OLDER WORKERS' TRAINING OPPORTUNITIES IN TIMES OF WORKPLACE INNOVATION.

ELISABETTA MAGNANI
School of Economics, The Australian School of Business,
The University of New South Wales,
Gate 2, High Street, ASB Building, Kensington, NSW 2052, AUSTRALIA.
Phone number: +61-2-9385-3370, Fax: +61-2-9313-6337, E-mail: E.Magnani@unsw.edu.au

Abstract.

Training (for workers) and innovation (for workplaces) are not free lunches. From the viewpoint of the firm, training is also highly risky, because there is uncertainty over the size of any future returns from employer-provided training. Stylized facts stress that constraints in achieving preferred working hours have major impacts on job satisfaction. Consequently hour constraints may lead to workers' job mobility and older workers' retirement. Firms internalize the risk of workers' mobility by reducing their training investments in these workers. I contrast this model with a signalling model of hour constraints where, in the face of asymmetric information over workers' quality and reliability, and so over profitability of training, workers may trade present hour constraints (at the current wage), for training (and future wage) opportunities. This set of reasoning implies that, empirically, we should observe a positive correlation between training and hour constraints at the individual level. I use two matched employer-employee datasets, for Australia and Canada respectively, to test the competing empirical implications of these two models for the link between hour constraints and training. The main result of this study is that there is little support for hour constraints as a signal of future reliability and productivity. Rather, hour constrained individuals appear to have less chances to receiving training. This result survives a number of robustness exercises that attempt to control for selection on observables and selection on unobservables that determine the hour constraint outcome. Institutional differences in the retirement funding system, and the differential appeal of outside option (the option of exiting the labour force) in Australia and Canada in the two survey years contribute to explain the different patterns of training and hour constraints older workers face in these two countries.

Keywords: Employer-provided training, hour constraints, older workers, technological change, organizational change. JEL codes: J1, J2, J6, O3.

1 Introduction

Population ageing is profoundly changing the overall age profile of the population and the composition of the labour force in OECD countries. In response to these demographic shifts, policies enacted to keep older workers in the labour force will need to operate hand in hand with labour market demand side actions that enhance the productivity of older workers. One of the difficulties that policy is encountering in the process of boosting older workers' labour force participation derives from the relatively narrow range of job opportunities available to them. Older workers are often forced to move across job situations because the characteristics of the job chosen in early years are not suitable anymore (Ruhm, 1990). Furthermore, older workers may want to reduce hours of work to make the transition into retirement smoother (Doeringer, 1990). In fact, the existing literature strongly suggests that retirement behaviour is often a product of labour market rigidities arising from the demand side (Hurd, 1996). As far as productivity enhancing tools are concerned, training plays a central role. It is well established that training activities are one of the largest contributions to firms' fixed costs of employment (Hamermesh and Pfann, 1996; Lynch and Black, 1998). Since it is a fixed costs, training is distributed unevenly among workers (Arulampalam and Booth, 1998). In particular, older workers systematically receive less training (Booth et al., 2002).

This paper links these stylized facts to another well documented trend in the intensity of work. Evidence illustrates that, in the face of rapid technology and organizational change, workers today endure more stress, work faster and more intensively, and put more effort into their jobs than they used to. This often leads to substantial gaps between the current and preferred length of working time, especially among older male workers, as documented in a comparative study for the European Union by Jolivet and Lee (2004) as well as by Stewart and Swaffield (1997) for the UK. Differences in the incidence of hour constraints across various age groups of workers have also been observed in a sample of Australian male employees interviewed within the 7th Wave of the Household, Income and Labour Dynamics in Australia (HILDA) database (Wooden, 2009).

In this paper, I argue that advances in the chances of policy makers to successfully boost older workers' labour force participation and productivity depend on our ability to better understand the connection between training opportunities and hour constraints, and how institutional factors may shape the trade-offs between the two. I first establish a theoretical link between employer-provided training and hour constraints, and then test the model implications for older workers. In doing so, I follow two different lines of investigation. In both instances, training (for workers) and innovation (for workplaces) are not free lunches. From the viewpoint of the firm, employer-provided training is also highly risky because there is uncertainty over the size of any future returns. Such uncertainty may be fuelled, among other things, by workers' hour constraints because job dissatisfaction induces voluntary mobility. The result is a *negative* effect of hour constraints on training opportunities. Also, the better workers' outside labour market opportunities are, the larger is the negative effect of hour constraints on training.

In the alternative scenario, a signalling model of hour constraint determination derives from asymmetric information over workers' quality and reliability (and so over the profitability of training). Workers may trade present working time (at the current wage) for training (and future wage) opportunities. Empirically, we should observe a *positive* correlation between training and hour constraints at the individual level. The trade-off between being hour constrained at the current wage, and higher future wages brought by training, will be more appealing: *(i)* the more effectively hour constraints signals workers' reliability and high future (post-training) productivity, *(ii)* the more training increases future productivity, *(iii)* the lower is the welfare cost of current hour constraints, *(iv)* the less appealing outside (working or non-working) opportunities are. Workers' heterogeneity that derives from observable characteristics may impact on all or some of these factors, providing an possible explanation to the distribution of hour constraints.

To test the relation between technological change, working hours, and training, I use two matched employer-employee data sets, namely the Australian Workplace and Industrial Relations Survey (AWIRS) and the Canadian Workplace and Employee Survey (WES). These databases offer detailed information on employer-provided training, technology and organizational changes around the times of the interview (1995 for AWIRS and 1999 for WES), as well as information on individual workers. Although clear differences in the survey design and in the wording of the questions prevent any possibility of actual international comparisons, the richness of these databases allows me to explore the robustness of my findings on what determines hour constraints and training.

This paper is organized as follows. Section two presents a set of broadly accepted stylized facts, which provide foundations for the analytical frameworks I use to investigate the link between technology change, training and hour constraints. Section three introduces the econometric strategy, describes the two matched employer–employee datasets used for my empirical analysis and discusses the results. Section four offers some conclusive remarks.

1.1 Results and Discussion

The main results can be summarized as follows: Age matters for the chances of experiencing hour constraints, but it does so in rather different ways in Australia and Canada. Specifically, while in Australia, older workers aged 55+ are *less* likely to be hour constrained than younger workers (those aged 25-29), in Canada there is no substantial different between these two age groups. The difference between AWIRS and WES samples of non-production workers is even more striking, with AWIRS non-production workers aged 55+ facing a drop in the risk of hour constraints relative to the age group 25-29, while WES non-production workers are more likely to face hour constraints relative to the reference group. A second important result is that there is no evidence that hour constraints endogenously emerge as a result of technology change. However, there is evidence that education, labour market assimilation and features of organizational change such as the increased practice of outsourcing at the workplace level, increase the chances of workers' hour constraints. Finally, estimates of a bivariate probit model of joint determination of the two outcomes indicates that the presence of hour constraints negatively impacts on the likelihood that a worker receives employer-provided training.

This last result, which addresses the focal question of this paper, survives a number of robustness exercises. In the first instance I perform a test of the hypothesis of "reverse causation" between hour constraints and training. Under this hypothesis, working hours respond to training expenditure because an employer's ability to set working hours may help in reducing the fixed costs (per employee) of training. The Canadian WES offers the opportunity to test this alternative explanation of a link between employer-provided training and workers' hour constraints. Importantly, the formal rejection of this reverse causation hypothesis strengthens the causal interpretation of my main result, a negative impact of hour constraints on workers' training opportunities.

I test the robustness of my results to the hypothesis that some observable characteristics drive the selection of those workers who are constrained in their working time. Propensity Score Matching (PSM) results indicate that the negative effect of hour constraints on training may be limited to Australia, where the favourable phase in the business cycle and the superannuation system have contributed to possibly more appealing outside opportunities for constrained workers than in Canada. Furthermore, PSM results indicate that the negative effect of hour constraints on training is larger in the age group 15-44 than in the age group 45+. Finally, the negative impact of hour constaints on training survives different hypotheses concerning the correlation across unobservable factors driving the two outcome specifications, for training and hour constraints, respectively.

2 Hour Constraints and Training: Stylized Facts

In terms of population size, GDP per capita, economic structure, import/export of technology, natural resource availability and trade composition it is hard to find two more similar countries than Canada and Australia. Economic policy in the 1990s also showed remarkable analogies as both countries underwent a major restructuring of their economies. Australia went through an extended series of labour market reforms with the expressed scope of increasing labour productivity often at the expense of regulation and protection surrounding employment (Campbell and Brosnan, 1999); Canada implemented the Free Trade Agreement with the United States. Doubtless the deep economic restructuring of these two countries has had substantial effects on labour productivity and utilization in both countries.

Importantly for the interpretation of some of my results, Canada and Australia also differ in terms of the business cycle in the survey year. For example, employment growth lagged the recovery of the economy after the recession in the early 1990s, with unemployment ranging from 7 percent to 15.5 percent in the various Canadian provinces in the late 1990s. Conversely, for Australia, 1995 is a year of continuing growth at unprecedented rates (between 4 and 5 percent in the period 1994–1997). Also, the Canadian and Australian performances in the 1990s differed significantly in terms of trends in working hours. Average working time stayed constant in Australia in the 1988-2000 period following a rapid rise in the early 1980s, while Canada witnessed an increasing trend in working hours in the period 1995-2000.

In analyzing the link between hour constraints and training opportunities in Australia and Canada, I rely on the following stylized facts:

1. *Training opportunities are unevenly distributed across workers* (Zeytinoglu et al., 2007; Bassanini et al., 2005; Booth et al., 2002; Sousa-Poza and Henneberger, 2000).

2. *Individuals differ widely in their quitting propensities.* As amply discussed in Booth et al. (2002), studies using individual-level surveys suggest that heterogeneity in quit rates can be captured by differences in individual-specific characteristics only in part.

3. *Substantial gaps between current and preferred length of working time exist and are widespread* (see Table 2, Bassanini et al., 2005). Stewart and Swaffield (1997) document substantial differences in the incidence of hour constraints across various age groups of workers. In particular, the percentage of workers stating that they would prefer to work fewer hours is monotonically rising with age.

4. *Hour constraints are a primary cause of job dissatisfaction* (Oswald, 1997). In some countries (e.g., the US) a downward sloping trend in job satisfaction has been reported, raising the important question of what may drive this trend and its overall consequences.

5. *Hour constraints trigger between-employer mobility.* Working hours have a significant impact on job satisfaction, motivation and retention of employees. The evidence in support of this statement is abundant and compelling (e.g., Altonji and Paxson, 1992; Clark, 2001; Cully et al., 1998).

6. *Hour constraints trigger older workers' exit from the labour force or mobility towards 'bridge' jobs to retirement* (e.g., Ruhm, 1990; Euwals, 2001; 1994; Maestas, 2004). The lack of opportunity for part-time and flexible-hours work at many establishments induce older workers' labor market withdrawal, while the abolition of minimum hour constraints reduces full retirement (Gielen, 2009; Gustman and Steinmeier, 1984; Blau and Shvydko, 2007).

6. *Overtime positively correlates with future promotions in hierarchies.* In this light, present hour constraints may arise from the investment character of overtime (e.g., Booth et al., 2003) and from the perceived signalling effects of hours of work (Anger, 2008).

These stylized facts illustrate the complex relationship that may exist between hour constraints, labour market opportunities and ageing. In the next sections, I model this trade-off in the face of technological and organizational change that makes employer-provided training necessary.

2.1 Training and hour constraints in a stationary environment

I begin by modelling the employment relationship as a long run equilibrium where the extensive margin of employment (number of workers) and the intensive margin of employment (working hours) are set to maximize long-run profits. I characterize a steady-state where actual hours h equals workers' desired hours h^* only in case of no mobility or search costs. In the most general case, this steady-state equilibrium predicts a negative impact of hour constraints on training. I then contrast this model with another one where the employment contract changes in the face of a technological shock, to which the employer has to respond with (additional) employer-provided training (next section). Hour constraints in the form $(h - h^* > 0)$ endogenously emerge so that workers can signal to employers the profitability of employers' investment in employer-provided training.

As in Magnani (2003), the representative firm produces output Y by means of the production function $Y = F(E; K, \Delta)$, where E represents skilled workers. Training transforms unskilled workers N into skilled labour E. As in Hoon and Phelps (1992), the firm's employment level of skilled labour E is the solution of a dynamic optimization problem that consists of maximizing the expected present discounted value of its cash flows (expression (1)) when internal skilled labour E is employed, subject to the law regulating the relationship between skilled labour E and unskilled labour N

$$\max_E S_0 = \int_0^{\infty} [F_t(E, \Delta; K) - W_t E_t] \exp(-rt) dt \tag{1}$$

$$s.t.\ dE/dt = N_t - q_t E_t \tag{1a}$$

where K is capital, Δ is a productivity parameter, W_t is the internal skilled wage, q is the quitting rate of skilled labour E and r is the exogenously determined interest rate.

Assuming that production technologies are Constant Returns to Scale (CRS) for ease of exposition, we define $k = K/E$. Let $f(.)$ indicate output per skilled worker. With long-term contracts, the steady state value λ^E that the manufacturing firm attributes to a skilled worker E depends on the flow of profits the firm earns after deducting wage and per unit training costs. Thus, as in Hoon and Phelps (1992), in a steady-state the value that an employer attributes to a skilled worker is defined by the following expression

$$\lambda^E = \frac{MP^E - W}{r + q} \tag{2}$$

where $MP^E = [f(k_t, \Delta) - k_t f'(k_t, \Delta)]$ is the marginal product of skilled labour and W is the internal skilled wage.

Expression (2) should clarify that the decision of entering into a long-term relationship with a worker positively correlates with the productivity of internal labour E and with its skill, and negatively correlates with a worker's quitting propensity for any (exogenously given) internal skilled wage W and market interest rate r.

To optimally choose the intensive margin of employment, namely working hours h, I draw upon the stylized fact five above and assume that $q = q(|h - h^*|)$, with $q'(.) > 0$ for W sufficiently rigid, which implies that $\lambda^E = \lambda^E(h)$. Since (2) expresses steady state conditions, we can write $n_t = \overline{n}$. Under these conditions, the intensive margin of employment h solves the following constrained maximization problem

$$\max_h \frac{MP^E(h) - W}{r + q} \tag{3}$$

$$s.t. \quad h \leq h^{\max} \tag{3a}$$

$$q = q(|h - h^*|), \text{ with } q'(.) > 0 \text{ for } W \text{ sufficiently rigid} \tag{3b}$$

$$h^* = \arg\max U(C, T - h) \tag{3c}$$

Expression (3a) introduces the constraints imposed by a legal maximum number of hours; expression (3b) imposes a positive relationship between hour constraints $|h - h^*|$, i.e., the distance between employers' chosen hours h and workers' preferred hours h^*, and quitting probability for a wage W sufficiently rigid; expression (3c) relates the individual preferred hours h^* to his/her permanent utility from consumption and leisure $U(C, T - h)$. I express the f.o.c. of maximization problem (3)-(3c) as follows:

$$\frac{\partial \lambda_{Et}}{\partial h} = \frac{1}{(r+q)^2}\left\{(r+q)\frac{\partial[f(k_t,\Delta)-k_t f'(k_t,\Delta)]}{\partial h}-\frac{\partial W}{\partial h}\right\}- \qquad (4)$$
$$-\frac{1}{(r+q)^2}\lambda^E\frac{\partial q(.)}{\partial h}=0$$

It is clear that longer working hours may negatively affect productivity, potentially require higher wages and may increase the chances of a worker's voluntary mobility. Convexity assumptions guarantee that there is an equilibrium level of hours, say h^F , which is the optimal intensive margin of employment that the firm sets. Abstracting from search costs and other market imperfecction, which may inhibit a perfect match (Sousa-Poza and Henneberger, 2000), and assuming workers can move to find employment elsewhere or to exit from the labour force, this will imply that $h^F = h^*$.

In summary, by expression (2) individuals may be differently valuable to the firm, depending on their trustworthyness, i.e., their propensity to quit. The optimal setting of the intensive margin of employment, primarily working hours, implies that *(i)* some workers, depending on the type of market imperfection and search costs they face, may be hour constrained even in the long run, and *(ii)* hour constraints will have a negative impact on the chances of receiving training.

2.2 Working hours and training in the face of technology shocks and asymmetric information.

To study the effect of hour constraints on training I allow for the possibility, explored in Sousa-Poza and Henneberger (2000) and Anger (2008), that working hours are used as a screening device. let assume that in the long run equilibrium $h^F = h^*$ and no hour constraints exist. In this section I allow for endogenous determination of hour constraints and training opportunities in the face of technology shocks the disturb that long-run training path outlined above. I investigate a firm's response to technological shocks in the face of asymmetric information over the future returns from any re-training of employees. Figure 1 below summarizes the sequence of events.

