Why is Job Security Lower for Maori and Pacific Island Workers? The Role of Employer-Provided Training

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Abstract

Maori and Pacific Island workers are more likely than other workers to transit from employment to unemployment whereas exit rates from unemployment are relatively less dispersed across ethnic groups. Hence, lack of job security appears to raise the unemployment rate for Maori and Pacific Islanders. This paper uses unit record data to examine one source of lower job security, which is that Maori and Pacific Island workers may receive less employer-provided training. The results suggest that training reduces employer-induced separations, but even controlling for training, and for age, years of schooling, gender, marital status and industry, there is an identifiable effect of Maori and especially Pacific Islanders experiencing higher involuntary job losses. Moreover, once the available characteristics of workers and their jobs are controlled for, Maori have the same incidence of training and may receive even more intensive training than do Pakeha workers. In contrast, Pacific Island and Other ethnic group workers have a significantly lower level of employer-provided training. Thus, job training does not explain all of the ethnic differences in involuntary unemployment rates and some ethnic minorities appear to receive a lower level of job training which cannot be explained by their known social characteristics and their occupation and industry. Of course there may be social characteristics for which we have not been able to control, which further explain part of the differences in experiences between the ethnic groups.

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I. Introduction

A large literature describes and attempts to explain the disparity between labour market outcomes for different ethnic groups in New Zealand, with particular emphasis on the gap between Maori and non-Maori (Easton, 1995, Winkelmann and Winkelmann, 1997, Te Puni Kokiri, 1998, Winkelmann, 1998). This literature mainly studies employment, unemployment and participation rates but earlier research by Grimmond (1993) on labour market dynamics is also relevant. In particular, Maori and Pacific Island workers experienced low job security between 1986 and 1991, with their probability of losing a job being more than twice as high as it was for other workers. Moreover, once unemployed, Maori and Pacific Island job-seekers had the lowest probability of finding new jobs, although the disparity across ethnic groups was not as dramatic as for the employment-to-unemployment transition.

One factor that is missing from previous explanations of these disparities in job security (and hence, in unemployment rates) across ethnic groups is differences in the amount of employer-provided training received by workers. The relevant feature of employer-provided training is that it often teaches skills specific to a particular firm. Consequently, workers are unwilling to pay the full cost of this training (typically in the form of lower wages) because they would lose their investment if they separated from the firm, so the firm has to contribute some of the cost as well (Becker, 1964). Given this investment by the firm in training a worker, the firm will be less willing to release that worker during an economic downturn (Fair, 1985), so workers with firm-specific training tend to have greater job security. In support of this line of reasoning, a recent survey suggests that the participation rate in employer-provided training is significantly lower for Maori and Pacific Island workers than for other groups (Gobbi, 1998).

The objective of this paper is to report new empirical evidence, from unit-record data, on the relationship between employer-provided training and job security in New Zealand. In addition, we explore the question of whether the ethnic differences in the incidence of employer-provided training reported by Gobbi (1998) persist after conditioning on other variables like age, education, industry and occupation of employment. If these ethnic effects persist after controlling for other observable characteristics, and if employer-provided training has a demonstrable effect on job security, it would strengthen the case for interventions that aim to increase participation in employer-provided training by Maori and Pacific Island workers.

Although previously unexamined in New Zealand, a large overseas literature studies the question of whether receiving employer-provided training depends on ethnicity, conditional on other observable characteristics. This literature provides mixed results. Some U.S. studies show that blacks have a lower probability of receiving training (Duncan and Hoffman, 1979), others show no difference between groups (Veum, 1996) and one study even suggests that blacks receive more training than whites (Altonji and Spletzer, 1991). Similar ambiguity comes from the U.K., where Booth (1991) finds no significant ethnic differences while Shields and Price (1999) find large disparities in training that are not explained by average ethnic group characteristics. Hence, empirical results for New Zealand are needed to aid policy making because the international literature provides no consistent guidance.

One other deficiency of the international literature is that it usually ignores the relationship between the incidence and the volume of training, with most studies just answering the question: ‘who gets trained?’[1] This narrow focus might exaggerate the inequality in training if the relationship between incidence and volume is negative. A negative relationship would occur if workers who have a low likelihood of undertaking training receive a larger volume (i.e., more courses, days or hours) of training once over the initial hurdle. Therefore, the final contribution of this paper is to empirically model the volume of training conditional upon the prior selection into training, using models in the tradition of Heckman (1979).

The next section updates Grimmond's (1993) study of labour market dynamics for the 1994-98 period to see whether the puzzle that motivates the paper – low job security for Maori and Pacific Island workers – still exists. Following that, the data and econometric methods used for the subsequent analysis are described. An empirical model of the risk of involuntary job loss is introduced and estimated in Section IV. Models that estimate the probability of workers participating in employer-provided training are reported in Section V, while the following section reports on the analysis of the volume of training. Section VII concludes.

II. Aggregate evidence from gross labour force flows

Although it is usual to study the dynamics of worker flows between the three labour force states of employment (*E*), unemployment (*U*) and non-participation (*N*), ignoring movements into and out of the non-participation state shows that the steady-state unemployment rate depends on just two transition probabilities (Borjas, 1996). The transitions that matter are the risk of employed workers losing their job, *pr*(*EU*), and the probability of unemployed workers finding a job, *pr*(*UE*):

$$\frac{U}{E+U} = \frac{pr(EU)}{pr(EU)+pr(UE)} \qquad (1)$$

A higher risk of job-loss raises the unemployment rate while a higher likelihood of successful job search lowers the unemployment rate.

Empirical evidence on these transition probabilities for workers in each ethnic group can be calculated from the quarterly Household Labour Force Survey (HLFS). One-eighth of sampled households are rotated out of the HLFS each quarter and replaced by a new sample, leaving seven-eights common to the surveys in any two adjacent quarters. Thus, the flows between employment states can be measured by comparing the employment status of individuals in two consecutive quarters and the transition probability for, say, employment to unemployment, can be calculated as:

$$pr(EU) = \frac{n(EU)}{n(EE) + n(EN) + n(EU)} \tag{2}$$

where $n(EU)$ is the number of workers who had been employed in quarter_{t-1} but are unemployed in quarter_t.

Figure 1 shows that the risk of job loss is considerably higher for Maori and Pacific Island workers than it is for workers from other ethnic groups (particularly European/Pakeha). In fact, $pr(EU)$ averaged only 1.2 percent for Pakeha workers, but 3.3 percent for Maori workers and 2.7 percent for Pacific Islands workers over the 1994-98 period. In addition to the lower average level, the job security of the non-Pakeha ethnic groups also appears to vary more with the business cycle. The other relevant feature of the employment-to-unemployment transition probability, not shown by Figure 1, is that it is more variable across ethnic groups than are any of the other transition probabilities. For example, the average $pr(EU)$ for Maori workers is three times higher than for Pakeha workers, while the ratio of highest to lowest averages for the unemployment-to-employment transition is less than 2:1. Hence, it is likely that a study of the factors causing the job insecurity of non-Pakeha workers will explain more of the variability in unemployment rates across ethnic groups than will a study of, say, ethnic differences in job search practices of the unemployed.[2]

(Figure 1 about here)

III. Data and Methods

The data used in this study come from the Education and Training Survey (ETS), which was a one-off survey conducted by Statistics New Zealand as a supplement to the September 1996 Household Labour Force Survey (HLFS). The ETS was the first major survey of job-related training in New Zealand, and it asked respondents aged 15-64 about their participation in external and in-house training and in study towards a qualification during the previous 12 months.[3]

Although the ETS has a sample of 22,257, not all of these observations are available for the current paper because questions about in-house training were only asked of those who had worked for wages or salaries in the 12 months prior to the survey (n=13,988). Further exclusions are needed for respondents with missing data on the volume of training or years of schooling (n=751). Thus, one estimating sample, which may include people who had previously worked but were not working at the time of the survey, has 13,237 observations. However, no data on usual hours of work and length of tenure in the previous job are available for the currently unemployed (or for some current workers), so a sample of the currently employed with the full range of data available is restricted to 11,003 observations.

