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# Migration and inter-industry mobility of UK graduates: Effect on earnings and career satisfaction

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## **Abstract**

Career progression is often associated with migration and/or industry change, but the relationship between the two, and their effect on the earnings and career satisfaction of recent graduates are not well understood. We analyse the relationship between migration and inter-industry mobility using longitudinal microdata on 5,000 recent UK graduates who finished their studies in 2002/03, and who were surveyed 6 months and 3 ½ years after graduation. We define migration as a move of more than 15 km from the location of employment, and analyse the effects of a locational move in conjunction, or in the absence of, a change in industry. We allow for the possibility of selection bias, whereby unobservable characteristics may lead graduates to both change their location and/or industry, and earn a higher or lower salary, by estimating a treatment effects model with multinomial choice. Our results indicate that the effect on both earnings and career satisfaction of a change in location is positive, and there is a strong negative effect associated with changing both location and industry. The results also show that the subject of study is an important determinant of both migration choice and career outcomes for UK graduates.

**Keywords:** Inter-regional migration, earnings, personal characteristics, self-selection, treatment effects, graduates.

## 1. Introduction

University graduates are a special category of job seekers in that they are highly educated and, as the literature on graduation migration has shown, also highly mobile (Whisler et al., 2008; Faggian and McCann, 2009). In a study based on longitudinal data for graduating classes from the late 1970s to the early 1990s, Kodrzycki (2001) finds that college graduates are at least twice as likely to move from the US state where they attended college or high school than young adults with fewer years of schooling. These characteristics mean that graduates are particularly interesting for the analysis of regional economic growth. For instance, Faggian and McCann (2006) show that universities can act as a conduit to attract human capital into a region, while Abel and Deitz (2009) find that colleges and universities help raise human capital levels by increasing both the supply and demand for skilled labour. This occurs as universities tilt the structure of local labour markets towards occupations that are more human capital intensive (Beeson and Montgomery, 1993; Abel and Deitz, 2009).

There is also a great deal of policy interest in the career paths of graduates, particularly in the light of recent government policy on higher education in the UK. Following the significant expansion in higher education provision in the 1990s, the then Department for Education and Skills (DfES) commissioned a survey on the career paths of graduates, entitled the “Class of ‘99” (Purcell et al., 2005). The authors find that, immediately after graduation, almost half of the 1998/99 cohort were working in non-graduate occupations, that is, occupations that do not require a graduate degree, although this proportion fell to 15% four years after graduation.<sup>1</sup> There is also a mismatch between the subject studied and the field of work; a recent study by the Chartered Institute of Personnel and Development (CIPD) shows that 46% of the graduates are currently working in a field different from the one for which they are qualified (CIPD, 2010).

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<sup>1</sup> These are defined on the basis of the 2000 version of the Standard Occupational Classification (SOC2000). They include occupations for which employers have traditionally required a degree (solicitors, doctors, scientists, secondary school teachers), modern graduate occupations (IT professionals, senior managers in large organisations), jobs for which graduates are being increasingly recruited in large numbers (occupational therapists, surveyors, management consultants), and ‘niche’ graduate occupations (planning and quality control managers, hotel managers and nurses). The jobs include generally cover managers, senior officials, professionals, associate professionals and technical workers. See Elias and Purcell (2004) for a detailed description.

The difficulties encountered by new graduates have been found to be highly subject specific. For instance, recent research on creative arts graduates shows that many struggle to find a graduate-level job outside of the creative sector (only 49% achieve this), while earnings are less than those of other graduates in both the creative and non-creative sectors (Comunian et al., 2010), a situation that persists into the medium term (Abreu et al., 2011). The DfES analysis also found that career paths are strongly related to subject studied; the percentage of graduates in non-graduate occupations is lower in medicine, education and engineering, and higher in the arts and humanities.

These findings raise interesting issues regarding the sources of variation in the career paths of graduates, such as how do migration and/or a change in industry of employment help to shape graduate earnings and career prospects, and how do personal characteristics such as age, gender, ethnicity and degree characteristics affect this choice. So far there has been little research on graduate migration in conjunction with industry change, other than the descriptive analyses discussed above. This is also true of the literature on migration more generally; few studies have extended the migration framework to incorporate both locational and industry change, Gallaway (1969), Nakosteen and Zimmer (1982), Shaw (1991) and Krieg (1997) being notable exceptions.

This paper extends the existing literature on graduate migration in three ways. First, we study the impact of both migration and industry change on the career outcomes of recent graduates, and analyse how personal characteristics affect both the migration strategy and the outcomes. Second, we move beyond a focus on monetary rewards to also consider the effects of migration and industry change on career satisfaction, which has been shown to be an important consideration for highly skilled workers (Mathios, 1989). Third, we allow for sample selection in both migration and industry change and estimate a multinomial treatment effects model (Deb and Trivedi, 2006). Our aim is allow for the possibility that migrants who change industry differ from migrants who do not change industry in ways that also affect their subsequent earnings and career satisfaction, an issue first raised by Gallaway (1969). The only similar approach to ours is Nakosteen and Zimmer (1982), who also allow for double selection according to migration and industry change, but assume that the industry change precedes (and is a determinant of) migration, rather than treating the choice as simultaneous. We also use a latent factor approach to

allow for selection in both observable and unobservable characteristics (see also Nakosteen et al., 2008, although their latent factor model is used in a different context).

The remainder of the paper is organised as follows: Section 2 discusses the previous literature and presents our conceptual framework. Section 3 details our methods and data. The descriptive and regressions results are presented in Sections 4 and 5, and Section 6 concludes.

