ISSN 1178-2293 (Online)

University of Otago
Economics Discussion Papers
No. 0906

School of Business
Unlimited Future, Unlimited Possibilities
Te Kura Pakihi

June 2009

When do students intend to return?

Determinants of students' return intentions using a multinomial logit model

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[♣] I would like to express my gratitude to Robert Alexander and Murat Genç for their invaluable comments and insightful suggestions.

Abstract

Using a multinomial logit model, this paper looks at the determinants of when tertiary level international students intend to return home upon completion of their studies in New Zealand, be it not return, return immediately, return after some working stint, or return after some further education. Good perceptions of home have a strong positive impact on the probability of returning immediately, with perception of home lifestyle having the strongest impact. Contrary to received wisdom, perception of wage does not play a dominant role in determining when students intend to return home.

JEL Classification: C25, J61

Keywords: Students' migration, multinomial logit model, return intention

1.0 Introduction

Adapting Stark's (2005) analogy, let there now be two orchestras in the world: a mediocre orchestra (MO), and an excellent orchestra (EO). Suppose that an orchestra player from the MO will have a chance to be admitted into the EO to learn more about musicianship. Upon joining the EO, he has broader opportunities to learn from master musicians, and more performance opportunities to hone his new-found skills. Although the MO and the EO pay are similar, there are fewer learning and performing opportunities available to him back at the MO. He now contemplates either not returning at all or delaying his return to the MO.

This analogy strikes a chord with the questions addressed in this paper. This paper looks at the return time frame of international students, that is, whether the students intend to return immediately to their home countries after finishing their studies abroad, to delay their return for some education or work purposes, or not to return at all. The paper aims to identify the determinants of such intended return time frames.

Most students studying abroad intend not to return at all or to delay their return home for work purposes. This is the main conclusion of this paper. This paper contributes to the empirical literature by looking at when students intend to return home upon completion of their current studies in New Zealand. Except for a handful of qualitative studies (Baruch, Budhwar, & Khatri, 2007; Glaser, 1978), the students' non-return literature lacks quantitative studies addressing the question of when students return.

This paper differs from other studies in the students' non-return literature which typically look at whether or not students intend to return (Li, Findlay, Jowett, & Skeldon, 1996) or at the intensity of their return intentions (Gungor & Tansel, 2008; Zweig, 1997). In particular, this paper looks at when students intend to return home upon completion of studies abroad, i.e., return immediately, delay their return for work purposes, delay their return for educational purposes, or not return at all. Using a multinomial logit model, the paper identifies the key determinants affecting such intentions.

While most studies using discrete choice models interpret only the coefficient signs and statistical significance, this study goes further to provide more comprehensive interpretations, including those of different measures of marginal effects, changes in outcome probabilities when variables of interest alter, and a graphical presentation of the odds between outcome probabilities. This paper addresses the intricacies of a non-linear model of when students intend to return.

The paper is organized as follows. The next section describes the dependent and explanatory variables. Section 2 sets up the multinomial logit model, followed by two specification tests. Section 3 discusses the main results in terms of discrete change and odds ratios of outcomes. The following section looks at the robustness of the model. The final section concludes.

1.1 Data

Individual level data are used in this study. These data are obtained through an online questionnaire survey distributed via the two participating universities (Otago and Canterbury) international offices. The survey was conducted between March and May 2007. There were 512 respondents from Otago and 269 from Canterbury, with response rates of 20.17% and 11.7%. The lower response rate from Canterbury may be due to the questionnaire's being sent out just once instead of three times at Otago. After excluding students who were bonded to return home, the final usable sample totals 623 respondents.

The total number of the target population for this study is 20,515 international students. Cavana et al (2001, p. 278) and Krejcie & Morgan (1970), suggest that a sample size of 377 respondents is needed for a population size of 20,000. Hence, the current study's sample size of 623 respondents is adequate for the population of international students considered. Soon (2008) gives further details of the survey used to obtain the study's sample.

1.2 Descriptive statistics

Table 1 shows the breakdown of the six outcome categories. These six outcome categories are the alternatives available for the respondents in the survey questionnaire used in data collection. The six alternatives are: whether a student intends not to return at all (Not return), return immediately (Immediate), return after an internship engagement (Internship), return after obtaining another degree (Degree), return after gaining some working experience (Job) which is of a more short term nature, or return after establishing a career (Career) which is of a more long term nature. These alternatives eventually make up the multinomial (polychotomous) dependent variable in this paper.

[Table 1 about here]

Due to some of the outcome categories having relatively few observations (e.g., Internship, Degree, and Career), the outcome categories are pooled into four categories to make up the 4-outcomes dependent variable. The 'Internship' and 'Degree' categories are combined into one as 'Education', while the 'Job' and 'Career' categories as 'Work'. For ease of interpretation, the four outcomes are referred to as 'Not return' ($n=284$), 'Immediate' ($n=115$), 'Education' ($n=48+31=79$), and 'Work' ($n=34+111=145$). The 'Education' and 'Work' outcomes denote a delayed return intention. The pooling of the outcomes is formally tested in Section 2.1.

Table 2 shows the breakdown of the explanatory variables by each of the four outcomes. There are three sets of explanatory variables: personal and socio-economic variables, education-related variables, and perception-related variables. Appendix A supplies a brief description of both the dependent and explanatory variables.

[Table 2 about here]

Table 2 shows that about 45% of the students (respondents) have no intention to return, 18% intend to return immediately, and the rest intend to delay their return, either for education or work purposes. These are the actual sample proportions of the students selecting one of the four outcomes. Those who intend to return immediately are, on average, older (mean age = 26.2) than those who intend otherwise. Likewise for those with the most work experience (mean years of work experience = 2.2).

Only about a quarter (*26.5%*) of those who initially intend to return (i.e. the ‘initialreturn’ variable) would return immediately, with a majority (*18.6+35.1=53.7%*) of them intending to delay their return. More than half of the students whose family supports their non-return intention do not intend to return (*55%*). Half of the doctoral students (*50.7%*) have no intention to return. Likewise *50.7%* of those who have been foreign-educated (i.e., the ‘hselsewhr’ variable) prior to their current degree in New Zealand. Also, *56.8%* of the health-science students have no intention to return.

The perception-related variables are perceptions of six different aspects of the students’ home countries. A third of those who have favourable perceptions on the home working environment (goodHwenv; *33.1%*), opportunities for knowledge use (goodHoppk; *35.1%*), and lifestyle (goodHlife; *33.3%*), intend to return immediately. However, *37.7%* of those who have good perceptions of home wages, do not intend to return.