$Here\ Figure\ 1$

I assume that workers know about their own post-training productivity more than their employers (asymmetric information). To extract information about workers' post-training reliability and productivity, an employer may ask employees to work longer hours than the preferred hours h^*. Clearly, to signal to the employer her reliability and the productivity of the training the worker may receive, a worker will accept to work longer hours in the present (at the current value of wage W_t) to enjoy a higher level of post-training consumption. In other words, working hours $h^{**} > h^*$ signal a high employee's productivity to employers. As Anger (2008) clearly explains in the case of uncompensated overtime, the negative relationship between the cost of working time and the post-training value of a worker is a necessary condition for the working hours signalling model that I draw below.[1]

To be more specific, I will show that in the face of technological shocks, but before any training occurs, longer working hours and the consequent hour constraints will endogenously emerge. Formally, as in the canonical "take it or leave it" hours model, the employer sets working hours h with $h > h^*$ with the following workers' maximization problem in mind

$$\begin{aligned}
\max|_h U_t &= U(C_t, T_t - h_t, E(C_{t+1})) && (5)\\
s.t. h_t &\leq h^{\max} && (5a)\\
C_t &\leq W_t h_t && (5b)\\
E(C_{t+1}) &\leq \tau(h_t)W_{t+1}h_t + (1-\tau(h_t))W_t h_t && (5c)\\
C_{t+1} &> C_t \text{ if productivity increases with training} && (5d)\\
U(C_t, T - h_t, E(C_{t+1})) &\geq U_{outside} \text{ a participation constraint at time t} && (5e)
\end{aligned}$$

where $U(.)$ is utility at time t, which depends on leisure $(T - h_t)$, current consumption C_t and future consumption C_{t+1}. Note that $C_{t+1} > C_t$ if a worker's receives training, but its expected value at time t depends on the probability of receiving training $\tau = \tau(h_t)$, with $\tau'(.) > 0$, which positively responds to the "signalling" effect of working hours h_t. The first order condition of a worker's maximization problem is thus:

$$-U_h + U_{C_t} W_t + U_{C_{t+1}}(W_{t+1} - W_t)\tau'(.) \geq 0 \qquad (6)$$

The solution h^{**} to the maximization problem (5)-(5e) above has two important implications. First, expression (6) for the first order condition clearly states that the optimal level of hours h^{**} incorporates the effect of working hours on the expected returns from future training, namely $U_{C_{t+1}}(W_{t+1} - W_t)\tau'(.)$, which is the wage gain from retraining $(W_{t+1} - W_t)$ weighted by the marginal change in terms of probability of receiving training $\tau'(.)$ and by the marginal utility of future consumption $U_{C_{t+1}}$. This expected return from future training is what makes expression (6) different from the expression that defines the steady-state level for the worker's preferred hours h^* in (3c). Secondly, expression (6) also indicates that failure to take into

[1] It is not difficult to think of situations where such a condition is not satisfied. Family and caring responsibilities are example of factors that can substantially push the cost of long working time upwards, without necessarily affecting the post-training value of a worker. In all these cases, clearly the signalling model fails to be a reasonable explanation for hour constraints.

account the signalling effect of hours would amount to working hours h^{**} satisfying the following inequality condition: $-U_h + U_{C_t} W_t > 0$: working time h^{**} is too long (leisure time is too short). In other words, at the given current wage W_t (and ignoring the intertemporal effect of longer hours) working time is too long and workers are hour constrained. This consideration is important because in survey databases (such as the Australian AWIRS or the Canadian WES, among others) it is usual practice to frame the question of hour constraints in reference to the current wage only[2]. As Lang and Kahn (1998) and Sousa-Poza and Henneberger (2000) have emphasized, slight changes in the phrasing of questions can lead to significant changes in the obtained results.

Note that the consideration of the signalling effect of working hours implies that, if the post-training productivity is high and the value of signalling is positive and higher than the disutility derived from longer working time, a worker will respond to the employer's demand for longer hours h^{**} for a given level of current wage W_t by staying with the current employer rather than quitting. This is an example of separating equilibria, where distinct types of employees choose different strategies. Thus, the persistence of an employment relationship, despite the presence of hour constraints at a given wage W_t, delivers two important pieces of information to the firm, namely loyalty to the employer and a higher post-training productivity. This argument establishes a *positive relationship* between hour constraints and training opportunities. More specifically, in the face of technology shocks, the signalling-through-hour-constraints argument has the following implications:

(i) hour constraints are disproportionately observed among those workers who are likely to have a high post-training productivity;

(ii) the use of hours as a signalling device is less likely if the current external option $U_{outside}$ is appealing;

(iii) hour constraints respond to technology shocks;

(iv) the probability of training *positively* responds to a worker's hours.

The next section will use two employer-employee databases to investigate the empirical relationship between hour constraints and training opportunities. Implications *(i)* and *(ii)* derived from my simple theoretical frameworks call for an exploration of the distribution of hour constraints in a cross section of workers differ-

[2] Note that this worker is also likely to answer positively to the typical "hour constraint" question: "Would you prefer to work less/more hours at the current wage rate if this change leads to a change in salary?" For example, the Canadian WES questionnaire asks the following WES employee survey (p.6): "Thinking about the total number of hours you usually work per week, would you, at the same hourly wage rate, prefer to work:

1 The same number of hours for the same pay? ——> Go to Question 13

2 Fewer hours for less pay?

3 More hours, for more pay? ——> Go to Question 12 (c)"

entiated by age, family situation, labour marker opportunities and outside options. In particular, if outside opportunities are rosier for senior workers in some countries than in others, these country-specific differences could be relevant and contribute to explaining the trade-off between hours and training that older workers face in workplaces affected by technology change. The argument *(iii)* above requires the testing of whether technological change at the workplace level increases workers' chances of being constrained in their working time. The prediction states in point *(iv),* which clearly differentiates the two theoretical arguments' on the effect of hour constraints on training, is the focus of my empirical analysis.

3 The Empirical Strategy and the Data

To test the implications of my model for the relationship between hour constraints and training I use two matched employer–employee surveys, namely the Canadian Workplace and Employee Survey (WES-1999)) and the Australian Workplace Industrial Relations Survey (AWIRS-1995). These two surveys are quite similar in terms of target populations, sample design and survey objectives, as discussed in Appendix A. Most importantly, considerable work has been devoted to making them comparable in terms of variables (see Appendix B for details). Despite this, these two datasets still present a number of differences that prevent me from carrying out a true comparative analysis. For this reason I limit the use of the WES database to an exploration of the robustness of my findings vis-a-vis the impact of competitiveness, innovation, technology use and human resource management on training and hour constraints.

Despite the differences in the question designs in AWIRS and WES, the indicator variable *training* measures employer-provided workers' training that occurred in the last 12 months. The AWIRS-1995 employee questionnaire asks the following question: "*Has your employer provided you with any training to help you do your job over the last 12 months?*" A similar question is asked by the employee survey in WES-1999: "*Did you receive any job-related classroom training related to your job that was provided by your employer (over the past 12 months)?*" Clearly, the training questions in the two surveys are different. However, in both WES and AWIRS samples I refer to employer-provided training. See Appendix B for details on construction of this variable.

Sample restriction strategies have been used to allow for indentification of the focal relationship. From the sample of workers aged 15 and plus extracted from the two databases, I only exclude those employed on a part-time basis, since part-time employees are usually not candidates for training (and often are involuntary parttimers). Similarly, I exclude those working on fixed contract because they are not typically candidates for training. Note that neither group is large; for example, fixed term contract workers represent only about 9% of the full AWIRS sample. Also, the populations covered in the two surveys are somewhat different (Australia excludes small businesses and includes public sector employees, Canada does the opposite). Appendix A further details the sampling design and the use of weights in WES and AWIRS. Given the nature of the AWIRS-1995 database and the complex sample design, I use complex sample design procedures to reduce the risk of a distorted view of the population and to obtain information about the populations from which the various samples are drawn.

A few caveats apply to my empirical analysis. Clearly, matched employer-employee data allow for the solution of a number of identification problems arising whenever workplace-specific factors are correlated with individual-specific determinants of a given outcome (Hamermesh, 2008). However, neither AWIRS nor WES link subsequent workers' interviews. Consequently, the mobility aspects of my argument, as developed in the previous section, cannot be directly tested. Also, by using two surveys, namely AWIRS-1995 and WES-1999, I do not have a chance to control for unobserved heterogeneity, both at the firm-level and at the worker's level. Secondly, as the training variables in the Australian AWIRS are categorical, no information is available on the intensity of training (i.e. the number of hours devoted to training, the number of employees concerned, or the amount of training expenditure). However, the WES survey provides information on a workplace training expenditure.

The unconditional means derived from both WES and AWIRS databases show that sizeable fractions of the full populations of workers would like to work less (*Happy with less hours=1*). The probability of this kind of hour constraint increases with age, from 18.8% in the age range 15-44 to 19.8% in the age group 45+ in the AWIRS samples, from 10.8% in the age range 15-44 to 12.7% in the age group 45+ in the WES samples (see Table 1a and Table 1b for details). Tables 1a and 1b also show that training declines with age, from 56% declaring to have received training in the age group 15-44, to 47% in the age group 45+ in AWIRS, and from 63% to 57% when we go from the age group 15-44 to the age group 45+ in the WES data.

3.1 Technology and organizational change in workplace organization. Comparing WES and AWIRS.

Often workplace innovation involves more than one aspect and the various aspects of technological and organizational change are determined by complementarities and synergies (Lynch, 2007). For this reason, it is important to measure the complex interaction between technological change and organizational change and their relationship to training. The richeness of both databases in capturing the various faces of workplace changes is very useful in this respect. In particular, I rely on the following questionnaire items:

1. *Organizational Restructuring.* The variable (*Org Restruct=0,1)* takes value one if a major reorganization of workplace structure (for example, changing the number of management levels, restructuring whole divisions or sections) has occurred in the past 12 months.

2. *Task Restructuring.* A number of questions in the two datasets investigate the nature of major changes to the way workplaces function and how employees do their work (for example, changes in the range of tasks done, changes in the type of work done). These questions lead to the construction of the indicator variables *(Task Restruct=0,1).*

3. *No. of casual workers increased.* It takes value one if a workplace has experienced greater reliance on temporary workers in the last 12 months.

4. *No. of outside contractors (outsourcing) increased,* which takes value one if the use of contractors has increased in the last 12 months.

To measure technological change at the workplace level I use the following indicator variables:

5. *Technological benchmarking.* A positive answer to the question: "Does this workplace engage in technological benchmarking?" translates into a positive value to the dummy (*Wp Tec. Bench.).*

6. *New office technology.* An indicator variable *(Office tech)* takes value one if computer technology that is not used by production workers has been introduced in the workplace in the survey period.

7. *New machinery.* A dummy variable takes value one when there has been an introduction of new machinery in the reference period, zero otherwise. Note that *(New machinery)* is constructed to indicate computer technology or new machinery that is used only by production workers.

Clearly, the technological change questions in the two surveys are different (Australia asks about new office technology while Canada asks about computer-controlled or computer-assisted technology, specifically mentioning examples in retail and manufacturing processes; Australia asks about the previous two years, Canada about the previous year). Appendix B discusses in detail comparability issues between WES and AWIRS measures of workplace organizational and technological innovation.

Tables 1a and 1b, which report the summary statistics for AWIRS and WES samples, respectively, clearly illustrate that the processes of technological change in Australia and Canada differ sharply. If we consider the full samples, Tables 1a and 1b reveal a more intense adoption of office technology and new machinery in Australia than in Canada, where other forms of organizational change, such as "task restructuring", "organizational restructuring" and "technology benchmarking" as defined above, dominate instead.

The AWIRS summary statistics across the three main samples (workers of all ages, workers aged 15-44 and workers aged 45 and plus) in Table 1a clearly indicate that workplace-specific characteristics related to the intensity of technological change are not dramatically different across the three age groups. Consequently, it can be argued that, whatever is the sorting process that governs the allocation of workers into workplaces, this process does not appear to be related to the intensity of organizational and technological change. The only relevant differences across the age groups are the relatively higher proportion of centralized bargaining agreements and downsizing events occurring in workplaces where workers aged 45 and plus are employed. The differences I observe across the age groups in the WES samples are more marked (see Table 1b). For example, centralized bargaining is more common in workplaces where older workers rather than younger workers are; in fact 33% of WES older workers are in workplaces where there is some centralization in bargaining as opposed to 22% of workers aged 15-44). Task restructuring, organizational restructuring and an increased use of casual workers are more common in Canadian workplaces employing workers aged 45 and plus. However, these differences are not sharp, again supporting the idea that, although I cannot rule out the possibility of matching between employees and workplaces, such processes must be either slow or of limited intensity.

3.2 Workers' training and the distribution of training opportunities

To clarify the link between hour constraints and training in times of technological change, I start with some empirically tractable research questions. Does technological/organizational change increase the need for employer-provided training? How are training opportunities distributed in a sample of workers who differ by age? In particular, how does technological change impact training for older versus younger workers? To explore these questions I estimate a latent variable model as follows:

$$\begin{aligned} Training_{it} &= \begin{matrix} 1 \text{ if } T^*{}_{it} \geq 0 \\ 0 \text{ otherwise} \end{matrix} \\ T^*{}_{it} &= g(X^1_{it}, WP^1_{it}) + \varepsilon_1 \end{aligned} \tag{7}$$

This equation specifies the event of employer-provided training as a function of a latent dependent variable $T^*{}_{it}$ that depends on individual-specific characteristics for individual i, namely X^1_{it}, and workplace characteristics WP^1_{it}, primarily organizational and technological innovation. The vector X^1_{it} contains information on age, gender, education, a quadratic in tenure with the current employer. This vector also includes information about a worker's integration in the domestic labour market, which I measure by a set of three variables, namely "*Years since migration*" (*Yrs since im)*, whether a person is born in the country considered (*Local born)* and "*Labour market assimilation*" *(Lm assimil)* as proxied by the language spoken at home.[3]. Workplace-specific characteristics WP^1_{it} are: firm's size, government or non-government type, profit or non-profit objective of the firm, whether there is a central bargaining agreement in place in the workplace (*Centr Barg Agr).* To control for product market competition, I distinguish between import competition (*Import comp=0,1),* and domestic competition, through a series of indicator variables (*Dom: intense; Dom: strong; Dom: moderate; Dom: some;* the omitted indicator is for limited domestic competition). The last set of workplace specific characteristics refers to the occurrence of technological change and organizational change in the last two years as described above.

Tables 2a and 2b, for AWIRS and WES, respectively, report the marginal effects of right hand side variables on the probability of a worker's training. Table 2a clearly illustrates that training opportunities differ by workers' age. The marginal effect of being 55+ on the probability of receiving training in this Australian dataset is *(-16.4%)* relative to the group of workers aged 25-29 and *(-16%)* relative to the group of workers aged 45-49 (last column). A worker's gender appears to be important with male workers receiving more training (a rise of about *(5%)* in the sample of workers aged 45+). Individual-specific characteristics, particularly education and tenure, increase the chances of receiving training in both samples of workers (15+) and in the sample of older workers (45+). Clearly, training is not equally distributed among production and non-production workers, but rather it is clearly skewed towards workers in non-production jobs, which increase the probability of training by *10-11%* in the three AWIRS samples. As often found in studies on the return to languistic skill, "*Labour market assimilation*" as proxied by the language spoken at home has a sizeable marginal impact on workers' training, ranging from *+5.7%,* in a full sample, to *+16.8%,* in a sample of older workers aged 45+.

Among the workplace characteristics, it is interesting to note that the size of Australian workplaces has a very small impact (and usually it is non-statistically significant) on training, although it reduces training opportunities for older workers in the AWIRS sample. Table 2a also reports a positive impact of import competition and of domestic competition on workers' training.

Turning to the impact of technological and organizational change on workers'

[3] For Australia: "Labour market assimilation"=1 if English, 0 otherwise. For Canada, "labour market assimilation"=1 if English or French, 0 otherwise.

training, Table 2a illustrates that both the introduction of office technology *"Office Tech"* and the workplace's committement to investment in new technology, as indicated by the dummy variable for technology benchmarking "*Wp Tec. Bench.*", have a significant and expectedly positive impact on training, although this may vary depending on the age group considered. For example, while the introduction of new office technology increases the chances of training by *3%* in a full sample of workers, this is mostly due to increased training opportunities for younger individuals, those aged (15-44), as the introduction of new office technology has no effect on training for older workers. Instead, technological benchmarking appears to benefit training across the three groups of workers, with older workers benefiting more than younger workers (*+7%* instead of *+4.3%).* Interestingly, the variables for workplace organizational change are jointly statistically significant at the 99% level in the group of older workers, where task restructuring *(Task Restruct=1)* increases workers' training by almost *4%.*

Interestingly, these effects are also present in samples of Canadian workers as illustrated by Table 2b. Table 2b confirms the negative impact of the age dummy for 55+ on the probability of workers' training *(-21%* relative to the group of workers aged 25-29 and *(-15.6%)* relative to those aged 45-49 in the group of older workers, those aged 45+. The education level, the holding of a non-production job and assimilation in the local labour market, all appear to significantly increase the probability of workers' training. Table 2b confirms the role of market competition for workplace training decisions. The positive impact of import competition combines with a positive impact of the indicator variables for intense and strong domestic competition on older workers' training opportunities, although in general domestic competition has a negative impact on workers' training in the full sample and in a sample of workers aged 15-44.

Technological change, particularly the introduction of new office technology, *Office tech=1,* and the workplace technology benchmarking activities *(Wp Tec. Bench=1*, impacts positively on workers' training in the full sample of Canadian workers, where these two variables increase the chances of workers' training by *6.5%* and *4.6%*, respectively. Howevery, these two variables are not statistically significant in a sample of older workers. Organizational change, particularly the restructuring involving the job and task design as captured by the dummy variable for task restructuring (*Task Restruct=1)*, increases the chances of training by about *9%* in the three age samples in Table 2b for WES.

Overall, these results reinforce the view of training opportunities unequally distributed among younger and older workers, production and non-production jobs and workplaces subject to technology and organizational change.

3.3 The distribution of hour constraints across workers

The first model sketched in the previous section clarifies that in a steady state context, there is no reason for hour constraints to exist in the absence of labour market frictions, as the employer incorporates his/her knowledge of employees' likelihood of quitting in the face of less-than-optimal hours. Hour constraints are more likely among those workers who face high search and mobility costs, should their working time be unsuitable. However, in the context of a signalling model where hours and training respond to technological change, hours may well rise above h^* to play the signalling role discussed above. In the signalling model, hour constraints are more likely to emerge among workers with low costs of overtime and (perspectively) high returns from training.

