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## An Analysis of Gender Differences in UK Graduate Migration Behaviour

Alessandra Faggian,<sup>\*</sup> Philip McCann<sup>\*\*</sup> and Stephen Sheppard<sup>\*\*\*</sup>

### Abstract

In this paper we employ dichotomous, multinomial and conditional logit models in order to analyse the employment-migration behaviour of some 300,000 UK university graduates. By controlling for a range of variables related to human-capital acquisition and local economic conditions, we are able to distinguish between different types of sequential migration behaviour from domicile to higher education and on to employment. Our findings indicate that UK female graduates are generally more migratory than male graduates. We suggest that the explanation for this result lies in the fact that migration can be used as a partial compensation mechanism for gender bias in the labour market.

JEL Classifications: R230, J160, J240

### 1. Introduction

The theoretical relationships between human capital acquisition, employment returns and migration behaviour have been the subject of several analyses. Many variants of the basic Becker (1964) formulation have been applied to employment search models, and empirical evidence generally supports the basic conclusions of these formulations. In general, individuals with higher levels of human-capital tend to be more migratory, achieving greater employment returns both by reason of their greater human-capital and also their mobility.

There is one problem which has received relatively little attention, and this is the question of how these relationships are affected by gender. As a result of the interaction between human-capital acquisition and search behaviour, are men more geographically mobile than women or not? Lacking empirical evidence to the contrary, most (male) commentators would assume that men are more mobile than women. The implicit assumption is that men tend to be more attached to their careers than women, and that men are therefore more likely to make the necessary moves required in order to achieve promotion. On the other hand, women are implicitly assumed to be relatively more attached to their locality than men, for reasons of family support networks etc.

The seminal work of Ravenstein (1886), however, casts doubt on some of these arguments. His fifth 'law' of migration suggests that women are more mobile than men, at least across short distances (Ravenstein 1886, 1889; Lee 1966). Where this is empirically found to be true, it is often assumed that the explanation may be related to coupling and marriage. Some observers argue that women may be more migratory than men because they will generally have to move according to the

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employment locations of their male partners or spouses (Detang-Dessendre and Molho 2000), particularly in situations where women partially, temporarily or permanently leave the workforce in order to rear children. After controlling for these life-cycle effects, it is asserted that women are less migratory than men, because the wages they earn (Naylor et al. 1998) and the number of hours they work tend to be lower than men (Madden 1981), thereby reducing the returns to mobility. Once again, however, the overall evidence on these points is very limited. More importantly the existing evidence concerning gender differences in migration behaviour largely ignores the interaction between human-capital and migration.

The issue we explore in this paper is the effect of gender on the interaction between human capital acquisition and employment-migration behaviour among UK university graduates. We examine the migration behaviour of students from domicile to higher education and then from higher education to first employment. Controlling for the effects of human-capital acquisition as well as variations in regional economic conditions, we estimate the relationship between geographic mobility and gender. Our results produce both strong and surprising conclusions. Women are found to be generally more inter-regionally mobile than men, even when we control for differences in human capital acquisition. In the spirit of Ravenstein (1886), we interpret our findings as evidence for the argument that women use migration as a means of partially compensating for gender differences in the ease of accessing labour markets.

The paper is organized as follows. In the next section we discuss the interrelationships between human-capital, gender and interregional migration, with particular reference to university graduates. In section 3 we explain our analytical approach to modelling these interrelationships. In section 4 we present details of the data we employ, and in section 5 we provide a detailed analysis of our results. In section 6 we present a discussion and interpretation of our findings.

## ***2. Human Capital, Gender and Graduate Migration***

Migration research suggests that the likelihood of an individual graduate moving between regions will be positively related to the human-capital characteristics of the individual (Sjaastad 1962), as well as to inter-regional differences in both regional wages and regional employment opportunities. At the same time, there is a large body of research that suggests the extent of the previous migration of an individual is highly correlated with their subsequent migration behaviour (DaVanzo 1976, 1983; DaVanzo and Morrison 1981; Vanderkamp 1971; Newbold 1997). Combining human-capital migration models (Sjaastad 1962; Schwartz 1973) with models of spatial job-search (Simpson 1992; Hertzog et al. 1985; Molho 1986), we expect a positive correlation between previous migration and subsequent on-migration, and a positive correlation between these migration-on-migration propensities and the wages earned. The actual strength of these effects and resulting migration propensities will differ according to how the local wages vary relative to national economic conditions, because the wage at a particular location will act as a benchmark for comparing alternative market opportunities (Richmond Cooper 1994). However, this should be observed even after correcting for differences in the human-capital of any individual (Becker 1964) and the employment opportunities available at any particular location (DaVanzo 1978).

In the case of university graduates there is some limited evidence regarding their migration behaviour (refs). However, the general human-capital migration arguments outlined above would imply that after adjusting for the relative economic attractiveness of particular locations, students graduating with higher grades and qualifications would generally be expected to be more migratory than students achieving lower grades, because their returns to migration will tend to be relatively higher. At the same time, the likelihood of a graduate moving in order to enter employment after university will be positively related to the extent of the initial migration from domicile to higher education (McCann and Sheppard 2001).

What is missing in this analysis, however, is the question of gender. Although there have been a range of studies of graduate migration (Fenske et al. 1974; Fryman 1988; Mixon and Hsing 1994; Hsing and Mixon 1996), there is no large scale detailed micro-econometric analysis of gender-migration issues for university graduates. In the case of the UK labour market neither is there any previous empirical work on the effects of gender on the interaction between human-capital acquisition and the sequential migration behaviour of graduates. Where evidence on graduate-gender issues exists within the human-capital or migration literature, there is either no migration element (Harmon et al. 2001) or no human-capital element to the analysis (Fielding 1993). For example, if we simply observe the human-capital acquisition of UK students, we see that men have historically performed better than women (McNabb et al. 2002)<sup>1</sup>, at least until recently. Based on the arguments above these findings would tend to suggest that historically, male graduates will have been more mobile than women. On the other hand, an alternative view presented in the work of Fielding and Halford (1993) and Boyle and Halfacree (1995) based on census data from the 1970s and early 1980s, suggested that migration to the South East of England was biased much more in favour of upwardly mobile employment status occupations for women than for men, and this was particularly the case for women working in the service sector.<sup>2</sup> However, in this research, no evidence on the human-capital status of the migrant was provided, and therefore the observed gender differences in migration were simply assumed by the authors to be related to possible age differences between the genders and the types of coupling effects described above.

On the basis of the existing UK research, the lack of previous data means that there is currently no agreement as to the relationship between gender, migration and human-capital acquisition, although most analysts would tend to either disagree with Ravenstein (1885), or alternatively explain any observations of highly-mobile females in terms of life-cycle and coupling effects. Our research is the first such work which is able to integrate gender, human-capital and mobility within a coherent framework.

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<sup>1</sup> Other things being equal, women perform better than men across the university population as a whole (Naylor et al. 2001). However, in terms of actual degree grade outcomes, men still perform better. McNabb et al. (2002) find that the reason for this is that women are over-represented in subjects in which a lower proportion of top grades are given, and partly because of the under-performance of women at the top end of the academic scale.

<sup>2</sup> At the same time, movements away from the South East were associated with downwards labour mobility for women, whereas the effects on men were largely neutral.

In order to consider how these gender, mobility and human-capital issues may be modelled in the case of UK students, we first draw attention to the differences between the initial migration decision made by a new student applicant, and the subsequent second migration decision made by the university graduate.

A student can initially consider university courses in many parts of the UK, and on the basis of the suitability of the course and the prestige and reputation of the institution, can make a decision as to where to apply for admission. At the same time, the higher educational institution chooses to admit or reject the student applicant on the basis of the student's educational qualifications. All UK university tuition costs are cross-subsidised by the UK government, such that all tuition fees paid actually by students are invariant with respect of either the course or the university. As such, variations in the costs of education depend entirely on the local costs of living in the vicinity of the university. Spatial search arguments and human capital models would suggest that allowing for variations in the local costs of living, the higher the ability of the student applicant, the greater will be the range and variety of the potential set of choices available to the student. Consequently, we would expect that the observed migration of the student from domicile to higher education will tend to increase with the ability of the student and the ranking of the institution (McCann and Sheppard 2001). Yet, in addition to variations in personal characteristics, whether an individual student actually chooses to study locally or to migrate to obtain higher education will also depend on a range of other economic and social variables which characterise the environment at both the domicile and higher educational locations.

