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Ethnicity and UK graduate migration: An identity economics approach

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Abstract

This paper reports on the employment migration behavior of non-White ethnic minority graduates in the United Kingdom for the 2018/2019 graduation cohort, which is the last cohort to enter the labor market before the COVID-19 pandemic. Using data from the new Graduate Outcomes survey and controlling for a rich set of background characteristics, the findings indicate that ethnic minority graduates are more likely than their White counterparts to find work in ethnically diverse areas of the United Kingdom after leaving higher education. An identity utility framework is then formalized that combines identity economics with traditional approaches of human capital theory and job search theory. A test of an ethnic identity-based hypothesis reveals that Asian, Black, and Mixed-background graduates are comparatively more likely to migrate to areas with higher ethnic diversity levels, rather than less diverse areas. In addition to traditional explanations based on human capital theory and job search theory, this paper argues that these patterns are best explained by ethnic identity norms, which introduce a preference for working in ethnically diverse places. However, the results should be interpreted with some caution because of concerns related to heterogeneity within the ethnic group classifications used in the paper and possible omitted and unobserved variables.

KEYWORDS
ethnicity, graduate migration, identity economics

1 | INTRODUCTION

The impact of interregional migration on graduate labor market outcomes has been extensively covered in the literature (Ghosh & Grassi, 2020; Kidd et al., 2017; Mitze & Javakhishvili-Larsen, 2020; Perales, 2017). Despite significant scholarly interest in UK graduate migration, limited research has specifically explored ethnic differences in migration behavior, with the notable exception of Faggian et al.'s (2006) influential study on ethnicity and sequential graduate migration. Part of the empirical problem that arises from using observational data to analyse the relationship between ethnicity and migration is that the underlying cause of any correlation between the two variables remains unclear. For example, the source of correlation could be because ethnicity has a causal effect on migration; or that lower average human capital endowments among ethnic minorities (EMs) means they have fewer job opportunities across wider distances, or any number of factors that affect decisions related to education or migration, including discrimination in the labor and housing markets. Previous studies (Abreu et al., 2015; Faggian et al., 2006; Kidd et al., 2017; Mosca & Wright, 2010) have indicated that non-White EM graduates are, on average, less geographically mobile compared with their White peers. They are more likely to work in or near their pre-higher education (HE) domicile, which has significant implications for the lifetime earnings and social mobility of EMs in particular. While these studies have provided valuable insights into the relationship between ethnicity and sequential migration behavior (Faggian et al., 2006), sector-based migration (Abreu et al., 2015), and earnings (Kidd et al., 2017), this paper aims to address several important gaps in our understanding of the relationship between ethnicity and employment migration among UK graduates.

First, the preference for working in ethnically diverse areas is a likely—yet untested—factor that may account for the different migration patterns of EM graduates. The spatial clustering of EMs in the UK has been well documented in the literature (Johnston et al., 2002; Zwysen & Demireva, 2020), and research indicates that EMs report higher life satisfaction when living in areas with a high concentration of co-ethnics (Knies et al., 2016). This paper contributes to this stream of literature by examining the relationship between graduate migration and ethnic diversity levels at the place of employment, focusing specifically on administrative units that correspond to the local authority or unitary authority (LAUA) level in England and Wales and equivalent areas in Scotland and Northern Ireland. Unlike previous research which has predominantly modeled interregional flows of graduates (e.g., at the NUTS1 scale), this paper considers lower levels of geographic disaggregation to gain a better understanding of graduate migration at the local level. This approach recognizes that HE systems differ between England and the devolved nations of the United Kingdom, which may impact selection into HE and subsequent migration behavior (Faggian et al., 2007a). This paper diverges from the conventional focus on co-ethnic concentration in the literature by examining the impact of aggregate ethnic diversity levels on migration patterns, which is an approach that acknowledges evidence that overall ethnic diversity levels may impact migration upon entry to HE (Gamsu et al., 2019).

Moreover, this paper uses a novel data set provided under licence by the Higher Education Statistical Authority (HESA) to investigate migration differences across ethnic groups in the United Kingdom. Previous studies of ethnicity and graduate migration have primarily relied on the Destination of Leavers from Higher Education (DLHE) survey, which was administered by HESA from 2002 to 2018. This paper uses the successor to the DHLE survey, namely the Graduate Outcomes (GO) survey, for the 2018/2019-year cohort, which was the last year cohort to enter the labor market before the COVID-19 pandemic. The GO survey data contains more detailed background information on graduates than previous studies have been able to use, which allows this study to better address selection issues and control for factors that are known to influence migration and employment outcomes.

While human capital theory and job search theory have been extensively used to explain graduate migration patterns (e.g., Faggian & McCann, 2009; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017), limited attention has been given to alternative theoretical explanations. This calls for exploring new approaches to better understand the factors driving the differing migration patterns of EM graduates. Identity economics (Akerlof & Kranton, 2000) is a promising candidate because of its intuitive appeal in explaining differences in migration outcomes across ethnic groups, as well as its application in previous studies that use large secondary data sets like the GO survey (e.g., Bertrand et al., 2015; Casey & Dustmann, 2010). The central insight from identity economics applied here is that ethnic identity may influence migration outcomes because deviating from group norms is inherently costly. Therefore, EM graduates may sometimes forgo the financial benefits of employment migration because they gain psychic satisfaction by migrating to (or staying in) ethnically diverse areas for work. Economists have long understood that motivations for migration include psychic costs and returns (Sjaastad, 1962). This paper uses identity economics to suggest what these ethnicity-related motives may be and formalizes a method for analysing them.

