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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 do not differ significantly when using propensity score matching as opposed to standard regression techniques. The premium 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; propensity score matching

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

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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 organisation, in the expectation that this will improve their organisation'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, 2010) 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.

We contribute to the literature in three 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. Third, we estimate the expected wage returns to HIM among employees not currently exposed to them. As we discuss, this may offer insights into why it is that HIM is not as prevalent as early advocates had anticipated.

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 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).

There are at least three other reasons to expect firms to raise their wages on adopting HIM which are not 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.[1] 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.

[1] 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. 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 potential wage distribution queue for union jobs and union employers pick the best from that queue. 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.[2]

Empirical evidence in respect of HIM effects on wages is mixed. Some studies find a positive relationship (eg. Appelbaum et al., 2000; Hamilton et al., 2003; Helper et al., 1993; Forth and Millward, 2004; Handel and Levine, 2006; Osterman, 2006); some find positive and negative effects (eg. Handel and Gittleman, 2004); while others find no significant effects (eg. Black et al., 2004). Reviewing the

[2] 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).

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.[3] As noted in the introduction, 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. As well as introducing these work and wage histories into regression analyses, we use them to match HIM employees with non-HIM employees with similar characteristics using propensity score matching (PSM) methods. These matching estimators enable us to recover not only the effects of HIM on the wages of workers exposed to them, but also the expected wage returns to HIM among employees not currently exposed to them.

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 percent participated (Lehto and Sutela, 2005) in the interviews, which took place mostly in October-

[3] 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 HPWS 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, eg. Renaud et al (2004).

December 2003, with some taking place in the beginning of January 2004. Owing to missing information on some variables for some workers, the sample size used in this study is 3782 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.

Following Kalmi and Kauhanen (2008) we capture four different aspects of HIM. Self-managed teams are defined as teams that select their own foremen and decide on the internal division of 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 for training equals one if the employee has participated in employer-provided training during the past 12 months. A dummy for incentive pay equals one if the individual is personally subject to performance-related pay.

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. Again, 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 more than one of the HIM practices (self-managed teams, information sharing, employer-provided training or incentive pay) is present. In addition we construct variables not tested by Kalmi and Kauhanen (2008). First, we construct count variables for having one, at least two, at least three, or all four HIM practices. Second we construct a set of dummy variables which identify specific combinations of HIM which are significant either because they are common in the data or of theoretical significance. They include four HIM bundles incorporating incentive pay, the rationale being that if HIM wage effects are associated with greater worker effort or motivational effects, one might anticipate these will be larger in the presence of incentive pay.

The work history variables include the number of past job switches (defined as a change of establishment), unemployment episodes (both number of episodes and their length in months), past employment months, an indicator for having worked in a big firm (firm with more than 300 employees), length of tenure with current employer, past average earnings (1990-2001) and past earnings growth (average over periods 1999-2000 and 2000-2001). As part of sensitivity analyses, we 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). All of the above work history variables are from the longitudinal register data. In addition, we use information in QWLS to form an indicator for persons who have had more than three different professions over their working life.

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 the programme.

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.

We control for gender, age, marital status, educational level, union membership status, usual weekly hours worked, plant size, multi-plant firms, foreign ownership, industry (with fourteen dummy variables) and public sector employer. 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 performance related pay (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

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

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 $\alpha_i \sim N(\alpha_i, \sigma_i^2)$, 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 $\sigma_i^2 = \delta\alpha_i$, 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 effort. The optimal, expected utility maximizing effort leads to wage (and output)

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

where $\phi_j = \gamma_{0j} + \gamma_{1j}log(\gamma_{1j})$. In a firm with HIM (performance-based pay) 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

$$(3) \qquad {}_{ij}^{HIM} = \phi_j - \mu_j + \gamma_{1j}\alpha_j$$

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 ${}_{ij}^{HIM} > w_{ij}^{N}$, or $\gamma_{1j}\alpha_i - \mu_j > \gamma_{1j}(1{-}\delta)\alpha_i$. This can be stated as $\alpha_i > \mu_j/\gamma_{1j}\delta$. One 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 α_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 α_i is higher.[4]

There are other aspects of HIM systems besides performance-based pay. These can be illustrated with the same model. Working in a HIM firm may involve team work. This could be introduced into the model by making the assumption of higher productivity in team work than in non-team work, for

[4] This can be tested by including interactions of HIM with human capital (education) in the estimated model or, as we 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.

example. This would give an advantage to HIM jobs even in fixed-wage firms. However, perhaps the simplest way to illustrate this is to assume that the difference in team and non-team work is that in team work with group-based performance pay the cost of monitoring is lower, as the team members will monitor each other's effort. This has the straightforward implication that if a firm uses a bundle of HIM practices, performance-based pay 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.

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

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

where X is a vector of observable characteristics of individuals and their employer with betas being coefficients to be estimated. We test the sensitivity of results to the inclusion of work history variables in the X vector. 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.

An alternative to OLS to control for bias on observables is the semi-parametric statistical matching approach known as propensity score matching (PSM) (Rosenbaum and Rubin, 1983; Heckman et al., 1999) which compares wage outcomes for employees exposed to HIM with 'matched' non-HIM employees. The method shares the causal identification assumption of the OLS in that it yields unbiased estimates of the treatment impact where differences between individuals affecting the outcome of interest are captured in their observed attributes. However, matching has three distinct advantages relative to regression in identifying an unbiased causal impact of HIM on wages. First, it is semi-parametric, so it does not require the assumption of linearity in the outcome equation. 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 short-comings 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 – what is referred to in the literature as the conditional independence assumption (CIA).[5] As in the case of the OLS estimates, the sensitivity of results to data quality is assessed by altering the information set entering estimation and, in particular, the exclusion and inclusion of the work history variables.[6]

We estimate the propensity to be exposed to each HIM variable with a probit estimating a (0,1) variable identifying individuals' HIM status. The variants of these models which incorporate the work history variables are presented in Table 1 and are discussed in Section 5 below. To obtain the effect of treatment-on-the-treated for those participants with support we use matching which operates by constructing counterfactuals from the non-participants. There are a number of ways of defining this counterfactual using the propensity score. 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 the identical approach when searching for comparators for the untreated among the treated.