## 2. Previous literature and conceptual issues

The literature on migration has largely abstracted from the issue of inter-industry mobility, despite significant evidence to suggest that many migratory moves also involve a change in industry of employment (Greenwood, 1975). The consequences of ignoring this issue are highlighted by Gallaway (1969) in a comment on an earlier article by Lansing and Morgan (1967), who had found that geographically mobile workers had lower incomes than non-mobile workers, contradicting the human capital model of migration (Sjaastad, 1962). Gallaway (1969) shows that the wages of migrants are higher than those of non-migrants if one treats industry movers and stayers as separate groups. He shows that the lower earnings for migrants observed by Lansing and Morgan (1967) are due to the lower wages of industry-movers, who make up a large proportion of migrant workers, and concludes that this is a reflection of the lower productivity and involuntary turnover experienced by industry-movers. This finding is supported by other studies on occupational mobility, which show that industry changes lead to lower earnings, unless they occur within certain high-tech sector such as the semi-conductor industry (Ong and Mar, 1992). This can be interpreted as representing a loss in the value of sector-specific skills and information, or alternatively as the loss of employer-specific advantages such as incentive pay schemes (Kletzer, 1996).

A few studies have attempted to further disentangle these findings and analyse the combined effects of industry change and migration on earnings, using multivariate techniques. Industry change can be conceptualised, following the Sjaastad (1962) approach to migration, as an investment in human capital, with industry-movers obtaining higher expected lifetime returns (after controlling for switching costs) from working in a different industry. All studies in the literature start from this premise, but differ in their treatment of the first stage migration equation,

particularly in the choice of migration categories (some also control for employer and occupational change), and in how they deal with the selectivity bias highlighted by Gallaway (1969).

A first set of studies include dummy variables representing the different migration categories in a post-move wage equation, while controlling for selectivity bias. This is a treatment effects model, which is also the approach followed in this paper. For instance, Krieg (1997) include a dummy variable for locational change in the earnings equation, and allow for selectivity in terms of locational change only. The effect of simultaneous changes in occupation and/or employer are then assessed using interaction terms with the selectivity-corrected migration dummy, and the authors find that a simultaneous change in location, occupation and employer has a significantly negative effect on earnings three years after migration. However, this approach does not control for selectivity in both migration and industry change, and it is likely the coefficients are affected by selectivity bias in the latter.

A second approach is based on an endogenous switching model, with a first stage that involves estimating a migration choice model, and a second stage that estimates earnings equation for each of the groups in the migration choice model. The selectivity is controlled for by allowing the error terms of the first stage of the model to be correlated with the error terms of the second stage (the outcome equation). Nakosteen and Zimmer (1982) estimate an endogenous switching model with double selection, where the first stage is composed of two equations, one for migration change and one for industry change. They assume that the decision on industry change precedes that on migration and affects the decision to migrate. The second stage of the model then estimates earnings equations for the four types of individuals (Non-migrants, Industry Migrants, Region Migrants and Industry/Region Migrants). Their results strongly support the hypothesis of selection in both migration and industry change, and in the first stage they find that women are less likely to move industry or migrate, while ethnic minorities are more likely than white individuals to change industry, but less likely to migrate. A similar approach, although one that is based on the Heckman two-step sample selection model, is used by Shaw (1991), who finds that “movers” in terms of industry and location are well-educated workers who are seeking good job matches with employers.

While the endogenous switching approach is useful for understanding the underlying differences in the coefficients of the earnings equation for different groups of workers, our focus is on estimating the returns to migration and/or industry change in a Mincer model of earnings (extended to cover career satisfaction). Moreover, the endogenous switching approach is computationally demanding when the first stage involves a polychotomous choice (Maddala, 1983, 275-278). We therefore use the treatment effects approach but allow the first stage choice model to be of a multinomial nature, with individuals choosing between four migration categories (based on change in location and/or industry of employment).

### 3. Data and methods

Our empirical strategy allows for the possibility that unobservable characteristics that lead an individual to choose migration and/or industry change will also affect their subsequent (post-migration) salary and career satisfaction. We therefore estimate a model composed of two stages; the first stage follows the literature in treating migration and industry change as investments in human capital, while the second stage is based on a Mincer-type model of earnings.

#### 3.1 Model specification

In the first stage of the model, the individual chooses a migration strategy out of four mutually exclusive choices, namely to stay at the current location and in the current industry (“No change”), to move to a new location but remain in the same industry (“Location only”), to change industry but remain at the same location (“Industry only”) or to change both location and industry (“Both”). Let  $V_{ij}^*$  denote the indirect utility associated with the  $j$ th treatment,  $j=0,1,\dots, J$  and:

$$V_{ij}^* = \mathbf{z}'_i \alpha_j + \sum_{k=1}^J \delta_{jk} l_{ik} + \eta_{ij}, \quad (1)$$

where  $\mathbf{z}_i$  is a set of exogenous covariates with associated parameters  $\alpha_j$ , and  $\eta_{ij}$  are i.i.d. error terms. The indirect utility  $V_{ij}^*$  is also a function of unobserved characteristics that are common to the individual's migration strategy and outcome (salary and career satisfaction), such as entrepreneurial spirit, captured by the latent factors  $l_{ik}$ , which are assumed to be independent of  $\eta_{ij}$ . Without loss of generality, let  $j = 0$  denote the control group and  $V_{i0}^* = 0$ .

While  $V_{ij}^*$  is not observed, we do observe the choice of migration strategy in the form of a set of binary variables  $d_j$ . These are collected into a vector  $\mathbf{d}_i = [d_{i1}, d_{i2}, \dots, d_{iJ}]$ . We follow Deb and Trivedi (2006) in assuming that the probability of selecting a given migration strategy, conditional on the latent factors, has a Mixed Multinomial Logit structure:

$$\Pr(\mathbf{d}_i | \mathbf{z}_i, \mathbf{l}_i) = \frac{\exp(\mathbf{z}'_i \alpha_j + l_{ij})}{1 + \sum_{k=1}^J \exp(\mathbf{z}'_i \alpha_k + l_{ik})}, \quad (2)$$

where  $j = 0, 1, 2, \dots, J$ .