2.0 Multinomial logit model specification

The multinomial logit (MNL) model is typically used when there is no clear-cut ordering of the outcomes. The MNL model can be derived from random utility maximization (RUM) theory. According to RUM theory, an individual (a decision-maker) is assumed to choose the alternative that yields him the highest utility. His utility can be described by a utility function. This function depends on the characteristics of the individual. The utility function has a deterministic and a stochastic component. The stochastic component is only relevant to the researcher, as each individual is assumed to know perfectly the utility of each alternative (Manski, 1977).

Let the utility for a student *i* faced with *J* alternatives and choosing alternative *m* be:

$$U_{im} = \boldsymbol{X}_i \boldsymbol{\beta}_m + \varepsilon_{im} \qquad (1)$$

The probability of choosing alternative *m* over other alternatives is when

$$P(Y_i = m) = P(U_{im} > U_{ij}) \qquad \forall j \neq m \qquad (2)$$

In order to obtain the MNL model, the error term ε in equation (1) is assumed to be independent and identically distributed (iid) with a Weibull (or type I extreme-value) distribution (McFadden, 1974, p. 111), as follows:

$$F(\varepsilon) = exp[-exp(-\varepsilon)] \qquad (3)$$

This type of error distribution results in the MNL model, where, given a set of individual-specific characteristics $\boldsymbol{X}_i$, the probability of student *i* choosing alternative *m* is:

$$P(Y_i = m \mid \boldsymbol{X}_i) = \frac{exp(\boldsymbol{X}_i\boldsymbol{\beta}_m)}{\sum_{j=1}^{J} exp(\boldsymbol{X}_i\boldsymbol{\beta}_j)} \qquad \text{with } \boldsymbol{\beta}_1 = 0 \text{ and } \forall j \neq m \tag{4}$$

The arbitrarily chosen $\boldsymbol{\beta}_1$ is set to zero (i.e. the base outcome category in the MNL model) for the purpose of model identification. The coefficients of the remaining outcome categories are interpreted relative to the base category. Equation (4) shows that the outcome probabilities vary with changes in the explanatory variables in a non-linear fashion.

The paper fits an MNL model with a 4-outcome dependent variable, such that,

$$Y = \begin{cases} 1 & \text{if a 'Not Return' intention is stated} \\ 2 & \text{if an 'Immediate' intention is stated} \\ 3 & \text{if an 'Education' intention is stated} \\ 4 & \text{if a 'Work' intention is stated} \end{cases} \tag{5}$$

The ‘Not return’ outcome is chosen as the base outcome category because of its intuitive nature. It serves as the reference point for all other outcome categories. This outcome category is the only one which denotes a non-return intention, while the other three outcome categories pertain to an intention to return, be it either an immediate or a delayed return. The ‘Not return’ category also has the highest number of observations.

2.1 Specification Test I: Pooling of outcomes

This section looks at how the outcomes can be pooled. A pair of outcomes can be pooled if it is indistinguishable with respect to $\boldsymbol{X}$. A pair of outcomes is indistinguishable with respect to $\boldsymbol{X}$ if $\boldsymbol{X}$ does not significantly affect the odds of outcome *m* versus outcome *n* (Anderson, 1984, p. 2).

Prior to the preferred 4-outcome model, 6-outcome and 3-outcome MNL models have been fitted. The paper does not report the basic estimation results of the latter two models. The pooling of outcomes tests are applied on all three specifications to determine if any pairs of outcomes could be pooled further. The pooling of outcomes can give a more parsimonious specification, which is especially critical in MNL models where the parameters proliferate with the number of outcomes and explanatory variables.

Table 3 shows three results panels. Each panel corresponds to a different specification of the dependent variable. The Wald test and likelihood ratio (LR) test are used to test for the hypothesis that a pair of outcomes can be combined. The pooling of outcomes in MNL models was developed by Cramer & Ridder (1991), whereas the LR test for such pooling was developed by Caudill (2000).

[Table 3 about here]

Insignificant tests indicate that two outcomes are indistinguishable. However, there are some mixed results from the two types of test. For example, in the 6-outcome specification, the insignificant Wald test suggests that the Career-Internship pair of outcomes may be combined, while the significant (at 10% level) LR test suggests not.

In the 4-outcome specification, there are also competing results. The insignificant Wald test suggests the pooling of the Education-Work pair, while the significant LR test suggests otherwise. Since there are some mixed results from the tests, this paper adopts a middle ground with the 4-outcome specification. The 4-outcome specification is more parsimonious than the 6-outcome specification. At the same time, it can discern more information than the 3-outcome specification. A 3-outcome specification may obscure important information as to whether students prefer a delayed return for education or for work purposes.

2.2 Specification Test II: Independence of irrelevant alternatives (IIA)

The Hausman-McFadden (HM) (1984) and Small-Hsiao (SH) (1985) tests are used to test for the violation of the IIA property. Table 4 shows the results of the tests. Both tests compare the estimated coefficients from the full model to those from a restricted model that omits one of the alternatives. The null hypothesis to be tested is that the odds between a pair of alternatives are independent of other alternatives.

[Table 4 about here]

The HM test shows negative chi-squared test statistics. Such negative test statistics are common (Long & Freese, 2006, p. 244-5) and indicate that the IIA property is not violated (Hausman & McFadden 1984, p. 1226). The results are further supported by the SH test, where all the test statistics are insignificant, giving further evidence that the IIA property holds.

The tests results suggest no IIA problem, indicating that the MNL model suits the data in hand. The tests also indicate that the unobserved factors can be assumed to be independent across alternatives, implying that the alternatives are dissimilar (Amemiya, 1985, p. 298). Here, the tests results suggest that the students do not view the four alternatives as close substitutes. Since the IIA property is not violated, the four alternatives may be considered as dissimilar and distinct from one another.

Since no test can be conclusive, the best advice is to use an MNL model when the alternatives are dissimilar (Amemiya, 1981, p. 1517) or when the alternatives can be plausibly assumed to be distinct and weighed independently in the eyes of the decision-maker (McFadden 1974, p. 113).

Having justified the use of a 4-outcome model and checked for the IIA assumption, the next two sections discuss the main results from the MNL model. Note that, in discussing the results from nonlinear discrete choice models such as the MNL model, the coefficient estimates are rarely of interest in themselves, apart from the coefficient sign and significance level.

3.0 Results discussion I: Discrete changes analysis

This section discusses the results in terms of discrete changes. Table 5 is an alternative way to look at how a discrete change in a variable impacts the outcome probabilities. A scenario depicts a hypothetical student with a certain set of characteristics. Scenario 1 is the baseline scenario on which all subsequent hypothetical scenarios are based. The baseline scenario is set at the mean values of continuous variables and at the modal values of dummy variables. A student with the set of characteristics in Scenario 1 observes the highest probability in having a non-return intention, where *Pr(Not return)=0.5976*. The outcome probabilities of Scenario 1 serve as the benchmark probabilities, to which the outcome probabilities of other scenarios are compared.