In our baseline estimates between 0.2 and 1.0 percent of employees are lost through the enforcement of common support, depending on the HIM variable in question and whether we are recovering the average treatment-on-the-treated (ATT) or the average treatment-on-the-untreated (ATU). For performance-related pay and training the proportion of employees off common support rose when conditioning on the work history variables, implying that some cases which appeared to have reasonable counterfactuals on the basis of cross-sectional data were, in fact, quite different to their matched comparators when one also conditioned on work histories. For example, the percentage of employees in receipt of training for whom there was no matched comparator rose from 0.3 percent to 1 percent when we conditioned on the fuller set of X's including work histories. Figure 1 illustrates the area of common support. The upper panel corresponds to a probit model where the dependent variable is a dummy variable for any HIM practice without work history variables and the lower panel to an otherwise similar specification but with work history variables.[7] In both cases the treated

[5] Matching is thus able to eliminate two of the three sources of estimation bias identified by Heckman, Ichimura, Smith and Todd (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 other source of bias is the one 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 dependent on the richness of the available data.

[6] For a recent paper in the same spirit but with a different substantive focus (namely active labour market programme evaluation) see Lechner and Wunsch (2010).

[7] The latter is the model presented in the first column of Table 1.

observations which are off support are largely found in the top end of the distribution of the propensity score.

[INSERT FIGURE 1 ABOUT HERE]

To be effective, matching should balance characteristics across the treatment and comparison groups. Appendix Table A3 presents comparisons of the means in the characteristics used to match HIM and non-HIM employees in the case of "any HIM" as the treatment, as well as a measure of the 'distance' of the marginal distributions of relevant characteristics in both groups (Rosenbaum and Rubin, 1985). For a given covariate, the standardised difference after matching is defined as the difference of the sample means in the treated and matched non-treated subsamples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups. Overall, the quality of the match seems good, the mean absolute standardised bias for all covariates being 2.8% for the matched individuals. Standardised bias for each variable tends to range from –5.8% (secondary school education) to +7.3% (university education). For the other treatment variables the biases have a similar order of magnitude; the mean absolute standardised biases for profit related pay, training, team work, and information sharing are 3.5, 3.2, 2.5 and 3.0 percent respectively.[8] As a further indication of the quality of the matching, Figure 2 shows the earnings history of the treated and controls before and after matching. Matching has clearly succeeded in making the past earnings growth quite similar. Figure 2 and Table A3 show that the earnings difference which is significant in the unmatched sample becomes statistically non-significant in the matched sample.

[INSERT FIGURE 2 ABOUT HERE]

There is some debate in the literature regarding the usefulness of reweighting estimators and alternative matching estimators (Busso et al., 2009; Froelich, 2004). We test the sensitivity of our results to a nearest neighbour matching estimator which minimises the bias across treatment and comparison groups at the expense of less efficiency.

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. The bootstrapped standard error for the post-match difference is based on 1,000 replications.

[8] Although achieving a reasonable balance on the *X*'s entering the participation equation is an indicator of how good the match is on observables, it cannot provide an indication as to whether the CIA is plausible.

5. Results

Before presenting estimates of HIM effects on employees' wages we explore the correlates of employees' exposure to HIM. Table 1 presents the marginal effects from probit equations for ten measures of HIM. Column 1 estimates the probability of having any one of the four HIM practices ('any HIM') versus having none for the whole sample. Columns 2-5 use the same model specification but estimate the probability of exposure to each of the four separate HIM practices, namely performance-related pay, training, self-managed teams, and information sharing. The models in columns 2-5 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 performance-related pay or has no HIM practices at all. Robust standard errors are presented in parentheses. Columns 6 to 9 estimate the probability of having between 1 and all four HIM practices compared to having none while column 10 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 variables are jointly significant in all models, with pseudo-R-squared between 0.06 and 0.42. The probit model seems to work best for performance-related pay and training, whereas the pseudo R-squared is lower for self-managed teams and information sharing.

[INSERT TABLE 1 ABOUT HERE]

Our primary interest is the role of the work history variables. They are jointly statistically significant in all ten models. 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 three of the four HIM practices, the exception being information sharing. A one standard deviation increase in past average earnings over the period 1990-2001 is associated with a 2.2 percentage point increase in the probability of working in a HPWS job in 2003. 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 0.9 percentage point increase in the probability of working in a HPWS job in 2003. This effect is statistically significant for three of the four HIM practices, the exception being performance-related pay. 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 by 2003. The effect is statistically significant in the case of performance-related pay, training and the HPWS measure. The number of lay off episodes is significantly negatively correlated with information sharing and HPWS. We had 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, might also influence HIM exposure, but this was not generally the case. One exception is the 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 performance-related pay, information sharing and 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. In fact, the results were less clear cut than anticipated. Large firm experience was positively and significantly associated with receiving performance-related pay, training and being in a HPWS job.[9] However, experience of employment in manufacturing was not statistically significant.

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. 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 Table 1 and is apparent for all but one of the HIM indicators.[10]

Table 2 presents the effects of HIM on earnings. There are five panels, one for 'any HIM' and one for each separate HIM measure. Each panel contains two rows. The first row presents results which condition on demographic and employer characteristics only. The second row also incorporates the work history variables. Each row contains three columns. The first column presents results from the OLS; the second column presents the ATT from the kernel matching estimator; and the third column

[9] As one might have anticipated, current employment in a larger workplace and in a multi-establishment firm rather than a single-establishment firm, were positively associated with being in an HPWS job, though these results were driven by performance-related pay and training.

[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. The results are insensitive to this alteration. This, coupled with the fact that HIM wage returns are relatively homogeneous across tenure sub-groups (see later) lends credence to our main findings.

presents OLS results run solely on the sub-set of cases for which the matching indicates there is common support.

[INSERT TABLE 2 ABOUT HERE]

Panel A presents the effect of being exposed to any of the four 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 21 per cent compared to a 'like' employee with similar characteristics who is not in an HIM job. The ATT effect based on kernel matching is a little higher, although the difference is not statistically significant. Running the OLS on the common support makes little difference to the results. Row two indicates that conditioning on work history variables leads to a reduction in the premium of about one-sixth, a reduction that is statistically significant at a 99 percent confidence interval. This is the case for all three estimates.[11]

A similar pattern of results is apparent in Panels B through E, although the wage returns are somewhat higher for performance-related pay and training than they are for self-managed teams and information sharing. In each case 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 percent confidence interval.

As noted earlier, matching enables us to recover the average treatment effect for the untreated (ATU) as well as the ATT. The weighted sum of the two is the average treatment effect (ATE), namely the impact that HIM would have on a randomly chosen employee (assuming, of course, that the CIA holds). The ATT, ATU and ATE are presented in Appendix Table A4. The table replicates the five panels A to E for the HIM variables used in Table 2, with the left-hand column presenting the ATT which was presented as the second column in Table 2.

As in Table 2, the effects of HIM on wages tend to be smaller conditioning on employees' work histories. But what is particularly striking about the results is the similarity of the ATT and ATU in the case of "any HIM", performance-related pay and training. The results are somewhat different for self-managed teams and information sharing. Conditioning on work histories the ATU wage returns to self-managed teams appear greater than those for the ATT whereas, in the case of information sharing the ATT effect is larger than the ATU effect.