In addition, this paper is relevant to current policy debates concerning human capital flight, which is often cast as a question of fairness in the UK because graduates tend to leave economically disadvantaged regions in favor of more prosperous areas in London and the South East of England (Swinney & Williams, 2016). Concerns have also been raised about the efficient allocation of human capital across the United Kingdom, since by age 27, 65% of graduates live in the same area they lived in at age 16 (Britton et al., 2021). These debates have prompted various policy responses, including calls to fund graduate retention schemes through the Northern Powerhouse (HM Treasury, 2016), the introduction of a new geographical mobility marker by HESA (HESA, 2022), and a £5.6 million initiative funded by the Office for Students to improve job matching for geographically immobile graduates (OfS, 2020). Therefore, a better understanding of ethnic differences in graduate migration patterns at the local level may offer valuable insights for consequential policy debates related to local economic growth and competitiveness.

In line with previous studies, this paper classifies ethnicity according to the following UK Census-aligned major ethnic groupings recommended by the UK Office for National Statistics (ONS): Asian or Asian British ("Asian"), black, black British, Caribbean or African ("Black"), mixed or multiple ethnic groups ("Mixed"), other ethnic groups ("Other"), and white ("White"). Ethnicity here is self-reported, and it should be acknowledged that previous studies suggest these categories may be unreliable when they are applied to heterogeneous populations (Zwysen & Longhi, 2018). The empirical approach consists of four steps that analyse the relationship between an individual's self-reported ethnicity and where they are employed geographically 15 months after leaving HE. Two baseline estimations are used to understand, first, the relationship between an individual's ethnicity and the ethnic composition omo/>oyment location and, second, the relationship between ethnicity and the probability of migrating for work. Then, the identity economics thesis is examined by formalizing an identity utility function and testing the following hypothesis:

> Compared with White graduates, EM graduates are more likely to seek employment outside of their home domicile in a more ethnically diverse location than in a less diverse location.

This is done using a multinomial logit model (MNL) that classifies graduates into migration categories based on their movement to more or less diverse areas. Finally, a two-level alternative specification that controls for anticipated wages at the employment destination is substituted for the main MNL. The main source of potential endogeneity in this paper comes from omitted variables, and, therefore, a rich set of controls for personal characteristics is introduced into the models to reduce selection bias. In addition to the main empirical strategy, two appendices include robustness checks to demonstrate, first, that the interaction of ethnicity and three markers of individual human capital levels does not change the results and, second, that the outsized influence of Greater London in the UK labor market is not a factor.

The structure of this paper is as follows. The next section provides an overview of the literature related to graduate migration and ethnicity. The third section provides a brief overview of identity economics and formalizes an identity-based utility function that will be used in this paper. The fourth section details the empirical strategy, data, and estimation methods, which is followed by a discussion of the results. The final section offers concluding remarks.

2 | LITERATURE REVIEW

The economics literature tends to view human migration as utility-maximizing behavior, drawing primarily on human capital theory and job search theory to explain graduate migration patterns (Faggian & McCann, 2009). Studies examining the relationship between migration and degree classification (i.e., the final grade awarded which ranges from first-class to third-class honours and unclassified degrees in the UK system) as a measure of individual human capital levels have consistently found that higher levels of human capital increase the likelihood that a graduate will migrate for work (Faggian & McCann, 2009; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017). There is long-standing evidence of ethnic differences in degree classifications (Leslie, 2005), which suggests that the interaction of ethnicity and degree classification may have a unique effect on migration that cannot be solely attributed to these factors alone. Studies have also found a positive association between migration and other markers of individual human capital levels, such as the selectivity of the institution attended (e.g., Russell Group) or an institution's position in rankings like the Research Assessment Exercise (Faggian et al., 2007b; Kidd et al., 2017). These studies highlight the importance of considering the confounding effect of human capital levels, as well as the interaction effect of human capital levels and ethnicity, when examining the impact of ethnicity on graduate migration.

However, the positive relationship between individual human capital levels and migration may not hold in all contexts, as highly skilled individuals may be less mobile due to having better job opportunities in their current location, as suggested by job search theory (Bartel, 1979; Faggian, 2021). For example, Faggian and McCann (2009) use job-search theory to explain an observed London effect where individuals with higher degree classifications exhibited lower mobility when Greater London observations are included in their analysis. The London effect is supported by empirical findings in the literature that interregional migrants tend to chase higher nominal wages, that interregional wage differentials and migration flows depend on job-matching in UK regions, and that job matching in an area is related to its rank-order in an urban hierarchy beginning with Greater London (Faggian & McCann, 2009). The London effect suggests a need to include robustness checks in any analysis of UK employment migration to demonstrate that the inclusion of Greater London does not change the results. The existing literature provides a good understanding of how graduate migration trends in Greater London compare with other regions of the UK, largely because Greater London is counted among the NUTS1 statistical regions of the UK and, until 2011, was one of the nine former Government Offices for the Regions. However, little is known about the other localities which are investigated in this paper.