Scenario 2 depicts a hypothetical middle-aged female doctoral student who has been working prior to coming to New Zealand for her (i.e., as indicated by the modal value of *male=0* from the baseline scenario) current study. All her other characteristics are the same as in the baseline scenario. Her probability of having a non-return intention has increased about 12% from the baseline probability of 0.5976 to the current probability of 0.6681.

[Table 5 about here]

Scenario 3 depicts a 24 year old (the mean age of the sample) female doctoral student with no working experience, and who has been staying in New Zealand for five years. This scenario is typical of undergraduate honours students who continue directly with their doctoral studies. Her probability of having a non-return intention has increased about 27% from the baseline probability of 0.5976 to the current probability of 0.7585.

Scenario 4 depicts a female health science undergraduate who has studied abroad before (*hselsewhr=1*), and whose family is supportive of her non-return intention. Her probability of having a non-return intention has increased about 42% from the baseline probability of 0.5976 to the current probability of 0.8515. A 42% increase in Pr(Not return) is non-trivial, pointing out the important combined effect of changes in those three variables (i.e., ‘hselsewhr’, ‘hscience’, and ‘supportive’).

Scenarios 2 to 4 show the factors (i.e., the variables or students’ characteristics) which are important in increasing the probability of having a non-return intention. By contrast, Scenario 5 depicts the factors that are important in affecting the intention to return immediately. The hypothetical student in Scenario 5 has only good perceptions of her home country. Her probability of intending to return immediately is now 0.7194, about six times higher than the baseline probability of 0.1223. The evidence here lends support to the hypothesis that good perceptions of different aspects of home have a large positive impact on return intentions.

The last three scenarios 6 to 8 dissect the impact of selected home perception variables separately. Contrary to the received wisdom from the literature, good perceptions of wage competitiveness at home (goodHwage) do not have as large an impact as that of good perceptions of knowledge use opportunities at home (goodHoppk) and good perceptions of home lifestyle (goodHlife). For example, a good perception of home wage only increases the Pr(Y=Immediate) from 0.1223 to 0.1932, corresponding to an increase of about 58% in Pr(Y=Immediate). A good perception on home lifestyle, on the other hand, increases the Pr(Y=Immediate) from 0.1223 to 0.3365, an increase of about 175% in Pr(Y=Immediate). This increase is about three times as large as that caused by the good home wage perception. The evidence here suggests that other aspects may be more important than wages in affecting return intentions.

3.1 Results discussion II: Odds ratios analysis

In addition to discrete changes, we can also examine the odds ratios between outcomes. An odds ratios analysis differs from a discrete change analysis in two ways. First, discrete changes depend on the amount of change and the set of explanatory variables examined. Second, discrete changes give only the level of outcome probabilities, but not the odds of how likely one outcome is compared to another.

Table 6 shows the odds ratios for six pairs of outcomes. In the 4-outcome MNL model, there are 12 pairs of outcomes. The odds ratios of the remaining six pairs of outcomes can be easily computed from Table 6. For example, the log-odds coefficient of age for the ‘Immediate: Not return’ outcome pair is 0.0408 with its corresponding odds ratios coefficient of $exp(0.0408)=1.0417$. If the odds are inverted, then the log-odds coefficient of age for the ‘Not return: Immediate’ outcome pair becomes -0.0408 with its corresponding odds ratios coefficient of $exp(-0.0408)=0.96$. The statistical significance remains unchanged for the inverted odds.

[Table 6 about here]

For each additional year of residence in New Zealand, the odds of intending to return immediately versus that of not returning decrease by a factor of 0.8331, or more intuitively, decrease by about 17%, ceteris paribus. Alternatively, one can look at the inverted odds. For each additional year of residence in New Zealand, the odds of having no return intention versus that of to return immediately are about 1.2 times greater, ceteris paribus, or equivalently, increase about 20%.

Even from the brief interpretation above, one can see the large number of comparisons between outcomes. This makes it difficult to present interpretations in a systematic manner. Furthermore, it is difficult to see if there are any patterns between the odds and the variables just by eyeballing the table. A graphical presentation may help delineate any existing patterns. An odds ratios plot holds the same tabular information, in addition to drawing out patterns.

Odds ratios plots: An explanation

The odds ratios plot, originated by Long (1987), shows the patterns of the effects of changes in the explanatory variables on the odds of different outcome pairs. The odds ratio plot can keep track of the coefficient sign, the coefficient magnitude, and the statistical significance as in its tabular counterpart. At the same time, it is superior to the tabular form because it can extract patterns obscured in the table.

There are two scales on an odds ratio plot. The lower scale shows the log-odds coefficients, while the upper scale shows its corresponding odds ratios coefficients.

Positive log-odds coefficients translate into odds ratios coefficients of more than one, while odds ratios between zero and one are the counterparts of negative log-odds coefficients.

A letter inside the plot denotes an outcome, so in order to avoid ambiguity, it is advisable to use a different letter for each outcome. A letter lying straight along the same vertical line denotes the selected base outcome. If a letter is to the right of another letter, increases in an explanatory variable make the outcome to the right more likely to occur. The horizontal position of a letter thus reflects the coefficient sign.

The distance between a pair of letters (outcomes) indicates the magnitude of effects of a change in an explanatory variable. The wider the distance, the larger the effects are. The magnitude of effects can be read from either scale. The magnitude of effects is typically measured relative to the base outcome. It is best to read the more accurate magnitude from Table 6.

A connecting line between any two letters means that the odds of the two outcomes are statistically insignificant with respect to the variable. The odds of a pair of outcomes are statistically significant with respect to the variable when there is no connecting line between the two letters. Note that there is no meaning to the vertical distances between the letters. The vertical distances are to make the connecting lines easily seen.

Odds ratios plots: A discussion of results

The following four odds ratios plots contain all the information from Table 6. The ‘Not return’ outcome is the base outcome as seen by the vertically-aligned letter ‘N’. Plot 1 examines the patterns of the effects of changes in continuous variables on the odds of different outcome pairs. Plots 2 to 4 pertain to different sets of dummy explanatory variables – demographic and family-related variables, education-related variables, and home perception-related variables.

[Plot 1 about here]

From Plot 1, having stayed another additional year in New Zealand (yrsinNZ) significantly decreases the odds of having an ‘Immediate’ return intention versus a non-return intention by about 17%. The significance of the decrease can be seen by not having any connecting line between I and N. Longer stay duration in New Zealand increases the odds of having a non-return intention, as represented by the letter N at the extreme right-hand side.

Being a year older increases the odds of having an immediate return intention versus a non-return intention by about 4%. Younger students tend to delay their returns for either education or work purposes, as indicated by the letters E and W positioned leftmost. However, none of the pairs of outcome odds is significant with regards to age.

