruments (previous shares of PRP, team work, information sharing and autonomy).[14] The estimates in Panel D use the share of more than 1 HIM aspect in 1997 by 2-digit industry as an instrument for more than 1 HIM aspect in 2003. The first stage of these IV models works well by applying the criteria of Staiger and Watson (1997), as reported in the notes to Table A4. The Sargan test of overidentifying restrictions is clearly passed in the specification of Panel C. The specification in Panel D is based on the use of only one instrument so it is not possible to conduct the Sargan test for the validity of the instrument. The IV point estimates are much larger in Panels C and D compared to their OLS equivalent in Panel P of Table A3, but the standard errors for the IV estimates are also (much) larger. In Panel D this renders the premium statistically non-significant when detailed work history variables are incorporated. A

[13] The method removes some of the bias that is associated with the simple matching estimator in finite samples when the matching is not exact (Abadie *et al.,* 2001: 9-10).

[14] The question on appraisal was introduced to QWLS in 2003 and lagged training is dropped because its inclusion results in a violation of the Sargan test of overidentifying restrictions.

possible reason for the higher IV point estimates compared to the earlier OLS estimates is the measurement error in individual level reporting of HIM exposure which is reduced when using industry averages. Under this scenario the OLS estimates would be downward biased. But there are two further possible reasons for the OLS to be downwardly biased. First, those exposed to HIM may have unobservable characteristics which are significantly negatively correlated with wages, though it is unclear why this might be the case. Second, if the returns to HIM are heterogeneous and the IV approach is recovering a LATE (Local Average Treatment Effect) the causal impact for 'compliers' may be greater than for other treated individuals. (In our case this means those workers, whose entry to a HIM firm has been affected by their working in an industry which has a high incidence of HIM practices.) In any event, in all the estimates presented in Table A4 the HIM premium falls with the introduction of work history variables.

6. Conclusions

There are a number of studies linking HIM to higher wages but, to our knowledge, the evidence presented here is the first to account for detailed employee wage and work histories. This proves to be important since the results indicate that employees' work histories are a significant predictor of subsequent entry to an HIM job. Although the effects do not all point in one direction, there are clear indications that it is more able workers – as indicated by past earnings and earnings growth – who are more likely to be found in HIM jobs. A further indication that this is the case is the strong positive association between high educational qualifications and using HIM practices in one's job.

Using OLS we identify a wage premium of around 20 per cent before conditioning on work and wage histories. This falls by around one-fifth when we add in these controls which have been absent in other studies. This suggests an upward bias in existing studies in the wage returns to HIM due to positive selection into HIM associated with what has hitherto been unobserved worker quality. Both the OLS and PSM estimates presented only account for selection on observables. Even with rich work and wage histories it is very unlikely that these estimates are purged of all bias associated with worker ability. However, when we run IV estimates we continue to find a large HIM wage premium which, if anything, is larger than the premium recovered by OLS, but also falls substantially when conditioning on work and wage histories.

Although there is heterogeneity in the wage returns to HIM across types of employee, the differences are not particularly striking. Instead, what is notable is the difference in the size of the HIM premium across different types of HIM practice. The premium is largest for training and smallest for autonomy but what is even more striking is the variance in the wage premium attached to different HIM bundles and the increasing returns to the number of HIM practices used. Self-managed teams and job autonomy constitute a basis for theoretically relevant combinations of HIM, according to Harvard school of HIM scholars. The bundles that are constructed around self-managed teams tend to produce somewhat higher wage premia than the ones based on job autonomy after controlling for rich work history data. The results on bundles also show that continuous development of skills at work (measured by employer-provided training) increase the wage returns to HIM.