On graduating from higher education and entering first employment, the graduate must subsequently make a second migration decision. All graduates can conduct a labour market search in the region of their domicile, the region of their higher education institution, or they may seek to conduct a broader, national, labour market search. The advantage of the first choice is that they may be able to exploit local labour market networks and family connections to facilitate an efficient search for employment. Graduates will tend to be more familiar with the community from which they have come than they are with alternative areas, and this may increase their psychic costs of long-distance mobility. At the same time, after spending time in a region for higher education, graduates may also become reasonably familiar with the local economic environment in which they studied, and here there may also be possibilities for exploiting local labour market networks and social connections in order to find employment.

The human capital and search models discussed above suggest that the more successful graduates will be more geographically mobile at this second migration stage (Sjaastad 1962; Hertzog et al. 1985). However, how these graduates actually respond to these opportunities may also depend on their previous personal mobility history (DaVanzo 1976, 1983). For students who initially chose to study in a different region to their domicile region, it may be that this initial process of moving means that their psychic costs of mobility were, or have subsequently become, relatively lower than those of the students who remained to study in their domicile region. This would allow them to more easily conduct a national labour market search, thereby generating more attractive employment positions in occupations or industries with a higher growth potential and wages. Following the arguments of DaVanzo (1976, 1983), the outcome here will be that these students will be expected to exhibit

increased subsequent mobility relative to students who initially chose to study in the region of their domicile.

### 3. Modelling the Sequential Migration Behaviour of UK University Graduates

In general terms we can demonstrate how migration for employment and utility are related. In order to do this, we can suppose there are  $J$  potential locations ( $j = 1, \dots, J$ ) in which the migrant  $i$  ( $i = 1, \dots, I$ ) may enter employment. Assuming that information is spatially mediated, and that personal and family ties play an inhibiting role in the migration decision, the migration decision will be subject to distance-deterrence effects (Gordon 1978). This would suggest that the migration decision incurs financial, psychic and emotional costs, which are in part a function of the distance from the migrant's original location  $L$  to the subsequent location  $j$ , but which also depend on the whether the migrant has previously been a migrant (DaVanzo 1976, 1983). Therefore, we can write the **deterministic (observable) part of the** utility function of the individual  $i$  moving from  $L$  to location  $j$  as:

$$V_{ij} = V(\mathbf{X}_i, \mathbf{Y}_j, d_{Lj}) \quad (1)$$

where  $\mathbf{X}_i$  is a vector of personal and human-capital characteristics of  $i$ ,  $\mathbf{Y}_j$  is a vector of characteristics of the region  $j$ , and  $d_{Lj}$  represents the costs (monetary and personal) associated with a migration move over a distance  $d_{Lj}$ . Utility in this sense represents the expected returns to human capital of the individual migrant, after controlling for the costs of migration. Introducing a random error of unexplained individual, educational and location-specific variables given as  $e_j$ , the migration-utility function becomes:

$$U_{ij} = V(\mathbf{X}_i, \mathbf{Y}_j, d_{Lj}) + e_{ij} \quad (2)$$

Utility is now composed of a deterministic portion of observable personal and location characteristics and a random portion containing the unobservable attributes of both the individuals and the location alternatives.

On this argument, the probability  $P(m_{ij})$  that an individual  $i$  will migrate from their original location  $L$  to a particular alternative location  $j$  for employment, is the probability that the individual will maximise their potential returns to human capital by entering into employment in that particular alternative region  $j$  rather than in any other region, including the original region  $L$ . Formally, we can represent this as:

$$P(m_{ij}) = \text{prob} [ V(\mathbf{X}_i, \mathbf{Y}_j, d_{Lj}) + e_{ij} > U_{ij'} = V(\mathbf{X}_i, \mathbf{Y}_{j'}, d_{Lj'}) + e_{ij'} ] \quad (3)$$

$$j \neq j'$$

$$L \in j'$$

$$j, j' \in J$$

**(I would remove the second line, as  $j'$  is not a set, but a point as well, therefore  $L$  cannot belong to  $j'$ )**

Following the discussion above described by equations (1)-(3), if we assume that utility has a deterministic portion [ $V(\mathbf{X}_i, \mathbf{Y}_j, d_{Lj})$ ] which is linear in its parameters and

an error term  $e_{ij}$  which has a **Gumbel** distribution<sup>3</sup> we can employ different types of logit models in order to model the various characteristics of the sequential migration process.

If there are only two choice alternatives available, then estimating the probability that an individual will choose  $y_1 = 1 = \text{migrate}$  as against  $y_2 = 0 = \text{do not migrate}$ , can be modelled simply by using a dichotomous logit model, the structure of which is given as (Train 2001; Wooldridge 2002):

$$P_i(y_1) = \frac{1}{1 + e^{-\mathbf{N}_{ij}\boldsymbol{\beta}_{ij}}} \quad (4)$$

where  $\mathbf{N}_{ij}$  is the vector of both individual-specific personal characteristics and also choice-specific characteristics, and  $\boldsymbol{\beta}_{ij}$  represents the vector of parameters to be estimated.

On the other hand, in the case of more than two choice alternatives between different sequential migration types, we must distinguish explicitly between the characteristics of the chooser from the characteristics of the choices.<sup>4</sup> Therefore, in the case of more than two choice alternatives of different sequential migration types ( $k = 1, \dots, K$ ) in which we focus only on the characteristics of the chooser, the structure of the pure multinomial (MNL) logit model is given as (Train 2001; Wooldridge 2002):

$$P_i(k) = \frac{e^{\boldsymbol{\beta}_i \mathbf{X}_i}}{\sum_l e^{\boldsymbol{\beta}_i \mathbf{X}_i}} \quad (5)$$

where  $\mathbf{X}_i$  is the vector of personal characteristics, and  $\boldsymbol{\beta}_i$  represents the vector of personal parameters to be estimated.

A pure conditional logit model would exhibit a similar structure to equation (5), except that in this case  $\mathbf{X}_i$  would be replaced by  $\mathbf{Y}_j$  which represents the vector of the characteristics of the location choices rather than the personal characteristics, and the vector of parameters to be estimated would be  $\boldsymbol{\beta}_j$  rather than  $\boldsymbol{\beta}_i$ .

In order to estimate the likelihood of different types of sequential migration behaviour occurring as a function of both personal and choice characteristics, it is therefore necessary to construct a hybrid logit model the structure of which is given as:

$$P_i(k) = \frac{e^{\boldsymbol{\beta}_k \mathbf{W}_k + \gamma_{ij} \mathbf{Z}_{ij}}}{\sum_K e^{\boldsymbol{\beta}_k \mathbf{W}_k + \gamma_{ij} \mathbf{Z}_{ij}}} \quad (6)$$

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<sup>3</sup> Also known as either a double exponential distribution or a Type I Extreme Value distribution.

<sup>4</sup> Some researchers (Greene 2004) perceive the MNL model to be simply an extension of the dichotomous logit model in which the dependent variable has more than two categories. On the other hand, other researchers (Powers and Xie 2000; Heji et al. 2004) make an explicit distinction between the pure MNL model, which contains information only about the choosers, and the pure conditional model, which contains information only about the choice alternatives.

where  $\mathbf{W}_k$  is a vector of choice-specific parameters,  $\mathbf{Z}_{ij}$  is a vector combining both choice-specific and individual-specific characteristics, and  $\beta_k$  and  $\gamma_{ij}$  are the respective vectors of parameters to be estimated.

In order to model the various characteristics and causes of the different types of sequential migration behaviour of UK university graduates we employ these three different types of logit approaches in a tripartite process of analysis. Firstly, within a multinomial framework we consider the effects of an individual's gender, ethnicity and other personal and educational characteristics in determining the type of sequential migration behaviour that an individual exhibits in moving to and from university. Secondly, we focus specifically on the second stage of this sequential migration process after graduating from university. Here, within a dichotomous logit framework, we consider the individual's second stage migration behaviour after graduation and into employment, as a function of their previous migration behaviour from domicile to university, plus a range of gender, ethnic and other personal, educational and regional characteristics. Thirdly, within the framework a hybrid conditional logit model, we consider how the various types of sequential migration behaviour exhibited by the individual are related to both individual personal and regional characteristics.