One important caveat for the analysis concerns the definition of ethnicity in the survey. Ethnic identification of individuals in the HLFS is effectively by the household head rather than the individual concerned, and a hierarchical procedure is used to classify those who specify multiple ethnic groups (respondents are allowed to choose up to three groups). Anyone who chooses Maori and any other ethnic group is categorised as “Maori”, anyone who chooses Pacific and anything except Maori is categorised as “Pacific” and anyone who chooses Other and anything except Maori or Pacific is categorised as “Other”. This classification system, which has been described by some commentators as arbitrary (Chapple, 2000), must be kept in mind when interpreting the empirical results. This is especially because Chapple and Rea (1998) show that labour market outcomes are much less favourable for those who identify solely as Maori compared with the ‘mixed’ Maori group (who comprise one-quarter of the total categorised as Maori).

Many of the variables of interest in the ETS are of binary form, including questions about whether a worker lost their job and whether they received employer-provided training. Therefore, probit estimation is appropriate,

$$\Pr\left(p_j = 1 \middle| \mathbf{x}_j\right) = \Phi\left(\mathbf{x}_j b\right) \tag{3}$$

where p_j is the outcome of the 0-1 variable for the jth observation, Φ is the standard cumulative normal, $\mathbf{x}_j$ is the vector of explanatory variables for observation j and b is the vector of coefficients to be estimated. These probit coefficients are not directly interpretable, but marginal effects for continuous variables can be calculated (at the mean) as:

$$\left.\frac{\partial \Phi(\mathbf{xb})}{\partial x_i}\right|_{\mathbf{x}=\bar{\mathbf{x}}} = f(\bar{\mathbf{x}}\mathbf{b})b_i \tag{4}$$

where $\mathbf{b}$ is the vector of estimated coefficients and f is the normal density. For dummy variables, the discrete change in probability when the dummy variable switches from zero to one is calculated as $\Phi(\bar{\mathbf{x}}_1\mathbf{b}) - \Phi(\bar{\mathbf{x}}_0\mathbf{b})$ where $\bar{\mathbf{x}}_1 = \bar{\mathbf{x}}_0 = \bar{\mathbf{x}}$ except that the ith elements of $\bar{\mathbf{x}}_1$ and $\bar{\mathbf{x}}_0$ are set to one and zero, respectively (StataCorp, 1997).

Other variables of interest in the ETS data are observed only after a possibly non-random selection process. For example, the volume of training received (number of events, days or hours) is observed only for those who reported participating in training in the 12 months prior to the survey. In some cases, there may be interest in the marginal effects of the explanatory variables on the expected volume of training across the population of all workers, rather than just the marginal effects for those who received training. The appropriate model is then a regression equation, $y_j = \mathbf{z}_j a + u_{1j}$ where the dependent variable for observation j is observed according to the selection equation:

$$\mathbf{x}_j b + u_{2j} > 0 \qquad \text{where} \qquad u_1 \sim N(0, s) \qquad u_2 \sim N(0,1) \qquad corr(u_1, u_2) = r\ . \tag{5}$$

Non-random selection implies that the two equations are not independent (i.e., $r \neq 0$) so applying standard techniques to the regression equation will produce biased estimates of the underlying relationship for the population. One common solution is to augment the regression equation with the Mills ratio estimated from the selection equation (Heckman, 1979):

$$m_j = \frac{f\left(\mathbf{x}_j \hat{b}\right)}{\Phi\left(\mathbf{x}_j \hat{b}\right)} \tag{6}$$

with the statistical significance of the coefficient on this added variable, $l = rs$, providing a test of sample-selection bias. In this framework, the $\hat{a}$ should be unbiased estimates for the population once m_j is included in the regression equation. An alternative to this two-step procedure is maximum likelihood estimation of a, b, r, and s with the selection and regression equations estimated jointly (StataCorp, 1997).

In what follows, we use a recursive structure to model the relationship between training and job security. In the next section of the paper job security is modelled as depending on training, while subsequent equations model training as depending on exogenous variables only. Hence, correlations between the disturbances of the job security and training equations are ignored by this recursive structure. If such correlations are present, due, for example, to non-random placement of workers into company training programs, they could bias the estimated training effect in the job security equation. This bias can be corrected with a "treatment effects" model, where the Mills ratio from a training receipt probit is added to the job security equation for both those who receive the treatment (that is, receive training) and those who do not (Greene, 2000).

IV. Training and Involuntary Job Loss

The unwillingness of firms to release workers with firm-specific skills during an economic downturn (Fair, 1985) suggests that employer-provided training should reduce the risk of involuntary job loss. To empirically test this proposition, we model the factors that cause a worker to be either laid off, dismissed or made redundant from their last job.[4] These types of job loss can be thought of as involuntary, although the distinction with worker-initiated separations is not always clear. For example, if workers perform badly the firm may dismiss them or else may simply not grant them pay increases so that eventually they quit.

Previous studies of displaced workers suggest that these workers are likely to be less educated than the employed workforce, with ethnic minorities over-represented and women under-represented amongst the displaced (Kletzer, 1998). Hoarding labour by holding onto skilled workers during a recession is costly because wages may exceed the value of marginal product. Hence, age is a relevant characteristic because it affects the period available to the firm for repaying labour hoarding costs. On the other hand, younger workers may be cheaper to release during a recession because they haven't built up seniority and redundancy entitlements and they may also be more likely to quit because they have greater returns to job search. Similarly, married workers may be viewed as more favourable prospects for hoarding by firms because they may be less mobile due to the need for migration decisions to be advantageous for the whole family rather than just the individual worker. Finally, the risk of involuntary job loss is also likely to depend on product demand uncertainty, which may vary by industry.[5] Hence, the model is specified as:

$$pr(Job\ loss) = f\left(Age,\ Age^2,\ School\ \ years,\ Female,\ Ethnicity,\ Married,\ Industry,\ Training\right)$$

Table 1 reports probit estimates of the risk of involuntary job loss for the sample who had worked for wages and salaries at some stage in the 12 months prior to the survey. Only 173 of the 13,237 people in this sample were unemployed due to involuntary dismissal, layoffs or redundancy (with a further 1307 unemployed for other reasons). Taking account of the sampling weights, the average risk of involuntary job loss is 1.1 percentage points. The purpose of the model is to see whether in-house training reduces the risk of involuntary job loss, with four different versions estimated, corresponding to different training variables (incidence, number of episodes, days and hours).[6]

(Table 1 about here)

Regardless of how in-house training is measured, it appears to reduce the risk of involuntary job loss. Workers who participated in in-house training were 0.36 percentage points less likely to be dismissed, laid off or made redundant, which *ceteris paribus*, corresponds to a reduction of one-third in the risk of involuntary job loss. Each training episode reduces the risk of job loss by 0.2 percentage points (column ii), while each day of training reduces the risk by just over 0.1 percentage points (column iii). These training effects are large relative to some other factors in the model. For example, one day of in-house training has about the same effect on the risk of job loss as does one year of post-primary schooling. This difference in orders of magnitude may reflect the greater specificity of in-house training, with employers less willing to lose part of their investment by discharging trained workers.