If employees are paid their marginal product then the substantial wage premium we identify may reflect increased productivity on the part of those workers when they are exposed to HIM practices. However, the idea that HIM practices engender higher labour productivity wherever they are deployed raises the question as to why diffusion of HIM across firms has not been as rapid or as widespread as some early commentators imagined. One possible explanation is that HIM adoption is optimal such that those employees exposed to HIM are the ones able to use those practices to increase labour productivity while, in the case of non-HIM employees, firms have chosen to avoid HIM because the productivity benefits are outweighed by the costs. The comparison of the ATT and ATU wage returns to HIM are illuminating in this regard since the ATT and ATU estimated with PSM are very similar implying an incentive on the part of non-HIM employees to take HIM jobs. The fact that they are not in HIM jobs may be because they are effectively 'rationed' by employers (in much the same way as union jobs are rationed under Abowd and Farber's (1982) model). Employers may choose not to deploy HIM despite these predicted wage gains to workers for one of two reasons. The first possibility is that the costs of HIM adoption are heterogeneous and, in the case of non-adopters, these costs outweigh the labour productivity gains which our wage premium estimates imply. The second possibility is that the estimated wage returns to HIM for those not currently exposed to HIM may arise for reasons other than labour productivity improvements and, as such, do not proxy the potential returns firms may gain through their adoption. To make further progress on this issue one requires firm-level data, ideally linked to employee data, to explore heterogeneity across firms as well as employees in the costs and benefits of HIM adoption.

Future research on this issue would also benefit from firm-level data to overcome the problem of unobservable heterogeneity between HIM and non-HIM firms which may simultaneously affect wage setting and the propensity for HIM adoption. Our employee-level data may overstate the effects of HIM on wages if, for instance, both HIM adoption and higher wages are a function of firm level unobservable traits such as good management.

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Table 1a. Work history as determinant of HIM practices.

	(1) Any HIM	(2) Any team based PRP	(3) Any organization based PRP	(4) Any training	(5) Any self-managed teams	(6) Any information sharing	(7) Any appraisal	(8) Any autonomy
Controls								
Individual								
Female	-0.0259*	-0.0534	-0.109***	-0.0280	-0.0647	-0.0677***	-0.0708**	-0.0956***
	(0.0138)	(0.0356)	(0.0387)	(0.0190)	(0.0398)	(0.0255)	(0.0285)	(0.0274)
Age <=34	0.00307	0.0271	0.0378	0.0190	-0.00284	0.00929	0.0277	0.0251
	(0.0203)	(0.0542)	(0.0603)	(0.0269)	(0.0552)	(0.0369)	(0.0412)	(0.0392)
Age 45-54	-0.0134	-0.0108	-0.0310	-0.0240	-0.0341	-0.00455	-0.0764**	-0.0187
	(0.0171)	(0.0442)	(0.0493)	(0.0233)	(0.0441)	(0.0314)	(0.0367)	(0.0333)
Age 55-64	-0.0392*	-0.00703	-0.00496	-0.0753**	-0.0526	-0.0299	-0.100**	-0.0609
	(0.0224)	(0.0537)	(0.0584)	(0.0319)	(0.0517)	(0.0380)	(0.0452)	(0.0412)
Married	0.00885	0.0393	-0.0104	0.00960	0.00841	0.0218	0.0313	0.0387
	(0.0137)	(0.0353)	(0.0387)	(0.0190)	(0.0379)	(0.0258)	(0.0294)	(0.0280)
Secondary education	0.0209	0.0429	0.0541	0.0482**	0.0197	0.0284	0.00995	0.0113
	(0.0160)	(0.0435)	(0.0464)	(0.0226)	(0.0473)	(0.0308)	(0.0342)	(0.0326)
Polytechnic education	0.0854***	0.150**	0.225***	0.158***	0.214***	0.181***	0.179***	0.167***
	(0.0157)	(0.0599)	(0.0552)	(0.0211)	(0.0540)	(0.0293)	(0.0340)	(0.0325)
University education	0.0837***	0.208**	0.190**	0.145***	0.242***	0.217***	0.172***	0.194***
	(0.0178)	(0.0921)	(0.0951)	(0.0215)	(0.0744)	(0.0307)	(0.0429)	(0.0373)
Union member	-0.00896	0.0108	0.0657	0.00539	-0.0145	-0.0746***	-0.00237	-0.0727***
	(0.0147)	(0.0415)	(0.0442)	(0.0214)	(0.0425)	(0.0262)	(0.0321)	(0.0276)
Piece rate indicator	0.00232	-0.0130	-0.0489	-0.0739	0.0791	-0.107	0.0118	-0.0364
	(0.0284)	(0.0731)	(0.0748)	(0.0539)	(0.0824)	(0.0659)	(0.0578)	(0.0629)
Usual weekly hours	0.00266***	0.00213	0.00484*	0.00473***	0.00667***	0.00471***	0.00744***	0.00526***
	(0.000833)	(0.00237)	(0.00274)	(0.00125)	(0.00230)	(0.00157)	(0.00206)	(0.00165)
Employer								
Plant size 10-49	0.0158	0.152***	0.0769	0.0419**	0.0438	0.00647	0.0985***	-0.0104
	(0.0145)	(0.0504)	(0.0479)	(0.0197)	(0.0416)	(0.0273)	(0.0315)	(0.0292)
Plant size >=50	0.0518***	0.315***	0.243***	0.0900***	0.0974**	0.0494	0.195***	0.00886
	(0.0161)	(0.0522)	(0.0509)	(0.0215)	(0.0485)	(0.0310)	(0.0336)	(0.0341)
Part of multi-plant firm	0.0497***	0.141***	0.178***	0.101***	-0.0273	0.0570**	0.125***	0.0662**
	(0.0149)	(0.0414)	(0.0407)	(0.0206)	(0.0454)	(0.0285)	(0.0320)	(0.0303)
Foreign firm	0.000275	-0.0184	-0.0119	0.0263	0.00872	-0.0217	0.0164	-0.0284
	(0.0236)	(0.0473)	(0.0536)	(0.0293)	(0.0714)	(0.0461)	(0.0430)	(0.0485)
Public sector	0.0146	0.0307	0.106	0.0621**	-0.0353	0.00876	0.0275	-0.0165
	(0.0199)	(0.0698)	(0.0727)	(0.0274)	(0.0573)	(0.0367)	(0.0461)	(0.0401)