[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 3 focuses on the number of HIM practices to which the employee is exposed. This is important because, as Appendix Table A2 shows, whereas 77 percent of employees were exposed to at least one of the four HIM practices, over half of HIM employees (41 percent of the whole sample) 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 is larger for those exposed to more practices. Having conditioned on work histories, the wage premium for a single HIM practice is around 13 percent; 18 percent for two practices; and 25 percent for three practices. The wage premium for all four practices is even larger, but the number of employees exposed to all four practices is very small. The wage premium for employees working in HPWS (Panel E) falls by around one-fifth having conditioned on work histories, but it remains sizeable and significant at around 20 percent.

[INSERT TABLE 4 ABOUT HERE]

The HPWS regimes with two or more HIM practices encompass eleven combinations. Table 4 presents the wage premia associated with those HIM bundles which were common enough in the sample to permit robust estimation. Five of these eight include training; four include PRP; four include teams; and five include information sharing. 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, ranging from no significant effect in two instances (Panels C and F), to premia in excess of 25 percent in two other instances (Panels G and H). Employees exposed to performance-related pay but to none of the other three HIM practices, receive a wage premium of around 12-14 percent relative to those exposed to no HIM (figures not shown in the table). This effect is similar to the combination of performance-related pay and information sharing (Panel B). However, the returns to performance-related pay are greater when combined with training (Panel A), and are even greater when supplemented with information sharing (Panel G). Contrary to predictions in Lemieux et al. (2009) the combination of performance-related pay and team-working is not associated with a large wage premium. Indeed, this is one of the two bundles that generate no significant wage premium. The wage premium associated with training in isolation is 17 percent (not shown), but combinations incorporating training consistently produce larger wage premia. Exposure to either self-managed teams or information sharing in isolation is not associated with a wage premium (not shown). When combined (Panel F) they also fail to produce a wage premium. However, their use alongside training produces the largest wage premium of all the bundles (Panel H).

Finally, we subject the results presented in Table 2 Panel A (our 'baseline' estimates for the effects of 'any HIM') to a number of sensitivity analyses including alterations to the conditioning *X*'s (changes to the work history, dropping occupational controls), the dependent variable (self-reported earnings, hourly earnings, the residuals from a first stage wage equation), employee sub-group analysis (high and low educated; high and low earners; long and short tenured; those in small and large plants; private sector employees); and the matching estimator. These are reported in Appendix Table A5. The overriding impression is just how insensitive the results appear to be to these robustness checks. The one exception is Panel K which reports much lower wage returns to any HIM for employees in the top half of the wage distribution than for other employees.

6. Discussion and 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, earnings growth, and 'good' work histories – 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.

We identify a wage premium of around 21 percent before conditioning on work histories and prior wages. This falls by around one-sixth 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 unobserved worker quality.

Although there is some 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 self-managed teams 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.

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 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 PSM estimated ATT and ATU are very similar in most cases 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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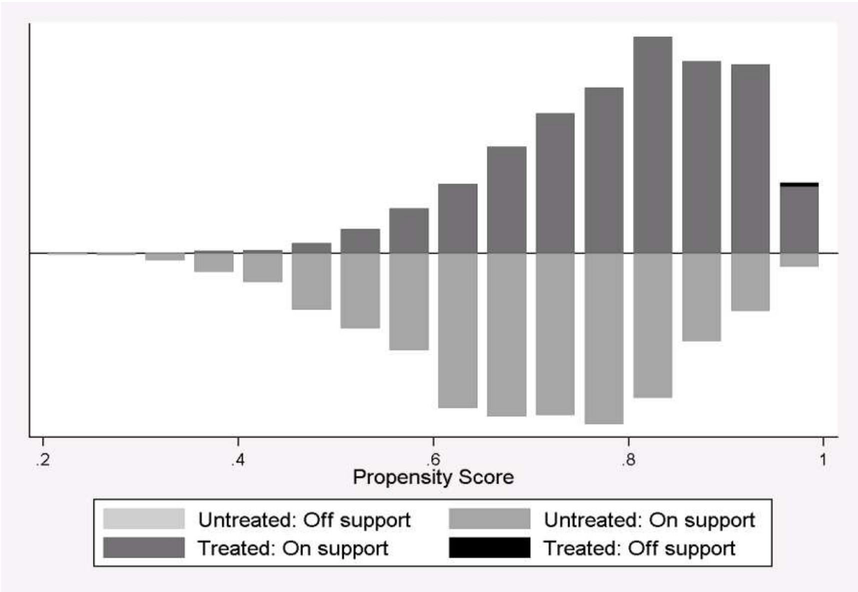
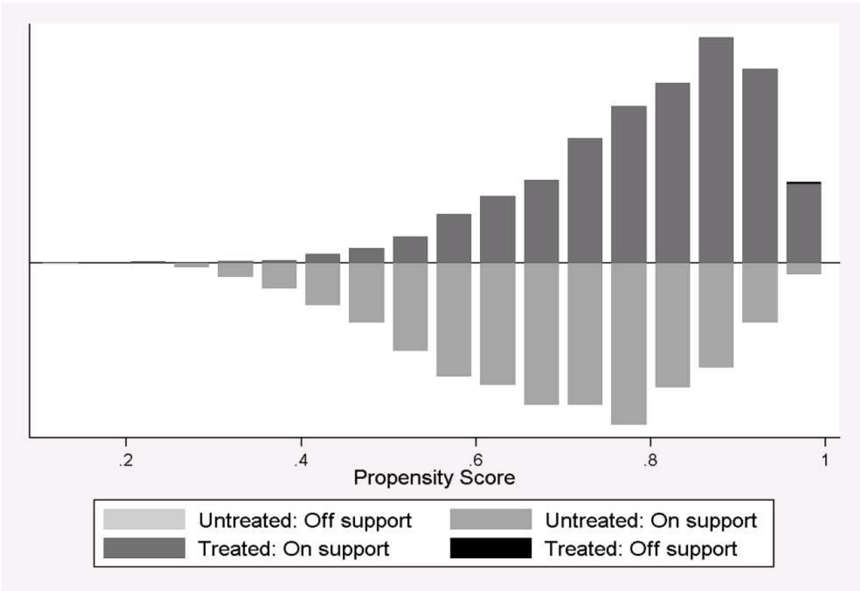
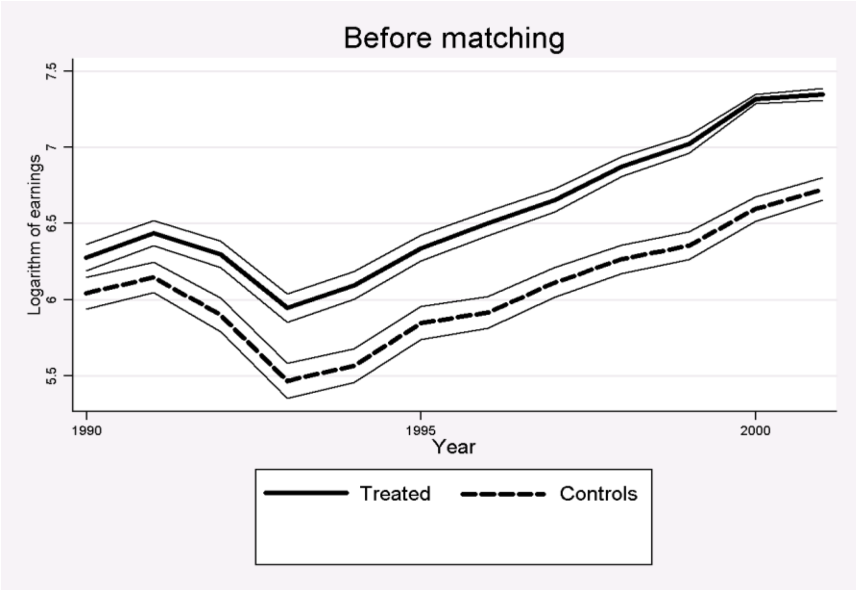
Figure 1. Common support in matching.

