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Skills Mismatch and Returns to Training in Australia: Some New Evidence

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Skill Mismatch and Returns to Training in Australia: Some New Evidence*

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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 the Heckman selection model to account for selection bias in training as well as work participation. The evidence shows that training has a significant positive impact on wages. Also, training ameliorates the disadvantage associated with the mismatch between formal education and required education. In addition, training is most valuable to the undereducated and young workers, and assists in the restoration and replenishment of human capital.

Keywords: Training; Education; Overeducation; Undereducation; Earnings; 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 measures of two possible discrepancies between actual education attainment levels and the required level of education appropriate for particular occupations. For a given task, this required level of education can be considered a benchmark; employees with more education than the required level are said to be overeducated while those with fewer qualifications are seen to be undereducated. Studies have observed that the overeducated earn more than their peers with less education, but that the return to extra education is a fraction of that associated with required education. In contrast, undereducation carries an earnings penalty but this is smaller than the returns to required education.[2] Voon and Miller (2005) and Kler (2005) show that the international evidence also holds for Australia.

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

[2] See Hartog (2000), Dolton and Vignoles (2000) and Büchel and Mertens (2004).

The above studies have 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 to simply augment 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.[3] Although, it can overlap with the first two, the third motivation highlights *human capital depreciation*. Dubin (1972), Rosen (1975) and Mincer and Ofek (1982) argue that human capital theory needs to explicitly incorporate depreciation. Skill obsolescence has been associated with wear, atrophy, as well as technological and organisational change (de Grip 2006; MacDonald and Weisbach 2004; Blechinger and Pfeiffer 2000).

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 an important remedy for skill obsolescence (de Grip 2006; de Grip and van Loo 2002).[4] An in-depth study by van Loo *et al.* (2001) shows that employees' willingness and capacity to participate in training are key mitigating factors counteracting human capital depreciation. However, recent research takes care to attend to some serious challenges when estimating returns to training. This literature shows that the wage effect of training is much lower than previously thought (Kuruscu 2006; Schøne 2004).

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

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

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

of training on labour income as well as its indirect effect on returns to required education, undereducation and overeducation. We consider only training that is financed by employers since self-financed training can be undertaken for reasons that may be unrelated to labour productivity. We also consider Kuruscu's (2006) claim that existing measures of participation in training may suffer from selection bias. 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.

II Background

Over the last two decades, extensive empirical research has shown that the incidences of undereducation and overeducation are high in European countries, the USA and in Australia.[5] The evidence shows that the overeducated receive markedly lower returns for additional years of education when compared to workers with the same level of education but who are matched to an appropriate job[6]. The undereducated, on the other hand, receive a wage premium compared to those with the same but just the right level of education for the job, although their total earnings are usually smaller than those received by co-workers in the same line of occupation (Voon and Miller 2005; Kler 2005; Büchel and Mertens 2004; Hartog 2000).

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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.

The literature on over and undereducation has tended to take either one of two directions. The first relates to the measurement of job-skill mismatch. This requires an estimate 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 the assumption of a symmetry in the distribution of required education. Self-reported methods avoid the symmetry assumption but rely on subjective assessments (Kler 2005).

The second direction observed in the literature has attempted to shed light on the forces that generate skill mismatch with particular emphasis on the role of new technologies. One interpretation is what Voon and Miller (2005) refer to as *technological change theory* that 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 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. Thus, the theory can be seen as an alternative to human capital theory.

In Australia, the incidences of undereducation and overeducation are closely linked to the debate on skill shortage. Kelly and Lewis (2003) attribute this problem to the increasing demand for skills that cannot instantaneously be matched by the supply of skills. This alternative interpretation pays attention to rapid changes in the demand for new skills and alludes to skill obsolescence as a possible driver of skill shortages and mismatch. A report prepared by the Department of Education Science and Training (2006) provides extensive discussion of the current state of play in the market for skills in Australia. An important finding of the report is that there is a shortage of core skills that are scarce amongst new graduates. This seems to vindicate earlier claims by Groot and Maassen van den Brink (1996) and Sloane *et al.* (1996) who raise the possibility that overeducation could mask a lack of specific job-related skills by highly educated workers, rather than being simply the product of an over-supply of highly skilled workers in firms that fail to adopt new technologies (the standard interpretation of the *technological change hypothesis*). Their evidence suggests that the overeducated actually lack skills which are very important at the workplace. Work by Allen and van der Velden (2002) and Chevalier and Lindley (2006) support this interpretation. 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 alternative formulation of the *technological change theory*.

Work-related learning directly links to job training and raises the possibility that a broader definition of human capital is needed that allows for skill formation beyond formal education. This is what is proposed by Acemoglu and Pischke (1999). They break with the standard view of training as equivalent to schooling and outline 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. Acemoglu and Pischke (1999) emphasise that new technologies make training indispensable but labour market imperfections may lead to suboptimal levels of workplace training.

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 (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 suggests that skill obsolescence plays a role in explaining job-skill mismatch and returns to undereducation and overeducation. de Grip and Van Loo (2002) make a direct link between skill

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

obsolescence due to non-use and overeducation. They suggest that overeducated workers can 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. This is also consistent with findings in Allen and van der Velden (2002). Gould *et al.* (2002) claim that skill obsolescence partly explains income dispersion within income groups while Green *et al.* (1999) find that the overeducated tend to have fewer numeracy skills than those whose skills match the job requirements.

According to the above, 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 substantial returns to training (Ryan and Watson 2003). We also know that training facilitates the development of human capital and is complementary to technological change (Baldwin and Johnson 1995). In the context of technological change, 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 job (Arulampalam *et al.* 2004). This confirms a similar finding by van Smoorenburg and van der Velden (2000) showing that training contributes to the resolution of the job-skill mismatch. Sanders and de Grip (2004) show that low-skilled workers become more employable after training. Further, the literature demonstrates the importance of employee attitudes to training; de Grip and van Loo (2002) and van Loo *et al.* (2001) show that employees' willingness to participate in training can counter human capital depreciation. The empirical evidence in Australia also points to significant returns from job training but the estimates vary in magnitude.[8]

Note, however, the evidence that has emerged from the above literature attributes a return to job training that is often higher than that of education. Schøne (2004) considers this to be a major puzzle since the average duration of training is much shorter than the time spent on formal education. Goux and Maurin (1997) and Kuruscu (2006) also argue that it is plausible that firms select the most productive or skilled workers for job training. If participation in training is contaminated by this kind of selection bias, existing estimates of returns to job training will be biased. Kuruscu (2006) accounts for this bias and shows that previous studies have over-estimated the value of training. Overwhelmingly, however, current empirical research on the value of training fails to correct for firm selection bias (Ryan and Watson 2003).

III Methodology

We examine three key hypotheses regarding the impact of training on wages and whether job training is valuable to workers whose skills do not match with those

[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).

