Returns to Training and Skill Mismatch: Evidence from Australia

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Abstract

This paper utilises Australian data to evaluate the effect of firm-provided job training on labour income. It also examines whether training can shed light on the effects of skill-job mismatch. We employ a trivariate model to account for firm selection bias in training and worker selection in full-time employment participation. The evidence shows that training has a significant positive impact on wages and assists in the augmentation and replenishment of human capital. Further, training ameliorates the disadvantage associated with the mismatch between formal education and required education.

Keywords: Training; Education; Overeducation; Wages; Human capital depreciation
J.E.L. Classification: J240; J300; I210.

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I Introduction

Labour economics research has long established that education and human capital are associated with higher earnings (Sianesi and van Reenen 2003). Evidence also indicates that similar levels of education can yield quite diverse earning outcomes within narrowly defined occupational classes (Devroye and Freeman 2002; Cawley *et al.* 1998). As a result, recent research has paid attention to the idea of a job-skill mismatch (OECD 2001; Wößmann 2003; Gibbons and Waldman 2004). Following Duncan and Hoffman (1981), a new literature has emerged that treats undereducation and overeducation as phenomena of mismatch between the supply of, and demand for, educated workers (Harmon *et al*. 2003; Sloane *et al.* 1999).[1]

Undereducation and overeducation are two measures of mismatch between actual education attainment levels and the required or just-right level of education appropriate for particular occupations. Employees with more education than the required level are said to be overeducated while those with fewer qualifications are considered to be undereducated. Studies have observed that overeducation is associated with a wage penalty while undereducation results in a wage premium.

The literature on over and undereducation has coexisted with a substantial literature on training, but there has been little interaction between the two fields, despite the fact that training could be a response to situations of job-skill mismatch. Economic theory highlights three principal motivations for training. The first derives from *human capital theory* and considers training as an augmentation of human capital. *Search and matching theory* treats training as a supplement to education since its main function is to bridge the gap between generic skills and job-specific skills.[2] Although, it can overlap with the first two, the third motivation highlights *human capital depreciation* attributed to physical wear, skill atrophy, as well as technological and organisational change (de Grip 2006; MacDonald and Weisbach 2004). Dubin (1972), Rosen (1975) and Mincer and Ofek (1982) all advised of a more comprehensive account of the role of training in the context of skill depreciation.

[1] Note, a variety of interpretations exist regarding the cause of overeducation. Linsley (2005) and Voon and Miller (2005) offer more comprehensive reviews.

[2] van Smoorenburg and van der Velden (2000) provide more details.

Training can improve the links between existing skills and the skills required for the rapid implementation of new technologies (Buchtemann and Soloff 2003) and may be a key mitigating factor counteracting skill obsolescence (de Grip 2006; de Grip and van Loo 2002).[3] However, recent research has suggested that existing estimates of the returns to training lack credibility due to selection effects and that the actual wage effect of training is much lower than previously thought.[4]

This paper re-examines the role of job training in a framework that allows for the existence of job-skill mismatch. We utilise Australian data to assess the direct effect of training on labour income as well as its indirect effect on returns to required education, undereducation and overeducation. The paper is organised as follows. Part II provides a review of the relevant literature and the main motivation for this study. Part III outlines our methodology and describes the data. Part IV presents the empirical results. Finally, part V concludes.

[3] Three decades ago, Liles (1972) also argued the case for training as an important defence mechanism against skill obsolescence.

[4] For example, see Goux and Maurin (2000) and (Kuruscu 2006).

II Background

Over the last two decades, empirical research indicates that the incidences of undereducation and overeducation are high in European countries, the USA and in Australia.[5] The evidence shows that, when compared to peers with the just right level of education for the job, the overeducated receive markedly lower returns for additional years of education[6] while the undereducated receive a wage premium (Hartog 2000; Kler 2005; Büchel and Mertens 2004;Voon and Miller 2005).

The skill mismatch literature has evolved in two main directions. One emphasises measurement issues and, in particular, the estimation of required education, against which actual education levels can be benchmarked. One technique for deriving such an estimate is the *objective method*, involving professional assessments of the minimum years of training required to perform key tasks in a particular occupation. Other approaches include the *statistical method* that defines required education as the mean or median of the observed distribution of years of education in a particular occupation, and worker *self-reported estimates* of the years of education required to perform their job. The objective method seems conceptually superior but it is rarely available on a continuous basis. The statistical method rests on a symmetry in the distribution of required education. Self-reported methods avoid the symmetry assumption but rely on subjective assessments (Linsley 2005; Kler 2005).

The second direction observed in the literature examines the role new technologies play in the emergence of skill mismatch. One interpretation is what Voon and Miller (2005) refer to as *technological change theory*, which highlights changes in the skill composition of a job due to technological change. New graduates are equipped with skills that are better aligned with emerging technology but firms are slow to adjust to new technology. As result, these new workers are overeducated. Conversely, as firms adapt to new technologies, existing workers become undereducated. Principal

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[5] See Groot and Maassen van den Brink (2000), Dolton and Vignoles (2000), Voon and Miller (2005) and Kler (2005).

[6] Theory predicts that overeducation should be a temporary phenomenon as over-qualified workers move to other jobs that achieve better job-skill matches. Indeed, the literature points to a higher rate of job turnover for the overeducated (Groot and Maassen van den Brink 2000) but Sloane et al. (1999) and Hartog (2000) observe that the mismatch can persist with the overeducated failing to benefit from higher mobility.

advocates of technological change theory, e.g. de Oliveira *et al.* (2000), explain this mismatch in terms of adjustment costs and assume that the overeducated are well equipped to meet the demands of new technology.

In recent times, public debate in Australia has emphasised skill shortages that Kelly and Lewis (2003) attribute to rapid changes in demand for new skills. This interpretation alludes to skill obsolescence as a possible driver of skill shortages and mismatch. A Department of Education Science and Training (2006) report claims that there is also a shortage of core skills amongst new graduates in Australia. British data also suggest that the overeducated tend to have fewer numeracy skills than those whose skills match the job requirements (Green *et al.* 1999). This seems to vindicate earlier claims by Groot and Maassen van den Brink (1996) and Sloane *et al.* (1996) who raised the possibility that overeducation could mask a lack of job-specific skills by highly educated workers, rather than being simply the product of an over-supply of skilled workers. Conversely, the undereducated may have the opportunity to learn new skills on the job that compensate for the lack of formal education. These insights point to the importance of complementarities between formal education and work-related learning as an extension to the *technological change theory*.

Standard models of the human capital approach to labour outcomes often assume that experience and education jointly absorb the work-related learning effect, and that training is equivalent to schooling. However, Acemoglu and Pischke (1999) have called for a more explicit account of job training. They have proposed a theoretical framework under which firms and employees can gain from both general and job-specific training. They also observe that the productivity gains from on-the-job training cannot be substituted by formal education given the critical role of training in bridging the gap between general-purpose education and job-specific skills. Thus, the authors conclude that new technologies make training indispensable.

Human capital depreciation integrates the concepts of human capital and technological change.[7] The view that human capital is a depletable asset has been explicit in the works of Rosen (1975) and Mincer and Ofek (1982). Rosen (1975) paid attention to the natural decay of human capital due to ageing, while Mincer and Ofek

[7] The neglect of human capital depreciation is noted by Solow (1999) and Groot (1998).

(1982) proposed the 'use-it-or-lose-it' hypothesis of human capital depreciation by observing that workers who had career interruptions experienced a decline in their wages. This view of human capital has found application in new models of unemployment, such as those proposed by Ljungqvist and Sargent (2004, 1998).

The early studies emphasised *technical* depreciation that related to the deterioration of the physical condition of human capital. More recent studies have emphasised *economic* depreciation as an equally important source of depreciation. Here, the focus is on the *value* of human capital that can depreciate as a result of changes in the job or work environment (Arrazola *et al.* 2004). Typical examples are skills, jobs and occupation affected by the diffusion of information technology and organisational change (MacDonald and Weisbach 2004; de Grip 2006).

The human capital depreciation literature has also begun to explore the relation between skill obsolescence and job-skill mismatch. de Grip and Van Loo (2002) make a direct link between skill obsolescence due to non-use and overeducation. Consistent with evidence in Allen and van der Velden (2002), the authors show that the overeducated experience diverse degrees of skill depreciation as a result of ageing, career interruptions due to sickness or maternity leave, non-use of skills and technological/organisational change.

Both the undereducated and the overeducated can be affected by *technical* or *economic* skill obsolescence. More importantly, what emerges from the literature of human capital depreciation is the critical role of training as a means of restoring and replenishing human capital. An important finding in Mincer and Ofek (1982), for example, is that employees with career interruptions managed to restore their human capital through new investment. Moreover, the authors note that 'readaptation ("repair") of skills is likely to be more efficient than new investments in human capital' (p. 19).

Ever since Liles (1972), numerous studies have confirmed the value of workplace training. We now know that there are positive returns to training (Ryan and Watson 2003). We also know that training is complementary to technological change (Baldwin and Johnson 1995). With respect to the latter, skills become obsolete while new skills are slow to integrate into the workplace and training can narrow the gap between skills acquired at school and skills required at the workplace (Arulampalam *et al.* 2004). Further, van Smoorenburg and van der Velden (2000) find that training also contributes to the resolution of the job-skill mismatch. Australian evidence also points to substantial returns to job training but the estimates vary in magnitude.[8]

Yet, there is an important caveat to the above. It is plausible that firms select the most skilful workers for job training. If participation in training is contaminated by selection, existing estimates of returns to job training will be biased. Goux and Maurin (2000) and Kuruscu (2006) account for such bias and show that previous studies have over-estimated the value of training.