These considerations are important for three main reasons. First, they motivates the use of an indicator variable for hour constraints ($h^{**}-h^*$) as a dependent variable in my empirical analysis since, assuming that h^* were the preferred hours before the change, the desire to work less at the current level of wage models the change in hours caused by changing conditions (rather than modeling the original employer-employee match). This choice of dependent variable also fits the nature of the Australian and Canadian surveys I use, where workers are asked questions on whether they are happy with the current number of working hours, or whether instead they would like to work less/more hours. This question on whether, at the current level of wage, a worker would like *less hours* is used to construct an indicator variable, "*Happy Less Hours*", which takes value one if less working hours are preferred to the current number and takes value zero if the respondent, individual i, is happy with the current number, or would like to work less hours than the current number. Secondly, the theoretical frameworks presented in section two, clearly have different implications for the distribution of hour constraints in a large sample of workers. This motivates the use of a large set of worker-specific controls, which aim to capture both a worker's skill and potential post-training productivity, as well as a worker's outside options, for example in the case of older workers. Thirdly, the signalling model relies on the responsiveness of hour constraints to workplace-specific variables that capture the extent of technology change. Empirically, I rely on the following probit specification:

$$\begin{aligned} \textit{Happy Less Hours}_{it} &= \begin{matrix} 1 \text{ if } |H^{**}-H^*|_{it} \geq 0 \\ 0 \text{ otherwise} \end{matrix} \\ |H^{**}-H^*|_{it} &= f(X_{it}^2, WP_{it}^2) + \varepsilon_2 \end{aligned} \tag{8}$$

where H^* is the worker's optimal number of hours (see equations 3-3c above) and H^{**} is the employer-set working time. Thus the indicator variable "*Happy Less*

Hours"takes value one if, at the current wage W_t less working hours are preferred, or $|H^{**} - H^{*}|_{it} \geq 0$. Following Stewart and Swaffield (1997), I estimate the probability of hour constraints as dependent on a number of individual-specific factors entering X_{it}^{2}. This vector includes age dummy variables, gender, a quadratic in tenure, a measure of the risk of unemployment (*downsizing*)[4], and dummy variables for educational attainment. A potentially important determinant of the emergence of hour constraints is a worker's integration in the domestic labour market, which I measure by a set of three variables, namely "*years since migration*", whether a person is born in the country considered (*local born),* and "*labour market assimilation*" as proxied by the language spoken at home. Given that I focus on full-time workers, I do not include a variable for actual working time.[5] As in Stewart and Swaffield (1997), I assume that hours of work are correlated with the weekly salary paid, so I control for the individual's weekly gross salary (in ranges). As in Anger (2008) and equally importantly for my argument, controlling for the current wage is a way of separating two different effects of current working hours, namely their productive effect and their signalling effect. Longer working time should be correlated with a higher chance to receive training, independently of whether this extra working time is "productive", or not, if their is a positive signalling effects of longer hours. Lastly, I proxy a worker's sensitivity to hour constraints by including, among the regressors for hour constraints, the number of family dependents differentiated by age (below the age of four, between the age of four and twelve and aged thirteen or older). As emphasized in my modelling in the previous section, I aim to test whether hour constraints endogenously emerge as a direct response to technological or organizational change at the workplace level or in response to competition in the labour markets. All these variables are included in the set of workplaces characteristics WP_{it}^{2}.

Tables 3a and 3b, for AWIRS and WES, respectively, report the marginal effects of right hand side variables on the probability of a worker being hour constrained. These tables illustrate significant differences in the probability of being hour constrained in a set of workers who differ by age. In the full samples of Australian and Canadian workers in Tables 3a and 3b, respectively, the event of hour constraint is less likely among workers aged below 24 relative to the age group 25-29 in both samples. The probability of being hour constrained increases for the central age

[4]To measure the risk of unemployment, we rely on a positive response to the question of whether the WES workplace has downsized as a form of organizational change in the last year. Approximately 20% of the 22,000 employees were in Canadian workplaces that experienced downsizing. AWIRS asks the question of whether the workplace management has downsized/decreased staff in the last two years. Approximately 5% of Australian workplaces experienced downsizing in the last two years.

[5]Sousa-Poza and Henneberger (2000) show cross-country evidence that this variable is only statistically significant in a sample of women, who are more likely to be in part-time employment.

workers relative to those aged 25-29, specifically, workers aged (35-49) in the Australian sample, and workers aged (40-54) in the Canadian sample. This is consistent with evidence for UK workers for whom the age profile in actual hours does not match the age profile in desired hours (Stewart and Swaffield, 1997).

A comparison between Tables 3a and 3b delivers an important result when I consider the marginal effect of older age on the probability of being hour constrained for the age group 55+. While Australian workers (55+) appear to face a *lower* probability of being constrained relative to the central age group 25-29, being 55+ does not significantly impact on the likelihood of this event in sets of Canadian workers. One possible explanation for this pattern relies on the substantially higher gross pension wealth that Australians enjoy at retirement age, compared to the elders in Canadian (OECD 2007, see Table: *Gross pension wealth by sex and earnings,* p. 43). As the discussion I carried out in the previous section has illustrated, the responsiveness of workers' quitting decisions to excessively long hours depends on workers' outside options. These outside options are obviously more appealing in countries where the post-retirement economic prospects are rosier, and in fact these prospects increase the chance that job dissatisfaction caused by hour constraints leads to retirement. This result suggests that institutional differences in the way retirement schemes in Australia and Canada are designed and have performed in the years around the survey dates may indeed affect workers' propensity to retire, particularly in the face of the possibility of being hour constrained.

Among the individual-specific characteristics, both the Canadian and the Australian findings illustrate the importance of labour market assimilation and the non-production nature of the job held for the likelihood of being hour constrained. Labour market assimilation has similar positive effects on the probability of (*Happy Less Hours=1)* in AWIRS and WES samples, (*+6.9%-7.4%* in AWIRS samples, and *+5.7%-7.7%* in WES samples, in Table 3a and Table 3b, respectively). The presence of children, particularly the very young, has usually the expected positive impact on the probability of being hour constrained in a sample of Canadian workers (Table 3b), but it is not statistically significant in a sample of Australian workers (Table 3a).[6] Information about the individual wage is used to construct indicator variables of the appropriate weekly salary range.[7] Wages lower than the reference range ($500-$799

[6] Austen (2005) uses (2003) OECD labour force statistics to highlight the substantial differences in female participation rates in paid work in Canada and Australia (62% and 56%, respectively). This gap in participation rates is substantially larger in samples of women aged 25-39.

[7] I have not pursued the issue of the potential endogeneity of the individual wage in a setting for hour constraints. Stewart and Swaffield (1997) discuss the difficult issue of appropriate instruments for wages in a setting for working hours. Even with instrumenting (education, qualification, firm size, regional age-specific unemployment rates), Stewart and Swaffield (1997) conclude that the wage coefficient in a specification for desired hours is rather insensitive to the instrumenting of the

a week) reduce the chance of of a positive outcome for *Happy Less Hours*, but wages higher than the reference range increase this event. Interestingly, a high education level significantly increases the probility of hour constraints in AWIRS samples, but it does not have any impact in WES specifications for hour constraints.

Importantly, and contrary to what a signalling model would predict, I do not find any evidence that technological change increases the chances of hour costraints. In both AWIRS and WES samples, the three indicators for technology change are statistically non-significant if taken individually. A set of $\chi - squared$ tests of joint significance is reported at the bottom of Tables 3a and 3b, and indicates that technology change variables are not jointly statistically significant.

The workplace-specific indicator variable for *Downsizing* is usually non-statistically significant, but decreases the chance of hour constraints in the AWIRS sample of workers aged 45+ (*-4.6%*), although a production/non-production break in the full sample suggests that this impact is different (and consistently non-statistically significant) in production and non-production workers. Organizational change significantly impacts the chances of hour constraints only in WES samples, where organizational change variables are jointly statistically significant at the 90% and 95% level in a sample of workers of any age and in a sample of those aged 45+, respectively. Changes in a job design (*Task restruct*) reduce the likelihood of hour constraints in samples of prime-age workers, while worforce casualization (*Casuals up)* does so in a sample of older workers. In the WES samples, I find a positive correlation between an intensification of a workplace's practice to outsource part of the operations that were previously kept within the boundaries of the firm (*Outsource up),* and the probability that workers, those of any age and those aged 45+ are hour constrained. The marginal effects are +3.2% and +8.1%, respectively, as Table 3b illustrates. It is interesting that a workplace's practice, such as outsourcing, that potentially increases workers' sense of job insecurity and fear of redundancy (William, 2008), has such a sizeable impact on the chances of hour constraints, particularly among older workers, those who may be more vulnerable to tight labour market conditions prevailing in Canada in the late 1990s.

Both sets of AWIRS and WES estimation results for the probability of *Happy Less Hours* suggest that production and non-production workers substantially differ in terms of chances of being hour constraints (results are available upon request). For example, the probabilities of excessively long working times computed at the AWIRS samples means are 9% and 20%, for production and non-production workers, respectively. In the AWIRS samples, high levels of education increase the chance of hour constraints among non-production workers only. Labour market assimilation matters for both

wage (p. 533).

groups of workers in AWIRS and WES, but the variable *Years Since Immigration* matters for production workers only. Importantly, female workers are substantially more likely to face hour constraints when they hold non-production jobs, but gender appears to be irrilevant in a sample of AWIRS production workers. Most importantly for my focus on older workers, being 55+ reduces the chances of being hour constrained in a sample of AWIRS non-production workers, but it does not have any impact for production workers and it increases the chances of being hour constrained relative to the age group 25-29 by about *4%* in a sample of WES non-production workers.

In summary, I find some evidence that hour constraints are disproportionately observed among those workers who are likely to have a high post-training productivity, primarely workers in non-production/skilled jobs, those with high weekly earnings, well-educated individuals, those who are well integrated in their labour markets. There is evidence that the chances of hour constraints may be negatively affected by good retirement perspectives (as it is for those 55+ in Australia in the survey year), but positively affected by outsourcing practices at the workplace level, particularly in tight labour market conditions. Importantly to shed light on the main question this paper addresses, hour constraints do not appear to respond to technology shocks, and they are not consistently affected by feature of organizational change that go hand in hand with technology change (Linch, 2007).

I now approach the central question of my investigation, whether workers' excessively long working time is positively correlated with training opportunities, as predicted by a signalling model. It is also worth to exploring whether the better post-retirement economic opportunities older workers face in Australia, compared to those in Canada, affect their training opportunities.

3.4 Do hour constraints increase the chance of receiving training?

Is the probability of training positively correlated to a worker's hour constraints? The signalling model sketched in the previous section illustrates that when technology shocks occur, workers face a trade-off between an optimal working time, with less training opportunities, and being hour constrained, but being offered training opportunities. An argument according to which workers accept being constrained in their working time, at the current level of wage, to access better training opportunities implies that, empirically, I should find a positive impact of hour constraints on training opportunities, once the endogeneity of hour constraints is taken into account. Hence, the following econometric exercise has one main objective, namely to measure the effect that hour constraints have on workers' training opportunities.

Econometrically, I investigate the relationship between two individual-level dependent variables, namely the categorical variable for the occurrence of hour constraints and the categorical variable for the training event. The core of the empirical analysis is thus a two equation probit model. I employ an endogenous treatment model where the first dependent variable (the dummy variable for the emergence of a positive response to the question related to an excessive working time or *Happy Less Hours=1*), appears as an independent variable in the second equation for the probability of training. This specification produces the following recursive, simultaneous equation model:

$$\begin{aligned} Training_{it} &= \begin{array}{c} 1 \text{ if } T^{*}{}_{it} \geq 0 \\ 0 \text{ otherwise} \end{array} && (9) \\ T^{*}{}_{it} &= g(X^{1}_{it}, WP^{1}_{it}, Hour\ Constraints) + \varepsilon_1 \\ Happy\ Less\ Hours_{it} &= \begin{array}{c} 1 \text{ if } |H^{**} - H^{*}|_{it} \geq 0 \\ 0 \text{ otherwise} \end{array} && (10) \\ |H^{**} - H^{*}|_{it} &= f(X^{2}_{it}, WP^{2}_{it}) + \varepsilon_2 \end{aligned}$$

where the two identically distributed errors are correlated, or $Corr(\varepsilon_1; \varepsilon_2) = \rho$ (Greene 2003), to take into account the possibility of unobserved factors that impact upon both events, namely training and the emergence of hour constraints. Unless we find evidence that $\rho = 0$, the probit analysis of single equations will give inconsistent parameter estimates.

Tables 4a and 4b report the coefficients and marginal effects of *Happy Less Hours* estimated by means of bivariate probit models for AWIRS and WES samples, respectively. As clearly illustrated in Greene (1998), the marginal effect of the second outcome variable (*Happy Less Hours)* on the first outcome variable, namely training, needs to be computed as the difference between two conditional probabilities, *P(Y1=1| Y2=1)* and *P(Y1=1| Y2=0).* Also, note that the estimated correlation ρ between the error terms is consistently and statistically significantly negative in all samples. This negative correlations between the error terms $(\varepsilon_1; \varepsilon_2)$ may be due to a workplace's financial constraints that limit the training opportunities offered to the workplace employees. If financial constraints are binding, workers will need to rely more heavily on signalling to receive training. The effect is a $Corr(\varepsilon_1; \varepsilon_2) < 0$. These estimated correlation coefficients provide a foundation for the use of a bivariate probit model instead of a simpler probit model to address my question.

Tables 4a and 4b illustrate that being hour constrained has a large and negative impact on a worker's chances of receiving employer-provided training. All other results reported in Tables 2a and 2b and in Tables 3a and 3b are confirmed (results are available upon request). Interestingly, the effect of hour constraints on training opportunities appears to be larger for workers in prime age than for workers in the full samples, in both AWIRS and WES estimations. Also, this effect is larger in a sample of AWIRS non-production workers compared to a sample of AWIRS production workers.

Taken together these two findings suggest that the negative effect of hour constraints on training may be larger the better outside labour market opportunities workers face. Overall, a finding that hour constraints has a negative effect on training casts doubt on the relevance of the main implication of the signalling model of working hours described in section two. I now proceed by discussing the robustness of my results.

3.5 Robustness exercises.

3.5.1 Propensity Score Matching and the average treatment effect (of hour constraints) on the treated

I start by assuming that the selection of workers into the group of treated, those who face hour constraints, is a result of a selection process driven by observable characteristics, both those that are employer-specific and those that are worker-specific chracteristics (as specified in the probit model of Tables 2a and 2b). Propensity Score Matching (PSM) attempts to overcome the problem of the existence of a selection bias arising from a set of observable characteristics X. The average treatment effect (training) on the treated (D=1) (those workers who are facing hour constraints of the type *Happy Less Hours=1*) could be computed as $E(Y1 - Y0|D = 1) = E(Y1|D = 1) - E(Y0|D = 1)$.

Obviously to carry out this computation I need to construct the counterfactual E(Y0 | D=1) – the outcome participants would have experienced, on average, had they not participated. In other words the focal question that PSM methodology tackles is: what is the effect of hour constraints on observationally "equivalent" workers that only randomly select into the groups of "treated" and "non-treated" individuals? The application of PSM estimation strategies relies on the ability to "construct" the counterfactual. To find a matching-pair for each recipient unit, I consider the two groups of treated and control workers in the region of common support of the propensity score, and then I construct a weighted average of the outcomes of more non-treated workers where the weight given to non-treated worker h' is in proportion to the closeness of the estimated propensity score of h and h'. Operationally, I compute propensity scores $p(x) \equiv \Pr(D = 1|X = x)$ by estimating the probability of (*Happy Less Hours*) as a function of the same large set of factors listed in Tables 3a and 3b[8] Figures 2a-6a and Figures 2b-6b illustrate the

[8]In the selection of the specification we use to compute the ATT of (*Happy Less Hours*) on

distribution of propensity scores in samples of AWIRS workers and WES workers, respectively. Tables 5a–5b illustrates the estimated Average Treatment effects on the Treated (ATT) for AWIRS and WES samples, respectively, with Nearest Neighbor Matching method and Kernel matching method in the top panel and bottom panel, respectively.

Tables 5a and 5b report the estimated ATT resuls. The effect of hour constraints on the probability of training is consistently negative and statistically significant at the 95% level in the full sample of Australian workers, but it is not statistically significant in samples of Canadian workers. Table 5a illustrates that, whatever the matching method used is, the hour constraint event reduces the probability of training by about *5%* in the full sample of AWIRS workers. Kernel matching estimates, reported in the bottom panel of Table 5a, reveal that the negative effect of hour constraints on training is larger in a AWIRS sample of workers in prime age (15-44) compared to older workers (*-5.3% vs. –3.9%*). While there is evidence that the effect of working time constraints may significantly differ in Australian samples of production and non-production workers, I cannot conclude about the direction of this inequality (*-3.3%* vs. *-4.4%* if a Nearest Neighbor Matching method is use; *-8%* vs. *-4.4%*, if a Kernel matching method is used). Importantly however, all these effects are negative and statistically significant, a fact that support the main hypothesis of a negative effect of hour constraints on training opportunities.

It is important to express a significant limitation of this method of analysis. As clearly argued in Siamesi (2001) the Propensity Score Matching method relies on two main assumptions: *(i)* the Conditional Independence Assumption (CIA) holds[9]; *(ii)* the common support assumption[10]. Even with these important caveats in mind, these results offer support to my findings concerning a negative impact of hour constraints on training.

3.5.2 More robustness findings

Clearly, the propensity score matching method is useful to control for selection on observables. In other words, matching can handle non-random selection if all factors affecting selection decision are observed and can be used in the matching

workers' training we are bound to satisfy the common support requirement and the balancing property requirement.

[9]The CIA states that all relevant differences between the group of workplaces that undergo vertical disintegration and the group of workplaces that do not, are captured by a set of observable characteristics Δ, such that the event Y0 is independent from the focal control D, conditional on the propensity $p(x)$, where $p(x) \equiv \Pr(D = 1|\Delta = x)$.

[10]The common support assumption states that in the control group the distribution of the estimated propensity to vertically disintegrate is as similar as possible to the distribution of such propensity in the "treated" group.

equation. If there is a remaining selection on observables and/or unobservables that are correlated with the selection and the outcome variable, then the estimates will be biased. The use of a matched employer-employee database provides an invaluable contribution to the solution of this problem, but up to a certain point. In a panel data framework, the propensity score matching method and the difference-in-difference estimator can be used in combination to control for selection on both observables and unobservables that are inherent in the data. However, AWIRS and WES have a very limited panel structure. To explore the issue of the role of selection on "unobservables", I draw upon Altonji et al., (2005) and Rosenbaum (1995). In Table 6 I display estimates of the marginal effect of the event (*Happy Less Hours=1*) that correspond to various assumptions about ρ, the correlation between the error components in the equation for (*Happy Less Hours*) and *(Training).* I rely on the values of ρ from an unconstrained bivariate probit model (see Tables 4a and 4b) to limit this discussion to negative values of this correlation between unobservables. Thus, the correlation between unobservables in the two outcome specifications is allowed to vary between *(-0.1)* and *(-0.9)* in Table 6.

