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SHOULD I STAY OR SHOULD I GO? GRADUATE MOBILITY, EDUCATION MISMATCH, AND REGIONAL LABOUR MARKETS

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Abstract
This paper looks at the determinants of graduates' job-education mismatch, with a particular reference to geographical mobility as key factor explaining Danish university graduates' likelihood of being or not being overeducated in their first job after college. By making use of a unique matched employee-employer database with information on all the individuals and all the workplaces in Denmark, we track the inter-regional mobility patterns of recent graduates from university to work, and their domicile before starting college. Our estimation model takes into account both individual and regional characteristics, while controlling for selective access to employment, as well as for possible endogeneity between mobility and employment. Overall, results show a positive impact of post-college mobility in reducing the graduates' likelihood of being over-educated. At the same time, the labour markets characteristics of the region of origin as well as of the region of destination appear important predictors for estimating the graduates' overeducation likelihood.

Jelcodes:J24,J61

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Keywords: Overeducation, Graduate mobility, Education-job mismatch

JEL classification : J24, J61, R23

1. INTRODUCTION

Since the advent of the endogenous growth theories (Lucas, 1988; Romer, 1990), human capital has become crucial to explain economic growth and development; the level and the quality of university graduates in a certain region has been unanimously regarded as a central factor determining its economic performance (Pike et al, 2010). At the same time, the human capital investment theory (Becker, 1962) has argued that individuals optimize their education choices based on the expected returns to schooling. Both when looking at the macro (country), meso (regional) or at the micro (individual) level, it is apparent that graduates can maximise their own returns to education or their contribution to aggregated economic performances, only to the extent to which they can actually use their education and skills in their workplace. In other words, the private and public returns of their education can be maximised only to the extent to which their qualifications match the ones required to perform their jobs.

Today overeducation - a particular type of education-job mismatch - is a widespread phenomenon which involves on average one-fourth of all workers in advanced countries (Quintini, 2011). Understanding the determinants of overeducation becomes relevant both from a macro and from a micro perspective, since overeducated workers have been generally associated with lower incomes and lower jobs satisfaction (e.g. Hartog, 2000; Allen and van der Velden, 2001; Nielsen, 2011); similarly, higher percentages of overeducated workers can jeopardize faster rates of aggregate economic growth (McGuinness et al., 2015).

The literature on overeducation has been growing extensively over the past decades (e.g. Quintini, 2011; McGuinness et al., 2015; Green and Zhu, 2010). Several studies have been looking at the determinants of over education (e.g. Ramos and Sanromá, 2013; Jauhiainen, 2011; Diem and Wolter,2014) as well as the implications of overeducation in terms of earnings, job satisfaction and its stability over time (e.g. Verdugo and Verdugo, 1989; Allen and van der Velden, 2001; Hartog, 2000). Considerably less attention has been devoted to study the relationship between spatial mobility and overeducation and only very recently a few studies have started addressing the gap by analysing together patterns of inter-regional mobility and overeducation (Hensen et al, 2009; Iammarino and Marinelli, 2015; Croce and Ghignoni, 2015).

Our paper focuses on recent university graduates in Denmark and, in particular, it looks at the extent to which their inter-regional mobility can explain, among other factors, their probability of being over-educated. By looking at both post-college mobility as well as their region of origin before starting college and by making use of two different measures of overeducation, the paper provides a more nuanced picture on how spatial mobility affects education mismatch.

The literature on compensating differentials has demonstrated that individuals are willing to accept lower compensation when living close to the ones they love or when they value other intrinsic aspects of their job (e.g. more free time, better work-life balance, higher social responsibility) (e.g. Helliwell and Huang, 2010; Mavromaras et al, 2013). For that reason, we expect that individuals who live in the region where they grew up are more likely to have a mismatch, regardless of the mobility behavior they might have experienced between high school and university. Second, mobility itself might not be beneficial also when the individual is already located in an attractive labor market area which can offer various job opportunities that match a graduate's education level. Returning, or staying in this area might actually be the best strategy for avoiding a mismatch.

The study is set in Denmark; we make use of the Danish Integrated Database for Labour Market Research and we identify a sample of graduates that graduated in the period 1994-2008. By keeping in the sample only all those graduates in their first spell of tertiary education which they started up to the age of 25, we identify 225.564 graduates. Based on the information on the higher education institution they graduated from, the location where they lived prior to enrolment, and post-college location of residence, we are able to track their mobility patterns. As we can also access information on their first job after college, and subsequent occupation, we created two education mismatch measures. The rich dataset allows us to control for a whole range of determinants of mismatch, including education disciplines, parental education and family status as well as the regional characteristics of their region of study and of destination. Furthermore, the richness of the dataset allows us to deal also with methodological challenges of sample selection and endogeneity.

Our findings demonstrate that post-college mobility indeed leads to a better education-job match, meaning that mobile graduates are on average less likely to be over-educated. However, this positive effect is moderated by the location where the graduate ends up working. Overall, the positive effect of this mobility completely disappears when the graduate returns to the region where he/she lived prior to enrolment in college. Graduates might give up some labour market benefits by returning to live in close vicinity of family and friends. Another aspect that needs to be considered, however, is that some regions offer better opportunities compared to others. Thus, some graduates might already be located in an area with better labour market opportunity (Büchel and van Ham, 2003; Jauhianinen, 2011); thus, moving would not necessarily benefit them. Subsample analysis indeed demonstrates this to be the case.

The paper is structured as follows. In the next section we continue with a theoretical overview of the literature on graduate mobility, education mismatch and overeducation. Then, we present the empirical part of the paper by describing the database and the econometric approach of the paper. In Section 4 we present our analysis and discuss the results. The last section concludes.