III Methodology

This section outlines the methodology we have adopted in order to examine two research questions. Does job training impact on wages? Is job training valuable to workers whose skills do not match with those required at the workplace? The starting point for our analysis is to partition actual years of education, S_A, into required years of education, S_R (i.e., the average of years of actual education), years of overeducation, S_O, being equal to (S_A-S_R) if $S_A > S_R$ and zero otherwise, and years of undereducation, S_U, being equal to (S_R-S_A) if $S_A < S_R$ and zero otherwise. In doing so, we follow Voon and Miller (2005) who, in turn, draw on Duncan and Hoffman (1981) and Hartog (2000).

Voon and Miller (2005) estimate the following model:

$$\ln W_i = \mathrm{B_i} q + \eta_i = \alpha\, S_{R,i} + \beta\, S_{U,i} + \gamma\, S_{O,i} + \mathrm{X_i}\phi + \eta_i \qquad (1)$$

where $\ln W_i$ is the log of average weekly earnings for worker i, B_i is a composite vector of independent variables that contains $S_{R,i}$, $S_{O,i}$, $S_{U,i}$ (i.e., required education, overeducation and undereducation respectively), and X_i which is also a vector of other

[8] See, for example, Chapman and Tan (1992) who report returns in the range of 6%-7% and Lamb *et al.* (1998) estimate the return to be 4%. More recent studies place the estimates in the range of 7% - 10% (Long 2001).

explanatory variables including a quadratic effect for experience, $E_{i.}$ α, β, γ, θ, ϕ are parameters, q is a summary vector of coefficients and η_i is a random error term.

In our analysis, we extend Voon and Miller (2005) to account for training as a determinant of wage income. First, we allow for a direct effect where training enters as an additional variable in the X vector. That is, we consider the possibility that training directly assists workers to augment their human capital. This *direct* effect applies equally to all workers and is our *first* research question.

Further, we examine whether training helps bridge the wage gap between acquired and required skills. One plausible explanation for this is the job-skill *matching* hypothesis whereby training provides workers with skills that are complementary to those acquired through education and without which educational knowledge would be under-utilised. This is the *indirect* training effect and the *second* research question.

We examine the consistency of this model model with Australian labour market data. We do so by partitioning undereducation into undereducation with participation in current training, $S_{U,T}$, and undereducation without current training, $S_{U,NT}$. Likewise, overeducation is partitioned into overeducation with current training, $S_{O,T}$, and overeducation without current training, $S_{O,NT}$. We also allow required education to interact with training participation. Equation (2) summarises these three decompositions.

$$S_A = (S_{R,T} + S_{R,NT}) - (S_{U,T} + S_{U,NT}) + (S_{O,T} + S_{O,NT}) \tag{2}$$

In defining undereducation and overeducation, we adopt the standard of the statistical or ‘realised matches’ method, as in Voon and Miller (2005). More precisely, required education, S_R, is the mean of observed years of education, S_A, by occupation.

We define the new decompositions as follows:

$$S_{R,T} = \begin{cases} S_R, \text{ if } \quad TP = 1 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3a}$$

$$S_{R,NT} = \begin{cases} S_R, \text{ if } \quad TP = 0 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3b}$$

$$S_{U,T} = \begin{cases} S_R - S_A, \text{ if } S_A < S_R \text{ and } \ TP = 1 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3c}$$

$$S_{U,NT} = \begin{cases} S_R - S_A, \text{ if } S_A < S_R \text{ and } \ TP = 0 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3d}$$

$$S_{O,T} = \begin{cases} S_A - S_R, \text{ if } S_A > S_R \text{ and } \ TP = 1 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3e}$$

and

$$S_{O,NT} = \begin{cases} S_A - S_R, \text{ if } S_A > S_R \text{ and } \ TP = 0 \\ \\ 0 \ \text{ if otherwise} \end{cases} \tag{3f}$$

Note that TP is an indicator variable that takes the value of one if the person participated in firm-provided training and zero otherwise. Thus, this paper extends (1) to consider the following model:

$$\ln W = \sum_{k=T,NT} \alpha_k S_{R,k} + \sum_{k=T,NT} \beta_k S_{U,k} + \sum_{k=T,NT} \gamma_k S_{O,k} + \mathrm{X}_i \phi + \delta TT_i + \varepsilon \tag{4}$$

Given k=T,NT, and the cross-section subscript implied, $S_{R,T}$, $S_{R,NT}$, $S_{U,T}$, $S_{U,NT}$, $S_{O,T}$ and $S_{O,NT}$, have all been defined in (3a)–(3f), TT is the log of training time (human capital augmenting), X is the vector of covariates observed in (1) and ε is an error term. Parameters δ and α_T summarise the human capital augmenting, *direct* effect of training while β_T and γ_T capture the *indirect* effect relating to skill matching, possibly the result of skill restoration and replenishment.

It follows that the data would be consistent with the direct effect if we reject null *Hypothesis 1* that says that all workers or workers whose skills match well those required on the job do not benefit from training; i.e., H_0: $\delta \leq 0$ or H_0: $\alpha_T \leq \alpha_{NT}$ in (4). The indirect effect predicts that workers whose skills do not match those required ought to earn higher wages when they receive training. Thus, for this to be valid it would require a rejection of null *Hypothesis 2*, that is, H_0: $\beta_T \leq \beta_{NT}$ or H_0: $\gamma_T \leq \gamma_{NT}$.[9]

Our empirical methodology accounts for two selection effects: employment participation and training participation. We adapt the approach of Di Tommaso (1999) and of Goux and Maurin (2000) who examine twin selection criteria; the former training and mobility, the latter employment and fertility. More precisely, we consider the following three-equation system:

$$\ln W_i^* = B_i q + \delta TT_i^* + \eta_i = \alpha\, S_{R,i} + \beta\, S_{U,i} + \gamma\, S_{O,i} + X_i \phi + \delta TT_i^F + \eta_i \qquad (5a)$$

$$TP_i^* = Y_i \varphi + Z_i \xi + \psi \ln W_i^* + u_i \qquad (5b)$$

$$EP_i^* = Y_i b + V_i c + dTT_i^* + e_i \qquad (5c)$$

Equation (5a) is equivalent to (1) except that here the log of wages is an unobservable latent variable due to censoring and 'incidental truncation' where the latter is the result of a worker's choice regarding participation in employment, EP^*, (more details below). B is the vector of independent variables introduced in (1), TT^F is the log of

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[9] Note, however, the data utilised in this paper, described in more detail in the next section, are limited to *current* participation in training. This would bias our results downwards if training acts as payment in kind or it takes time to impact on wages. Blandy *et al.* (2000) and Veum (1999) find that this is particularly relevant to young workers. Note, however, the counter effect of depreciation of the training effect on wages (Blundell *et al.* 1999).

training time as a latent variable (i.e., what training time would have been had firm selection not occurred) since its outcome depends on training participation set by the firm, TP^F, and subsequently training participation by the worker, TP^*, η_i, u_i and e_i are assumed to be independent, identically and normally distributed, and Z, Y, and V are vectors of explanatory variables. We observe here that (5b) is about worker selection of training participation while TT^F is pre-determined by the firm with TP^F defining the selection process, discussed below.

For identification purposes, we follow Goux and Maurin (2000) to utilise variable vectors Z and V that explain training and employment participation respectively, but not wages (i.e., $Z \not\subset V$, $Z \not\subset B$ and $V \not\subset B$). As in Di Tommaso (1999), since we do not have empirical estimates of TP^* and EP^*, we use the observed indicator variables TP and EP: $TP=1(TP^F>0)$ and $EP=1(EP^*>0)$.

Instead of observing $\ln W^*$, we observe variable lnW defined as

$$\ln W = \begin{cases} c_{\max}, & if\ EP_i = 1\ and\ \ln W_i^* \geq c_{\max} \\ \ln W_i^*, & if\ EP_i = 1\ and\ 0 < \ln W_i^* \leq c_{\max} \\ 0, & if\ EP_i = 0 \end{cases} \tag{6}$$

In (6), the complete range of values for $\ln W^*$ is unobservable due to right-censoring at c_{max}[10] and due to worker non-participation in employment.

Estimation of the trivariate model (5) is challenging in several ways. First, the dependent variable in the wage equation is a latent variable, mainly due to worker choice regarding labour market participation. Second, worker participation in training depends on unobservable wages. Third, wages are also determined by training time that is in itself a latent variable due to firm selection. Fourth, training time could be a consideration by workers in their decision to seek employment. Obviously, it is impossible to control for all these factors in a single estimation procedure, as acknowledged by Di Tommaso (1999) and Goux and Maurin (2000).

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[10] The Australian Bureau of Statistics imposes right-censoring in wages and income data to maintain confidentiality. There were relatively a few observations where lnW was greater than $c_{max}=\ln(1180)$: 748 men and 89 women. Estimation results were also obtained by ignoring right-censoring and these were very similar to those reported below.

Note the last two challenges differentiate our trivariate model from that studied by Di Tommaso (1999) and Goux and Maurin (2000). In order to tackle all four issues, we make the following assumptions in this study. First, firms have full control over how much training time is provided to workers. Second, firm selection in training is independent of workers' decision to participate in employment. Third, we follow Di Tommaso (1999) and assume that education is a weakly exogenous variable. Fourth, workers can choose whether to participate in training. Finally, each worker accurately predicts the quantity of training she expects to receive from firms and takes this into account when selecting to participate in employment.

