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Does high involvement management lead to higher pay?

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Summary. Using nationally representative survey data for Finnish employees linked to register data on their wages and work histories we find that 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, which suggests that existing studies' estimates are upwardly biased owing 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.

Keywords: High involvement management; High performance work system; Incentive pay; Information sharing; Team working; Training; Wages

1. Introduction

In recent decades many employers have introduced practices that are designed to maximize 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, sharing information, incentive pay and supportive practices such as employer-provided training and associated recruitment methods. Collectively they constitute 'high involvement management' (HIM). There is a sizable literature exploring the links between these practices and firms' performance (Bloom and Van Reenen, 2011) 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 maximize returns from their investment in HIM. Accordingly, if one cannot control for worker sorting (i.e. the process

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where job seekers and available jobs are matched in the labour market) by ability, estimates of HIM's effect on employees' wages are likely to be upwardly biased.

Empirical evidence in respect of HIM effects on wages is mixed. Some studies find a positive relationship (e.g. Appelbaum *et al.* (2000), Helper *et al.* (2002), Hamilton *et al.* (2003), Forth and Millward (2004), Handel and Levine (2006) and Osterman (2006)) and some find positive and negative effects (e.g. Handel and Gittleman (2004)), whereas 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) concluded 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 a survey which forms part of the data that we use in this paper, found that 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 that are necessary to account adequately for worker selection into HIM.

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 representative 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. Limitations of the data have made it difficult for previous studies to account for non-random worker exposure to HIM practices. We accomplish this by conditioning on work and wage histories, and as a robustness check by matching HIM with non-HIM employees on the basis of their prior labour market experiences. Conditioning on observable employee histories allows us to evaluate the potential upward bias in the earlier estimates of the HIM wage premium.

In the empirical analysis we explain earnings by a dummy variable, which indicates whether the worker is in an HIM job. The baseline models are estimated with ordinary least squares (OLS), assuming that after conditioning on a rich set of observable worker characteristics the errors are independent of the HIM status. There are some earlier empirical studies that have used experiments to identify causally the changes in management practices on various outcomes (Bruhn *et al.*, 2010; Bandiera *et al.*, 2011; Bloom *et al.*, 2011). However, none of those studies have randomly assigned HIM practices across firms and studied their subsequent effects on wages.

The remainder of the paper is structured as follows. The following section reviews the theoretical and empirical literatures linking HIM to employees' wages. Section 3 introduces our linked survey and register data. Section 4 outlines the theoretical framework underpinning our investigation and Section 5 the empirical strategies that we adopt. Section 6 reports the results and Section 7 concludes.

2. Theoretical and empirical literatures

There are four reasons why we 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 precondition for the success of HIM (Appelbaum *et al.*, 2000). Second, increased job autonomy and the devolution of decision-making responsibilities to employees allows them to utilize 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 that are allocated to them by managers and supervisors. 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. The observation that greater employee effort is induced by a switch to performance-based pay has been firmly established in earlier research (Hamilton *et al.*, 2003; Boning *et al.*, 2007). 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 effect 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 minimize the problem (Freeman *et al.*, 2010).

There are at least four 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 that employees have sufficient bargaining power to extract a share of these additional rents. But whether HIM employees have more or less bargaining power than 'like' employees who are not exposed to HIM is uncertain, *a priori*.

The second reason is that HIM employers may also raise their wages above those offered in the market to reduce quit rates to ensure that they recoup the full value of their investments in HIM (see Cottini *et al.* (2011)). In this case higher wages are paid for efficiency wage reasons. The third reason is that 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. The fourth reason that is particularly important for our analysis is positive worker selection in which the most able workers are being sorted into HIM. Lazear (2000) has documented the importance of worker selection in the context of productivity effects of compensation based on piece rates. Furthermore, Bandiera *et al.* (2012) present experimental evidence according to which changes in team composition by ability explain a substantial part of the productivity effects of different incentive mechanisms. Positive worker selection can be based on observable worker characteristics such as qualifications but also on worker ability that is rarely observable to the analyst. Different empirical strategies are needed to deal with worker selection based on observables and unobservables (see Section 5 below).

The eight 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, compensating differentials or positive worker selection). But worker sorting may induce a spurious 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 that are 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. In this paper, we use the adjective good to refer to work histories exhibiting high and/or rising wages and stable employment with few spells of unemployment. When histories are unobservable to the analyst—as is usually so—estimated wage returns to exposure to HIM will be upwardly biased since the workers who are 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.

3. Data

Our data are the Quality of Work Life Survey (QWLS) 2003 of Statistics Finland. The initial sample for the QWLS is derived from a monthly Labour Force Survey, where a random sample of the working-age population is selected for a telephone interview. The 2003 QWLS was based on Labour Force Survey respondents in October and November who were 15–64-year-old wage and salary earners with a normal weekly working time of at least 5 h. 5270 individuals were selected for the QWLS sample and invited to participate in a personal face-to-face interview. Out of this sample, 4104 people or around 78% participated (Lehto and Sutela, 2005) in the interviews, which took place mostly in October–December 2003, with some taking place at the beginning of January 2004. Owing to missing information on some variables for some workers, the sample size that was used in this study is 3779 observations.

In addition to the HIM practices that the worker is exposed to in her employment (which are discussed below) the QWLS contains information on the type of job that the employee does and the nature of the employer, together with employees' personal characteristics and work experience. Statistics Finland supplements the QWLS with information from the Labour Force Survey on, for example, working time and exact 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 Statistics Finland.

The QWLS data are 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). The FLEED are constructed from several registers on individuals and firms that are maintained by Statistics Finland. In particular, the FLEED contain information from employment statistics, which records each employee's employer during the last week of each year. We match the QWLS data and the FLEED by using unique personal identifiers (i.e. identification codes for individuals). We have followed the employees over the period 1990–2003. This is exact matching and there are no misreported identification codes. We therefore avoid problems that are associated with errors in record linkages (e.g. Ridder and Moffitt (2007)). In each year, we can also link information on the firm and establishment to each person.