2. CONCEPTUAL BACKGROUND

Graduate overeducation, regional labour markets and spatial mobility

Since education and competences represent crucial factors to be competitive in today's knowledge economy, talking about overeducation might seem a paradox. Nevertheless, the broad debate on overeducation has been stimulated by the realisation that in several advanced countries the expansion of the participation in higher education has been faster than the increase in the demanded levels of educations (Hartog, 2000). Today non-negligible levels of overeducated workers are nearly ubiquitous in advanced countries with high rates of tertiary attainment; however, overeducation rates are particularly high in those places where mass participation in higher education has not been accompanied by a high rate of skilled employment creation (Barone and Ortis, 2011).

The importance of looking at overeducation is clear because overeducation has been proved to have negative effects both for the individual and for the economy where the overeducated individuals work. At the individual level it has been widely proven that overeducation worsens individual conditions compared to their well-matched counterparts, such as lower salaries or higher rate of job dissatisfaction (e.g. Green and Zhu, 2010; Nielsen, 2011; Hartog, 2000). At the aggregate level, overeducation may still be positively correlated to regional economic performances (Ramos et al, 2012), but the correlation could be highly stronger if all the competences and qualifications of the regional labour force were properly used and mobilized by individuals in their workplaces.

Recent university graduates represent a particularly relevant segment to analyse for different reasons. First, fresh graduates are new workers that can bring up-to-date knowledge into the production system and therefore grease and enhance firms' innovative capacities. Secondly, fresh graduates are likely to be the ones more affected by overeducation, as one can expect that negative economic cycles impact more severely over fresh qualified workers than onto old-qualified ones that probably have already gained a permanent job position. Thirdly, it is important to prevent young graduates from being overeducated as soon as possible as being overeducated at the beginning of a career can represent a trap which significantly delays the transition into proper "graduate-jobs" (Baert et al, 2013). Several studies have been carried out on graduate overeducation both looking at its determinants (e.g. Verhaest and Van der Velden, 2013; Chevalier, 2003) as well as at its outcomes (e.g. Green and Zhu, 2010; Mavromaraset al, 2013). Evidence is mixed and still not conclusive. For instance, in some studies gender seem to matter (e.g. Chevalier,2003), but for others, the opposite is true (e.g. Dolton and Silles, 2003). The discipline of study generally appears to be an important explanatory factor for graduate overeducation: several studies found that graduates from humanistic fields have consistently higher overeducation ratios than graduates in Science, Technology, Engineering and Mathematics (STEM) disciplines (e.g. Barone and Ortiz, 2011; Chevalier,2003). Both the place of study and being a migrant seem to matter. In line with other literature (e.g. Nieto et al, 2013; Sanromá et al, 2015), Nielsen (2011) has analysed educated migrants in Denmark and found that foreigners are more likely to be mismatched; further, immigrants educated in Denmark are significantly less likely to be overeducated than foreign educated graduates.

Despite the abundance of studies on overeducation, very few of them have focused on the importance of economic geography and spatial mobility. Büchel and van Ham (2003) have been the first ones to underline the importance of regional labour markets characteristics in determining overeducation. In their paper, they find that the size of regional labour markets in Western Germany is strictly significant to determine the likelihood of finding a suitable job; likewise, individuals that have the possibility to move by car (and therefore look for a job on a larger labour market area) substantially decreases their probability of being overeducated. Similarly, Huber (2012) showed that both within-country and crossborder commuters in EU—15 countries have lower over-education rates than non-commuter. Ramos and Sanromá (2013) confirmed that the sizes of Spanish local labour markets and the possibility of extending the job search to other labour markets by commuting are relevant factors in explaining overeducation. Finally, Jauhiainen (2011) confirmed that living in larger regional labour markets in Finland decreases the odds of being overeducated. Being aware of this, over recent years some studies have started at looking at the segment of population of our interest, i.e. recent graduates, and at the relationship between their spatial mobility patterns and their job market outcomes. First, Hensen et al (2009) demonstrated that graduate geographical mobility in the Netherlands– measured as a straight line distance in kilometers between the municipality where each graduate got his/her education and the place where he/she ends up working – significantly reduces their probability of having jobs below their acquired educational level. Very recently two different Italian studies confirmed the same patterns. Iammarino and Marinelli (2015), after controlling the endogenous relationship between migration and employment, found that internal graduate migration in Italy is associated to a higher likelihood to find employment and to a lower probability of overeducation. Similarly, Croce and Ghignoni (2015) looked at the same problem in the same country, but by using a different sample; after controlling for endogeneity of spatial mobility and sample selection, similar results were found: the commuting time that graduates spend daily to reach their work seems to significantly reduce the probability of educational mismatch.

Our paper aims to contribute to this literature, by providing – to the best of our knowledge – the first systematic analysis of overeducation among Danish graduates and its relationship with internal graduate mobility. Our study is based on a sample of graduates that is remarkably larger than that used in any of the mentioned previous studies. It uses two measures of overeducation; it controls both for selective access to employment, as well as for possible endogeneity between mobility and employment. Finally, unlikeprevious studies, it checks if the region where the graduates move after their education is indeed their region of origin (i.e. region where the graduate lived before starting college) or to another region.

Measuring education-job mismatch, overeducation and overskilling

Before moving to our analysis, it is worth defining what we mean by education-job mismatch, overeducation and overskilling.

Even if the term education-job mismatch and overeducation are often used interchangeably, the former represents a broader concept than the latter and can be of two types, i.e. vertical or horizontal. When the worker’s educational *level* is not adequate for their job, a *vertical mismatch* occurs; in particular, when the worker’s educational level is higher than the one required for his/her job we define it as overeducation. On the other hand, a *horizontal mismatch* occurs when a worker's educational field does not match the one that is needed for his/her jobs. Our analysis of this paper is entirely focused on vertical mismatches; since we are considering only the most educated segment of the population, we only look at overeducation (and not also at undereducation).

The literature in the past years has also strongly distinguished between *overeducation* (which is defined generally as the possession of formal educational qualifications that are higher than the one required by the job) from *overskilling* (defined as the possession of more skills than the ones that are required in the job) (e.g. Allen and Van der Velden, 2001; Chevalier,2003). Individuals that have the same kind of education, due to several factors (e.g. different quality of education institutions, different job experience or innate ability that each individual has) can develop a different level of skills. Therefore, individuals that are overeducated are not necessarily overskilled and viceversa[1]. Given the detailed data available on education and occupation, we focus our analysis looks only at measures.