The outcome equation explains the career situation of an individual 3 ½ years after graduation, and we use two outcome variables, the natural logarithm of the annual salary in 2006 (deflated to 2004 prices using the Average Earnings Index), and a binary variable to indicate whether the graduate is “very satisfied” with their career at the time of the second survey.<sup>2</sup> The expected value of the outcome variable is given by:

$$E(y_i | \mathbf{d}_i, \mathbf{x}_i, \mathbf{l}_i) = \mathbf{x}'_i \beta + \sum_{j=1}^J \gamma_j d_{ij} + \sum_{j=1}^J \lambda_j l_{ij}, \quad (3)$$

where  $\mathbf{x}_i$  is a set of exogenous covariates with associated parameter vector  $\beta$ , and  $\gamma_j$  is a vector of treatment effects relative to the control choice (“None”). Because  $E(y_i)$  is a function of the latent

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<sup>2</sup> The variable used for career satisfaction implies that all other responses, including “fairly satisfied”, “not very satisfied” and “not at all satisfied” are grouped together. The reason is that we find that the distinction between “very satisfied” and “fairly satisfied” has the greatest explanatory power, with very few respondents choosing “not very satisfied” and “not at all satisfied”. We also want to capture good career outcomes, so “very satisfied” is an obvious choice.



factors  $l_{ij}$ , the outcome is affected by the unobserved characteristics that also affect selection into the treatment. We assume that the outcome variables, the natural logarithm of salary in 2006, and the binary variable indicating whether an individual is “very satisfied” with his/her career, follow a normal distribution, i.e., in the case of the binary variable we estimate the second stage using a Probit model.

As noted in Deb and Trivedi (2006), and discussed in Walker et al. (2004) and Maddala (1983), identification of the model requires that the scale of each choice equation be normalised, if restrictions are not to be placed on the parameters or intercepts. In addition, the covariance between the errors of the choice equations needs to be fixed. This is achieved by imposing a set of normalisation restrictions  $\delta_{jk} = 0$  for all  $j \neq k$ , that is, each choice is affected by a unique latent factor. In addition, we restrict the coefficients so that  $\delta_{jj}=1$  for all  $j$  in order to normalise the scale of each choice equation. The resulting model can be estimated using a Maximum Simulated Likelihood (MSL) approach.<sup>3</sup> While it is not strictly necessary that the vector of covariates  $\mathbf{z}_i$  includes additional variables relative to  $\mathbf{x}_i$  for the model to be identified, we include three exclusion restrictions, discussed in detail in Section 3.3.

## 3.2 Data

The analysis is based on data collected by the Higher Education Statistical Agency (HESA) on students who graduated from UK higher education institutions (HEIs) at the end of the academic year 2002/03. The analysis is based on three data streams, the Students in Higher Education Institutions, the Destinations of Leavers from Higher Education (DLHE), and the Longitudinal Destinations of Leavers from Higher Education (LDHLE).

The 2002/03 Students in Higher Education Institutions is an administrative data set containing records on all 2,362,815 students enrolled in UK HEIs (169 institutions) during the 2002/03 academic year. For each student the records provide information on personal characteristics (such

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<sup>3</sup> The model was estimated using the `mtreatreg` command in Stata (available by typing “net search mtreatreg”), an extension of the `treatreg` command to a multinomial setting, created by Partha Deb, Hunter College, CUNY.

as age, gender, ethnicity), course characteristics, and the location of parental domicile (at the postcode level ).

In addition, HESA undertakes a yearly DLHE survey to gather information on employment circumstances of graduates six months after graduation; the survey is sent to all UK-domiciled graduates of the previous academic year. It contains information on employment circumstances (full-time, part-time, self-employed, in higher education), annual salary, the sector of employment (4 digit SIC code), the occupation code of his/her job (SOC code) and the location of employment. In the 2002/03 survey, 307,652 valid responses were returned by UK-domiciled graduates, achieving a response rate of 75%.

In 2006 HESA also commissioned a follow-up survey, sending more detailed questionnaires to a sample of the graduates who had responded to the 2002/03 DLHE survey, approximately three years after the original survey. The sample included a higher proportion of graduates of black, mixed and other ethnic backgrounds, as well as a higher proportion of graduates with foundation degrees, graduates who had received research council funding, graduates domiciled in Northern Ireland, Scotland and Wales, and teacher training and health-care graduates. The LDLHE survey was sent to a 20% sample of the original cohort, and achieved 24,823 valid responses, corresponding to a 40% response rate (or 8% of the original cohort).<sup>4</sup> The analysis is based on recent graduates who are employed (full-time or part-time), self-employed or doing voluntary work, for whom salary information is available both in January 2004 (via the DLHE survey) and November 2006 (via the LDLHE survey). Since salary, industry and location information is only available for those who fall into these categories, the analysis is based on a sample of 7,060 individuals.<sup>5</sup>

We define migration using a distance-based measure, so that individuals who move beyond a given distance threshold are taken to be migrants. Since the Students in Higher Education Institutions data is based on administrative data, we have the full postcode of place of domicile

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<sup>4</sup> All the descriptive statistics and regressions presented in the paper are weighted to adjust for the over-sampling of these sub-groups, using sampling weights and other information provided by HESA.

<sup>5</sup> Unemployment rates for graduates are relatively low, of the students in the 2002/03 cohort who responded to the surveys, 5.2% were unemployed six months after graduation, and only 2.6 were unemployed 3 ½ years after graduation.

and of the higher education institution for all students in the data set. For the two surveys, however, we have less precise information. Of the respondents to the DLHE who provided information on the location on their place of work, only 29% provided the full postcode, with the remainder providing only the postcode district. In the case of the LDLHE survey only the postal district was recorded for all respondents who filled in this question. In order to maintain consistency between the various stages of the analysis, we define migration as a move of more than 15km from the centroid of the postal district of the respondent's place of work. The choice of threshold distance is based on Faggian et al. (2006), who find that a radius of 15km is appropriate to capture most urban areas in the UK.

In terms of sector mobility, we follow the UK Standard Classification of Economic Activities 2003, and focus on the 2 digit SIC code (or division), comprising a medium level of disaggregation, e.g., Manufacture of Textiles. However, we are interested in how the results vary with the level of industry aggregation, and we also report the findings for the 1, 3 and 4 digit SIC code levels for comparison purposes. These refer to the section (e.g., Manufacturing), through to the group (e.g., Manufacture of other Textiles), and class (e.g., Manufacture of Carpets and Rugs).