In the first part of our tripartite analysis, the results of which are discussed in detail in section 5.1, we examine the effects of various gender, ethnic and other personal and educational characteristics on the likelihood of the individual exhibiting any particular one of the five types of sequential migration behaviour possible. In the two stage sequential migration process to and from university we can group all students and graduates into one of five separate types of sequential migration types. In order to do this we have therefore generated a categorical response variable that divides the sample into five groups. We find it heuristically helpful to refer to these groups as follows: category 1 are the *repeat migrants* who leave their domicile region for higher education and then find first employment in a region that is separated both from their original domicile and also the location of the educational institution<sup>5</sup>; category 2 are *return migrants*, who return to find first employment near their original domicile after having acquired higher education in a different region; category 3 are *university stayers* who move away from their domicile for higher education but then find first employment in the same community where they received their education; category 4 are *late migrants* who attend higher education near their domicile and then search and find first employment in a region away from both their original domicile and educational institution; category 5 are *non-migrants*, who both acquire higher education and also find first employment within 15 km of their original domicile.

We assume that in descending order of mobility, the most mobile group are the *repeat migrants* (category 1), followed by the university stayers (category 3), the late

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<sup>5</sup> In our econometric analysis we define two locations as being in the same area if they are within 15 km of each other. The reason for this is that almost all individual UK urban areas have a radius of less than 15 km. The only real exception to this is London, but even here, from a travel time perspective, London is generally regarded as being made up of a series of distinct urban areas, each of which is less than 15 km in diameter.



migrants (category 4), the return migrants (category 2), and finally the non-migrants (category 5).

In order to identify the effects of gender, human-capital and other personal characteristics on determining the types of sequential migration behaviour exhibited by individuals, we can employ a multinomial (MNL) logit model to estimate the likelihood of an individual exhibiting one of these five alternative migration types, as a function of a range of personal characteristics. The results of this estimation process are given in Tables 3a and 3b.

In our multinomial model setup, we do not necessarily assume that students have perfect foresight as to their subsequent human capital acquisition and employment outcomes after graduation. As such, we do not interpret these multinomial migration categories as reflecting **ex-ante** rational expectations types of choices. Rather, as we have already stated, we interpret these outcomes as simply reflecting the likelihood of an individual exhibiting one of these five alternative migration types, as a function of a range of personal characteristics. The reason for this is that attendance at university is likely to be associated with range of personal learning effects, which will be directly related to both degree attainment and also to a wider set of personal and inter-personal experiences and networks. As such, university graduates make employment-migration decision on the basis of quite different information sets than is the case of the education-migration decisions made by the student prior to entering university. For this reason, it is also important to consider these sequential stages of migration separately, and given that the focus of our paper is on employment migration of university graduates, we focus specifically on the second stage migration movement.

In second part of our tripartite analysis, the results of which are discussed in section 5.2, we therefore focus specifically on the second stage of this sequential migration process in which the recent graduate enters into employment after leaving university. In order to model the individual's second stage migration behaviour after graduating from university, as a function of their previous migration behaviour from domicile to university, plus a range of personal and regional characteristics, our model proceeds to estimate the binary choice between choosing to work in the current original region as against migrating to another region for employment. Following our earlier discussion, the analysis of this utility structure can appropriately be undertaken by employing a dichotomous logistic framework (Train 2001; Wooldridge 2002), in which we construct a categorical response variable whereby 1 represents migration away from the original location  $L$  in order to enter into employment in an alternative region, and 0 represents entering into employment in the original region  $L$ . In our empirical model, we do not employ an explicit distance measure associated with for each graduate  $i$ . However, we do know whether each student initially migrated away from their domicile area in order to attend to university, and following the arguments of DaVanzo (1976, 1983) any such previous migration behaviour will be expected to lower the psychological and emotional costs of subsequent migration. We would therefore expect that irrespective of the actual distances moved, students who moved away from their home region for education will be expected to exhibit increased subsequent mobility relative to those students who initially chose to study in the region of their domicile. This dichotomous logit model therefore allows us to estimate the odds that after graduating from university, an individual will choose to enter into employment in an alternative region rather than in their original region  $L$ , as a

function of their individual personal and human capital characteristics, plus the characteristics of their domicile locations. The estimates for this exercise are given in Tables 4a and 4b.

In the third stage of our tripartite analysis, the results of which are discussed in detail in section 5.3, we employ a hybrid conditional logit model in order to combine all of the information concerning the effects of personal characteristics on determining migration behaviour, with the effects of local regional characteristics. In order to do this, we construct interactive variables which combine information on the ethnic, age, gender, and human capital characteristics of the individuals with the characteristics of the different types of migration. In this model, the treatment of wages is also different from the other two models in which domicile wages are exogenously given. The reason for this is that in the hybrid conditional model, it is necessary for us to construct an index of wage gain SALINDEX associated with each migration type, in order that different wage indices are associated with each different migration type and for each location moved to. Therefore, we calculate the wage index for each sequential migration type as the proportionate increase in wages in the first stage of migration (calculated as the difference between the university and domicile area wage levels divided by the domicile wage level) plus the proportionate increase in wages in the first stage of migration (calculated as the difference between the employment and university area wage levels divided by the university wage level).<sup>6</sup> The results of this estimation process are given in Table 5.

#### **4. Data and Data Sources.**

Our student information comes from the Higher Education Statistics Agency (HESA) student leavers' questionnaire, and provides us with data on 482,558 UK domiciled students who graduated from UK higher education institutions between 1997 and 2000. The survey provides information on the gender of the student, the subject studied in higher education, and the level of attainment of the student, in terms of the highest degree level achieved,<sup>7</sup> and the grade of their respective degree<sup>8</sup>. The HESA data also allows us to identify those individuals in full-time permanent employment between six and eighteen months after graduation, and also provides us with detailed information about the higher education institution at which the student studied. We combine this information with data from the 1996 UK Research Assessment Exercise (RAE), which provides detailed rankings across the UK's 190 higher education institutions according to their research quality.

As is typical of these types of location studies, the spatial resolution of our data depends upon the variable. The finest resolution is available for the location of the student's domicile, the higher education institution attended, and the first employment, because the HESA data also provides us with the postcode district details of each of these locations. There are 2700 postcode districts in Great Britain<sup>9</sup>,

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<sup>6</sup> Note that in this model, the *non-migrants* are removed from the sample because the wage increase index is always zero.

<sup>7</sup> In terms of Bachelor, Masters or **Ph.D.** degree.

<sup>8</sup> For UK Bachelor degrees, the ranking of degrees in descending order is Class 1, class 2.1, class 2.2, and class 3.

<sup>9</sup> The postcode districts have an average area of 84.9 sq. km and an average population of 21162.

and our geographical information system MAPINFO allows us to identify the geographical centre point of each of the postcode districts. These UK postcode districts average 5 km in radius over England, Wales, and Scotland, and for urban areas the average size is much smaller so that locations for most observations are accurate to within 1 or 2 km. This information is used to provide very accurate details of the geographical migration behaviour of each student to and from higher education.

On the other hand, for most other economic data, the coarsest spatial units are the fifty-four local authority district-based counties of England and Wales defined by the 1974 Local Government Act, plus the nine regional councils of Scotland as defined in 1975.<sup>10</sup> These are the units for which employment data, wage data, productivity data, and income data are available. Since our models are estimated with individual students as the unit of observation, we always make use of the finest resolution available to us which is consistent across all spatial economic variables. Variables that are available at a coarser resolution are assumed to be constant throughout the spatial unit, so that, for example, the local employment conditions for an observation are those of the county containing the postcode that identifies the location.

The spatial data we employ comes from a variety of sources. Our wage data comes from the UK New Earnings Survey (NES) for each of the relevant years, which provides detailed wage levels for managerial (white-collar) activities broken down by county<sup>11</sup>. Data on county unemployment rates, activity rates, and population densities,<sup>12</sup> all come from the Office for National Statistics.

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<sup>10</sup> In England, seven of these counties are the metropolitan county councils covering the largest urban agglomerations of over one million people. In Scotland, the three separate island councils are combined into a single council for the purposes of our analysis. The average employment size of the areas is 330825.