Table 6 illustrates that the marginal effect of hour constraints on training is consistently negative and robust to changes in the (negative) constrained correlation between error terms in the specifications of the two outcomes variables, in both AWIRS and WES samples. Interestingly, when this negative error correlation increases in absolute value from -0.1 to -0.9, the estimated marginal effect also increases in absolute value. While there is no doubt both worker's unobserved heterogeneity and workplace-specific unobserved heterogeneity may play an important role in determining training and hour constraints outcomes, the negative effect of hour constraints on training persists and it is sizeable even in the case of a low correlation between unobservables. These results suggest that the evidence of a negative effect of hour constraints on training is considerably robust to hypothesis about the role of unobserved factors on both outcome variables.

I further test the robustness of my results by exploring the possibility that the correlation between training and hour constraints is due to "reverse causation": working hours may respond to training expenditure because an employer may attempt to increase working hours to reduce the costs (per employee) of training. Because of employers' management of working times in the face of large training costs I should expect to find a *positive impact* of training expenditure (per employee) on hour constraints, once we control for other firms' and workers' specific characteristics. To test the hypothesis that hour constraints arise endogenously in the face of training investments because of an employer's attempt to reduce per-employee costs, I exploit information on training expenditure contained in the Canadian WES questionnaire, but absent in the Australian AWIRS questionnaire, and construct a measure of training expenditure per employee *(Training expend/E).* The probit regression results for hour constraints (see Table 7) clearly illustrate that training expenditure is not a statistically significant determinant of hour constraints in samples of Canadian workers aged 15-65 and aged 15-44, respectively. After controlling for the same large set of workplace-specific features capturing market conditions that were utilized in the econometric specification illustrated in Table 3b, training expenditure does not impact on workers' chance of being hour constrained in these two samples. In a sample of older Canadian workers (45+), training expenditure per employee is statistically significant, but negatively signed. In short, based on this results, I can rule out the possibility that the correlation between hour constraints and training results from the firm's cost minimizing objectives.

4 Conclusions

Hours of work can play a very important role in a dynamic model of labour supply (Keane, 2009). Hours can be productive in the sense that they allow workers to accumulate human capital. Alternatively, in a signalling model hours can play a non-productive role, as well as a productive one, by signalling employers workers' future productivity, reliability, ambition and profitability that derives from investments in human capital via training. Anger (2008) provides evidence in support of this argument. I contrast a signalling-model of hour constraints with a model where hour constraints reduce, rather than increase, the probability of training, by negatively impacting on workers' job satisfaction and by increasing quitting propensities.

From these two theoretical frameworks I draw implications on *(i)* the distribution of hour constraints in a cross section of workers who differ by age, labour market opportunities and type of job (production and non-production); *(ii)* the effect of technological change on hour constraints and training; *(iii)* the effect of hour constraints on workers' training opportunities. The focal question of whether hour constraints impact on workers' training opportunities is particularly relevant in times of technological change, when indeed the future productivity of all workers in general, and older workers in particular, may require employer-provided training.

I test the empirical relationship between hour constraints and training by using two matched employer-employee data, namely AWIRS-1995 and WES-1999. The main results can be summarized as follows:

(i) Older workers consistently face more limited training opportunities than younger workers (here those aged 25-29), in both Australia and Canada.

(ii) Workers aged 35-49 in Australia, and workers aged 40-54 in Canada are

more likely to experience excessively long working time compared to the reference age group 25-29.

(iii) While in Australia, workers aged 55+ are less likely to experience excessively long working times *(-5%)* than the reference age group (25-29), in Canada workers aged 55+ do not significantly differ in their chances of being hour constrained from the reference age group (25-29).

(iv) Training opportunities indeed respond to technological change, particularly when it is indicated by the introduction of new office technology and new machinery and firms' ongoing commitment to be technology benchmarkers.

(v) Workers' chances of facing excessively long working times do not respond to technology change.

(vi) In both countries, hour constraints are more likely to occur among non-production workers and those well assimilated in the local labour markets. However, in Canada, where the late 1990s are times of tight labour market conditions, hour constraints appear to be unevenly distributed among those workers with young children and those employed in workplaces adopting ousourcing practices.

(vii) I find robust support to my hypothesis that hour constraints negatively impact on workers' training opportunities in all WES and AWIRS samples. Propensity Score Matching results reveal interesting cross-country differences: the effect of hour constraints is negative in all AWIRS samples, but it is nihil in WES samples. These results cast doubt on the signalling model of hour constraints.

Drawing upon these results, two main conclusions need to be emphasized. These findings suggest that better labour market opportunities due to the particular phase in the Australian business cycle, and rosier alternative retirement opportunities that Australian older workers face due to their pension system (superannuation) compared to Canadian older workers, may be responsible for both results *(iii)*, *(vi)* and *(vii)* above, namely a lower probability of hour constraints among Australian older workers relative to the base group of younger workers, an increase in workers' hour constraints in Canada as a response to workplaces' outsourcing, and the robustness of the negative impact of hour constraints on training in Australian samples. Further investigation on the way financial considerations, for example the distribution of wealth and the institutional arrangements governing the provision of social security payments, may impact on older workers' labour market opportunities may be a fruitful direction of future research.

Secondly, hour constraints limit workers' training opportunities, possibly by conveying employers information about the risk of workers' voluntary mobility. Taken together these findings suggest that the most vulnerable groups, e.g., women with family responsibilities, or workers with health constraints, may be facing a double disadvantage, namely higher chances of being hour constrained and more limited training opportunities. Equally important, given evidence of older workers' preferences towards smoothing their transition from the labour force into retirement through a gradual reduction of working hours (Ruhm, 1990), older workers may end up with limited training opportunities if they are constrained to work longer hours than preferred.

Appendix A.

The Canadian WES (1999) and the Australian AWIRS (1995) easily compare in terms of *target populations, sample design* and *survey objectives* as discussed below:
.

1. *Target populations.* The populations covered in the two surveys are somewhat different. Australia excludes small businesses and includes public sector employees. The WES framework is stratified by industry, region, and size. Thus, the AWIRS concentrates on workplaces with 20 or more employees in all states and territories of Australia. The main exclusions are agriculture, forestry and fishing and defence industries.The WES has a broader sample in terms of workplace size. All workplaces were targeted that were operating in Canada in March 1999 and that had at least one paid employee in March 1999 who received a Canada Customs and Revenue Agency T-4 Supplementary form, with the following exceptions: (1) Workplaces in Yukon, Nunavut and Northwest Territories; (2) Workplaces operating in crop production and animal production; fishing, hunting and trapping; private households; religious organizations; and public administration. The WES survey is also more limited in terms of not including public administration. A more detailed WES industry exclusion list is the following: crop production / animal production; fishing, hunting and trapping; religious organizations; private households; federal government public administration; provincial and territorial public administration; local, municipal and regional public administration; Aboriginal public administration; international and other extra-territorial public administration.

2. *Sample design.* There are also strong similarities in terms of sample design. Both datasets are stratified random samples from official workplace registers. The AWIRS sampling frame was stratified on five employment size bands and 18 industry groups, thus providing 90 strata. The workplace response rate was relatively high (80%). Although the unit of observation is the workplace (not a firm), an employee survey collected information regarding the workplaces' employees. The WES framework is stratified by industry (14), region (6), and size (3), which is defined using estimated employment.[11] This process partitions the target population into 252 strata. Thus, the WES is representative of Canadian workplaces at the industry, region, and size breakout level. Estimates based on employees are representative of the total Canadian workforce only. The WES-1999 response rates were: workplace – 95.2%; employee – 82.8%. It is important to stress that due to sampling design, employees are not made representative of the workplace itself in either of the two surveys. Both AWIRS and WES can be used for either workplace or employee levels of analysis and both provide weights for each level. In our analysis, we focus on the employee level with workplace control variables. Thus we use the employee weights and use the workplace identifier to control for cluster design effects.

[11] The size stratum boundaries are typically different for each industry/region combination. The cut-off points defining a particular size stratum are computed using a model-based approach. The sample is selected using Neyman allocation.

3. *Survey objectives.* Both AWIRS and WES examine the way in which employers and their employees respond to the changing competitive and technological environment. Information on workforce characteristics and job organization is important in understanding the dynamics and nature of the workplace. Lastly, the fact that both AWIRS and WES were originally designed with the scope of investigating the organizational and technological change at the *workplace level* that are the focus of this paper, is reflected in a number of analogies in the questionnaire design and in the definition of the main variables.

4 *Period of reference in the two surveys.* The WES' reference period is April 1, 1998-March 31, 1999 for most questions. The AWIRS' reference period is mainly the last two years.

Appendix B.

WES-1999 and AWIRS-1995 are highly comparable in terms of the survey questions on workplace organizational and technological innovation, as discussed below:

1. *Job Training:* The AWIRS has a more general conceptualization of training than WES. The AWIRS variable E16 asks: "Has your employer provided you with any of the following training OVER THE LAST 12 MONTHS? Clearly, here training includes any training which is provided or paid for by an employer, whether a worker did it at his/her workplace or somewhere else. Three options are provided: E16A: "Employer provided job training last year"; E16B: "Employer provided OH&S training last year" (training in occupational health and safety); and E16C: "Employer provided English training last year" (training to read or write English). For the AWIRS I have focused only on E16A and excluded E16B and E16C. Thus, the AWIRS concept of training is "job training". The WES asks two types of training questions: on-the-job and classroom: JOBTR - Received on-the-job training: In the past twelve months, have you received any informal training related to your job (that is on-the-job training)? And, CLASSTR - Received classroom training: In the past twelve months, have you received any classroom training related to your job? Where classroom training includes: - All training activities which have a pre-determined format, including a pre-defined objective - Specific content - Progress may be monitored and/or evaluated. To match the AWIRS with the WES data, the WES on-the-job and classroom training responses are combined into job training. This was done by coding sub-category responses to the on-the-job and classroom training groups of variables so that (1) occupational health and safety, environmental protection and (2) literacy or numeracy items for each type of training could be omitted (ie. this makes the conceptualization "identical" to the AWIRS, from the perspective that both AWIRS and WES conceptualization is general training that can include on-the-job and classroom training, and can be referred to as "employer-provided job-training".

2. *Organizational Restructuring.* AWIRS questions related to "the introduction of major reorganization of workplace structure (for example, changing the number of management levels, restructuring whole divisions, sections and so on)" lead to the construction of a dummy variable (*Org Restruct=0,1)*, which takes value one if the workplace manager answered positively to the question above. In the WES, the employer survey Question 20 asks whether a workplace experienced any of the following forms of organizational change between April 1, 1998 and April 1, 1999: *(i)* Increase/decrease in the degree of centralization, *(ii)* Downsizing (reducing the number of employees on payroll to reduce expenses; *(iii)* Reduction in the number of managerial levels (de-layering). The variable (*Org Restruct=0,1)* takes value one if any of these events has occurred in the past 12 months.

3. *Task Restructuring.* In the AWIRS, the question on "major changes to how non-managerial employees do their work (for example, changes in the range of tasks done, changes in the type of work done)" leads to the construction of the indicator variables *(Task Restruct=0,1)*, a positive answer assigning a value of one to the dummy variable. In the WES, the employer survey Question 20, asks whether a workplace experienced (i) Greater integration among different functional areas; (ii) Greater reliance on job rotation, multi-skilling; (iii) Implementation of total quality management; (iv) Re-engineering (redesigning processes to improve performance and cost). A positive answer to any of the above assigns a positive value to the dummy variable *(Task Restruct).*

4. *Use of casual workers.* Some of the variables asked at the managerial level can be directly related to the use of alternative employment arrangements. The AWIRS section on organizational changes asks whether there has been an increase in the number of casual workers employed in the last 12 months. Similarly, the Canadian WES asks if the workplace has experienced greater reliance on temporary workers in the last 12 months. Positive answers to these questions is indicated by a positive value of the indicator variable (*Casuals up=0,1*).

5. *Use of outside contractors (outsourcing).* In this case, as in the previous case, AWIRS and WES questionnaires are highly comparable. A positive answer to the question on whether there has been "Greater reliance on external suppliers of products /services (outsourcing)" assigns value one to the indicator variable *(Outsource up=0,1).*

To measure technological change at the workplace level, I use the following indicator variables:

6. *Technological benchmarking.* The WES employer survey, Section G, Question 34, asks the following: "Please rate the following factors with respect to their relative importance in your workplace general business strategy: (i) Undertaking research and development; (ii) Developing new products / services; (iii) Developing new production / operating techniques." If any of these options is evaluated as important, very important or crucial, the dummy variable (*Wp Tec. Bench)* takes value one, zero otherwise. The AWIRS asks about *changes that happened in the last 2 years in this workplace.* In particular, a positive answer to the question "Does this workplace engage in technological benchmarking?" translates into a positive value for this indicator variable.

7 *Other technology variables: New office technology.* The AWIRS question asks: "Which, if any, of the changes listed, happened at this workplace in the last two years? (1) duoftec – bf1a: "Introduction of major new office technology (not just routine replacement)"; (2) dunewmach –bf1b: "Introduction of major new plant, machinery or equipment (not just routine replacement)". Notice that the AWIRS does not necessarily imply a mutually exclusive use of the technology across occupation groups. While the Australian AWIRS asks about new office technology, the Canadian WES asks about computer-controlled or computer-assisted technology, specifically mentioning examples in retail and manufacturing processes.

   Because the AWIRS technological change questions are more restrictive than the WES, I narrowed the focus of the WES by coding the new office technology variable (computer-controlled or computer-assisted technology, and other technologies or machinery) to involve non-production workers only, such as managers, professionals, technical/trades, marketing/sales, clerical/administrative, and other occupation groupings. In the WES employer survey, question 45 (a) asks "Between April 1and March 31, has your workplace implemented computer-controlled or computer-assisted technology? For example, retail scanning technologies, manufacturing robots, optical, laser, audio, photographic technologies, hydraulic or other mechanical technologies." Question 45 (b) asks about the groups that use this technology. An indicator variable "*New office technology*" is identified by the fact that this computer technology is not used by production workers.

8 *Other technology variables: New machinery.* Section G of the WES employer survey asks Question 46 (a): "Between April 1, and March 31, has your workplace had any major implementations of other technologies or machinery?" The AWIRS asks whether there has been any implementation of new machinery. Positive answers to these questions amount to a value of one of the indicator variable "*New machinery.*" The new machinery variable was identified as a technological change used by production workers with no trade/certification. Notice that neither variable excludes the possibility that the technology is used by the other occupation groupings. Thus, the specification is about identification and not exclusion.

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Table 1a: AWIRS samples: Summary Statistics: Workers aged 15 and plus (Full sample)

variable	mean	sd	se(mean)	p50	N	p10	p90
			Dependent variables				
otjtraining	.6162326	.4863236	.0045461	1	11444	0	1
happylessh~s	.1909129	.3930377	.0036741	0	11444	0	1
			Workers' variables				
age15_20	.0336901	.1804381	.0016867	0	11444	0	0
age21_24	.1030437	.3040292	.002842	0	11444	0	1
age30_34	.1521181	.359151	.0033573	0	11444	0	1
age35_39	.1492552	.3563554	.0033312	0	11444	0	1
age40_44	.1409357	.3479704	.0032528	0	11444	0	1
age45_49	.1233958	.3289054	.0030746	0	11444	0	1
age50_54	.0852391	.2792493	.0026104	0	11444	0	0
age55plus	.0635863	.2440252	.0022811	0	11444	0	0
male	.6269134	.483646	.004521	1	11444	0	1
yrs since im	5.10705	10.713	.1001434	0	11444	0	25
local born	.7495219	.4333073	.0040505	1	11444	0	1
lm_assimil	.935797	.245125	.0022914	1	11444	1	1
tenure	6.421904	6.775861	.0633396	4	11444	0	16
non-prod job	.7599419	.4271372	.0039928	1	11444	0	1
High sc grad	.1851945	.3884723	.0036314	0	11444	0	1
Some post sec	.1674618	.373404	.0034905	0	11444	0	1
Under-grad	.1452395	.3523575	.0032938	0	11444	0	1
Diploma	.095442	.2938373	.0027467	0	11444	0	0
Post-grad	.1053648	.3070363	.0028701	0	11444	0	1
children_0_4	.1930308	.5064013	.0047338	0	11444	0	1
children_4_12	.3279144	.7058586	.0065983	0	11444	0	1
children_>=13	.294645	.6872335	.0064241	0	11444	0	1
wage_lt200	.0116488	.107304	.0010031	0	11444	0	0
wage_200_499	.2848837	.4513788	.0042194	0	11444	0	1
wage_80~1099	.1713164	.3768016	.0035223	0	11444	0	1
wage_gt1100	.0708191	.2565336	.002398	0	11444	0	0
		Workplace variables and Market competition					
workpl. size	294.3914	501.7999	4.690743	109	11444	33	748
harvest	.0181372	.1334535	.0012475	0	11444	0	0
manufactures	.2347912	.4238868	.0039624	0	11444	0	1
con_tran_ut	.1484544	.3555654	.0033238	0	11444	0	
Import comp	.2178217	.4127836	.0038586	0	11444	0	1
Dom: intense	.2652751	.4414989	.0041271	0	11444	0	1
Dom: strong	.2462877	.4308669	.0040277	0	11444	0	1
Dom: moderate	.0655756	.2475496	.0023141	0	11444	0	0
Dom: some	.0138884	.117033	.001094	0	11444	0	0
		Workplace vars: Unionization, technology and organizational change					
Centr_bar_agr	.4930944	.4999742	.0046737	0	11444	0	1
office tech	.4846222	.4997853	.0046719	0	11444	0	1
new machinery	.3188642	.4660566	.0043566	0	11444	0	1
wp tec. bench	.6349495	.4814654	.0045007	1	11444	0	1
task restruct	.4001253	.4899449	.0045799	0	11444	0	1
org restruct	.4954556	.5000012	.0046739	0	11444	0	1
casuals up	.1384944	.3454332	.0032291	0	11444	0	1
outsource up	.0530495	.2241421	.0020952	0	11444	0	0
downsizing	.0539852	.2259983	.0021126	0	11444	0	0