The overseas pattern of males and minority ethnic groups being over-represented in the ranks of the displaced workers (Kletzer, 1998) seems to occur in New Zealand, and there is also an age pattern with the risk of job loss falling until age 41 years but rising thereafter. The ethnic effects appear to be large, especially for Pacific Island workers whose risk of involuntary job loss is approximately twice as high as for workers from other ethnic groups. The statistical significance of the ethnic effects suggests that the low degree of job security for Maori and Pacific Island workers is not just due to their low levels of education and training and industrial distribution. For example, the only two industry effects that are statistically significant suggest lower job security in construction and higher job security in 'transport, storage and communication'. But Pacific Island workers are under-represented in construction and Maori and Pacific Island workers are over-represented in the transport sector.[7] Perhaps some other personal characteristics that are correlated with ethnicity and affect job security are excluded from the model or else there are structural effects causing Maori and Pacific Island workers to have a higher risk of involuntary job loss than workers from other ethnic groups with otherwise identical characteristics.[8]

These personal characteristics that may affect job security but are excluded from the model may also affect the probability of workers receiving training, especially if, say, "diligence", "initiative" or "perseverance" are observable to employers even if not to econometricians. But the results for the involuntary job loss model are not greatly altered when the estimation method allows the disturbances in the job security equation to be correlated with the disturbances from an equation modelling the receipt of training (Appendix Table 1). These "treatment effects" results show that the coefficients on the training variables are approximately 10 percent lower when the Mills ratio from a probit equation for the receipt of employer-provided training is added to the job loss equation to control for the possibly endogenous placement of workers into training programs. The statistical significance of the coefficients is also reduced somewhat, although statistical imprecision also affects the estimate of λ, which indicates that the selection bias is barely significant at the $p<0.10$ level. Hence, the recursive equation structure, of modelling job security as depending on training and training as depending on exogenous variables only, appears to be statistically acceptable.

V. The Incidence of Training

The existing evidence from cross-tabulations is that Maori and Pacific Island workers are least likely to receive in-house job training (Gobbi, 1998). However, this evidence is based only on point estimates rather than on tests of statistical significance and it does not control for the effects of other variables. To see whether these ethnic effects are statistically significant, we estimate an analysis of covariance model of the probability of participating in in-house training. The model is estimated on the sample of 11,003 currently employed workers to allow comparisons with the results of subsequent models that will use the full set of covariates (including variables available only for the currently employed).

(Table 2 about here)

In contrast to European/Pakeha workers, who are the base group, the probability of participating in in-house training is six percentage points lower for Maori and 'Other' workers and 13 percentage points lower for Pacific Island workers. All of these differences are statistically significant (column 1, Table 2). If separate ethnic *and* gender effects are allowed, the ethnic effects dominate with no significant differences between male and female participation rates within ethnic groups but significant differences across ethnic groups. Thus the fully specified models will use ethnic and gender intercept dummy variables but not interactions between the two, in contrast to some previous models (Veum, 1996).

What covariates should be added to the models reported in Table 2? A fairly standard set of variables in previous studies of employer-provided training includes worker characteristics (age, education levels, marital status, occupation, tenure) and characteristics of the job (hours worked, industry).[9] All of these variables are included in the model, so as to be sure that any ethnic effects that persist after controlling for other influences are not just due to excluded relevant covariates. Moreover, we use both age and experience in alternate specifications, because there is debate about which of the two to include in human capital equations (Winkelmann, 1998a).

Controlling for the full set of worker and job characteristics, currently employed Maori have a probability of participation in in-house training that is only two percentage points lower than for the base group (European/Pakeha), and this difference is not statistically significant (column (i), Table 3). However, the participation probability remains significantly lower for Pacific Island and 'Other' workers (approximately seven percentage points). The addition of the covariates thus explains two-thirds of the gap in participation probabilities for Maori workers (i.e., the unexplained gap falls from -6.0 percentage points in Table 2 to -1.9 percentage points in Table 3) and just under one-half for Pacific Island workers (-13.2 compared with –7.4 percentage points) but causes the unexplained component to rise for 'Other' workers. These ethnic effects are roughly the same if age is replaced with years of potential labour market experience (column (ii)).

(Table 3 about here)

Differences in schooling levels across ethnic groups are the single most important observable factor explaining differences in the probability of receiving in-house training. On average

Maori workers have 4.8 years of post-primary schooling while Pakeha workers average 5.9 years and this causes the training rate of Maori workers to be 1.3 percentage points lower.[10] The average schooling level of Pacific Island workers is even lower, at 4.4 years and this causes their training probability to be 1.9 percentage points lower. In contrast, workers from the ‘Other’ ethnic group average 7.0 years of post-primary schooling, so their probability of receiving in-house training should be 1.4 percentage points higher than for Pakeha workers, which is why the unexplained gap in participation that is captured by the ethnic group dummy variable rises for ‘Other’ workers once covariates are added.

The other main contributors to the lower probability of Maori and Pacific Island workers receiving in-house training are differences in the distribution of workers across occupations and differences in tenure. The probability of being a “Plant and machine operator and assembler” is twice as high for Maori (17.2 versus 8.0 percent) and three times as high for Pacific Island workers (23.8 percent) as it is for Pakeha workers and this lowers the training probabilities by 1.1 and 1.8 percentage points. The over-representation of Maori and Pacific Island workers in “Elementary” occupations also lowers their training probabilities (by 1.0 and 1.5 percentage points). The shorter tenure in the current job causes the training probability of Maori workers to be 1.0 (0.8) percentage point lower for Maori (Pacific Island) workers than for Pakeha workers.

Although the main purpose of the models in Table 3 is to see whether ethnic differences in training probabilities persist after controlling for covariates, several interesting results emerge from the control variables. First, in the sample of currently employed workers there is no difference in training probabilities between men and women. Second, the probability of receiving in-house training rises with years of potential labour market experience, peaking at

17 years and falling thereafter (or peaking at age 36 in the column (i) estimates). This non-linear pattern may reflect the tension felt by employers in training younger workers: there is a longer payoff period from such workers but they are also more mobile which increases the risk of the employer losing their investment. Third, training is much more likely for full-time workers, presumably because this training investment should yield greater returns per period than would a similarly sized investment in training part-time workers.