### 3.3 Variables included in the analysis

Our analysis ultimately seeks to explain earnings and career satisfaction for recent graduates, 3 ½ years after graduation, as a function of personal characteristics, type of university, course attended and subject studied while controlling for the effects of a change in location or industry, given possible selectivity into this choice. We estimate Mincer-type model (Mincer, 1974; Heckman et al., 2006; Lemieux, 2006) and include the following variables as covariates in  $x_i$  (see Eq. 3):

- *Female*: A dummy variable to indicate whether the respondent is female, in order to control for differences in salary and career satisfaction between male and female graduates. While we cannot directly measure sex discrimination, the coefficient in the salary model gives an indication of whether female graduates tend to earn lower salaries. The coefficient with respect to career

satisfaction may be different; previous research has found that female graduates are more altruistic and value their job environments more relative to their male counterparts (Chevalier, 2007).

- *Age and Age (sq)*: In traditional Mincer equations it is generally assumed that (log) earnings are a non-linear function of experience, which is typically measured using age minus years of schooling minus five (the school starting age). In our case, however, we do not have information on the total years of schooling, since we only know the degree awarded to each graduate and the year they started that particular course. We do not know how long each graduate studied before entering the course they graduated from in 2002/03. In order to avoid introducing additional measurement error, we therefore use age and age squared as proxies for experience.

- *Ethnicity*: We control for the ethnicity of the respondent by using dummy variables to indicate whether he/she is white, black, Asian or of other ethnicity. Although (as with gender) we cannot explicitly test for racial discrimination, the coefficient does give an indication of the differences in salary and career satisfaction of non-white graduates relative to those of white graduates.

- *Type of university*: We control for differences in human capital by using a series of dummy variables to capture the quality and type of the degree course. In particular, we control for the type of university attended by classifying higher education institutions into four categories: Russell Group and 1994 Group (research-intensive universities), other old universities, post-1992 institutions (former polytechnics and new universities), and specialised colleges. We merge the Russell and 1994 groups because several institutions that were part of the 1994 Group in 2002/03 subsequently became part of the Russell Group, so that it is difficult to distinguish between them. This set of variables is intended to act a rough measure of quality (Hussain et al., 2009).

- *Type of degree*: The analysis includes all students who were enrolled in first or higher degrees (but excluding further education and other vocational courses), who graduated in the 2002/03 academic year. We include both undergraduate and postgraduate students in order to test the advantage in terms of earnings and career satisfaction of studying to a postgraduate level, after

controlling for subject and other characteristics.<sup>6</sup> The type of degree is classified into undergraduate degrees, postgraduate degrees and other first degrees (e.g., undergraduate diploma or professional qualification). This set of dummy variables intends to capture the Mincerian schooling effect (Psacharopoulos, 1994), and we would expect higher level degrees to lead to higher wages and greater career satisfaction.

- *Subject*: We include the subject of study in the form of nine dummy variables capturing broad subject areas (health sciences, biological sciences, physical sciences, social sciences, business, humanities, creative arts and combined courses). The motivation is that different subjects can lead to different levels of salary and job satisfaction after graduation, after controlling for the type of university, degree and personal characteristics (Machin and Puhani, 2003).

- *Change in location or industry*: The remaining variables are the treatment effect dummies, capturing whether a change in location (“Location only”), a change in industry (“Industry only”) or a change in both location and industry (“Both”), relative to the base category (“No change”), results in higher salary and career satisfaction levels, after accounting for selectivity into the choice of migration strategy.

While these covariates are taken from the Mincer earnings model literature, they are also appropriate to model career satisfaction as an alternative measure of success 3 ½ years after graduation. This alternative measure is inspired by the literature on the career paths of artists and arts graduates, who are frequently motivated by non-monetary incentives (Abbing, 2002; Comunian et al., 2010; Abreu et al., 2011). The models using the natural logarithm of salary and career satisfaction are therefore estimated using the same set of covariates  $x_i$ .

Now turning to the first stage of the estimation process, our model includes most of the variables of the second stage (with the exception of the treatment effects), and three additional exclusion restrictions to aid identification. However, the motivation for including the variables, and hence

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<sup>6</sup> Because we include both first degree and postgraduate students we are unable to use degree classification as an explanatory variable, since it is not available for all degree types.

the interpretation of the coefficients, is different from that in the outcome regressions. The following variables are included in  $\mathbf{z}_i$  (see Eq. 1):

- *Female*: We control for gender by including a dummy variable for female graduates. The literature on migration has generally considered the issue of gender only in connection with tied moves of couples or households. However, a few studies have recently analysed the issue more explicitly. Faggian et al. (2007) find that women are in general less migratory, but if female graduates do migrate, they are more likely to migrate repeatedly, a finding supported by Schneider and Kubis (2009). However, in the case of industry or occupational analysis, the literature has generally found that women are less likely to change job or industry (Nakosteen and Zimmer, 1982; Linneman and Graves, 1983). We investigate the effect of gender on both location and industry change.

- *Age and Age (sq)*: The cost of migration is greater for older workers, who are generally more settled in their current location and therefore have higher psychic costs of migration, and for whom the benefits are lower since the lengths of their working lives, over which the benefits are accrued, are shorter. The literature has found that age is a strong negative determinant of migration. We control for the effect of age on migration by include age (in years), and also age squared, to allow for non-linearities.

- *Ethnicity*: The literature has generally found that ethnic minorities tend to have lower migration propensities, perhaps due to lower access to information (which increases search costs), more limited resources to move, or because they may face discrimination at the destination (Faggian et al., 2006; Lee and Roseman, 1997; White and Wolaver, 2006). In terms of industry change, Nakosteen and Zimmer (1982) find that non-white workers are more likely to change industry than their white counterparts, but there is no statistically significant effect on locational change (although the coefficient is negative). We test the effect of ethnicity on the propensity to migrate by including ethnicity dummies (black, Asian, and other ethnicity).

- *Type of university*: The human capital model of migration predicts that individuals with higher human capital are more mobile, since the benefits from migration are greater (Sjaastad, 1962).

The search costs for educated workers are also greater than for less educated individuals; this applies in particular to those who attend elite institutions and as a result have greater access to influential networks. In the absence of a robust measure of years of schooling we use three variables to account for human capital in the analysis, the type of university attended (Russell or 1994 Group, other old university, post 1992 university or specialised college), the type of degree achieved (undergraduate, postgraduate or other first degree), and the subject studied.

