Is Computing Different?

Comparing the Determinants of Computer-Related and Other Subject Matter Training in New Zealand

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Abstract

There is growing interest by policy makers in the gap between those who have skills in information technologies and those who do not, due, in part to the concern that this gap contributes to rising income inequality. In this paper, unit record data are used to examine the factors that determine whether individuals study computer-related subjects and participate in computer-related training provided by employers and other agencies. The results from bivariate probit models suggest that the factors determining participation in computer-related training differ significantly from the factors determining participation in other subject matter training. Thus, general policies to raise training rates may have less impact on the acquisition of information technology skills than would more specific interventions. The results suggest that interventions that focus school attainment and non-metropolitan location would have a significantly greater effect on the receipt of computer training than they do on other forms of training.

I. Introduction

There is growing interest by policy makers in the gap between those who have skills in information and communication technologies (ICT) and those who do not, in part due to the concern that this gap contributes to rising income inequality. The ICT sector has also recently been recognised by the New Zealand government as one of three priority sectors, due to its potential to improve productivity across the economy.[2] Given this importance, finding out which sectors of the population lack access to ICT skills can provide a first step in improving the skills available in the economy.

On the basis of overseas research, several groups have been identified in New Zealand who are most likely to be disadvantaged in terms of ICT skills, including Maori and Pacific peoples, those with few formal qualifications, the unemployed, and women and girls.[3] But it would be helpful to have empirical evidence from New Zealand before policies are introduced to improve the participation of certain groups in ICT training, in case the patterns that are found overseas do not hold.

In this paper, unit record data from the 1996 Education and Training Survey are used to examine the factors that determine whether individuals gain qualifications in computing and information technology, and participate in computer-related training provided by employers and other agencies. In particular, we investigate whether the factors determining participation

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[2] *Growing an Innovative New Zealand*. Available on the internet at http://www.beehive.govt.nz.

[3] *Closing the Digital Divide – What do we Know About the Digital Divide in New Zealand*. Available on the internet at http://www.executive.govt.nz/minister/maharey/divide/01-01.htm.

in these types of training and qualifications programs differ from the determinants of other subject matter training and qualifications.

The primary purpose of this enquiry is to see whether *general* policies to improve participation in training are all that is needed for improving ICT skills in New Zealand, or whether more *specific* policies are needed. One potential cause of the need for more specific policies would be if the determinants of an individual's participation in computer-related training differed in a significant way from the determinants of participation in other subject-matter training. The practical importance of our enquiry is underlined by the continued increase in the Industry Training Fund, and the creation of the New Technology Fund. These funds enable New Zealand workers to participate in formal workplace training, with increasing reliance placed on computer-based training.

The next section of the paper discusses previous literature on training, paying particular attention to recent economic analyses of workplace computing skills. Section III describes the survey data that we use and the econometric methods that are adopted. The main results of the paper are in Section IV, while conclusions and policy implications are in Section V.

II. Previous Literature

Becker's human capital theory (Becker, 1964) explains why enterprises are keen to train workers and why workers are keen to undertake some form of training or qualification. Workers hope for higher wages in the future and enterprises hope for increased productivity and output. Training can be either specific to the enterprise or general, with specific training being more useful to the enterprise that provides or finances it. The distribution of training may therefore be affected by not only the costs and benefits of the training, but by the ability of the worker to finance any training not paid for by the enterprise.

The most recent reviews of the relationship between firm and worker characteristics, and the incidence of training are by Blundell *et al* (1996), Groot (1997) and OECD (1999). These reviews each found that the incidence of training was higher for workers that were; male, younger, better educated, employed full-time, employed by a large firm and employed in the public sector. One caveat to these findings is that problems exist with the measurement of training; Barron *et al (1997)* questioned the reliability of training measures in their study based on a 1993 U.S. survey that linked the responses of firms and workers to questions about the receipt of on-the-job training. It also must be noted that just because some groups receive less training than others, perhaps reflecting non-random selection into many training schemes, this does not imply that they may have received too little training. There also needs to be some idea about the demand for training before conclusions can be drawn about the adequacy of who has received training.

There are several reports by the OECD that compare the levels of training in various countries. The OECD *Employment Outlook (1999)* ranked NZ 6th highest out of 24 OECD countries in the level of participation in career or job-related training and 2nd highest in hours of training. Of these two measures, the participation rate may be the more reliable because there is likely to be less measurement in the reported incidence of training than in the reported volume (either in terms of hours or expenditure) of training (OECD 1997).

Previous New Zealand studies have focused on ethnic and gender differences in the incidence of training. Overall, males and females in NZ have similar participation rates in training, but male employees are more likely to receive employer support for any study or training (Gobbi (1998)). Gibson & Watene (2001) show that there are differences in participation rates in employer –provided training for Maori and Pacific Islanders, although much of the gap can be explained by other observable characteristics such as education. But no one in New Zealand has previously studied who receives computer-related training compared to other subject matter training.

