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Trained and Drained? A Parameter Simulation on the Return Timeframe of University Students Studying Abroad

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Abstract. Using a sample of 623 international students studying in New Zealand universities, this paper shows how parameter simulations can be used to actually visualize the impact of the explanatory variables on the probabilities of when the students intend to return home, i.e. return immediately upon completion of studies, after some further studies, after a stint working, or to never return at all. The results from the simulations, combined with a multinomial logit model, show that perceptions of lifestyle and opportunities to apply one's internationally acquired knowledge in the home country have the largest impact on the probability of intending to never return at all.

Keywords: parameter simulation; discrete choice model; student nonreturn; brain drain; migration

1. Introduction and Literature Review

According to the International Organization for Migration's (IOM) 2010 World Migration Report [1], the migration of people pursuing educational opportunities is an important trend with implications for future highly skilled migration flows. The trend for students to study abroad looks set to continue and with it, the strong likelihood that many will not return to their home country [2][3][4][5]. At the two extremes, students studying abroad may return home immediately upon completion of their studies or never to return at all, opting to migrate permanently. Different return timeframes may translate into either a permanent brain drain phenomenon to the home country, or a transitory brain circulation phenomenon.

The New Zealand Department of Labour published a report on the staying-on rates of international students in New Zealand [6]. It estimates that 27% of the international students who began their studies in the 1999/00 and 2000/01 cohorts (with a combined total of approximately 47,400 international students) have continued to stay on in New Zealand after completing their studies, either for work and/or residence purposes.

Although the pool of literature is saturated with studies on brain drain and student nonreturn/migration, there is only a handful of them which specifically examine the intended return timeframe [7][8]. Using a binary logit model, [7] dichotomized the intended return timeframe into (i) intend to return to one's home country within four years and (ii) after four years. [8] used an OLS model to examine the factors of the intended return timeframe, where they used five categories of return timeframes ranging from (i) return home immediately, (ii) return after a year of practical training, (iii) return a few years after graduation, (iv) stay abroad for career advancement, and (v) reside abroad.

The literature lacks micro-level econometric studies which address the question of return timeframe. This is especially so in the context of New Zealand as the host country of study. Furthermore, to date, it appears that there are yet to be any studies examining this specific issue using a parameter simulation approach. This paper attempts to fill this literature gap.

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Using a parameter simulation approach, this paper looks at the determinants of the intended return timeframe – factors determining if the (i) students intend to return home immediately after graduation, (ii) intend to delay their return for some further education or work purposes, or (iii) not to return home at all.

2. Data and Methodology

The target population is all full-time international students currently studying at tertiary level programmes in New Zealand's eight universities. Tertiary-level students here refer to those studying at the levels of Bachelor/Honours, Masters, and Ph.D. degrees. The sampling frames are the lists of currently enrolled full-time international students maintained by the international offices of the eight universities.

The international offices of the eight universities in New Zealand were contacted. However, only Otago University and Canterbury University allowed their international students to participate in the web-based survey. There were 512 respondents from Otago and 269 from Canterbury, representing response rates of 31.4% (512 from 1,633) and 24.1% (269 from 1,116) each. The final usable sample size totals 623 respondents. A dependent variable with four outcome categories is constructed as follows:

- Return home immediately after finishing one's current study (Immediate)
- Return after obtaining a higher or another qualification than the current one (Education)
- Return after gaining work experience (Work)
- Not return home at all or migrating permanently (Not return)

Empirical studies using discrete choice models typically report the predicted outcome probability. The results hence obtained constitute only one set of outcome probabilities for each outcome, i.e., only one set of actual sample-estimated outcome probabilities. We do not know how the distribution of the outcome probability looks like. A visual of such a distribution would allow an instant grasp of the mean probability, spread around the mean, probability range, and skewness of the probability distribution. There seems to be no known empirical studies on brain drain or student nonreturn/migration that follows the recommendation by [9] of always doing a post-estimation parameter simulation.

The main purpose of a parameter simulation is to enable the plotting of the distributions of the outcome probabilities. The plots allow a visual grasp of the inherent uncertainty by way of the distributions' spread. The distribution plots reveal how different or how far apart the means of the outcome probabilities are. The further apart the means of the outcome probabilities, the more distinguishable the effect a variable has on the outcome probabilities. A variable that exhibits a more distinguishable effect suggests more policy repercussions.