Results for the (larger) sample of workers who had worked for wages or salaries at some stage in the 12 months prior to the survey are reported in columns (iii) and (iv) of Table 3. These equations exclude job characteristics because information on tenure and usual hours is unavailable for people who are not currently employed. This use of a broader sample and fewer covariates causes two changes to the results: the gap in participation probabilities rises to three percentage points for Maori and becomes statistically significant, while a significant gap in female participation rates also emerges. The apparent gender bias is easiest to explain and is due to the exclusion of the usual hours of work variable: females average fewer work hours than males, which lowers their probability of receiving in-house training, so excluding the hours variable leaves the female intercept dummy to soak up this effect. But the change in the covariates is not the cause of the change in the Maori intercept. Instead, it reflects systematic differences in the two samples, with a disproportionate number of those Maori who did not receive in-house training having worked at some stage in the year prior to the survey but not being currently employed.[11] This over-representation of Maori in the group who had once worked but were not currently working is in accord with Figure 1, which shows that the job security of Maori workers was lowest, relative to other ethnic groups, in the year prior to the survey.

VI. The Volume of Training

The results in the previous section suggest that there are considerable inequalities across ethnic groups in their participation in in-house training. However, the extent of the inequality is reduced somewhat once account is taken of the differences in average characteristics across ethnic groups. The final step needed in assessing the overall degree of inequality in in-house training is to analyse the volume of training. If workers from groups with low training probabilities receive less intensive training than other trainees (e.g., fewer training episodes or days), looking just at the incidence of training will understate the level of inequality. Conversely, a negative relationship between the incidence and volume of training means that the overall degree of inequality is overstated by looking at incidence alone.

The Education and Training Survey has three measures of the volume of in-house training: the number of training episodes in the previous 12 months, the number of days spent on each of the four most recent training courses, and the average number of hours per day spent on each of those courses.[12] An estimate of the total days spent training per year is formed by summing the number of days across each of the four courses, while an estimate of total hours is made by summing the product of days and average hours for each event. We focus mainly on the number of training episodes and training days because these two contribute to much of the variation in total hours. Because the volume variables are positively skewed we use logarithmic transformations, following the approach typically used with earnings equations.

Amongst the workers who received in-house training, the number of training episodes is nine percent higher and the number of training days approximately 30 percent higher for Maori workers than for the base group of European/Pakeha (Table 4).[13] None of the other ethnic group variables are statistically significant. Thus, taking account of the volume of training causes the measured inequality in training between Maori and Pakeha workers to be reduced.[14] But the inferences about gaps in training for workers from the Pacific Islands and 'Other' ethnic groups are not altered by these results for training volumes.

The negative relationship between the incidence and volume of employer-provided training for Maori workers is somewhat puzzling.[15] It does not seem to be an artefact of the statistical procedures used here, because it is also noted by Gobbi (1998), who measures volume by the *median* hours of training, which should be robust to the presence of outliers. One possible explanation is that employers provide training for remedial purposes, so the lower average level of education of Maori workers might mean that it takes longer to train them to the desired level.[16] But if this was the case, the same pattern should also be apparent for Pacific Island workers, who have an even lower average level of schooling. An alternative explanation views individual worker's previous experience of education or training as the main determinant of their future demand for training. Because many Maori workers may have had poor experiences at school they are deterred from seeking job training but if they can get over this initial hurdle and have a positive training experience, they may become much more enthusiastic and demand a large amount of training.[17] Although this pattern should also hold for Pacific Island workers, they may be less forthright in asking for training due to cultural factors and lack of English language skills (see below).

The control variables show a number of differences in the volume regressions from their behaviour in the probits for receipt of in-house training. Potential labour market experience has no effect on the volume of training, despite being a strong determinant of the incidence of training.[18] The schooling level of workers appears to affect the number of training episodes (as well as incidence) but not the total number of days spent training. The statistical significance of marital status and length of tenure is also reduced, compared with the probit models. However, occupations that had lower incidence of training compared with the base group of administrators and professionals also have lower volumes of training, while differences in the volume of training across industries are more apparent than were differences in training rates.

(Table 4 about here)

The results for the volume regressions change only slightly once a correction is applied for the non-random selection of workers who receive in-house training. To the extent that the joint estimation of the selection and regression equations (by maximum likelihood) is successful,[19] the results in the last columns of Table 4 should apply to the population of all workers, rather than just to those who received training. Thus, in a hypothetical world where all workers receive in-house training, the results suggest that the expected days of training would be 35 percent higher for Maori workers than for Pakeha workers, all other recorded social characteristics being the same. In contrast, there would be no statistically significant difference in the expected volume of training across other ethnic groups. Given the extent to which observable characteristics are controlled for in the regressions, it is difficult to explain why Maori workers would be expected to receive this higher volume of training.

A notable feature of the selectivity corrected estimates is that there is a negative correlation between the disturbances of the selection and regression equations.[20] This suggests that unobservable characteristics that improve the likelihood of receiving in-house training also act to reduce the volume of training received. It is difficult to explain what could cause such behaviour, although it is the same pattern (but more precisely estimated) that Veum (1996) finds. There are few other studies of the volume of training with which to compare these results. A frequently cited one, by Altonji and Spletzer (1991), ignores problems of selection bias and simply uses OLS estimation of training volume equations, over the full sample of workers who did and did not report the receipt of any training.[21]

Heckman sample selectivity models are known to be sensitive to modelling assumptions, with the identification of the regression model requiring the exclusion of some (continuous) variable that is a part of the selection equation (Deaton, 1997).[22] Hence, in the current context, one must find variables that affect the probability of being trained but not the amount of training received. It is difficult to find theoretical motivations for this sort of behaviour, so we used explicitly statistical criteria: the quadratic in years of potential labour market experience played a large role in the participation equations but not in the OLS equations for the volume of training. Thus we achieved identification by excluding the experience variables from the regression when estimating the maximum likelihood selectivity corrected model. As a check on the robustness of the results to both this exclusion restriction and our functional form assumptions, a variety of other specifications of the model were estimated. These alternative estimators include two-step and maximum likelihood estimation of the sample selectivity model, and the Tobit estimation that assumes that the same mechanism generates both the selection and the regression equations.

(Table 5 about here)

Table 5 contains a summary of the results of these other models for the ethnic intercept variables which are our main focus.[23] In nine out of the 12 cases the intercept variable for Maori is positive and statistically significant, with the only exceptions being for the Tobit estimates and maximum likelihood estimates for the number of days of training.[24] Hence, it seems to be a reasonably robust finding that Maori workers (both those receiving training and others) have an expected volume of in-house training that exceeds that of Pakeha workers. There is no consistent pattern for the other two groups, so for Pacific Islands and ‘other’ workers, there is no systematic variation in the volume of in-house training that would alter inferences about the pattern of inequality in training that one would make from just studying training rates.

VII. Summary and Implications

Maori and Pacific Island workers continue to experience lower job security and higher unemployment rates than other workers in New Zealand. The purpose of this paper has been to see whether differences across ethnic groups in the amount of employer-provided training can explain these unsatisfactory labour market outcomes. The relevant feature of this job training is that it involves an investment by the employer in the worker, thus reducing the likelihood that the worker will be released during an economic downturn.