Traditionally, overeducation has been measured by using subjective or objective indicators. The *subjective indicators* are usually those based on interviews where the employees are asked directly about the match between their education level and the educational attainment required for their job. Therefore, it is the respondent him/herself who establishes if and to which extent he/she is overeducated. The *worker-self assessment* has the advantage of being based on up-to-date and specific information for each occupation. However, since it lacks rigorous and standard instructions, individuals can easily over- or under- estimate the qualifications that are really needed for their occupation (Hartog, 2000; Chevalier, 2003).

The *objective indicators* consist mainly of two different approaches, i.e. the job analysis approach and the statistical approach. The *job analysis* is based on a systematic evaluation by job analysts who create "dictionaries" and associate a level of skills and of education that is necessary for each occupational title (e.g. Quintini, 2011). In this sense, a graduate is defined overeducated if he/she is employed in a job that requires - according to the "dictionary of occupations" - lower qualifications than the ones he/she has. One of the main drawbacks of this approach is that job categories are broad and therefore heterogeneity of difficulty between jobs in the same occupational title might be substantial (Hartog, 2000). Also, since the labour market is dynamic, occupational dictionaries can easily become obsolete. The *statistical approach* (also known as *realised matches* approach) is based on the distribution of education within each specific occupation. The required occupation is defined by the occupational level that individuals in a certain occupation have usually attained, i.e. by looking mode or the mean of the workers in that occupation. A person is then over educated if his/her level of education is one

[1] Indeed, different studies have proved this. For instance, in his seminal study on overskilling and overeducation Allen and van der Velden (2001) found that while overeducation had a strong negative impact on individuals' wages, overskilling did not.

standard deviation above the mean - as suggested first by Verdugo and Verdugo (1989) - or *different from the mode* (Kiker et al., 1997). Therefore, the statistical approach does not have any reference to the real skills needed for a job, but is merely determined by the job demand-offer dynamics. For instance, if employers start demanding academic degrees for jobs that need the skills usually associated to a secondary school diploma, these jobs will be defined as "graduate jobs" according to the statistical approach. This, in turn, can lead to a relevant under-estimation of the over-education rate present in a certain occupation[2].

Although all the methods to measure overeducation have limitations, the literature has consistently pointed out that the job analysis approach appears conceptually superior (Hartog, 2000; Barone and Ortis, 2011). As previously mentioned, measures of over education vary according to the subjective and objective indicators that are used. In our analysis, as described below, we make use of a measure based on job analysis and one based on the statistical approach, finding that the two measures show strong positive correlations coefficients. This is also demonstrated by the different regression results that remain largely consistent across the two different overeducation indicators.

3. DATA AND METHODS

To investigate the impact of pre- and post-college mobility on education mismatch, it is a requirement that we: (i) identify the location the graduate resided prior to attending college, (ii) the location of the higher education institution the graduate obtained his/her degree from, (iii) the location where the person lives in the year following obtaining the degree. To operationalize these constructs, we rely on the detailed information available in the Danish Integrated Database for Labour Market Research (IDA). IDA is a linked employer-employee dataset created from government registers and maintained by Statistics Denmark. The database contains information on *all* individuals and workplaces in Denmark since 1980.[3] Its universal character, including the ability to follow individuals, their educational history, career trajectory, and the location where they live and attend study, makes this database suitable for the study at hand.

3.1. Sample

Our sample consists of individuals that completed their first spell of tertiary education (either professional bachelor, academic bachelor, master or PhD degree) in 1995 or afterwards. With first spell of tertiary education we refer to the period from first enrolment into a tertiary level of education to

2 The underestimation of overeducation based on the statistical method can be even more relevant considering the fact that job-demand deficiencies in highly-qualified occupations can produce a domino-effect into lower qualified ones (Gordon, 2002). In fact, if qualified workers (who cannot afford remaining in a long period of unemployment while looking for a job) accept a job that needs lower qualifications, they will potentially "bump-down" other job-searchers which have the right qualifications for those jobs a rung or two below (*ibidem*).

3 See Timmermans (2010) for a more detailed description of IDA.

graduation and the subsequent exit from college for at least two consecutive years. Consequently, a spell of tertiary education might involve several consecutive (and completed) college educations (from bachelor to master to PhD) and we allow for the student to take one year of absence prior to enrolling into a second tertiary education program. To illustrate, a person that moved from finishing a bachelor degree, immediately enrolling into a master program and graduating from this program will be considered to have one spell of college education. When a person graduates from college and enrols after at least two years of absence from college (e.g. a person who graduated with a master degree enrolling in a PhD program after couple of years of work-experience) has started with his or her second spell of tertiary education. Therefore, we remove from our sample those individuals that studied throughout the entire period of analysis.

We set the lower bound year restriction of graduating in 1995 as the occupation code, one of the main variables needed to identify an education mismatch, is only available from 1995 onwards. In this way we can identify the occupation of the individual in the graduation year[4]. We keep in our sample only individuals that we can observe the year prior to enrolment into college. Furthermore, the person should not have obtained a tertiary level of education prior to this enrolment, nor should be older than 25 years of age at first enrolment.

Finally, we have to pose further restrictions in our sample, since we are interested in the location where the person lived prior to enrolment, the location of the higher education institution which granted the degree to each graduate, and the location where the person lived up to three years following graduating. First, in those instances where any of these variables are missing or indicated as unknown, the observation will be excluded from the sample. Second, there are instances where the graduate has been employed in a firm more than a year prior to graduating; in the case the person does not start a new job within three years following the year of graduating, his/her observation will be removed from the sample because we are not able to match this individual with a new job following his or hers graduationFinally, we excluded those instances where the individual got a military profession after graduation. Based on these criteria, we end up with a total sample of 225.564 individuals.