- *Type of degree*: We use the type of degree achieved to control for human capital (see previous).

- *Subject*: We use dummies for the subject studied to account for human capital, but also to control for the unique career paths of certain subjects such as education and the health sciences, where graduates spend a period of additional training in a local school or hospital, which limits locational and industry change in the period immediately following graduation.

In addition, we include three exclusion restrictions to help with identification. They are intended as instruments for the migration variable in the outcome regressions. We use three variables:

- *Migrated to attend university*: Whether the respondent migrated to attend university, or not. We define migration in this context as a move beyond the boundaries of the Local Authority District or Unitary Authority (LAD/UA) of their place of domicile. The literature on migration has shown that previous migratory moves are highly correlated with subsequent moves, and after controlling for the type of university attended and the degree awarded, we would not expect to see a direct effect on salary or career satisfaction 3 ½ years after graduation, except indirectly via the subsequent choice of migration strategy.

- *Migrated after graduation*: Whether respondent migrated from the region of study within 6 months of graduation, where migration is again defined by a move from the LAD/UA of the institution. This variable is also highly correlated with subsequent migration, and as before, once we control for personal characteristics, human capital and the nature of the first job after graduation (see below), we would not expect to see an effect on salary or career satisfaction 3 ½ years after graduation, except indirectly via the propensity to change location or industry.

- *First job required degree*: We include this variable to capture whether the qualification obtained was a requirement for the first job obtained after graduation (either because it was a formal requirement, because it was expected, or because it provided an advantage). This is intended to capture whether the first job after graduation was a graduate-level job, with in turn affects the probability of a corrective locational or industry change later on. We expect this variable to have no direct impact on salary or career satisfaction, except through its effect on migration strategy.

The three variables perform well in the first stage of the model, as shown in Table A1 (in the Appendix). With “None” as the base category in a Multinomial Logit model of migration choice, the variables are jointly significant in all three equations of the model. This holds for all levels of industry disaggregation. Although no equivalent of the overidentifying restrictions test has been developed for this empirical framework, the instruments perform well when used in a test based on a linear IV framework using a GMM approach (Table A2). Hansen’s J test statistic is not significant for either of the two outcome variables, at any level of industry disaggregation (Hansen, 1982).

#### 4. Descriptive statistics

In order to provide an overview of the relationships analysed in the multivariate model, we first present some descriptive statistics for the percentage of graduates in our sample who changed location and/or industry between 6 months and 3 ½ years after graduation, and their career outcomes.<sup>7</sup> We are primarily interested in the results where industry is defined at the 2 digit SIC code level (in keeping with the previous literature), but will also present and discuss results for other levels of sectoral disaggregation, for comparison purposes.

The percentages of graduates in each migration category are given in Table 1. We focus on the second column of Table 1, which shows the proportions in each category for 2 digit SIC code industries. The base category is no location or industry change (“None”), and 43% of graduates

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<sup>7</sup> The DLHE and LDLHE survey dates were 15 January 2004 and 27 November 2006, respectively, for the cohort of students who graduated in 2002/03. All descriptive are weighted using survey sampling weights.



fall into this category, while a further 23% also remain at the same location, but change industry. Of those graduates who migrate, 52% also change industry, a figure that is very close to the 56% found by Gallaway (1969). This contrasts significantly with the 35% of the non-migrants who change industry. As we vary the sectoral definition and the level of sectoral aggregation becomes more narrow (as we move from left to right in Table 1), a larger proportion of graduates in each migration category is shown to have changed industry. This holds for both migrants and non-migrants, and simply shows that more graduates change narrow sector than broad sector.

The policy reports discussed in Section 1 show that the propensity to change industry is highly subject-specific, and this can also be seen in Table 2. Graduates from the physical sciences, business and the creative arts are the most likely to change industry at the 2 digit SIC code, while those in the health sciences and education are the least likely to change. This is probably linked to the specialised nature of the training received in the latter subjects, and the difficulties involved in applying that training to other occupations. As we move to a more narrow definition at the 4 digit SIC code these large gaps largely disappear.

Tables 3-5 show basic descriptive statistics for the dependent variables used in the multivariate models. Tables 3-4 show the mean and median salaries for graduates in each migration category at 6 months and 3 ½ years after graduation (the 2006 salaries have been deflated to make them comparable to the 2004 salaries). The most successful category of graduates at 6 months are those who will subsequently change location, while the least successful are those who will change both industry and location and those who will change industry. This result remains unchanged after 3 ½ years, with those who changed location and those who remained in the same location and industry being the most successful. The findings also indicate that there is a degree of selectivity in the migration decision, and that those who change industry (either in the same location or through a move to another location) remain at a disadvantage 3 ½ years after graduation. Table 5, showing the same indicators for the variable for career satisfaction, confirm this. Graduates who changed location or remained the same are more likely to be “very satisfied” with their careers than those who changed industry or changed both industry and location.<sup>8</sup>

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<sup>8</sup> The variable on career satisfaction is only available in the LDLHE survey at 3 ½ years after graduation, and not in the DLHE survey, so comparisons over time are not possible.

## 5. Regression results

The estimation results are shown in Tables 6-9. For each of the two dependent variables,  $\ln(\text{salary})$  and career satisfaction, we show the results corresponding to the 2 digit SIC code, and then discuss the implications of varying the definition of industry change (by changing the level of sectoral disaggregation).

### 5.1 Results on graduate earnings

Turning first to the model for  $\ln(\text{salary})$ , the results for the first stage of the model (corresponding to Eq. 2) are shown in the first three columns in Table 6, while the final column gives the results for the linear regression of  $\ln(\text{salary})$  (corresponding to Eq. 3). The coefficients in the first three columns report the relative risk ratios for each choice relative to the base category which is no change. The coefficients for gender and age are as expected. Being female decreases the odds of changing both location and industry by 40%, but does not affect the other options. Every additional year of age decreases the odds of changing industry by 13% and also decreases the odds of changing both industry and location by 21%.