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:

$$\ln W_i = \alpha S_{R,i} + \beta S_{U,i} + \gamma S_{O,i} + \sum_{j=1}^{n} \theta_j \mathrm{E}^{\mathrm{j}} + \mathrm{X_i}\phi + \eta_i \qquad (1)$$

where $\ln W_i$ is the log of average weekly earnings for worker i, $S_{R,i}$, $S_{O,i}$, $S_{U,i}$ stand for required education, overeducation and undereducation respectively, the fourth term is a polynomial of experience, E_j, n is usually set equal to two, X_i is a vector of other explanatory variables, α, β, γ, θ, ϕ are parameters 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 *human capital* effect applies equally to all workers. We call this *Hypothesis 1.* When evaluating this hypothesis, our empirical methodology takes account of Kuruscu's (2006) concern that firms may have a preference for skilled workers when they invest in job training. The argument goes that firms select skilled workers for training in anticipation of relatively greater productivity gains. We overcome this problem by utilising rich survey data that allows us to account for this kind of bias and estimate training time selected by the worker.

Further, we examine whether training impacts on the return to formal education. More precisely, we consider the idea that training can help bridge the 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. Let us call this *Hypothesis 2.* The third principal theory involves *human capital depreciation* due to technological change. One expression of this is the impact of technological change on occupations as a whole. Allen and van der Velden (2002) call this 'occupational' skill obsolescence that can result in an increase or a decrease in the level of required education. Let us summarise this effect of human capital depreciation as *Hypothesis 3A*. It may also be the case that some groups, particularly older workers, are more vulnerable to human capital obsolescence. We use the term *Hypothesis 3B* for this possibility.

By extending Voon and Miller's (2005) model, we examine the consistency of the above hypotheses with Australian labour market data. To do so, we partition 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 since it can shed light on *Hypothesis 3A*. 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:

$$S_{R,T} = \begin{cases} S_R, \text{ if } \quad TRAIN = 1 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3a)$$

$$S_{R,NT} = \begin{cases} S_R, \text{ if } \quad TRAIN = 0 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3b)$$

$$S_{U,T} = \begin{cases} S_R - S_A, \text{ if } S_A < S_R \text{ and } \; TRAIN = 1 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3c)$$

$$S_{U,NT} = \begin{cases} S_R - S_A, \text{ if } S_A < S_R \text{ and } \; TRAIN = 0 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3d)$$

$$S_{O,T} = \begin{cases} S_A - S_R, \text{ if } S_A > S_R \text{ and } \; TRAIN = 1 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3e)$$

and

$$S_{O,NT} = \begin{cases} S_A - S_R, \text{ if } S_A > S_R \text{ and } \; TRAIN = 0 \\ \\ 0 \text{ if otherwise} \end{cases} \qquad (3f)$$

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

$$\ln W = \alpha_1 S_{R,T} + \alpha_2 S_{R,NT} + \beta_1 S_{U,T} + \beta_2 S_{U,NT} + \gamma_1 S_{O,T} + \gamma_2 S_{O,NT} + \delta T + Z_i b + \varepsilon \qquad (4)$$

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 been defined in (3a) – (3f) above, T is training time (human capital augmenting), Z is a vector that consolidates the fourth and fifth terms in (1) and ε is an error term. Parameter δ summarises the *direct* effect of training while α_1, β_1 and γ_1 can capture two main *indirect* effects: skill matching, and skill restoration or replenishment.

It follows from the above that the data would be consistent with *Hypothesis 1* if $\delta>0$ in (4). *Hypothesis 2* predicts that workers whose skills do not match those required ought to earn higher wages when they receive training. Thus, for this hypothesis to be valid it would require $\beta_1 > \beta_2$ and/or $\gamma_1 > \gamma_2$. Provided that required education is an accurate measure of job-skill match, model (4) can also be utilised to assess *Hypothesis 3A* by examining whether training leads to wage differentials within the group that appears to have just the right level of education. Simply put, if skill obsolescence is the cause of shifts in the skill composition of occupations, we should observe a training effect at the occupational level as firms adapt to changes in technology. Therefore, a finding of $\alpha_1>\alpha_2$ would be consistent with *Hypothesis 3A*. Finally, model (4) facilitates a test of *Hypothesis 3B* by examining whether $\delta_i \neq \delta_j$ and at least one of δ_i or δ_j is positive, i and j being two different groups of workers. Note, however, the data utilised in this paper, which are described in more detail in the next section, are limited to *current* participation in job training. This constraint would bias our results downwards if training acts as payment in kind or it takes time to impact on wages.[9] In order to compensate for this limitation, we extend analysis of the training-mismatch nexus to past training by considering the role of experience as a proxy for the stock of work-related learning and training.

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

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[9] 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).

years of education to arrive at a measure of total years of education, S_A.[10] Third, SET 97 provides extra information on working patterns and history that are vital for the estimation of a Mincer-type earnings equation. For instance, the empirical literature suggests that job tenure is an important variable (Cardoso 2005). SET 97 allows us to incorporate this kind of information as well as information on training. Finally, 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.

SET 97 provides rich information that facilitates detailed examination of the role of training in influencing labour market outcomes. The survey records whether an individual worker has participated in a training course in 1997 (i.e., if the original variable, EXTR, is greater than zero). It also makes possible to distinguish between in-house training and external training or between employer-funded external training and employee-funded external training. We confine our study to in-house training and employer-funded training to account for selection bias in job training and to estimate its contribution to labour income. Further, we seek to extend analysis to past training by considering the role of experience as a proxy for the stock of training.

[10] See the Appendix for more details.

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.[11] Note that highly skilled workers[12] 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.[13] 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 27.2% of the low skilled undereducated workers underwent training:

[11] 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.

[12] We define 'high skill' or '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 are defined as the 'low skill' or 'unskilled' workers. Persons not in employment with less than 11.5 years of education (i.e., the mean for this group) were assigned to the unskilled group while the rest were treated as skilled.

[13] Details are available from the authors.

most conspicuous are tradespersons, intermediate production and transport workers, and labourers and related workers with only 21.5%, 18.5% and 18.9% having participated in training respectively. Conversely, skilled workers exhibit much higher rates of training participation: 54.9% of the skilled undereducated and 65.9% 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 about here -

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, 16.2% of men and 15.1% of women appear to be undereducated while 15.5% of men and 10.9% of women 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 have a higher incidence (in percentage terms) of undereducation than men.

Table 2 also presents a summary of the proportion of men and women who participated in training course in 1997. It shows that among the undereducated (overeducated) in full-time employment, 47% (60.6%) of women and 36.6% (51.3%) of men participated in training. 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 31.8% of the older workers, 27.2% of low skilled workers and 20.8% of NESOB workers participated in training. This compares with the 42.9%, 54.9% and 42.6% of younger, skilled and Australia-born workers respectively. Note that this pattern is even more striking amongst undereducated part-time workers; 22.5% of the unskilled and 13.2% of NESOB participated in training. Finally, we observe that the rates of training of the overeducated are consistently higher than those of the undereducated. Some full-time overeducated are even more over-represented in job training: 60.6% of women, 64% of workers in large firms, and 66% of highly skilled workers.

- Table 2 about here -

Next, we estimate equation (1) and consider the following X_i variables suggested 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); a dummy variable for married persons (MAR); a dummy for males (MALE); a dummy for overseas-born workers from English-speaking countries (ESOB); a dummy for overseas-born workers from non-English-speaking countries (NESOB); a dummy for public sector employment (GOV).