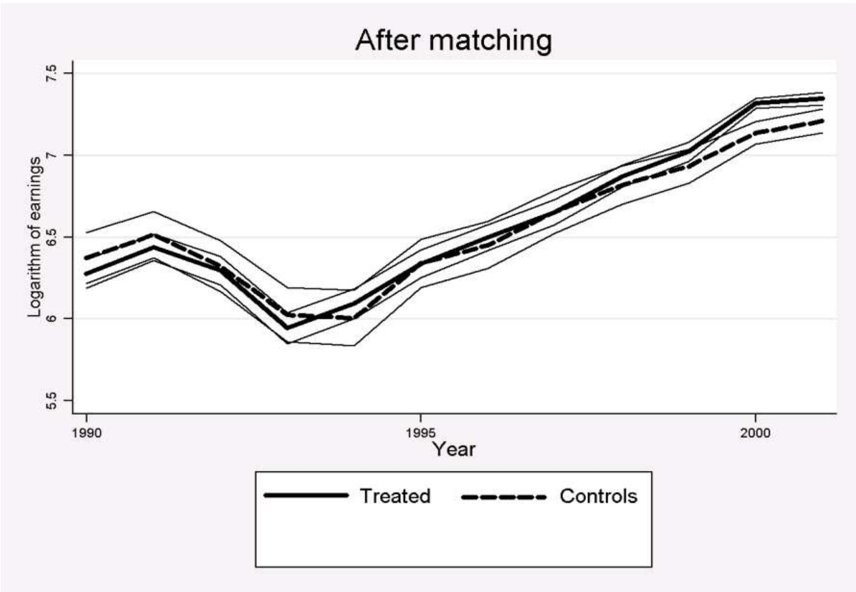




Notes: The figures are based on the probits used in Panel A of Table 2. The upper panel corresponds to the specification in row 1 while the lower panel corresponds to the specification in row 2.

Figure 2. The earnings history of the treated and controls before and after matching.





Notes: The figures are based on the specification in Panel A of Table 2. Thin lines indicate 95 per cent confidence intervals.

Table 1. Work history as determinant of innovative workplace practices.

	(1) Any HIM	(2) Any PRP	(3) Any training	(4) Any self-managed teams	(5) Any information sharing	(6) 1 HIM practices	(7) 2 HIM practices	(8) 3 HIM practices	(9) 4 HIM practices	(10) HPWS ("more than one aspect")
Controls										
Individual										
Female	-0.0265	-0.0843***	-0.0182	-0.0476	-0.0575**	-0.0172	-0.0482*	-0.0748**	-0.00187	-0.0537**
	(0.0162)	(0.0293)	(0.0207)	(0.0333)	(0.0261)	(0.0263)	(0.0284)	(0.0327)	(0.00276)	(0.0244)
Age <=34	0.00391	-0.00274	0.0195	-0.00576	0.0123	-0.00862	0.0161	-0.00733	0.00552	0.0123
	(0.0233)	(0.0429)	(0.0287)	(0.0462)	(0.0371)	(0.0378)	(0.0399)	(0.0461)	(0.00629)	(0.0342)
Age 45-54	-0.00266	-0.0237	-0.0104	-0.0105	0.00970	0.00603	-0.0182	-0.0251	0.000178	-0.0139
	(0.0192)	(0.0365)	(0.0244)	(0.0375)	(0.0315)	(0.0298)	(0.0342)	(0.0380)	(0.00329)	(0.0297)
Age 55-64	-0.0496**	-0.0390	-0.0832**	-0.0436	-0.0311	-0.0788**	-0.0492	-0.0476	-0.00151	-0.0477
	(0.0252)	(0.0441)	(0.0327)	(0.0435)	(0.0382)	(0.0373)	(0.0419)	(0.0434)	(0.00315)	(0.0369)
Married	0.00456	0.0258	0.00852	0.00480	0.0248	-0.0132	0.0302	0.0129	0.00764**	0.0272
	(0.0159)	(0.0301)	(0.0204)	(0.0323)	(0.0262)	(0.0246)	(0.0287)	(0.0319)	(0.00382)	(0.0248)
Secondary education	0.0192	0.0105	0.0469*	0.00698	0.0105	0.0195	0.0290	0.0343	-0.000974	0.0315
	(0.0185)	(0.0340)	(0.0242)	(0.0401)	(0.0312)	(0.0289)	(0.0344)	(0.0414)	(0.00335)	(0.0294)
Polytechnic education	0.127***	0.189***	0.197***	0.202***	0.208***	0.123***	0.240***	0.321***	0.00799	0.232***
	(0.0180)	(0.0366)	(0.0224)	(0.0494)	(0.0307)	(0.0327)	(0.0340)	(0.0507)	(0.00864)	(0.0271)
University education	0.142***	0.277***	0.204***	0.281***	0.284***	0.118**	0.297***	0.438***	0.0452	0.269***
	(0.0189)	(0.0444)	(0.0224)	(0.0705)	(0.0314)	(0.0468)	(0.0379)	(0.0658)	(0.0378)	(0.0268)
Union member	-0.0196	-0.00646	-0.00890	-0.0209	-0.0920***	-0.0120	-0.0538*	0.00184	-0.0121	-0.0397
	(0.0169)	(0.0322)	(0.0224)	(0.0359)	(0.0269)	(0.0278)	(0.0308)	(0.0365)	(0.00887)	(0.0262)
Usual weekly hours	0.00317***	0.00584***	0.00474***	0.00577***	0.00473***	0.00304**	0.00497***	0.00881***	0.000614**	0.00579***
	(0.000997)	(0.00190)	(0.00133)	(0.00190)	(0.00158)	(0.00151)	(0.00172)	(0.00213)	(0.000300)	(0.00154)
Employer										
Plant size 10-49	0.0255	0.116***	0.0482**	0.0321	0.00207	0.0209	0.0480	0.0801**	0.00377	0.0547**
	(0.0168)	(0.0335)	(0.0213)	(0.0354)	(0.0278)	(0.0267)	(0.0309)	(0.0385)	(0.00391)	(0.0262)
Plant size >=50	0.0851***	0.262***	0.117***	0.0934**	0.0612*	0.0826***	0.141***	0.167***	0.0141	0.145***
	(0.0185)	(0.0348)	(0.0232)	(0.0421)	(0.0316)	(0.0303)	(0.0336)	(0.0440)	(0.00883)	(0.0283)
Part of multi-plant firm	0.0597***	0.178***	0.106***	-0.0319	0.0474	0.0379	0.135***	0.0831**	0.00551	0.121***
	(0.0173)	(0.0310)	(0.0221)	(0.0374)	(0.0289)	(0.0277)	(0.0317)	(0.0373)	(0.00502)	(0.0269)
Foreign firm	0.0400	0.0405	0.0697**	0.0639	0.0350	0.0661	0.0545	0.0527	0.00803	0.0457
	(0.0248)	(0.0421)	(0.0301)	(0.0649)	(0.0449)	(0.0432)	(0.0455)	(0.0514)	(0.00914)	(0.0375)
Public sector	0.0520**	0.0810	0.107***	0.0111	0.0449	0.0689*	0.120***	0.0128	0.0321	0.0896**
	(0.0229)	(0.0510)	(0.0295)	(0.0504)	(0.0381)	(0.0376)	(0.0430)	(0.0565)	(0.0254)	(0.0364)