Hence, we adopt the following two-stage procedure. In the first stage, we model firm behaviour with respect to training time to account for potential selection bias. Again, this is on the basis that, at least as far as the firm is concerned, firm selection in training is largely independent of workers' decision to participate in employment. Given a set of worker characteristics and firm selection preferences, firms can then predict potential training time, TT^F. More formally, we model training time provided by the typical firm as part of a bivariate model:

$$TT_i^F = Q_i\alpha + \eta_i \tag{7a}$$

$$TP_i^F = Q_i\beta + R_i\gamma + u_i \tag{7b}$$

Equation (7a) infers a typical firm's decision regarding the training time offered to worker *i*. Q and R are vectors of explanatory variables that may include variables considered by workers in (5b), and TT^F is observed iff a second unobserved latent variable, TP^F, exceeds the zero threshold, which effectively translates into $TT=TT^F$ if $TP>0$ and $TT=0$ if $TP=0$; TT is the observed measure of training time. Also, the two error terms, η_t and u_t, are assumed to be bivariate, normally distributed with a correlation coefficient ρ, $\eta_t \sim N(0, \sigma^2)$ and $u_t \sim N(0, 1)$; i.e., the variance of u_i is normalised to 1 because only TP, not TP^F, is observed.[11] Intuitively, the firm makes

[11] Note that most explanatory variables in (7a) and, especially, (7b) summarise observable characteristics of all workers and persons not currently in employment.

two joint decisions: it decides who participates in training, and determines the time the selected worker undergoes training.

In order to identify the model, we consider Q to be a vector of explanatory variables in the outcome equation (7a) that is a subset of the independent variables in the selection function (Wooldridge 2006); i.e., $R \not\subset Q$. Model (7a)-(7b) is a training selection model as proposed by Heckman (1979) and is estimated simultaneously using maximum likelihood estimation (MLE). Given the relation between TT and TT^F, and the incidental truncation of the latter based on the outcome of TP, TT^F can also be expressed as follows

$$TT_i^F = \begin{cases} TT_i = Q_i\alpha + \eta_i\,, & if\ TP_i > 0 \\ \\ TT_i^P + \rho\sigma\lambda\,, & if\ TP_i = 0 \end{cases} \tag{8}$$

where TT_i is the observed measure of the log of training time, TT_i^P is the MLE linear prediction of TT^F from equation (7a), and the term $\rho\sigma\lambda$ is the selectivity bias comprising of the correlation coefficient ρ, the standard deviation of η_t, σ, and the inverse Mills ratio, λ.[12]

In the second stage of estimation, we define TT^F as in (8) and proceed to estimate the trivariate model (5a)-(5c). Here, for the purpose of a parsimonious model, we exclude part-time workers from the analysis in order to avoid additional problems associated with multinomial models of employment participation (Laplagne, Glover and Shomos 2007). Thus, hereafter EP and EP^* refer to worker participation in full-time employment.

We again employ MLE to simultaneously account for (a) right-censoring with a tobit model and Heckman selection in the modelling of wages; (b) worker participation in

[12] This is the ratio of the standard normal probability density function to its cumulative probability while ρ and σ have been defined earlier. See Green (2008), for detail.

training, and (c) worker employment participation. The wage equation (5a) is the outcome equation and *full-time* employment participation (5c) is the selection equation. It is assumed that knowledge of the predicted value of TT^F is quickly diffused amongst current and potential workers. Also, we conjecture that TT^F is an important factor in the employment equation (5c).

Data

Voon and Miller (2005) and Kler (2005) utilise the ABS (1996) *Census of Population and Housing Household Sample File* (HSF). It provides information on the educational attainment and earnings of Australians by gender, age, marital status, birthplace, working hours and occupation. The HSF dataset is particularly useful since it permits estimation of required education at the two-digit level of occupational classification (ASCO2). On the downside, the HSF data do not distinguish between labour income and income from other sources. Further, HSF provides estimates of the highest educational qualification and not the years spent on education.

This study utilises the ABS (1997) *Survey of Education and Training* Unit Record File (SET 97) for the following reasons. First, SET 97 provides data on weekly labour income. Access to labour income data is crucial for the estimation of returns to education. Second, SET 97 offers detailed information on the time individuals have spent on education. In contrast to HSF, SET 97 allows for a more accurate measure of the number of years Australians have invested on education. We thus exploit information on the first and second highest qualification achieved and convert these to years of education to arrive at a measure of total years of education, S_A.[13] Third, in utilising SET 97, we acknowledge the trade-off between better measures for education and labour income, on one hand, and one-digit occupational classifications (ASCO2). Thus, the high level of aggregation in the occupation classes has implications for our measure of required education. Given the research questions pursued here, however, we have little choice but to utilise SET 97.

[13] See the Appendix for more details.

SET 97 provides rich information that facilitates detailed examination of the link between training and labour market outcomes. The survey records whether an individual worker has participated in a training course in 1997. It also makes possible to distinguish between employer-funded training and employee-funded training. We confine our study to employer-funded training to account for selection bias in job training and to estimate its contribution to labour income.

IV Results

Table 1 summarises the employment shares of occupational classes, the average years of required education, as well as the incidence of required education, undereducation and overeducation.[14] Note that highly skilled workers[15] exhibit higher levels of required education. Also intuitive is the finding that the incidence of undereducation is higher for low skill workers. Yet, managers and administrators, professionals are over-represented in the incidence of undereducation and overeducation. This seems puzzling but relates to the fact that the distribution of education is characterised by fat tails for this occupational class. We suspect this is partly due to the 2-digit occupational aggregation in SET 97 and partly due to the fact that the standard deviation of education for this occupational group varies widely between full-time and part-time employees as well as across industries.[16] In squared brackets, columns 3-5 in Table 1 also report the share of full-time workers who had undergone training for each respective ASC02 class as well as by skill level. These show that the majority of the low skilled did not participate in job training. For example, only 21.7% of the low skilled undereducated workers underwent training: most conspicuous are tradespersons, intermediate production and transport workers, and labourers and related workers with only 15.9%, 16% and 16.4% having participated in training

[14] Estimates in Tables 1-2 are based on the convention of plus or minus one standard deviation from the mean of required years of education as the respective thresholds for overeducation and undereducation. Required education is the weighted mean of actual years of education using the SET 1997 person cross-section weights to adjust for a sampling bias by the Australian Bureau of Statistics in favour of persons currently in employment and marginally attached to the labour market.

[15] We defined ‘skilled’ workers as those who report to be in one of the following occupations: managers; professionals; associate professionals and tradespersons with more years of education than the group average. The residual ASCO2 classes were considered to be ‘unskilled’ workers. Persons not in employment and with more than 11.5 years of education (i.e., the mean for this group) were assigned to the skilled group.

[16] Details are available from the authors.

respectively. Conversely, skilled workers exhibit much higher rates of training participation: 43.6% of the skilled undereducated and 47.3% of the skilled overeducated participated in training. Note also the relatively high share of overeducated managers and administrators and professionals who underwent training.

Table 1. Incidence of Undereducation, Overeducation and Training by Occupation and Skill: Full-Time Workers, Australia, 1997

ASCO2 Class	Employment share (%)	Required education (years)	Just-right education (%) [with training] (%)	Undereducation (%) [with training] (%)	Overeducation (%) [with training] (%)
Managers and administrators	6.4	13.9	51.0 [40.4]	26.2 [44.4]	22.8 [52.1]
Professionals	18.9	15.2	68.0 [51.4]	17.6 [45.6]	14.4 [46.8]
Associate professionals	11.1	12.5	66.8 [46.5]	18.4 [41.3]	14.8 [47.2]
Tradespersons	15.8	12.5	74.3 [30.8]	20.6 [15.9]	5.1 [39.2]
Advanced clerical and service workers	3.70	11.9	85.8 [41.2]	7.9 [32.6]	6.3 [52.2]
Inter. clerical, sales & service workers	17.0	11.7	71.3 [43.3]	13.2 [35.5]	15.5 [46.7]
Inter. production & transport workers	11.4	10.9	69.6 [26.2]	12.9 [16.0]	17.5 [34.7]
Elem. clerical, sales & service workers	6.19	11.0	79.2 [29.8]	5.1 [30.2]	15.7 [31.5]
Labourers & related workers	9.60	10.5	72.2 [18.5]	12.6 [16.4]	15.1 [26.3]
Low skill workers	49.7	11.3	71.8 [30.7]	17.1 [21.7]	11.8 [37.0]
High skill workers	50.3	13.6	68.7 [43.9]	14.6 [43.6]	13.4 [47.3]
All full-time workers		12.5	70.2 [37.5]	15.8 [31.9]	13.9 [42.1]

Note: Figures in squared brackets are group percentages of workers in firm-provided training. Percentages may not sum up to 100 due to rounding. Required education is the *weighted* mean of actual education by occupational class using the SET 1997 cross-section weights. The high skill group comprises of the first four ASCO2 classes excluding tradespersons whose years of education are below the group average. Here, it excludes persons not in employment. Only employer-provided training is considered.
Source: ABS 1997 Survey of Education and Training, Unit Record File (CURF).