Robust weighted OLS estimates are presented in Table 3. The returns to required education are about 10% 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. Also, as in previous studies, both coefficients are smaller in absolute terms than the coefficients of required education. The fact that the coefficient on undereducation is smaller in absolute terms than the coefficient on required education implies that the 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 relative to those who have the same level of education and 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 difference 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 and GOV coefficients for men and the MAR and ESOB coefficients for women. For men, the marriage premium of 10.1% 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.

- Table 3 about here -

There are two main issues with the estimates in Table 3. First, they do not account for selection bias in the decision to participate in employment. As shown by Heckman (1979) and confirmed in an Australian study by Kler (2005), OLS estimates will be biased due to misspecification if labour income is observed due to a selection bias in the decision to participate in employment. Second, the specification used to derive the results in Table 3 does not allow estimation of the returns to training. The latter task, however, is not trivial. We first need to consider the possibility that participation in training is selection biased if, for example, firms select highly skilled workers for training on the premise that these workers are more productive (Kuruscu 2006).

To take account of these issues, we re-estimate equation (1) and expand the set of variables in X to incorporate training. Estimation then proceeds in two steps, where, in the first step, we deal with the possibility of firm selection bias in training. This is important since existing estimates of returns to training have recently been challenged on the basis that the average training course is of relatively short duration (Schøne 2004). In the second step, we recover estimates of the returns to training time, in the context of an environment in which workers are identified according to whether they have required education, or instead are characterised by over education or under education.

In the first step we account for firm selection bias in training. The empirical literature has neglected this issue and, as a consequence, is silent on the question of what estimation procedure is most appropriate in dealing with this issue. One possible strategy is the approach adopted by Di Tommaso (1999) who models the joint decisions of women's participation in the labour market and fertility to account for the problem of endogeneity and correlation between these two decisions. However, the empirical question tackled by Di Tommaso (1999) is very different to the one we face here. She deals with an individual who takes full responsibility for the two decisions that have binary outcomes but are jointly determined. The problem we confront here, in sharp contrast, pertains to decisions that are determined independently by two different agents. We analyse only employer-provided training and, therefore, it is the firm that makes the selection decision for training, while the worker takes the firm's decision as given and determines his or her level of participation in the labour market.

We exploit SET 1997 information on time spent on training during 1997 in order to model weekly hours spent in employer-provided training (TT)[14] by current employees and to account for firm selection bias in training. Given that TT is highly skewed, we take the log of TT, LTT, as our dependent variable and employ Heckman's (1979) two-step selection model. Skill obsolescence and mismatch create a role for training (de Grip *et al.* 2005). Thus, we conjecture that undereducation (S_U) and overeducation (S_O) are key determinants of training. We also allow for a gender effect on training on the basis there might be gender differences with regard to employment status and household time allocation. Further, we control for cultural factors that may play a role in training participation. Thus, we include MALE and NESOB as indicator variables for being a male and born overseas in a non-English-speaking country respectively. We consider additional dummy variables for participation in an external training course (TX), for participation in a training course that was assessed (TASS); for self-assessments of the first three main training courses as providing skills that are transferable to other employers (TTOE), and for part-time employment (PT). In the selection equation, we include variables that are likely to influence employer selection in training. We focus on groups of workers that may be perceived by firms to be more

[14] In the appendix, there is more detail and summary statistics on the variables used in this study. Note, persons not currently employed are excluded in the modelling of training time while training that is self-financed by employees is ignored throughout this study.

able to learn and improve their productivity through training. One candidate variable is an indicator for having completed more than 12 years of education (HED). Another is a dummy variable for the incidence of undereducation (DS_U). This follows from the maintained hypothesis that training may be particularly useful in cases of skill-job mismatch and from existing evidence of a wage premium associated with undereducation. Intuitively, firms may have an incentive to select the undereducated for training since the evidence suggests that undereducated workers are more productive than those with the same level of education that match the level required but they also earn less than their co-workers in the same occupation. Also included are dummy variables for participation in further education in 1997 (DE), for being at least 50 years old (AGE50) and for casual work (CAS) as well as GOV, NESOB, MAR.

The Heckman estimation results appear in column one, Table 4. These show that training is indeed not free of selection bias given that both the coefficient estimates and the selection regression diagnostics (i.e., ρ, σ and λ) are highly significant statistically. The former suggest that undereducated workers, those undertaking further education and public sector employees are all more likely to be selected by the firm to participate in training. Conversely, firms seem to be less inclined to pay for job training if workers are older, of NESOB background or are on casual employment. In the training equation, we note that undereducation, overeducation, males and NESOB positively predict hours spent on training. Morever, as expected, training that takes place outside the firm, is assessable or offers transferable skills has the greatest impact on workers' time spent on training. Also intuitive is the negative coefficient for part-time workers.

- Table 4 about here -

The next step utilises the Heckman two-stage predicted scores, TT_N, the Heckman selection predictions, TT_S,[15] and actual training time, TT, to arrive at an estimate of *realised* predicted training time, TT_R, that is corrected for firm selection bias. Simply put, we account for the fact that the Heckman prediction may not be realised since firms may choose to offer less training than what would be predicted on the basis of worker characteristics alone; our ultimate goal is to obtain estimates of returns to training time that actually occurs and that is selection corrected. To do this, we impose the constraint that realised time for any individual, TT_R, should not be greater than actual time, TT.

At the individual level, we identify two main scenarios as most relevant in identifying *realised* worker selected training, TT_R. These correspond to the respective cases in which TT > TT_N and TT < TT_N. In the first scenario, the constraint is not binding. Thus, realised training time is set equal to that predicted by the model at the second-stage of Heckman estimation; i.e., TT_R = TT_N. In cases where TT < TT_N the above constraint is binding. Thus, we account for the selection effect and define *realised* training time to be TT_R = λTT where λ=TT_N/(TT_N+ TT_S). Note that TT_R is set equal to zero when the worker did not actually participate in employer-financed training.

Columns 1-2 in Table 5 report the Heckman estimates of equation (4) when the realised measure of worker selected training time, TT_R, is used. These estimates allow for a selection bias in the choice between participation and non-participation in

[15] TT_N and TT_S are the Heckman predictions converted to hours, then standardised and subsequently re-centred to have the same sample mean and sample standard deviation as TT.

the labour market.[16] Note we extend Voon and Miller's (2005) model to include tenure (TEN) and tenure squared (TEN^2) divided by 100. The following variables are used in the selection equation: a constant, ED9 (a dummy for the attainment of nine years of education at most); AGE50 (a dummy for being more than 50 years old); NESOB (a dummy for being born O/S in a non-English-speaking country); CARE (a dummy for being a carer of elderly and young children); DIS (a dummy for having a disability), LONEP (a dummy for being a single parent); KIDS14 (a dummy for the presence of kids below 14 years old) and DE (a dummy for further education).

- Table 5 about here -

The returns to required education, overeducation and undereducation are similar to those reported in Table 3. Undereducation associates with a wage premium (i.e., the difference between the return to required education and the absolute value of the return to undereducation) while overeducation results in a wage penalty (i.e., the difference between the return to overeducation and the return to required education). We note also that the coefficients for E, E^2, TEN, TEN^2, NESOB have the expected sign. The results also confirm the importance of a marriage premium for men as in Voon and Miller (2005) but here we also find a 3.1% marriage premium for women. The latter result contrasts sharply with the -3.5% penalty reported by Chapman *et al.* (2001) but is consistent with a premium of 3.6% in Borland *et al.* (2004) but much lower than the premium of 11.2% reported by Breusch and Gray (2004). Also, public sector employment here has a negative sign for men and is insignificant for women.