A parameter simulation is basically a Monte Carlo simulation exercise. Here, the multinomial logit (MNL) model is first estimated. The MNL model is used because the outcomes of the dependent variable have no clear-cut ordering. The MNL model is derived from random utility maximization theory. According to this theory, an individual (a decision-maker; a student in this case) 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 and also the attributes of the alternatives. However, in this study, we do not have alternative-specific attributes. The utility function (U) has a deterministic ($\boldsymbol{X\beta}$) and a stochastic component (ε). The stochastic component is only relevant to the researcher, whereas each individual is assumed to know perfectly the utility of each alternative [10]. Let the utility for a student i faced with J alternatives and choosing alternative m be:

$$U_{im} = \boldsymbol{X}_i \boldsymbol{\beta}_m + \varepsilon_{im} \tag{1}$$

The probability of choosing alternative m over other alternatives is when

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

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

$$F(\varepsilon) = exp[-exp(-\varepsilon)] \tag{3}$$

This implies that given a set of individual-specific characteristics $\boldsymbol{X}_i$, the probability of student i choosing alternative m is:

$$P(Y_i = m \mid \boldsymbol{X}_i) = \frac{exp(\boldsymbol{X}_i\boldsymbol{\beta}_m)}{\sum_{j=1}^{J} exp(\boldsymbol{X}_i\boldsymbol{\beta}_j)} \tag{4}$$

with $\boldsymbol{\beta}_1 = 0$ and $\forall j \neq m$.

$\boldsymbol{\beta}_1$ is arbitrarily set to zero (i.e. the base outcome in the MNL model) for model identification purpose. The coefficients of the remaining outcomes are interpreted relative to the base outcome. This paper fits an MNL model with a 4-outcome dependent variable, Y, 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 MNL model estimation gives a vector of parameter estimates. Each of the parameter estimates has a mean and a standard deviation, from which a theoretical distribution can be generated and subsequently plotted. However, the distribution of outcome probabilities cannot be plotted just yet because the estimation from the actual sample has only produced only one estimate so far – a point estimate. What a parameter simulation does is, after the model estimation, it randomly draws or simulates a hundred or a thousand or indeed any number, M, of simulations of such parameter estimates from their theoretical distributions.

Say now we let M=1,000, then the 1,000 simulated parameter estimates can be used to compute any quantities of interest. Here, the quantities of interest are the outcome probabilities. For each outcome (i.e. Not return, Immediate, Education, and Work), 1,000 thousand simulated outcome probabilities are computed and then a probability distribution for the outcome can now be plotted. The outcome probabilities can be computed and then plotted for any values of interest of the explanatory variables. The parameters here are simulated holding other explanatory variables at their representative values while changing the values of the explanatory variable(s) of interest. The representative values used here are the mean values for continuous explanatory variables and mode values of categorical explanatory variables. The number of simulations, M, can be increased for a more accurate plot of the outcome probability distributions, i.e. the shape, the mean, the standard deviation, and other statistical features of the distributions. In this paper, all the outcome probability distributions are plotted from 10,000 simulated parameters estimates, i.e., M=10,000. Figure 1 is based on some hypothetical scenarios of substantive interest.

3. Findings and Discussion

Figure 1 looks at how perceptions of different aspects of the home country affect the probability of intending to migrate permanently (i.e. not to return home at all). The probability distributions here are plotted holding at any one time, only one home aspect to be favourable while the remaining five home aspects to be unfavourable (with all other explanatory variables held at their representative values). Among the home perception factors, perceptions of lifestyle have the largest impact on the probability of migrating permanently (Panel b). This is seen from the two means of *Pr(Y=Not return)* having the furthest distance apart. The two distributions here have the least overlap, indicating the strong impact of the perceptions of lifestyle. Small overlaps also suggest that the means of the distributions may not be statistically or practically different from one another.