Work history								
Number of job switches	0.00279	0.00163	0.0189	0.00568	0.00199	0.00845	0.00115	0.0158*
	(0.00443)	(0.0121)	(0.0129)	(0.00593)	(0.0119)	(0.00836)	(0.00923)	(0.00911)
Number of employment	4.53e-05	0.000493	0.000375	0.000283	-6.75e-06	0.000212	0.000302	0.000999*
months	(0.000266)	(0.000660)	(0.000866)	(0.000363)	(0.000611)	(0.000451)	(0.000586)	(0.000531)
Number of	-0.000502	-0.000671	-0.00265*	-0.00154**	-0.00119	-0.000319	-0.00211**	-0.000477
unemployment months	(0.000418)	(0.00132)	(0.00142)	(0.000617)	(0.00130)	(0.000781)	(0.000989)	(0.000849)
Ever worked in the	-0.0109	-0.0141	0.0232	-0.0143	-0.0406	-0.00346	-0.0532	-0.0147
manufacturing sector	(0.0178)	(0.0435)	(0.0445)	(0.0250)	(0.0514)	(0.0326)	(0.0366)	(0.0352)
Ever worked in a firm	0.0400***	0.132***	0.105***	0.0654***	0.0132	0.0449	0.102***	0.0482
with over 300 workers	(0.0145)	(0.0407)	(0.0402)	(0.0198)	(0.0452)	(0.0284)	(0.0298)	(0.0309)
Number of layoff	-0.00474	-0.0288	-0.0159	-0.00524	-0.00699	-0.0251*	-0.0202	-0.0237*
episodes	(0.00610)	(0.0193)	(0.0194)	(0.00869)	(0.0190)	(0.0132)	(0.0131)	(0.0136)
Past average earnings	0.0136*	0.000781	0.0115	0.0191**	0.0420**	0.0215*	0.0417***	0.0174
	(0.00695)	(0.0174)	(0.0206)	(0.00968)	(0.0190)	(0.0126)	(0.0150)	(0.0141)
Past average earnings	0.00965	0.0173	0.0531	0.0220	0.0564	0.0278	0.0456*	0.0278
growth	(0.0110)	(0.0330)	(0.0369)	(0.0157)	(0.0374)	(0.0209)	(0.0270)	(0.0231)
Worked over 10 years	0.0378**	0.0789	0.100*	0.0464**	0.0801*	0.0739**	0.0274	0.0567*
with current employer	(0.0164)	(0.0508)	(0.0519)	(0.0227)	(0.0478)	(0.0309)	(0.0363)	(0.0337)
Had over 3 professions	0.0252	0.0342	0.0676	0.0310	0.0389	0.0319	0.0480	0.0446
over working life	(0.0158)	(0.0458)	(0.0505)	(0.0224)	(0.0486)	(0.0315)	(0.0330)	(0.0327)
Pseudo R-squared	0.0767	0.2671	0.3032	0.1448	0.1260	0.1146	0.2052	0.1037
F-test statistic for work history variables	43.51	24.69	35.26	65.91	22.53	33.20	59.59	42.34
p-value	0.0000	0.0060	0.0001	0.0000	0.0126	0.0003	0.0000	0.0000
N	3779	875	1140	2701	1027	1953	1745	1795