[16] Coverage of the SET was extended to people who were marginally attached to the labour market in 1997 and who did not have a wage at the time. This group constitutes 7.5% of the sample and facilitates estimation of the Heckman model since the procedure requires the modelling of behaviour of Australians who chose not to be employed.

For women, our results indicate that the ESOB and public sector effects observed by Voon and Miller (2005) may be due to a sample selection bias.[17] More importantly, we find that the coefficients for training time, TT_R, are positive and significant for both men and women. They suggest that job training time has substantial returns: 6.8% for men and 4.7% for women. This gender gap seems consistent with evidence in Arulampalam *et al.* (2004).[18]

For comparison with previous studies, we also obtained estimates of returns to training participation by when ignoring selection bias. That is, we replaced TT_R with the indicator variable TRAIN that takes the value of one if the individual has participated in employer-sponsored job training and zero otherwise. The complete set of results is not reported due to space consideration but the estimated return to training participation was found to be 11.6% for men and 8.5% for women. These are very similar to the estimate reported by Booth (1991) for British workers but are much higher than the return of 6%-7% in Chapman and Tan (1992) and the 4% estimate of Lamb *et al.* (1998).[19] More recent studies place the estimated returns in the range of 7%-10% (Long 2001). Together with the returns to realised training time reported in Table 5, these estimates confirm Kuruscu's (2006) claim that returns to training are much lower than previously reported, once we account for firm selection.

In the selection equation, we observe that having low education adds considerably to the probability of participation in the labour market for both men and women. Ageing, NESOB background, being a carer, disability and further formal education

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[17] Voon and Miller (2005) do not account for this possibility while Kler (2005) seems to be constrained by HSF data limitations and is, thus, unable to consider key selection variables such as training, caring, disability and current participation in education.

[18] Note that our measure of realised training time is uncorrelated with the residuals from the wage Heckman equation suggesting that our results are not contaminated by specification error. These correlations are reported in the notes to Table 5.

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

seem to discourage participation. Note also that the presence of young children encourages labour market participation for men but has the opposite effect for women.

The results in Table 5 suggest that training directly impacts on labour income and that we cannot reject *Hypothesis* 1; that is, the human capital hypothesis. Yet, such a finding needs to be treated with some caution since this hypothesis can overlap with the human capital depreciation hypothesis, *Hypothesis 3B*. This is because a group of workers that are vulnerable to skill obsolescence may cause the coefficient estimate of δ to be significant even though $\delta=0$ for many individuals.

In an attempt to distinguish these two hypotheses, we first examine whether the effect of training is similar for workers with varying degree of skills. We draw on Harmon *et al*. (2003) who claim that the returns to education may not be homogeneous across the income distribution. They utilise quantile regression and find that returns increase with quartiles and attribute this to a complementarity between ability and education. We seek to employ this estimation procedure to shed light on the constancy of the training coefficient. Columns 3-4 in Table 5 present the results of inter-quantile regression estimates that test the null of zero difference between the coefficients in the 0.75 quartile and those in the 0.25 quartile. The estimates are based on simultaneous quantile regressions that jointly estimate the 0.75 and 0.25 quartile estimates. The results show that, for men, the return to training increases by 4.6 percentage points as we move from the lowest quartile to the top quartile in the earnings distribution. This substantial increase, however, is not evident amongst women. Yet again, compared to women with very low skills, more skilled women earn an extra 1.7% if they are undereducated and an extra 2.6% if they are overeducated. These results suggest that the data are consistent with the human capital depreciation theory, *Hypothesis 3B*, for full-time male workers in Australia.

We proceed to examine whether training plays any role in cases of skill mismatch. More precisely, we seek to estimate model (4) to test whether participation in training makes a difference in estimates of returns to required education, overeducation and undereducation. The model permits an examination of the three key hypotheses of job training: *human capital*; *job search and matching*, and *human capital depreciation*.

One simple test of the first hypothesis, what we call *Hypothesis 1*, is to see whether the direct training effect observed in Table 5 persists when we control for training effects in the event of mismatch, as measured by undereducation or overeducation. If it still persists, it would indicate that training augments human capital for *all* workers taking part in training and *Hypothesis 1* cannot be dismissed for Australia.

We thus consider model (4) and again employ the Heckman model using *realised* worker selected training, TT_R, and interact required education, undereducation and overeducation with *current* participation in employer-provided training. Estimation results appear in columns 1-2 in Table 6 and confirm those in Table 5 with respect to experience, marriage, place of birth, public sector and tenure. In Table 6, however, the coefficients of required education and undereducation contrast sharply with those in Table 5. We find that training impacts significantly on returns to required education and undereducation. Namely, men and women who apparently had just-the-right education but did not participate in job training earned less than those who did participate. Also in Table 6, Wald test estimates and one-sided tests[20] confirm that these differences are statistically significant at 5% confidence level. This important finding seems to be consistent with Hypothesis 1 but it also raises the question of whether the 'realised matches' method used to estimate required education is an

[20] That is, one-sided tests of the individual null hypotheses: $\alpha_1 \leq \alpha_2$, $\beta_1 \leq \beta_2$ and $\gamma_1 \leq \gamma_2$.

adequate measure of skill-job match. Of the undereducated, the wage gap between those in training and others also seems significant for men.

- Table 6 about here -

Furthermore, Table 6 shows that the coefficient of TT_R remains positive and significant for men, although reduced in magnitude, but has become insignificant for women. We interpret the evidence for men to be in favour of *Hypothesis 3A* and the evidence for women to be contradictory to *Hypothesis 1* or *human capital theory*. Note also that the evidence in support of *Hypothesis 3A* hints to the idea that the training effect on required education may not be exclusively due to measurement problems.

Analysis of the role of training, so far, has focused on the flow measure of *current* training. Yet, Blandy *et al.* (2000) and Veum (1999) suggest that training participation is often discontinuous and irregular and, more importantly, it takes time to produce results. Although SET 97 does not measure the incidence of past training, Table 1 highlights the fact that the majority of workers participate in job training. By extrapolation, we conjecture that worker *i* has a stock of job training experience, STE_i, which is a function of past training time, PTT_i, the skill depreciation rate, *d*, and current training time, TT_i. We also assume that past training experience is an increasing function of work experience; that is, $\psi(E_i)$. More formerly,

$$\boldsymbol{STE_i} = (1-\boldsymbol{d})\,\boldsymbol{PTT_i} + \boldsymbol{TT_i} = (1-\boldsymbol{d})\,\psi(\boldsymbol{E_i}) + \boldsymbol{TT_i} \qquad (5)$$

We seek to apply this concept of a training stock, STE, to gain further insights on the value of *past* training in the presence of skill mismatch. We re-define the indicator variable TRAIN in (3a) – (3f) to take the value of one if a worker has at least ten years of work experience and zero otherwise. We then repeat the Heckman estimation exercise using model (4). The estimation results appear in columns 3-4 in Table 6 and show that the wage premium associated with undereducation disappears for both men and women who have less than ten years of work experience.[21] Most surprising, however, is the effect of work experience on overeducation. Contrary to expectations, it is the overeducated with relatively more work experience that pay the highest wage penalty. Men and women in this group earn only 2.3% and 2.7% return respectively for a year of education in excess of the required level. These estimates contrast sharply with the 6.8% - 6.9% return received by the relatively inexperienced overeducated. This finding is consistent with the view that some overeducated persons may be less able to learn new job skills than others (Chevalier and Lindley 2006; van Smoorenburg and van der Velden 2000). On the other hand, the overeducated may be more susceptible to the 'use-it-or-loose-it' form of human capital depreciation (de Grip 2006; de Grip *et al.* 2005). Nonetheless, the large return associated with inexperienced overeducation stands but it is not yet transparent whether this is due to 'inexperience' *per se* or due to the combined effect of training and inexperience.