Work history										
N of job switches	-0.000725	0.00688	0.00196	-0.00131	0.00398	-0.00879	0.00839	0.00819	0.000600	0.00767
	(0.00506)	(0.00957)	(0.00633)	(0.0100)	(0.00836)	(0.00815)	(0.00881)	(0.01000)	(0.000781)	(0.00760)
N of employment months	0.000277	-4.03e-05	0.000572	0.000231	0.000504	0.000383	0.000419	0.000628	-1.16e-05	0.000433
	(0.000307)	(0.000587)	(0.000384)	(0.000514)	(0.000451)	(0.000484)	(0.000504)	(0.000560)	(4.52e-05)	(0.000436)
N of unemployment	-0.000807	-0.00237**	-0.00194***	-0.00120	-0.000373	-0.000577	-0.00197**	-0.00302**	-6.25e-05	-0.00202**
months	(0.000494)	(0.00104)	(0.000663)	(0.00110)	(0.000793)	(0.000767)	(0.000976)	(0.00122)	(0.000146)	(0.000839)
Ever worked in the	-0.0132	-0.0187	-0.0216	-0.0343	-0.00454	-0.0367	0.00651	-0.0571	-0.000938	-0.00901
manufacturing sector	(0.0203)	(0.0348)	(0.0269)	(0.0423)	(0.0330)	(0.0323)	(0.0362)	(0.0376)	(0.00239)	(0.0311)
Ever worked in a firm	0.0371**	0.108***	0.0629***	-0.0145	0.0297	0.0236	0.0836***	0.0895**	0.00231	0.0798***
with over 300 workers	(0.0169)	(0.0293)	(0.0215)	(0.0366)	(0.0288)	(0.0281)	(0.0305)	(0.0358)	(0.00335)	(0.0256)
N of layoff episodes	-0.00769	-0.0197	-0.00584	-0.00621	-0.0270**	-0.00155	-0.0245*	-0.0182	-0.00820	-0.0225*
	(0.00712)	(0.0130)	(0.00924)	(0.0155)	(0.0131)	(0.0112)	(0.0140)	(0.0171)	(0.00502)	(0.0117)
Past average earnings	0.0143*	0.0282*	0.0186*	0.0302*	0.0198	0.0117	0.0263*	0.0222	0.00367	0.0257**
	(0.00821)	(0.0149)	(0.0105)	(0.0162)	(0.0130)	(0.0129)	(0.0143)	(0.0163)	(0.00225)	(0.0124)
Past average earnings	0.0185	0.0304	0.0343*	0.0565*	0.0384*	0.00112	0.0728***	0.0366	0.00319	0.0638***
growth	(0.0135)	(0.0295)	(0.0179)	(0.0331)	(0.0228)	(0.0217)	(0.0254)	(0.0360)	(0.00284)	(0.0227)
Worked over 10 years	0.0455**	0.0810**	0.0385	0.0599	0.0669**	0.0590*	0.0727**	0.0102	0.00308	0.0590**
with current employer	(0.0191)	(0.0370)	(0.0246)	(0.0410)	(0.0317)	(0.0313)	(0.0350)	(0.0400)	(0.00440)	(0.0295)
Had over 3 professions	0.0299	0.0619*	0.0307	0.0319	0.0331	0.0449	0.0319	0.0202	0.00831	0.0337
over working life	(0.0186)	(0.0350)	(0.0244)	(0.0412)	(0.0319)	(0.0302)	(0.0357)	(0.0416)	(0.00721)	(0.0299)
Pseudo R-squared	0.1035	0.2668	0.1580	0.1340	0.1290	0.0611	0.1605	0.2483	0.4239	0.1804
F-test statistic for work history variables	52.27	58.77	70.48	21.72	34.48	7.44	59.66	35.56	24.56	72.61
p-value	0.0000	0.0000	0.0000	0.0166	0.0002	0.0064	0.0000	0.0001	0.0062	0.0000
N	3782	2007	2949	1270	2195	2216	1998	1253	910	2431

Notes: Marginal effects from probit estimations reported. Innovative workplace practices from QWLS 2003 are defined following Kalmi and Kauhanen (2008). 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. The estimates in Columns 1-5 are applied in matching in Panels A-E of Table 2 while the estimates in Columns 6-10 are applied in Panels A-E of Table 3. All models include 13 unreported industry dummies. Robust standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Innovative workplace practices as determinants of earnings: baseline specifications.