The results suggest that job training reduces the risk of involuntary job loss, so differences in training probabilities across ethnic groups are likely to contribute to the unsatisfactory labour market outcomes for Maori and Pacific Island workers. But although Maori workers are less likely to receive job training, much of the gap reflects observable characteristics such as low schooling levels, and they also receive a higher volume of training than other workers. Hence, it may not be appropriate to develop job training policies that specifically target Maori workers because whether they are disadvantaged depends on the particular measure of training considered and they will also tend to benefit from the use of more general targeting rules on characteristics such as low levels of schooling. Moreover, the classification system used to allocate individuals to ethnic groups in the Household Labour Force Survey gives further grounds for caution in using ethnicity as a targeting characteristic when attempting to raise the level of employer-provided training.

In contrast to the situation for Maori workers, most of the participation gap in job training for Pacific Island workers is not explained by observable characteristics and the volume of training they receive is lower than for other groups (although usually not by a statistically significant amount). A similar pattern is apparent for workers from the 'Other' ethnic group, whose observed characteristics – especially school years – would predict an above average incidence of training. The gap in training for these workers may be due to their more recent entry into New Zealand if overseas schooling counts less highly in employers minds when allocating workers to training courses or if they face difficulties due to language skills. Evidence for this comes from an analysis of the qualitative questions on the ETS, with Pacific Island and 'Other' respondents being the most likely to use "lack of English" as an explanation for their dropping out of, or not attempting, job-related training courses (Watane and Gibson, 2001).

Although this study has provided information on some of the determinants and effects of training, and thus goes some way towards explaining the disparities in labour market outcomes across ethnic groups, much remains to be explained. In particular, it would be useful to know whether the returns to employer-provided training differ by ethnic group, which would presumably affect worker demand for job training programs. It would also be useful to know more about what causes differences in educational attainment across ethnic groups, seeing as this so strongly affects the receipt of employer-provided training.

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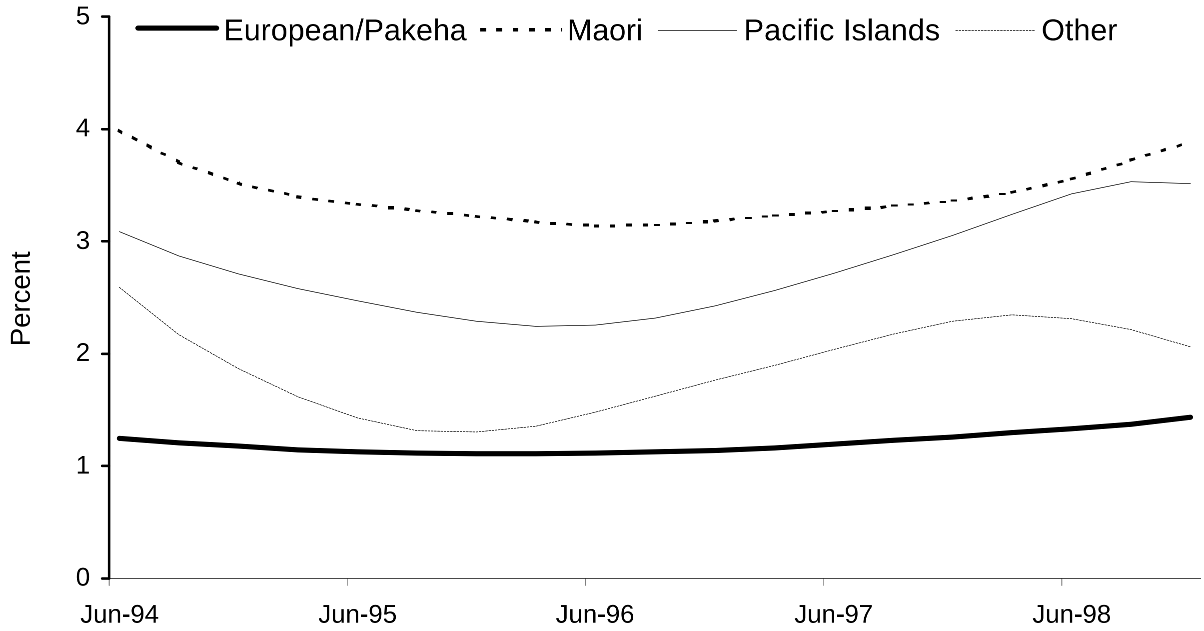
Fig 1: Probability of Employment to Unemployment Quarterly Transition



Source: Authors calculations from quarterly gross labour force flows data supplied by Statistics New Zealand from the Household Labour Force Survey. The raw data on transition probabilities by quarter have been smoothed using the robust locally weighted regression procedure of Cleveland (1979), with a bandwidth of 0.9.

Table 1: Probit Estimates of the Effect of In-house Training on Risk of Involuntary Job Loss

	Mean	(i)	(ii)	(iii)	(iv)
Age	36.00	-0.065	-0.064	-0.059	-0.060
		(1.63)	(1.62)	(1.61)	(1.61)
Age squared	14.40	0.008	0.008	0.007	0.007
(÷ 100)		(1.59)	(1.58)	(1.56)	(1.56)
Years of post-primary	5.72	-0.137	-0.135	-0.124	-0.127
education[a]		(4.12)	(4.10)	(3.99)	(4.01)
Female	0.49	-0.430	-0.425	-0.401	-0.412
		(2.83)	(2.81)	(2.84)	(2.86)
Married (=1)	0.63	-0.116	-0.119	-0.111	-0.115
		(0.65)	(0.67)	(0.67)	(0.68)
Ethnic Group					
Maori	0.09	0.508	0.516	0.484	0.495
		(2.12)	(2.16)	(2.16)	(2.17)
Pacific Islands	0.04	0.998	0.983	0.935	0.958
		(2.73)	(2.75)	(2.78)	(2.80)
Other[b]	0.04	0.548	0.542	0.498	0.514
		(1.35)	(1.35)	(1.33)	(1.34)
Training variables					
Received training (=1)	0.24	-0.355	…	…	…
		(1.67)			
No. of training episodes	0.51	…	-0.193	…	…
			(2.00)		
No. of days training	1.46	…	…	-0.112	…
				(2.71)	
No. hours training	8.83	…	…	…	-0.016
					(2.44)
Industry[c]					
Mining		2.011	2.018	2.086	2.109
		(1.30)	(1.31)	(1.38)	(1.38)
Manufacturing		0.272	0.274	0.271	0.277
		(0.67)	(0.68)	(0.72)	(0.72)
Electricity, gas, water		1.689	1.712	1.654	1.678
		(1.27)	(1.29)	(1.31)	(1.31)
Construction		1.585	1.588	1.488	1.514
		(2.29)	(2.32)	(2.32)	(2.32)
Wholesale/retail trade		0.071	0.071	0.077	0.076
		(0.18)	(0.19)	(0.22)	(0.21)
Transport and storage		-0.675	-0.669	-0.614	-0.626
		(2.01)	(2.01)	(1.99)	(1.98)
Business and finance		0.048	0.055	0.066	0.069
		(0.11)	(0.13)	(0.17)	(0.17)
Social services		0.048	0.056	0.075	0.069
		(0.13)	(0.15)	(0.22)	(0.20)
Wald tests for coefficient restrictions					
All slopes = 0		$\chi^2_{(17)}$=103	$\chi^2_{(17)}$=101	$\chi^2_{(17)}$=103	$\chi^2_{(17)}$=103

Industry effects = 0	$\chi^2_{(8)}$=22.8	$\chi^2_{(8)}$=22.9	$\chi^2_{(8)}$=22.9	$\chi^2_{(8)}$=22.9
Pseudo-R^2	0.059	0.060	0.063	0.062

Notes: The coefficients give the change in probability of involuntary job-loss for a one-unit change in each explanatory variable. All coefficients have been multiplied by 100 and the mean risk of involuntary job loss is 1.09 percent. Numbers in ( ) are *t*-statistics, calculated from heteroscedastically-robust standard errors. The sample size is 13,237 and the estimates are weighted by the population sampling weights. The models all include an intercept.