An additional year of working experience (workyrs) increases the odds of returning immediately (I) or delaying return for work purpose (W) versus a non-return intention. However, changes in age or in working experience are statistically insignificant on the odds of all outcome pairs, as shown by the lines connecting each of the outcomes.

[Plot 2 about here]

In Plot 2, for a student who initially intends to return (initialreturn), the odds of having an immediate return intention versus a non-return intention are about 4.7 times significantly higher than a student who has no such initial intention. The plot also shows that a student who initially intends to return is significantly likelier to either return immediately, or delay his return for work or education purposes than not return at all. This is indicated by the cluster of I, W, and E on the right of N. However, there is no statistical significance differentiating among the three I, W, and E intention outcomes. A change in the 'initialreturn' variable has a large impact on the odds, as indicated by the wide horizontal distance between N and other outcomes at the right-hand cluster.

Due to the large odds magnitude exhibited by the initial intention variable, there may be concern that this variable may be essentially measuring the same thing as the dependent variable and should be excluded from the model. A restricted version model is estimated (unreported here) without this variable and we found nontrivial changes in coefficients magnitudes and signs. The correlation coefficient between the 'initialreturn' variable and the dependent variable is a relatively low 0.45. We further performed a restriction test on the 'initialreturn' variable and found it to be statistically significant at the 1% level. This suggests the inclusion of this variable in the model.

In contrast to the ‘initialreturn’ variable, a change in the ‘supportive’ variable has a somewhat smaller mirror image effect on the odds. A student whose family supports his non-return intention increases his odds of a non-return intention versus other return intentions. This is shown by the letter N on the far most right and the other three outcomes clustered to the left. The odds of having an immediate return intention versus a non-return intention significantly decrease by about 56% for a student with such a supportive family.

The effects of the other three variables – being single, being a male, and coming from a good socio-economic background (dadtertiary) – on the odds, are insignificant. Besides being insignificant, the effects of these three variables have lower impacts, as compared to those of the ‘initialreturn’ and ‘supportive’ variables. Lower impacts of the effects can be seen from the smaller horizontal distances between two outcomes at different ends.

[Plot 3 about here]

Plot 3 shows that a doctoral student is most likely to have a non-return intention than other return intentions. The odds of a doctoral student intending to delay return for work purposes (W) versus that for education purposes (E) are about 4.2 times significantly higher than a non-doctoral student. The E on the extreme left-hand side indicates that doctoral students tend least to delay return for education purposes, as compared to the other three return intentions clustered on the right-hand side. This may be due to the nature of a doctoral study as a terminal degree.

Being a health science student (hscience), as compared to that of a science student, significantly decreases his odds of having an immediate return intention versus a non-return intention by about 67%. Or conversely, his odds of having a non-return intention to that of returning immediately is about 3 times higher, ceteris paribus. Simply put, he is more likely to have a non-return intention. This is indicated by the letter N at the far end right.

Also, health science or commerce students, as compared to science students, are less likely to intend to return immediately. This is indicated by the letter I at the far left end. Being a student from the humanities discipline as compared to a science student, does not have any impact on any pairs of odds. Whether or not a student has studied abroad (hselsewhr) before also does not have any impact on any pairs of odds.

[Plot 4 about here]

Among the home perception-related variables shown in Plot 4, perceptions on home lifestyle (goodHlife) have the largest impact on the odds of outcomes, as indicated by its largest horizontal distance. For a student who prefers his home lifestyle, his odds of having an immediate return intention versus a non-return intention are about 5.4 times significantly higher than a student who perceives otherwise. At the same time, his odds of delaying his return for education and work purposes versus a non-return intention are about 2.9 times and 2.3 times significantly higher than a student who does not prefer the home lifestyle.

For a student who has good perceptions on knowledge use in his home country (goodHoppk), his odds of having an immediate return intention versus a non-return intention are about four times significantly higher than a student who perceives otherwise. At the same time, his odds of delaying return for education purpose versus a non-return intention are about 2.2 times significantly higher than otherwise. However, the odds of the ‘Work-Not return’ pair are insignificant.

Plot 4 has a general pattern where all outcomes are on the right of N. This pattern implies that, students who have good perceptions of their home countries, would either intend to return immediately or to delay their return, rather than not returning at all. Also note the similar patterns for four of the variables – goodHwenv, goodHwage, goodHoppk, and goodHlife – where students with favourable perceptions of those home aspects are most likely to return immediately, followed by delaying their return for education purposes, and delaying their return for work purposes. A non-return intention is the least of what they have in mind.

Contrary to the received wisdom from the literature, good perceptions on the wage aspect in one’s home country (goodHwage) have one of the smallest impacts on the odds, among the perception-related variables. The three perception variables that have the largest impact are goodHlife, goodHoppk, and goodHfren, in that order. Perceptions on race equality at home also do not have any significant impact on any pairs of odds.

4.0 Robustness check

A robustness check gives an idea about the confidence one can place in the primary model's results. This section checks for the robustness of the paper's primary model, which is the MNL model with 4 outcome categories. The estimation results of three different model specifications are compared with the results of the primary model for substantial changes in key variables, either in the forms of different coefficient signs or statistical significance.

Model M1 from Table 7 is the paper's primary model. The estimated coefficients in M1 are the log-odds coefficients. All coefficients signs and statistical significance in the three result panels (Immediate, Education, Work) of models M1 to M4 are interpreted relative to the base outcome – 'Not return'.

[Table 7 about here]

Model M2 includes only the set of perception-related variables as its explanatory variables. The coefficient signs of the significant variables are the same between M1 and M2, with some slight differences in the statistical significance of some of the perception variables in each panel. While there is a danger of omitting important variables in M2, this specification demonstrates the robustness of the conclusions that can be drawn from perception-related variables.

Three interaction terms are added in the M3 specification. The doctoral level of study is interacted with the disciplines of study. Only one of the interaction terms –

‘phdCOM’ in the ‘Work’ results panel – is significant at the 10% level. The signs and significance of most key variables remains unchanged, with the exceptions of the statistical significance of two disciplines of study variables: health science and commerce. The primary model excluded interaction terms as there are no strong theoretical reasons for their inclusion.

M4 takes on a different functional form in which it includes the squared terms of the three continuous variables age, years of residence in New Zealand, and years of working experience. None of the squared terms is significant and the results from M4 are essentially the same as the primary model M1. The statistical insignificance also suggests no nonlinearity in the three continuous variables, that is, the outcome probabilities do not exhibit reversing trends as these variables increase in values. The primary model does not use any squared terms as there is no strong evidence for their inclusion in the literature.

The robustness checks performed using M2 to M4 suggest that the results from the primary model M1 are reasonably robust to changes in subsets of explanatory variables (M2) and functional form (M3, M4). The discussion in this section suggests that one can have considerable confidence in the primary model’s results.