AWIRS samples: Summary Statistics: Workers aged 15-44

variable	mean	sd	se(mean)	p50	N	p10	p90
			Dependent variables				
otjtraining	.6327802	.4820762	.0052924	1	8297	0	1
happylesshour	.1881797	.3908792	.0042912	0	8297	0	1
			Workers' variables				
age15_20	.0464129	.2103904	.0023098	0	8297	0	0
age21_24	.1419575	.3490276	.0038318	0	8297	0	1
age30_34	.2095646	.4070224	.0044685	0	8297	0	1
age35_39	.2056205	.4041787	.0044372	0	8297	0	1
age40_44	.1941592	.3955759	.0043428	0	8297	0	1
age45_49	0	0	0	0	8297	0	0
age50_54	0	0	0	0	8297	0	0
age55plus	0	0	0	0	8297	0	0
male	.6153266	.4865473	.0053415	1	8297	0	1
yrs since im	3.622622	8.484747	.093149	0	8297	0	17
local born	.7847282	.4110355	.0045125	1	8297	0	1
lm_assimil	.9368191	.2433028	.0026711	1	8297	1	1
Tenure	4.899931	4.999845	.0548903	3	8297	0	12
Non-prod job	.7754432	.4173153	.0045815	1	8297	0	1
High sc_grad	.1938954	.3953717	.0043406	0	8297	0	1
Some Post-sec	.1670802	.3730699	.0040957	0	8297	0	1
under-grad	.1590652	.3657589	.0040155	0	8297	0	1
Diploma	.0987096	.2982897	.0032747	0	8297	0	0
Post-grad	.1038379	.3050685	.0033492	0	8297	0	1
children_0_4	.255883	.5713354	.0062724	0	8297	0	1
children_4_12	.3870239	.7557642	.0082971	0	8297	0	2
children_>=13	.212244	.5819476	.0063889	0	8297	0	1
wage_lt200	.0136357	.1159803	.0012733	0	8297	0	0
wage_200_499	.2998185	.4582059	.0050304	0	8297	0	1
wage_80~1099	.1645054	.3707559	.0040703	0	8297	0	1
wage_gt1100	.0578893	.233548	.002564	0	8297	0	0
			Workplace variables and Market competition				
Workpl. size	287.5838	490.3747	5.383535	107	8297	33	731
harvest	.0166781	.1280698	.001406	0	8297	0	0
manufactures	.2307543	.4213409	.0046257	0	8297	0	1
con_tran_ut	.1470686	.3541956	.0038885	0	8297	0	
Import comp	.2209702	.4149254	.0045552	0	8297	0	1
Dom: intense	.2777841	.4479333	.0049176	0	8297	0	1
Dom: strongp	.2537412	.4351775	.0047776	0	8297	0	1
moderatecomp	.0651632	.2468284	.0027098	0	8297	0	0
somecomp	.011499	.1066217	.0011705	0	8297	0	0
			Workplace vars: Unionization, technology and organizational change				
Centr_bar_agr	.4687814	.4990545	.0054788	0	8297	0	1
office tech	.4881455	.4998896	.005488	0	8297	0	1
new machinery	.3163209	.4650678	.0051057	0	8297	0	1
wp tec. bench	.6305329	.4826896	.0052992	1	8297	0	1
task restruct	.3984207	.4896024	.0053751	0	8297	0	1
org restruct	.4897863	.4999258	.0054884	0	8297	0	1
casuals up	.1380352	.3449577	.0037871	0	8297	0	1
outsource up	.0525798	.2232066	.0024505	0	8297	0	0
downsizing	.049211	.2163213	.0023749	0	8297	0	0

AWIRS samples: Summary Statistics: Workers aged 45 and plus

variable	mean	sd	se(mean)	p50	N	p10	p90
Dependent variables							
otjtraining	.5724144	.494807	.0088204	1	3147	0	1
happylesshour	.1981502	.3986693	.0071066	0	3147	0	1
Workers' variables							
age15_20	0	0	0	0	3147	0	0
age21_24	0	0	0	0	3147	0	0
age30_34	0	0	0	0	3147	0	0
age35_39	0	0	0	0	3147	0	0
age40_44	0	0	0	0	3147	0	0
age45_49	.4501473	.4975876	.0088699	0	3147	0	1
age50_54	.3109517	.4629566	.0082526	0	3147	0	1
age55plus	.2319626	.4221523	.0075252	0	3147	0	1
male	.6575954	.4745896	.00846	1	3147	0	1
yrs since im	9.037808	14.38086	.2563519	0	3147	0	34
local born	.6562956	.4750193	.0084677	1	3147	0	1
lm_assimil	.9330904	.249905	.0044548	1	3147	1	1
tenure	10.45208	8.8845	.1583743	8	3147	1	24
Non-prod job	.7188944	.4496104	.0080147	1	3147	0	1
High Sc grad	.1621547	.3686512	.0065715	0	3147	0	1
Some post-Sec	.1684724	.3743447	.006673	0	3147	0	1
Under-grad	.108629	.3112226	.0055478	0	3147	0	1
Diploma	.0867895	.2815711	.0050193	0	3147	0	0
Post-grad	.1094079	.3121999	.0055652	0	3147	0	1
children_0_4	.0265985	.1816684	.0032384	0	3147	0	0
children_4_12	.1713927	.5210007	.0092873	0	3147	0	1
children_>=13	.5128427	.8722056	.0155479	0	3147	0	2
wage_lt200	.0063876	.0796792	.0014204	0	3147	0	0
wage_200_499	.2453365	.4303549	.0076715	0	3147	0	1
wage_80~1099	.1893518	.3918501	.0069851	0	3147	0	1
wage_gt1100	.1050572	.3066758	.0054668	0	3147	0	1
Workplace variables and Market competition							
Workpl. size	312.4179	530.5268	9.457121	115	3147	34	764
harvest	.0220012	.1467104	.0026152	0	3147	0	0
manufactur~g	.2454809	.4304403	.007673	0	3147	0	1
con_tran_u~s	.1521242	.3591983	.006403	0	3147	0	
Import comp	.2094846	.4070054	.0072552	0	3147	0	1
Dom: intense	.2321516	.4222723	.0075274	0	3147	0	1
Dom: strong	.2265508	.418666	.0074631	0	3147	0	1
Dom: moderate	.0666678	.2494854	.0044473	0	3147	0	0
Dom: some	.0202155	.1407591	.0025092	0	3147	0	0
Workplace vars: Unionization, technology and organizational change							
Centr_bar_agr	.5574751	.4967646	.0088553	1	3147	0	1
off tech	.4752924	.4994685	.0089035	0	3147	0	1
new machinery	.3255988	.4686726	.0083545	0	3147	0	1
wp tec. bench	.6466444	.4780879	.0085224	1	3147	0	1
task restruct	.4046391	.4909001	.0087507	0	3147	0	1
org restruct	.5104677	.4999699	.0089124	1	3147	0	1
casuals up	.1397103	.3467414	.006181	0	3147	0	1
outsource up	.0542933	.2266316	.0040399	0	3147	0	0
downsizing	.0666272	.2494149	.004446	0	3147	0	0

Table 1b: WES samples: Summary Statistics: Workers aged 15 and plus (Full sample)

variable	mean	sd	se(mean)	p50	N	p10	p90
			Dependent variables				
otjtraining	.5333145	.4989028	.00372	1	17986	0	1
happylesshour	.1147168	.3186887	.0023763	0	17986	0	1
			Workers' variables				
age15_20							
age21_24							
age30_34	.1425733	.3496469	.0026071	0	17986	0	1
age35_39	.1688305	.3746125	.0027933	0	17986	0	1
age40_44	.1675195	.3734494	.0027846	0	17986	0	1
age45_49	.1422654	.3493318	.0026048	0	17986	0	1
age50_54	.1118495	.31519	.0023502	0	17986	0	1
age55plus	.0895199	.2855006	.0021288	0	17986	0	0
male	.5404384	.4983759	.0037161	1	17986	0	1
yrs since im	4.102246	10.23251	.0762983	0	17986	0	20
local born	.8165957	.3870084	.0028857	1	17986	0	1
lm_assimil	.9246271	.2639994	.0019685	1	17986	1	1
Tenure	8.904214	8.320459	.0620412	6	17986	1	21
Non-prod job	.9443257	.229298	.0017098	1	17986	1	1
High Sc grad	.1826195	.386365	.0028809	0	17986	0	1
Some Post-Sec	.294564	.4558592	.0033991	0	17986	0	1
Under-grad	.1545384	.3614741	.0026953	0	17986	0	1
Diploma	.2014254	.4010763	.0029906	0	17986	0	1
Post-grad	.0697601	.2547494	.0018995	0	17986	0	0
children_0_4	.1725238	.4466451	.0033304	0	17986	0	1
children_4_12	.3446729	.6720051	.0050108	0	17986	0	1
children>=13p	.3920626	.7780665	.0058016	0	17986	0	2
wage_80~1099	.2108856	.4079487	.0030419	0	17986	0	1
wage_gt1100	.1769935	.3816738	.0028459	0	17986	0	1
			Workplace variables and Market competition				
Workpl. size	427.3904	1226.101	9.14237	50	17986	6	1058
harvest	.0174852	.1310743	.0009774	0	17986	0	0
manufactures	.2141249	.4102253	.0030588	0	17986	0	1
con_tran_ut	.1843979	.3878191	.0028918	0	17986	0	1
Non_profit	.1784597	.3829099	.0028552	0	17986	0	1
Import comp	.4296101	.4950342	.0036912	0	17986	0	1
Dom: intense	.2117181	.4085374	.0030462	0	17986	0	1
Dom: strong	.3570007	.4791283	.0035726	0	17986	0	1
Dom: moderate	.2878001	.45275	.0033759	0	17986	0	1
Dom: some	.1853439	.3885871	.0028975	0	17986	0	1
			Workplace vars: Unionization, technology and organizational change				
centr_bar_agr	.2566236	.436782	.0032568	0	17986	0	1
office tech	.1321036	.3386127	.0025249	0	17986	0	1
new machinery	.0703653	.2557687	.0019071	0	17986	0	0
wp tec. bench	.730375	.4437773	.003309	1	17986	0	1
task restruct	.5928105	.4913244	.0036635	1	17986	0	1
org restruct	.4671664	.4989347	.0037203	0	17986	0	1
casuals up	.1010144	.3013562	.0022471	0	17986	0	1
outsource up	.1961092	.3970632	.0029607	0	17986	0	1
downsizing	.1991559	.3993767	.0029779	0	17986	0	1

WES samples: Summary Statistics: Workers aged 15-44

variable	mean	sd	se(mean)	p50	N	p10	p90
			Dependent Variables				
otjtraining	.5641961	.4958831	.0045984	1	11629	0	1
happylesshour	.1083479	.3108327	.0028824	0	11629	0	1
			Workers' Variables				
age15_20							
age21_24							
age30_34	.2172164	.4123689	.003824	0	11629	0	1
age35_39	.2572203	.4371206	.0040535	0	11629	0	1
age40_44	.255223	.4360053	.0040432	0	11629	0	1
age45_49	0	0	0	0	11629	0	0
age50_54	0	0	0	0	11629	0	0
age55plus	0	0	0	0	11629	0	0
male	.5421249	.4982438	.0046203	1	11629	0	1
yrs since im	2.677595	7.589632	.07038	0	11629	0	11
local born	.8472915	.3597218	.0033358	1	11629	0	1
lm_assimil	.9283142	.2579781	.0023923	1	11629	1	1
tenure	6.456184	5.833402	.0540942	5	11629	1	15
non-prod job	.9445167	.2289309	.0021229	1	11629	1	1
high sch grad	.1795923	.383864	.0035596	0	11629	0	1
some post sec	.2922638	.4548224	.0042177	0	11629	0	1
under-grad	.1634137	.3697586	.0034288	0	11629	0	1
diploma	.2265517	.418618	.0038819	0	11629	0	1
post-grad	.0568379	.2315426	.0021471	0	11629	0	0
children_0_4	.2489982	.5208253	.0048297	0	11629	0	1
children_4_12	.448858	.7382849	.0068463	0	11629	0	2
children_>=13	.2904088	.6724643	.0062359	0	11629	0	1
wage_80~1099	.2048612	.4036175	.0037428	0	11629	0	1
wage_gt1100	.1427927	.3498764	.0032445	0	11629	0	1
			Workplace variables and market competition				
Workpl size	344.136	1012.375	9.387938	43	11629	6	831
harvest	.0174314	.1308779	.0012137	0	11629	0	0
manufactur~g	.217919	.4128498	.0038284	0	11629	0	1
con_tran_u~s	.1941191	.395538	.0036679	0	11629	0	1
non_profit	.1415086	.3485604	.0032323	0	11629	0	1
import comp	.4456958	.4970637	.0046094	0	11629	0	1
DOm: intense	.2291214	.4202856	.0038974	0	11629	0	1
Dom: strong	.3692309	.4826173	.0044754	0	11629	0	1
Dom: moderate	.3034707	.4597765	.0042636	0	11629	0	1
Dom: some	.1974402	.3980844	.0036915	0	11629	0	1
			Workplace vars: unionization, technology and organizational change				
centr_bar_agr	.2207041	.4147392	.003846	0	11629	0	1
office tech	.1347252	.3414445	.0031663	0	11629	0	1
new machinery	.0724191	.2591918	.0024035	0	11629	0	0
wp tec. bench	.7383513	.4395512	.004076	1	11629	0	1
task restruct	.5813234	.4933634	.004575	1	11629	0	1
org restruct	.4549276	.4979857	.0046179	0	11629	0	1
casuals up	.0900304	.2862376	.0026543	0	11629	0	0
outsource up	.1958244	.396851	.0036801	0	11629	0	1
downsizing	.186202	.3892864	.0036099	0	11629	0	1

WES samples: Summary Statistics: Workers aged 45 and plus

variable	mean	sd	se(mean)	p50	N	p10	p90
			Dependent variables				
otjtraining	.4743286	.4993798	.0062633	0	6357	0	1
happylessh~s	.1268818	.3328667	.0041749	0	6357	0	1
			Workers' variables				
age15_20	0	0	0	0	6357	0	0
age21_24	0	0	0	0	6357	0	0
age30_34	0	0	0	0	6357	0	0
age35_39	0	0	0	0	6357	0	0
age40_44	0	0	0	0	6357	0	0
age45_49	.4140017	.4925875	.0061781	0	6357	0	1
age50_54	.3254896	.4685943	.0058772	0	6357	0	1
age55plus	.2605087	.4389467	.0055054	0	6357	0	1
male	.537217	.4986522	.0062542	1	6357	0	1
yrs since im	6.823423	13.54295	.1698584	0	6357	0	31
local born	.7579646	.4283493	.0053724	1	6357	0	1
lm_assimil	.9175846	.2750182	.0034493	1	6357	1	1
tenure	13.58011	10.15711	.1273926	11	6357	2	28
non-prod job	.9439609	.2300153	.0028849	1	6357	1	1
high sch grad	.1884015	.3910632	.0049048	0	6357	0	1
some post sec	.2989577	.4578373	.0057423	0	6357	0	1
under-grad	.137586	.3444921	.0043207	0	6357	0	1
diploma	.1534327	.3604324	.0045206	0	6357	0	1
post grad	.0944425	.2924663	.0036682	0	6357	0	0
children_0_4	.0264527	.1729781	.0021695	0	6357	0	0
children_4_12	.1456724	.4612652	.0057853	0	6357	0	1
children_>=13	.586228	.9168646	.0114995	0	6357	0	2
wage_80~1099	.2223927	.4158862	.0052161	0	6357	0	1
wage_gt1100	.2423193	.4285201	.0053746	0	6357	0	1
			workplace variables and market competition				
workpl size	586.4117	1542.371	19.34473	79	6357	6	1398
harvest	.0175881	.1314589	.0016488	0	6357	0	0
manufactures	.2068778	.405099	.0050808	0	6357	0	1
con_tran_ut	.1658298	.3719571	.0046652	0	6357	0	1
non_profit	.2490389	.4324904	.0054244	0	6357	0	1
import comp	.3988853	.4897076	.006142	0	6357	0	1
Dom: intense	.1784767	.3829436	.004803	0	6357	0	1
Dom: strong	.3336404	.4715501	.0059143	0	6357	0	1
Dom: moderate	.2578683	.4374955	.0054872	0	6357	0	1
Dom: some	.162239	.3686989	.0046243	0	6357	0	1
			workplace vars: unionization, technology and organizational change				
centr_bar_agr	.3252322	.4684984	.005876	0	6357	0	1
office tech	.1270961	.3331067	.0041779	0	6357	0	1
new machinery	.0664422	.2490731	.0031239	0	6357	0	0
wp tec. bench	.7151399	.4513833	.0056613	1	6357	0	1
task restruct	.6147517	.4866922	.0061042	1	6357	0	1
org restruct	.4905433	.4999499	.0062705	0	6357	0	1
casuals up	.1219947	.3273054	.0041051	0	6357	0	1
outsource up	.1966532	.3974991	.0049855	0	6357	0	1
downsizing	.2238988	.4168878	.0052287	0	6357	0	1

Table 2a. Probit Specification for Training: marginal effects[1]