[a] Years at secondary school plus full-time equivalent years of post-secondary educational study.

[b] Includes those who do not specify their ethnic group.

[c] The excluded industry is "agriculture, hunting, forestry and fishing".

Table 2: Probit Estimates of the Effect of Ethnicity on the Probability of Participating in In-house Training

	Females and males pooled	Separate slopes by gender		Test for pooling males and females
		Females	Males	
European/Pakeha	ref	-0.007	ref	*p*=0.484
		(0.70)		
Maori	-0.060	-0.043	-0.079	*p*=0.203
	(3.70)	(1.80)	(3.70)	
Pacific Islands	-0.132	-0.137	-0.130	*p*=0.824
	(6.52)	(5.08)	(4.46)	
Other[a]	-0.055	-0.067	-0.050	*p*=0.731
	(2.03)	(1.75)	(1.37)	
Wald test (slopes = 0)	$\chi^2_{(3)}$=55.52	$\chi^2_{(7)}$=58.99		

Notes: The coefficients give the probability of participating in in-house training, relative to the probability for the reference group. The mean probability of participating in in-house training is 0.264. Numbers in ( ) are *t*-statistics, calculated from heteroscedastically-robust standard errors. The sample size is 11,003 and the estimates are weighted by the population sampling weights.

[a] Includes those who do not specify their ethnic group.

Table 3: Probit Estimates of the Effect of Ethnicity on the Probability of Participating in In-house Training: Conditional on Other Covariates

	Currently employed workers				Worked in past 12 months			
	(i)		(ii)		(iii)		(iv)	
	$\partial P/\partial X$	$\|t\|$	$\partial P/\partial X$	$\|t\|$	$\partial P/\partial X$	$\|t\|$	$\partial P/\partial X$	$\|t\|$
Ethnic Group								
Maori	-0.019	(1.13)	-0.021	(1.24)	-0.030	(2.14)	-0.033	(2.32)
Pacific Islands	-0.074	(3.33)	-0.075	(3.38)	-0.061	(3.24)	-0.063	(3.30)
Other[a]	-0.068	(2.64)	-0.065	(2.50)	-0.077	(3.61)	-0.074	(3.46)
Other Demographics								
Female	0.006	(0.53)	0.007	(0.62)	-0.040	(4.13)	-0.039	(3.96)
Age	0.019	(5.87)	…	…	0.023	(8.61)	…	…
Age^2 (÷100)	-0.026	(6.51)	…	…	-0.029	(8.77)	…	…
Years of experience[b]	…	…	0.006	(3.62)	…	…	0.010	(7.20)
$Experience^2$ (÷100)	…	…	-0.018	(4.96)	…	…	-0.023	(7.69)
Years of schooling[c]	0.012	(6.22)	0.011	(5.28)	0.013	(7.55)	0.013	(7.34)
Married	0.038	(3.25)	0.044	(3.76)	0.042	(4.12)	0.046	(4.50)
Job Characteristics								
Tenure	0.001	(7.75)	0.001	(7.69)	…	…	…	…
Usual weekly hours	0.004	(11.0)	0.004	(11.0)	…	…	…	…
Occupation[d]								
Clerical	-0.049	(3.40)	-0.051	(3.54)	-0.064	(5.13)	-0.065	(5.27)
Sales and service	-0.056	(3.59)	-0.059	(3.77)	-0.084	(6.46)	-0.085	(6.59)
Agriculture and fishery	-0.153	(4.79)	-0.155	(4.83)	-0.146	(5.81)	-0.147	(5.85)
Trades	-0.148	(8.66)	-0.150	(8.76)	-0.145	(9.66)	-0.146	(9.78)
Plant operators	-0.115	(6.55)	-0.116	(6.61)	-0.117	(7.80)	-0.118	(7.84)
Elementary	-0.143	(7.77)	-0.145	(7.86)	-0.165	(11.5)	-0.166	(11.5)
Industry[e]								
Mining	0.083	(0.96)	0.085	(0.97)	0.145	(1.78)	0.149	(1.81)
Manufacturing	-0.010	(0.26)	-0.009	(0.22)	0.012	(0.37)	0.014	(0.42)
Electricity, gas, water	0.112	(1.73)	0.114	(1.74)	0.121	(2.13)	0.123	(2.14)
Construction	-0.034	(0.80)	-0.032	(0.75)	-0.009	(0.24)	-0.006	(0.16)
Wholesale/retail trade	-0.019	(0.48)	-0.021	(0.52)	-0.007	(0.22)	-0.008	(0.24)
Transport and storage	0.034	(0.76)	0.035	(0.79)	0.060	(1.58)	0.062	(1.62)
Business and finance	0.019	(0.46)	0.022	(0.51)	0.025	(0.72)	0.028	(0.80)
Social services	0.092	(2.26)	0.093	(2.28)	0.088	(2.67)	0.090	(2.70)
Pseudo-R^2	0.104		0.102		0.090		0.089	
Wald tests for coefficient restrictions								
All slopes = 0	$\chi^2_{(24)} = 906.7$		$\chi^2_{(24)} = 900.3$		$\chi^2_{(22)} = 903.0$		$\chi^2_{(22)} = 903.3$	
Industry effects = 0	$\chi^2_{(8)} = 80.6$		$\chi^2_{(8)} = 81.7$		$\chi^2_{(8)} = 74.1$		$\chi^2_{(8)} = 75.4$	
Occupation effects = 0	$\chi^2_{(6)} = 132.5$		$\chi^2_{(6)} = 135.3$		$\chi^2_{(6)} = 215.6$		$\chi^2_{(6)} = 218.3$	
Sample size	11003		11003		13237		13237	

Note: The coefficients give the change in probability of participating in in-house training for a unit change in each explanatory variable. The mean probability of participating in in-house training is 0.264. Models include an intercept. The estimates are weighted by the population sampling weights. Numbers in ( ) are *t*-statistics, calculated from heteroscedastically-robust standard errors.

[a] Includes those who do not specify their ethnic group.

[b] This is potential labour market experience calculated as age minus post-primary school years minus 12.

[c] Equivalent full-time years of secondary school and post-secondary school educational study.
[d] The excluded occupations are administrators, professional and associate professionals.
[e] The excluded industry is "agriculture, hunting, forestry and fishing".