Notes: Marginal effects from probit estimations reported. Reference category for age is 35-44 and the one for education consists of those with comprehensive education only. Work history refers to the years 1990-2001. (Past average earnings change is for the years 1999-2000 and 2000-2001.) The past average annual earnings 1990-2001 are deflated to the year 2000 by using the consumer price index. All models include 14 unreported industry dummies. Robust standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 1b. Work history as determinant of HIM practices.

Controls	(1) Total number of HIM practices	(2) HPWS ("more than one aspect")
Individual		
Female	-0.186***	-0.0504***
	(0.0443)	(0.0184)
Age <=34	0.115*	0.0125
	(0.0691)	(0.0266)
Age 45-54	-0.0196	-0.0208
	(0.0561	(0.0231)
Age 55-64	-0.0695	-0.0516*
	(0.0648)	(0.0301)
Married	0.108**	0.0160
	(0.0468)	(0.0188)
Secondary education	0.0752	0.0152
	(0.0660)	(0.0222)
Polytechnic education	0.507***	0.133***
	(0.0682)	(0.0209)
University education	0.631***	0.132***
	(0.0814)	(0.0225)
Union member	-0.119**	-0.0292
	(0.0492)	(0.0194)
Piece rate indicator	-0.277***	-0.0297
	(0.108)	(0.0440)
Usual weekly hours	0.0136***	0.00438***
	(0.00308)	(0.00120)
Employer		
Plant size 10-49	0.0768	-0.0504***
	(0.0575)	(0.0184)
Plant size >=50	0.261***	0.0125
	(0.0589)	(0.0266)
Part of multi-plant firm	0.264***	-0.0208
	(0.0579)	(0.0231)
Foreign firm	0.0324	-0.0516*
	(0.0637)	(0.0301)
Public sector	0.0551	0.0160
	(0.0768)	(0.0188)
Work history		
Number of job switches	0.0238*	0.00532
	(0.0135)	(0.00601)
Number of employment	0.00171**	0.000269
months	(0.000864)	(0.000355)
Number of unemployment	-0.00422**	-0.00104*
months	(0.00188)	(0.000601)
Ever worked in the	0.00686	-0.0147
manufacturing sector	(0.0571)	(0.0244)
Ever worked in a firm with	0.0866*	0.0554***
over 300 workers	(0.0499)	(0.0199)
Number of layoff episodes	-0.0760***	-0.0130
	(0.0260)	(0.00886)
Past average log earnings	0.0813***	0.0192**
	(0.0260)	(0.00956)
Past average log earnings	0.124***	0.0282*
growth	(0.0451)	(0.0157)
Worked over 10 years	0.0414	0.0507**
with current employer	(0.0540)	(0.0223)
Had over 3 professions	0.0793	0.0247
over working life	(0.0562)	(0.0221)
Pseudo R-squared	0.0456	0.1285
F-test for work history variables	94.16	59.72
p-value	0.0000	0.0000
N	3779	2752

Notes: Marginal effects from Poisson (Column 1) and probit (Column 2) estimations. The dependent variable in Column 1 is the total number of HIM practices. The highest category includes those with 5 or 6 HIM practices; there are no observations with all 7 practices. The average number is 1.81. Reference category for age is 35-44 and for education comprehensive education. Work history refers to the years 1990-2001. (Past average earnings change is average of 1999-2000 and 2000-2001.) The past average annual earnings are deflated using the consumer price index. All models include 14 unreported industry dummies. Robust standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2. HIM practices as determinants of earnings: baseline specifications.