To capture the key concepts in the HIM literature adequately 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 with team-based PRP (14% compared with 7%). A dummy for training that captures continuous development of skills at work equals 1 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 1 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 1 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 by 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; 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 1 if at least two of the seven HIM practices are present. In addition, we construct several other variables. First, we construct a count variable for the number of HIM practices which runs from 0 to 5 where 5 identifies employees exposed to five or more practices.

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 197 HIM bundles (i.e. all possible combinations of 1–7 HIM practices) we focus on bundles that are sufficiently common to support robust analysis. Job autonomy is usually understood to be at the core of HIM, often allied to team working. The centrality of direct employee involvement in decision making means that emphasis is placed on the degree to which teams were self-directed or self-managed. Training, appraisal and sharing information 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). 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', i.e. rights to appropriate some of the rents that are associated with taking on that control. Without return rights employees may be loathe to expend the additional efforts that are implied by HIM practices. To foster the group effort that is 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 can have different effects.

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 (a firm with more than 300 employees), the number of lay-off episodes, past average earnings (1990–2001) and past earnings growth (the average over the periods 1999–2000 and 2000–2001). All of the above work history variables are linked to the QWLS from the longitudinal register data. In addition, we use information in the QWLS to form an indicator for people who have been more than 10 years with their 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 (dummy variables for lower white-collar and upper white-collar employees in 2000, with blue-collar workers 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 expect a positive effect of recent wage growth on the propensity to enter HIM workplaces over 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 before entering the programme 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 logarithm 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 logarithm 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, multiplant firms, foreign ownership, public sector employer and industry (with 14 dummy variables). To avoid omitted variables bias, all specifications include among the control variables an indicator for workers who are paid a piece rate. (Less than 1% of all workers are subject to the combination of team-based PRP or organization-based PRP with piece rates.) All these variables are based on the data on individuals in the QWLS. Descriptive statistics for dependent and independent variables are presented in Table 1 with those for the HIM variables presented in Table 2.

4. Theoretical framework

To formalize the arguments, consider the simple model that was used in Lemieux *et al.* (2009). Their emphasis was 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 that are 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 the marginal product

Table 1. 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 $\leqslant$ 34 years	0.2811	0.4496	QWLS
Age 35–44 years	0.2612	0.4394	QWLS
Age 45–54 years	0.2959	0.4565	QWLS
Age 55–64 years	0.1616	0.3681	QWLS
Married	0.7506	0.4327	QWLS
Comprehensive education only	0.1663	0.3724	QWLS
Secondary 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 $\geqslant$ 50	0.3985	0.4897	QWLS
Part of multiplant 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	Business register
Ever worked in a firm with over 300 workers	0.2930	0.4552	Business register
Number of lay-off episodes	0.3041	0.9464	FLEED
Past average log-earnings	6.3748	1.5636	FLEED
Past average log-earnings growth	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

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 the 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 both to the worker and to the firm 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 $0 < \delta < 1$.

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 fixed supply of effort. The wage is based on output (1) which is fixed, given the fixed effort. Given the contract wage, the worker maximizes expected utility by choosing the fixed effort. This leads to wage (and output)

$$\begin{aligned} w_{ij}^{\mathrm{N}} &= \phi_j + \gamma_{1j}(\tilde{\alpha} - \sigma_i^2) \\ &= \phi_j + \gamma_{1j}(1-\delta)\tilde{\alpha}_i \end{aligned} \qquad (2)$$

where $\phi_j = \gamma_{0j} + \gamma_{1j}\ln(\gamma_{1j})$. In a firm with HIM the wage varies with effort, since now output (1) is not fixed. The worker chooses his expected utility maximizing effort, given the dependence of wage on effort, after observing the 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

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

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 on the basis of 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 $\tilde{w}_{ij}^{\mathrm{HIM}} > w_{ij}^{\mathrm{N}}$, or

Table 2. Incidence of various HIM variables†

HIM indicator	*Mean*
Baseline specifications (Table 5)	
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 6)	
1 HIM practice	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 7)	
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 5–7)	
No HIM (N = 629)	0.1664

†The base is the whole sample in all cases.

$\gamma_{1j}\tilde{\alpha}_i - \mu_j > \gamma_{1j}(1-\delta)\tilde{\alpha}_i$. 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 receive a higher expected return to skills (the coefficient of $\tilde{\alpha}_i$ 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 an 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. 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 levels of education. The model also has four other predictions that are more difficult to test with our linked data. First, the wage intercept should be lower in HIM jobs than non-HIM jobs because the firm factors in the costs of monitoring in the PRP case. This can be tested by looking at the 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 HIM than non-HIM jobs. Third, the returns to observable job characteristics will be smaller in HIM than non-HIM 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 HIM than non-HIM jobs. But, since we do not have multiple observations per each firm, we cannot test this.

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 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. We might also expect 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.

5. Econometric modelling

In the empirical analysis we run regressions of the form

$$\ln(W_i) = X_i\beta + \delta\,\mathrm{HIM}_i + \varepsilon_i \tag{4}$$

where X_i is a vector of observable characteristics of individuals and their employer with βs being coefficients to be estimated. HIM_i 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 observable worker and workplace characteristics. ε_i is a random component. In the theory that was presented above, the wage is related to mean $\tilde{\alpha}_i$ of the random ability, conditional on observed worker characteristics. Further, there is selection of high ability workers to HIM firms. However, we do not observe $\tilde{\alpha}_i$, so it is part of the error term.