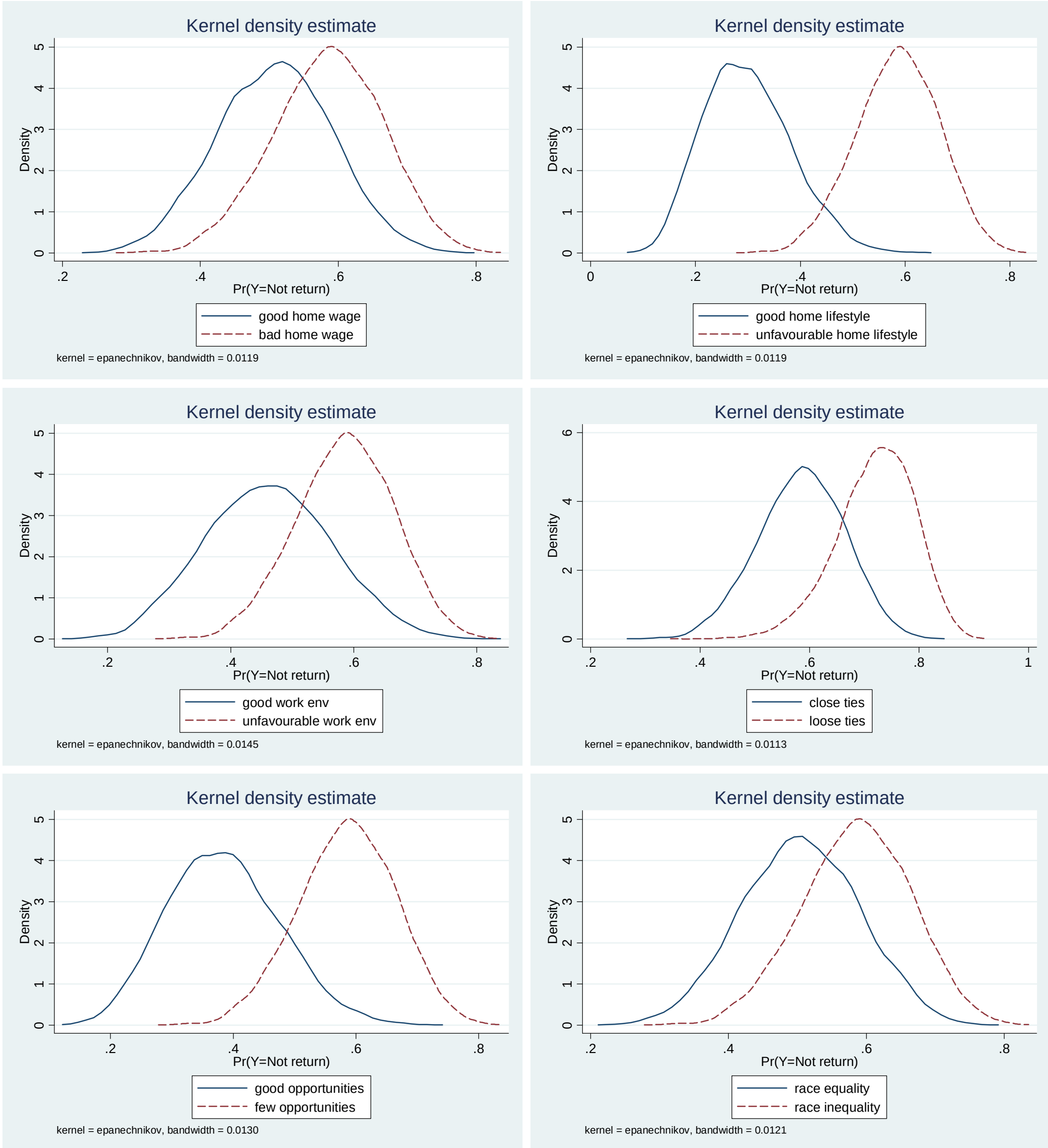

Fig. 1: Probability distributions of the 'Not return' outcome based on perceptions of home

From Figure 1, it appears that perceptions of skill use opportunities in the home country have the second largest impact on the probability of migrating permanently (Panel e). This is seen from the two means of Pr(Y=Not return) being distinctly apart, though not as distant as those of the lifestyle perception factor. Students are less likely to migrate permanently if they prefer the lifestyle in their home country and if there are ample opportunities there to use their acquired skills.

As opposed to the received literature, perceptions on wage competitiveness in the home country do not have as strong as an impact on the probability of migrating permanently as the perceptions on home lifestyle and skill use opportunity. This is suggested by the relatively large distributions' overlap and the less distinct probability means between students who have good perceptions of wage competitiveness and students who do not (Panel a).Figure 1 also reveals that having bad perceptions of the home aspects will always result in a higher probability of migrating permanently. This is shown by the dotted-line distributions being always on the right of the solid-line distributions. Students with bad perceptions of home, regardless of which home aspects, are likelier to migrate permanently.

4. Conclusion

This paper addresses the issue of when the students intend to return home upon finishing their studies in New Zealand. Applying parameter simulation on a multinomial logit model, we are able to identify key determinants of the students' intended return timeframes ranging from intending to return immediately, delaying their return for some work or education purposes, or intending not to return at all (migrate permanently).

From the findings, we notice a common trait, that is, the more pertinent intended return timeframes for the sample of students here are between migrating permanently and returning immediately. There appears to be much less importance placed on delayed return for education or work purposes. Perceptions of the kind of lifestyle and skill use opportunities in the home country have the largest impact on the probabilities of migrating permanently and returning immediately. Home governments should capitalize on these two factors if they want to encourage their students to return immediately.

Parameter simulations offer at least two major advantages in interpreting the estimation results of a discrete choice model. First, parameter simulations enable the plotting of outcome probability distributions. From these plotted distributions, we have an instant grasp of the variable(s) that has the strongest effect on a particular outcome probability. Stronger effects are manifested through more distinct distributions, i.e., entirely separated distributions or only a small portion of overlap. Second, the plotted distributions incorporate the notion of uncertainty associated with statistical inferences, where a wider distribution spread denotes higher uncertainty.

This paper contributes to the literature by first examining a relatively overlooked aspect of the brain drain/student nonreturn literature – when do students intend to return home. Secondly, the paper demonstrates the effective use of parameter simulations in identifying factors that have strongly distinguishable effects on outcome probabilities. We believe that this study is one of the few, if any, studies in brain drain/student nonreturn that incorporates a parameter simulation approach. Its use should therefore be adopted more widely, especially in empirical brain drain and migration studies using discrete choice models.

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