Table 2 summarises the incidence of required education, undereducation and overeducation for various groups of full-time and part-time employees. Here, we see that amongst full-time workers, 15.1% of women and 16.2% of men appear to be undereducated while 10.9% of women and 15.5% of men are overeducated. With the exception of the third figure, our estimates differ from those in Voon and Miller (2005) who find that 13.7% of men and 18.5% of women are undereducated and 13.6% of women are overeducated. The discrepancy may be due to differences in the measurement of actual years of education or due to the 2-digit SET 97 aggregation of occupational classifications.

Note, the incidence of both undereducation and overeducation seems to be lower amongst the younger workers (i.e., less than 50 years old). We also observe that older workers (i.e., 50 and above years old) and those born overseas in a non-English-speaking country (NESOB) are highly overrepresented amongst the undereducated and the overeducated. Similar patterns are observed amongst part-time workers. The main difference is that now women exhibit a higher incidence (in percentage terms) of undereducation than men.

Table 2 also displays the proportion of men and women who participated in training course in 1997. It shows that among the undereducated (overeducated) in full-time employment, 35.9% (42.6%) of women and 29.8% (41.9%) of men participated in training.[17] Also, unskilled, older and NESOB workers exhibit a high incidence of no participation in training. For example, of the undereducated in full-time employment, only 26.5% of the older workers, 21.7% of low skilled workers and 15.1% of NESOB workers participated in training. This compares with the 33.8%, 43.6% and 34.7% of younger, skilled and Australia-born workers respectively. Note that this pattern is even more striking amongst undereducated part-time workers; 17.5% of the unskilled and 10.5% of NESOB participated in training. Finally, we observe that the rates of training of the overeducated are consistently higher than those of the undereducated.

[17] The data appendix contains more detail and summary statistics on the variables used in this study. Note, training that was self-financed by employees or by third parties is ignored throughout this study. Also, 38% of men and 41% of women in full-time employment participated in firm-financed training. In contrast, 15% of men and 25% of women in part-time employment took part in training.

Some full-time overeducated are even more over-represented in job training: 43% of young workers, 52.7% of workers in large firms, and 47.3% of highly skilled workers.

Table 2. Incidence of Undereducation, Overeducation and Training: Australia, 1997

	Just-right education (%)		Under-education (%)		Over-education (%)	
	Total	Workers undergone training	Total	Workers undergone training	Total	Workers undergone training
			Full-Time Employees			
Gender: Women	73.9	39.0	15.1	35.9	10.9	42.6
Gender: Men	68.3	36.6	16.2	29.8	15.5	41.9
Young: Below 50	72.8	37.9	13.8	33.8	13.4	43.0
Old: 50 plus	56.3	34.6	26.8	26.5	16.9	38.2
Firm Size: Small	70.7	20.5	17.7	16.8	11.5	24.3
Firm Size: Large	69.9	51.6	14.3	47.3	15.9	52.7
Skill Level: Low	68.7	30.7	17.1	21.7	14.2	37.0
Skill Level: High	71.8	43.9	14.6	43.6	13.6	47.3
Birthplace: NESOB	66.2	28.9	16.2	15.1	17.6	36.9
Birthplace: AUS	71.3	38.9	15.9	34.7	12.8	44.2
			Part-Time Employees			
Gender: Women	78.0	23.9	12.7	21.3	9.4	33.0
Gender: Men	76.3	15.3	11.3	12.4	12.4	14.8
Young: Below 50	80.5	21.8	9.6	19.4	9.8	26.0
Old: 50 plus	57.7	20.9	29.9	18.5	12.4	28.9
Firm Size: Small	74.7	12.7	14.9	12.2	10.3	15.7
Firm Size: Large	81.3	32.9	8.8	35.1	9.9	41.8
Skill Level: Low	79.3	18.0	10.6	17.5	10.1	24.0
Skill Level: High	72.4	33.5	17.2	22.1	10.4	33.4
Birthplace: NESOB	66.7	15.8	13.8	10.5	19.5	15.9
Birthplace: AUS	79.6	21.9	11.9	20.1	8.5	27.8

Note: Percentages may not sum up to 100 due to rounding. Only employer-provided training is considered.
Source: ABS 1997 Survey of Education and Training, Unit Record File (CURF).

We proceed with the two-stage procedure in the estimation of model (5). In the first stage, we utilise data on all persons whose employment status is known in order to model training time, TT^F, provided by firms in the bivariate model (7a)-(7b). The observable variable, TT, is weekly hours spent in employer-provided training by current employees.

In the outcome equation, (7a), the following explanatory factors were considered: participation in an assessed training course (TASS); participation in a training course that provided skills that are transferable to other employers (TTSK);[18] at most ten years of education (EDU10); more than 15 years of education (EDU15); age (AGE); AGE squared and divided by 100; part-time employment (PTE); being a male (MALE). All except AGE and AGE2 are indicator variables taking the value of one if a worker has the particular characteristic and zero otherwise. The selection equation (7b) includes all of the above variables plus the following indicator variables: being married (MAR); NESOB; public sector employee (GOV); union member (UNION). The choice of variables was based on data availability and literature emphasis[19] on age, education, intensity and purpose of training, and employment status.

The Heckman selection estimation results appear in Table 3. They show that all low education levels, part-time employment, and NESOB background are associated with a lower probability of being selected for training. On the other hand, tertiary education, age (although non-linear), union membership, public sector employment, marriage and participation in a training course that is assessed or provides transferable skills all add to the probability of being selected for job training. The positive effect of assessed training may reflect ability but the effect of transferable skills is surprising given the prediction of human capital theory emphasising firm-specific skills (Acemoglu and Pischke 1999). However, this finding could be consistent with the view that firms select workers for training as part of a strategy towards lower skilled labour turnover (Green and Heywood 2007).

[18] TASS and TTSK can be positive when workers do not receive firm-provided training but have participated in other training courses financed by the worker or third parties.

[19] See, for example, Ryan and Watson (2003), and Buchtemann and Soloff (2003).

Table 3. A Model of Training Time: All Persons, Australia 1997

(A) Training Time	
Constant	-1.550 (0.193)
Assessed training (TASS)	0.370 (0.043)
Training for skills (TTSK)	0.544 (0.039)
Education: ≤10 years (EDU10)	-0.080 (0.039)
Education: >15 years (EDU15)	0.145 (0.036)
AGE	0.031 (0.009)
AGE squared/100	-0.036 (0.012)
Part-time employee (PTE)	-0.460 (0.037)
MALE	0.145 (0.031)
(B) Training Participation	
Constant	-2.050 (0.103)
Assessed training (TASS)	1.041 (0.026)
Training for skills (TTSK)	0.553 (0.032)
Education: ≤10 years (EDU10)	-0.316 (0.025)
Education: >15 years (EDU15)	0.135 (0.028)
AGE	0.056 (0.006)
AGE squared/100	-0.076 (0.008)
Part-time employee (PTE)	-0.041 (0.026)
MALE	-0.040 (0.022)
Married (MAR)	0.054 (0.025)
O/S Born, NESOB	-0.317 (0.033)
Public sector (GOV)	0.606 (0.026)
Union member (UNION)	0.491 (0.024)
Observations	22140
ρ	-0.225 (0.042)
σ	1.066 (0.012)
λ	-0.239 (0.047)
LR of indep. equations: $\chi^2(1)$	25.45

Standard-errors in parentheses. In (A), the dependent variable is the log of training time (TT).
Source: ABS 1997 Education and Training, CURF.

In panel (A) of Table 3, the outcome equation indicates that firms provide more training time to workers with post-secondary qualifications and those who take part in courses that are assessable or provide transferable skills. Males and younger but relatively more mature workers receive more training while the opposite seems to be the case amongst part-time employees and workers above the age of 43 years old (i.e., based on the net, quadratic effect of AGE). The lower part of Table 3 contains some summary statistics. These show that the correlation coefficient of the error terms, ρ, is significant and a likelihood ratio test rejects the null of independent equations. Both of these statistics suggest evidence of firm selection in job training.

Results in Table 3 allow us to estimate TT^F, as defined in (8), and proceed with the estimation of the trivariate model (5a)-(5c).[20] Note that the dependent variable, $\ln W^*$, in (5a) exhibits *incidental* truncation due to non-participation in the labour market and right censoring imposed by the Australian Bureau of Statistics.[21]

In the wage equation (5a), we consider the same explanatory variables used by Voon and Miller (2005): required education (S_R); undereducation (S_U); overeducation (S_O); years of experience (E); experience squared and divided by 100 (E^2), as well as the following indicator variables: married (MAR); public sector employment (GOV); overseas-born worker from English-speaking countries (ESOB), and NESOB. In addition, we allow for a direct training effect, TT^F, whose unobserved component was estimated in stage one.

In the training participation equation (5b), we employ a similar set of explanatory variables as in equation (7b), except that we drop MALE and MAR and add an indicator variable for caring for children of 0-14 years old (KIDS14). Since (7b) refers to workers' decision, we also allow for expected earnings, $\ln W^*$, to influence worker participation in training. In addition to TT^F, in (5c), we draw on Laplagne, Glover and Shomos (2007) to consider the following factors: EDU10; EDU15; E; E^2; MAR; NESOB; KIDS14, and an indicator variable for having a disability (DIS).

MLE estimate results of the trivariate system (5a)-(5c) appear in the first two columns of Table 4. These indicate that returns to required education are about 12% for men and 11% for women. These are significant but substantially lower than the 18% and 15% respective estimates reported by Voon and Miller (2005). The coefficient of undereducation is negative while that of overeducation is positive. As in previous studies, both coefficients are smaller in absolute terms than the coefficients of required education. The smaller coefficient for undereducation implies that the

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[20] Roodman's (2007) conditional (recursive) mixed process estimator, CMP, was used in STATA. In maximising the likelihood function, we relied on the Davidon-Fletcher-Powell (DFP) algorithm and fixed the seed number to allow for replication.