Table 4: Volume of In-house Training Regressions

	No selectivity correction				Sample-selectivity corrected			
	ln(episodes)		ln(days)		ln(episodes)		ln(days)	
	b	|*t*|	*b*	|*t*|	*b*	|*t*|	*b*	|*t*|
Ethnic Group								
Maori	0.088	(1.82)	0.271	(3.08)	0.097	(2.00)	0.301	(3.44)
Pacific Islands	-0.105	(1.58)	0.143	(0.93)	-0.072	(1.07)	0.204	(1.31)
Other[a]	-0.032	(0.50)	-0.053	(0.59)	-0.006	(0.09)	-0.005	(0.06)
Other Demographics								
Female	0.040	(1.32)	-0.056	(1.10)	0.037	(1.19)	-0.069	(1.34)
Years of experience[b]	0.001	(0.23)	-0.009	(1.28)	…	…		
Experience^2 (÷100)	0.000	(0.61)	0.000	(0.04)	…	…		
Years of schooling[c]	0.015	(2.80)	0.008	(0.89)	0.013	(2.34)	0.016	(1.79)
Married	-0.033	(1.09)	-0.048	(1.00)	-0.054	(1.78)	-0.115	(2.36)
Job Characteristics								
Tenure	0.000	(1.63)	0.001	(1.34)	0.000	(0.37)	0.000	(0.77)
Usual weekly hours	0.004	(3.71)	0.009	(4.58)	0.003	(2.24)	0.007	(3.62)
Occupation[d]								
Clerical	-0.083	(2.15)	-0.122	(1.98)	-0.065	(1.66)	-0.097	(1.55)
Sales and service	-0.013	(0.29)	0.032	(0.41)	0.010	(0.23)	0.068	(0.87)
Agriculture and fishery	0.013	(0.13)	-0.116	(0.69)	0.087	(0.84)	-0.022	(0.12)
Trades	-0.185	(3.43)	-0.208	(2.09)	-0.122	(2.15)	-0.140	(1.37)
Plant operators	-0.125	(2.34)	-0.148	(1.45)	-0.079	(1.41)	-0.096	(0.93)
Elementary	-0.142	(2.29)	-0.306	(2.79)	-0.079	(1.19)	-0.238	(2.12)
Industry[e]								
Mining	0.292	(1.65)	0.856	(2.99)	0.264	(1.47)	0.824	(2.81)
Manufacturing	0.222	(2.46)	0.318	(1.96)	0.226	(2.43)	0.328	(2.00)
Electricity, gas, water	0.379	(3.11)	0.419	(2.08)	0.344	(2.79)	0.373	(1.83)
Construction	0.182	(1.76)	0.179	(1.04)	0.192	(1.83)	0.187	(1.07)
Wholesale/retail trade	0.122	(1.31)	0.157	(0.97)	0.131	(1.38)	0.178	(1.08)
Transport and storage	0.216	(2.17)	0.319	(1.86)	0.204	(2.01)	0.315	(1.81)
Business and finance	0.266	(2.83)	0.383	(2.33)	0.260	(2.70)	0.387	(2.32)
Social services	0.285	(3.26)	0.472	(3.03)	0.253	(2.81)	0.420	(2.65)
Intercept	0.103	(0.87)	0.686	(3.22)	0.367	(2.38)	0.803	(3.56)
Selectivity correction (l)					-0.145	(2.69)	-0.149	(2.58)
R^2	0.055		0.063		…		…	
Wald test (slopes = 0)	$F_{(24,2839)}$=5.75		$F_{(24,2839)}$=6.30		$\chi^2_{(22)}$ = 45.75		$\chi^2_{(22)}$ = 79.86	

Note: The regressions are estimated on the sample of workers receiving in-house training (*N*=2864), with the sample-selectivity corrected results from a maximum likelihood model where the selection equation is estimated on the sample of *N*=11003 workers with full data available. The estimates are weighted by the population sampling weights. Absolute *t*-statistics are calculated from heteroscedastically-robust standard errors.

[a] Includes those who do not specify their ethnic group.

[b] This is potential labour market experience calculated as age minus post-primary school years minus 12.

[c] Equivalent full-time years of secondary school and post-secondary school educational study.

[d] The excluded occupations are administrators, professional and associate professionals.

[e] The excluded industry is "agriculture, hunting, forestry and fishing".

Table 5: Sensitivity Analysis for Volume of In-house Training Regressions

Estimation method/ exclusion restrictions[a]	Dependent variable	Conditional Ethnic Effects: Maori	Pacific Island	Other
OLS	# of episodes	0.213	-0.192	-0.153
		(2.00)	(1.33)	(1.21)
OLS	# of days	6.317	5.005	-1.334
		(2.06)	(1.52)	(1.58)
Two-step / experience	# of episodes	0.270	-0.131	-0.022
		(2.53)	(0.91)	(0.16)
Two-step / experience	ln(# of episodes)	0.114	-0.072	0.022
		(2.35)	(1.08)	(0.33)
Two-step / experience	# of days	6.121	5.461	-0.251
		(2.08)	(1.65)	(0.30)
Two-step / experience	ln(# of days)	0.285	0.249	0.095
		(3.19)	(1.60)	(0.95)
ML / experience	# of events	0.230	-0.139	-0.111
		(2.16)	(0.95)	(0.86)
ML / experience	# of days	6.619	5.507	-0.945
		(3.06)	(1.66)	(1.17)
ML no exclusions	# of events	0.222	-0.157	-0.125
		(2.07)	(1.08)	(0.97)
ML no exclusions	# of days	1.733	-1.845	-3.441
		(1.17)	(1.14)	(2.89)
Tobit	# of events	-0.097	-0.783	-0.650
		(0.65)	(3.61)	(2.73)
Tobit	# of days	1.669	-2.057	-3.560
		(1.13)	(1.24)	(2.70)

Note: The sample and other variables in the model are as reported in Table 4. Estimates are weighted by the population sampling weights and *t*-statistics in ( ) are based on heteroscedastically-robust standard errors.

[a] Two-step estimation uses a probit model to form the Mills' ratio which is then added to the regression model, while maximum likelihood (ML) estimates the parameters of the two models simultaneously. The Tobit estimator assumes that the same mechanism generates both the selection equation and the regression model.