The overseas literature on training is beginning to focus on computer-related training, in part because one explanation for the rising wage inequality that is being experienced in many countries is the increased demand for workers with computer-based skills (Autor *et al.*, 1998; Acemoglu, 2001). For example, Green *et al.* (2001) show that more education enhances the development of computing skills at work, but with respect to other skills, less educated workers make up for their lower education through more work-based learning. They also show that education has an insignificant impact on the acquisition of computing skills if workers stay in the same job for at least five years. Hence education's impact on the ability to acquire skills is mediated by its impact on job mobility. That is, if education raises the ability to acquire computing skills over time, people raise their utilisation of computing skills by changing jobs.

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). It is the first major survey of job-related training in New Zealand. The survey asked respondents aged 15-64 about their participation in training either provided by an employer or externally (denoted *in-house* and *external*)[4] and in study towards a qualification during the previous year.

Although the ETS has a sample of 22,257, not all of these observations are available for the current paper. For our analyses of external training and study towards a qualification we restrict the sample to 20,809 respondents who were not still in secondary school and who had complete data on the training measures and other explanatory variables. More restrictions were needed on the sample for the analysis of in-house training, because questions about this type of training were only asked of those who had worked for wages or salaries in the 12 months prior to the survey (n=13,988). After omitting observations with missing data, a sample of 13,262 people was available for the model of in-house training. However, some of these people who had worked for wages or salaries in the previous 12 months were not currently employed at the time of the survey, so information on factors that might affect the receipt of training – such as tenure and usual work hours – is not available. Thus, a more restricted sample for a further analysis of in-house training is the 11,025 survey

[4] The definitions used by the ETS are that *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.

respondents who were wage or salary workers at the time of the survey and who had full details available on their training, schooling and employment characteristics.

For each in-house and external training course (up to a maximum of four) the survey asked respondents about the main subject of the course, where "computing" was included as a choice along with eight other broad subject areas. A slightly finer breakdown of subjects studied towards a qualification is available from the survey, with "computing and information technology" one of 13 broad fields that were identified. For each course studied or training program completed, respondents could only choose one main subject from the list but by covering up to four recent training episodes the survey is able to handle those respondents who received training across several subject areas.

The distribution of training by subject matter is shown in Table 1. It appears that computing is the third most frequently listed field for in-house training. Of those workers who received in-house training, 17.8 percent nominated computing as the main subject for at least one (of up to four) of the training courses they had participated in during the previous 12 months. This is likely to underestimate the extent of computer related training however, because some of the other subjects, such as "professional and technical" (which is the most frequent subject of training) and "clerical and office" are likely to have some computing component. A somewhat larger proportion of those participating in external training (21.9 percent) listed computing as the main subject, making it the second most frequent choice for this type of training.

(Table 1 about here)

The second half of Table 1 shows that computing and information technology is a less frequently listed subject amongst the survey respondents who had gained either school or other qualifications,[5] or trade and vocational certificates in the previous 12 months. Once again, however, the reported 5.5 percent of those working towards or receiving a qualification in computing and information technology is likely to be an underestimate of the exposure to computer-related qualifications. Presumably, many of those respondents who nominated the broad subject of "business and administration" were also gaining qualifications that were, at least in part, related to information and communication technologies. This broadness of the subject indicators in the dataset must be kept in mind when interpreting the econometric results below.

The other important feature of the training reports in the survey is that participation in computer-related training is not a mutually exclusive category because respondents were able to specify multiple training episodes. Indeed, it appears that many of the people who indicating receiving training in computer-related areas also received training in other areas (Table 2). The first two panels of Table 2 show that one-half (one-third) of respondents who had participated in computer-related training in-house (externally) had also participated in other subject matter training in the previous 12 months. This overlap is rather less apparent for study towards qualifications, most probably because the greater time commitment needed for such study precludes many people from having multiple qualifications during a 12-month period. Table 2 also shows that only 24 percent of those

[5] The criteria for the qualification being counted by the survey were that it takes more than the equivalent of three months of full-time study.

eligible for in-house training did actually receive any training in the last 12 months. The proportion was even lower for external training at 13 percent, and only 15 percent received a qualification in any subject in the last 12 months.

(Table 2 about here)

One methodological implication of the survey respondents indicating training in multiple areas is that it prevents us using some econometric methods, such as the multinominal logit, which assume mutually exclusive categories. It also seems likely that simply analysing the dichotomous decision of whether or not a person participated in computer related training will be an inefficient modelling method, because it ignores information which may be relevant to this choice, such as whether or not the respondent participated in other subject matter training.

Therefore, we use a modelling method which allows us to focus on two binary variables, allowing four possible outcomes: a person participated in both computer-related and other subject matter training, a person participated in computer but not other training (and *vice versa*) and a person participated in no training. The bivariate probit estimation method allows the errors in the two probit models to be correlated, reflecting the fact that there are likely to be unobserved factors influencing the decision of an individual to gain skills in one subject matter rather than another. This estimation framework also allows hypothesis tests of whether the coefficients are equal across the two equations. In other words, these hypothesis tests may indicate whether different characteristics are associated with the receipt of computer training versus the receipt of other subject matter training.