3.2. Variables

Education mismatch

The main dependent variable in our study is a dummy variable indicating a “one” if there is a mismatch and a “zero” when the graduate’s occupation following graduation is matched with his or her level of

[4] Note that the majority of graduates starts a job in the year they graduate.

education. More specifically, we identify a mismatch when the person is overeducated in his or her occupation. Based on the existing literature (Hartog, 2000; Chevalier, 2003; Verdugo and Verdugo,1989; Kiker et al, 1997) on graduate mobility and education mismatch, we create two measures of mismatch: job analysis (MM_JA), and the statistical approach based on the mean and standard deviation of education years within each occupation class (MM_STDEDUC).

In the MM_JA approach, we take as point of departure the ISCO first-digit occupational class and we look at the corresponding skills and education level as defined by the International Labour Organization (ILO, 2012, see Table 1). A graduate is mismatched when: (i) the individual is employed in a one-digit occupation class that is higher than or equal to four (i.e. low skilled white collared worker or blue collared worker); and (ii) when a person with an academic bachelor or higher is employed in a one-digit occupation class that is lower or equal to three (i.e. technicians and associate professionals). In MM_STDEDUC a person is overeducated when the years of education of the graduate is one standard deviation above the average years of education in a given three-digit ISCO occupation class. Based on these two approaches the share of mismatches are 20.41 percent in MM_JA and 35.30 percent in MM_STEDUC.

Table 1: Occupation class and tertiary education match

ISCO-08 MAJOR GROUPS	**ISCED-97 GROUPS**
1 – Managers, senior officials and legislators	6 - Second stage of tertiary education (leading to an advanced research qualification) 5a - First stage of tertiary education, 1st degree (medium duration)
2 - Professionals	6 - Second stage of tertiary education (leading to an advanced research qualification) 5a - First stage of tertiary education, 1st degree (medium duration)
3 - Technicians and associate professionals	5b - First stage of tertiary education (short or medium duration)
4 - Clerks 5 - Service and sales workers	4 - Post-secondary, non-tertiary education
6 - Skilled agricultural and fishery workers	3 - Upper secondary level of education
7 - Craft and related trades workers 8 - Plant and machine operators, and assemblers	2 - Lower secondary level of education
9 - Elementary occupations	1 - Primary level of education

Source: ILO, 2012, pag. 14

Interregional Mobility

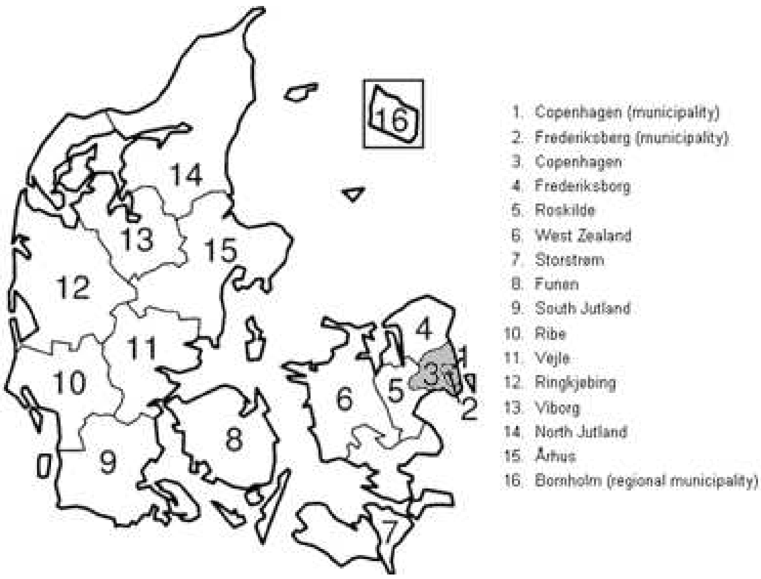
On all individuals in the sample we have information on the municipality where they live, study and work. The municipality, however, is too small of a level of aggregation to determine whether people are migrants. For that reason, we aggregate the location of the individual to the level of Danish counties; more specifically, the county structure prior to the Danish regional reform from 2007 (see Figure 1). The motive for using this county structure is twofold. First, we deem the present-day regional structure (five administrative regions) to be too large geographic entities for this kind of analysis. Given its size, we would underestimate the effects of interregional mobility as this mobility would occur less frequently. Second, the old Danish counties resemble to a large extent Danish labour market region, but divides some large labour market regions in smaller units, most notably the island of Sealand in the east[5]. Third, all these counties have at least one higher education institution (i.e. university college) within their borders; this is not the case for local labor market areas. Despite this structure, we made one small adjustment as the municipality of Copenhagen and Frederiksberg will be merged with the larger Copenhagen county (the three regions highlighted in grey in Figure 1).

Based on the regional classification and the location of graduates prior, during and after completing their tertiary education, we create the following three variables: **Post-college movers**, which are graduates that after graduating live in another region than the region in which they studied; **Pre-college movers**, which are those individuals that migrated between the region where they lived prior to enrolling into college and the region where they studied; and **Origin**, which has the value "one" when after graduating the graduate lives in the same region as where he/she lived prior to enrolment into a tertiary education.[6]

[5] Based on commuting patterns would be considered to be one labor market area but covers an area covering nearly 150 km in width and length.

[6] To have a more detailed classification and adapting what defined by Faggian and McCann (2009), we have also classified Danish graduates into the five different categories considering the region of origin, region of study, and post-graduation region simultaneously. *Stayers* are graduates that studied and live in the same region the region of origin (i.e. the region they live prior to attending college). *Stickers* are graduates that studied in another region and remain in that region after graduating. *Returners* are graduates that studied in another region and returned to the region of origin to work. *Late movers* are graduates that remained in the region of origin to study but live in another region after graduating. *Movers* are graduates who attended college in another region and live in a third region after they graduated.