HIM practice	OLS	ATT	OLS (conditional on common support)
Panel A: Any HIM v none (N = 3782)			
Without work history	0.2065***	0.2173***	0.2065***
	(0.0227)	(0.0315)	(0.0227)
With work history	0.1705***	0.1874***	0.1722***
	(0.0220)	(0.0308)	(0.0219)
Panel B: Any PRP v no HIM (N = 2007)			
Without work history	0.2313***	0.2543***	0.2320***
	(0.0230)	(0.0376)	(0.0230)
With work history	0.1887***	0.2361***	0.1882***
	(0.0223)	(0.0399)	(0.0223)
Panel C: Any training v no HIM (N = 2949)			
Without work history	0.2518***	0.2542***	0.2519***
	(0.0216)	(0.0334)	(0.0215)
With work history	0.2093***	0.2269***	0.2065***
	(0.0210)	(0.0350)	(0.0209)
Panel D: Any self-managed teams v no HIM (N = 1270)			
Without work history	0.2076***	0.2130***	0.2088***
	(0.0353)	(0.0602)	(0.0352)
With work history	0.1652***	0.1588***	0.1645***
	(0.0340)	(0.0610)	(0.0339)
Panel E: Any information sharing v no HIM (N = 2195)			
Without work history	0.2039***	0.2312***	0.2021***
	(0.0272)	(0.0466)	(0.0272)
With work history	0.1667***	0.2010***	0.1668***
	(0.0262)	(0.0430)	(0.0262)

Notes: The outcome is the logarithm of register-based annual earnings (2003). ATTs are calculated based on Kernel matching (Epanechnikov). ATUs and ATEs are reported in the Appendix (Table A4). Matching is performed by using the region of common support for the propensity scores. Caliper is set at 0.001. The number of observations refers to OLS and ATT specifications before imposing the common support condition. Bootstrap standard errors for ATTs (1,000 replications) in parentheses. For OLS robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Innovative workplace practices as determinants of earnings: count specifications.

HIM practice	OLS	ATT	OLS (conditional on common support)
Panel A: 1 HIM practice v none (N = 2216)			
Without work history	0.1580***	0.1451***	0.1574***
	(0.0242)	(0.0378)	(0.0242)
With work history	0.1383***	0.1240***	0.1381***
	(0.0236)	(0.0380)	(0.0237)
Panel B: 2 HIM practices v none (N = 1998)			
Without work history	0.2239***	0.2323***	0.2238***
	(0.0258)	(0.0397)	(0.0257)
With work history	0.1777***	0.2008***	0.1780***
	(0.0254)	(0.0404)	(0.0254)
Panel C: 3 HIM practices v none (N = 1253)			
Without work history	0.3000***	0.3267***	0.3130***
	(0.0289)	(0.0561)	(0.0275)
With work history	0.2558***	0.2360***	0.2558***
	(0.0284)	(0.0600)	(0.0285)
Panel D: 4 HIM practices v none (N = 910)			
Without work history	0.4474***	0.4403***	0.4161***
	(0.0691)	(0.1357)	(0.0639)
With work history	0.3576***	0.3723**	0.2928***
	(0.0669)	(0.1528)	(0.0645)
Panel E: HPWS ("more than one aspect") v none (N = 2431)			
Without work history	0.2469***	0.2657***	0.2469***
	(0.0239)	(0.0363)	(0.0238)
With work history	0.1963***	0.2360***	0.1969***
	(0.0235)	(0.0380)	(0.0234)

Notes: The outcome is the logarithm of register-based annual earnings (2003). ATTs are calculated based on Kernel matching (Epanechnikov). Matching is performed by using the region of common support for the propensity scores. Caliper is set at 0.001. The number of observations refers to OLS and ATT specifications before imposing the common support condition. Bootstrap standard errors for ATTs (1,000 replications) in parentheses. For OLS robust standard errors reported. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Innovative workplace practices as determinants of earnings: specific bundles.

HIM practice	OLS	ATT	OLS (conditional on common support)
Panel A: PRP and training v none (N = 1263)			
Without work history	0.2650***	0.2647***	0.2645***
	(0.0310)	(0.0528)	(0.0311)
With work history	0.2175***	0.2273***	0.2149***
	(0.0319)	(0.0567)	(0.0323)
Panel B: PRP and information sharing v none (N = 974)			
Without work history	0.1731***	0.1978**	0.1609***
	(0.0476)	(0.0929)	(0.0471)
With work history	0.1323***	0.1654*	0.1185**
	(0.0456)	(0.0904)	(0.0466)
Panel C: PRP and self-managed teams v none (N = 882)			
Without work history	0.0398	0.0377	0.0584
	(0.1335)	(0.3263)	(0.1169)
With work history	-0.0406	-0.0806	-0.0875
	(0.1127)	(0.2985)	(0.0652)
Panel D: Training and self-managed teams v none (N = 958)			
Without work history	0.1984***	0.2240**	0.2075***
	(0.0410)	(0.0822)	(0.0377)
With work history	0.1802***	0.2087**	0.1851***
	(0.0391)	(0.0906)	(0.0370)
Panel E: Training and information sharing v none (N = 1332)			
Without work history	0.2417***	0.2416***	0.2453***
	(0.0323)	(0.0629)	(0.0320)
With work history	0.2078***	0.2106***	0.2112***
	(0.0311)	(0.0614)	(0.0310)
Panel F: Self-managed teams and information sharing v none (N = 914)			
Without work history	0.0606	0.0654	0.0665
	(0.1844)	(0.2837)	(0.1882)
With work history	-0.0092	-0.0591	-0.0031
	(0.1813)	(0.2602)	(0.1819)
Panel G: PRP, training and information sharing v none (N = 1113)			
Without work history	0.3014***	0.3358***	0.3084***
	(0.0334)	(0.0672)	(0.0317)
With work history	0.2581***	0.3303**	0.2577***
	(0.0332)	(0.0886)	(0.0319)
Panel H: Training, self-managed teams and information sharing v none (N = 958)			
Without work history	0.2949***	0.2807**	0.3042***
	(0.0577)	(0.1409)	(0.0587)
With work history	0.2708***	0.2770*	0.2795***
	(0.0555)	(0.1452)	(0.0597)

Notes: The outcome is the logarithm of register-based annual earnings (2003). ATTs are calculated based on Kernel matching (Epanechnikov). Matching is performed by using the region of common support for the propensity scores. Caliper is set at 0.001. The number of observations refers to OLS and ATT specifications before imposing the common support condition. Bootstrap standard errors for ATTs (1,000 replications) in parentheses. For OLS 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
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			
N of job switches	1.7816	1.5464	FLEED
N of employment months	102.6729	45.1923	FLEED
N 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
N of layoff episodes	0.3041	0.9464	FLEED
Past average earnings	6.3748	1.5636	FLEED
Past average 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 treatment variables.