5.0 Conclusions

As expected, a student with good perceptions of all the aspects of his home country would be more likely to intend to return immediately after finishing his studies. However, not all of the perceived aspects have the same effect on the outcome probabilities or on the odds of the outcomes. Preference over one's home lifestyle has the largest positive impacts on a student's intention to return immediately. Indeed, it appears that the students want to return to familiar lifestyle, culture, and way of life.

Lifestyle preference, good opportunities for skills utilization, close-knit social ties, good working environment at home are all more important than just high wages offered by the home country. The first four factors are found to exert the largest impact between choosing to return immediately or not to return at all. Therefore, home governments seeking to attract return migration of scholars may need to re-examine the return schemes to emphasize other aspects than just the pecuniary compensation aspect. Failure to do so may result in lukewarm success of such repatriation schemes.

Initial return intentions also have a large impact on the probabilities and the odds of current return intentions. Students who initially intend to return tend either to return immediately or delay their return, rather than not to return at all. A future extension of the paper may look at whether there are changes in the initial return intentions and if there are, what factors determine such changes.

Disciplines of study, especially the health science and commerce disciplines, have positive impacts on a student's intention not to return and negative impacts on a student's intention to return immediately. This may be due to these two disciplines being unsuitable and irrelevant at the home country. For example, a student from the health science discipline may be trained with technologies that are not available at his home country, hence his inclination of not returning. The impacts of the disciplines of study on delayed return intentions are generally not significant.

The factors examined here do not have any specifically large impacts on the probability of a delayed return, be it a delay for education or work purposes. The factors generally affect the most the intention of not returning. This may be an indication that the permanent brain drain phenomenon is more pertinent than the less damaging case of brain circulation.

One could question the use of intentions rather than observed behaviour as there may be a divergence between intentions and actual subsequent behaviour. However, divergence may simply reflect the dependence of behaviour on events not yet realized at the time of survey (Manski, 1990, p. 940). That means, if there are no unexpected events occurring between the time a person is asked of his intention and the time of actual behaviour, then a person's intention is the best prediction of his future behaviour.

The paper contributes to the recent empirical students' migration literature by looking at the issue of the students' intended return timeframe, instead of the more typical question of whether or not they intend to return, or the intensity of their return intention. The question of when students intend to return is crucial as it may translate into either a permanent or a temporary brain drain issue for the home country.

Table 1: Outcome categories breakdown

When return	n	%
Not return	284	45.59
Immediate	115	18.46
Internship	31	4.98
Degree	48	7.70
Job	111	17.82
Career	34	5.46
Total	623	100.00

Table 2: Descriptive statistics

Explanatory Variables	Not return *Y=1*	Immediate *Y=2*	Education *Y=3*	Work *Y=4*	Total
	4-outcome dependent variable				
Continuous variables					
age	24.3	26.2	22.8	24.5	-
yrsinNZ	3.0	2.1	2.9	2.6	-
workyrs	1.1	2.2	0.5	1.4	-
Dummy variables					
Demographic and socio-economic variables					
single	257 (45.9)	100 (17.9)	74 (13.2)	129 (23.0)	560 (89.9)
male	134 (45.0)	52 (17.5)	38 (12.8)	74 (24.8)	298 (47.8)
initialreturn	48 (19.8)	64 (26.5)	45 (18.6)	85 (35.1)	242 (38.8)
supportive	166 (55.0)	42 (13.9)	30 (9.9)	64 (21.2)	302 (48.5)
dadtertiary	182 (44.9)	76 (18.8)	54 (13.3)	93 (23.0)	405 (65.0)
Education-related variables					
phd	78 (50.7)	34 (22.1)	5 (3.3)	37 (24.0)	154 (24.7)
hselsewhr	142 (50.7)	36 (12.9)	35 (12.5)	67 (23.9)	280 (44.9)
science*	105 (44.7)	48 (20.4)	25 (10.6)	57 (24.3)	235 (37.7)
hscience	63 (56.8)	11 (9.9)	11 (9.9)	26 (23.4)	111 (17.8)
humanities	52 (40.9)	32 (25.2)	18 (14.2)	25 (19.7)	127 (20.4)
commerce	64 (42.7)	24 (16.0)	25 (16.7)	37 (24.7)	150 (24.1)
Perception-related variables					
goodHwenv	42 (29.6)	47 (33.1)	22 (15.5)	31 (21.8)	142 (22.8)
goodHfren	179 (38.7)	102 (22.0)	60 (13.0)	122 (26.4)	463 (74.3)
goodHrace	85 (37.6)	38 (16.8)	39 (17.3)	64 (28.3)	226 (36.3)
goodHwage	87 (37.7)	67 (29.0)	29 (12.6)	48 (20.8)	231 (37.1)
goodHoppk	46 (26.9)	60 (35.1)	30 (17.5)	35 (20.5)	171 (27.5)
goodHlife	36 (21.4)	56 (33.3)	30 (17.9)	46 (27.4)	168 (27.0)
Total	284 (45.6)	115 (18.4)	79 (12.7)	145 (23.3)	623 (100.00)

Note:

1. n(%)
2. Mean figures (in years) for continuous variables.
3. A 4-outcome dependent variable, $Y = 1, 2, 3, 4$.
4. Row totals pertain to each explanatory variable, while column totals pertain to each outcome.
5. *The 'Science' discipline is the base group among the four disciplines of study.

Table 3: Tests for pooling of outcomes

	Wald test		LR test	
Outcome pairs	chi2	df	chi2	df
6-outcome specification				
Career-Job	17.44	19	19.45	19
Career-Degree	22.53	19	26.68	19
Career-Internship	21.74	19	**28.23***	**19**
Career-Immediate	**39.08*** **	**19**	**52.42*** **	**19**
Career-Not retun	**42.97*** **	**19**	**49.57*** **	**19**
Job- Degree	17.09	19	19.51	19
Job-Internship	15.80	19	23.68	19
Job-Immediate	**38.71*** **	**19**	**45.41*** **	**19**
Job-Not return	**83.32*** **	**19**	**102.84*** **	**19**
Degree-Internship	16.20	19	18.82	19
Degree-Immediate	**28.92***	**19**	**36.11*** **	**19**
Degree-Not return	**75.34*** **	**19**	**93.80*** **	**19**
Internship-Immediate	**28.46***	**19**	**44.57*** **	**19**
Internship-Not return	**42.84*** **	**19**	**53.73*** **	**19**
Immediate-Not return	**128.60*** **	**19**	**203.70*** **	**19**
4-outcome specification				
Immediate-Education	**39.76*** **	**19**	**52.71*** **	**19**
Immediate-Work	**50.26*** **	**19**	**60.67*** **	**19**
Immediate-Not return	**129.24*** **	**19**	**203.68*** **	**19**
Education-Work	22.22	19	**27.81***	**19**
Education-Not return	**88.56*** **	**19**	**115.01*** **	**19**
Work-Not return	**92.13*** **	**19**	**116.30*** **	**19**
3-outcome specification				
Immediate-Delayed	**54.81*** **	**19**	**66.76*** **	**19**
Immediate-Not return	**129.73*** **	**19**	**204.11*** **	**19**
Delayed-Not return	**113.31*** **	**19**	**156.70*** **	**19**

Note:

1. Significant at the *10%, **5%, and ***1% level.
2. H_0: A pair of outcomes can be pooled as one.
3. An insignificant test indicates indistinguishability between a pair of outcomes, suggesting pooling of the outcomes. A significant test suggests against pooling.
4. The 4-outcome specification pools the Degree-Internship pair as Education and Job-Career pair as Work.
5. The 3-outcome specification pools the Education-Work pair as Delayed.