[21] There were 4615 left-censored observations (i.e., currently not in employment, NIE, see data appendix) and 837 full-time workers with wages right-censored. Note, 1279 persons were excluded from econometric analysis, for they did not report employment status.

Table 4. Returns to Education and Training in Australia: A Trivariate Model

(A) Wages Equation	Men	Women	Men	Women
Constant	4.444 (0.042)	4.574 (0.043)	5.203 (0.042)	5.211 (0.038)
Required Education (S_R)	0.118 (0.003)	0.110 (0.003)		
- with Training ($S_{R,T}$)			0.081 (0.003)	0.075 (0.003)
- without Training ($S_{R,NT}$)			0.057 (0.003)	0.057 (0.003)
Undereducation (S_U)	-0.032 (0.004)	-0.028 (0.004)		
- with Training ($S_{U,T}$)			-0.010 (0.006)	-0.014 (0.005)
- without Training ($S_{U,NT}$)			-0.039 (0.003)	-0.044 (0.003)
Overeducation (S_O)	0.040 (0.004)	0.035 (0.004)		
- with Training ($S_{O,T}$)			0.042 (0.004)	0.044 (0.008)
- without Training ($S_{O,NT}$)			0.033 (0.003)	0.031 (0.003)
Experience (E)	0.042 (0.002)	0.032 (0.002)	0.032 (0.001)	0.025 (0.001)
E squared/100 (E^2)	-0.066 (0.003)	-0.054 (0.004)	-0.043 (0.003)	-0.037 (0.002)
Married (MAR)	0.109 (0.011)	0.025 (0.010)	0.050 (0.001)	0.006 (0.015)
Public Sector (GOV)	-0.001 (0.011)	0.045 (0.011)	-0.054 (0.018)	0.005 (0.011)
O/S Born, ESOB	0.008 (0.014)	0.009 (0.015)	-0.007 (0.007)	-0.001 (0.009)
O/S Born, NESOB	-0.105 (0.014)	-0.040 (0.014)	-0.065 (0.014)	-0.026 (0.015)
Log of Training Time (TT^F)	0.034 (0.007)	0.032 (0.007)	0.010 (0.004)	0.012 (0.003)
(B) Training Equation				
Assessed training (TASS)	0.948 (0.031)	0.678 (0.032)	0.053 (0.022)	0.039 (0.026)
Training for skills (TTSK)	0.300 (0.039)	0.208 (0.038)	-0.043 (0.001)	-0.059 (0.025)
Education: ≤10 years	-0.214 (0.037)	-0.338 (0.043)	0.290 (0.030)	0.306 (0.001)
Education: >15 years	-0.023 (0.042)	0.039 (0.045)	-0.332(0.037)	-0.535 (0.001)
AGE	0.030 (0.012)	0.086 (0.012)	-0.111 (0.007)	-0.099 (0.001)
AGE squared/100	-0.050 (0.015)	-0.122 (0.016)	0.098 (0.008)	0.093 (0.001)
Kids (KIDS14)	0.003 (0.034)	-0.481 (0.038)	-0.034 (0.020)	-0.115 (0.001)
O/S Born, NESOB (EDU10)	-0.235 (0.048)	-0.225 (0.048)	0.119 (0.043)	0.112 (0.057)
Public sector (GOV)	0.856 (0.039)	1.061 (0.043)	0.154 (0.060)	0.055 (0.046)
Union member (UM)	0.167 (0.030)	0.118 (0.031)	0.042 (0.017)	-0.004 (0.001)
Log of Wages ($\ln W^*$)	0.776 (0.033)	0.145 (0.039)	2.758 (0.021)	3.190 (0.001)
(C) Employment Equation				
Education: ≤10 years	-0.190 (0.032)	-0.351 (0.039)	-0.229 (0.033)	-0.408 (0.045)
Education: >15 years	-0.225 (0.044)	0.001 (0.055)	-0.137 (0.046)	0.146 (0.001)
Experience (E)	0.002 (0.007)	0.048 (0.008)	0.009 (0.007)	0.057 (0.011)
E squared/100 (E^2)	-0.038 (0.012)	-0.125 (0.015)	-0.053 (0.012)	-0.142 (0.023)
Married (MAR) (EDU10)	0.132 (0.038)	0.001 (0.036)	0.189 (0.042)	-0.040 (0.041)
O/S Born, NESOB	-0.238 (0.039)	-0.202 (0.047)	-0.214 (0.040)	-0.270 (0.048)
Log of Training Time (TT^F)	0.539 (0.025)	0.492 (0.024)	0.083 (0.032)	0.060 (0.035)
Kids (KIDS14) (AGE1524)	-0.029 (0.037)	-0.880 (0.041)	-0.052 (0.039)	-0.988 (0.058)
Disable (DIS)	-0.061 (0.032)	-0.214 (0.030)	-0.100 (0.035)	-0.351 (0.046)
Age: 15-24 years old	-0.218 (0.062)	-0.171 (0.069)	-0.288 (0.069)	-0.326 (0.081)
Observations	10064	6595	10064	6595
Wald test: H_0: $\alpha_T <= \alpha_{NT}$			[0.001]	[0.001]
Wald test: H_0: $\beta_T <= \beta_{NT}$			[0.001]	[0.001]
Wald test: H_0: $\gamma_T <= \gamma_{NT}$			[0.047]	[0.041]

Standard-errors in parentheses. Estimates of the constants in panels (B) and (C) are available from the authors. In square brackets are p-values of one-sided tests of coefficients with H_0: $c_T \leq c_{NT}$ where c=α, β, γ; parameters in equation (4). *Source*: ABS 1997 *Education and Training* Unit Record File.

undereducated earn a wage premium relative to those who have the same level of education but who are in jobs where that level is required. Note that the overeducated pay a wage penalty compared to those with the same level of education that are matched to a job requiring that level of education.

Our estimate for undereducation is almost identical to that in Voon and Miller (2005) but the estimate for overeducation is substantially lower than in Voon and Miller (2005). We attribute this to the fact that the dependent variable in Voon and Miller (2005) includes income other than labour income given the fact that non-labour income positively associates with education levels (Campbell 2006). Most other coefficients are significant at the 5% confidence level except the ESOB coefficient and that of GOV for men. For men, the marriage premium of 10.9% compares with the 9.2%, 8.9% and 11.1% estimates reported by Voon and Miller (2005), Borland *et al.* (2004) and Breusch and Gray (2004) respectively. Although much smaller in size, married women also gain a premium. The latter result contrasts sharply with the -3.5% penalty reported by Chapman *et al.* (2001) but is consistent with the premium reported by Breusch and Gray (2004) and the 3.6% estimate in Borland *et al.* (2004). Our estimates of the wage penalty associated with NESOB are comparable to those reported by Voon and Miller (2005) for both men and women. However, our estimate of the public sector premium for women is lower. These differences may be due to the importance of training or selection effects since MAR and NESOB enter significantly the employment selection equation in panel (C) while GOV is an important factor in worker training participation in panel (B).

In panel (A), the coefficients of training time, TT^F, are positive and significant for both men and women and suggest that the log of training time, TT^F, yields a return of 3.4% for men and 3.2% for women; the coefficients can also be interpreted as training elasticities. These, however, are much lower than the returns of 6%-10% in Chapman and Tan (1992) and (Long 2001) but closer to the 4% estimate in Lamb *et al.*

(1998).[22] The evidence in Table 4 supports Kuruscu's (2006) claim that returns to training are much lower than previously reported, once we account for firm selection. Thus, the results indicate that training directly affects wage outcomes and that we can reject *Hypothesis* 1 that suggests that training does not augment human capital.

Panel (B) in Table 4 indicates that course quality and transferability of skills are key incentives for worker participation in training. Union membership, public sector employment and expected earnings also encourage training participation; the latter is confirmatory evidence of feedback effects in the wages-training nexus, especially for men. Conversely, lower levels of education, NESOB background and caring for young children for women discourage participation in job training.

Panel (C) in Table 4 summarises the factors that are important in employment participation. Here, low levels of education, experienced women, married men, disability, NESOB and KIDS14 associate with lower levels of participation, as in previous studies (Laplagne, Glover and Shomos 2007). In contrast, however, young and highly educated males tend to participate less in employment. Finally, it is important to note that expected training time, TT^F, has a positive and statistically significant effect on participation in full-time employment for all workers.

We proceed to examine whether training plays a role in skill mismatch. We thus substitute model (4) in (5a) and re-estimate the trivariate model. Again, we employ training time, TT^F, and interact required education, undereducation and overeducation with *current* participation in employer-provided training. The results appear in columns 3-4 of Table 4 and confirm the qualitative results in columns 1-2 except that public sector now clearly associates with a wage *penalty* for men and the coefficient estimates for NESOB and marriage are much smaller in absolute terms for men but are statistically insignificant for women. We still find a training effect, although its size has reduced to 1% for men and 1.2% for women.

Moreover, participation in job training impacts significantly on returns to required education, undereducation and overeducation. Namely, men and women who had just-the-right education but did not participate in job training earned respectively 2.4% and

[22] For a summary of the empirical evidence on the effect of training, see Ryan and Watson (2003) and Long (2001).