HIM indicator	Mean
Baseline specifications (Table 2)	
Any HIM	0.7713
Any performance-related pay	0.3020
Any training	0.5510
Any self-managed teams	0.1071
Any information sharing	0.3517
Count specifications (Table 3)	
1 HIM practices	0.3572
2 HIM practices	0.2996
3 HIM practices	0.1026
4 HIM practices	0.0119
HPWS ("more than one aspect")	0.4141
Specific bundles (Table 4)	
PRP and training	0.1052
PRP and information sharing	0.0288
PRP and self-managed teams	0.0045
Training and self-managed teams	0.0246
Training and information sharing	0.1235
Self-managed teams and information sharing	0.0130
PRP, training and information sharing	0.0656
Training, self-managed teams and information sharing	0.0246

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

Table A3. Test of covariate balancing based on the specification 'any HIM v none'.

Variable	Sample	Mean Treated	Mean Control	% bias	% reduct. of |bias|	t-statistic	p-value
Female	Unmatched	0.5178	0.5291	-2.3		-0.58	0.5590
	Matched	0.5182	0.5252	-1.4	38.1	-0.54	0.5930
Age <=34	Unmatched	0.2641	0.3357	-15.7		-4.11	0.0000
	Matched	0.2646	0.2701	-1.2	92.4	-0.47	0.6410
Age 45-54	Unmatched	0.3065	0.2576	10.9		2.76	0.0060
	Matched	0.3065	0.3152	-1.9	82.1	-0.72	0.4720
Age 55-64	Unmatched	0.1591	0.1713	-3.3		-0.85	0.3940
	Matched	0.1588	0.1565	0.6	81.5	0.24	0.8140
Married	Unmatched	0.7594	0.7191	9.2		2.40	0.0170
	Matched	0.7593	0.7439	3.5	62.0	1.35	0.1780
Secondary education	Unmatched	0.4028	0.5536	-30.5		-7.88	0.0000
	Matched	0.4033	0.4318	-5.8	81.1	-2.20	0.0280
Polytechnic education	Unmatched	0.3134	0.1667	34.9		8.49	0.0000
	Matched	0.3134	0.3090	1.0	97.0	0.36	0.7200
University education	Unmatched	0.1346	0.0525	28.5		6.64	0.0000
	Matched	0.1339	0.1128	7.3	74.4	2.43	0.0150
Union member	Unmatched	0.7988	0.7657	8.0		2.09	0.0370
	Matched	0.7990	0.8095	-2.5	68.3	-1.00	0.3160
Usual weekly hours	Unmatched	34.6060	33.0380	20.6		5.70	0.0000
	Matched	34.6120	34.3970	2.8	86.3	1.22	0.2230
Plant size 10-49	Unmatched	0.3587	0.4173	-12.0		-3.12	0.0020
	Matched	0.3594	0.3442	3.1	74.1	1.21	0.2270
Plant size >=50	Unmatched	0.4394	0.2634	37.5		9.35	0.0000
	Matched	0.4386	0.4553	-3.5	90.5	-1.27	0.2030
Part of multi-plant firm	Unmatched	0.4363	0.3741	12.7		3.24	0.0010
	Matched	0.4355	0.4491	-2.8	78.1	-1.04	0.2980
Foreign firm	Unmatched	0.1063	0.0559	18.5		4.43	0.0000
	Matched	0.1052	0.0928	4.6	75.4	1.58	0.1150
Public sector	Unmatched	0.3725	0.2925	17.0		4.31	0.0000
	Matched	0.3732	0.3625	2.3	86.5	0.85	0.3960
N of job switches	Unmatched	1.7981	1.7366	4.0		1.02	0.3070
	Matched	1.7990	1.7656	2.2	45.7	0.82	0.4110
N of employment months	Unmatched	105.8400	92.4350	29.3		7.70	0.0000
	Matched	105.8000	104.1700	3.6	87.8	1.40	0.1620
N of unemployment months	Unmatched	7.3794	12.8660	-31.6		-8.95	0.0000
	Matched	7.3746	7.9553	-3.3	89.4	-1.54	0.1230
Ever worked in the manufacturing sector	Unmatched	0.2475	0.2471	0.1		0.02	0.9800
	Matched	0.2480	0.2564	-1.9	-1933.3	-0.73	0.4640
Ever worked in a firm with over 300 workers	Unmatched	0.3076	0.2448	14.1		3.55	0.0000
	Matched	0.3068	0.3041	0.6	95.7	0.220	0.8230
N of layoff episodes	Unmatched	0.2689	0.4289	-16.0		-4.35	0.0000
	Matched	0.2695	0.2886	-1.9	88.1	-0.83	0.4080
Past average earnings	Unmatched	6.5117	5.9467	35.6		9.45	0.0000
	Matched	6.5099	6.4844	1.6	95.5	0.65	0.5140
Past average earnings change	Unmatched	0.1086	0.1252	-3.3		-0.86	0.3910
	Matched	0.1093	0.1012	1.6	51.2	0.65	0.5140

Worked over 10 years	Unmatched	0.4329	0.3054	26.6		6.72	0.0000
with current employer	Matched	0.4320	0.4391	-1.5	94.4	-0.54	0.5860
Had over 3 professions	Unmatched	0.1412	0.1445	-1.0		-0.25	0.8050
over working life	Matched	0.1408	0.1507	-2.8	-197.9	-1.07	0.2840

Notes: Industry indicators not reported.

Table A4. Innovative workplace practices as determinants of earnings: decomposing average treatment effect.

HIM practice	ATT	ATU	ATE
Panel A: Any HIM versus none			
Without work history	0.2173***	0.2248***	0.2190***
	(0.0315)	(0.0396)	(0.0272)
With work history	0.1874***	0.1882***	0.1876***
	(0.0308)	(0.0430)	(0.0266)
Panel B: Any PRP v no HIM			
Without work history	0.2543***	0.2933**	0.2713***
	(0.0376)	(0.0546)	(0.0330)
With work history	0.2361***	0.2324**	0.2345**
	(0.0399)	(0.0501)	(0.0320)
Panel C: Any training v no HIM			
Without work history	0.2542***	0.2527***	0.2538***
	(0.0334)	(0.0440)	(0.0289)
With work history	0.2269***	0.1969***	0.2183***
	(0.0350)	(0.0448)	(0.0295)
Panel D: Any self-managed teams v HIM			
Without work history	0.2130***	0.2285***	0.2235***
	(0.0602)	(0.0634)	(0.0489)
With work history	0.1588***	0.2020***	0.1881***
	(0.0610)	(0.0629)	(0.0486)
Panel E: Any information sharing v no HIM			
Without work history	0.2312***	0.1963***	0.2174***
	(0.0466)	(0.0515)	(0.0370)
With work history	0.2010***	0.1615***	0.1854***
	(0.0430)	(0.0521)	(0.0351)

Notes: The outcome is the logarithm of registed-based monthly earnings in 2003. The specifications are the same as those in the second column of Table 2. ATT = Average Treatment effect on the Treated, ATU = Average Treatment effect on the Untreated and ATE = Average Treatment Effect. ATE is weighted average of ATT and ATU. Bootstrap standard errors (1,000 replications) in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix A5. Innovative workplace practices as determinants of earnings: various robustness checks.