Table 4: IIA tests

Omitted	chi2	df	P>chi2	evidence
HM test				
Immediate	-16.738	40	-	-
Education	-5.599	40	-	-
Work	-28.383	40	-	-
Not return	-7.516	40	-	-
SH test				
Immediate	39.333	40	0.500	for H0
Education	33.538	40	0.755	for H0
Work	44.050	40	0.304	for H0
Not return	37.905	40	0.565	for H0

Table 5: Hypothetical scenarios of discrete change effects on outcome probabilities

	Scenarios							
Variables	1	2	3	4	5	6	7	8
age	24	35						
single	1							
male	0							
yrsinNZ	2.7		5					
workyrs	1.3	5	0					
phd	0	1	1					
hselsewhr	0			1				
hscience	0			1				
humanities	0							
commerce	0							
initialreturn	0							
supportive	0			1				
dadtertiary	1							
goodHwenv	0				1			
goodHfren	1							
goodHrace	0				1			
goodHwage	0				1	1		
goodHoppk	0				1		1	
goodHlife	0				1			1
Predicted outcome probabilities								
Pr(Not return)	0.5976	0.6681	0.7585	0.8515	0.0421	0.5187	0.3919	0.3035
Pr(Immediate)	0.1223	0.1514	0.0594	0.0218	0.7194	0.1932	0.3214	0.3365
Pr(Education)	0.0847	0.0108	0.0193	0.0221	0.1407	0.0944	0.1225	0.1274
Pr(Work)	0.1954	0.1698	0.1628	0.1047	0.0979	0.1937	0.1642	0.2326

Note:

1. Scenario 1 is the baseline scenario, where the predicted outcome probabilities are computed holding continuous variables at mean values and dummy variables at modal values.
2. Changes in other hypothetical scenarios are relative to the baseline scenario.
3. The predicted outcome probabilities of other scenarios would differ if the baseline scenario changes.

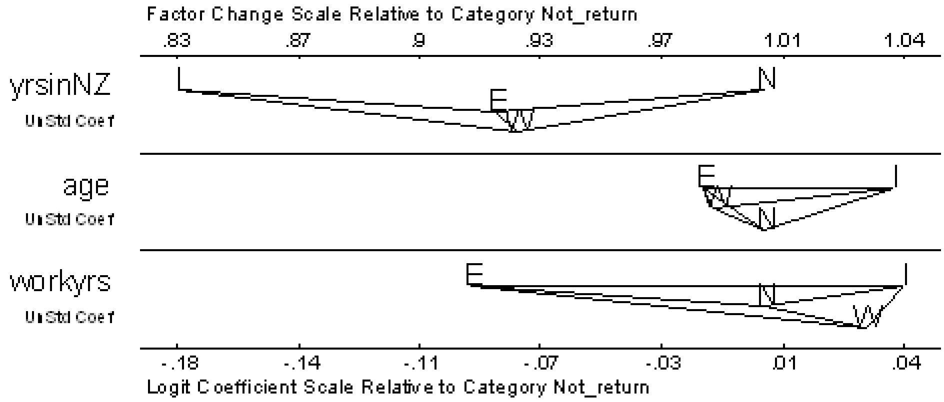
Table 6: Log-odds and odds ratios coefficients

Variables	outcome *m*: outcome *n*					
	I:N	E:I	E:N	W:I	W:E	W:N
age	0.0408	-0.0590	-0.0182	-0.0564	0.0026	-0.0156
	1.0417	0.9427	0.9820	0.9452	1.0026	0.9846
single	0.2104	-0.6507	-0.4403	-0.2803	0.3704	-0.0699
	1.2342	0.5217	0.6439	0.7556	1.4483	0.9325
male	-0.0381	0.1598	0.1217	0.1588	-0.0010	0.1207
	0.9626	1.1732	1.1294	1.1721	0.9990	1.1283
yrsinNZ	**-0.1825****	0.0998	-0.0828	0.1065	0.0067	-0.0761
	0.8331	1.1049	0.9205	1.1123	1.0067	0.9267
workyrs	0.0440	-0.1348	-0.0908	-0.0122	0.1226	0.0318
	1.0450	0.8739	0.9132	0.9879	1.1305	1.0324
phd	-0.4887	**-1.1596***	**-1.6483*****	0.2818	**1.4414****	-0.2069
	0.6134	**0.3136**	**0.1924**	1.3255	**4.2266**	0.8131
hselsewhr	-0.1423	-0.1518	-0.2941	0.2358	0.3875	0.0934
	0.8673	0.8592	0.7452	1.2659	1.4733	1.0979
hscience	**-1.1139****	0.4664	-0.6475	0.5614	0.0950	**-0.5525***
	0.3283	1.5943	0.5234	1.7531	1.0996	**0.5755**
humanities	-0.0959	0.2216	0.1257	-0.1157	-0.3373	-0.2116
	0.9085	1.2480	1.1339	0.8907	0.7137	0.8093
commerce	**-0.7289****	**0.7761***	0.0472	0.5016	-0.2745	-0.2273
	0.4824	**2.1729**	1.0483	1.6513	0.7600	0.7967
initialreturn	**1.5521*****	0.2213	**1.7735*****	0.2444	0.0231	**1.7966*****
	4.7216	1.2477	**5.8913**	1.2769	1.0233	**6.0289**
supportive	**-0.8235*****	0.0658	**-0.7578*****	0.3048	0.2390	**-0.5187****
	0.4389	1.0680	**0.4687**	1.3564	1.2700	**0.5953**
dadtertiary	0.3724	-0.1029	0.2696	-0.2141	-0.1112	0.1584
	1.4513	0.9022	1.3094	0.8073	0.8948	1.1716
goodHwenv	**0.7211****	-0.2608	0.4603	-0.3742	-0.1134	0.3470
	2.0567	0.7704	1.5846	0.6879	0.8928	1.4148
goodHfren	**0.9569*****	**-0.8498***	0.1072	-0.1969	**0.6529***	**0.7600*****
	2.6037	**0.4275**	1.1131	0.8213	**1.9211**	**2.1383**
goodHrace	0.0276	0.5470	**0.5746***	0.3554	-0.1916	0.3830
	1.0280	1.7281	**1.7764**	1.4268	0.8256	1.4667
goodHwage	**0.5993****	-0.3492	0.2501	-0.4663	-0.1171	0.1330
	1.8208	0.7053	1.2841	0.6273	0.8895	1.1423
goodHoppk	**1.3883*****	**-0.5975***	**0.7909****	**-1.1400*****	-0.5426	0.2483
	4.0081	**0.5502**	**2.2053**	**0.3198**	0.5812	1.2818
goodHlife	**1.6897*****	**-0.6045***	**1.0852*****	**-0.8376*****	-0.2331	**0.8521*****
	5.4178	**0.5464**	**2.9601**	**0.4328**	0.7921	**2.3446**