We proceed to further refine the interaction of training and experience with mismatch. Again, we re-define TRAIN in order to account for an asymmetric experience effect. For required education and undereducation in equations (3a) – (3d), TRAIN is set equal to one if the worker has had current training *or* more than ten

[21] More precisely, the wage premiums of 6% (=10.7%-4.7%) and 7.9% (=10.8%-2.9%) that undereducated men and women observed in Table 5 turn into a wage penalty of -6.8% (=10.7%-17.5%) for men and a minimal premium of 0.4% (=10.7%-10.3%) for women. Note also, the one-sided tests of the null of $\beta_1 \leq \beta_2$ are highly significant for both men and women.

years of work experience and equal to zero if otherwise. In the case of overeducated workers in equations (3e) - (3f), TRAIN is equal to one if the worker has had current training *and* less than ten years of work experience and equal to zero if otherwise. We impose this asymmetry in light of the evidence in columns 3-4 in Table 6 and in order to more precisely test whether that result is purely due to an 'inexperience' effect or due to the training of the inexperienced overeducated. Columns 1-2 in Table 7 present the estimation results. Here, the combined effect of *current* and *past* training on undereducation is higher than the effect of *current* training in columns 1-2 of Table but similar to that of the *stock* of training (i.e., work experience) in columns 3-4 of Table 6. Further, the combined effect of *current* and *past* training on overeducation (row six, Table 7) is now higher than the effect of *current* training or work inexperience (row seven, Table 6. This confirms the view by Chevalier and Lindley (2006) who caution against the treatment of the overeducated as a homogeneous group. They distinguish between the 'apparent' overeducated who are able to benefit from job training and the 'genuine' overeducated who are trapped in low-skill jobs that do not require training. Further, the results here allude to an important 'youth-training' effect in overeducation and suggest that the work inexperience effect in Table 6 is mainly driven by considerable learning by the young overeducated facilitated by job training. We consider this to be consistent with the proposition that the stock of training ameliorates the effect of skill mismatch for the undereducated and the young overeducated.[22]

- Table 7 about here -

[22] For completeness, we also investigated whether a 'young-training' effect is present in undereducation by re-defining TRAIN to be consistent with the treatment of overeducation. We did not find such an effect to be statistically significant.

Furthermore, the coefficient estimates of TT_R in Table 7 show that both men and women boost their labour income by 5.3% and 3% respectively when they participate in job training. This result is supportive of *Hypothesis 1* (i.e., human capital theory) but it cannot exclude *Hypothesis 3B* (i.e., skill obsolescence).

Overall, the evidence so far is broadly consistent with all the three main hypotheses of training since: (a) the coefficient estimates of TT_R were positive and significant (*Hypothesis 1*);[23] (b) training appears to be valuable in bridging the gap between acquired and required skills (*Hypothesis* 2); (c) training made a difference amongst workers with the just-right education (*Hypothesis 3A*), and (d) the direct effect of training captured by the TT_R coefficient was found to be 2.3% – 4.6% higher for the highly skilled, columns 3-4 in Table 5 (*Hypothesis 3B*). Obviously, finding (d) casts some doubt on the validity of *Hypothesis 1*.

In order to illuminate further on the importance of the three principal hypotheses in Australia, we finally partition the gender samples further on the basis of age and re-estimate (4). We distinguish between young workers (i.e., 15-35 years old) and mature workers (i.e., 36-65 years old). This partition of the samples is based on two key insights in the *human capital depreciation* literature: (a) age is a major factor that is traditionally associated with skill obsolescence, and (b) lack of training can accelerate the depletion of human capital[24].

In columns 3-4 of Table 7 are Heckman estimates of (4) for young workers where we employ the same definition of TRAIN as in the last set of regressions, see columns 1-2, Table 7. The results are striking. First, the wage premium received by the

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[23] The estimate for women in Table 5 was an exception but could be due to the *current* training being a weak proxy for the stock of training experience.

[24] See, for instance, de Grip (2006) and de Grip and van Loo (2002). Richardson (2004) also makes the link between skill obsolescence and age.

undereducated remains for those with current training or more than ten years of work experience but almost vanishes for women and even becomes a huge wage penalty for men. Second, the wage penalty associated with overeducation disappears for young men and shrinks to -1.8% (i.e., 10% minus 11.8%) for young women who participate in job training and have less than ten years of work experience. However, the rest of the overeducated young workers still experience the wage penalty observed previously. Third, the marriage premium and the NESOB effect reported in earlier tables also become insignificant for both genders. Fourth, the coefficient estimate of TT_R is no more significant for women at 10% confidence level.[25]

Last but not least important are the estimation results presented in columns 5-6 of Table7. These pertain to the mature group of workers aged 36 years and above.[26] The results can be summarised as follows: (a) training has no impact on returns to required education, (b) current or past training increases the wage premium in undereducation to a record high so far (i.e., a minimum absolute value of 1.2% and 1.8% for men and women); (c) lack of training experience, on the other hand, has little effect on the wage premium of the undereducated; (d) job training is also of little value to mature overeducated workers for whom the wage penalty remains considerable[27], and (e) the direct effect of current training time is again around 6% for both men and women.

In the context of strong interaction effects between training and mismatch in columns 1-4 of Table 7, we interpret findings (b)-(d) above to indicate clear support for *Hypothesis 2*. Figure 1 more succinctly illustrates the point. It makes it obvious

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[25] Due to space limitations, estimates in Table 7 are reported at two decimal points. As a result of rounding, the level of statistical significance is not always obvious but detailed estimates are available upon request.

[26] TRAIN is again defined on the basis of an asymmetric experience effect but due to a shift in the average level of experience and sample limitations, we use twenty-five and fifteen years of experience as the thresholds for required education and undereducation, and overeducation respectively.

[27] In Table 7, one-sided tests of coefficient estimates confirm results (a) to (d).

that job training boosts labour income substantially. However, the grains from job training seem greater for young workers and the undereducated.