HIM practice	*Without work history*	*With work history*
A: Any HIM v none (N = 3779)	0.1885***	0.1515***
	(0.0269)	(0.0261)
B: Any team based PRP v no HIM (N = 875)	0.2058***	0.1808***
	(0.0310)	(0.0310)
C: Any organization based PRP v no HIM (N = 1140)	0.2445***	0.2066***
	(0.0312)	(0.0309)
D: Any training v no HIM (N = 2701)	0.2592***	0.2123***
	(0.0241)	(0.0234)
E: Any self-managed teams v no HIM (N = 1027)	0.2206***	0.1728***
	(0.0348)	(0.0334)
F: Any information sharing v no HIM (N = 1953)	0.2035***	0.1627***
	(0.0307)	(0.0298)
G: Any appraisal v no HIM (N = 1745)	0.2150***	0.1632***
	(0.0288)	(0.0282)
H: Any autonomy v no HIM (N = 1795)	0.1932***	0.1498***
	(0.0315)	(0.0311)

Notes: OLS estimates. The dependent variable is the logarithm of annual earnings (2003). Robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. HIM practices as determinants of earnings: HIM count specifications.

HIM practice	*Without work history*	*With work history*
A: 1 HIM practice v none (N = 1650)	0.1264***	0.1104***
	(0.0297)	(0.0288)
B: 2 HIM practices v none (N = 1679)	0.1510***	0.1199***
	(0.0311)	(0.0311)
C: 3 HIM practices v none (N = 1289)	0.2593***	0.2006***
	(0.0273)	(0.0270)
D: 4 HIM practices v none (N = 934)	0.3292***	0.2834***
	(0.0324)	(0.0319)
E: 5-6 HIM practices v none (N = 719)	0.3957***	0.3477***
	(0.0463)	(0.0444)
F: HPWS ("more than one aspect") v none (N = 2752)	0.2169***	0.1688***
	(0.0271)	(0.0265)

Notes: OLS estimates. The dependent variable is the logarithm of annual earnings (2003). Robust standard errors reported. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. HIM practices as determinants of earnings: specific bundles.

HIM practice	*Without work history*	*With work history*
A: Self-managed teams and training v none (N = 898)	0.2942***	0.2512***
	(0.0347)	(0.0345)
B: Self-managed teams and information sharing v none (N = 837)	0.2793***	0.2261***
	(0.0574)	(0.0557)
C: Self-managed teams, training and information sharing (N = 771)	0.3509***	0.3070***
	(0.0484)	(0.0463)
D: Autonomy and training v none (N = 1376)	0.2978***	0.2435***
	(0.0267)	(0.0271)
E: Autonomy and information sharing v none (N = 1271)	0.2359***	0.1913***
	(0.0378)	(0.0377)
F: Autonomy, training and information sharing v none (N = 1039)	0.3296***	0.2799***
	(0.0316)	(0.0319)
G: Self-managed teams and autonomy v none (N = 834)	0.2716***	0.2271***
	(0.0432)	(0.0413)
H: Self-managed teams, autonomy and training v none (N = 770)	0.3279***	0.2798***
	(0.0446)	(0.0445)
I: Self-managed teams, autonomy and information sharing v none (N = 758)	0.3176***	0.2794***
	(0.0570)	(0.0524)
J: Self-managed teams, autonomy, training and information sharing v none (N = 719)	0.3471***	0.3083***
	(0.0586)	(0.0549)
K: Team based PRP and self-managed teams v none (N = 657)	0.1516**	0.1075
	(0.0607)	(0.0686)
L: Team based PRP and autonomy v none (N = 709)	0.2825***	0.2747***
	(0.0506)	(0.0497)
M: Organization based PRP and self-managed teams v none (N = 675)	0.3619***	0.3143***
	(0.0581)	(0.0556)
N: Organization based PRP and autonomy v none (N = 798)	0.3284***	0.2842***
	(0.0373)	(0.0365)
O: Team based PRP and information sharing v none (N = 724)	0.2599***	0.2224***
	(0.0438)	(0.0439)
P: Team based PRP and appraisal v none (N = 758)	0.2459***	0.2053***
	(0.0343)	(0.0341)
Q: Team based PRP, information sharing and appraisal v none (N = 682)	0.2588***	0.2173***
	(0.0515)	(0.0500)
R: Organization based PRP and information sharing v none (N = 814)	0.2999***	0.2376***
	(0.0384)	(0.0376)
S: Organization based PRP and appraisal v none (N = 876)	0.2965***	0.2429***
	(0.0313)	(0.0306)
T: Organization based PRP, information sharing and appraisal v none (N = 727)	0.3351***	0.2770***
	(0.0446)	(0.0438)

Notes: OLS estimates. The dependent variable is the logarithm of annual earnings (2003). Robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1. Descriptive statistics of the variables.