The formal specification of the bivariate probit model is (Greene, 2000, p.849):

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\begin{aligned}
& y_1^* = \beta_1' \mathbf{x}_1 + \varepsilon_1 , \qquad && y_1 = 1 \quad if \quad y_1^* > 0, \ \ 0 \ otherwise \\
& y_2^* = \beta_2' \mathbf{x}_2 + \varepsilon_2 , \qquad && y_2 = 1 \quad if \quad y_2^* > 0, \ \ 0 \ otherwise \\
& E[\varepsilon_1] = E[\varepsilon_2] = 0 && \\
& Var[\varepsilon_1] = Var[\varepsilon_2] = 1 && \\
& Cov[\varepsilon_1, \varepsilon_2] = \rho &&
\end{aligned}
$$

where y_1^* and y_2^* are the unobserved latent variables reflecting the demand for training. This model can be estimated by maximum likelihood methods (StataCorp, 1999). One important hypothesis to test with this model is whether the disturbances are correlated across the two equations, $H_0: \rho = 0$, because if this restriction holds the model consists of independent probit equations which can be estimated separately. Hence, in the current setting if this restriction holds we could focus just on the 0-1 variable for whether individuals participated in computer-related training.

In common with univariate probit models, the bivariate probit coefficients are not directly interpretable, but more familiar marginal effects can be calculated, showing the effect that changes in the explanatory variables have on the probability of participating in training. But with a bivariate probit model there are a variety of marginal effects available, depending on whether one is interested in joint, conditional, or marginal probabilities. For the current study we are mainly interested in the determinants of computer-related training so we focus on the marginal probabilities with conditioning on whether people participated in other forms of training. To make the interpretation of the results easier we present the marginal effects in the form of elasticities rather than as probability derivatives; otherwise the lower mean probability of participating in computer-related training can interfere with the comparison of marginal effects across the training equations. These elasticities give the percentage change in the probability of participating in each type of training or qualification following a one-percent change in the explanatory variable. In the interests of easier interpretation, these calculations ignore the fact that, logically speaking, some of the explanatory variables cannot change infinitesimally because they are discrete characteristics (StataCorp, 1999).

Explanatory variables

To explain participation in computer-related and other subject matter training, we include a fairly standard set of variables that are also used in previous studies of employer-provided training (for example, see Gibson and Watene, 2001). For our models of in-house training, these variables include worker characteristics (age, education levels, marital status, occupation, tenure) and characteristics of the job (hours worked, industry).[6] In addition, we pay particular attention to the location of employment, distinguishing three mainly metropolitan regions (Auckland, Wellington, Canterbury) from the rest of the country, because some of the literature on the "digital divide" emphasises a rural-urban component.[7] The variables related to occupations and job characteristics are not relevant to the external training and qualifications choices of respondents, but overall labour market status is likely to be relevant to those two types of training and study so we include indicator variables for wage workers, employers, the self-employed and the unemployed.

[6] 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.

The means and standard deviations of the explanatory variables used in the models of in-house training, external training, and qualifications are reported in Table 3. Comparing across the samples, it is apparent that those who were eligible for in-house training (and hence were employed at some time during the 12 months prior to the survey) have accumulated slightly more post-primary schooling and are less likely to be either female or from the Maori and "Other" ethnic groups.

(Table 3 about here)

IV. Results

Table 4 contains the bivariate probit results for the determinants of participation in in-house training. We note at the outset that the disturbances appear to be significantly correlated across the two equations (?=0.27). This indicates that the omitted characteristics determining participation in one type of training are related to the unobserved factors determining participation in the other type of training. Hence, modelling the decision to participate in just one type of training would ignore relevant information. Another key finding of the estimation results is that the cross-equation restrictions needed to pool the two models into one are decisively rejected ($p<0.000$). In other words, some or all of the coefficients in the computer training equation have a different structure than what they have in the equation for other subject matter training.

The probability of receiving in-house training for both computing and other subject areas rises with age but at a declining rate. For computer-related training the probability peaks at

[7] Neels Botha et al. (2001) "Addressing the rural digital divide in New Zealand" Social Systems Research Unit, AgResearch Limited.

age 41, while for training in other subjects the probability peaks at age 38. Thus there is no evidence to suggest that older workers are particularly disadvantaged in the receipt of computer-related training – instead, their likelihood of receiving all types of in-house training declines, presumably because of the shorter remaining working life over which the firm and worker can recoup their investments

(Table 4 about here)

The incidence of in-house training is higher for males and lower for people from ethnic minority groups. However, the ethnic effect is not statistically significant in the equation for computer-related training. Moreover, the comparison of coefficients across equations suggests that the gender and ethnic effects are in no way particular to computer-related training because similar patterns occur for training in other subjects.