Figure 1: Danish counties



Source:

Other variables

In addition to the main variables of interest we create a series of control variables. First a set of demographic variables on the individual in our sample, i.e. gender, age upon completing the first spell of tertiary education, immigrant status (i.e. whether the person is a Dane, migrant or second generation migrant). Family characteristics tend to be determinants on mobility behaviour and for that reason we control for marital status, a dummy variable on having children, the education level of the parents, and whether parents live in the region of study and/or region of origin. For human capital we include the year of graduation, the highest level of education (making a distinction between professional bachelor, academic bachelor, master and PhD) and the discipline of education making a distinction between a pedagogical, arts, humanities, social science, natural science, engineering, medical, food sciences, agriculture and police. The geographic area as such is also an important determinant, thus we created a set of dummy variables using the above-mentioned regional classification on the region of origin, the region of study and the region where the person lived following graduation. Finally, we created a set of dummy variables on the two-digit NACE industry classification and a variable indicating the years of job experience in the year of graduation.

3.3. Descriptive statistics

In this section we will present some of the descriptive statistics on the sample. First in Table 2, we present an overview of mobility patterns we observe among our graduates. As mentioned previously, we have a total sample of 225,564 graduates of these graduates, 34.2 percent lived in a different region after graduation compared to the region where they studied. Fourty-eightpercent of the graduates live in the same region as the before enrolling into college. In the column on the right we limit to those graduates who we identify to be employed up to three years after graduating; this means that 18,964 individuals are not employed. Among those employed, 31.8 percent moved region and over 52 percent are in the same region as before enrolment. The vast majority of graduates are classified as stayers, i.e. they studied in the same region where they lived prior to enrolment and do not move after graduation. The second-largest group are classified as stickers, i.e. those that moved to another region to study and stayed in the region after graduation. Continuous movers, those that live in different region in all the three stages, and returners are nearly the same size. Late movers, those that only move following graduation, is the smallest category.

Tablel 2: Post-college mobility patterns

Variable	Full sample (n=225,564)	Conditional on employment (n=206,600)
	percent	Percent
Post-college mobility	34.2%	31.8%
Origin	48.0%	52.4%
Stayer		40.7%
Sticker		27.4%
Returner		11.6%
Later movers		8.6%
Continuous mover		11.5%

In Table 3 we present the overall person-level characteristics of the graduates in our sample, again making a distinction between full sample and conditional on employment. The majority of the graduates in our sample are women and one out of three graduates in the sample has children. Over 96 percent of our sample are Danish nationals, who completed their education around the age of 27. The average spell of tertiary education is 6 years while the average year of work experience in the year of graduating is just over three years. Most graduates have either a master degree or professional bachelor; the low number of academic bachelors can be explained by the tendency of academic bachelors to continue with a master degree.

Table 3: Person-level characteristics of graduates

Variable	Full sample			Conditional on employment		
	N	Mean	Std	N	Mean	Std
Female	225,564	0.635	0.481	206,600	0.636	0.481
Children	225,564	0.357	0.479	206,600	0.358	0.479
Immigrant	225,564	0.023	0.150	206,600	0.020	0.140

Second Generation	225,564	0.011	0.106	206,600	0.011	0.102
Age upon graduating	225,564	27.375	2.765	206,600	27.311	2.684
College degree father	209,735	0.380	0.485	192,783	0.377	0.485
College degree mother	218,862	0.396	0.489	200,932	0.392	0.488
Pre-graduation job experience (yrs)	219,500	3.128	1.963	204,836	3.177	1.899
Length of education spell (yrs)	225,564	6.174	2.749	206,600	6.112	2.680
Academic Bachelor	225,564	0.071	0.257	206,600	0.063	0.244
Master	225,564	0.472	0.499	206,600	0.471	0.499
PhD	225,564	0.019	0.136	206,600	0.019	0.136

3.4. ECONOMETRIC MODEL

Endogeneity and sample selection bias

Other studies investigating mobility and education mismatch have recognized the threat of sample endogeneity and selection bias (e.g. Croce and Ghignoni, 2015; Iammarino and Marinelli, 2015). The problem of sample selection bias arises when the subsample in the population of interest is non-random (Bushway et al., 2007). In our study we are interested in education mismatch among graduates, which requires them to be employed; a bias thus occurs as those who are employed will be different compared to graduates who remain unemployed. However, mobility itself is also endogenous; thus, in the econometric specification in this paper, we have to deal with these two problems simultaneously.

To solve this problem, we follow an approach similar to the one applied by Iammarino and Marinelli (2015), where in the first step we estimate a mobility equation with the following specification:

$$Mobility_{post-college} = f(X_i, X_{education,})$$

From this post-college mobility equation, we retrieve the inverse mills ratio (IMR). After this first model, we estimate a Heckman selection model (Heckman, 1979) to deal with the selection bias. In the first step, the selection equation, we estimate the probability of the person being employed after graduating. The selection model is specified as follows:

$$Employment \quad = f(X_{demo}, X_{education,}\ ExcRestriction, \text{IMR})$$

A challenge in using Heckman is identifying a valid exclusion restriction. Such a variable must explain the likelihood of a graduate to be employed but not be correlated with the probability of having an education mismatch. In our model we have included a total of three of such identifiers. First, being a mother, as this explains why an individual is employed but not having an education mismatch; second, the share of higher educated in the region of study; third, a measure that the employment rate among graduates from the same study program[7] that graduated the year prior. As a last step, we estimate the outcome equation that explains the education mismatch.

$$EduMismatch \quad = f(X_{demo}, X_{education,})$$

4. RESULTS

In Appendix A1 we demonstrate the Probit model used to create the inverse mills ratio to deal with the endogeneity of mobility on employment, instruments in this table are education level of the parents. Previous studies have included previous moves as an instrument but in this study, previous moves appeared to be correlated with employment. It is worth noting that, in line to what has been found by previous studies, pre-college migration behaviour is strongly positively correlated with the likelihood of subsequent mobility (e.g. Faggian et al, 2007a, b; Faggian and McCann, 2009). Differently from Faggian et al (2007a), however, our findings found that female graduates are not generally more migratory than male graduates.