The effect of the ethnicity differs for location and industry moves. Being of black ethnicity increases the odds of changing industry by 76%, but decreases the odds of changing location and also decreases the odds of changing both industry and location. A similar result holds for Asian minorities with respect to changing industry (it increases the odds relative to white graduates). These results indicate that black graduates are either more likely to resolve an unsatisfactory job match by changing industry rather than migrating. The latter would be in keeping with the literature on migration, which has found that ethnic minorities are less geographically mobile.

The results for type and quality of education show that having attended a Russell or 1994 group university reduces the odds for changing industry by 34%, as does attending a specialised college or having a postgraduate degree. This would suggest that a higher quality and more specialised education results in a better field of work match, reducing the likelihood of industry change.

Having a postgraduate degree or other first degree also lowers the odds of changing location, in keeping with the migration literature. The results for the subject of study are also as expected, with degrees in the health sciences or education lowering the odds of changing industry or of changing both industry and location, and a degree in business increasing the odds of changing both industry and location (since it provides skills suited to a wide range of industries and occupations).

The last three coefficients reported in Columns 1-3 of Table 6 correspond to the exclusion restrictions. The coefficients are also as expected; having migrated to university increases the odds of changing location or both location and industry by 76% and 68%, respectively, having migrated immediately after graduation increases the odds of a subsequent migration by 53%, and having had a job that required a degree (i.e., a graduate-level job) immediately after graduation reduces the odds of changing industry or both industry and location. This last result also supports the finding that a change in industry is a reaction to a mismatch between the degree course and the sector of employment.

Now turning to the second stage of the model, we estimate a linear regression model (Eq. 3) for the  $\ln(\text{salary})$  3 ½ years after graduation, using a Mincer equation approach. The model allows for selectivity into migration groups, based on both observable and unobservable characteristics. The results for gender and age are again as expected. Being female results in earnings that are 16% lower than those of male graduates, while every additional year of age (proxying for labour market experience) adds 4% to earnings. We find no effects of ethnicity on earnings after controlling for sample selection bias due to migration or industry change.

With respect to the education variables, having attended a Russell or 1994 Group university results in an 8% increase in earnings (relative to having attended an “other old university”), while a degree from a post-1992 university results in 6% lower earnings, and one from a specialised college in 7% lower earnings. Similarly, higher levels of education in the form of a postgraduate degree result in 18% higher earnings. In terms of the subject studied, a degree in the health sciences or business adds to earnings (in the order of 6% and 10%, respectively), and a degree in

the biological sciences, creative arts and education leads to lower earnings, with the effect being particularly strong for the creative arts (12% lower earnings).

The model allows us to estimate the return to different migration categories, relative to remaining in the same location and industry (“No change”). The results indicate that changing both industry and location (“Both”) results in a fall in earnings of 11%, while a change in location results in an increase in earnings of 9%. There is no statistically significant effect for a change in industry, although the coefficient is negative. The results suggest that changing both industry and location requires a greater period of adjustment than changing location only. The results also provide evidence of a positive selection in unobservables for graduates who change both industry and location, and of negative selection for those who change location only.

Finally, we run the same model at different levels of sectoral disaggregation; the results are shown in Table 7. As we move to more narrow categories there are more graduates who fall into the “Both” and “Industry only” categories, and fewer in the “Location only” and “None” categories. A move from left to right along Table 7 therefore picks up the effects of more subtle industry moves. The results indicate that the return to migration increases as categories become narrower. For the 4 digit SIC code the “Location only” group now includes those who stay within their narrow sector but migrate, and are therefore more likely to realise high returns to their education and industry-specific capital. The returns are in turn lower for those who change both industry and location. This group is now wider than before, including all the migrants who changed narrow job category, and is therefore likely to be picking up graduates who are not well matched to their jobs.

## 5.2 Results on career satisfaction

We next report on the results for the dependent variable measuring career satisfaction. We use a distinction between graduates who are “very satisfied” and all other categories in order to capture good career outcomes. The results for the first stage are virtually identical to those for the previous model, so we focus on the differences in the outcome regression.

Unlike in the previous model, gender or age do not seem to affect career satisfaction, but ethnicity does. Being of black, Asian or of other non-white ethnicity results in significantly lower levels of career satisfaction. There are no statistically significant effects for the quality of education variables, but the subject studied does affect career satisfaction, which is significantly lower for the creative arts, and significantly higher for education.

Finally, turning to the returns to migration variables, the results are very similar to those in the previous model. Changing both industry and location leads to lower levels of career satisfaction, while changing location only results in higher levels of career satisfaction. However, when varying the definition of industrial aggregation we find a few differences. Most notably, the coefficient for returns to a change in industry is statistically significant and negative when the model is run at the 3-4 digit SIC code levels. This implies that as we also consider people who changed narrow sector, we find that changing sector has a more negative effect on career satisfaction. It seems that changing narrow sector has a more negative impact on morale than changing broad sector, after controlling for selectivity effects.

The results also indicate positive selectivity for those who changed both location and industry, and negative selectivity for those who changed location only.

## 6. Conclusions

A small but growing literature has studied the determinants of graduate migration, but has not considered the determinants and outcomes of a simultaneous change in industry of employment. In this paper we address this issue explicitly, by estimating a multinomial treatment effects model with selectivity in both observable and unobservable characteristics. We consider two outcome variables, the salary and career satisfaction of graduates 3 ½ years after graduation.

Our results indicate that graduates who change location fare better than those who do not change location or industry, but those who change both location and industry do worse. In keeping with the literature on migration this could indicate that the costs and period of adjustment are greater for migratory moves that also involve career change. With respect to personal characteristics, we

find that female graduates are less likely to change both industry and location, and also earn lower salaries than their male counterparts. Moreover, we find that ethnicity has a substantial effect on migration strategy. We find that black graduates are more likely than white graduates to change industry, and less likely to migrate.

Our results also show that having a higher quality and more specialised education results in a lower likelihood to change industry, suggesting that the match between degree and field of work is a better one for more qualified graduates. The subject studied also significantly affects the likelihood of migration and the career outcome. For instance, business graduates, who are more flexible in their migration strategy, also earn higher salaries.