The likelihood of receiving training in both subjects is higher for workers who have accumulated more years of post-primary schooling, although for computer-related training the effect is significant only at the $p<0.07$ level. Moreover, the magnitude of the schooling effect is proportionately less in the computer training equation, with the elasticity of the participation probability with respect to years of schooling only two-thirds as high as it is for other subject matter training. In other words, the advantages bestowed on the highly schooled, in terms of greater likelihood of being trained, are rather less apparent with computing. This may reflect the fact that people who have already accumulated a lot of schooling have also had good exposure to computers and so do not require further training.

It is notable that the differing impact of schooling is the only one of the demographic characteristics that is significantly different across the two equations.

In comparison with workers elsewhere, those who are located in Auckland, Wellington or Canterbury are significantly more likely to receive in-house computer training. On the other hand, they are significantly less likely than workers elsewhere to receive training in other subjects. Thus there does appear to be somewhat of an urban-rural divide, although whether it denotes disadvantage for the non-metropolitan areas depends on whether computer training is more valuable to workers than is training in other subjects.

There are considerable occupational differences in the exposure to in-house training, with the more 'basic' occupations, like sales, trades, agricultural and plant operators having lower training rates than the managerial, administrative, professional and technical workers. These patterns exist for both computing and other subject areas of training, with the exception of the clerical group, who have computer training at similar levels to the professional group but other subject matter training at similar levels to the basic occupations.

Table 5 contains the results when the model is re-estimated on the sample of currently employed workers. This smaller sample allows two extra variables to be added to the model: length of tenure at the current employer and usual weekly hours of work. The likelihood of being trained is higher for the longer-tenure and full-time workers, where this presumably reflects the decisions by firms to invest in workers whose employment relationship is likely to last and from whom they can extract the maximum pay-back, in terms of work hours. However, neither of these two factors differs in their effect on computer and other subject matter training and the other cross-equation comparisons reported in Table 4 are unchanged when these two variables are added to the model.

(Table 5 about here)

The results for external training are shown in Table 6. Again, as for in-house training, the disturbances appear to be significantly correlated across the two equations (?=0.28). Hence, modelling the decision to participate in just one type of training would ignore relevant information. Just as with in-house training, the probability of receiving external training in both computing and other subject areas rises with age but at declining rate. For computer-related training the probability peaks at 41, the same age as for in-house training, and for other subjects it peaks at a lower age of 32. Hence older people are more likely to want computer-related training, perhaps reflecting the fact that these are not skills that were commonly taught when they were at school.

Participation in external training courses where the main subject is computing is significantly higher for females than for males (Table 6). In contrast, this gender difference does not extend to the other subject matter training. There are significant ethnic differences in participation rates for external training. For computer-related training, people from all three ethnic minority groups have significantly lower participation probabilities. But for other subjects, it is only the Pacific Island and 'other' ethnic groups who have a lower probability of receiving training. In other words, the lower external training for Maori is restricted to computing, while for Pacific Island and 'other' ethnic groups, external training rates are low both for computing and for other subjects.

In common with the pattern for in-house training, more years of post-primary schooling increases the likelihood of receiving external training in both computing and other subjects. Once again, the magnitude of the schooling effect is proportionately less in the computer training equation, with the elasticity of the participation probability being only one-half as high as it is in the equation for other subject matter training.

(Table 6 about here)

Respondents from Auckland, Wellington and Canterbury were more likely to participate in computer-related external training than were respondents from other parts of New Zealand. Those from Canterbury were also more likely to receive other subject matter training, while there were no differences between Auckland, Wellington and the rest of the country. Hence, in parallel with the results for in-house training, being located in Auckland and Wellington has a significantly greater effect on the receipt of computer training than on the receipt of other subject matter training.

The results for the labour force variables in Table 6 show that, in comparison to the excluded group who are not in the labour force, training rates in both computing and other subjects are higher for wage workers, the self-employed and the unemployed. The pattern is different for employers, who have significantly higher training rates for other subjects but not for computer-related training. Thus, most of the labour force variables do not indicate particular labour force states which could be targeted if policy wished to specifically increase access to computer-related training.

Table 7 shows the results for the respondents who undertook study for some form of qualification in the previous 12 months. The probability of attaining a qualification declined with age, although at a diminishing rate for the non-computer related subjects. There is no significant difference between men and women in the participation rates for computer-related training, whereas men were much less likely than women to be studying for qualifications in other subjects. The indicator variables for the ethnicity of respondents were statistically insignificant in all cases but one: people of 'other' ethnicity have a higher probability of studying for non-computer related qualifications.

(Table 7 about here)

Previous schooling is a significant predictor of current study for a qualification, for both computing and other subjects. However, for each extra year of schooling already obtained, the percentage change in the probability of gaining a qualification is only two-thirds as high for a computer-related qualification as for one in any other subject. Thus, lack of previous educational attainment may be less of a barrier to the acquisition of computer-related qualifications than it is a barrier to obtaining qualifications in other areas.