Tables 4 present the results of the Heckman Probit on the full sample of graduates. This table shows six models: the uneven columns are the models with as a dependent variable the first mismatch indicator (MM_JA), while the even columns have as a dependent variable the mismatch indicators based on the standard deviation of education within the occupation class (MM_STDEDUC). In Model 1 and Model 2 we focus on the post-college mobility only, in Model 3 and Model 4 we include the dummy variable whenever the graduate appears to be in the pre-college region, and in Model 5 and Model 6 we include an interaction effect. This interaction indicates whether graduates returned to the region of origin.

Before focusing on the mismatch, we will report on the selection equation. The Rho value is above zero, which indicates that there is indeed a selection bias in our sample. The selection equation shows that contrary to what others have found, post-college movers are less likely to be employed. As expected, those that after their graduation are in the pre-college area, either having remained in the area or returned after college, are more likely to be employed. However, interaction effects reveail that this appears to happen onlyfor those individuals individuals that return.). Those individuals that are classified as stayers are less likely to be employed compared to those that have demonstrated to be more mobile. Women with children (one of our instruments) are less likely to be employed while the employment rate among students that graduate from the same study program (our second

[7] Same study program is defined as those graduates with the same education discipline from the same higher education institution.

instrument) is significant and positive. Overall employment rates, as used in other studies appeared to be correlated both with employment and with education mismatch.

Similar to previous studies on graduate mobility and education mismatch, we observe that mobility is associated with a better match (i.e. the graduates are less likely to be over-educated). As expected, those that are in the region of origin (either stayers, or returners) are more likely to be overeducated although mobility still appears to have a positive effect. When including the interaction effect, mobility remains positive; however, this mobility is only positive for those graduates that do not return to the region of origin. This might be an indicator that individuals forfeit labor market benefits to be close to family and friends; these results are consistent in the two different matching estimators. When turning our attention to some of the other variables, we tend to find expected coefficients in most cases, for example: individuals with higher educated parents are more likely to have a match; those with a longer education are more likely to have a match that fits their qualification; engineering and medicine and health graduates are more likely to be matched with an occupation in line with their education; and immigrants are less likely to find a match compared to Danes. However, there also appear to be some differences between the two matching indicators. Most apparent is the effect of having a PhD degree, which is more likely to be matched in the first matching method (job analysis) but less likely so in the second matching method (statistical approach). A potential explanation on this difference is that in the first approach PhD are more likely to appear in one of the higher categories; however, the share of PhD in the total population is relatively low, which means that they will quickly be among the highest educated in their occupation class and thus be identified as over-educated.

Table 4: Heckman Probit Education Mismatch All Regions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Matching	JA	STDEDUC	JA	STDEDUC	JA	STDEDUC
Main equation						
Post-college mobility	-0.042***	-0.062***	-0.038***	-0.055***	-0.078***	-0.099***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Origin			0.041***	0.045***	0.011	0.011
			(0.01)	(0.01)	(0.01)	(0.01)
Post_college mobility*Origin					0.086***	0.095***
					(0.02)	(0.01)
College degree father	-0.050***	-0.055***	-0.051***	-0.056***	-0.051***	-0.056***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College degree mother	-0.073***	-0.062***	-0.073***	-0.062***	-0.073***	-0.062***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pre-graduation job experience (yrs)	-0.018***	0.056***	-0.019***	0.055***	-0.018***	0.055***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.002	-0.041***	-0.003	-0.043***	-0.002	-0.042***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Children	-0.043***	-0.008	-0.044***	-0.009	-0.043***	-0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dane			Benchmark			
Immigrant	0.068	0.176***	0.062	0.169***	0.061	0.171***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Second generation	0.052	0.040	0.040	0.028	0.040	0.030
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Length of education spell (yrs)	-0.012***	-0.035***	-0.012***	-0.034***	-0.013***	-0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pedagogics			Benchmark			
Linguistics	0.480***	-0.063***	0.482***	-0.062***	0.478***	-0.064***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Arts	0.925***	0.620***	0.923***	0.618***	0.915***	0.616***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Natural Sciences	0.057*	-0.514***	0.059*	-0.512***	0.055*	-0.515***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Social Sciences	0.375***	-0.258***	0.376***	-0.257***	0.374***	-0.259***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Engineering	-0.389***	-0.945***	-0.387***	-0.943***	-0.390***	-0.947***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Food Science	0.788***	0.276***	0.790***	0.279***	0.783***	0.273***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Agriculture	0.139***	-0.808***	0.144***	-0.802***	0.141***	-0.806***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Transport (Maritime academy)	0.471***	-0.142**	0.467***	-0.145**	0.453***	-0.147**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Health and Medicine	-0.356***	-1.352***	-0.354***	-1.349***	-0.357***	-1.351***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Police and Defence	-0.369***	1.287***	-0.360***	1.297***	-0.368***	1.294***
	(0.10)	(0.05)	(0.10)	(0.05)	(0.10)	(0.05)
Professional Bachelor			Benchmark			
Academic Bachelor	1.308***	0.632***	1.308***	0.632***	1.300***	0.629***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Master	0.266***	0.624***	0.270***	0.628***	0.272***	0.627***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PhD	-0.098*	3.305***	-0.090*	3.312***	-0.086*	3.312***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Constant	0.104	-1.194***	0.075	-1.226***	0.099	-1.199***
	(0.17)	(0.15)	(0.17)	(0.15)	(0.17)	(0.15)
employment equation						
Post-college mobility	-0.263***	-0.263***	-0.263***	-0.262***	-0.648***	-0.646***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Origin	0.190***	0.185***	0.192***	0.189***	-0.363***	-0.361***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Post_college mobility*Origin					0.936***	0.930***
					(0.03)	(0.03)
Children	0.220***	0.222***	0.220***	0.221***	0.225***	0.227***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female	0.103***	0.103***	0.103***	0.103***	0.115***	0.115***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Children*Female	-0.281***	-0.283***	-0.281***	-0.283***	-0.306***	-0.309***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share of the labor force w/ college degree in region of study	1.112	0.870	1.110	0.867	1.589**	1.321*
	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)
Unemployment rate in region of study	-2.554*	-2.521*	-2.551*	-2.522*	-0.480	-0.546
	(1.16)	(1.16)	(1.16)	(1.16)	(1.17)	(1.17)
Employment rate students in the same study program (lag)	0.134***	0.146***	0.135***	0.146***	0.186***	0.198***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Inverse Mills Ratio	-0.438***	-0.429***	-0.437***	-0.429***	0.476***	0.474***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Constant	4.634***	4.645***	4.632***	4.641***	2.758***	2.800***
	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)
athrho	0.132***	0.295***	0.139***	0.300***	0.179***	0.303***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Log Likelihood	-104676.09	-128890.83	-104663.30	-128870.39	-104099.08	-128307.98
rho	0.131	0.286	0.138	0.291	0.177	0.294
N	198,409	198,409	198,409	198,409	198,409	198,409