- Figure 1 about here -

However, *Hypothesis 2* may overlap with *Hypothesis 3* if preliminary evidence by de Grip *et al.* (2005) is confirmed in future research. They find that workers who are themselves in job mismatch exhibit much higher rates of 'cognitive decline' (i.e., human capital depreciation). Further, jointly considered, findings (c)-(e) are consistent with *Hypothesis 3B* since the coefficient estimates of TT_R (i.e., human capital augmenting effect) were observed earlier to be either smaller in size than that of mature workers or were statistically insignificant. Also, the persistence of a wage premium in undereducation and a wage penalty in overeducation are seen as further evidence in favour of human capital depreciation theory (i.e., *Hypothesis 3B*).

Overall, the evidence is consistent with the idea that training is used to bridge the gap between acquired skills or formal education and required skills at the workplace. It also supports the view that a lack of job training is central to explaining the wage penalty associated with overeducation. A similar effect is observed for the undereducated; those who receive training seem to recover the income loss due to undereducation. Thus, the results suggest that standard measures of undereducation and overeducation mask substantial differences within the undereducated and overeducated. Moreover, they indicate that training mainly 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 older workers.

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 7% and 5% for men and women respectively. 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 the disadvantage of deficient levels of formal education can be ameliorated through subsequent training. Even for those who are overeducated, there appears to be a wage benefit from further training. Indeed, we find evidence that workers who fail to appreciate the potential gains from training are at a serious disadvantage. This is especially true of the undereducated and young workers.

We also sought to evaluate the relevance of three 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 the unskilled and matured aged workers. Overall, the evidence seems most consistent with *matching theory* and with the *human capital depreciation* hypothesis.

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* the actual cause of the disappearing wage penalty for the overeducated? 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
AGE50	D	Age ≥ 50 years	0.16		0	1
CARE	D	Carer for the elderly/kids.	0.07		0	1
CAS	D	Casual employment.	0.21		0	1
DE	D	Participation in further education utilising data on 'Full-time or part-time study status for qualification enrolled for in 1997' (CSFTPT).	0.10		0	1
DIS	D	Disabled.	0.19		0	1
DS_U	D	Undereducated.	0.37		0	1
ED9	D	Education of ≤ 9 years.	0.15		0	1
ESOB	D	Overseas-born in an English speaking country.	0.10		0	1
E	C	Years of experience.	21.4	12.63	1	54
E^2	C	E squared/100.	6.18	6.20	0	29
GOV	D	Public sector employment.	0.17		0	1
HED	D	Education of ≥ 12 years.	0.48		0	1
KIDS14	D	Children aged 14 years old, at most.	0.34		0	1
LONEP	D	Single parent.	0.04		0	1
MALE	D	Male.	0.54		0	1
MAR	D	Married.	0.59		0	1
NESOB	D	Overseas-born in a non-English speaking country.	0.15		0	1
PT	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 TRAIN=1 and zero if otherwise.	0.37	0.99	0	10
$S_{O,NT}$	C	Overeducation without training: equals S_O if TRAIN=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 TRAIN=1 and zero if otherwise.	4.53	6.19	0	15
$S_{R, NT}$	C	Undereducation without training: equals S_R if TRAIN=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 TRAIN=1 and zero if otherwise.	0.27	0.81	0	8
$S_{U, NT}$	C	Undereducation with training: equals S_U if TRAIN=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
TEN^2	C	Tenure squared/100	0.83	1.59	1	6
TASS	D	Participation in a training course that was assessed.	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.	1.04	2.15	0	21
TT_N	C	Heckman prediction of worker selected hours spent on firm-sponsored training.	0.96	1.39	0	16
TT_S	C	Heckman prediction of firm selected hours spent on firm-sponsored training.	0.86	1.01	0	8
TT_R	C	Realised weekly hours spent on employer-provided training.	0.15	0.38	0	7
TTOE	D	Self-reported assessment that the first three main training courses attended provided skills that are transferable to other employers.	0.09		0	1
TRAIN	D	Participation in employer-financed training.	0.38		0	1
TX	D	Participation in an external training course financed by the employer.	0.49		0	1
W	C	Weekly earnings: 'usual weekly earnings in job with main period employer' (EARNMPE).	529	304	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.

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 [60.1]	26.2 [53.8]	22.8 [74.8]
Professionals	18.9	15.2	68.0 [70.6]	17.6 [60.9]	14.4 [69.8]
Associate professionals	11.1	12.5	66.8 [57.6]	18.4 [48.1]	14.8 [61.8]
Tradespersons	15.8	12.5	74.3 [37.9]	20.6 [21.5]	5.1 [44.2]
Advanced clerical and service workers	3.70	11.9	85.8 [48.6]	7.9 [41.3]	6.3 [70.5]
Inter. clerical, sales & service workers	17.0	11.7	71.3 [51.6]	13.2 [43.8]	15.5 [53.4]
Inter. production & transport workers	11.4	10.9	69.6 [29.7]	12.9 [18.5]	17.5 [39.2]
Elem. clerical, sales & service workers	6.19	11.0	79.2 [36.9]	5.1 [39.3]	15.7 [37.9]
Labourers & related workers	9.60	10.5	72.2 [22.6]	12.6 [18.9]	15.1 [27.9]
Low skill workers	49.7	11.3	71.8 [36.8]	17.1 [27.2]	11.8 [42.0]
High skill workers	50.3	13.6	68.7 [57.3]	14.6 [54.9]	13.4 [65.9]
All full-time workers		12.5	70.2 [47.3]	15.8 [40.0]	13.9 [53.8]

Note: 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.

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	51.0	15.1	47.0	10.9	60.6
Gender: Men	68.3	45.2	16.2	36.6	15.5	51.3
Young: Below 50	72.8	47.9	13.8	42.9	13.4	54.8
Old: 50 plus	56.3	43.3	26.8	31.8	16.9	49.5
Firm Size: Small	70.7	32.3	17.7	26.1	11.5	36.8
Firm Size: Large	69.9	59.9	14.3	54.3	15.9	64.0
Skill Level: Low	68.7	36.8	17.1	27.2	14.2	42.0
Skill Level: High	71.8	57.3	14.6	54.9	13.6	65.9
Birthplace: NESOB	66.2	36.0	16.2	20.8	17.6	43.4
Birthplace: AUS	71.3	49.2	15.9	42.6	12.8	56.8
			Part-Time Employees			
Gender: Women	78.0	30.7	12.7	27.9	9.4	43.5
Gender: Men	76.3	20.7	11.3	21.1	12.4	26.5
Young: Below 50	80.5	28.1	9.6	27.7	9.8	37.7
Old: 50 plus	57.7	27.9	29.9	23.2	12.4	40.3
Firm Size: Small	74.7	20.0	14.9	19.9	10.3	28.6
Firm Size: Large	81.3	38.2	8.8	40.9	9.9	51.6
Skill Level: Low	79.3	22.9	10.6	22.5	10.1	33.5
Skill Level: High	72.4	44.8	17.2	33.2	10.4	51.0
Birthplace: NESOB	66.7	20.7	13.8	13.2	19.5	27.2
Birthplace: AUS	79.6	28.6	11.9	28.2	8.5	39.5

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.