Unsurprisingly, all of the groups who were in the labour force were less likely to be studying for qualifications. However, the effect for the self-employed and unemployed was not statistically significant in the equation for computer study. Finally, in contrast to the results for in-house and external training, there were no significant regional effects in the equation for computer-related qualifications.

V. Conclusions

In this paper, factors determining participation in computer-related training provided either by employers or by other agencies, or obtained as study towards a qualification have been investigated. A particular focus of the paper has been to see whether the determinants of computer-related training and study differ from the determinants of other subject matter training. Evidence for any such differences could be used to support targeted policies that aim to specifically increase the computer-related skills that have recently been targeted by the New Zealand government as a priority area.

To answer the research questions posed, bivariate probit equations were estimated to study the joint decision of whether to participate in computer-related training and whether to participate in other subject matter training. Amongst the most noteworthy of the results are the following: there is no evidence that older workers are particularly disadvantaged in the receipt of computer-related training – instead, their likelihood of receiving all types of in-house training declines with age. Accumulated schooling is less of a determinant of computer-related training than of other subject matter training. Put the other way around, those with low levels of schooling may have relatively better access to computer training than they do to other types of training. Although this initially appears paradoxical, it may reflect the need to provide remedial training to these people; because not having accumulated much schooling they also may not have had the chance to get much exposure to computers.

Regional effects showed that workers in the three main metropolitan areas of Auckland, Wellington and Canterbury are more likely to receive computer-related training than are workers from non-metropolitan areas. This pattern contrasts with training for other subjects, where people in rural and the smaller metropolitan areas appear to have greater participation rates than are reported in the major metropolitan areas. Occupational differences also existed, with the 'basic' occupations, like sales, trades agricultural and plant operators receiving less in-house training in all subject areas.

Overall, the results support the use of specific policies to raise participation rates for computer-related training, as part of the desired improvement of ICT skills in New Zealand. While general policies for improving access to training in all subjects would have some beneficial effects on ICT training, factors such as schooling, occupation and location appear to offer more subject-specific effects.

In terms of methodological implications, the fact that the determinants of computer-related training differ from the determinants of other subject matter training suggests the need for more disaggregated study of education and training decisions. Most of the academic literature on training disaggregates according to either the different forms of training (e.g., in-house versus external) or the different beneficiaries of training (e.g., by gender or ethnic group) without considering variation by the subject matter of the training. The results reported here apply only to the incidence of training, and there is no guarantee that they hold for other, volume-based measures of training (e.g., days or hours), which is a topic for future research.

Table 1: Distribution of training by subject matter and by type of training: in-house, external or by qualification

Subject	Type of Training	
	Inhouse	External
	%	%
Professional and Technical	29.7	30.9
Managing Others	16.1	10.2
Service and Sales	17.2	13.5
Computing	17.8	21.9
Health and Safety	22.5	11.7
Trade	7.3	8.4
Clerical and Office	3.2	3.9
Self Management	9.7	10.2
Orientation	4.3	N/A
Other	4.9	6.3
N	3121	2414
		Qualification
Not Specified		0.6
Maori		5.1
Business and Administration		24.2
Health		9.1
Education		9.0
Social Sciences and Humanities		10.9
Sciences		4.9
Engineering and Technology		8.6
Architecture, Planning, and Construction		5.0
Agriculture, Forestry and Fishery		3.0
Computing and Information Technology		5.5
Manufacturing		1.9
Arts and Crafts		4.1
Miscellaneous		11.8
Other		5.5
N		2779

Note:
Percentages sum to more than 100% as people could participate in more than one training course over the survey period. The sample size, *N* refers to the number of respondents who received either in-house or external training, or studied for a qualification.

Table 2: Frequency of Participation in Computer-Related and Other Subject Matter Training

A. In-House Training

	Received other subject matter training	Did not receive other subject matter training	TOTAL
Received computer-related training	250 (0.02)	265 (0.02)	515
Did not receive computer-related training	2606 (0.20)	10141 (0.76)	12747
TOTAL	2856	10406	13262

B. External Training

	Received other subject matter training	Did not receive other subject matter training	TOTAL
Received computer-related training	150 (0.01)	364 (0.02)	514
Did not receive computer-related training	1900 (0.10)	18395 (0.87)	20295
TOTAL	2050	18759	20809

C. Qualifications

	Received other subject matter qualification	Did not receive other subject matter qual.	TOTAL
Received computer-related qualification	25 (0.00)	128 (0.01)	153
Did not receive computer-related qualification	2626 (0.14)	18251 (0.85)	20877
TOTAL	2651	18379	21030

Note: Results are based on the samples described in the text. Numbers in ( ) are weighted-population proportions, whereas sample frequencies are unweighted.