Model specification	OLS	ATT	OLS (conditional on common support)
Panel A: Using only past average earnings to describe work history			
Without work history	0.2065***	0.2173***	0.2065***
	(0.0227)	(0.0315)	(0.0227)
With work history	0.1770***	0.1953***	0.1772***
	(0.0218)	(0.0309)	(0.0218)
Panel B: Including socio-economic status in 2000 to describe work history			
Without work history	0.2065***	0.2173***	0.2065***
	(0.0227)	(0.0315)	(0.0227)
With work history	0.1604***	0.1836***	0.1608***
	(0.0221)	(0.0314)	(0.0221)
Panel C: Using the residual from the earnings equation as outcome variable			
Without work history	0.2164***	0.1976***	0.2164***
	(0.0244)	(0.0759)	(0.0244)
With work history	0.1738***	0.1666***	0.1740***
	(0.0239)	(0.0290)	(0.0239)
Panel D: Using self-reported monthly wage from QWLS as outcome variable			
Without work history	0.1501***	0.1750***	0.1504***
	(0.0149)	(0.0263)	(0.0149)
With work history	0.1298***	0.1610***	0.1307***
	(0.0143)	(0.0254)	(0.0143)
Panel E: Using hourly earnings as outcome variable			
Without work history	0.1670***	0.1891***	0.1673***
	(0.0160)	(0.0268)	(0.0160)
With work history	0.1349***	0.1611***	0.1352***
	(0.0153)	(0.0253)	(0.0153)
Panel F: Estimating separately for the highly educated only			
Without work history	0.2212***	0.2663***	0.2193***
	(0.0366)	(0.0314)	(0.0373)
With work history	0.1974***	0.2193***	0.1946***
	(0.0363)	(0.0300)	(0.0365)
Panel G: Estimating separately for the low educated only			
Without work history	0.1972***	0.1823***	0.1972***
	(0.0274)	(0.0312)	(0.0274)
With work history	0.1618***	0.1558***	0.1621***
	(0.0257)	(0.0308)	(0.0257)

Panel H: Estimating separately for those with less than 5 years' tenure			
Without work history	0.1967***	0.2069***	0.1972***
	(0.0373)	(0.0298)	(0.0368)
With work history	0.1756***	0.1971***	0.1721***
	(0.0354)	(0.0309)	(0.0354)
Panel I: Estimating separately for those with more than 5 years' tenure			
Without work history	0.1945***	0.2047***	0.1950***
	(0.0314)	(0.0325)	(0.0314)
With work history	0.1685***	0.1890***	0.1686***
	(0.0301)	(0.0289)	(0.0301)
Panel J: Estimating separately for the bottom half of the 2003 wage distribution			
Without work history	0.1371***	0.1174***	0.1372***
	(0.0313)	(0.0314)	(0.0313)
With work history	0.1204***	0.0927***	0.1204***
	(0.0308)	(0.0301)	(0.0308)
Panel K: Estimating separately for the top half of the 2003 wage distribution			
Without work history	0.0686***	0.0862***	0.0688***
	(0.0150)	(0.0331)	(0.0149)
With work history	0.0589***	0.0819***	0.0592***
	(0.0139)	(0.0307)	(0.0138)
Panel L: Estimating separately for the private sector only			
Without work history	0.1881***	0.2220***	0.1910***
	(0.0235)	(0.0315)	(0.0234)
With work history	0.1556***	0.2051***	0.1561***
	(0.0231)	(0.0300)	(0.0231)
Panel M: Estimating separately for the small plants only			
Without work history	0.2129***	0.2306***	0.2129***
	(0.0304)	(0.0304)	(0.0304)
With work history	0.1697***	0.1878***	0.1695***
	(0.0295)	(0.0318)	(0.0295)
Panel N: Estimating separately for the large plants only			
Without work history	0.1880***	0.2009***	0.1887***
	(0.0285)	(0.0306)	(0.0285)
With work history	0.1723***	0.1914***	0.1707***
	(0.0274)	(0.0308)	(0.0274)
Panel O: Estimating separately for those who have worked 12 months in 2003			
Without work history	0.1777***	0.2043***	0.1766***
	(0.0244)	(0.0304)	(0.0244)
With work history	0.1430***	0.1728***	0.1434***
	(0.0229)	(0.0315)	(0.0229)

Panel P: Using bias-corrected matching			
Without work history	0.2065***	0.2017***	
	(0.0227)	(0.0230)	
With work history	0.1705***	0.1687***	
	(0.0220)	(0.0220)	
Panel Q: Using nearest neighbour matching			
Without work history	0.2065***	0.1869***	0.1953***
	(0.0227)	(0.0302)	(0.0222)
With work history	0.1705***	0.1618***	0.1548***
	(0.0220)	(0.0301)	(0.0210)

Notes: The outcome is the logarithm of register-based annual earnings (2003) except otherwise stated. All robustness checks are based on the specification 'any HIM v none'. In Panel B socio-economic status from 2000 is taken from FLEED. In Panel C the earnings equation from which the residual has been calculated contains the following controls: female, age, married and education. In Panel D the logarithm of self-reported wage from QWLS 2003 is based on the midpoints of monthly wage groups (19 groups). In Panel E the outcome variable is hourly earnings, calculated based on information from LFS. In Panel F the highly educated sample consists of those with at least polytechnic education. In Panel M the small plants are those with less than 50 workers. ATTs are calculated using Kernel matching (Epanechnikov) except in Panel P in which bias-corrected matching method by Abadie et al. (2001, 2011) is applied and in Panel Q in which nearest-neighbour matching (one-to-one matching with replacement) is used. Matching is performed using the region of common support for the propensity scores. Caliper is set at 0.001. Bootstrap standard errors for ATTs (1,000 replications) in parentheses. For OLS robust standard errors reported. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.