We are interested in different treatment effects of HIM (e.g. Blundell and Costa Dias (2009)). The average treatment effect ATE is defined, by using equation (4), as

$$\mathrm{ATE} = E[\ln(W_i^{\mathrm{HIM}}) - \ln(W_i^{\mathrm{N}})] = \delta + E[\varepsilon_i^{\mathrm{HIM}} - \varepsilon_i^{\mathrm{N}}] = \delta \tag{5}$$

where the superscript HIM refers to potential wage (and error) in HIM work, i.e. $\ln(W_i^{\mathrm{HIM}}) = X_i\beta + \delta + \varepsilon_i^{\mathrm{HIM}}$, and correspondingly superscript N refers to non-HIM work, i.e. $\ln(W_i^{\mathrm{N}}) = X_i\beta + \varepsilon_i^{\mathrm{N}}$. The average treatment effect on the treated, ATT, from being in HIM work is defined as

$$\mathrm{ATT} = E[\ln(W_i^{\mathrm{HIM}}) - \ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 1] = \delta + E[\varepsilon_i^{\mathrm{HIM}} - \varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 1] \tag{6}$$

where $\mathrm{HIM}_i = 1$ indicates the group of workers who are actually observed in HIM work. The second term in equation (6) is the unobservable gain from HIM jobs. In a similar way, it is possible to define the average treatment effect on the untreated, ATU, i.e. the potential wage gain from HIM for those who are not observed in HIM work,

$$\mathrm{ATU} = E[\ln(W_i^{\mathrm{HIM}}) - \ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 0] = \delta + E[\varepsilon_i^{\mathrm{HIM}} - \varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 0]. \tag{7}$$

Since we observe the workers in only one state, in HIM work or in non-HIM work, we do not know the counterfactual, e.g. what those observed in HIM work would have earned in non-HIM work. The treatment effects cannot be directly calculated and consequently there are difficulties in interpreting the parameter δ estimated from equation (4) as the causal effect of HIM when the workers are not assigned randomly to HIM and non-HIM jobs. In practice we must estimate the effect of HIM as

$$\begin{aligned} &E[\ln(W_i^{\mathrm{HIM}})|\mathrm{HIM}_i = 1] - E[\ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 0] \\ &\quad = E[\ln(W_i^{\mathrm{HIM}}) - \ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 1] + E[\ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 1] - E[\ln(W_i^{\mathrm{N}})|\mathrm{HIM}_i = 0] \\ &\quad = \delta + E[\varepsilon_i^{\mathrm{HIM}} - \varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 1] + E[\varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 1] - E[\varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 0] \\ &\quad = \delta + E[\varepsilon_i^{\mathrm{HIM}}|\mathrm{HIM}_i = 1] - E[\varepsilon_i^{\mathrm{N}}|\mathrm{HIM}_i = 0]. \end{aligned} \tag{8}$$

Therefore the parameter δ measures ATT, the causal effect of HIM, only if selection into HIM is uncorrelated with the wage equation error. As argued above, this does not necessarily hold.

We use three different strategies to estimate the model. First, the baseline specifications are estimated as linear regressions with OLS, controlling for an extensive set of observable characteristics in the X_i-vector. The idea in the regression approach is that conditionally on X_i the errors are assumed to be independent of the HIM status (the conditional independence assumption (CIA)), i.e.

$$E[\varepsilon_i^{\mathrm{HIM}}|X_i, \mathrm{HIM}_i = 1] = E[\varepsilon_i^{\mathrm{N}}|X_i, \mathrm{HIM}_i = 0] = 0 \tag{9}$$

in which case $\mathrm{ATT} = \delta$ is estimated from equation (4). We test the sensitivity of the baseline OLS results to the inclusion of different sets of observable characteristics. In particular, we examine whether the inclusion of workers' wage and work histories changes the results. This would indicate that without their inclusion equation (9) is not likely to hold. If the effects of HIM are heterogeneous, the regression approach still estimates only one parameter. However, we can run regressions for different subsamples to obtain heterogeneous estimates.

Second, we use propensity score matching (PSM) to condition on the observable characteristics (Rosenbaum and Rubin, 1983; Heckman *et al.*, 1998; Caliendo and Kopeinig, 2008). The method compares wage outcomes for employees exposed to HIM with 'matched' non-HIM employees and the dimensionality is reduced by conditioning on the probability of HIM status. The method shares the causal identification assumption of the OLS in that it yields unbiased estimates of the treatment effect where differences between individuals affecting the outcome of interest are captured in their observed attributes. However, matching has three distinct advantages relative to OLS regression in identifying an unbiased causal effect of HIM on wages. First, it is non-parametric, so it does not require the assumption of linearity in the outcome equation as in equation (4). Second, it leaves the individual causal effect completely unrestricted so heterogeneous treatment effects are allowed for and no assumption of constant additive treatment effects for different individuals is required. Thirdly, matching estimators highlight the problem of common support and thus the shortcomings of parametric techniques which involve extrapolating outside the common support (Heckman *et al.*, 1998).

PSM relies on the assumption that counterfactual outcomes are independent of treatment status having conditioned on observable traits. A probit model is estimated for the probability of being in HIM work and the estimated probability is denoted $p(X_i)$. It is assumed that conditional on $p(X_i)$ the outcomes (wages) are independent of the HIM status (the CIA given the propensity score). Further, it is assumed that HIM status is not perfectly predictable given X_i, i.e. $0 < p(X_i) < 1$ (the common support assumption). Matching can thus eliminate two of the three sources of estimation bias that were identified by Heckman *et al.* (1998): the bias due to difference in the supports of X in the treated and control groups (failure of the common support condition) and the bias due to the difference between the two groups in the distribution of X over its common support. The remaining source of bias is that due to selection on unobservables. This highlights the importance of the CIA since, if this holds, selection on unobservables ceases to be a problem. The appropriateness of the CIA is primarily dependent on the richness of the available data.