significance levels***< 0.01; **<0.05; *0.10

Note: not reported variables in the main equation are industry variables, region variables. In the selection equation we only reported the mobility measures, the exclusion criteria and the Inverse Mills Ratio. Full regression tables are available from the authors.

In Table 4 we ran our analysis on the entire sample of graduates; however, by focusing on mobility in this context we ignore the fact that some graduates might actually come from regions with ample labor market opportunities, whereas others come from regions with a rather small labour market (with a limited number of "graduate-occupations"). Consequently, their move would not result in a better education match. To investigate this in greater detail we created two subsamples. First, a subsample of graduates that lived in Copenhagen prior to enrolment in college; contrary to the overall sample, it might actually be beneficial for them to return as the labor market for Copenhagen offers better opportunities. The second subsample takes those individuals that prior to moving lived in one of the region classified as remote[8] and with inferior labor market prospects. When these graduates return, they are confronted with less interesting options and have fewer opportunities to land a job that matches their qualifications. Tables 5 present the results of the Heckman Probit on these subsamples on only those that before college lived in Copenhagen and those that before college lived in remote areas.

In the Copenhagen Models, again those that move have a higher likelihood of starting an occupation that fits with their educational background. The two different matching models, however, show some different results. In Model 7, those that stay in the region are not necessarily better matched compared to those that leave the region but remain in the area where they study (stickers). Those that return to Copenhagen, pay again a slight price. The results of Model 8 differ: movers' benefits nearly disappear when the mover is returning to the Copenhagen area. A stayer in this model, appears to benefit from having a better education match, albeit on the 10 percent level of significance.

The difference with those individuals from remote areas is most pronounced as staying and returning is indeed "punished" with a lower probability that the individual finds a job that matches his/her education profile. Although again there are some differences depending on the matching estimator applied.

Table 5: Heckman Probit Education Mismatch Copenhagen and Remote Regions

	Model 7	Model 8	Model 9	Model 10
Region sample	Copenhagen Area		Remote Areas	
Matching	JA	STDEDUC	JA	STDEDUC
Main equation				
Post-college mobility	-0.222***	-0.154**	-0.058*	-0.099***
	(0.06)	(0.05)	(0.02)	(0.02)
Origin	0.086	-0.381*	0.030	0.102*
	(0.18)	(0.15)	(0.05)	(0.04)
Post_college mobility*Origin	0.195**	0.131*	0.154***	0.158***
	(0.07)	(0.06)	(0.04)	(0.04)
College degree father	-0.065***	-0.050***	-0.059**	-0.075***
	(0.02)	(0.02)	(0.02)	(0.02)

[8] Remote areas are the regions 6, 7, 9, 10, 12, and 16 in Figure 1.

College degree mother	-0.082***	-0.061***	-0.102***	-0.056**
	(0.02)	(0.01)	(0.02)	(0.02)
Pre-graduation job experience (yrs)	-0.008	0.046***	-0.022***	0.064***
	(0.01)	(0.00)	(0.01)	(0.01)
Female	-0.001	-0.063***	-0.003	-0.027
	(0.02)	(0.02)	(0.02)	(0.02)
Children	-0.098***	-0.032*	-0.042*	0.005
	(0.02)	(0.02)	(0.02)	(0.02)
Dane		Benchmark		
Immigrant	0.051	0.170***	0.006	0.119
	(0.06)	(0.05)	(0.09)	(0.08)
Second generation	0.063	0.058	-0.014	0.240*
	(0.05)	(0.04)	(0.14)	(0.12)
Length of education spell (yrs)	-0.006	-0.028***	-0.007	-0.031***
	(0.00)	(0.00)	(0.01)	(0.00)
Pedagogics		Benchmark		
Linguistics	0.473***	-0.078*	0.448***	-0.090*
	(0.04)	(0.03)	(0.04)	(0.04)
Arts	0.989***	0.521***	0.854***	0.798***
	(0.05)	(0.05)	(0.08)	(0.08)
Natural Sciences	0.180***	-0.439***	-0.088	-0.624***
	(0.05)	(0.04)	(0.05)	(0.05)
Social Sciences	0.456***	-0.211***	0.318***	-0.325***
	(0.04)	(0.03)	(0.04)	(0.04)
Engineering	-0.224***	-0.794***	-0.539***	-1.002***
	(0.04)	(0.03)	(0.04)	(0.04)
Food Science	0.862***	0.350***	0.689***	0.238**
	(0.06)	(0.06)	(0.08)	(0.07)
Agriculture	0.110	-0.832***	0.236***	-0.728***
	(0.08)	(0.07)	(0.07)	(0.06)
Transport (Maritime academy)	0.297	-0.429*	0.376**	-0.267*
	(0.18)	(0.18)	(0.12)	(0.12)
Health and Medicine	-0.344***	-1.302***	-0.398***	-1.456***
	(0.04)	(0.03)	(0.04)	(0.03)
Police and Defence	-0.779**	1.346***	-0.162	1.329***
	(0.26)	(0.09)	(0.18)	(0.12)
Professional Bachelor		Benchmark		
Academic Bachelor	1.303***	0.597***	1.343***	0.673***
	(0.04)	(0.03)	(0.04)	(0.04)
Master	0.221***	0.551***	0.233***	0.658***
	(0.03)	(0.03)	(0.03)	(0.03)
PhD	-0.179*	3.141***	-0.191*	3.478***
	(0.08)	(0.09)	(0.09)	(0.12)
Constant	0.644	-0.189	-0.096	-2.516***
	(0.51)	(0.44)	(0.35)	(0.31)
employment equation				