<sup>11</sup> The wage levels we employ in our models are not the wages earned by graduates immediately on gaining first employment. Because initial UK graduate earnings differ very little by region, except for London wages, using the starting salaries immediately after graduation would fail to provide a reasonable measure of the expected returns to human capital. A standard approach in labour market models is therefore to assume that an individual graduate who chooses to enter a particular occupation in a particular region on graduating from a higher education institution does so with a view to staying in that chosen occupation and region for life (Naylor et al. 1998). Therefore, we use average regional white-collar managerial wages as a measure of the expected average lifetime earnings for university graduates in a particular region, and there are two justifications for adopting this approach. The first is that each individual student makes a migration decision on the assumption that the expected long-run average wage at a location is exogenous of their own individual migration decision. The second reason is that the acquisition of job-specific and region-specific human-capital engenders ‘lock-in’ (David 1985) effects which tend to be localised because of informal labour market contacts and localised information on the nature of workers in specific firms. These information issues provide incentives for individuals to remain in the same region over a lifetime of working, and within UK labour markets, and indeed, less than 1% of the UK working population actually undertake inter-regional migration moves per annum, while less than 2% of the unemployed make such moves (McCormick 1997).

<sup>12</sup> We employ these variables as proxies for the position of a location within the national urban hierarchy on the basis that there is much evidence to suggest that the generation of job-opportunities for UK university graduates in particular, may be related to the rank-order of the area within the national urban hierarchy, which is centred around the South East of the England (Fielding 1991, 1992; McCann and Sheppard 2001). In addition, other authors (Ciccone and Hall 1996) argue that variations in the local population density are a good proxy for local productivity variations, due to the role of local positive spillovers.

The explanatory variables used in our models are listed in Table.1. Variables with either the prefix or suffix DOM relate to the domicile location of the student, those with the prefix or suffix UNI relate to the higher education location, and those with the prefix or suffix FIN relate to the final employment location of the graduate.

As we can see from the database, of the five different types of sequential migration behaviour, by far the most common type is that of category 1, the *repeat migrants*, followed by the *university stayers*, the *non-migrants*, the *late migrants* and finally the *return migrants*.

## **5. Results and Analysis**

As we discussed in section 3, our approach here is to employ three different types of logistic models in order to understand the nature and determinants of UK graduate migration behaviour.

### **5.1 Multinomial Logit Model**

In our multinomial model we estimate the likelihood of an individual exhibiting one of the five alternative migration types, as a function of a range of personal and educational characteristics. Here we include as regressors all of the variables which relate to the personal and educational characteristics of the individual, plus the economic characteristics of the domicile location of the individual. We interpret these domicile economic characteristics as contributing to the initial personal formation of the student, and such information is appropriately included within a MNL framework because such variables do not change according to the type of sequential migration behaviour exhibited.<sup>13</sup>

As mentioned in section 3, we assume that in descending order of mobility, the most mobile group are the *repeat migrants* (category 1), followed by the university stayers (category 3), the late migrants (category 4), the return migrants (category 2), and finally the non-migrants (category 5).

The results of our multinomial model are given in Table 3. As we see here, our results<sup>14</sup> correspond broadly to the predictions of human capital-migration model. The estimated coefficients indicate that increasing human capital (from THIRD to FIRST in ascending order) is associated with an increasingly higher probability of being either a *late migrant* or a *repeat migrant*, except for the highest grade (class 1) which exhibits the least likelihood of being a *repeat migrant*.<sup>15</sup> Increasing human capital is

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<sup>13</sup> It is important to note that the multinomial model fails the IIA independence-of-irrelevant-alternatives assumptions. However, this outcome is not problematic, because there are no additional sequential migration categories which could possibly be added to the model. The reason is that in our multinomial logit model we are not explicitly estimating the choice of migrating to particular locations, as in Knapp et al. (2004), but rather we are estimating the likelihood of exhibiting one particular type of sequential migration behaviour.

<sup>14</sup> The pseudo R-squared value of 0.1403 is reasonable level of fit for a logit model, for which a value above 0.2 is indicative of extremely good model fits (Louviere et al. 2000, p.54).

<sup>15</sup> This result appears to be consistent with the argument of Bartel (1979) who argued that the very highest skill workers tend to be less mobile than those immediately below them, because these workers normally have the both the first and the best choice of opportunities available to them. As such, they can take advantage of the very best jobs locally available without having to move, thereby forcing

also associated with a decreasing likelihood of being either a *return migrant* or a *university stayer*. Similarly, graduation from a high ranking (RAEINDEX) research university is associated with increasing mobility for all types of migration behaviour. Meanwhile, being sponsored (SPONSOR) by an organisation which requires the graduate to enter into employment with that organisation also increases the likelihood of exhibiting all types of migration behaviour, relative to the *non-migrant* case, except for that of the *university stayer*.

Confirming work elsewhere (Faggian et al. 2006), our results suggest that in comparison with being Caucasian, Afro-Caribbean (BLACK) or Asian (ASIAN) ethnicity reduces the likelihood of a graduate exhibiting any type of migration behaviour relative to the *non-migrant* case, as does the age (AGE) of the graduate. The distance of the domicile area from London (DLOND) and the population density of the domicile area (PDNDOM) also tend to reduce mobility. Both unemployment in the domicile region (UEDOM) and also specialization (LQM, LQBK, LQPB) in the domicile region reduce the likelihood of exhibiting any kind of migration behaviour relative to the case of the *non-migrant*, except in the case of the *late migrant*, whereby both higher local unemployment and higher specialisation encourage late migration behaviour to alternative regions. Similarly, an increasing activity rate in the domicile environment (EACTDOM) reduces the likelihood of being either a *repeat migrant* or a *university stayer*.

In terms of the subjects studied, the results are rather mixed, with graduates who have studies arts (ARTS) subjects tending to be more likely to be *university stayers* and *return migrants*, and less likely to be *late migrants*, whereas science (SCIENCE) and social science (SOCSCIE) graduates are more likely to be late migrants. Also, graduates whose domicile regions have a high number of universities (DOMCOINS) tend to be less migratory, and are more prone to stay in the university area for employment. Graduates from Wales (WALESDOM) tend to be less migratory while those originally from Scotland (SCOTDOM) tend to be more migratory, for all types of migration except for *late migrants*.

In terms of the focus of this paper which is the impact of gender on migration, the positive and significant coefficients on the gender variable (GENNUM) mean that male graduates are more likely to be either *repeat migrants*, *return migrants*, *university stayers* or *late migrants* than female graduates. As such, males appear to be systematically more migratory than females across all the different sequential migration types.

## **5.2 Dichotomous Logit Model**

The results of our dichotomous models are given in Tables 4a and 4b.<sup>16</sup> Table 4a provides the estimates of the likelihood of the recent graduate moving away from the university location in order to enter into employment elsewhere, including the

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others to move. Moreover, once they acquire such jobs, the opportunity costs of moving may be very high.

<sup>16</sup> The pseudo R-squared values for these two models depicted in Tables 4a and 4b of 0.0355 and 0.0515 are much lower than the MNL model. However, this is not surprising because in these two models, both the second stage migration responses and also the explanatory variable PREVMIGR are composites of the more detailed migration types employed in the MNL model.

domicile location. Table 4b provides the estimates of the likelihood of the recent graduate moving away from the domicile location in order to enter into employment elsewhere, including the university location.

As we see in Table 4a, migration away from university to employment is positively and increasingly associated with increasing human capital acquisition, from THIRD to FIRST class degree results, and also for postgraduate degrees. In the case of migration away from domicile to employment, higher levels of human capital up to TWOONE reduce the likelihood of remaining in the domicile region, and a FIRST class degree increases the likelihood of moving away. These observations correspond broadly both to the human capital migration theory predictions, and also to the MNL observations above.

As with the MNL model, in Table 4a we see that graduates who have received industrial sponsorships (SPONSOR) are also relatively migratory in terms of moving away from university for employment. However, as we see in Table 4b, the majority of these sponsored students tend to work in their domicile regions, because such sponsorships are arranged in advance of attending university, and as such, most tend to be related to the home environment of the student.

Older (AGE) graduates are always found to be statistically less migratory than younger graduates (Faggian et al. 2006) irrespective of whether mobility is defined as being away from university or domicile. Meanwhile, graduates with Afro-Caribbean (BLACK) or Asian (ASIAN) ethnicity are less migratory away from university than are white graduates. Similarly, graduates who have studied for either science (SCIENCE) or social science (SOCSCIE) degrees are more migratory than arts (ARTS) graduates, a picture which again is largely reflected in the MNL estimates above.