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 effect that HIM would have on a randomly chosen employee. The effect of treatment on the treated, ATT, for those participants with support is defined as

$$\begin{aligned}\mathrm{ATT} &= E_{p(X)|\mathrm{HIM}=1}[E[\ln(W_i^{\mathrm{HIM}})|p(X_i), \mathrm{HIM}_i = 1] - E[\ln(W_i^{\mathrm{N}})|p(X_i), \mathrm{HIM}_i = 0]] \\ &= E[\ln(W_i^{\mathrm{HIM}})|p(X_i), \mathrm{HIM}_i = 1] - E_{p(X)|\mathrm{HIM}=1}[E[\ln(W_i^{\mathrm{N}})|p(X_i), \mathrm{HIM}_i = 0]] \qquad (10)\end{aligned}$$

where the first term on the right-hand side is the mean wage observed in HIM work and the second term is the mean wage of the matched group of workers in the region of common support. There are various ways of defining this counterfactual by using the propensity score. We use kernel matching in which case ATT is calculated as

$$\mathrm{ATT} = \frac{1}{N_{\mathrm{HIM}}} \sum_{i \in \mathrm{HIM}=1} \left\{ \ln(W_i) - \sum_{j \in M_i} \omega_{ij} \ln(W_j) \right\} \qquad (11)$$

where ω_{ij} are the kernel weights that are attached to individuals j who form the comparison group for individual i, N_{HIM} is the number of people in HIM work and M_i is the set of observations matched to i. We use an Epanechnikov kernel estimator with a 0.001 caliper 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 an identical approach when searching for comparators for the untreated among the treated.

As an alternative matching estimator we apply bias-corrected matching using the method of Abadie *et al.* (2001) and Abadie and Imbens (2011). The aim of this method is to remove some of the bias that is associated with the simple matching estimator in finite samples when the matching is not exact. The mean outcome of the treated is compared with the mean outcome of the untreated matches, with a regression-based adjustment for the difference in covariate values. Denote $\hat{\beta}$ the estimated parameters from a regression of the outcome on the covariates using only the matched sample. ATT is then calculated as

$$\mathrm{ATT} = \frac{1}{N_{\mathrm{HIM}}} \sum_{i \in \mathrm{HIM}=1} \left[\ln(W_i) - \frac{1}{N_{M_i}} \sum_{j \in M_i} \{\ln(W_j) + (X_i - X_j)\hat{\beta}\} \right] \tag{12}$$

where N_{M_i} is the number of observations matched to i; we use one match per treated observation.

Third, we use instrumental variable (IV) estimation. This has the advantage that the validity of the IV approach is not dependent on the CIA as the OLS and matching estimates, and neither OLS nor PSM estimates can tackle worker sorting on unobservables. Worker characteristics that are not observed, even in rich linked data, can be for example worker motivation and attitude towards risk. The IV strategy is based on the assumption that there are variables Z_i that determine in a decision rule whether a worker is in HIM work, but, conditionally on X_i, Z_i is uncorrelated with the unobservables in the wage equation (and in the decision rule). This means that there is independent variation in Z_i given by at least one variable not included in X_i (the exclusion restriction). The IV estimation identifies ATT if the effects of HIM are homogeneous (Angrist and Pischke (2009), pages 151–158). Existence of heterogeneous effects implies that the IV estimate picks up the effect for those who are just induced to take an HIM job by the instrument. In this case the effect is called the local average treatment effect.

6. Results

6.1. Exposure to high involvement management

Before presenting estimates of HIM effects on employees' wages we explore the correlates of employees' exposure to HIM. Table 3 presents the marginal effects from probit equations for eight measures of HIM and Table 4 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 3 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. The models in columns (2)–(8) are run on subsets of the full sample to ensure that those scoring 0 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. We cannot compute standard errors that are clustered at the firm level, because in our primary data we do not have multiple workers for many of the firms. Column (1) of Table 4 estimates the count model for the number of HIM practices whereas column (2) estimates the probability of having two or more HIM practices (what we term an HPWS) compared with the probability of having no HIM practices. The independent variables are jointly significant in all models, with pseudo-R^2 between 0.08 and 0.30 in Table 3 (0.05 and 0.13 in Table 4). The probit models in Table 3 seem to work best for organization- and team-based PRP, whereas the pseudo-R^2 is lowest for autonomy and sharing information.

Our primary interest is the role of the work history variables and we do not report the marginal effects of the individual and firm characteristics. The work history variables are jointly statistically significant in all 10 models of Tables 3 and 4, 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 expected, past average earnings are positively associated with exposure to HIM practices. They are statistically significant for five of the eight HIM specifications in Table 3, the exceptions being team-based PRP, organization-based PRP and autonomy. An increase of 1 standard deviation in past average log-earnings (i.e. an increase of 1.56) over the period 1990–2001 is associated with an increase of 2.1 ($=0.0136 \times 1.56 \times 100$)

Table 3. 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*
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 months	4.53×10^{-5}	0.000493	0.000375	0.000283	-6.75×10^{-6}	0.000212	0.000302	0.000999‡
	(0.000266)	(0.000660)	(0.000866)	(0.000363)	(0.000611)	(0.000451)	(0.000586)	(0.000531)
Number of unemployment months	−0.000502	−0.000671	−0.00265‡	−0.00154§	−0.00119	−0.000319	−0.00211§	−0.000477
	(0.000418)	(0.00132)	(0.00142)	(0.000617)	(0.00130)	(0.000781)	(0.000989)	(0.000849)
Ever worked in the manufacturing sector	−0.0109	−0.0141	0.0232	−0.0143	−0.0406	−0.00346	−0.0532	−0.0147
	(0.0178)	(0.0435)	(0.0445)	(0.0250)	(0.0514)	(0.0326)	(0.0366)	(0.0352)
Ever worked in a firm with over 300 workers	0.0400§§	0.132§§	0.105§§	0.0654§§	0.0132	0.0449	0.102§§	0.0482
	(0.0145)	(0.0407)	(0.0402)	(0.0198)	(0.0452)	(0.0284)	(0.0298)	(0.0309)
Number of lay-off episodes	−0.00474	−0.0288	−0.0159	−0.00524	−0.00699	−0.0251‡	−0.0202	−0.0237‡
	(0.00610)	(0.0193)	(0.0194)	(0.00869)	(0.0190)	(0.0132)	(0.0131)	(0.0136)
Past average log-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 log-earnings growth	0.00965	0.0173	0.0531	0.0220	0.0564	0.0278	0.0456‡	0.0278
	(0.0110)	(0.0330)	(0.0369)	(0.0157)	(0.0374)	(0.0209)	(0.0270)	(0.0231)
Worked over 10 years with current employer	0.0378§	0.0789	0.100‡	0.0464§	0.0801‡	0.0739§	0.0274	0.0567‡
	(0.0164)	(0.0508)	(0.0519)	(0.0227)	(0.0478)	(0.0309)	(0.0363)	(0.0337)
Had over 3 professions over working life	0.0252	0.0342	0.0676	0.0310	0.0389	0.0319	0.0480	0.0446
	(0.0158)	(0.0458)	(0.0505)	(0.0224)	(0.0486)	(0.0315)	(0.0330)	(0.0327)
Pseudo-R^2	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