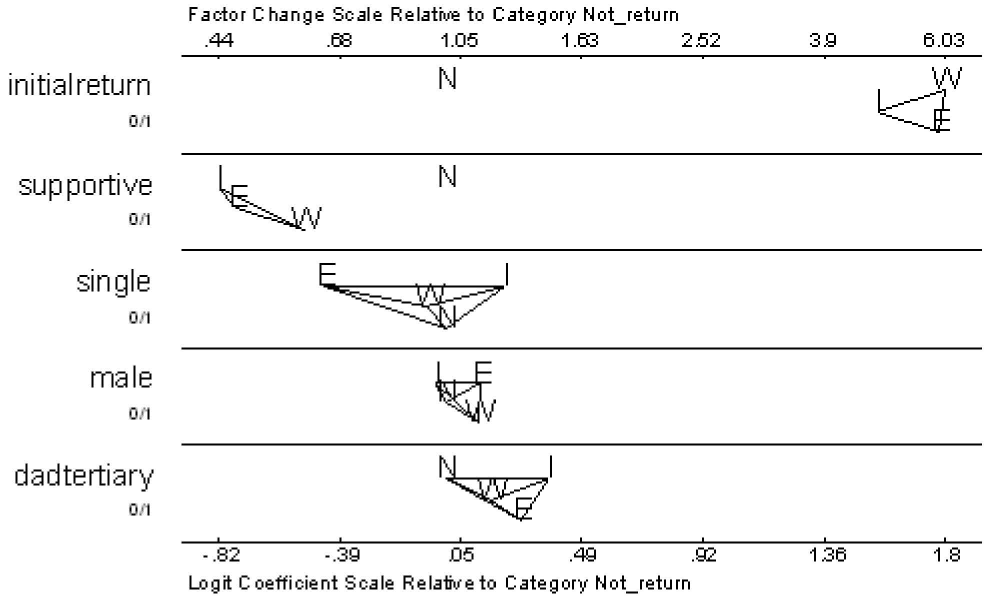
Note:

1. Significant at *10%, **5%, and ***1% level.
2. I = Immediate, N = Not return, E = Education, W = Work
3. Upper figure is the log-odds coefficient, b. Lower figure is its corresponding odds ratio coefficient, *exp*(b).