Table 3: Means and Standard Deviations for each Explanatory Variable by Type of Training

	Inhouse		External		Qualification	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	36.01	11.98	38.15	12.69	38.17	12.70
Age^2 (?100)	1439.91	917.85	1616.82	1014.91	1617.99	1015.58
Male	0.51	0.50	0.49	0.50	0.49	0.50
Maori	0.09	0.29	0.10	0.30	0.10	0.30
Pacific Islands	0.04	0.20	0.04	0.20	0.04	0.20
Other[a]	0.04	0.20	0.05	0.22	0.05	0.22
Yrs of Schooling[b]	5.73	2.84	5.43	2.88	5.43	2.88
Married	0.63	0.48	0.66	0.47	0.66	0.47
Wage worker			0.58	0.49	0.58	0.49
Employer			0.05	0.23	0.05	0.23
Self employed			0.10	0.29	0.10	0.30
Unpaid			0.01	0.09	0.01	0.09
Unemployed			0.05	0.21	0.05	0.21
Auckland	0.31	0.46	0.31	0.46	0.30	0.46
Wellington	0.14	0.35	0.13	0.33	0.13	0.33
Canterbury	0.14	0.35	0.13	0.34	0.13	0.34
Occupation						
Administrators & Managers	0.09	0.003				
Professionals	0.13	0.003				
Technicians	0.11	0.003				
Clerical	0.16	0.004				
Sales and service	0.18	0.004				
Agriculture and fishery	0.05	0.002				
Trades	0.09	0.003				
Plant operators	0.09	0.003				
Elementary	0.09	0.003				
Industry						
Agriculture, Forestry & Fishing	0.05	0.002				
Mining and Quarrying	0.004	0.001				
Manufacturing	0.18	0.004				
Electricity, Gas and Water	0.01	0.001				
Construction	0.05	0.002				
Trade and Hotels	0.23	0.004				
Transport and Communication	0.06	0.002				
Business and Finance	0.10	0.003				
Services	0.31	0.004				

Note: The estimates are weighted by the population sampling weights.

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

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

Table 4: Bivariate Probit Estimates of the Characteristics determining Participation in In-house Computer Related and Other Subject Matter Training

	Computer Related			Other Subjects			Ceoff Diff
	Coeff	*t*	ey/ex	Coeff	*t*	ey/ex	p-value
Age	0.051	(2.99)	4.48	0.077	(8.48)	3.98	0.167
Age^2 (?100)	-0.001	(2.83)	-2.20	-0.001	(8.78)	-2.10	0.108
Male	0.147	(2.63)	0.17	0.161	(4.73)	0.11	0.813
Maori	-0.045	(0.46)	-0.01	-0.100	(1.97)	-0.02	0.604
Pacific Islands	-0.202	(1.67)	-0.02	-0.138	(1.83)	-0.01	0.634
Other[a]	-0.031	(0.23)	-0.00	-0.268	(3.15)	-0.01	0.120
Years of Schooling[b]	0.017	(1.82)	0.23	0.042	(6.80)	0.32	0.020
Married	0.041	(0.66)	0.06	0.150	(4.22)	0.14	0.115
Auckland	0.221	(3.42)	0.11	-0.191	(4.76)	-0.06	0.000
Wellington	0.334	(5.37)	0.12	-0.202	(4.65)	-0.04	0.000
Canterbury	0.183	(2.32)	0.05	-0.038	(0.87)	-0.01	0.012
Occupation[c]							
Professionals	-0.104	(1.06)	-0.03	0.091	(1.44)	0.02	0.081
Technicians	0.095	(1.01)	0.03	0.034	(0.54)	-0.01	0.242
Clerical	0.122	(1.33)	0.05	-0.271	(4.34)	-0.06	0.002
Sales and service	-0.739	(5.83)	-0.30	-0.212	(3.35)	-0.05	0.000
Agriculture and fishery	-0.914	(3.03)	-0.11	-0.563	(4.73)	-0.04	0.262
Trades	-0.728	(4.10)	-0.16	-0.587	(7.75)	-0.08	0.463
Plant operators	-0.643	(4.42)	-0.17	-0.413	(5.67)	-0.06	0.123
Elementary	-1.084	(5.49)	-0.24	-0.683	(8.79)	-0.09	0.056
Industry[d]							
Mining and Quarrying	0.455	(1.06)	0.00	0.381	(1.61)	0.00	0.882
Manufacturing	0.353	(1.23)	0.16	0.089	(0.78)	0.02	0.392
Electricity, Gas and Water	0.798	(2.27)	0.02	0.398	(2.28)	0.01	0.270
Construction	0.380	(1.21)	0.05	0.007	(0.05)	0.00	0.264
Trade and Hotels	0.341	(1.17)	0.17	0.011	(0.10)	0.00	0.289
Transport and Communication	0.452	(1.52)	0.06	0.259	(2.09)	0.02	0.547
Business and Finance	0.443	(1.53)	0.10	0.159	(1.34)	0.02	0.362
Services	0.598	(2.11)	0.47	0.307	(2.76)	0.14	0.337
Constant	-3.311	(7.57)		-2.382	(11.49)		
Rho		.274 (8.85)					
Wald tests for coefficient restrictions					p-value		
All slopes = 0				?$^2_{(54)}$ = 1171.2	0.000		
Occupation effects = 0				?$^2_{(16)}$ = 323.6	0.000		
Industry effects = 0				?$^2_{(16)}$ = 71.5	0.000		
Pooling Computing & other subject matter				?$^2_{(27)}$ = 230.4	0.000		