†Marginal effects from probit estimations are reported. The reference category for age is 35–44 years and the reference category for education consists of those with comprehensive education only. Work history refers to the years 1990–2001. (The past average earnings change is the average 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. The controls include the individual and employer characteristics that are listed in Table 1 and 14 industry dummy variables. Robust standard errors are given in parentheses.

‡$p < 0.1$.

§$p < 0.05$.

§§$p < 0.01$.

Table 4. Work history as determinant of HIM practices†

	(1), total number of HIM practices	*(2), HPWS ('more than one aspect')*
Number of job switches	0.0238‡	0.00532
	(0.0135)	(0.00601)
Number of employment months	0.00171§	0.000269
	(0.000864)	(0.000355)
Number of unemployment months	−0.00422§	−0.00104‡
	(0.00188)	(0.000601)
Ever worked in the manufacturing sector	0.00686	−0.0147
	(0.0571)	(0.0244)
Ever worked in a firm with over 300 workers	0.0866‡	0.0554§§
	(0.0499)	(0.0199)
Number of lay-off 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 growth	0.124§§	0.0282‡
	(0.0451)	(0.0157)
Worked over 10 years with current employer	0.0414	0.0507§
	(0.0540)	(0.0223)
Had over 3 professions over working life	0.0793	0.0247
	(0.0562)	(0.0221)
Pseudo-R^2	0.0456	0.1285
F-test for work history variables	94.16	59.72
p-value	0.0000	0.0000
N	3779	2752

†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 five or six HIM practices; there are no observations with all seven practices. The average number is 1.81. Work history refers to the years 1990–2001. (The past average earnings change is the average for 1999–2000 and 2000–2001.) The past average annual earnings are deflated by using the consumer price index. The controls include the individual and employer characteristics that are listed in Table 1 and 14 industry dummy variables. Robust standard errors are given in parentheses.
‡$p<0.1$.
§$p<0.05$.
§§$p<0.01$.

percentage points in the probability of working in an HIM job in 2003 (Table 3, column (1)). The relationship between rising past earnings and HIM exposure is more moderate: an increase of 1 standard deviation in the rate of earnings increase averaged over the periods 1999–2000 and 2000–2001 is associated with an increase of 0.5 ($=0.010\times0.50\times100$) percentage points in the probability of working in an HIM job in 2003. However, the effect is not significant. Earnings growth has only a statistically significant marginal effect for appraisal in Table 3, but it is positive and significant for both the total number of HIM practices and the HPWS measure in Table 4. The finding is the opposite of the Ashenfelter dip that is apparent in the welfare evaluation literature whereby those entering welfare programmes have particularly poor earnings trajectories before entry to the programme relative to seemingly 'like' individuals who do not enter the programme (Ashenfelter, 1978).

The work history variables include some 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 lay-offs 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 3. It is also significant for both measures in Table 4. 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 lay-off episodes is significantly negatively correlated with sharing information and autonomy, and for the number of HIM practices in column (1) of Table 4. We expected that being a stable employee, as indicated by the 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 so. What did matter was tenure with the current employer. There is a significant positive association between working 10 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, sharing information, and autonomy, and for the HPWS measure. The tenure effect can, however, be due to selection, whereby workers benefiting from HIM are more likely to stay, or due to promotion, whereby workers with long tenures are promoted to positions that are associated with HIM.

The literature suggests that HIM practices are most common in larger firms and were pioneered in manufacturing (Wood and Bryson, 2009), so we expected 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 an HPWS job. Also, current employment in a large workplace and in a multiestablishment firm rather than a single-establishment firm are positively associated with being exposed to HIM (which is not reported in Tables 3 and 4). 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 generally good work histories—who are more likely to be found in HIM jobs. Further evidence for the view that employees with good work histories are more likely to be exposed to HIM 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 pattern (the results are not reported) and is apparent for all the HIM measures.

6.2. *Baseline regression estimates*

Table 5 presents the first set of OLS estimates of the effects of HIM on earnings. There are eight rows: one for 'any HIM' and one for each of the seven separate HIM measures. The second column presents results which condition on demographic and employer characteristics only. The last column also incorporates the work history variables.