1.8% less than those who did participate. Overeducation still results in a wage penalty and undereducation still associates with a wage premium[23] but the penalty for the former is 1% lower and the premium for the latter is about 3% higher when they receive training.[24] Hence, the effect of training seems asymmetric: the undereducated benefit much more than those with just-the-right education while the overeducated benefit the least. This asymmetry explains why the coefficient estimates for the direct training effect are lower than those observed in columns (1) and (2) in the same table.

Overall, the evidence in Table 4 seems to reject *Hypothesis* 1 and is consistent with the view that training has a direct effect on wages. This effect comprises of a small 1%-1.2% return to all workers and approximately 2% return to workers who are well matched in their job. The evidence also rejects *Hypothesis* 2 and provides support for an indirect effect where training proves rewarding in the presence of skill mismatch.

In panel (B), note that, in contrast to firm selection in Table 3, now both men and women are more (less) likely to participate in training if they are less (more) educated, are of NESOB background (care for children) or if they work in the public sector. Interestingly, males are less inclined to participate in firm-provided training if the show a preference for training courses with transferable skills.

In panel (C), some clear gender differences emerge with respect to participation in full-time employment. Highly educated males are less likely to be working in full-time jobs while the opposite appears to be the case for women. Also, low education, childcare and disability are more powerful disincentives to full-time employment for women than men.

Next, we examine the robustness of our empirical results by limiting our analysis to two sub-samples that are less likely to be subject to firm selection in job training. First, we draw on previous studies that highlight a link between worker turnover and training selection. Bewley (1999) and Green and Heywood (2007) have argued that high worker turnover is a major concern for firms. The former study has discussed extensively firms' principal objective to limit the loss of highly skilled workers as a

[23] The wage premium is the difference between the return to required education and the absolute return to undereducation.

[24] In columns 3-4, Wald one-sided tests of the null hypotheses: $\alpha_T \leq \alpha_{NT}$, $\beta_T \leq \beta_{NT}$ and $\gamma_T \leq \gamma_{NT}$ confirm that these differences are statistically significant at the 5% confidence level.

means to increased productivity. The second study claims that training is an integral part of a strategy to motivate and maintain highly valued skilled workers. Thus, management is more likely to select skilled workers for job training as an incentive towards a long-term relation between the firm and these workers.[25]

We exploit these insights to exclude from our sample workers who are highly skilled *and* are relatively new at their current employer.[26] The Maximum Likelihood estimation results using the remaining sub-sample appear in Table 5. Columns 1-2 have coefficient estimates of model (5a)-(5c) that are similar to those in columns 3-4 of Table 4, especially those of the log of training time, TT^F, and of required education.

We also explore the sensitivity of our results by restricting our sample even further to also exclude workers who report that they were inhibited or unable to participate in training in 1997. The SET 97 survey include two question in order to shed light on the main reasons or factors that explain why workers did not attend a training course. Self-reported answers to these questions were classified as (a) not applicable due to participation; (b) 'no need to attend training' or 'nothing could enable/encourage training'; (c) work-related factors; (d) other reasons (training or personal). In the analysis below, we have excluded workers who reported either (c) or (d) in either of the two questions.[27] Columns 3-4 in Table 5 present the estimation results that are, again, similar to those observed in columns 1-2 except that now training plays no role in cases of mismatch. This could be due to a considerable sample loss of mismatched workers. More importantly, the coefficients of TT^F and $S_{R,T}$ and $S_{R,NT}$ are of similar magnitude as before. Thus, we conclude that our first set of estimates in Table 4 appear to be free of selection bias.

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[25] There are alternative causes of firm selection in training, such as profit-sharing schemes (Morrison and Wilhelm 2004). However, data limitations do not allow us to control for these.

[26] These include managers, professionals, associated professionals, trades and advanced clerical (as classified by ASCO2) who have less than five years of tenure with the main employer. We also experimented with an alternative definition of skilled workers that included intermediate clerical workers and excluded trades workers. Qualitatively, the results were similar to those presented here.

[27] The original variable codes for these two series are "TRREASON" and "TRFACTOR".

Table 5. Returns to Education and Training in Australia: Robustness Tests

(A) Wages Equation	(1) Men	Women	(2) Men	Women
Constant	5.299 (0.034)	5.313 (0.054)	5.282 (0.001)	5.126 (0.049)
S_R with Training ($S_{R,T}$)	0.075 (0.003)	0.066 (0.003)	0.079 (0.002)	0.078 (0.004)
S_R without Training ($S_{R,NT}$)	0.048 (0.003)	0.050 (0.003)	0.054 (0.003)	0.048 (0.004)
S_U with Training ($S_{U,T}$)	-0.020 (0.004)	-0.013 (0.006)	-0.013 (0.009)	-0.030 (0.006)
S_U without Training ($S_{U,NT}$)	-0.033 (0.004)	-0.037 (0.004)	-0.028 (0.009)	-0.036 (0.006)
S_O with Training ($S_{O,T}$)	0.030 (0.003)	0.044 (0.005)	0.042 (0.006)	0.037 (0.005)
S_O without Training ($S_{O,NT}$)	0.026 (0.003)	0.024 (0.006)	0.031 (0.010)	0.041 (0.006)
Experience (E)	0.032 (0.001)	0.024 (0.002)	0.029 (0.001)	0.027 (0.002)
E squared/100 (E^2)	-0.042 (0.003)	-0.033 (0.004)	-0.037 (0.001)	-0.038 (0.005)
Married (MAR)	0.059 (0.008)	0.019 (0.006)	0.047 (0.001)	0.020 (0.009)
Public Sector (GOV)	-0.092 (0.012)	-0.002 (0.049)	-0.114 (0.024)	0.040 (0.016)
O/S Born, ESOB	-0.007 (0.009)	-0.013 (0.007)	-0.010 (0.001)	0.017 (0.012)
O/S Born, NESOB	-0.044 (0.015)	-0.022 (0.018)	-0.069 (0.001)	-0.001 (0.022)
Log of Training Time (TT^F)	0.010 (0.003)	0.008 (0.004)	0.016 (0.001)	0.015 (0.005)
(B) Training Equation				
Assessed training (TASS)	0.110 (0.023)	0.010 (0.024)	0.073 (0.001)	0.086 (0.031)
Training for skills (TTSK)	0.008 (0.028)	-0.042 (0.022)	-0.058 (0.001)	-0.041 (0.038)
Education: ≤10 years	0.250 (0.033)	0.328 (0.064)	0.243 (0.001)	0.283 (0.041)
Education: >15 years	-0.237 (0.036)	-0.442 (0.066)	-0.340 (0.028)	-0.511 (0.061)
AGE	-0.125 (0.008)	-0.100 (0.014)	-0.101 (0.001)	-0.159 (0.014)
AGE squared/100	0.110 (0.010)	0.094 (0.018)	0.087 (0.001)	0.174 (0.018)
Kids (KIDS14)	-0.040 (0.025)	-0.001 (0.047)	-0.043 (0.001)	0.063 (0.039)
O/S Born, NESOB (EDU10)	0.032 (0.050)	0.090 (0.070)	0.153 (0.001)	0.035 (0.076)
Public sector (GOV)	0.366 (0.041)	-0.069 (0.198)	0.363 (0.050)	-0.315 (0.059)
Union member (UM)	0.002 (0.021)	-0.006 (0.023)	0.023 (0.001)	0.003 (0.032)
Log of Wages ($\ln W^*$)	2.960 (0.036)	3.158 (0.092)	2.766 (0.001)	2.730 (0.059)
(C) Employment Equation				
Education: <=10 years	-0.198 (0.033)	-0.320 (0.043)	-0.194 (0.001)	-0.403 (0.046)
Education: >15 years	-0.464 (0.050)	-0.113 (0.073)	-0.296 (0.001)	-0.299 (0.075)
Experience (E)	0.023 (0.007)	0.070 (0.010)	0.013 (0.001)	0.038 (0.010)
E squared/100 (E^2)	-0.080 (0.013)	-0.159 (0.018)	-0.053 (0.001)	-0.095 (0.019)
Married (MAR)	0.219 (0.043)	-0.019 (0.048)	0.222 (0.066)	-0.135 (0.050)
O/S Born, NESOB	-0.268 (0.041)	-0.202 (0.053)	-0.313 (0.001)	-0.376 (0.060)
Log of Training Time (TT^F)	0.101 (0.030)	0.048 (0.053)	0.086 (0.001)	-0.031 (0.037)
Disable (DIS)	-0.098 (0.040)	-0.927 (0.048)	-0.069 (0.001)	-0.992 (0.053)
Age: 15-24 years old	-0.150 (0.036)	-0.276 (0.051)	-0.106 (0.001)	-0.301 (0.053)
Observations	8972	5567	7327	4803
Wald test: H_0: $\alpha_T <= \alpha_{NT}$	[0.001]	[0.001]	[0.001]	[0.001]
Wald test: H_0: $\beta_T <= \beta_{NT}$	[0.008]	[0.001]	[0.195]	[0.235]
Wald test: H_0: $\gamma_T <= \gamma_{NT}$	[0.150]	[0.001]	[0.247]	[0.701]

Standard-errors in parentheses. Estimates of the constants in panels (B) and (C) are available from the authors. In square brackets are p-values of one-sided tests of coefficients with H_0: $c_T \le c_{NT}$ where $c=\alpha, \beta, \gamma$; parameters in equation (4). *Source*: ABS 1997 *Education and Training* Unit Record File.