Graduates whose domicile locations are in Wales (WALESDOM) or Scotland (SCOTDOM) are less migratory in all conditions, and these findings presumably reflect cultural and institutional differences between these countries and England. As with the MNL estimates above, graduates whose domicile regions exhibit high unemployment (UEDOM), high activity rates (EACTDOM), high population density (PDNDOM), have a high density of local universities (DOMCOINS) and which are at a greater distance from London (DLONDON), also tend to be less migratory.

The positive and significant coefficient estimate for previous migration (PREVMIG) is the largest single coefficient in both Model 4a and Model 4b, and inclusion of this variable produces a significant increase in the overall goodness of fit of the model. This result provides strong support for the DaVanzo (1976, 1983) hypothesis that subsequent migration is highly correlated with previous migration.

If we compare the results from Table 4a with those of Table 4b, we also see that subsequent migration away from university, and to a much lesser degree away from domicile, is correlated with the research ranking (RAEINDEX) of the university. This finding supports the general argument that universities themselves provide an institution-specific indicator of human capital. Meanwhile, there is no evidence that the industrial specialization variables (LQM, LQBK, LQPB) in the domicile region have any explanatory power in terms of migration away from university, although

increased specialisation does appear to encourage migration away from the domicile region.

In terms of the focus of this paper which is the impact of gender on migration, the negative and significant coefficients on the gender variable (GENNUM) in both models implies that at the second stage of migration on graduating from university, women are consistently *more* mobile than men, irrespective of whether or not we define mobility as being away from the university location or away from the domicile location. Moreover, this is true irrespective of whether or not we control for previous migration, although the result is much stronger when previous migration is controlled for, as is reported here.

This result appears to be rather at odds with the previous multinomial logit results. However, the reason for these results is that women are much more likely to be *non-migrants* than males, and in the multinomial model, the baseline category employed is that of the *non-migrant*.

### **5.3 Conditional Logit Model**

In our conditional model, we estimate the likelihood of an individual exhibiting one of the five alternative sequential migration types discussed earlier as a function of personal and educational characteristics, after controlling for the local wage levels in each of the domicile, university and employment regions. However, the variables we employ in this model are slightly different to those employed in the previous two models, although they are constructed from the same dataset.

Firstly, as mentioned in section 4, we construct a wage variable appropriate for the conditional logit model structure which is given as (SALINDEX). This variable is calculated as the sum of the percentage increase in local (managerial white-collar) wages between the domicile and the university locations (calculated with respect to the domicile location), plus the percentage increase in such wages between the employment location and the university location (calculated with respect to the university location).<sup>17</sup> This wage index is unique for each type of sequential migration behaviour, and also reflects any learning effects which may take place as part of the sequential migration process. However, given our construction of the wage index necessary for the conditional logit specification, we therefore remove the case of the *non-migrants* from the analysis. As such our analysis now focuses only on the four migrant types, and the reference type we employ here is therefore that of the *repeat migrant*.

Secondly, we employ a rank-ordering index (GRADE) according to the final degree level achieved and also the final grade achieved in the student's degree classification. This variable is then used along with the other personal variables (ASIAN, BLACK, AGE, GENDER) which have been found in the dichotomous and MNL logit models to be significant in determining migration behaviour, in order to construct interactive variables appropriate for the conditional logit specification. Thirdly, we employ the dummies RETURN, UNISTAY and LATEMIG which represent each of the three

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<sup>17</sup> In terms of dealing with alternative locations which are not chosen as part of the sequential migration process, we simply impute the average white-collar managerial wages in all other locations as the appropriate value.

MNL sequential migration types of *return migrant*, *university stayer* and *late migrant*, respectively. These dummies are then used as regressors both individually and also as part of the interactive variables.

From Table 5, we see that all types of migration are less likely than that of the *repeat migrant*, as has already been seen in Table 2. Moreover, migration of any type is positively related to the local wage levels, in accordance with labour market theory. In terms of personal characteristics, graduates with Afro-Caribbean (BLACK) ethnicity are more likely to be *late migrants*, while graduates with Asian (ASIAN) ethnicity are more likely to be both *late migrants* and *university stayers* than Caucasian graduates. Older (AGE) graduates are more likely to be *late migrants* or *return migrants*. Graduates with higher degree levels and classifications (GRADE) are more likely to be *university stayers* or *late migrants* and less likely to be *return migrants*.

Finally, in terms of the impact of gender on migration, the positive and significant coefficients on each of the interactive gender-migration variables (GEND\*RET, GEND\*UNI, GEND\*LAT) implies that after controlling for wage variations associated with mobility, plus a range of personal and human-capital characteristics, we see that women are once again consistently *more* mobile than men, in that women are more likely to be *repeat migrants*.

The pseudo R-squared values for the conditional model are very good indeed, and not surprisingly, are also much higher than those for either the multinomial model or the dichotomous models. Moreover, the results of the Hausman test also imply that the conditional logit model passes the independence of irrelevant alternatives assumption, and as such it is not necessary for us to employ a nested structure.

## **6. Discussion and Conclusions**

Our various logit results appear to be largely consistent with human-capital-migration theory, in that mobility tends to be largely associated with acquired human capital, in the form of both the grade achieved and also the quality of the university attended by the student. In accordance with migration theory, inter-regional variations in wages are also a strong motivator of migration. As well as this, in accordance with the DaVanzo hypothesis we find that subsequent migration is also highly correlated with previous migration behaviour. In addition, we find that in the case of the UK, migration is also associated with individuals originally being domiciled in areas which are in more geographically central and economically stronger regions, which suggests something of a centre-periphery aspect to UK migration behaviour. Conversely, being older, or being a member of a non-white ethnic group, tends to reduce mobility. Similarly, studying for arts degrees, which tends to be less specific to employment needs, or being locally sponsored through university, also tend to reduce post-graduation mobility.

Our results are broadly consistent with all of the various major possible migration motives which are specified in the literature, except regarding one key issue. As we have seen at the beginning of this paper, in the absence of appropriate data, most commentators tend to assume that men are more geographically mobile than women. However, ever since the initial work of Ravenstein (1886), a small number of analysts (Fielding and Halford 1993; Boyle and Halfacree 1995) have argued that women are



more migratory than men, at least as far as the UK is concerned. Our results also find very strong support for the Ravenstein hypothesis. Women are more likely to be non-migrants than men. However, for those students and graduates who do exhibit some mobility, the results are very different. For this latter group, after controlling for human capital acquisition, previous migration behaviour, and the different types of sequential migration behaviour possible, once we incorporate both individual characteristics and the characteristics of the regions, then UK female university graduates are clearly more migratory than men.

While our results clearly demonstrate that, for the cohorts of the UK graduate population that exhibit some mobility, women are more migratory than men, exactly why this is the case is rather a different question. The suggestion that women may follow men because of existing (Detang-Dessendre and Molho 2000; Madden 1981) or prospective (Endlund 2002) coupling arrangements in which female migration patterns are determined primarily by the employment-migration behaviour of male partners, cannot be an explanation for our results here. There are two reasons for this. Firstly, the cohort of students in our dataset is primarily in the age group of 21-25, and very few of these will be in permanent coupling arrangements. This suggests that such coupling issues cannot be a primary motivating factor for the migration patterns. Secondly, for these alternative explanations to be correct, it would be necessary for the gender migration estimates to be insignificant, because the migration patterns of the two groups not be statistically different. The fact that our gender results are so clear suggests that other explanations must be found.

With no additional information, it appears that the best explanation for our results follows the seminal insight of Ravenstein (1886). In other words, women use migration as a means of partially compensating for gender differences in the ease of accessing labour markets. Indeed, there is a large body of evidence across a range of social science disciplines (Lissenburgh 2000; Blundell et al. 2000; Desai et al. 1999) which suggests that women are systematically discriminated against within the labour market. If this is so, then an increased spatial employment search on the part of women in order to access appropriate employment opportunities would be a rational response to such discrimination.