Note: The estimates are weighted by the population sampling weights, *t*-statistics are calculated from heteroscedastically-robust standard errors. N = 13262

Ey/ex are elasticities that give the percentage change in the probability of participating in in-house training following a one-percent change in the explanatory variable.

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

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

[c] The excluded occupations are Legislators, Administrators and Managers.

[d] The excluded industries are Agriculture, hunting, forestry and fishing

Table 5: Bivariate Probit Estimates of the Characteristics determining Participation in In-house Computer Related and Other Subject Matter Training: Currently Employed Workers

	Computer Related			Other Subjects			Ceoff Diff
	Coeff	*t*	ey/ex	Coeff	*t*	ey/ex	p-value
Age	0.038	(2.03)	3.27	0.060	(5.87)	3.02	0.290
Age^2 (?100)	-0.001	(2.09)	-1.75	-0.001	(6.62)	-1.74	0.187
Male	0.045	(0.75)	0.05	0.017	(0.44)	0.01	0.691
Maori	-0.025	(0.24)	-0.01	-0.045	(0.81)	-0.01	0.862
Pacific Islands	-0.244	(1.81)	-0.03	-0.160	(1.92)	-0.01	0.582
Other[a]	0.069	(0.50)	0.01	-0.213	(2.23)	-0.01	0.084
Years of Schooling[b]	0.014	(1.42)	0.19	0.036	(5.33)	0.27	0.052
Married	0.024	(0.38)	0.04	0.132	(3.42)	0.12	0.141
Tenure	0.002	(3.23)	0.25	0.003	(7.48)	0.21	0.223
Hours	0.010	(4.63)	0.91	0.014	(10.54)	0.70	0.181
Auckland	0.202	(2.95)	0.10	-0.201	(4.66)	-0.06	0.000
Wellington	0.294	(4.50)	0.11	-0.258	(5.58)	-0.06	0.000
Canterbury	0.174	(2.14)	0.05	-0.036	(0.76)	-0.01	0.023
Occupation[c]							
Professionals	-0.073	(0.71)	-0.02	0.142	(2.11)	0.03	0.070
Technicians	0.177	(1.79)	0.05	0.040	(0.61)	0.01	0.244
Clerical	0.248	(2.56)	0.10	-0.172	(2.56)	-0.04	0.000
Sales and service	-0.604	(4.54)	-0.23	-0.051	(0.74)	-0.01	0.000
Agriculture and fishery	-0.786	(2.47)	-0.07	-0.506	(3.58)	-0.03	0.395
Trades	-0.650	(3.57)	-0.15	-0.519	(6.50)	-0.07	0.511
Plant operators	-0.586	(3.84)	-0.15	-0.329	(4.22)	-0.05	0.105
Elementary	-0.904	(4.42)	-0.17	-0.478	(5.59)	0.05	0.054
Industry[d]							
Mining and Quarrying	0.404	(0.90)	0.00	0.212	(0.85)	0.00	0.712
Manufacturing	0.307	(1.02)	0.14	0.025	(0.19)	0.01	0.390
Electricity, Gas and Water	0.799	(2.18)	0.02	0.362	(1.88)	0.01	0.255
Construction	0.368	(1.13)	0.05	-0.067	(0.45)	-0.00	0.218
Trade and Hotels	0.338	(1.12)	0.16	-0.011	(0.08)	-0.00	0.290
Transport and Communication	0.394	(1.27)	0.06	0.181	(1.26)	0.01	0.531
Business and Finance	0.423	(1.40)	0.09	0.142	(1.03)	0.02	0.395
Services	0.607	(2.06)	0.48	0.310	(2.35)	0.14	0.356
Constant	-3.471	(7.140)		-2.564	(10.74)		
Rho		.226 (6.84)					

Wald tests for coefficient restrictions		p-value
All slopes = 0	$?^2_{(58)}$ = 1185.0	0.000
Occupation effects = 0	$?^2_{(16)}$ = 255.4	0.000

Industry effects = 0	?$^{2}_{(16)}$ = 74.9	0.000
Pooling Computing & other subject matter	?$^{2}_{(29)}$ = 224.8	0.000

Note: The estimates are weighted by the population sampling weights, *t*-statistics are calculated from heteroscedastically-robust standard errors. N = 11025

Ey/ex are elasticities that give the percentage change in the probability of participating in in-house training following a one-percent change in the explanatory variable.