Finally, we seek to shed some light on the nexus between job training and human capital depreciation by examining various groups that are likely to be susceptible to skill obsolescence due to physical wear or skill atrophy. In particular, we focus on the effects of ageing and career interruptions due to caring for young children. We observed earlier that ageing and career interruptions are key risk factors with respect to skill depreciation.

Based on the estimate of TT^F obtained in Table 3, Table 6 presents MLE estimation results for two groups of workers based on age: workers of less than 25 years of age and workers older than 50 years of age. The results show that the wage premium and penalty associated with undereducation and overeducation respectively are hardly evident amongst young workers. Further, young workers with just-the-right level of education benefit from training. However, it is the older workers who benefit most from training, provided they are well matched to their job. In fact, mature aged workers who participate in training exhibit substantial benefits: the wage premium is 68% for men and 53% for women.

Finally, Table 7 compares workers who care for young children to those without such a responsibility. According to Mincer and Ofek (1982), we should expect career interruptions, especially for women, to associate with a wage penalty but participation in training ought to compensate. Results in Table 7 confirm this prediction. The direct training effect (i.e., the TT^F coefficient) is not statistically significant amongst those who do not have young children. Conversely, the corresponding effect amongst workers with young children in the household is indeed positive and significant. Note also that the coefficient of TT^F is much higher amongst women. Further, the benefit of training to persons who are well matched in their jobs is much higher for workers with career interruptions, and even higher for women. However, workers without childcare responsibilities benefit from training when there is job mismatch while this is not the case for workers with young children.

Table 6. Returns to Education and Training in Australia: Age Effects

	(1): Young workers		(2): Older workers	
(A) Wages Equation	Men	Women	Men	Women
Constant	4.108 (0.118)	4.139 (0.104)	6.495 (0.408)	5.889 (0.615)
S_R with Training ($S_{R,T}$)	0.129 (0.008)	0.121 (0.006)	0.059 (0.007)	0.066 (0.010)
S_R without Training ($S_{R,NT}$)	0.105 (0.008)	0.106 (0.006)	0.035 (0.006)	0.043 (0.009)
S_U with Training ($S_{U,T}$)	-0.115 (0.016)	-0.102 (0.013)	-0.001 (0.010)	-0.009 (0.017)
S_U without Training ($S_{U,NT}$)	-0.125 (0.010)	-0.098 (0.010)	-0.009 (0.007)	-0.023 (0.011)
S_O with Training ($S_{O,T}$)	0.104 (0.012)	0.092 (0.009)	0.005 (0.008)	0.023 (0.021)
S_O without Training ($S_{O,NT}$)	0.101 (0.010)	0.078 (0.013)	-0.001 (0.007)	0.013 (0.014)
Experience (E)	0.094 (0.017)	0.080 (0.014)	-0.012 (0.017)	-0.008 (0.026)
E squared/100 (E^2)	-0.009 (0.108)	0.012 (0.087)	-0.001 (0.020)	0.001 (0.030)
Married (MAR)	0.011 (0.018)	0.004 (0.013)	0.055 (0.019)	-0.007 (0.021)
Public Sector (GOV)	-0.108 (0.037)	-0.006 (0.026)	0.020 (0.026)	0.177 (0.045)
O/S Born, ESOB	0.008 (0.027)	-0.012 (0.024)	-0.005 (0.015)	-0.006 (0.020)
O/S Born, NESOB	0.026 (0.052)	-0.009 (0.041)	-0.059 (0.031)	0.029 (0.038)
Log of Training Time (TT^F)	-0.001 (0.009)	0.003 (0.007)	0.002 (0.010)	0.031 (0.018)
(B) Training Equation				
Assessed training (TASS)	0.144 (0.059)	0.055 (0.059)	0.051 (0.043)	-0.010 (0.080)
Training for skills (TTSK)	0.070 (0.076)	-0.048 (0.066)	-0.022 (0.051)	-0.138 (0.088)
Education: ≤10 years	0.203 (0.072)	0.083 (0.087)	0.291 (0.063)	0.453 (0.093)
Education: >15 years	-0.067 (0.109)	-0.232 (0.109)	-0.206 (0.064)	-0.442 (0.194)
AGE	-0.354 (0.193)	-0.261 (0.303)	0.108 (0.204)	-1.247 (0.571)
AGE squared/100	0.157 (0.459)	-0.122 (0.708)	-0.068 (0.180)	1.121 (0.504)
Kids (KIDS14)	-0.054 (0.099)	-0.005 (0.101)	0.005 (0.047)	-0.044 (0.173)
O/S Born, NESOB (EDU10)	-0.108 (0.187)	-0.048 (0.206)	0.132 (0.088)	-0.064 (0.157)
Public sector (GOV)	0.275 (0.126)	0.085 (0.113)	-0.136 (0.075)	-0.406 (0.170)
Union member (UM) NION)	0.082 (0.050)	0.011 (0.064)	0.014 (0.038)	0.039 (0.070)
Log of Wages ($\ln W^*$)	2.924 (0.091)	3.855 (0.133)	2.573 (0.071)	2.970 (0.138)
(C) Employment Equation				
Education: ≤10 years	-0.711 (0.076)	-0.929 (0.095)	0.160 (0.079)	0.318 (0.121)
Education: >15 years	1.069 (0.207)	0.969 (0.201)	-0.185 (0.110)	-0.503 (0.210)
Experience (E)	0.611 (0.076)	0.697 (0.092)	-0.023 (0.091)	-0.569 (0.180)
E squared/100 (E^2)	-2.942 (0.509)	-3.110 (0.628)	-0.003 (0.106)	0.567 (0.206)
Married (MAR) (EDU10)	0.439 (0.160)	0.402 (0.127)	0.132 (0.085)	-0.372 (0.108)
O/S Born, NESOB	-1.265 (0.124)	-1.244 (0.140)	0.028 (0.079)	0.194 (0.123)
Log of Training Time (TT^F)	0.091 (0.077)	0.081 (0.089)	0.146 (0.074)	-0.309 (0.157)
Kids below 14 (AGE1524)	-0.198 (0.218)	-1.504 (0.154)	0.020 (0.099)	-0.381 (0.214)
Disable (DIS) (AGE50s)	-0.120 (0.090)	-0.408 (0.117)	-0.147 (0.068)	-0.320 (0.110)
Observations	1883	1504	1998	952
Wald test: H_0: $\alpha_1 <= \alpha_2$	[0.001]	[0.001]	[0.001]	[0.001]
Wald test: H_0: $\beta_1 <= \beta_2$	[0.294]	[0.593]	[0.195]	[0.223]
Wald test: H_0: $\gamma_1 <= \gamma_2$	[0.413]	[0.167]	[0.253]	[0.267]

Standard-errors in parentheses. Estimates of the constants in panels (B) and (C) are available from the authors. In square brackets are p-values of one-sided tests of coefficients with H_0: $c_T \leq c_{NT}$ where c=α, β, γ; parameters in equation (4). *Source*: ABS 1997 *Education and Training* Unit Record File.

Table 7. Returns to Education and Training in Australia: Career Interruption Effects

	(1): Kids present (KIDS14=1)		(2): No kids (KIDS14=0)	
(A) Wages Equation	Men	Women	Men	Women
Constant	5.392 (0.070)	5.309 (0.001)	5.319 (0.038)	5.375 (0.039)
S_R with Training ($S_{R,T}$)	0.082 (0.004)	0.097 (0.001)	0.076 (0.003)	0.069 (0.003)
S_R without Training ($S_{R,NT}$)	0.058 (0.003)	0.063 (0.001)	0.054 (0.003)	0.053 (0.002)
S_U with Training ($S_{U,T}$)	-0.018 (0.007)	-0.013 (0.018)	-0.011 (0.006)	-0.020 (0.005)
S_U without Training ($S_{U,NT}$)	-0.030 (0.005)	-0.032 (0.001)	-0.042 (0.004)	-0.040 (0.004)
S_O with Training ($S_{O,T}$)	0.040 (0.005)	0.052 (0.001)	0.041 (0.005)	0.038 (0.005)
S_O without Training ($S_{O,NT}$)	0.034 (0.004)	0.043 (0.008)	0.026 (0.004)	0.019 (0.004)
Experience (E)	0.024 (0.004)	0.004 (0.003)	0.030 (0.002)	0.022 (0.002)
E squared/100 (E^2)	-0.028 (0.007)	-0.004 (0.001)	-0.037 (0.003)	-0.027 (0.004)
Married (MAR)	0.029 (0.035)	0.019 (0.001)	0.023 (0.008)	0.016 (0.006)
Public Sector (GOV)	-0.119 (0.017)	-0.037 (0.026)	-0.113 (0.015)	-0.077 (0.017)
O/S Born, ESOB	0.011 (0.012)	0.010 (0.001)	-0.001 (0.009)	-0.009 (0.008)
O/S Born, NESOB	-0.088 (0.020)	-0.057 (0.058)	-0.020 (0.019)	-0.001 (0.019)
Log of Training Time (TT^F)	0.011 (0.006)	0.019 (0.001)	0.009 (0.005)	0.008 (0.004)
(B) Training Equation				
Assessed training (TASS)	0.088 (0.032)	0.379 (0.001)	0.088 (0.022)	0.013 (0.019)
Training for skills (TTSK)	-0.025 (0.035)	0.111 (0.103)	-0.025 (0.026)	-0.020 (0.020)
Education: ≤10 years	0.221 (0.049)	0.118 (0.001)	0.270 (0.032)	0.323 (0.040)
Education: >15 years	-0.388 (0.052)	-0.811 (0.001)	-0.253 (0.037)	-0.323 (0.054)
Age (years)	-0.083 (0.023)	-0.182 (0.005)	-0.101 (0.008)	-0.086 (0.009)
Age squared	0.067 (0.028)	0.237 (0.001)	0.085 (0.009)	0.075 (0.012)
O/S Born, NESOB (EDU10)	0.294 (0.067)	0.263 (0.194)	0.005 (0.056)	0.016 (0.062)
Public sector (GOV)	0.256 (0.056)	0.773 (0.001)	0.270 (0.044)	0.186 (0.053)
Union member (UM)	0.085 (0.029)	0.084 (0.001)	0.019 (0.020)	-0.007 (0.019)
Log of Wages ($\ln W^*$)	2.941 (0.060)	2.570 (0.001)	2.597 (0.037)	2.963 (0.057)
(C) Employment Equation				
Education: ≤10 years	0.023 (0.059)	-0.216 (0.065)	-0.328 (0.039)	-0.493 (0.048)
Education: >15 years	-0.175 (0.068)	-0.124 (0.001)	0.002 (0.059)	0.188 (0.076)
Experience (E)	-0.040 (0.017)	-0.002 (0.003)	0.018 (0.008)	0.049(0.010)
E squared/100 (E^2)	0.017 (0.032)	0.020 (0.001)	-0.060 (0.014)	-0.136 (0.018)
Married (MAR) (EDU10)	0.364 (0.165)	0.368 (0.001)	0.108 (0.042)	-0.027 (0.050)
O/S Born, NESOB	-0.044 (0.065)	0.235 (0.103)	-0.329 (0.050)	-0.392 (0.063)
Log of Training Time (TT^F)	0.084 (0.046)	0.132 (0.001)	0.097 (0.035)	0.119 (0.044)
Disable (DIS) (AGE50s)	-0.051 (0.061)	-0.019 (0.081)	-0.138 (0.041)	-0.300 (0.054)
Age: 15-24 years old	-0.152 (0.179)	0.188 (0.117)	-0.249 (0.074)	-0.496 (0.092)
Observations	3553	2216	6511	4379
Wald test: H_0: $\alpha_1 <= \alpha_2$	[0.001]	[0.001]	[0.001]	[0.001]
Wald test: H_0: $\beta_1 <= \beta_2$	[0.056]	[0.157]	[0.001]	[0.001]
Wald test: H_0: $\gamma_1 <= \gamma_2$	[0.138]	[0.112]	[0.002]	[0.001]