## References

Anderson, T., Forth, J., Metcalf, H., and Kirby, S., 2001, *The Gender Pay Gap: Final Report to the Women and Equality Unit*, Cabinet Office, London

Artis, M.J., (ed), 1997, *The UK Economy*, Oxford University Press, Oxford

Bartel, A.P., 1979, "The Migration Decisions: What Role does Job Mobility Play", *American Economic Review*, 69, 775-786

Becker, G., 1964, *Human Capital* NBER Columbia University Press, New York

Blundell, R., Dearden, L., Goodman, A. and Reed, H., 2000, "The Returns to Higher Education in Britain: Evidence from a British Cohort", *Economic Journal*, 110, 82-99

Boyle, P.J., and Halfacree, K.H., 1995, "Service Class Migration in England and Wales, 1980-1981: Identifying Gender-Specific Mobility Patterns", *Regional Studies*, 29.1, 43-57

Ciccone, A. and Hall, R.E., 1996, "Productivity and the Density of Economic Activity", *American Economic Review*, 86, 54-70

Cockburn, C., 1991, *In the Way of Women: Men's Resistance to Sex Equality in Organisations*, Macmillan, Basingstoke

DaVanzo, J., 1976, "Differences between Return and Nonreturn Migration: An Econometric Analysis" *International Migration Review*, 10, 13-27

DaVanzo, J., 1983, "Repeat Migration in the United States: Who moves back and who moves on?" *Review of Economics and Statistics* Vol.65, 552-559

DaVanzo, J. and Morrison, P.A., 1981 "Return and Other Sequences of Migration in the US" *Demography*, 18, 85-101

David, P., 1985, "CLIO and the Economics of QWERTY", *American Economic Review*, 75, 332-337

Desai, T., Gregg, P., Steer, J. and Wadsworth, J., 1999, "Gender and the Labour Market" in Gregg, P. and Wadsworth, J. (eds.), *The State of Working Britain*, Manchester University Press, Manchester, UK

Detang-Dessendre, C., and Molho, I., 2000, "Residence Spells and Migration: A Comparison for Men and Women", *Urban Studies*, 37.2, 247-260

Endlund, L., 200?,

Faggian, A., McCann, P., and S. Sheppard, "An Analysis of Ethnic Differences in UK Graduate Migration", 2006, *Annals of Regional Science*, 39, Forthcoming

Fenske, R.H., Scott, C.S., and Carmody, J.F., 1974, "Recent Trends in Studies of Student Migration", *The Journal of Higher Education*, 45.1, 61-74

Fielding, A.J., 1992, "Migration and Social Mobility: South East England as an Escalator Region" *Regional Studies*, 26.1, 1-15

Fielding, A.J., 1993, "Migration and the Metropolis: Recent Research on the Causes and Consequences of Migration in the Southeast of England" *Progress in Human Geography*, 17.2, 195-212

Fielding, A., and Halford, S., 1993, "Geographies of Opportunity: A Regional Analysis of Gender-Specific Social and Spatial Mobilities in England and Wales, 1971-81", *Environment and Planning A*, 25, 1421-1440

Fryman, J.F., 1988, "Factors in the Interstate Migration of College Students", *College and University*, 63, 234-247

Gordon, I.R., 1978, "Distance-deterrence and commodity values", *Environment and Planning A*, 10, 889-900

Greene W., 2004, *Notes from the Discrete Choice Modelling Course, Cemmap, London, 11<sup>th</sup> -13<sup>th</sup> February*

Grimshaw, D. and Rubery, J., 2001, *The Gender Pay Gap: A Research Review*, Equal Opportunities Commission Research Discussion Series, London

Heji, C., de Boer, P., Franses, P.H., Kloek, T. and van Dijk, H.K., 2004, *Econometric Methods with Applications in Business and Economics*, Oxford University Press, Oxford, UK

Herzog, H.W., Hofler, R.A., and Schlottman, A.M., 1985, "Life on the Frontier: Migrant Information, Earnings and Past Mobility" *Review of Economics and Statistics*, 67, 373-382

Hsing, Y., and Mixon, F.G., 1996, "A Regional Study of Net Migration Rates of College Students", *Review of Regional Studies*, 26, 197-209

Lee, E.S., 1966, "A Theory of Migration", *Demography*, 3.1, 47-57

Lissenburgh, S., 2000, "Gender Discrimination in the Labour Market: Evidence from the BHPS and EiB Surveys", Policy Studies Institute Research, Discussion Paper 3, London, UK

Louviere, J.J., Hensher, D.A. and Swait J.D., 2000, *Stated Choice Methods*, Cambridge University Press, Cambridge, UK

Madden, J.F., 1981, "Why Women Work Closer to Home", *Urban Studies*, 18, 181-94

McCann, P. and Sheppard, S., 2001, "Public Investment and Regional Labour Markets: The Role of UK Higher Education" in Felsenstein, D., McQuaid, R., McCann, P., and Shefer, D., (eds), *Public Investment and Regional Development*, Edward Elgar, Cheltenham

McCormick, B., 1997, "Regional unemployment and labour mobility in the UK", *European Economic Review*, 41, 581-589

McDowall, L. and Court, G., 1994, "Performing Work: Bodily Representations in Merchant Banks", *Environment and Planning D, Society and Space*, 12, 727-750

McNabb, R., Pal, S., and Sloane, P., 2002, "Gender Differences in Student Attainment: The Case of University Students in the UK", *Economica*, 69, 481-503

Mixon, F.G., and Hsing, Y., 1994, "College Student Migration and Human Capital Theory: A Research Note", *Education Economics*, 2.1, 65-73

Molho, I., 1986, "Theories of Migration A Review" *Scottish Journal of Political Economy*, 33, 396-419

Naylor, R., Smith, J., and McKnight, A., 2001, "Determinants of Occupational Earnings: Evidence for the 1993 UK University Graduate Population from the US", *Oxford Bulletin of Economics and Statistics*, 63.1, 29-60

Nelson, F.D., 1987, "Logit, probit and tobit" in Eatwell, J., Milgate, M., and Newman, P., (eds.), 1987, *The New Palgrave Econometrics*, Macmillan, London

Newbold, K.B., 1997, "Primary, return and onward migration in the US and Canada: Is there a difference?" *Papers in Regional Science*, 76.2, 175-198

Powers, D.A. and Xie, Y., 2000, *Statistical Methods for Categorical Data Analysis*, Academic Press, San Diego, USA

Ravenstein, E.J., 1885, "The Laws of Migration", *Journal of the Royal Statistical Society*, XLVIII, Part 2, 167-227, June

Ravenstein, E.J., 1889, "The Laws of Migration", *Journal of the Royal Statistical Society*, LII, 241-301, June

Train, K., 2003, *Discrete Choice Methods with Simulation*, Cambridge University Press, Cambridge, UK

Wooldridge, J., 2002, *Introductory Econometrics*, MIT Press

## TABLES

**Table 1.** Variable definitions

MIGTYPE	Migration type
GENNUM	Gender (male = 1)
UG	Undergraduate bachelor degree
FIRST	Class 1 Bachelor degree
TWOONE	Class 2.1 Bachelor degree
TWOTWO	Class 2.2 Bachelor degree
THIRD	Class 3 Bachelor degree
WALES	Wales dummy
SCOT	Scotland dummy
RAEINDEX	University RAE score
PDN	County population density
AGE	Age
SIC8MALE	Male employed in public sector activities
DLON	Distance of postcode district from London
UE	County unemployment rate
EACT	County activity rate
COINS	Number of county higher education institutions
BLACK	Afro-Caribbean ethnicity
ASIAN	Asian ethnicity
LQMA	County location quotient for manufacturing industry
LQBK	County location quotient for banking and finance
LQPB	County location quotient for public sector activities
SCIENCE	Science subject studied
SOCSCIE	Social science subject studied
ARTS	Arts subject studied
SPONSOR	Student with an industrial sponsorship requiring subsequent employment with the sponsor

**Table 2: Summary statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max
GENNUM	482558	.4455879	.497031		1
UG	482558	.8662358	.3403992		1
FIRST	482558	.0565694	.2310181		1
TWOONE	482558	.3473241	.4761203		1
TWOTWO	482558	.2769242	.4474792		1
THIRD	482558	.0534029	.2248358		0
WALESDOM	482558	.0458639	.2091901		1
SCOTDOM	482558	.0661392	.2485255		1
RAEINDEX	446393	4.173273	.4170992	3.0711	5.1862
PDNDOM	482558	1286.88	1547.505	8	4643
<b>AGE</b>	<b>481065</b>	<b>24.7421</b>	<b>6.161624</b>	<b>17</b>	<b>59</b>
SIC8MALE	482558	.0599078	.2373162		1
DLONDON	482558	196.1811	155.743		680
UEDOM	481033	.0218072	.0090113	.0047516	.0482171
DOMCOINS	482558	6.990163	7.260682		25
BLACK	482558	.0331214	.1789538		1
ASIAN	482558	.056787	.2314353		1
LQMADOM	469578	1.001197	.3130611	.3621622	2.405406
LQBKDOM	448467	1.032158	.3503487	.4370861	1.735099
LQPBDOM	481323	1.006501	.1409666	.5583333	1.5875
SCIENCE	482558	.1805793	.3846697		1
SOCSCIE	482558	.3774282	.4847439		1
ARTS	482558	.1951123	.3962875		1
<b>SPONSOR</b>	<b>410021</b>	<b>1.964778</b>	<b>.1843404</b>	<b>1</b>	<b>2</b>
EACTDOM	482558	78.6783	3.517166	70	84.81429