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## Tables

Table 1. Percentage of graduates who changed location and/or industry between 6 months and 3 ½ years after graduation

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Both	46.30	17.26	21.95	25.21
Industry only	21.94	23.08	34.73	42.47
Location only	17.32	16.21	11.52	8.27
None	44.45	43.45	31.79	24.06
<i>Total</i>	<i>100.00</i>	<i>100.00</i>	<i>100.00</i>	<i>100.00</i>

Table 2. Percentage of graduates who changed industry, by subject

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Health sciences	12.75	12.94	21.92	56.27
Biological sciences	48.62	50.78	67.63	73.70
Physical sciences	54.17	60.38	71.69	75.31
Social sciences	46.58	49.63	61.96	66.09
Business	53.18	56.73	68.11	73.98
Humanities	51.21	52.57	70.44	75.54
Creative arts	53.82	56.92	71.20	75.81
Education	22.72	25.88	62.19	65.96
Combined course	38.16	42.56	60.16	65.12
<i>All subjects</i>	<i>43.01</i>	<i>45.91</i>	<i>60.53</i>	<i>69.85</i>

Table 3. Mean and median salary 6 months after graduation, by category (based on 2 digit SIC codes)

	Both	Industry only	Location only	No change
Mean	16,108	18,687	21,305	20,233
<i>Median</i>	<i>15,000</i>	<i>17,000</i>	<i>18,000</i>	<i>18,000</i>

Table 4. Mean and median salary 3 ½ years after graduation, by category (based on 2 digit SIC codes)

	Both	Industry only	Location only	No change
Mean	21,604	21,766	25,450	24,769
<i>Median</i>	<i>20,000</i>	<i>20,000</i>	<i>23,000</i>	<i>23,000</i>

Table 5. Percentage of graduates who are “very satisfied” with their career 3 ½ years after graduation, by category (based on 2 digit SIC codes)

	Both	Industry only	Location only	No change
% of all graduates	33.25	32.18	44.44	43.89

Table 6. Treatment effects for ln(salary), 3 ½ years after graduation

	Both	Industry	Location	ln(salary)
Female	0.599 <sup>***</sup> (0.102)	0.991 (0.159)	0.862 (0.140)	-0.158 <sup>***</sup> (0.019)
Age	0.788 <sup>***</sup> (0.065)	0.866 <sup>**</sup> (0.054)	0.999 (0.073)	0.041 <sup>***</sup> (0.009)
Age (sq)	1.002 <sup>**</sup> (0.001)	1.001 (0.001)	1.000 (0.001)	-0.000 <sup>***</sup> (0.000)
Ethnicity: White <sup>†</sup>				
Ethnicity: Black	0.462 <sup>***</sup> (0.115)	1.759 <sup>***</sup> (0.308)	0.535 <sup>***</sup> (0.112)	0.003 (0.020)
Ethnicity: Asian	1.041 (0.209)	1.365 <sup>*</sup> (0.247)	0.961 (0.187)	0.031 (0.035)
Ethnicity: Other	0.791 (0.182)	1.210 (0.252)	0.889 (0.205)	0.034 (0.023)
Russell and 1994 group	0.680 (0.160)	0.656 <sup>*</sup> (0.160)	0.852 (0.179)	0.082 <sup>***</sup> (0.028)
Other old university <sup>†</sup>				
Post 1992 university	0.799 (0.186)	0.717 (0.167)	0.776 (0.159)	-0.055 <sup>*</sup> (0.028)
Specialised college	0.662 (0.202)	0.417 <sup>***</sup> (0.120)	0.613 <sup>*</sup> (0.158)	-0.072 <sup>**</sup> (0.033)
Undergraduate degree <sup>†</sup>				
Postgraduate degree	0.653 <sup>*</sup> (0.142)	0.710 <sup>**</sup> (0.124)	1.048 (0.190)	0.176 <sup>***</sup> (0.020)
Other first degree	0.803 (0.264)	1.240 (0.341)	0.546 <sup>**</sup> (0.137)	-0.157 <sup>***</sup> (0.039)
Health sciences	0.183 <sup>***</sup> (0.052)	0.245 <sup>***</sup> (0.061)	1.181 (0.272)	0.063 <sup>**</sup> (0.028)
Biological sciences	1.054 (0.350)	1.359 (0.417)	0.763 (0.256)	-0.082 <sup>***</sup> (0.031)
Physical sciences	1.309 (0.356)	1.363 (0.360)	0.691 (0.200)	0.019 (0.029)
Social sciences <sup>†</sup>				
Business	1.831 <sup>**</sup> (0.515)	2.088 <sup>***</sup> (0.549)	0.757 (0.240)	0.096 <sup>**</sup> (0.037)
Humanities	0.782 (0.257)	1.265 (0.373)	0.735 (0.220)	-0.029 (0.042)
Creative arts	1.045 (0.369)	1.480 (0.482)	0.886 (0.329)	-0.117 <sup>***</sup> (0.039)
Education	0.264 <sup>***</sup> (0.095)	0.580 <sup>*</sup> (0.176)	0.739 (0.216)	-0.082 <sup>**</sup> (0.040)
Combined course	0.595 (0.283)	1.446 (0.635)	0.887 (0.400)	0.018 (0.063)
Migrated to university	1.677 <sup>*</sup>	0.749	1.759 <sup>**</sup>	

	(0.496)	(0.188)	(0.486)	
Migrated after graduation	1.120	1.176	1.527**	
	(0.237)	(0.229)	(0.327)	
First job required degree	0.248***	0.365***	0.956	
	(0.042)	(0.060)	(0.169)	
No change <sup>†</sup>				
Both				-0.114***
				(0.029)
Industry only				-0.017
				(0.023)
Location only				0.091***
				(0.028)
$\lambda$ (Both)				0.083***
				(0.020)
$\lambda$ (Industry only)				-0.008
				(0.007)
$\lambda$ (Location only)				-0.033**
				(0.015)
Observations	5,033	5,033	5,033	5,033

Note: The table reports the results of a multinomial treatment effects model estimated using Maximum Simulated Likelihood. Columns 1-3 are the first-stage Mixed Multinomial Logit model for migration choice, and the coefficients report relative risk ratios. Column 4 is the second-stage linear regression model for  $\ln(\text{salary})$  in 2006 and the coefficients report marginal effects. The observations are weighted using survey sampling weights. Standard errors are in parentheses. \*\*\* significant at 1%; \*\* significant at 5%; \* significant at 10%.