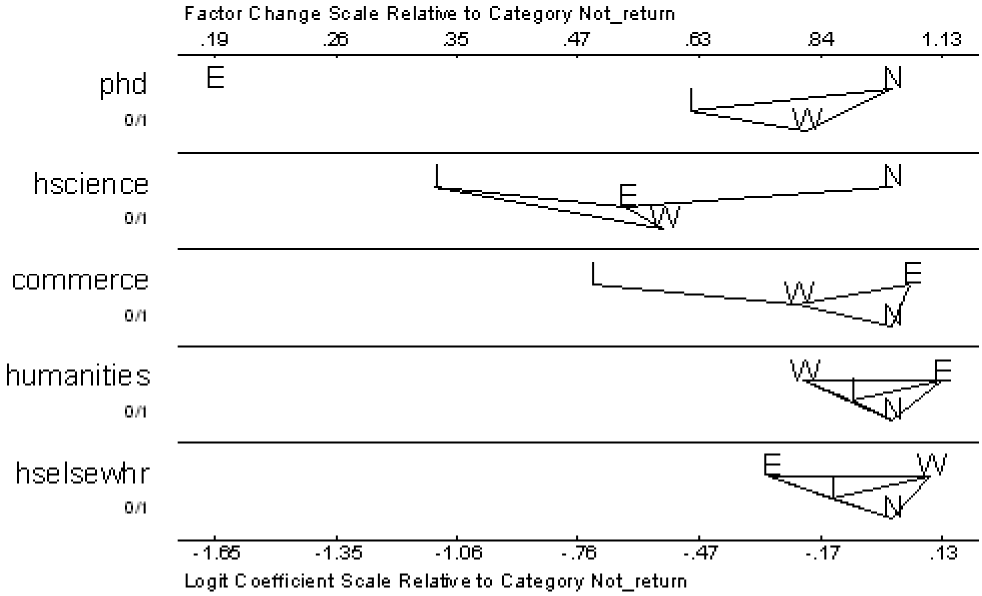
Plot 1: Continuous variables



Plot 2: Demographic and family-related variables



Plot 3: Education-related variables



Plot 4: Home perception-related variables

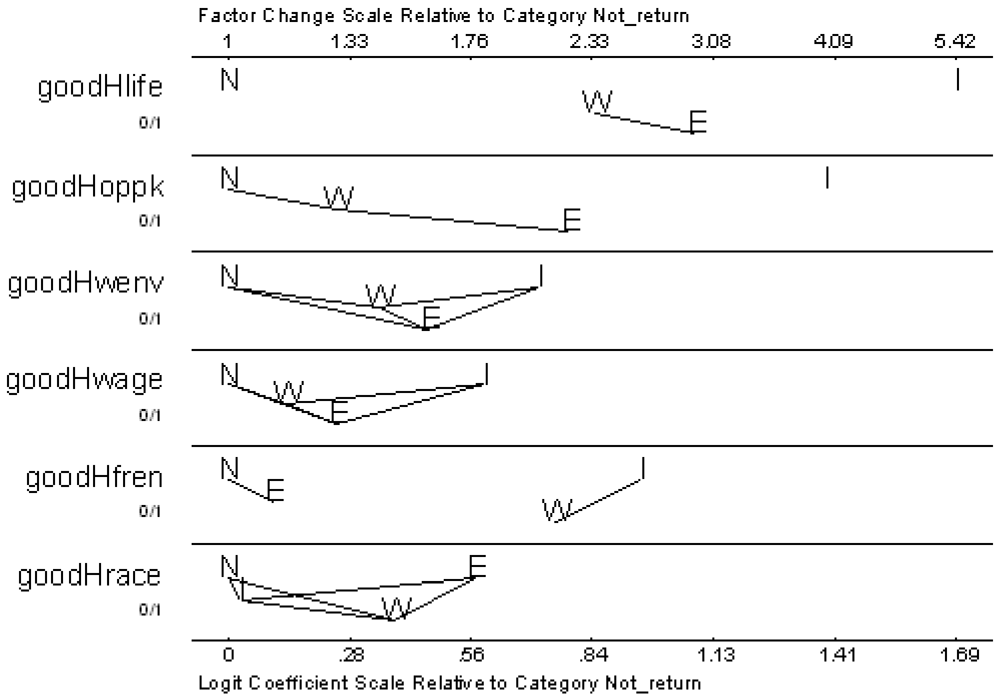


Table 7: Robustness Check

when4	M1	M2	M3	M4
Immediate				
age	0.0408		0.0415	0.1296
single	0.2104		0.253	0.1627
male	-0.0381		-0.024	-0.0665
yrsinNZ	**-0.1825****		**-0.1822****	**-0.3902****
workyrs	0.044		0.0502	-0.0475
phd	-0.4887		-0.1688	-0.4202
hselsewhr	-0.1423		-0.1387	-0.108
hscience	**-1.1139****		**-1.0330***	**-1.0998****
humanities	-0.0959		0.0288	-0.1009
commerce	**-0.7289****		-0.4583	**-0.7043***
initialret~n	**1.5521*****		**1.5708*****	**1.5462*****
supportive	**-0.8235*****		**-0.8195*****	**-0.8275*****
dadtertiary	0.3724		0.374	0.3912
goodHwenv	**0.7211****	**0.5415***	**0.7066****	**0.7663****
goodHfren	**0.9569*****	**1.3031*****	**0.9496****	**0.9833*****
goodHrace	0.0276	-0.1514	0.0328	0.0405
goodHwage	**0.5993****	**0.8315*****	**0.5782***	**0.5868****
goodHoppk	**1.3883*****	**1.3252*****	**1.3677*****	**1.4155*****
goodHlife	**1.6897*****	**1.6530*****	**1.6844*****	**1.6866*****
phdHSC			-0.2421	
phdHUM			-0.3737	
phdCOM			-0.9432	
agesq				-0.0015
yrsinNZsq				0.0281
workyrssq				0.0065

Table 7 (Continued): Robustness Check

when4	M1	M2	M3	M4
Education				
age	-0.0181		-0.0243	0.1092
single	-0.4403		-0.4618	-0.5143
male	0.1217		0.1147	0.1028
yrsinNZ	-0.0828		-0.0869	-0.2674
workyrs	-0.0908		-0.0886	-0.2022
phd	**-1.6483*** **		**-1.7059** **	**-1.5542*** **
hselsewhr	-0.2941		-0.292	-0.2587
hscience	-0.6475		-0.644	-0.6307
humanities	0.1257		0.1063	0.1218
commerce	0.0472		0.2168	0.0582
initialret~n	**1.7735*** **		**1.8064*** **	**1.7726*** **
supportive	**-0.7578*** **		**-0.7564*** **	**-0.7657*** **
dadtertiary	0.2696		0.2599	0.2972
goodHwenv	0.4603	0.3145	0.4469	0.4909
goodHfren	0.1072	0.3995	0.0942	0.1232
goodHrace	**0.5746***	**0.6238** **	**0.5945***	**0.6003***
goodHwage	0.2501	0.171	0.2426	0.233
goodHoppk	**0.7909** **	**0.9483*** **	**0.7638** **	**0.8171** **
goodHlife	**1.0852*** **	**1.2020*** **	**1.0876*** **	**1.0870*** **
phdHSC			0.4915	
phdHUM			0.8228	
phdCOM			-0.525	
agesq				-0.0025
yrsinNZsq				0.0228
workyrssq				0.0105

Table 7 (Continued): Robustness Check

when4	M1	M2	M3	M4
Work				
age	-0.0156		-0.0184	-0.0561
single	-0.0699		-0.0594	-0.0487
male	0.1207		0.1278	0.1102
yrsinNZ	-0.0761		-0.0833	-0.1069
workyrs	0.0318		0.0365	0.0873
phd	-0.2069		0.1595	-0.2122
hselsewhr	0.0934		0.089	0.0832
hscience	**-0.5525***		-0.3956	**-0.5566***
humanities	-0.2116		-0.1756	-0.2183
commerce	-0.2273		0.1047	-0.2352
initialret~n	**1.7966*****		**1.8397*****	**1.8020*****
supportive	**-0.5187****		**-0.5053****	**-0.5045****
dadtertiary	0.1584		0.1579	0.1581
goodHwenv	0.347	0.2052	0.3389	0.3374
goodHfren	**0.7600*****	**1.0138*****	**0.7267****	**0.7590*****
goodHrace	0.383	**0.4319***	0.4036	0.3863
goodHwage	0.133	0.1077	0.1041	0.132
goodHoppk	0.2483	0.3307	0.2139	0.2411
goodHlife	**0.8521*****	**0.9707*****	**0.8493*****	**0.8568*****
phdHSC			-0.5759	
phdHUM			0.0776	
phdCOM			**-1.1986***	
agesq				0.0007
yrsinNZsq				0.0044
workyrssq				-0.0047

Note:
1. For all models, the base outcome is ‘Not Return’.
2. Significant at the *10%, **5%, and ***1% level.

Appendix A: Variables' description

Variable description	Variable name
Multinomial dependent variable	when4
Intend not to return (Y=1; Not return)	
Intend to return immediately (Y=2; Immediate)	
Intend to return after some education stints (Y=3; Education)	
Intend to return after some working stints (Y=4; Work)	
Explanatory variables	
Continuous variables (in years)	
Age	age
Residence years/stay duration in New Zealand	yrsinNZ
Years of working experience at home country prior to current degree in New Zealand	workyrs
Categorical variables (binary dummies)	
Marital status	single
Gender	male
Level of study	phd
Have had studied abroad before	hselsewhr
Science-related discipline (reference group)	science
Health science-related discipline	hscience
Humanities-related discipline	humanities
Commerce-related discipline	commerce
Initial intention on returning prior to leaving home	initialreturn
Family support on non-return intention	supportive
Father's education level	dadtertiary
Good home country perception on wage competitiveness	goodHwage
Good home country perception on opportunities for knowledge use	goodHoppk
Good home country perception on working environment	goodHwenv
Good home country perception on lifestyle	goodHlife
Good home country perception on family bond and friends network	goodHfren
Good home country perception on race equality	goodHrace

Note: Sample size, n = 623

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