Post-college mobility	-1.148***	-1.139***	-0.555***	-0.553***
	(0.08)	(0.08)	(0.03)	(0.03)
Origin	-0.097	-0.090	-0.364***	-0.363***
	(0.09)	(0.09)	(0.06)	(0.06)
Post_college mobility*Origin	2.238***	2.220***	0.738***	0.733***
	(0.11)	(0.11)	(0.07)	(0.07)
Children	0.333***	0.333***	0.152***	0.153***
	(0.04)	(0.04)	(0.04)	(0.04)
Female	0.167***	0.167***	0.146***	0.143***
	(0.03)	(0.03)	(0.03)	(0.03)
Children*Female	-0.260***	-0.261***	-0.282***	-0.284***
	(0.04)	(0.04)	(0.05)	(0.05)
Share of the labor force w/ college degree in region of study	0.604	0.707	1.378	0.781
	(1.81)	(1.81)	(1.23)	(1.24)
Unemployment rate in region of study	0.108	0.321	-1.321	-1.540
	(4.30)	(4.29)	(2.65)	(2.64)
Employment rate students in the same study program (lag)	0.115	0.121	0.355***	0.378***
	(0.08)	(0.08)	(0.08)	(0.08)
Inverse Mills Ratio	0.542***	0.546***	0.258***	0.254***
	(0.09)	(0.09)	(0.08)	(0.08)
Constant	2.748***	2.667***	3.338***	3.498***
	(0.71)	(0.71)	(0.47)	(0.47)
athrho	0.112	0.176**	0.083	0.262***
	(0.08)	(0.06)	(0.08)	(0.06)
Log Likelihood	-26764.35	-32481.61	-20412.89	-25938.37
rho	0.111	0.174	0.083	0.256
N	48,083	48,083	42,458	42,458

significance levels***< 0.01; **<0.05; *0.10

Note: not reported variables in the main equation are industry variables, region variables, education level and education discipline. In the selection equation we only reported the mobility measures, the exclusion criteria and the Inverse Mills Ratio. Full regression tables are available from the authors.

5. CONCLUSIONS

The new growth theory and human capital investment theory have recognised that education is - at the macro (country) or meso (regional) level - positively associated with higher economic growth and - at the micro (individual) level - with higher earnings. However, maximising public or private returns to education depends substantially on the extent to which skilled individuals can actually use their education and capacities in their workplace. In this paper, we analyse the geographical mobility of recent Danish graduates and their subsequent integration into the Danish labour market to establish the relationship existing between post-college spatial mobility and the likelihood of overeducation.

The descriptive analysis shows that Danish graduates are only fairly mobile compared to other European countries such as the UK (Faggian and McCann, 2009). In fact, the two most represented

categories of graduates are those who never moved from their region of origin (for studying or for working); and those graduates that moved to a certain region to study and that have remained in that same region after completing their studies.
Our econometric analysis largely confirmed what suggested by recent literature (Iammarino and Marinelli, 2015; Croce and Ghignone, 2015; Hensen et al, 2009) and support our main research hypothesis that inter-regional mobility contributes to decrease the likelihood of being overeducated. However, in contrast to what expected, we found that post-college movers are less likely to find a new job within 3 years after graduating. When we look closer and check at the post-college region of destination, we see that those graduates that go back to their region of origin are more likely to be overeducated. However, the mobility indicator remains always significant and almost counterbalances the negative effect that being or returning to the region of origin may bring about. Furthermore, our results seem to point out rather clearly that regional labour markets specific characteristics matter more than other aspects (Jauhiainen, 2011). When we only consider graduates coming from the Copenhagen region, the coefficient for the region of origin remain highly significant but changes the sign, indicating that it might be beneficial for graduate from the Copenhagen region to return back to their region.
These preliminary results – even if they certainly need further validations– seem to point out that - despite the rhetoric about the uniform beneficial effects of migration - migrating *per se* is neither beneficial nor detrimental for overeducation. On the other hand, it is the characteristics of the local labour market of origin and of study that seem to really influence the graduates' probability of being overeducated.

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APPENDIX A1: POST-COLLEGE MOBILITY EQUATION

	Model Z1 Post-college mobility
Pre-college migration	0.487***
	(0.01)
College degree father	0.020**
	(0.01)
College degree mother	0.025***
	(0.01)
Unemployment rate region of study	1.238
	(0.73)
University in region of study	-0.013
	(0.01)
Married	0.068***
	(0.01)
Female	0.005
	(0.01)
Children	-0.004
	(0.01)
Femal*Children	-0.033*
	(0.01)
Dane	Benchmark
Immigrant	0.060*
	(0.03)
Second generation	0.079*
	(0.03)
Graduation age	0.016***
	(0.00)
Pre-graduation job experience (yrs)	0.003
	(0.00)
Professional Bachelor	Benchmark
Academic Bachelor	0.03
	(0.02)
Master	-0.055***
	(0.01)
PhD	-0.309***
	(0.03)
Pedagogics	Benchmark
Linguistics	0.356***
	(0.01)
Arts	0.393***
	(0.03)
Natural Sciences	0.228***
	(0.02)
Social Sciences	0.286***
	(0.01)
Engineering	0.333***
	(0.01)
Food Science	0.709***
	(0.03)
Agriculture	1.158***
	(0.03)
Transport (Maritime academy)	0.234***
	(0.05)
Health and Medicine	0.255***
	(0.01)
Police and Defence	1.536***
	(0.04)
Constant	-2.033***
	(0.08)
Log Likelihood	-100872.699
N	198,994