Migration Type	Frequency
1 Repeat migrant	53,323
2 Return migrant	2,150
3 University stayer	27,500
4 Late migrant	6,057
5 Non migrant	16,981

**Table 3: Sequential Migration Types: Multinomial Logit Model**(Outcome *non-migrants* is the comparison group)

Number of valid observations = 74800

Prob &gt; chi2 = 0.0000

Pseudo R-squared = 0.1403

	Coefficient	Std.Err.	z	P> z
<b>Repeat Migrants</b>				
GENNUM	.2771026	.0271564	10.20	0.000
UG	-.9843552	.0429829	-22.90	0.000
FIRST	1.01492	.054222	18.72	0.000
TWOONE	1.243856	.035261	35.28	0.000
TWOTWO	1.183426	.0374005	31.64	0.000
THIRD	1.085693	.0651508	16.66	0.000
WALESDOM	-.2778968	.0794833	-3.50	0.000
SCOTDOM	.6158073	.0876157	7.03	0.000
RAEINDEX	.3693273	.0340583	10.84	0.000
PDNDOM	-.0005181	.0000176	-29.48	0.000
AGE	-.0653496	.0014806	-44.14	0.000
SIC8MALE	-.3278821	.0488195	-6.72	0.000
DLONDON	-.0045667	.0001672	-27.32	0.000
UEDOM	-11.46527	3.110906	-3.69	0.000
DOMCOINS	-.0071896	.0033483	-2.15	0.032
BLACK	-.648248	.05602	-11.57	0.000
ASIAN	-.318118	.044149	-7.21	0.000
LQMADOM	-1.552051	.0772707	-20.09	0.000
LQBKDOM	-1.667702	.0921779	-18.09	0.000
LQPBDOM	-2.557411	.1356192	-18.86	0.000
SCIENCE	-.2167582	.0381563	-5.68	0.000
SOCSCIE	-.2071002	.0302176	-6.85	0.000
ARTS	.0262835	.0391365	0.67	0.502
SPONSOR	.0010624	.0000269	39.53	0.000
EACTDOM	-.0068715	.0062807	-1.09	0.274
CONST	10.08582	.6427851	15.69	0.000
<b>Return Migrants</b>				
GENNUM	.6331434	.0623552	10.15	0.000
UG	-.4447927	.1182229	-3.76	0.000
FIRST	.2470415	.1474835	1.68	0.094
TWOONE	.8030519	.0918642	8.74	0.000
TWOTWO	1.069396	.0943018	11.34	0.000
THIRD	1.129795	.1484635	7.61	0.000
WALESDOM	-.539124	.2405583	-2.24	0.025
SCOTDOM	.5773368	.22473	2.57	0.010
RAEINDEX	.3166174	.0672102	4.71	0.000
PDNDOM	-.0006259	.0000493	-12.69	0.000
AGE	-.0048318	.0016706	-2.89	0.004
SIC8MALE	-.7919987	.1342821	-5.90	0.000
DLONDON	-.0037346	.0004158	-8.98	0.000
UEDOM	-.2579198	7.488434	-0.03	0.973
DOMCOINS	.0090335	.0091424	0.99	0.323
BLACK	-.6497033	.1839785	-3.53	0.000

ASIAN	-.3636178	.1420702	-2.56	0.010
LQMADOM	-1.461071	.1734831	-8.42	0.000
LQBKDOM	-1.550688	.1957289	-7.92	0.000
LQPBDOM	-2.208312	.303967	-7.26	0.000
SCIENCE	-.4620673	.0941753	-4.91	0.000
SOCSCIE	-.472037	.0762399	-6.19	0.000
ARTS	.4685841	.0820723	5.71	0.000
SPONSOR	.0003883	.0000636	6.10	0.000
EACTDOM	.0118164	.0148402	0.80	0.426
CONST	2.647165	1.495369	1.77	0.077

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### University Stayers

GENNUM	.2494629	.0294993	8.46	0.000
UG	-.0660691	.0481135	-1.37	0.170
FIRST	.1973484	.0576271	3.42	0.001
TWOONE	.2418143	.0358867	6.74	0.000
TWOTWO	.2244019	.0385372	5.82	0.000
THIRD	.4817425	.0694464	6.94	0.000
WALESDOM	-.0868762	.0870158	-1.00	0.318
SCOTDOM	.7341945	.0954108	7.70	0.000
RAEINDEX	.2950663	.036549	8.07	0.000
PDNDOM	-.0005749	.0000205	-28.08	0.000
AGE	-.0632003	.0015323	-41.25	0.000
SIC8MALE	.2688811	.0553686	4.86	0.000
DLONDON	-.0036225	.0001821	-19.89	0.000
UEDOM	-8.350271	3.469056	-2.41	0.016
DOMCOINS	.0117096	.003838	3.05	0.002
BLACK	-.3843522	.0607493	-6.33	0.000
ASIAN	-.1220003	.0474557	-2.57	0.010
LQMADOM	-1.510478	.0834634	-18.10	0.000
LQBKDOM	-1.594157	.0991332	-16.08	0.000
LQPBDOM	-2.558172	.1478149	-17.31	0.000
SCIENCE	-.1336982	.0414245	-3.23	0.001
SOCSCIE	-.2771517	.0336196	-8.24	0.000
ARTS	.0950502	.0425838	2.23	0.026
SPONSOR	-.0006294	.0000285	-22.12	0.000
EACTDOM	-.0038221	.0069656	-0.55	0.583
CONST	8.06683	.7094532	11.37	0.000

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### Late Migrants

GENNUM	.3017001	.0406503	7.42	0.000
UG	-1.008675	.063985	-15.76	0.000
FIRST	1.019962	.0794382	12.84	0.000
TWOONE	.8782458	.0571638	15.36	0.000
TWOTWO	.8031196	.0604694	13.28	0.000
THIRD	.7547756	.0999066	7.55	0.000
WALESDOM	.1051233	.1071726	0.98	0.327
SCOTDOM	.1021167	.1230329	0.83	0.407
RAEINDEX	.1006138	.0526353	1.91	0.056
PDNDOM	-.0002143	.0000256	-8.37	0.000
AGE	-.0033867	.0011261	-3.01	0.003
SIC8MALE	-.2070144	.0675471	-3.06	0.002
DLONDON	-.0011823	.0002366	-5.00	0.000
UEDOM	11.54727	4.493462	2.57	0.010
DOMCOINS	-.0185463	.0049003	-3.78	0.000
BLACK	-.0941705	.0778923	-1.21	0.227
ASIAN	-.1215386	.0681006	-1.78	0.074
LQMADOM	.3849464	.1208167	3.19	0.001
LQBKDOM	.5468064	.1399507	3.91	0.000



LQPBDOM		.8236004	.2021215	4.07	0.000
SCIENCE		.1813289	.0564786	3.21	0.001
SOCSCIE		.0354023	.0464192	0.76	0.446
ARTS		-.1904636	.0636439	-2.99	0.003
SPONSOR		.0006962	.0000421	16.53	0.000
EACTDOM		.0069272	.0090594	0.76	0.444
CONST		-2.697393	.9271718	-2.91	0.004

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### Hausman tests of IIA assumption

Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted		chi2	df	P>chi2	evidence
RET		497.134	66	0.000	against Ho
UNI		287.707	66	0.000	against Ho
LATE		500.884	66	0.000	against Ho
NONMIG		723.312	64	0.000	against Ho

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### Small-Hsiao tests of IIA assumption

Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted		lnL(full)	lnL(omit)	chi2	df	P>chi2	evidence
RET		-3.62e+04	-3.61e+04	76.070	26	0.000	against Ho
UNI		-2.18e+04	-2.18e+04	117.669	26	0.000	against Ho
LATE		-3.10e+04	-3.10e+04	70.723	26	0.000	against Ho
NONMIG		-2.57e+04	-2.56e+04	265.157	26	0.000	against Ho

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**Table 4a Migration away from University to Employment: Dichotomous Logit Model**

Logit estimates  
 Log likelihood = -145057.09

Number of obs = 383574  
 LR chi2(26) = 10678.69  
 Prob > chi2 = 0.0000  
 Pseudo R2 = 0.0355

secmig	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
GENNUM	-.1457649	.0110405	-13.20	0.000	-.1674039	-.1241259
UG	-.2492106	.0207431	-12.01	0.000	-.2898664	-.2085548
FIRST	.4550317	.0251315	18.11	0.000	.4057748	.5042886
TWOONE	.3009256	.0178755	16.83	0.000	.2658903	.3359609
TWOIWO	.0824726	.0185704	4.44	0.000	.0460753	.1188699
THIRD	-.1236304	.0280955	-4.40	0.000	-.1786967	-.0685642
WALESDOM	-.1993635	.0393658	-5.06	0.000	-.276519	-.1222208
SCOTDOM	-.4858531	.0406766	-11.94	0.000	-.5655777	-.4061285
RAEINDEX	.0295109	.0122615	2.41	0.016	.0054788	.053543
PDNDOM	-.000039	.0000113	-3.44	0.001	-.0000612	-.0000168
AGE	-.000364	.0002004	-1.82	0.069	-.0007568	.0000289
SIC8MALE	.1068868	.0207437	5.15	0.000	.0662298	.1475437
DLONDON	-.000332	.0000747	-4.45	0.000	-.0004783	-.0001857
UEDOM	-2.773459	1.005449	-2.76	0.006	-4.744103	-.8028145
BLACK	-.1393854	.0330797	-4.21	0.000	-.2042205	-.0745504
ASIAN	-.1019867	.0240563	-4.24	0.000	-.1491361	-.0548372
LQMADOM	.0369708	.027241	1.36	0.175	-.0164207	.0903622
LQBKDOM	.042976	.0327116	1.31	0.189	-.0211376	.1070896
LQPBDM	-.0369063	.0498374	-0.74	0.459	-.1345857	.0607732
SCIENCE	.110852	.015848	6.99	0.000	.0797905	.1419135
SOCSCIE	.1108817	.012794	8.67	0.000	.0858059	.1359574
ARTS	-.2083521	.0157056	-13.27	0.000	-.2391346	-.1775696
SPONSORS	.0005181	.0000127	40.88	0.000	.0004933	.0005429
EACTDOM	-.0055019	.0026986	-2.04	0.041	-.0107911	-.0002126
DOMCOINS	-.0056014	.0021333	-2.63	0.009	-.0097826	-.0014201
PREVMIGR	.9130011	.0150241	60.77	0.000	.8835544	.9424478
_cons	-1.909666	.2608517	-7.32	0.000	-2.420926	-1.398406

**Table 4b Migration away from Domicile to Employment: Dichotomous Logit Model**

Iteration 0: log likelihood = -176848.49  
 Iteration 1: log likelihood = -168457.49  
 Iteration 2: log likelihood = -167757.06  
 Iteration 3: log likelihood = -167736.96  
 Iteration 4: log likelihood = -167736.93

Logit estimates  
 Log likelihood = -167736.93

Number of obs = 383574  
 LR chi2(26) = 18223.13  
 Prob > chi2 = 0.0000  
 Pseudo R2 = 0.0515

secmig	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
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PREVMI G	1. 545571	. 0156789	98. 58	0. 000	1. 514841	1. 576301
GENNUM	-. 1680634	. 009913	-16. 95	0. 000	-. 1874925	-. 1486342
UG	. 2467461	. 0175796	14. 04	0. 000	. 2122907	. 2812014
FI RST	. 0216631	. 0214097	1. 01	0. 312	-. 0202991	. 0636253
TWOONE	-. 2203168	. 0143968	-15. 30	0. 000	-. 248534	-. 1920997
TWOTWO	-. 4565114	. 0151065	-30. 22	0. 000	-. 4861195	-. 4269032
THI RD	-. 5970086	. 0241683	-24. 70	0. 000	-. 6443777	-. 5496396
WALESDOM	-. 1343182	. 0348447	-3. 85	0. 000	-. 2026125	-. 0660239
SCOTDOM	-. 4835342	. 0356921	-13. 55	0. 000	-. 5534894	-. 413579
RAEI NDEX	. 0175648	. 0111041	1. 58	0. 114	-. 0041989	. 0393286
PDNDOM	-. 0000225	. 0000102	-2. 21	0. 027	-. 0000425	-2. 57e-06
AGE	-. 0005078	. 0001696	-3. 00	0. 003	-. 0008402	-. 0001755
SIC8MALE	. 2414362	. 0188844	12. 78	0. 000	. 2044234	. 2784489
DLONDON	-. 0001738	. 0000669	-2. 60	0. 009	-. 0003049	-. 0000427
UEDOM	-2. 05884	. 9167803	-2. 25	0. 025	-3. 855696	-. 2619835
DOMCOI NS	-. 0037729	. 0019086	-1. 98	0. 048	-. 0075136	-. 0000322
BLACK	-. 0283595	. 0287239	-0. 99	0. 323	-. 0846573	. 0279383
ASI AN	. 0351444	. 0206169	1. 70	0. 088	-. 005264	. 0755527
LQVADOM	. 0886025	. 0243817	3. 63	0. 000	. 0408152	. 1363897
LQBKDOM	. 0514624	. 0296228	1. 74	0. 082	-. 0065973	. 109522
LQPBDOM	. 0666505	. 0449222	1. 48	0. 138	-. 0213955	. 1546965
SCI ENCE	. 1832909	. 0142154	12. 89	0. 000	. 1554293	. 2111525
SOCSCIE	. 1434999	. 0115731	12. 40	0. 000	. 1208169	. 1661829
ARTS	-. 1818723	. 0140831	-12. 91	0. 000	-. 2094747	-. 1542699
SPONSORS	-. 0001325	. 0000101	-13. 07	0. 000	-. 0001523	-. 0001126
EACTDOM	-. 0040586	. 002427	-1. 67	0. 094	-. 0088155	. 0006982
_cons	-2. 679453	. 2356535	-11. 37	0. 000	-3. 141326	-2. 217581

**Table 5: Sequential Migration Types: Conditional Logit Model**

Number of valid observations = 94768  
 Prob > chi2 = 0.0000  
 Pseudo R-squared = 0.2744

choice	Coef.	Std. Err.	z	P> z
SALINDEX	.362595	.0798954	4.54	0.000
RETURN	-2.509723	.1438197	-17.45	0.000
UNISTAY	-1.084818	.0633673	-17.12	0.000
LATEMIG	-2.746526	.1156768	-23.74	0.000
ASIAN*RET	-.2488497	.2334395	-1.07	0.286
ASIAN*UNI	.3375733	.079795	4.23	0.000
ASIAN*LAT	.6762392	.1221877	5.53	0.000
BLACK*RET	.1466898	.3484794	0.42	0.674
BLACK*UNI	.1555116	.1447514	1.07	0.283
BLACK*LAT	.4467005	.2264066	1.97	0.048
GEND*RET	.2544593	.0716179	3.55	0.000
GEND*UNI	.2976322	.0286704	10.38	0.000
GEND*LAT	.1854708	.0515099	3.60	0.000
AGE*RET	.0102216	.002578	3.97	0.000
AGE*UNI	.0013599	.0013037	1.04	0.297
AGE*LAT	.0104713	.0024727	4.23	0.000
GRADE*RET	-.2143433	.047518	-4.51	0.000
GRADE*UNI	.181992	.0194245	9.37	0.000
GRADE*LAT	.1560679	.0348773	4.47	0.000

**Hausman's test for assumption "Independence of Irrelevant Alternatives"**

Category	groups	#obs	Hausman	df	p
UniStayer	10914	32742	-59.00	4	1.0000
LateMig	10067	30201	0.00	4	1.0000
RepeatMig	2617	7851	0.00	5	1.0000
ReturnMig	9144	27432	0.00	3	1.0000