Sample: AWIRS Australian Workers

	All workers		Workers Aged 15-44		Workers Aged 45+	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
age15_20	0.074**	(0.033)	0.083***	(0.031)	-	-
age21_24	0.017	(0.023)	0.029	(0.021)	-	-
age30_34	-0.040**	(0.020)	-0.021	(0.017)	-	-
age35_39	-0.035	(0.022)	-0.013	(0.018)	-	-
age40_44	-0.043*	(0.022)	-	-	-	-
age45_49	-0.006	(0.023)	-	-	-	-
age50_54	-0.039	(0.026)	-	-	-0.031	(0.024)
age55plus	-0.164***	(0.031)	-	-	-0.159***	(0.030)
Male	0.008	(0.013)	-0.004	(0.015)	0.049**	(0.024)
Yrs since im	0.0005	(0.001)	0.0007	(0.001)	0.0004	(0.0002)
Local born	0.025	(0.026)	0.034	(0.031)	0.023	(0.051)
Lm_assimil	0.057**	(0.027)	0.019	(0.030)	0.168***	(0.045)
Tenure	-0.011***	(0.002)	-0.011***	(0.003)	-0.012***	(0.004)
$(tenure)^2$	0.0003***	(0.00009)	0.0003	(0.0002)	0.0003***	(0.0001)
Non-prod job	0.111***	(0.017)	0.115***	(0.020)	0.103***	(0.028)
Hs_grad	0.042***	(0.016)	0.044**	(0.018)	0.034	(0.033)
Some post sec	0.005	(0.016)	0.011	(0.019)	-0.009	(0.032)
Under-grad	0.155***	(0.018)	0.152***	(0.020)	0.157***	(0.036)
Diploma	0.098***	(0.020)	0.097***	(0.023)	0.095**	(0.040)
Post-grad	0.113***	(0.021)	0.101***	(0.024)	0.138***	(0.040)
Workpl size	-0.00001	(0.00001)	0.000002	(0.00001)	-0.00006***	(0.00002)
Import comp	0.056***	(0.020)	0.056**	(0.022)	0.070**	(0.032)
Competition_m	0.133***	(0.050)	0.124**	(0.055)	0.163**	(0.075)
Dom: Intense	0.015	(0.044)	0.026	(0.049)	-0.013	(0.065)
Dom: Strong	0.013	(0.043)	0.023	(0.049)	-0.008	(0.064)
Dom: Moderate	0.053	(0.045)	0.096**	(0.047)	-0.059	(0.077)
Dom: Some	0.065	(0.058)	0.151***	(0.056)	-0.066	(0.093)
Centr. Barg. Agr.	0.015	(0.014)	0.009	(0.017)	0.029	(0.024)
Office tech	0.032**	(0.015)	0.032*	(0.017)	0.031	(0.025)
New mach	-0.011	(0.016)	-0.014	(0.017)	0.004	(0.025)
Wp Tec Bench	0.043***	(0.015)	0.033*	(0.017)	0.070***	(0.025)
Task restruct	0.005	(0.015)	-0.008	(0.016)	0.042*	(0.024)
Org restruct	0.018	(0.015)	0.016	(0.016)	0.012	(0.023)
Casuals up	-0.022	(0.021)	-0.025	(0.024)	-0.011	(0.032)
Outsource up	0.020	(0.040)	-0.006	(0.042)	0.082	(0.052)
Observations	11444		8297		3147	
Wald chi2(.)	408.82***		262.98***		207.60***	
Joint significance of TC variables[2]	chi2(2)=4.70*		chi2(2)=3.80		chi2(2)=1.65	
Joint significance of OC variables[3]	chi2(5)=10.49*		chi2(5)=5.88		chi2(5)=15.67***	

[1] ***,**,* indicates statistical significance at the 1, 5 and 10% levels, respectively.

[2] Technological change variables are: "office tec." and "new machinery".

[3] Organisational change variables are: "wp tec. Bench", "task restruct", "org restruct", "casual up", "outsource up".

Table 2b. Probit Specification for Training: marginal effects[1]

Sample: WES Canadian Workers

	All workers		Workers Aged 15-44		Workers Aged 45+	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
age15_20	0.099	(0.090)	0.102	(0.085)	-	-
age21_24	-0.031	(0.047)	-0.027	(0.043)	-	-
age30_34	-0.057*	(0.033)	-0.045*	(0.027)	-	-
age35_39	-0.035	(0.034)	-0.020	(0.025)	-	-
age40_44	-0.019	(0.037)	-	-	-	-
age45_49	-0.064*	(0.037)	-	-	-	-
age50_54	-0.065	(0.041)	-	-	-0.004	(0.033)
age55plus	-0.212***	(0.037)	-	-	-0.156***	(0.031)
male	-0.079***	(0.019)	-0.073***	(0.023)	-0.090***	(0.028)
Yrs since im	0.001	(0.001)	0.005**	(0.002)	-0.001	(0.002)
Local born	0.093**	(0.047)	0.150***	(0.056)	0.031	(0.085)
Lm assimil.	0.069**	(0.034)	0.063	(0.042)	0.050	(0.058)
Tenure	-0.006**	(0.003)	-0.012**	(0.005)	-0.004	(0.005)
$(tenure)^2$	0.0002*	(0.0001)	0.0004*	(0.0002)	0.0001	(0.0001)
Non-prod job	0.120***	(0.035)	0.124***	(0.039)	0.116*	(0.062)
High Sc grad.	0.091***	(0.033)	0.105**	(0.041)	0.062	(0.054)
Some post-sec	0.171***	(0.030)	0.165***	(0.037)	0.181***	(0.048)
Under-grad	0.267***	(0.030)	0.291***	(0.034)	0.207***	(0.055)
Diploma	0.212***	(0.029)	0.205***	(0.036)	0.241***	(0.051)
Post-grad	0.265***	(0.030)	0.253***	(0.038)	0.273***	(0.054)
Workplace size	0.000005	(0.00001)	0.000006	(0.00001)	0.00001*	(0.00001)
Import comp	0.064**	(0.026)	0.066**	(0.030)	0.055	(0.040)
competition_m	-0.059	(0.044)	-0.113**	(0.052)	0.055	(0.064)
Dom: intense	0.032	(0.027)	0.015	(0.031)	0.086*	(0.044)
Dom: Strong	-0.021	(0.024)	-0.053*	(0.028)	0.070*	(0.040)
Dom: Moderate	-0.017	(0.024)	-0.021	(0.029)	-0.0008	(0.038)
Dom: Some	-0.059**	(0.026)	-0.054*	(0.031)	-0.073*	(0.043)
Centr Barg Agr	0.004	(0.020)	0.017	(0.025)	-0.015	(0.031)
Office tec	0.065**	(0.028)	0.067**	(0.031)	0.061	(0.046)
New mach	-0.041	(0.037)	-0.035	(0.041)	-0.049	(0.057)
Wp tec bench	0.046**	(0.023)	0.044	(0.028)	0.041	(0.036)
Task restruct	0.086***	(0.025)	0.081***	(0.032)	0.091**	(0.037)
Org restruct	0.015	(0.022)	-0.001	(0.026)	0.042	(0.036)
Casuals up	-0.049	(0.031)	-0.033	(0.033)	-0.078*	(0.044)
Outsource up	-0.013	(0.025)	0.016	(0.026)	-0.047	(0.042)
Observations	17986		11629		6357	
Wald chi2(.)	374.64***		207.60***		217.74***	
Joint significance of TC variables[2]	chi2(2)=5.49*		chi2(2)=4.55		chi2(2)=1.80	
Joint significance of OC variables[3]	chi2(5)=30.02***		chi2(5)=18.03***		chi2(5)=18.75***	

[1] ***,**,* indicates statistical significance at the 1, 5 and 10% levels, respectively.

[2] Technological change variables are: "office tec." and "new machinery".

[3] Organisational change variables are: "wp tec. Bench", "task restruct", "org restruct", "casual up", "outsource up".

Table 3a. Probit Specification for Hour Constraints: marginal effects[1] *Sample:* AWIRS Australian Workers

	All workers		**Workers Aged 15-44**		**Workers Aged 45+**	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
age15_20	-0.080***	(0.023)	-0.097***	(0.020)	-	-
age21_24	-0.034**	(0.017)	-0.049***	(0.016)	-	-
age30_34	0.016	(0.015)	-0.0008	(0.012)	-	-
age35_39	0.056***	(0.019)	0.031**	(0.015)	-	-
age40_44	0.040**	(0.018)	-	-	-	-
age45_49	0.050***	(0.019)	-	-	-	-
age50_54	0.014	(0.020)	-	-	-0.044***	(0.017)
age55plus	-0.048**	(0.019)	-	-	-0.105***	(0.018)
male	-0.031***	(0.012)	-0.029**	(0.012)	-0.026	(0.022)
Yrs since im	0.001*	(0.0008)	0.001	(0.001)	0.001	(0.001)
Local born	0.016	(0.020)	0.016	(0.023)	0.012	(0.038)
Lm_assimil	0.069***	(0.015)	0.067***	(0.019)	0.074***	(0.028)
Tenure	-0.0004	(0.002)	0.0008	(0.003)	0.0006	(0.003)
$(tenure)^2$	0.00005	(0.00006)	-0.00002	(0.0001)	0.00001	(0.00008)
Non-prod job	0.054***	(0.012)	0.052***	(0.014)	0.051**	(0.023)
High sch. grad	0.027**	(0.013)	0.040**	(0.016)	-0.010	(0.024)
Some post-sec	0.025	(0.015)	0.024	(0.018)	0.025	(0.028)
Under-grad	0.083***	(0.019)	0.089***	(0.022)	0.068*	(0.037)
Diploma	0.015	(0.017)	0.004	(0.019)	0.056	(0.036)
Post-grad	0.071***	(0.021)	0.057**	(0.024)	0.119***	(0.041)
Workplace size	0.000005	(0.00001)	-0.000007	(0.00001)	0.00002	(0.00002)
Import comp	0.023	(0.017)	0.023	(0.018)	0.027	(0.031)
Dom: Intense	-0.005	(0.028)	0.007	(0.032)	-0.042	(0.047)
Dom: Strong	-0.021	(0.027)	-0.016	(0.030)	-0.039	(0.048)
Dom: Moderate	-0.056**	(0.025)	-0.051*	(0.029)	-0.071*	(0.041)
Dom: Some	-0.076**	(0.031)	-0.076*	(0.045)	-0.078	(0.048)
Centr Barg Agr	0.0008	(0.011)	-0.008	(0.012)	0.024	(0.019)
Office Tech	-0.009	(0.011)	-0.009	(0.012)	-0.013	(0.019)
New mach	0.0005	(0.012)	0.005	(0.014)	-0.016	(0.020)
Wp tec. bench	-0.004	(0.011)	-0.010	(0.012)	0.013	(0.018)
Task restruct	0.011	(0.011)	0.008	(0.012)	0.019	(0.018)
Org. restruct	0.001	(0.010)	-0.008	(0.011)	0.027	(0.017)
Casuals up	-0.009	(0.014)	-0.012	(0.016)	0.003	(0.024)
Outsource up	-0.0007	(0.015)	0.012	(0.019)	-0.030	(0.033)
Children_0_4	0.007	(0.010)	0.008	(0.010)	-0.032	(0.039)
Children_5_12	-0.006	(0.006)	0.004	(0.007)	-0.040**	(0.016)
Children_13p	-0.002	(0.007)	0.009	(0.008)	-0.009	(0.010)
Downsizing	0.010	(0.020)	0.037	(0.025)	-0.046*	(0.027)
wage_lt200	-0.090**	(0.038)	-0.066	(0.048)	-0.154***	(0.023)
wage_200_499	-0.064***	(0.011)	-0.056***	(0.013)	-0.095***	(0.018)
wage_800_1099	0.051***	(0.013)	0.052***	(0.015)	0.053**	(0.023)
wage_gt1100	0.100***	(0.021)	0.094***	(0.026)	0.106***	(0.037)
Harvest	-0.034	(0.021)	-0.036	(0.023)	-0.042	(0.040)
Manufacturing	-0.005	(0.018)	-0.011	(0.019)	0.004	(0.033)
con_tran_utilites	-0.027*	(0.015)	-0.033**	(0.016)	-0.008	(0.028)
Observations	11444		8297		3147	
Wald chi2(.)	449.54***		314.87***		239.01***	
Joint significance of TC variables[2]	chi2(2)=0.65		chi2(2)=0.53		chi2(2)=1.45	
Joint significance of OC variables[3]	chi2(5)=1.45		chi2(5)=2.35		chi2(5)=5.04	

[1] ***,**,* indicates statistical significance at the 1, 5 and 10% levels, respectively.
[2] Technological change variables are: "office tec." and "new machinery".
[3] Organisational change variables are: "wp tec. Bench", "task restruct", "org restruct", "casual up", "outsource up".

Table 3b. Probit Specification for Hour Constraints: marginal effects[1]

Sample: WES Canadian Workers

	All workers		**Workers Aged 15-44**		**Workers Aged 45+**	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
age15_20	-0.102***	(0.007)	-0.099***	(0.007)	-	-
age21_24	-0.017	(0.039)	-0.042	(0.027)	-	-
age30_34	0.017	(0.024)	-0.015	(0.015)	-	-
age35_39	0.030	(0.025)	-0.008	(0.012)	-	-
age40_44	0.069**	(0.030)	-	-	-	-
age45_49	0.052*	(0.031)	-	-	-	-
age50_54	0.063*	(0.035)	-	-	0.004	(0.017)
age55plus	0.047	(0.031)	-	-	-0.011	(0.021)
male	-0.006	(0.012)	-0.016	(0.014)	0.020	(0.018)
Yrs since im	0.0007	(0.0009)	0.0004	(0.001)	0.002	(0.001)
Local born	0.008	(0.025)	0.004	(0.028)	0.026	(0.043)
Lm assimil	0.057***	(0.013)	0.041**	(0.016)	0.077***	(0.018)
Tenure	0.002	(0.002)	0.004	(0.003)	0.006**	(0.003)
$(tenure)^2$	-0.00008	(0.00005)	-0.0002	(0.0001)	-0.0002**	(0.00007)
Non-prod job	0.061***	(0.012)	0.047***	(0.015)	0.074***	(0.017)
High sch. grad	0.018	(0.025)	0.031	(0.036)	-0.010	(0.027)
Some post-sec	-0.0005	(0.021)	0.005	(0.031)	-0.004	(0.024)
Under-grad	0.027	(0.028)	0.025	(0.037)	0.032	(0.038)
Diploma	-0.013	(0.021)	-0.022	(0.028)	0.023	(0.032)
Post-grad	-0.002	(0.026)	0.018	(0.042)	-0.027	(0.027)
Workplace size	0.000002	(0.000)	0.00001**	(0.000)	-0.000004	(0.00001)
Import comp	0.028*	(0.015)	0.019	(0.016)	0.037	(0.026)
Dom: Intense	-0.0008	(0.015)	0.015	(0.018)	-0.029	(0.022)
Dom: Strong	-0.002	(0.014)	0.002	(0.015)	-0.002	(0.021)
Dom: Moderate	0.008	(0.013)	0.0002	(0.015)	0.035*	(0.021)
Dom: Some	-0.014	(0.014)	-0.005	(0.015)	-0.033	(0.021)
Centr Barg Agr	-0.004	(0.012)	-0.021	(0.015)	0.014	(0.019)
Office tech.	-0.016	(0.017)	-0.024	(0.016)	-0.010	(0.026)
New mach.	0.030	(0.029)	0.063	(0.039)	-0.022	(0.026)
Wp tec. bench	-0.010	(0.014)	-0.019	(0.017)	0.004	(0.019)
Task restruct	-0.023*	(0.013)	-0.030**	(0.015)	-0.005	(0.018)
Org. restruct	0.019	(0.014)	0.015	(0.015)	0.019	(0.021)
Casuals up	-0.019	(0.015)	0.010	(0.021)	-0.059***	(0.018)
Outsource up	0.032**	(0.015)	0.004	(0.014)	0.081***	(0.030)
children_0_4	0.021*	(0.011)	0.019*	(0.011)	0.021	(0.054)
children_5_12	0.008	(0.007)	0.012*	(0.007)	0.009	(0.015)
children_13p	-0.004	(0.007)	0.015	(0.010)	-0.017*	(0.009)
Downsizing	0.011	(0.015)	0.004	(0.016)	0.023	(0.025)
wage_200_499	-0.032**	(0.014)	-0.014	(0.017)	-0.068***	(0.017)
wage_800_1099	-0.002	(0.012)	0.010	(0.015)	-0.020	(0.018)
wage_gt1100	-0.003	(0.015)	0.016	(0.018)	-0.018	(0.022)
Harvest	-0.038***	(0.014)	-0.042***	(0.016)	-0.028	(0.027)
manufacturing	-0.011	(0.013)	-0.010	(0.014)	-0.006	(0.023)
con_tran_utilites	-0.007	(0.013)	0.005	(0.016)	-0.023	(0.020)
Observations	17976		11623		6353	
Wald chi2(.)	177.96***		158.91***		152.79***	
Joint significance of TC variables[2]	chi2(2)=1.39		chi2(2)=3.67		chi2(2)=1.64	
Joint significance of OC variables[3]	chi2(5)=10.08*		chi2(5)=7.06		chi2(5)=13.17**	

[1] ***,**,* indicates statistical significance at the 1, 5 and 10% levels, respectively.
[2] Technological change variables are: "office tec." and "new machinery".
[3] Organisational change variables are: "wp tec. Bench", "task restruct", "org restruct", "casual up", "outsource up".

Table 4a. Bivariate Probit Specification for Training (Y1) and Hour Contraints (Y2)[1]
Estimated coefficient and marginal effect of Hour Constraints on Training, S*ample:* AWIRS Australian Workers, various samples

	All workers	**Workers 15-44**	**Workers 45+**	**Non-production workers**	**Production workers**
Estimated coefficient	1.04*** (0.13)	1.19*** (0.13)	0.667** (0.29)	1.10*** (0.17)	1.24*** (0.20)
Corr(ε_1;ε_2)=ϱ	-0.69*** (0.08)	-0.78*** (0.09)	-0.48*** (0.16)	-0.73 (0.12)	-0.77*** (0.09)
F(.) test	17.39***	16.60***	7.05***	13.08***	6.08***
No. of Obs.	11444	8297	3147	8718	2726
Marginal effect	-0.52*** (0.07)	-0.62*** (0.08)	-0.35*** (0.13)	-0.56*** (0.11)	-0.51*** (0.04)

Table 4b. Bivariate Probit Specification for Training (Y1) and Hour Contraints (Y2)[1]
Estimated coefficient and marginal effect of Hour Constraints on Training, S*ample:* WES Australian Workers, various samples

	All workers	**Workers 15-44**	**Workers 45+**	**Non-production workers**	**Production workers**
Estimated coefficient	1.04*** (0.13)	1.19*** (0.13)	0.667** (0.29)	1.10*** (0.17)	1.24*** (0.20)
Corr(ε_1;ε_2)=ϱ	-0.69*** (0.08)	-0.78*** (0.09)	-0.48*** (0.16)	-0.73 (0.12)	-0.77*** (0.09)
F(.) test	17.39***	16.60***	7.05***	13.08***	6.08***
No. of Obs.	17986	11629	6357	16900	1086
Marginal effect	-0.52*** (0.07)	-0.62*** (0.08)	N/A *(a)*	-0.53*** (0.10)	N/A *(a)*

Note: *(a)* Unable to compute the marginal effect due to missing predicted values encountered within the estimation sample.