Table 3. Returns to Education by Full-time Workers in Australia, 1997: The Voon and Miller (2005) Model

	Robust weighted OLS	
	Men	Women
Constant	4.610 (0.042)	4.517 (0.047)
Required Education (S_R)	0.105 (0.003)	0.111 (0.003)
Undereducation (S_U)	-0.033 (0.004)	-0.029 (0.005)
Overeducation (S_O)	0.033 (0.004)	0.038 (0.005)
Experience (E)	0.040 (0.002)	0.034 (0.002)
EXP squared/100 (E^2)	-0.063 (0.003)	-0.058 (0.004)
Married (MAR)	0.101 (0.011)	0.017 (0.010)
O/S Born, ESOB	0.015 (0.015)	0.008 (0.016)
O/S Born, NESOB	-0.094 (0.013)	-0.038 (0.014)
Public Sector (GOV)	0.007 (0.010)	0.036 (0.012)
Observations	6840	3925
R^2 (overall)	0.35	0.39

Standard-errors in parentheses.
Source: ABS 1997 *Education and Training* Unit Record File.

Table 4. Modelling Training Time in Australia, 1997: Heckman Selection

Explanatory Variables		Selection Variables	
Constant	-1.225 (0.041)	Constant	-0.423 (0.028)
Undereducation (S_U)	0.050 (0.012)	Higher Education (HED)	0.488 (0.025)
Overeducation (S_O)	0.028 (0.010)	Undereducated (DS_U)	0.143 (0.025)
Male (MALE)	0.145 (0.028)	Further Education (DE)	0.353 (0.031)
O/S Born, NESOB	0.197 (0.047)	Public Sector (GOV)	0.587 (0.017)
External Training (TX)	0.479 (0.026)	O/S Born, NESOB	-0.401 (0.026)
Training Assessed (TASS)	0.649 (0.028)	Married (MAR)	0.123 (0.018)
Skills Transferable (TTOE)	0.530 (0.027)	Over 50yrs old (AGE50)	-0.228 (0.023)
Part-time Worker (PT)	-0.231 (0.035)	Casual Worker (CAS)	-0.598 (0.028)
Observations	16810		
Rho (ρ)	-0.278 (0.031)		
Sigma (σ)	1.097 (0.012)		
Lambda (λ)	-0.306 (0.036)		

Standard-errors in parentheses.
Source: ABS 1997 *Education and Training* Unit Record File.

Table 5. Returns to Education and Training by Full-time Workers in Australia, 1997: A Two-stage Heckman Selection Model

	Training Time		Inter-Quantile Regressions	
	Men	Women	Men	Women
Constant	4.844 (0.043)	4.761 (0.050)	0.528 (0.055)	0.279 (0.057)
Required Education (S_R)	0.107 (0.003)	0.108 (0.003)	-0.008 (0.004)	0.002 (0.004)
Undereducation (S_U)	-0.047 (0.004)	-0.029 (0.005)	0.011 (0.006)	0.017 (0.006)
Overeducation (S_O)	0.033 (0.004)	0.038 (0.004)	-0.001 (0.005)	0.026 (0.006)
Experience (E)	0.032 (0.002)	0.030 (0.002)	0.001 (0.002)	0.001 (0.003)
EXP squared/100 (E^2)	-0.051 (0.003)	-0.054 (0.004)	-0.001 (0.005)	0.003 (0.005)
Married (MAR)	0.057 (0.011)	0.031 (0.010)	-0.016 (0.017)	-0.025 (0.013)
O/S Born, ESOB	0.027 (0.014)	0.014 (0.015)	0.003 (0.017)	0.019 (0.019)
O/S Born, NESOB	-0.048 (0.013)	-0.039 (0.015)	-0.029 (0.020)	0.017 (0.019)
Public Sector (GOV)	-0.029 (0.010)	-0.020 (0.011)	-0.066 (0.013)	-0.046 (0.014)
Tenure (TEN)	0.014 (0.002)	0.023 (0.002)	-0.009 (0.003)	-0.009 (0.003)
TEN squared/100 (TEN^2)	-0.033 (0.008)	-0.074 (0.011)	0.024 (0.010)	0.025 (0.013)
Training Time (TT_R)	0.068 (0.010)	0.047 (0.014)	0.046 (0.015)	0.023 (0.019)
	Selection Equation			
Constant	0.252 (0.012)	-0.058 (0.019)		
Low Education (ED9)	0.606 (0.029)	0.090 (0.031)		
Over 50yrs old (AGE50)	-0.089 (0.023)	-0.212 (0.033)		
O/S Born, NESOB	-0.223 (0.024)	0.038 (0.031)		
Carer (CARE)	-0.159 (0.073)	-0.553 (0.050)		
Disable (DIS)	-0.110 (0.022)	-0.110 (0.030)		
Lone Parent (LONEP)	-0.279 (0.084)	0.099 (0.045)		
Kids below 14 (KIDS14)	0.230 (0.020)	-0.338 (0.029)		
Further Education (DE)	-0.399 (0.038)	-0.497 (0.048)		
Observations	11826	10878	6840	3925
Rho (ρ)	-0.811 (0.023)	-0.759 (0.041)		
Sigma (σ)	0.418 (0.012)	0.360 (0.017)		
Lambda (λ)	-0.339 (0.019)	-0.273 (0.027)		
Corr(TT_R, W_RES)	-0.015 [0.19]	-0.029 [0.07]		
0.75 Pseudo R^2			0.22	0.29
0.25 Pseudo R^2			0.24	0.27

Standard-errors in parentheses. TT_R is the *realised* predicted value of weekly hours on training from Table 4. When training participation, TRAIN, is used instead of TT_R, we obtain similar results except that the coefficient for TRAIN is 0.117 and 0.88 for men and women respectively, and both are statistically significant at 5% confidence level. Inter-quantile regression results are post-simultaneous quantile estimates using 500 bootstrap replications. Corr(TT_R, W_RES) is the pairwise correlation coefficient, p-values are in square brackets based on Bonferroni-adjusted significance levels, and W_RES is the residual of the corresponding wage equation. Note, regression estimates of W_RES against TT_R and a constant did not produce a statistically significant coefficient for TT_R (results are available from the authors).

Source: ABS 1997 *Education and Training* Unit Record File.

Table 6. Skill Mismatch and Training by Full-time Workers in Australia, 1997: Heckman Selection Model