Row (a) presents the effect of being exposed to any of the seven HIM practices on employees' wages. If we condition on demographic and current employer characteristics only, being in an HIM job is associated with a wage premium of around 19% compared with a 'like' employee with similar characteristics who is not in an HIM job. The last column reveals that conditioning

Table 5. HIM practices as determinants of earnings: baseline specifications†

HIM practice	*OLS estimates without work history*	*OLS estimates with work history*
(a) Any HIM *versus* none ($N = 3779$)	0.1885‡ (0.0269)	0.1515‡ (0.0261)
(b) Any team-based PRP *versus* no HIM ($N = 875$)	0.2058‡ (0.0310)	0.1808‡ (0.0310)
(c) Any organization-based PRP *versus* no HIM ($N = 1140$)	0.2445‡ (0.0312)	0.2066‡ (0.0309)
(d) Any training *versus* no HIM ($N = 2701$)	0.2592‡ (0.0241)	0.2123‡ (0.0234)
(e) Any self-managed teams *versus* no HIM ($N = 1027$)	0.2206‡ (0.0348)	0.1728‡ (0.0334)
(f) Any information sharing *versus* no HIM ($N = 1953$)	0.2035‡ (0.0307)	0.1627‡ (0.0298)
(g) Any appraisal *versus* no HIM ($N = 1745$)	0.2150‡ (0.0288)	0.1632‡ (0.0282)
(h) Any autonomy *versus* no HIM ($N = 1795$)	0.1932‡ (0.0315)	0.1498‡ (0.0311)

†The dependent variable is the logarithm of annual earnings (2003). The controls include the individual and employer characteristics listed in Table 1 and 14 industry dummy variables. Robust standard errors are reported.
‡$p < 0.01$.

Table 6. HIM practices as determinants of earnings: HIM count specifications†

HIM practice	*OLS estimates without work history*	*OLS estimates with work history*
(a) 1 HIM practice *versus* none ($N = 1650$)	0.1264‡ (0.0297)	0.1104‡ (0.0288)
(b) 2 HIM practices *versus* none ($N = 1679$)	0.1510‡ (0.0311)	0.1199‡ (0.0311)
(c) 3 HIM practices *versus* none ($N = 1289$)	0.2593‡ (0.0273)	0.2006‡ (0.0270)
(d) 4 HIM practices *versus* none ($N = 934$)	0.3292‡ (0.0324)	0.2834‡ (0.0319)
(e) 5–6 HIM practices *versus* none ($N = 719$)	0.3957‡ (0.0463)	0.3477‡ (0.0444)
(f) HPWS (‘more than one aspect’) *versus* none ($N = 2752$)	0.2169‡ (0.0271)	0.1688‡ (0.0265)

†The dependent variable is the logarithm of annual earnings (2003). The controls include the individual and employer characteristics listed in Table 1 and 14 industry dummy variables. Robust standard errors are reported.
‡$p < 0.01$.

on work history variables leads to a reduction in the premium of about a fifth, a reduction that is statistically significant at a 99% confidence interval.

A similar pattern of results is apparent in rows (b)–(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 highly significant.

Table 6 focuses on the number of HIM practices to which the employee is exposed. This is important because, as Table 2 shows, whereas 83% of employees were exposed to at least one of the seven HIM practices, over half of all employees (56%) were exposed to two or more HIM practices and were thus working in what we term an HPWS. 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%, 12% for two practices, 20% for three practices and 28% for four practices. The wage premium for five or more practices is even larger (row (e)), but the number of employees who are exposed to five or more practices is very small (Table 2). The wage premium for employees working in an HPWS (row (f)) falls by around a fifth having conditioned on work histories, but it remains sizable and significant at around 17%.

Table 7 presents the wage premia that are associated with those theoretically important HIM bundles which are sufficiently common in the sample to permit robust estimation. 14 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 subsample who were exposed to no HIM practices. The heterogeneity of the effects is striking. HIM premia range from 15% to 36% before conditioning on work histories (the second column) and no effect to 31% having included work history controls (the last column). As argued earlier in Section 3, 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 those based on job autonomy after controlling for work histories (see rows (a)–(c) *versus* (d)–(f)). Contrary to predictions of the Lemieux *et al.* (2009) model that was discussed above, the combination of team-based PRP and team working is not associated with a particularly large wage premium (row (k)). Interestingly, this is also the only bundle in Table 7 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 5 (row (d)) that showed that employer-provided training alone can produce particularly high wage returns. Also, wage returns to the bundles that include organization-based PRP seem to be higher than those based on team-based PRP (see rows (k) and (l) *versus* rows (m) and (n), and rows (o) and (p) *versus* rows (r) and (s)). Perhaps most notable of all is the finding that the wage premia in Table 7 are always lower with the controls for work history added. This confirms our main result regarding the role that is played by work history in the selection of workers into HIM jobs.

6.3. Additional specifications

We subject the results that were presented above to sensitivity analyses including alterations to the conditioning *X*s (changes to the work history, adding two-digit occupational group controls and spousal education), the dependent variable (the residuals from a first-stage wage equation, self-reported earnings and hourly earnings), estimating the effects in different earnings quantiles and employee subgroup 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). We use the HPWS measure in these analyses because it is defined for the broad set of observations, since the mean value of the HPWS is close to 0.5 (Table 2). This