TABLE 5a: PROPENSITY SCORE MATCHING RESULTS. AWIRS AVERAGE TREATMENT EFFECT OF AN INCREASE IN OUTSOURCING ON THE PROBABILITY OF TRAINING

NEAREST NEIGHBOR MATCHING METHOD

	Size of treated sample	Size of control sample	ATT	S.E.	t-statistics
Workers aged 45+	621	493	-0.07	0.032	2.24
Workers aged 15-44	1552	1283	-0.074	0.018	-4.01
Workers all ages	2173	1780	-0.050	0.017	-2.98
Production workers all ages	316	281	-0.033	0.049	-0.676
Non-Production workers all ages	1857	1508	-0.044	0.019	-2.289

Note: Standard errors are computed by means of the bootstrapping option.

KERNEL-MATCHING METHOD

	Size of treated sample	Size of control sample	ATT	S.E.	t-statistics
Workers aged 45+	621	2520	-0.039	0.024	-1.628
Workers aged 15-44	1552	6738	-0.053	0.012	-4.447
Workers all ages	2173	9262	-0.051	0.012	-4.261
Production workers all ages	316	2388	-0.080	0.029	-2.784
Non-Production workers all ages	1857	6835	-0.044	0.013	-3.519

Note: Standard errors are computed by means of the bootstrapping option.

TABLE 5b: PROPENSITY SCORE MATCHING RESULTS. WESAVERAGE TREATMENT EFFECT OF AN INCREASE IN OUTSOURCING ON THE PROBABILITY OF TRAINING

NEAREST NEIGHBOR MATCHING METHOD

	Size of treated sample	Size of control sample	ATT	S.E.	t-statistics
Workers aged 45+	771	689	0.049	0.029	1.717
Workers aged 15-44	1240	1117	0.000	0.027	0.015
Workers all ages	2011	1822	0.009	0.018	0.530
Production workers all ages	76	73	-0.066	0.091	-0.721
Non-Production workers all ages	1935	1755	-0.002	0.018	-0.103

Note: Standard errors are computed by means of the bootstrapping option.

KERNEL-MATCHING METHOD

	Size of treated sample	Size of control sample	ATT	S.E.	t-statistics
Workers aged 45+	771	5560	0.029	0.020	1.436
Workers aged 15-44	1240	10382	0.009	0.016	0.539
Workers all ages	2011	15888	0.009	0.012	0.761
Production workers all ages	76	923	-0.077	0.062	-1.233
Non-Production workers all ages	1935	14918	0.012	0.012	0.982

Note: Standard errors are computed by means of the bootstrapping option.

TABLE 6: SENSITIVITY ANALYSIS. ESTIMATES OF THE MARGINAL EFFECT(a) OF HOUR CONSTRAINT ON WORKERS' TRAINING FOR CONSTRAINED VALUES OF THE ERROR CORRELATIONS IN BIVARIATE PROBIT MODELS, AWIRS SAMPLES (b).

	***CORRELATION OF DISTURBANCES** (c)*								
	ρ=-0.1	*ρ=-0.2*	*ρ=-0.3*	*P=-0.4*	*ρ=-0.5*	*ρ=-0.6*	*ρ=-0.7*	*ρ=-0.8*	*ρ=-0.9*
ALL AWIRS WORKERS									
Estimated Coefficient	0.00	0.17***	0.34***	0.51***	0.68***	0.85***	1.00***	1.16***	1.31***
Standard Error	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Marginal effect	-0.07***	-0.14***	-0.21***	-0.28***	-0.36***	-0.45***	-0.53***	-0.62***	-0.71***
p>|T|	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	((0.00)
N	11444	11444	11444	11444	11444	11444	11444	11444	11444
AWIRS WORKERS AGED 15-44									
Estimated Coefficient	-0.01	0.16**	0.33***	0.50***	0.67***	0.83***	1.00***	1.15***	1.29***
Standard Error	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)
Marginal effect	-0.07***	-0.13***	-0.21***	-0.28***	-0.36***	-0.45***	-0.54***	-0.63***	-0.73***
p>|T|	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	8297	8297	8297	8297	8297	8297	8297	8297	8297
AWIRS WORKERS 45+									
Estimated Coefficient	0.05	0.22**	0.39***	0.56***	0.73***	0.89***	1.05***	1.21***	1.36***
Standard Error	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)	(0.07)
Marginal effect	-0.07***	-0.14***	-0.21***	-0.29***	-0.36***	-0.44***	-0.53***	-0.61***	-0.69***
p>|T|	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	3147	3147	3147	3147	3147	3147	3147	3147	3147
ALL WES WORKERS									
Estimated Coefficient	0.15**	0.34***	0.52***	0.71***	0.89***	1.07***	1.24***	1.41***	N/A *(d)*
Standard Error	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	
Marginal effect	-0.08***	-0.16***	-0.23***	-0.31***	-0.38***	-0.46***	-0.52***	-0.57***	
p>|T|	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
N	17986	17986	17986	17986	17986	17986	17986	17986	
WES WORKERS AGED 15-44									
Estimated Coefficient	0.12	0.31**	0.49 ***	0.68***	0.86***	1.04***	1.22***	1.38***	N/A *(d)*
Standard Error	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)	
Marginal effect	-0.08***	-0.16***	-0.24***	-0.32***	-0.40***	-0.47***	-0.54***	-0.60***	
p>|T|	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
N	11629	11629	11629	11629	11629	11629	11629	11629	
WES WORKERS 45+									
Estimated Coefficient	0.20*	0.38**	0.58***	0.76***	0.94***	1.11***	1.29***	1.46***	N/A *(d)*
Standard Error	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.09)	(0.09)	
Marginal effect (c)	N/A *(d)*	N/A *(d)*	N/A *(d)*	N/A *(d)*	N/A *(d)*	N/A *(d)*	N/A *(d)*	N/A *(d)*	
p>|T|									
N	6357	6357	6357	6357	6357	6357	6357	6357	

Notes: The marginal effect of the focal outcome (HAPPYLESSHOURS) is computed as (predict(p11)/predict(pmarg2))-(predict(p10)/(1-(predict(pmarg2)))) where p11 is the probability of the joint event (training=1) and (HAPPYLESSHOURS=1), and pmarg2 is the probability of the event (HAPPYLESSHOURS=1); (b) The explanatory variables for training are (HAPPYLESSHOURS), (worker's characteristics) (workplace's characteristics) as in the previous tables; (c) Models estimated as bivariate probits with the correlation ñ between error terms set to the values in column headings; *(d)*Unable to compute coefficients and marginal effect due to missing predicted values encountered within the estimation sample.

TABLE 7: HOUR CONSTRAINTS AND TRAINING EXPENDITURE PER EMPLOYEE, PROBIT SPECIFICATION, COEFFICIENTS AND STANDARD ERRORS. SAMPLE: WES CANADIAN WORKERS.

	All workers		Workers Aged 15-44		Workers Aged 45+	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
Age15_20	-1.368***	(0.27)	-1.658***	(0.26)		
Age21_24	-0.106	(0.25)	-0.338	(0.23)		
Age30_34	0.120	(0.12)	-0.105	(0.09)		
Age35_39	0.185	(0.12)	-0.0256	(0.074)		
Age40_44	0.318**	(0.12)				
Age45_49	0.222*	(0.13)				
Age50_54	0.263*	(0.14)			0.0380	(0.094)
Age55plus	0.199	(0.14)			-0.0126	(0.11)
Male	-0.0348	(0.060)	-0.0844	(0.076)	0.0763	(0.083)
Yrs since im	0.00350	(0.0048)	0.00367	(0.0081)	0.00958	(0.007)
Local born	0.0348	(0.15)	0.0499	(0.17)	0.170	(0.27)
Lm assimil	0.385***	(0.11)	0.264**	(0.13)	0.562***	(0.19)
Tenure	0.0105	(0.011)	0.0244	(0.02)	0.0286*	(0.015)
$(\text{tenure})^2$	-0.000466	(0.00031)	-0.00120	(0.00083)	-0.00092**	(0.0004)
Non-prod job	0.447***	(0.11)	0.364***	(0.13)	0.551***	(0.18)
High Sch. Grad	0.0977	(0.13)	0.154	(0.19)	-0.0527	(0.16)
Some post-sec	-0.000506	(0.12)	0.0160	(0.19)	-0.0402	(0.13)
Under-grad	0.141	(0.14)	0.125	(0.20)	0.124	(0.18)
Diploma	-0.0694	(0.13)	-0.154	(0.19)	0.0925	(0.16)
Post-grad	-0.00563	(0.14)	0.103	(0.22)	-0.191	(0.16)
Workplace size	0.0000316	(0.000026)	0.0000465	(0.000040)	0.0000324	(0.000041)
Non-profit	0.232*	(0.13)	0.130	(0.19)	0.356**	(0.18)
Import comp	0.128*	(0.078)	0.101	(0.089)	0.155	(0.13)
Dom: Intense	0.00341	(0.086)	0.0921	(0.10)	-0.178	(0.14)
Dom: Strong	0.0000104	(0.080)	0.0100	(0.091)	-0.0234	(0.12)
Dom: Moderate	0.0429	(0.074)	-0.00949	(0.091)	0.190*	(0.10)
Comp: Some	-0.0707	(0.079)	-0.0228	(0.091)	-0.165	(0.13)
Centr. Barg. Agr	-0.0349	(0.069)	-0.126	(0.093)	0.0683	(0.094)
Office tech.	-0.103	(0.10)	-0.145	(0.11)	-0.0816	(0.15)
New mach	0.142	(0.14)	0.279*	(0.17)	-0.100	(0.17)
Wp. Tec. Bench	-0.0586	(0.074)	-0.108	(0.095)	0.0288	(0.11)
Task restruct	-0.138*	(0.071)	-0.169*	(0.087)	-0.0784	(0.10)
Org. Restruct	0.125*	(0.064)	0.103	(0.079)	0.150	(0.10)
Casuals up	-0.118	(0.091)	0.0560	(0.11)	-0.402***	(0.14)
Outsource up	0.170**	(0.075)	0.0121	(0.083)	0.392***	(0.13)
Wage_lt200	0	(0)	0	(0)	0	(0)
Wage_200_499	-0.173**	(0.087)	-0.110	(0.11)	-0.377***	(0.12)
Wage_800_1099	-0.00485	(0.059)	0.0229	(0.076)	-0.0620	(0.088)
Training expend/E.	-0.000000045	(0.000000041)	0.0000000535	(0.000000053)	-0.0000002**	(0.000000073)
Constant	-2.233***	(0.24)	-1.845***	(0.30)	-2.607***	(0.33)
Observations	17976	17976	11623		6353	
Wald Chi(2)	156.6***		152.9***		136.5***	

FIGURE 1: WORKING HOURS AND TRAINING IN A SIGNALLING MODEL

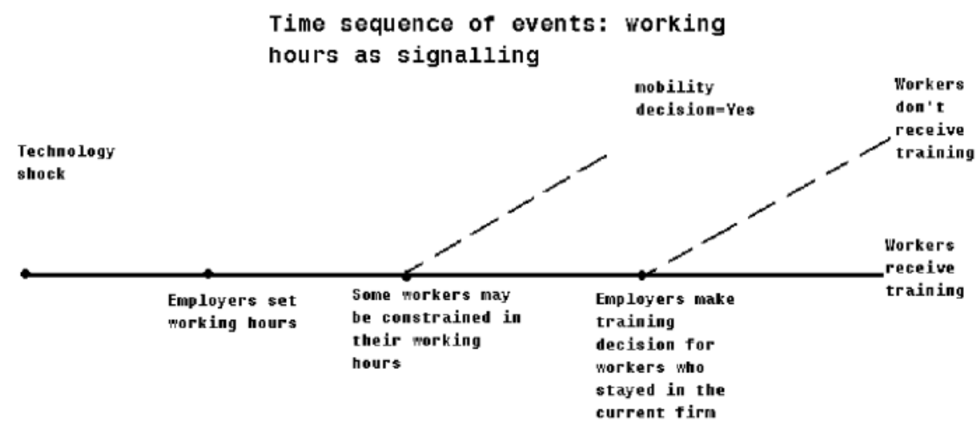


FIGURE 2a: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, AWIRS FULL SAMPLE

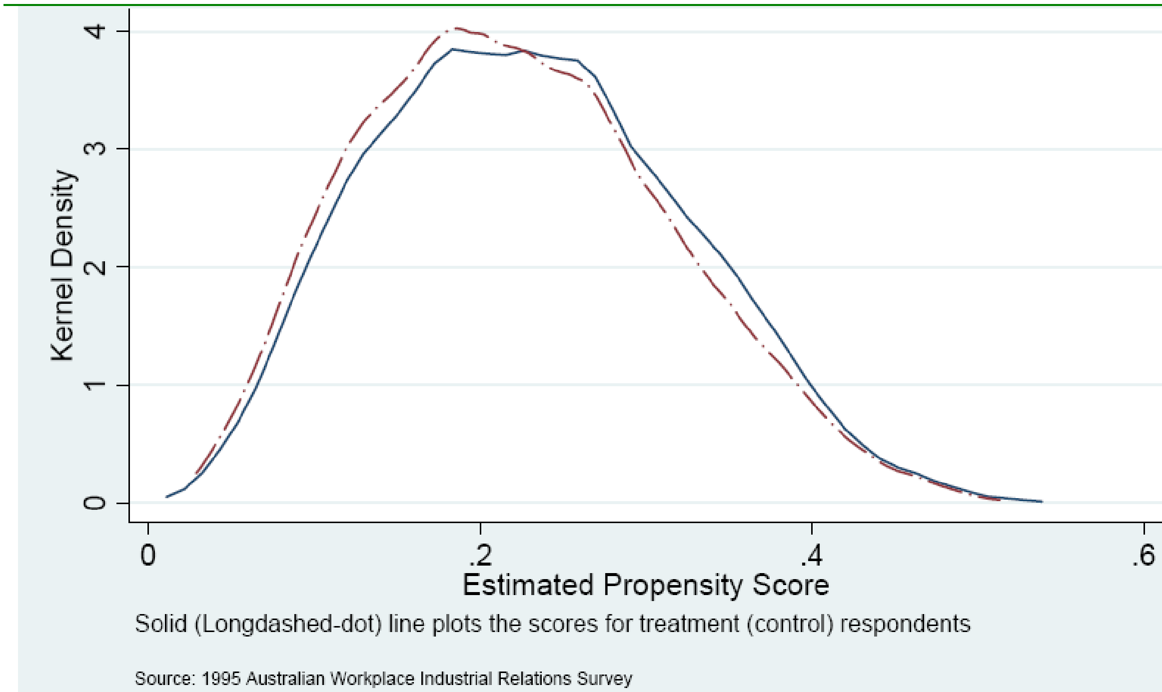


FIGURE 3a: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, AWIRS SAMPLE OF WORKERS AGED 15-44

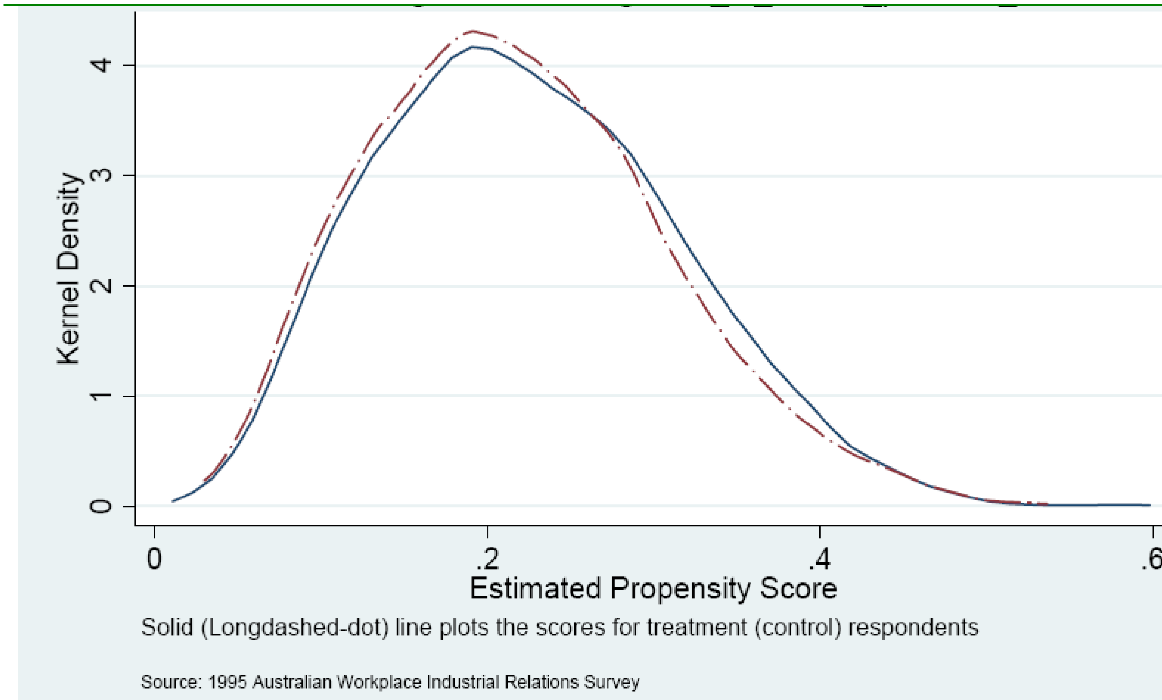


FIGURE 4a: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, AWIRS SAMPLE OF WORKERS AGED 45+