Standard-errors in parentheses. Estimates of the constants in panels (B) and (C) are available from the authors. In square brackets are p-values of one-sided tests of coefficients with H_0: $c_T \leq c_{NT}$ where c=α, β, γ; parameters in equation (4). *Source*: ABS 1997 *Education and Training* Unit Record File.

In summary, the evidence is consistent with the idea that training is human capital augmenting. It is also consistent with the view that training helps bridge the gap between acquired skills or formal education and required skills at the workplace. Conversely, lack of job training is central to explaining some of the wage penalty (premium) associated with overeducation (undereducation). Thus, the results suggest that standard measures of undereducation and overeducation mask differences within the undereducated and overeducated. Moreover, they indicate that training helps to alleviate the skill-job mismatch. Finally, the evidence strongly suggests that training acts as a catalyst in the restoration and replenishment of human capital, especially for the undereducated, older workers and persons with career interruptions associated with family responsibilities.

V Conclusion

The role of training in affecting labour market outcomes is a relatively under researched area in labour economics. This is especially true when compared to the extensive body of research analysing the impact of formal education.

We show that training has a significant impact on the wage experiences of workers, with wage premia around 3% for both men and women. Job training also has important effects when there is a mismatch between the formal educational requirements for particular occupations and the realised formal educational attainments of workers. In particular, we show that some of the wage premium associated undereducation can be attributed to job training. Even for those who are overeducated, there appears to be some wage benefit from further training.

We also sought to evaluate the relevance of two economic theories that postulate a role for job training. Thus, we have examined the importance of training for all workers and paid particular attention to the benefits of job training for bridging the gap between acquired and required skills. Overall, the evidence seems most consistent with an augmented *human capital hypothesis* that accounts for *skill depreciation*. Indeed, we find evidence that workers who fail to appreciate the potential gains from training are disadvantaged. This is especially true of workers who are susceptible to skill depreciation due to ageing or career interruptions. Further, we find strong support for the view that training is beneficial for *skill-job matching* for workers who are not well matched to their job.

There is scope for a great deal of further research in this area. Of prime importance would be to extend the analysis to include dynamic effects of training. Is it the case, for example, that the wage benefits to training dissipate over time? Is past experience in *training* a key source of the persisting wage premium amongst the undereducated? Answers to these questions await the availability of dynamic, longitudinal data.

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Appendix: Variable Definitions and Summary Statistics*

Label	Type	Definition	Mean	SD	Min	Max
AGE	C	Age in years.	35.8	12.6	15	62
AGE25	D	Age is less than 25 years old.	0.23		0	1
DIS	D	Has a disability (DISABLED).	0.19		0	1
EDU10	D	Education of ≤ 10 years.	0.33		0	1
EDU15	D	Education of > 15 years.	0.15		0	1
ESOB	D	Overseas-born in an English speaking country (MESC=2).	0.11		0	1
E	C	Years of work experience: = AGE - S_A - 4.	21.8	12.63	1	54
E^2	C	Experience squared/100.	6.35	6.20	0	29
EP	D	Full-time employment participation	0.50		0	1
GOV	D	Public sector employment.	0.18		0	1
KIDS14	D	Dependent children 0-14 years old.	0.35		0	1
MALE	D	Male.	0.54		0	1
MAR	D	Married.	0.60		0	1
NESOB	D	Overseas-born in a non-English speaking country (MESC=3).	0.14		0	1
NIE	D	Persons not in employment: 4615 in total. Of these, 1296 were not in the labour force, 1709 were marginally attached, and 1610 were unemployed. These exclude 1279 persons who did not report their employment status.	0.20		0	1
PTE	D	Part-time employment.	0.24		0	1
S_A	C	Actual years of education.	12.10	2.70	6	21
	S_A is the sum of $S1_A$ and $S2_A$ where the latter stand for years of education for the first and the second highest qualification respectively (H1LEVEL and H2LEVEL in SET 97). $S1_A$ was on the basis of 'H1LEVEL' and 'AGELEF' (i.e., age left school). We assigned 19 years of education to higher degrees, 17 to post-graduate diplomas, 16 to Bachelor degrees, 14 to skilled vocational training, 13 to under-graduate diplomas, 12.5 to basic vocational training or associate diplomas, 12 to secondary school, not stated or less than a semester's course, 11 if left school at age 17 year or over, 10 if left school at the age of 16 or still at secondary school, 9 if left at 15, 8 if left at 14, 7 if left school at 13 or under, and 6 if the person never attended secondary school. $S2_A$ took the value of 2 when the second qualification was a higher degree or a skilled vocational course, 1 if postgraduate diploma or undergraduate diploma and 0.5 if associate diploma or basic vocational course.					
S_O	C	Overeducation: equals (S_A-S_R) if S_A>S_R and zero if otherwise.	0.89	1.34	0	10
$S_{O,T}$	C	Overeducation with training: equals S_O if TP=1 and zero if otherwise.	0.37	0.99	0	10
$S_{O,NT}$	C	Overeducation without training: equals S_O if TP=0 and zero if otherwise.	0.38	0.96	0	9

S_R	C	The weighted mean of S_A by occupation 'in job with main period employer' (ASCO2) using the SET 1997 person weights to adjust for a sampling bias by the ABS in favour of persons currently in employment and marginally attached to the labour market.	12.3	1.56	10	15
$S_{R,\,T}$	C	Undereducation with training: equals S_R if TP=1 and zero if otherwise.	4.53	6.19	0	15
$S_{R,\,NT}$	C	Undereducation without training: equals S_R if TP=0 and zero if otherwise.	6.09	6.01	0	15
S_U	C	Undereducation: equals (S_R-S_A) if S_A<S_R and zero if otherwise.	0.66	1.16	0	9
$S_{U,\,T}$	C	Undereducation with training: equals S_U if TP=1 and zero if otherwise.	0.27	0.81	0	8
$S_{U,\,NT}$	C	Undereducation with training: equals S_U if TP=1 and zero if otherwise.	0.39	0.96	0	9
TEN	C	Tenure: years of employment in the current 'main' employer.	6.09	6.76	0	25
TASS	D	Participation in a training course that was assessed (T1ASSx; x=A,B,C,D).	0.15		0	1
TT	C	Hours spent on training by current employees (TIMECRS) divided by forty eight weeks. Training that is self-financed by employees was ignored.	0.41	1.47	0	21
TP	D	Participation in employer-financed training.	0.25		0	1
TTSK	D	Training for skills transferable to another employer (TxSKILL; x=1,2,3).	0.09		0	1
UM	D	Union member (UNIONMPE)	0.24		0	1
W	C	Weekly earnings: 'usual weekly earnings in job with main period employer' (EARNMPE). In ABS unit record confidentialised files, W is right-censored at $1180.	527	305	60	1180

* D=Indicator variable (=1 if condition applies); C=Continuous variable, SD=Standard deviation, MIN=Minimum value; MAX=Maximum value.

Note: The mean value for indicator variables stands for the share of those workers that meet the particular condition. The mean and standard deviations estimates are *weighted* by the person weights provided in SET 97.