Variable	Average	Standard Deviation	Source
Outcome			
Logarithm of annual earnings (2003)	7.5381	0.6971	FLEED
Controls			
Individual			
Female	0.5230	0.4995	QWLS
Age <=34	0.2811	0.4496	QWLS
Age 35-44	0.2612	0.4394	QWLS
Age 45-54	0.2959	0.4565	QWLS
Age 55-64	0.1616	0.3681	QWLS
Married	0.7506	0.4327	QWLS
Comprehensive education only	0.1663	0.3724	QWLS
Sedondary education	0.4381	0.4962	QWLS
Polytechnic education	0.2800	0.4491	QWLS
University education	0.1155	0.3197	QWLS
Union member	0.7911	0.4066	QWLS
Piece rate indicator	0.0478	0.2134	QWLS
Usual weekly hours	34.2205	7.1307	QWLS
Employer			
Plant size < 10	0.2290	0.4202	QWLS
Plant size 10-49	0.3725	0.4835	QWLS
Plant size >=50	0.3985	0.4897	QWLS
Part of multi-plant firm	0.4217	0.4939	QWLS
Foreign firm	0.0945	0.2926	QWLS
Public sector	0.3535	0.4781	QWLS
Work history			
Number of job switches	1.7816	1.5464	FLEED
Number of employment months	102.6729	45.1923	FLEED
Number of unemployment months	8.6227	15.9072	FLEED
Ever worked in the manufacturing sector	0.2470	0.4313	BR
Ever worked in a firm with over 300 workers	0.2930	0.4552	BR
Number of layoff episodes	0.3041	0.9464	FLEED
Past average log earnings	6.3748	1.5636	FLEED
Past average log earnings change	0.1119	0.4972	FLEED
Worked over 10 years with the current employer	0.4027	0.4905	QWLS
Had over 3 professions over working life	0.1423	0.3494	QWLS

Notes: FLEED = Finnish Longitudinal Employer-Employee Data, QWLS = Quality of Work Life Survey and BR = Business Register.

Table A2. The incidence of different HIM variables.

HIM indicator	Mean
Baseline specifications (Table 2)	
Any HIM	0.8336
Any team based PRP	0.0651
Any organization based PRP	0.1352
Any training	0.5483
Any self-managed teams	0.1053
Any information sharing	0.3504
Any appraisal	0.2953
Any autonomy	0.3085
Count specifications (Table 3)	
1 HIM practices	0.2702
2 HIM practices	0.2779
3 HIM practices	0.1746
4 HIM practices	0.0807
5 HIM practices or more	0.0302
HPWS ("more than one aspect")	0.5634
Specific bundles (Table 4)	
Self-managed teams and training	0.0712
Self-managed teams and information sharing	0.0550
Self-managed teams, training and information sharing	0.0376
Autonomy and training	0.1977
Autonomy and information sharing	0.1699
Autonomy, training and information sharing	0.1085
Self-managed teams and autonomy	0.0542
Self-managed teams, autonomy and training	0.0373
Self-managed teams, autonomy and information sharing	0.0341
Self-managed teams, autonomy, training and information sharing	0.0238
Team based PRP and self-managed teams	0.0074
Team based PRP and autonomy	0.0212
Organization based PRP and self-managed teams	0.0122
Organization based PRP and autonomy	0.0447
Team based PRP and information sharing	0.0251
Team based PRP and appraisal	0.0341
Team based PRP, information sharing and appraisal	0.0140
Organization based PRP and appraisal	0.0654
Organization based PRP and information sharing	0.0490
Organization based PRP, information sharing and appraisal	0.0259
Comparison group (Tables 2-4)	
No HIM (N = 629)	0.1664

Notes: The base is the whole sample in all cases.

Table A3. HIM practices as determinants of earnings: robustness checks.