Appendix Table 1: Estimated Effect of In-house Training on Involuntary Job Loss with Endogenous Treatment Effects

	(i)		(ii)		(iii)		(iv)	
	b	|*t*|	*b*	|*t*|	*b*	|*t*|	*b*	|*t*|
Demographics								
Age	-0.028	(0.63)	-0.028	(0.62)	-0.027	(0.64)	-0.027	(0.63)
Age squared (÷100)	0.000	(0.56)	0.000	(0.55)	0.000	(0.57)	0.000	(0.56)
Years of schooling[a]	-0.100	(2.81)	-0.098	(2.79)	-0.092	(2.78)	-0.094	(2.80)
Female	-0.459	(2.99)	-0.454	(2.97)	-0.430	(3.00)	-0.441	(3.02)
Married	-0.014	(0.08)	-0.018	(0.10)	-0.020	(0.12)	-0.021	(0.13)
Ethnic Group								
Maori	0.383	(1.65)	0.391	(1.69)	0.373	(1.71)	0.380	(1.71)
Pacific Islands	0.679	(1.95)	0.671	(1.94)	0.653	(1.98)	0.667	(1.99)
Other[b]	0.303	(0.79)	0.302	(0.79)	0.284	(0.80)	0.293	(0.81)
Training variables								
Received training (=1)	-0.313	(1.49)						
No. of training events			-0.172	(1.84)				
No. of days training					-0.103	(2.61)		
No. hours training							-0.015	(2.33)
Industry[c]								
Mining	2.980	(1.61)	2.978	(1.61)	2.997	(1.66)	3.030	(1.66)
Manufacturing	0.394	(0.94)	0.394	(0.95)	0.381	(0.98)	0.389	(0.98)
Electricity, gas, water	2.758	(1.72)	2.775	(1.73)	2.646	(1.73)	2.688	(1.73)
Construction	1.651	(2.37)	1.650	(2.39)	1.553	(2.39)	1.578	(2.39)
Wholesale/retail trade	0.194	(0.48)	0.193	(0.49)	0.186	(0.50)	0.189	(0.50)
Transport and storage	-0.586	(1.56)	-0.581	(1.56)	-0.540	(1.54)	-0.548	(1.54)
Business and finance	0.285	(0.58)	0.289	(0.59)	0.279	(0.61)	0.287	(0.61)
Social services	0.365	(0.82)	0.369	(0.84)	0.359	(0.87)	0.359	(0.85)
Mills ratio for treatment effects (l)[d]	0.669	(1.68)	0.658	(1.66)	0.591	(1.57)	0.606	(1.58)
R^2	0.061		0.062		0.064		0.064	
Wald test (slopes = 0)	$\chi^2_{(18)}$=102.9		$\chi^2_{(18)}$=101.8		$\chi^2_{(18)}$=104.0		$\chi^2_{(18)}$=103.7	

Notes: The coefficients give the change in probability (x100) of involuntary job-loss for a one-unit change in each explanatory variable. Numbers in ( ) are *t*-statistics, calculated from heteroscedastically-robust standard errors. The sample size is 13,237 and the estimates are weighted by the population sampling weights. The models all include an intercept.

[a] Years at secondary school plus full-time equivalent years of post-secondary educational study.

[b] Includes those who do not specify their ethnic group.

[c] The excluded industry is "agriculture, hunting, forestry and fishing".

[d] The Mills ratio comes from a probit model where the receipt of training depends on ethnic dummy variables, gender, marital status, school years, a quadratic in experience, and occupation and industry dummy variables.

Notes

[1] Altonji and Spletzer (1991) and Veum (1996) are exceptions, with the first study finding a negative relationship between incidence and volume and the second finding no relationship.

[2] In addition, transition probabilities involving the not-in-the-labour force state would be needed to fully explain the differences in unemployment rates across ethnic groups. For example, the two transition probabilities, $pr(EU)$ and $pr(UE)$, imply an unemployment rate of 12 percent for Maori workers over 1994-98, according to equation (1). In fact the unemployment rate for Maori averaged almost 18 percent because the other gross flows not included in equation (1) also caused inflows into Maori unemployment to exceed outflows.

[3] In-house training is that organized by an employer primarily to meet the needs of its own employees, is conducted in-house or externally, and is delivered by the company's own employees or external training providers. External training covers all other employment-related training for the employed and unemployed.

[4] The Household Labour Force Survey treats these three as a single category amongst the available reasons for leaving the last job. The other categories specified include retirement, sickness or injury, change of location, dissatisfaction with job, and reaching the end of a contract or a temporary or seasonal job.

[5] Firm size may also affect the stability of product demand but data are not available on this variable.

[6] Including all four training variables in the one equation, so as to construct some overall

index of training experience, is affected by the high correlation between the training measure with each coefficient on the individual training measures statistically insignificant at the $p<0.10$ level. Moreover, while there is a negative coefficient on the days of training variable there are *positive* coefficients for the other training variables, making it difficult to construct any index.

[7] The industry effects are jointly statistically significant, as seen from the Wald test results in Table 1. Occupational dummy variables were also included in one version of the model, following the suggestion of a referee, but these were always jointly statistically insignificant (at the $p<0.10$ level), so are excluded from the model reported in Table 1.

[8] The effect for Pacific Islanders may reflect their migration history, with less experience in the New Zealand labour market than would be predicted from their age. However, the survey did not collect information on years spent in New Zealand

[9] Some studies also include firm size but Blundell *et al.*, (1999) argue that this variable may be endogenous if workers choose the type of employer in order to obtain training and so drop it from their specification. Moreover, data on firm size is not available in the ETS dataset.

[10] Details on the average characteristics for each ethnic group are available in an unpublished appendix, which also includes probit models estimated separately by ethnic group, as a generalisation of the intercept dummy variable approach in Table 3.

[11] Maori comprise 15 percent of those who were not working at the time of the survey but had been employed in the previous 12 months but are only nine percent of the group who were

currently working for wages and salaries.

[12] The restriction to the four most recent courses should not be too serious because only 230 workers (representing 2.0 percent of the sample) reported more than four training episodes in the previous year.

[13] In semi-logarithmic models the percentage change for a dummy variable is calculated as $100\times[\exp(b_j) - 1]$ (Halvorsen and Palmquist, 1980). Thus, $100\times[\exp(0.271)-1]=31.1$.

[14] Because the difference in participation rates between these two groups was already not statistically significant once observed characteristics were controlled for, one could in fact say that the inequality is reversed.

[15] A similar pattern is found by Altonji and Spletzer (1991) for males compared with females.

[16] A variant of this explanation is that certain job-training subsidies could make it worthwhile for employers to give a higher volume of training to Maori workers, but there was no knowledge of such subsidy effects amongst the staff of Skill New Zealand who were interviewed.

[17] I am grateful to Ron Brown of Skill NZ for this explanation.

[18] The same lack of statistical significance applies if a quadratic in age is used instead of experience and the coefficients and *t*-statistics on the ethnic variables are unchanged when age is used instead of experience.

[19] The identification of the selectivity-corrected regression equation relies on exclusion restrictions for the quadratic term in labour force experience. Table 5 explores the sensitivity of the results to this assumption.

[20] This is not directly observed in Table 4 but can be inferred from the negative l coefficient on the Mills ratio, given that $l = rs$ and $s > 0$.

[21] Applying this approach suggests that Maori workers can expect 1.28 days more training per year than can Pakeha workers, with this difference being statistically significant (t=1.83). This gap in training days is equivalent to 23 percent of the mean training days for Pakeha workers (n=5.6).

[22] Otherwise the model is identified only by the non-linear construction of the selection term (the Mills ratio), which is the approach used by Veum (1996).

[23] The full results for these models are available from the authors.

[24] The Tobit coefficients show the effect of ethnicity on the volume of training, conditional on receiving training but correcting for the fact that those receiving training may differ systematically from those who do not. The coefficients in the Table 4 volume regressions often differ (by more than the scaling factor) from the coefficients on the same variable in the Table 3 probits for the receipt of in-house training. Hence, the restrictions implied by the Tobit model may not be appropriate.