Table 7. HIM practices as determinants of earnings: specific bundles†

HIM practice	*OLS estimates without work history*	*OLS estimates with work history*
(a) Self-managed teams and training *versus* none ($N = 898$)	0.2942‡	0.2512‡
	(0.0347)	(0.0345)
(b) Self-managed teams and information sharing *versus* none ($N = 837$)	0.2793‡	0.2261‡
	(0.0574)	(0.0557)
(c) Self-managed teams, training and information sharing *versus* none ($N = 771$)	0.3509‡	0.3070‡
	(0.0484)	(0.0463)
(d) Autonomy and training *versus* none ($N = 1376$)	0.2978‡	0.2435‡
	(0.0267)	(0.0271)
(e) Autonomy and information sharing *versus* none ($N = 1271$)	0.2359‡	0.1913‡
	(0.0378)	(0.0377)
(f) Autonomy, training and information sharing *versus* none ($N = 1039$)	0.3296‡	0.2799‡
	(0.0316)	(0.0319)
(g) Self-managed teams and autonomy *versus* none ($N = 834$)	0.2716‡	0.2271‡
	(0.0432)	(0.0413)
(h) Self-managed teams, autonomy and training *versus* none ($N = 770$)	0.3279‡	0.2798‡
	(0.0446)	(0.0445)
(i) Self-managed teams, autonomy and information sharing *versus* none ($N = 758$)	0.3176‡	0.2794‡
	(0.0570)	(0.0524)
(j) Self-managed teams, autonomy, training and information sharing *versus* none ($N = 719$)	0.3471‡	0.3083‡
	(0.0586)	(0.0549)
(k) Team-based PRP and self-managed teams *versus* none ($N = 657$)	0.1516§	0.1075
	(0.0607)	(0.0686)
(l) Team-based PRP and autonomy *versus* none ($N = 709$)	0.2825‡	0.2747‡
	(0.0506)	(0.0497)
(m) Organization-based PRP and self-managed teams *versus* none ($N = 675$)	0.3619‡	0.3143‡
	(0.0581)	(0.0556)
(n) Organization-based PRP and autonomy *versus* none ($N = 798$)	0.3284‡	0.2842‡
	(0.0373)	(0.0365)
(o) Team-based PRP and information sharing *versus* none ($N = 724$)	0.2599‡	0.2224‡
	(0.0438)	(0.0439)
(p) Team-based PRP and appraisal *versus* none ($N = 758$)	0.2459‡	0.2053‡
	(0.0343)	(0.0341)
(q) Team-based PRP, information sharing and appraisal *versus* none ($N = 682$)	0.2588‡	0.2173‡
	(0.0515)	(0.0500)
(r) Organization-based PRP and information sharing *versus* none ($N = 814$)	0.2999‡	0.2376‡
	(0.0384)	(0.0376)
(s) Organization-based PRP and appraisal *versus* none ($N = 876$)	0.2965‡	0.2429‡
	(0.0313)	(0.0306)
(t) Organization-based PRP, information sharing and appraisal *versus* none ($N = 727$)	0.3351‡	0.2770‡
	(0.0446)	(0.0438)

†The dependent variable is the logarithm of annual earnings (2003). The controls include the individual and employer characteristics listed in Table 1 and 14 industry dummy variables. Robust standard errors are reported.
‡$p < 0.01$.
§$p < 0.05$.

supports robust analysis for the wage effects of HIM. We are therefore examining the robustness of the results in row (f) of Table 6. The estimates are reported in Table 8. The overriding impression is just how robust the results appear to be to these sensitivity checks. We comment briefly on only the most interesting patterns.

The estimates in row (a) of Table 8 reveal that average past earnings are a particularly important contributor to the overall explanatory power of work history. The inclusion of additional

Table 8. HIM practices as determinants of earnings: robustness checks†

Model specification	*Estimates without work history*	*Estimates with work history*
(a) Using only past average earnings to describe work history	0.2169‡	0.1807‡
	(0.0271)	(0.0258)
(b) Including socio-economic status in 2000 to describe work history	0.2169‡	0.1521‡
	(0.0271)	(0.0270)
(c) Adding two-digit occupational indicators	0.1904‡	0.1505‡
	(0.0280)	(0.0281)
(d) Adding spousal education to the set of controls	0.1897‡	0.1500‡
	(0.0280)	(0.0281)
(e) Using the residual from the earnings equation as outcome variable	0.2334‡	0.1783‡
	(0.0283)	(0.0274)
(f) Using self-reported monthly wage from QWLS as outcome variable	0.1787‡	0.1505‡
	(0.0172)	(0.0166)
(g) Using hourly earnings as outcome variable	0.1840‡	0.1411‡
	(0.0187)	(0.0180)
(h) Quantile regression (q25)	0.2116‡	0.1399‡
	(0.0195)	(0.0255)
(i) Quantile regression (q50)	0.1745‡	0.1261‡
	(0.0143)	(0.0130)
(j) Quantile regression (q75)	0.1655‡	0.1245‡
	(0.0168)	(0.0159)
(k) Quantile regression (q90)	0.1704‡	0.1511‡
	(0.0325)	(0.0311)
(l) Estimating separately for those who have worked 12 months in 2003	0.1958‡	0.1501‡
	(0.0298)	(0.0278)
(m) Estimating separately for the highly educated only	0.2266‡	0.1827‡
	(0.0476)	(0.0490)
(n) Estimating separately for the low educated only	0.1976‡	0.1504‡
	(0.0334)	(0.0322)
(o) Estimating separately for those who have more than 10 years' tenure	0.1671‡	0.1157‡
	(0.0377)	(0.0315)
(p) Estimating separately for those who have less than 10 years' tenure	0.2192‡	0.1799‡
	(0.0378)	(0.0369)
(q) HIM introduced recently	0.2387‡	0.1951‡
	(0.0404)	(0.0411)
(r) Estimating separately for the small plants only	0.2414‡	0.1861‡
	(0.0369)	(0.0361)
(s) Estimating separately for the large plants only	0.1675‡	0.1365‡
	(0.0320)	(0.0304)
(t) Estimating separately for the private sector only	0.1938‡	0.1505‡
	(0.0301)	(0.0299)

†OLS estimates, except in rows (h)–(k). The dependent variable is the logarithm of register-based annual earnings (2003), except in rows (e)–(g). All robustness checks are based on the specification 'HPWS ("more than one aspect") *versus* none' in row (f) of Table 6. (b), Socio-economic status in 2000 from the FLEED. (c), Two-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 the Labour Force Survey. (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 fewer than 50 workers. The controls in all rows include the individual and employer characteristics listed in Table 1 and 14 industry dummy variables. Robust standard errors are reported.
‡$p < 0.01$.

controls in rows (b)–(d) lowers the premium a little. For instance, row (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 that is used, but the differences are not large (rows (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 (rows (h)–(k)), among those in employment continuously in 2003 (row (l)), by education (rows (m) and (n)) or in the private sector (row (t)). It does seem, however, that the wage returns to HIM are larger in small plants relative to large plants (rows (r) and (s)).