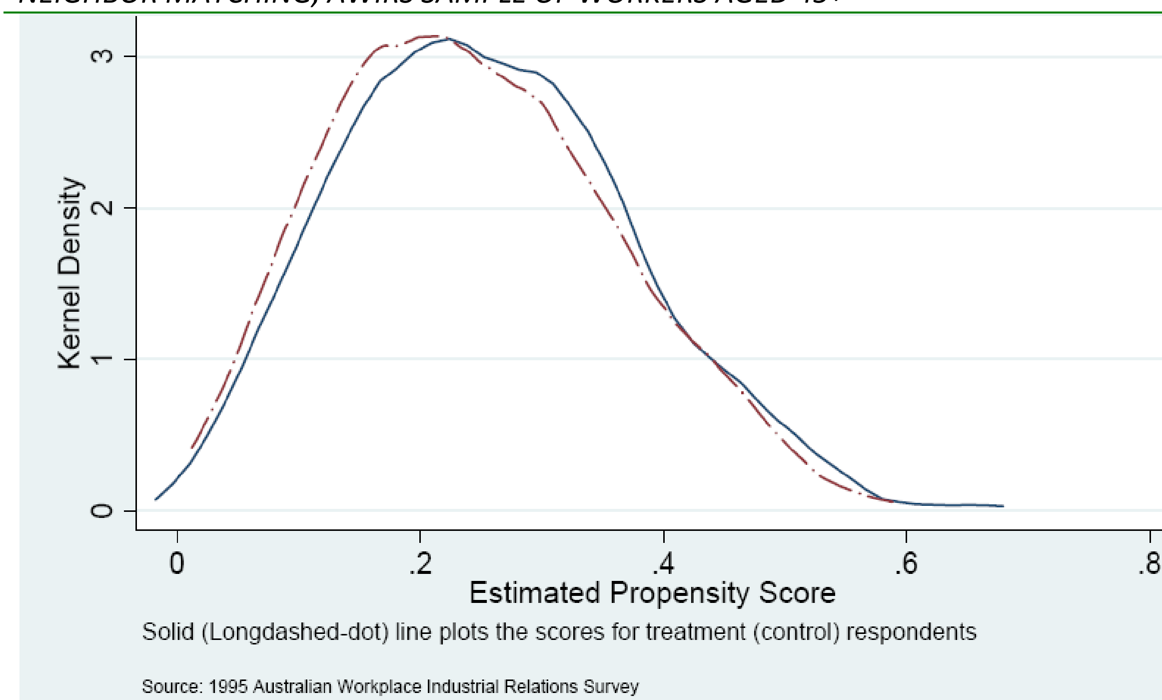
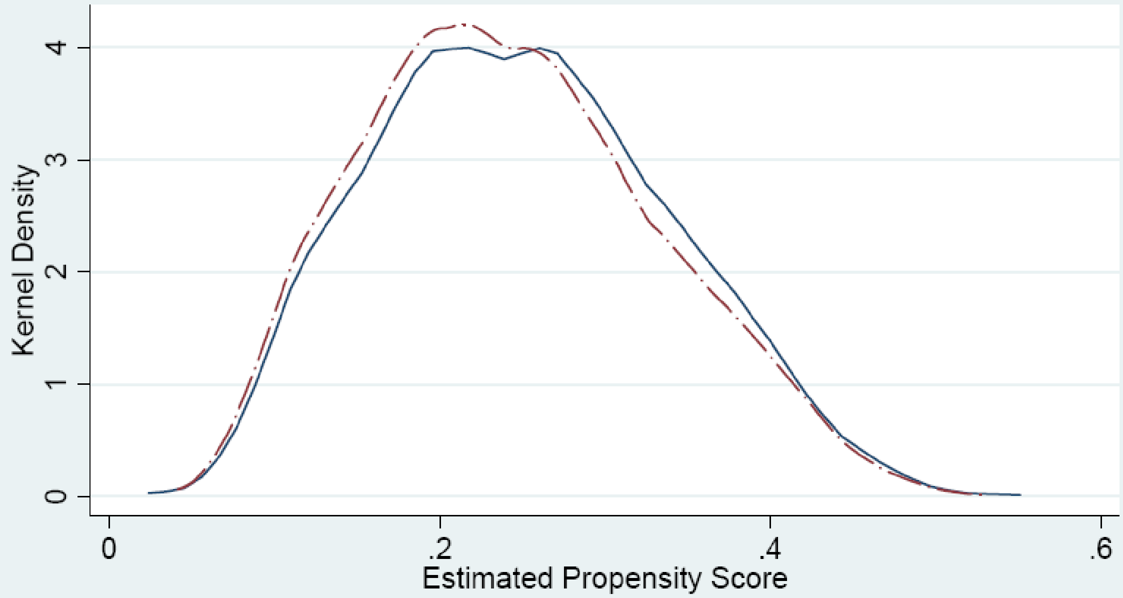


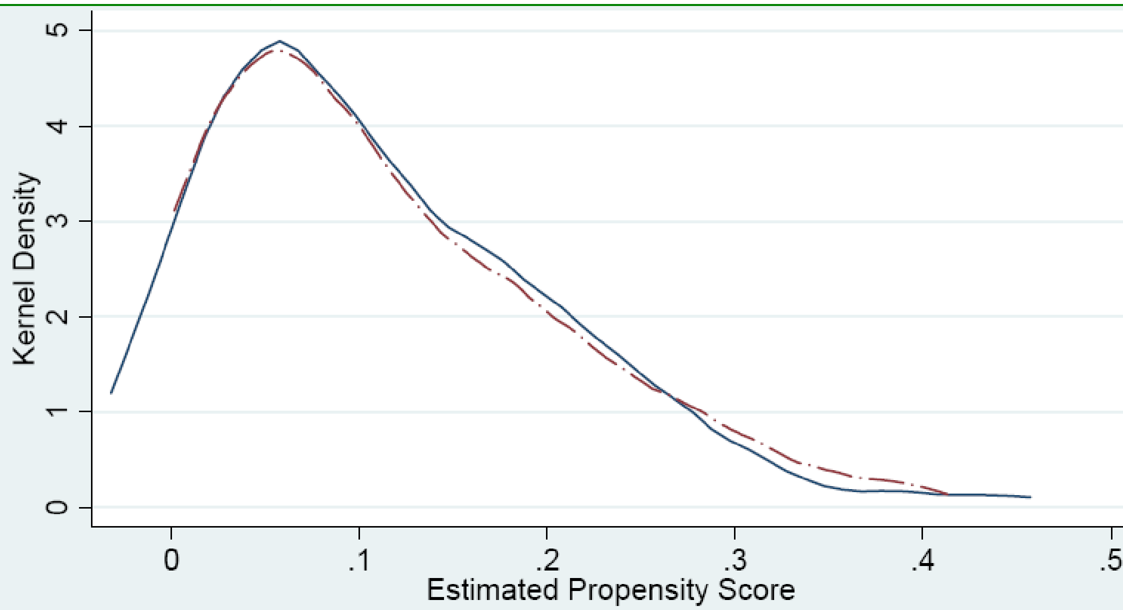
FIGURE 5a: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, AWIRS NON-PRODUCTION WORKERS



Solid (Longdashed-dot) line plots the scores for treatment (control) respondents

Source: 1995 Australian Workplace Industrial Relations Survey

FIGURE 6a: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, AWIRS PRODUCTION WORKERS



Solid (Longdashed-dot) line plots the scores for treatment (control) respondents

Source: 1995 Australian Workplace Industrial Relations Survey

FIGURE 2b: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, WES FULL SAMPLE

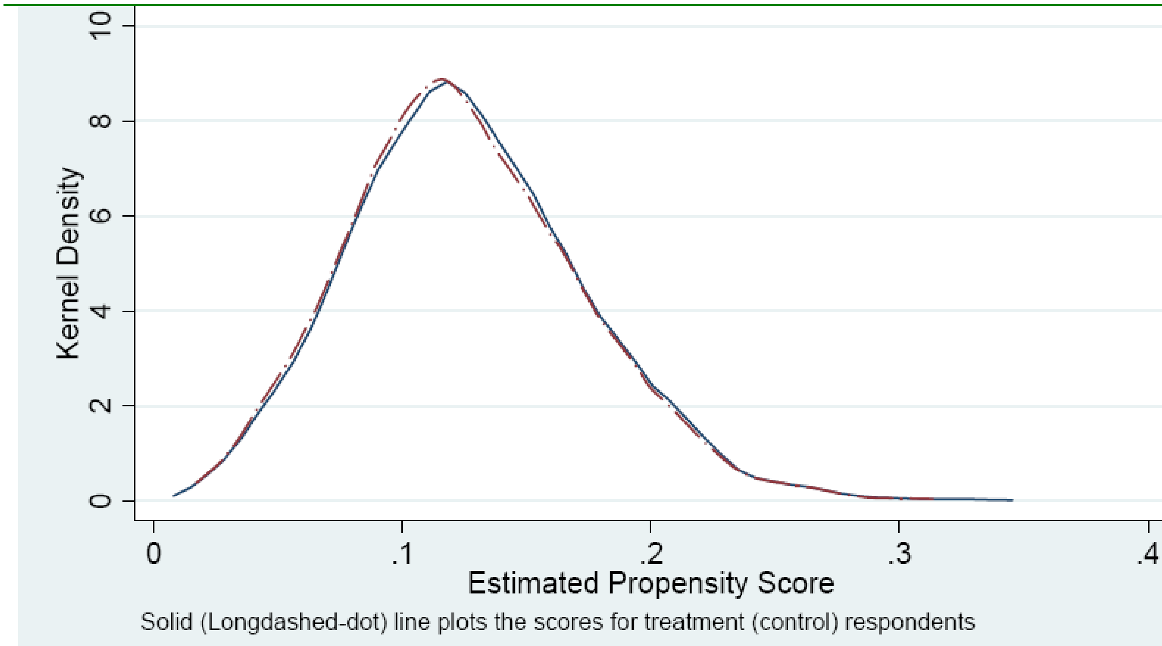


FIGURE 3b: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, WES SAMPLE OF WORKERS AGED 15-44

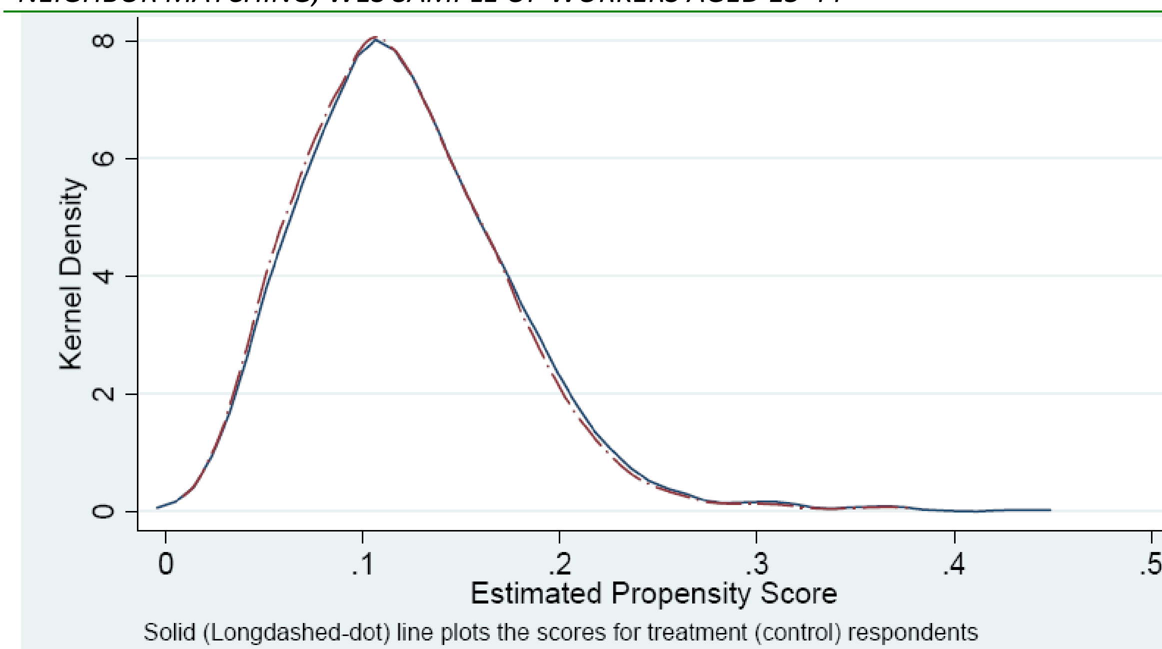


FIGURE 4b: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, WES SAMPLE OF WORKERS AGED 45+

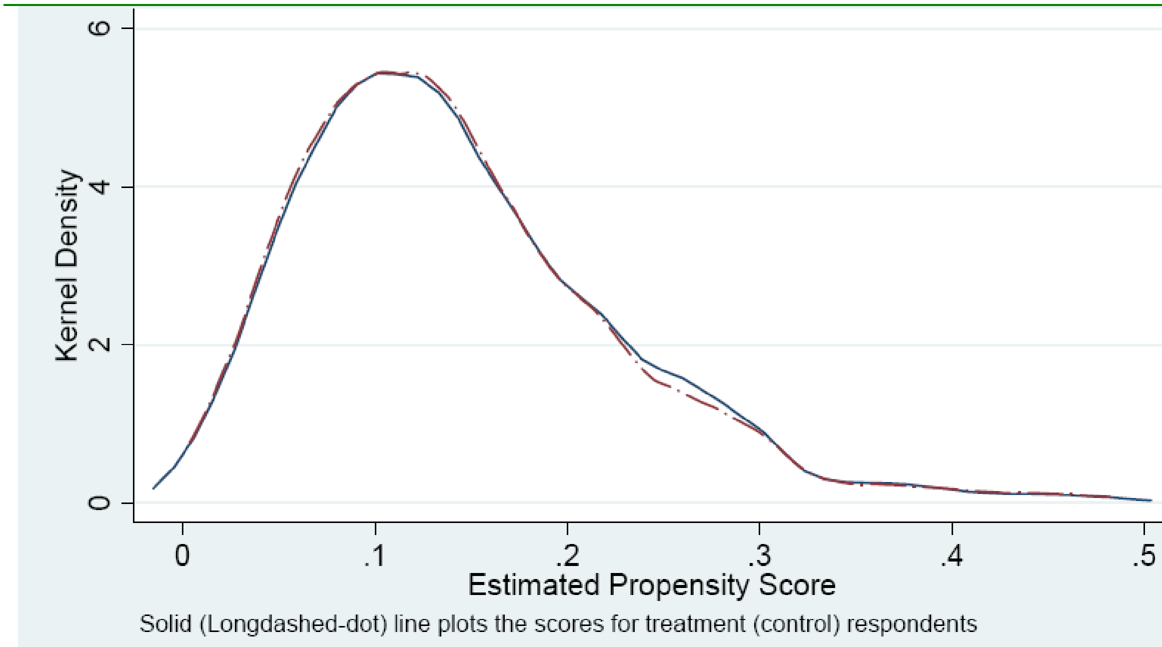


FIGURE 5b: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, WES NON-PRODUCTION WORKERS

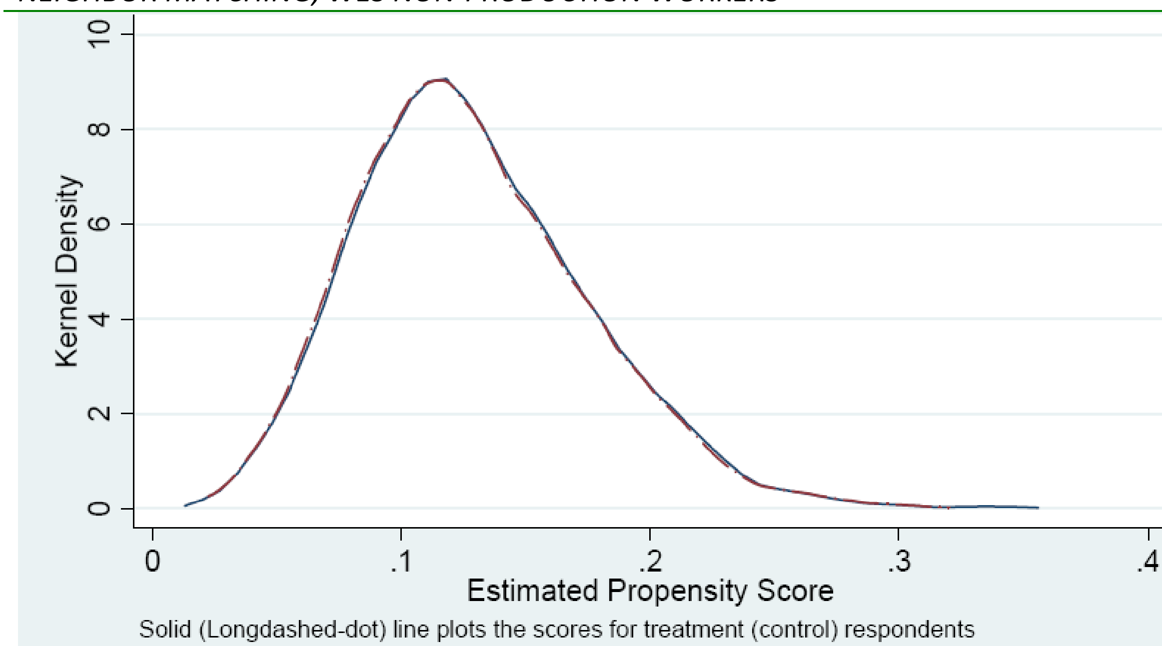


FIGURE 6b: KERNEL DENSITIES AND ESTIMATED PROPENSITY SCORES, NEAREST NEIGHBOR MATCHING, WES PRODUCTION WORKERS