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

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

[c] The excluded occupations are Legislators, Administrators and Managers.

[d] The excluded industries are Agriculture, hunting, forestry and fishing

Table 6: Bivariate Probit Estimates of the Characteristics determining Participation in External Computer Related and Other Subject Matter Training

	Computer Related			Other Subjects			Ceoff Diff
	Coeff	*t*	ey/ex	Coeff	*t*	ey/ex	p-value
Age	0.130	(8.24)	12.31	0.024	(2.82)	1.68	0.000
Age^2 (?100)	-0.002	(7.87)	-6.44	0.000	(3.64)	-1.14	0.000
Male	-0.171	(3.73)	-0.20	-0.019	(0.62)	-0.02	0.004
Maori	-0.256	(3.03)	-0.08	0.054	(1.11)	0.01	0.001
Pacific Islands	-0.409	(2.44)	-0.05	-0.433	(5.22)	-0.04	0.893
Other	-0.490	(3.51)	-0.06	-0.234	(3.18)	-0.02	0.100
Years of Schooling	0.039	(5.57)	0.49	0.091	(17.89)	0.86	0.000
Married	-0.103	(2.02)	-0.17	0.044	(1.26)	0.05	0.014
Wage Worker	0.333	(4.49)	0.46	0.296	(6.96)	0.31	0.657
Employer	0.201	(1.66)	0.02	0.543	(8.09)	0.05	0.011
Self Employed	0.193	(1.83)	0.04	0.377	(6.09)	0.06	0.120
Unpaid Worker	-0.160	(0.56)	-0.00	-0.060	(0.35)	-0.00	0.765
Unemployed	0.443	(3.63)	0.06	0.394	(5.61)	0.04	0.725
Auckland	0.289	(5.01)	0.15	0.053	(1.39)	0.02	0.000
Wellington	0.240	(3.81)	0.08	0.002	(0.05)	0.00	0.001
Canterbury	0.162	(2.48)	0.05	0.140	(3.35)	0.03	0.776
Constant	-4.809	(16.39)		-2.403	(15.03)		
Rho				0.278 (8.785)			
Wald tests for coefficient restrictions						p-value	
All slopes = 0				?$^{2}_{(32)}$ =776.58		0.000	
Pooling Computing & other subject matter				?$^{2}_{(16)}$ = 150.93		0.000	

Note: The estimates are weighted by the population sampling weights, *t*-statistics are calculated from heteroscedastically-robust standard errors. N = 20809

Ey/ex are elasticities that give the percentage change in the probability of participating in external training following a one-percent change in the explanatory variable.

Table 7: Bivariate Probit Estimates of the Characteristics determining Participation in Computer Related and Other Subject Matter Qualifications

	Computer Related			Other Subjects			Ceoff Diff
	Coeff	*t*	ey/ex	Coeff	*t*	ey/ex	p-value
Age	-0.020	(1.08)	-2.27	-0.121	(15.64)	-8.95	0.000
Age^2 (?100)	0.000	(0.13)	0.14	0.001	(10.75)	3.33	0.000
Male	0.112	(1.57)	0.15	-0.144	(4.62)	-0.13	0.001
Maori	0.067	(0.66)	0.02	0.044	(0.94)	0.01	0.835
Pacific Islands	0.118	(0.83)	0.02	-0.058	(0.80)	-0.01	0.277
Other	0.136	(1.06)	0.02	0.255	(3.89)	0.02	0.438
Years of Schooling	0.062	(6.11)	0.94	0.167	(28.35)	1.65	0.000
Married	-0.240	(3.27)	-0.47	-0.357	(10.75)	-0.45	0.147
Wage Worker	-0.215	(2.74)	-0.36	-0.256	(6.93)	-0.28	0.649
Employer	-0.718	(2.28)	-0.10	-0.505	(5.05)	-0.05	0.523
Self Employed	-0.025	(0.18)	-0.01	-0.465	(5.77)	-0.07	0.005
Unemployed	-0.010	(0.08)	-0.01	-0.205	(3.15)	-0.02	0.200
Auckland	0.144	(1.39)	0.09	-0.024	(0.62)	-0.01	0.092
Wellington	0.140	(1.07)	0.06	-0.104	(2.38)	-0.03	0.031
Canterbury	0.110	(1.07)	0.04	0.187	(4.61)	0.04	0.480
Constant	-2.040	(6.29)		1.113	(8.50)		
Rho			-0.163 (2.21)				
Wald tests for coefficient restrictions					p-value		
All slopes = 0				$?^2_{(30)}$ =2130.33	0.000		
Pooling Computing & other subject matter				$?^2_{(15)}$ = 174.10	0.000		

Note: The estimates are weighted by the population sampling weights, *t*-statistics are calculated from heteroscedastically-robust standard errors. N = 20809

ey/ex are elasticities that give the percentage change in the probability of participating in a qualification following a one-percent change in the explanatory variable.

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