Although we condition on extensive work and earnings histories we cannot 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, we might expect the HIM premium to be larger among short-tenured workers, the assumption being that those with long tenure were in post before the introduction of HIM since 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 (row (p)), but it remains large and significant even among those in post for at least 10 years (row (o)). The wage premium is also a little larger where HIM practices had been introduced recently (row (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 to deplete over time (Bryson and Freeman, 2010).

One cause of concern regarding the baseline results is that in conditioning on the prior earnings of employees who have been exposed to HIM we underestimate the effect of HIM on earnings. To address this we reran the results but truncated the earnings histories at 1999, i.e. 4 years before our survey indicators of exposure to HIM. The results were insensitive to this alteration (the results are not reported). This, coupled with the fact that HIM wage returns are significantly positive for both short and long tenured workers, lends credence to our main findings.

To test the specific implication of the theoretical framework that the returns to human capital are higher in HIM jobs, we also interacted the dummy for the highest education group with HIM. The interaction was not statistically significant (the results are not reported).

6.4. Causal effects

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 4. 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 (the results are not reported). The ATT-estimates in row (a) of Table 9 are a little higher than those obtained by using OLS (see row (f) of Table 6). However, again there is a significant reduction in the estimate after adding the work history variables to the propensity score estimator. OLS conditional on common support produces very similar results to those for OLS (the results are not reported) because we lose only a very small proportion (about 1%) of all observations by imposing the common support condition in matching. It also turns out that ATT and ATU are very

Table 9. HIM practices as determinants of earnings: 'causal' estimates†

Model specification	*Estimates without work history*	*Estimates with work history*
(a) PSM (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)

†The outcome is the logarithm of register-based annual earnings (2003). All estimates are based on the specification 'HPWS ("more than one aspect") *versus* none'. (a), ATTs are calculated by using kernel matching (Epanechnikov) and matching is performed by using the region of common support for the propensity scores. The caliper is set at 0.001 and the bandwidth at 0.06. (b), The bias-corrected matching method of Abadie *et al.* (2001) and Abadie and Imbens (2011) is used. In rows (a) and (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 (1000 replications) are given in parentheses. (c), (d), The IV estimates are for those who have less than 10 years' tenure. The controls include the individual and employer characteristics listed in Table 1 and 14 industry dummy variables. The results in row (c) use the shares of four HIM aspects in 1997 by two-digit industry as instruments (shares of PRP, team work, information sharing and autonomy). The first-stage F-statistic is 9.62. p-values for the Sargan test of overidentifying restrictions are reported in square brackets. The results in row (d) use the share of more than one HIM aspect in 1997 by two-digit industry as instrument for more than one HIM aspect in 2003. The first-stage F-statistic is 105.53. For IV estimates robust standard errors are reported.
‡$p < 0.01$.
§$p < 0.05$.

similar (the results are not reported). There is also striking similarity in the results for the other specifications that are used in Tables 5–7 with PSM compared with OLS (the results are not reported).

The bias-corrected matching method of Abadie *et al.* (2001) and Abadie and Imbens (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 (row (b) of Table 9).

Lastly, we present some IV estimates in rows (c) and (d) of Table 9 for employees who have less than 10 years' tenure. As noted above, these are the workers who may sort into HIM jobs and have high ability that is unobservable to the analyst. We use the lagged incidence of HIM in the same two-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 the QWLS before 2003.) The motivation for our IV strategy 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 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, which constitutes our exclusion restriction. The results in row (c) are based on four instruments (previous shares of PRP, team work, sharing information and autonomy). The question on appraisal was introduced into the QWLS in 2003 and lagged training is dropped because its inclusion results in a violation of the Sargan test of overidentifying restrictions. The estimates in row (d) use the share of more than one HIM aspect in 1997 by two-digit industry cell as an instrument for more than one HIM aspect in 2003.

The first stage of these IV models works well by applying the criteria of Staiger and Stock (1997), as reported in the footnotes to Table 9. This confirms that our instrument is relevant. The Sargan test of overidentifying restrictions is clearly passed in the specification of row (c). The specification in row (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 rows (c) and (d) compared with their OLS equivalent in row (p) of Table 8, but the standard errors for the IV estimates are also (much) larger. In row (d) this renders the premium statistically non-significant when detailed work history variables are incorporated.

The pattern that the IV causal estimates are larger than the OLS estimates has been noted in the context of the effects of various management policies previously (see Bloom *et al.* (2011)). A possible reason for the higher IV point estimates compared with 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, employees who are exposed to HIM may have unobservable characteristics which are significantly negatively correlated with wages, though it is unclear why this might be so. Second, more appealingly, if the returns to HIM are heterogeneous and the IV approach is recovering a local average treatment effect the causal effect for 'compliers' may be greater than for other treated individuals. In our case the local average treatment effect means the average effect on those workers, whose entry to an 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 that are presented in Table 9 the HIM premium falls with the introduction of work history variables, confirming our main finding.

7. Conclusions

There are various studies linking HIM to higher wages but, to our knowledge, the evidence that is presented here is the first to account for detailed employee wage and work histories. This proves to be important since the results show 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 so 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% before conditioning on work and wage histories. This falls by around a 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 the PSM estimates presented account only for selection on observables. Even with rich work and wage histories it is very unlikely that these estimates are purged of all bias that is 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 that is recovered by OLS, but it 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 that is attached to different HIM bundles and the increasing returns to the number of HIM practices that are used. Self-managed teams and job autonomy constitute a basis for theoretically relevant combinations of HIM, according to the Harvard school of HIM scholars. The bundles that are constructed around self-managed teams tend to produce somewhat higher wage premia than those 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 that 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 why the 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 who are exposed to HIM are those who can use those practices to increase labour productivity whereas, 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 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 the model of Abowd and Farber (1982) and Farber (1983)). 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 who are not currently exposed to HIM may arise for reasons other than improvements in labour productivity and, as such, do not proxy the potential returns that firms may gain through their adoption. To make further progress on this issue we require 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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