Model specification	*Without work history*	*With work history*
A: Using only past average earnings to describe work history	0.2169*** (0.0271)	0.1807*** (0.0258)
B: Including socio-economic status in 2000 to describe work history	0.2169*** (0.0271)	0.1521*** (0.0270)
C: Adding 2-digit occupational indicators	0.1904*** (0.0280)	0.1505*** (0.0281)
D: Adding spousal education to the set of controls	0.1897*** (0.0280)	0.1500*** (0.0281)
E: Using the residual from the earnings equation as outcome variable	0.2334*** (0.0283)	0.1783*** (0.0274)
F: Using self-reported monthly wage from QWLS as outcome variable	0.1787*** (0.0172)	0.1505*** (0.0166)
G: Using hourly earnings as outcome variable	0.1840*** (0.0187)	0.1411*** (0.0180)
H: Quantile regression (q25)	0.2116*** (0.0195)	0.1399*** (0.0255)
I: Quantile regression (q50)	0.1745*** (0.0143)	0.1261*** (0.0130)
J: Quantile regression (q75)	0.1655*** (0.0168)	0.1245*** (0.0159)
K: Quantile regression (q90)	0.1704*** (0.0325)	0.1511*** (0.0311)
L: Estimating separately for those who have worked 12 months in 2003	0.1958*** (0.0298)	0.1501*** (0.0278)
M: Estimating separately for the highly educated only	0.2266*** (0.0476)	0.1827*** (0.0490)
N: Estimating separately for the low educated only	0.1976*** (0.0334)	0.1504*** (0.0322)
O: Estimating separately for those who have more than 10 years' tenure	0.1671*** (0.0377)	0.1157*** (0.0315)
P: Estimating separately for those who have less than 10 years' tenure	0.2192*** (0.0378)	0.1799*** (0.0369)
Q: HIM introduced recently	0.2387*** (0.0404)	0.1951*** (0.0411)
R: Estimating separately for the small plants only	0.2414*** (0.0369)	0.1861*** (0.0361)
S: Estimating separately for the large plants only	0.1675*** (0.0320)	0.1365*** (0.0304)
T: Estimating separately for the private sector only	0.1938*** (0.0301)	0.1505*** (0.0299)

Notes: OLS estimates, except in Panels H to K. The dependent variable is the logarithm of register-based annual earnings (2003), except in Panels E-G. All robustness checks are based on the specification 'HPWS ("more than one aspect") v none' in Panel F of Table 3. B: Socio-economic status in 2000 from FLEED. C: 2-digit occupational indicators are jointly statistically significant. D: The sample consists of those who are married. E: The earnings equation from which the residual has been calculated has female, age, married and education as explanatory variables. F: The logarithm of self-reported wage from QWLS 2003 is based on the midpoints of 19 monthly wage groups. G: The dependent variable is hourly earnings, based on information from LFS. M: The highly educated sample consists of those with at least polytechnic education. Q: Estimated only for those who have reported that HIM has been introduced "over the past few years" (53% of the whole sample). R: The small plants are those with less than 50 workers. Robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A4. HIM practices as determinants of earnings: 'causal' estimates.

Model specification	*Without work history*	*With work history*
A: Propensity score matching (ATT)	0.2418***	0.1807***
	(0.0339)	(0.0258)
B: Bias-corrected matching (ATT)	0.2181***	0.1822***
	(0.0271)	(0.0252)
C: IV estimation	0.5406**	0.4726**
	(0.2423)	(0.2320)
	[p=0.3642]	[p=0.1949]
D: IV estimation	0.3700**	0.2747
	(0.1862)	(0.1790)

Notes: The outcome is the logarithm of register-based annual earnings (2003). All estimates are based on the specification 'HPWS ("more than one aspect") v none'. A: ATTs are calculated using Kernel matching (Epanechnikov) and matching is performed using the region of common support for the propensity scores. Caliper is set at 0.001. B: Bias-corrected matching method of Abadie *et al.* (2001, 2011) is used. In Panels A-B the mean difference between the log wages of the treated and untreated employees in the matched sample is the point estimate for the 'impact' of HIM on employees' wages. Bootstrap standard errors for ATTs (1,000 replications) in parentheses. C-D: The IV estimates are for those who have less than 10 years' tenure. The results in Panel C use the shares of four HIM aspects in 1997 by 2-digit industry as instruments (shares of performance-related pay, team work, information sharing and autonomy). The 1st stage F-statistics is 9.62. p-values for the Sargan test of overidentifying restrictions are reported in square brackets. The results in Panel D use the share of more than 1 HIM aspect in 1997 by 2-digit industry as instrument for more than 1 HIM aspect in 2003. The 1st stage F-statistics is 105.53. For IV estimates robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.