	Current training participation		Experience (10 years +)	
	Men	Women	Men	Women
Constant	4.926 (0.043)	4.822 (0.051)	4.918 (0.046)	4.817 (0.054)
Required Education				
- with Training ($S_{R,T}$)	0.107 (0.003)	0.107 (0.003)	0.109 (0.003)	0.111 (0.003)
- without Training ($S_{R,NT}$)	0.099 (0.003)	0.102 (0.003)	0.104 (0.003)	0.105 (0.003)
Undereducation				
- with Training ($S_{U,T}$)	-0.035 (0.006)	-0.023 (0.007)	-0.036 (0.004)	-0.027 (0.005)
- without Training ($S_{U,NT}$)	-0.050 (0.005)	-0.034 (0.007)	-0.175 (0.014)	-0.103 (0.018)
Overeducation				
- with Training ($S_{O,T}$)	0.028 (0.005)	0.043 (0.006)	0.023 (0.004)	0.027 (0.005)
- without Training ($S_{O,NT}$)	0.039 (0.005)	0.031 (0.006)	0.069 (0.010)	0.062 (0.008)
Experience (E)	0.031 (0.002)	0.030 (0.002)	0.026 (0.002)	0.024 (0.003)
EXP squared/100 (E^2)	-0.049 (0.003)	-0.053 (0.004)	-0.042 (0.004)	-0.045 (0.005)
Married (MAR)	0.053 (0.010)	0.031 (0.010)	0.042 (0.011)	0.023 (0.005)
O/S Born, ESOB	0.030 (0.014)	0.015 (0.015)	0.026 (0.013)	0.015 (0.015)
O/S Born, NESOB	-0.036 (0.013)	-0.027 (0.015)	-0.049 (0.013)	-0.036 (0.015)
Public Sector (GOV)	-0.045 (0.010)	0.008 (0.011)	-0.032 (0.010)	0.008 (0.011)
Tenure (TEN)	0.012 (0.002)	0.022 (0.003)	0.012 (0.002)	0.022 (0.002)
TEN squared/100 (TEN^2)	-0.027 (0.008)	-0.069 (0.011)	-0.027 (0.008)	-0.070 (0.011)
Training Time (TT_R)	0.023 (0.011)	0.010 (0.014)	0.068 (0.010)	0.049 (0.013)
Observations (*n*)	16810	16810	16810	16810
Rho (ρ)	-0.807 (0.024)	-0.748 (0.045)	-0.800 (0.027)	-0.741 (0.046)
Sigma (σ)	0.413 (0.012)	0.354 (0.017)	0.405 (0.013)	0.351 (0.017)
Lambda (λ)	-0.334 (0.019)	-0.265 (0.029)	-0.324 (0.021)	-0.260 (0.029)
$W_{SR,T=SR,NT}$ [H_0: $\alpha_1 \leq \alpha_2$]	45.14 [0.000]	12.92 [0.000]	9.04 [0.001]	10.36 [0.000]
$W_{SU,T=SU,NT}$ [H_0: $\beta_1 \leq \beta_2$]	3.83 [0.025]	1.69 [0.097]	89.96 [0.000]	16.68 [0.000]
$W_{SO,T=SO,NT}$ [H_0: $\gamma_1 \leq \gamma_2$]	2.29 [0.935]	1.75 [0.093]	18.59 [0.999]	12.63 [0.999]

Standard-errors in parentheses. Estimation results for the selection equation are not reported but are available upon request. In the last three rows, the Wald statistic is distributed as F(*r*, *n*-*r*) where *n* is the number of observations and *r* is the number of restrictions; here it is F(1, 16809). P-values of one-sided tests of coefficients in square brackets.
Source: ABS 1997 *Education and Training* Unit Record File.

Table 7. Job-Skill Mismatch and Training by Full-time Workers, 1997: Asymmetric Experience Effects

	All ages		Young		Mature	
	Men	Women	Men	Women	Men	Women
Constant	4.890 (0.04)	4.80 (0.00)	4.300 (0.09)	4.156 (0.08)	5.112 (0.12)	5.388 (0.16)
$S_{R,T}$	0.108 (0.00)	0.108 (0.00)	0.111 (0.00)	0.118 (0.00)	0.099 (0.00)	0.102 (0.00)
$S_{R,NT}$	0.107 (0.00)	0.102 (0.01)	0.117 (0.00)	0.120 (0.00)	0.098 (0.00)	0.102 (0.01)
$S_{U,T}$	-0.037 (0.00)	-0.027 (0.01)	-0.058 (0.01)	-0.054 (0.01)	-0.012 (0.01)	-0.018 (0.01)
$S_{U,NT}$	-0.189 (0.02)	-0.099 (0.02)	-0.180 (0.01)	-0.110 (0.02)	-0.044 (0.03)	-0.051 (0.02)
$S_{O,T}$	0.074 (0.01)	0.071 (0.01)	0.114 (0.01)	0.100 (0.01)	0.023 (0.01)	0.027 (0.01)
$S_{O,NT}$	0.027 (0.00)	0.032 (0.00)	0.043 (0.01)	0.028 (0.01)	0.015 (0.00)	0.029 (0.01)
E	0.030 (0.00)	0.028 (0.00)	0.100 (0.01)	0.093 (0.01)	0.010 (0.01)	-0.001 (0.01)
E^2	-0.048 (0.00)	-0.052 (0.00)	-0.271 (0.03)	-0.261 (0.03)	-0.021 (0.01)	-0.006 (0.01)
MAR	0.047 (0.01)	0.022 (0.01)	0.010 (0.01)	0.016 (0.01)	0.081 (0.02)	-0.004 (0.01)
ESOB	0.026 (0.01)	0.015 (0.01)	0.052 (0.02)	0.041 (0.02)	0.018 (0.02)	-0.004 (0.02)
NESOB	-0.049 (0.01)	-0.035 (0.01)	-0.007 (0.03)	-0.040 (0.02)	-0.088 (0.01)	-0.051 (0.02)
GOV	-0.035 (0.01)	-0.017 (0.01)	-0.013 (0.02)	0.018 (0.01)	-0.031 (0.01)	0.023 (0.01)
TEN	0.013 (0.00)	0.023 (0.00)	0.022 (0.00)	0.031 (0.00)	0.011 (0.00)	0.016 (0.00)
TEN^2	-0.029 (0.01)	-0.071 (0.01)	-0.096 (0.03)	-0.135 (0.03)	-0.018 (0.00)	-0.046 (0.01)
TT_R	0.053 (0.01)	0.030 (0.01)	0.040 (0.02)	0.018 (0.02)	0.064 (0.01)	0.060 (0.02)
n	16810	16810	8159	8159	8651	8651
ρ	-0.802 (0.02)	-0.746 (0.04)	-0.647 (0.08)	-0.573 (0.18)	-0.021 (0.15)	-0.820 (0.03)
σ	0.407 (0.01)	0.352 (0.02)	0.377 (0.02)	0.290 (0.03)	0.319 (0.01)	0.392 (0.02)
λ	-0.327 (0.02)	-0.263 (0.03)	-0.244 (0.04)	-0.167 (0.06)	-0.007 (0.01)	-0.322 (0.03)
$W_{SR,T=SR,NT}$	0.49 [0.243]	9.51 [0.001]	9.56 [0.999]	0.74 [0.805]	0.21 [0.322]	0.04 [0.577]
$W_{SU,T=SU,NT}$	90.9 [0.000]	10.9 [0.000]	57.5 [0.000]	6.31 [0.006]	1.37 [0.121]	1.92 [0.083]
$W_{SO,T=SO,NT}$	20.7 [0.000]	16.6 [0.000]	37.1 [0.000]	45.1 [0.000]	1.19 [0.138]	0.04 [0.578]

Standard-errors in parentheses. Estimation results for the selection equation are not reported but are available upon request. In the last three rows, the Wald statistic is distributed as F(*r*, *n*-*r*) where *n* is the number of observations and *r* is the number of restrictions. The 'young' workers group comprises of persons who are 35 years at most. Older workers form the 'mature' workers group.). In square brackets are P-values of one-sided tests of coefficients where H_0: q1 ≤ q2 and q=α, β, γ; i.e., the parameters in (4).
Source: ABS 1997 *Education and Training* Unit Record File.

Figure 1. Skill Mismatch, Training and Aging