Table 7. Treatment effects for  $\ln(\text{salary})$ , at different levels of industry disaggregation

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Both	-0.121***	-0.114***	-0.112***	-0.311***
	(0.030)	(0.029)	(0.031)	(0.043)
Industry only	-0.027	-0.017	-0.004	-0.053
	(0.024)	(0.023)	(0.022)	(0.046)
Location only	0.082***	0.091***	0.130***	0.284***
	(0.027)	(0.028)	(0.029)	(0.036)

Table 8. Treatment effects regression for career satisfaction, 3 ½ years after graduation

	Both	Industry	Location	Very satisfied
Female	0.614*** (0.103)	0.992 (0.160)	0.891 (0.144)	0.013 (0.027)
Age	0.797*** (0.061)	0.868** (0.054)	0.978 (0.073)	0.002 (0.010)
Age (sq)	1.002** (0.001)	1.001 (0.001)	1.000 (0.001)	-0.000 (0.000)
Ethnicity: White <sup>†</sup>				
Ethnicity: Black	0.483*** (0.116)	1.782*** (0.312)	0.524*** (0.110)	-0.093*** (0.032)
Ethnicity: Asian	1.085 (0.218)	1.369* (0.251)	0.946 (0.184)	-0.069** (0.033)
Ethnicity: Other	0.779 (0.180)	1.221 (0.255)	0.901 (0.203)	-0.072** (0.035)
Russell and 1994 group	0.670* (0.154)	0.640* (0.155)	0.826 (0.176)	-0.044 (0.040)
Other old university <sup>†</sup>				
Post 1992 university	0.785 (0.176)	0.711 (0.166)	0.767 (0.157)	-0.038 (0.035)
Specialised college	0.716 (0.213)	0.431*** (0.124)	0.620* (0.159)	-0.031 (0.048)
Undergraduate degree <sup>†</sup>				
Postgraduate degree	0.667* (0.142)	0.702** (0.122)	1.021 (0.188)	0.042 (0.028)
Other first degree	0.834 (0.264)	1.214 (0.330)	0.548** (0.140)	0.065 (0.042)
Health sciences	0.186*** (0.053)	0.244*** (0.061)	1.141 (0.266)	-0.050 (0.038)
Biological sciences	1.089 (0.358)	1.383 (0.424)	0.753 (0.249)	0.052 (0.053)
Physical sciences	1.342 (0.361)	1.346 (0.354)	0.687 (0.199)	0.008 (0.043)
Social sciences <sup>†</sup>				
Business	1.878** (0.529)	2.085*** (0.548)	0.752 (0.237)	0.024 (0.046)
Humanities	0.824 (0.265)	1.234 (0.365)	0.694 (0.205)	0.038 (0.048)
Creative arts	1.080 (0.382)	1.433 (0.466)	0.887 (0.322)	-0.106* (0.059)
Education	0.269*** (0.095)	0.568* (0.173)	0.720 (0.214)	0.096* (0.053)
Combined course	0.609 (0.286)	1.406 (0.619)	0.806 (0.359)	-0.082 (0.075)
Migrated to university	1.713* (0.361)	0.757 (0.354)	1.644* (0.199)	



	(0.492)	(0.189)	(0.429)	
Migrated after graduation	1.052	1.186	1.631**	
	(0.221)	(0.229)	(0.344)	
First job required degree	0.232***	0.357***	0.998	
	(0.039)	(0.059)	(0.169)	
No change <sup>†</sup>				
Both				-0.323***
				(0.052)
Industry only				-0.055
				(0.066)
Location only				0.280***
				(0.049)
$\lambda$ (Both)				0.342***
				(0.042)
$\lambda$ (Industry only)				0.029
				(0.068)
$\lambda$ (Location only)				-0.348***
				(0.032)
Observations	5,006	5,006	5,006	5,006

Note: The table reports the results of a multinomial treatment effects model estimated using Maximum Simulated Likelihood. Columns 1-3 are the first-stage Mixed Multinomial Logit model for migration choice, and the coefficients report relative risk ratios. Column 4 is the second-stage Probit model for career satisfaction (“very satisfied”) in 2006 and the coefficients report marginal effects. The observations are weighted using survey sampling weights. Standard errors are in parentheses. \*\*\* significant at 1%; \*\* significant at 5%; \* significant at 10%.

Table 9. Treatment effects for career satisfaction, at different levels of industry disaggregation

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Both	-0.311***	-0.323***	-0.226***	-0.216***
	(0.058)	(0.052)	(0.050)	(0.032)
Industry only	-0.053	-0.055	-0.294***	-0.282***
	(0.063)	(0.066)	(0.040)	(0.038)
Location only	0.284***	0.280***	0.212***	0.258***
	(0.065)	(0.049)	(0.071)	(0.071)

## Appendix

Table A1. Chi squared tests for joint significance of the instruments

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Chi squared (Both)	63.88 <sup>***</sup>	64.77 <sup>***</sup>	51.06 <sup>***</sup>	37.66 <sup>***</sup>
<i>p-value</i>	0.000	0.000	0.000	0.000
Chi squared (Industry)	46.94 <sup>***</sup>	42.66 <sup>***</sup>	31.42 <sup>***</sup>	29.89 <sup>***</sup>
<i>p-value</i>	0.000	0.000	0.000	0.000
Chi squared (Location)	16.36 <sup>***</sup>	15.00 <sup>***</sup>	26.00 <sup>***</sup>	20.52 <sup>***</sup>
<i>p-value</i>	0.001	0.002	0.000	0.000

Table A2. Overidentifying restrictions test based on IV (GMM)

	1 digit SIC code	2 digit SIC code	3 digit SIC code	4 digit SIC code
Hansen's J (salary)	0.351	0.421	0.109	0.007
<i>p-value</i>	0.554	0.516	0.741	0.932
Hansen's J (satisfaction)	2.076	2.367	1.509	0.599
<i>p-value</i>	0.150	0.124	0.219	0.439