Existing research suggests that EMs are less migratory than their White peers due to factors such as limited access to information, higher search costs, limited resources for relocation, and potential discrimination at the destination (Abreu et al., 2015; Faggian et al., 2006; Zwysen & Longhi, 2018). Yet, evidence of the relationship between ethnicity and migration among the general population is mixed. UK Census records indicate that, on average, EMs are less migratory than White British individuals across long and short distances (Darlington-Pollock et al., 2019); however, longitudinal evidence from Scotland suggests that EMs are more mobile across shorter distances (McCollum et al., 2021). Moreover, UK Census data indicate that, on average, EMs migrate from areas of high ethnic concentrations to areas with lower concentrations (Simpson & Finney, 2009). Regarding graduate migration, studies using DLHE survey data have consistently found that EMs are less mobile than their white peers (Abreu et al., 2015; Faggian et al., 2006; Kidd et al., 2017; Mosca & Wright, 2010). However, these studies have been limited to controlling for background characteristics that include age, gender, and disability status. The GO survey data used in this paper provides more detailed information, which allows for controlling for confounding effects related to the role of ethnicity in intergenerational human capital accumulation (Borjas, 1992), additional access to information through private school networks (Green et al., 2017), and the impact of socioeconomic status specifically on graduate migration (Wielgoszewska, 2018).

The spatial clustering of EMs in the United Kingdom is well-established in the literature, and cited explanations include the cost and availability of housing, discrimination, access to ethnic goods, and the maintenance of positive social connections (Johnston et al., 2002; Zwysen & Demireva, 2020). Evidence suggests that EMs are more likely to originate from deprived areas with fewer graduate employment opportunities (Feng et al., 2015), which means that EMs who look for employment in their home domicile may face challenges in accessing graduate jobs (Zwysen & Longhi, 2018). There is evidence that EMs experience higher life satisfaction when they live in areas with high concentrations of co-ethnics (Knies et al., 2016), but EM clustering has also been associated with negative attitudes and lower life satisfaction among the majority White British population (Dustmann & Preston, 2001; Longhi, 2014). More generally, the creative class thesis suggests that highly educated workers are attracted to diverse and tolerant places (Florida, 2014), which finds empirical support in the United Kingdom (Clifton, 2008). Further research is required to understand the extent and implications of spatial clustering among EMs in the context of graduate migration. Moreover, evidence suggests that norms within ethnic groups may influence the migration behavior of HE students. For example, an analysis of DLHE data reveals that students from British Bangladeshi and Pakistani backgrounds are more likely to stay local and attend nearby universities, while White and Black students exhibit similar migration behavior (Donnelly & Gamsu, 2018).

These findings are attributed to expectations among British Asian Muslims that their children stay local, and also to the possible effect of Islam's prohibition of interest-bearing student loans on the affordability of migration for HE. Conversely, Donnelly and Gamsu (2018) suggest that White and Black families may encourage their children to migrate for HE as part of the process of gaining independence as young adults. Similarly, evidence suggests that the migration decisions of HE students are influenced by familiarity with and a preference for ethnic diversity, as EM students often choose university locations that have similar or higher levels of ethnic diversity compared with their pre-HE domiciles (Gamsu et al., 2019). Overall, these studies suggest that ethnicity shapes the migration decisions of HE students. Further research is required to establish whether these trends, especially the preference for ethnically diverse places, also extend to the migration decisions of graduates. Economists have long understood that employment migrants have nonpecuniary motives (Sjaastad, 1962), and identity economics specifies what these ethnicity-related motives may be and suggests a method for analysing them (Akerlof & Kranton, 2010).

3 | AN IDENTITY UTILITY FRAMEWORK FOR GRADUATE MIGRATION

Identity economics, first introduced by Akerlof and Kranton's (2000) seminal paper, explores how an individual's identity, alongside financial motives, can shape their decision-making in contexts such as migration (e.g., Casey & Dustmann, 2010; Prinz, 2019). The three theoretical building blocks of identity economics are identity, social groups, and norms. There is a debate in the wider social sciences about measuring identity (Abdelal et al., 2006), but identity economics conceptualizes identity as an individual's self-classification into social groups. The most common markers of identity used in the identity economics literature are observables in the form of self-reported gender and ethnicity (e.g., Akerlof & Kranton, 2000, 2002, 2005; Bertrand et al., 2015; Casey & Dustmann, 2010). The identity economics literature makes a conceptual distinction between identity—or an individual's social categorization—and the utility an individual derives from their social categorization. Identity utility, like other economic conceptions of utility, is assumed to be latent in any consistent set of choices and unobserved by the analyst.

Following Manski (2000), the economic study of social interactions begins with conceptualizing economic agents as individual decision makers with preferences expressed formally through utility functions, expectations through individual probability distributions, and constraints through choice sets. This section will address preferences and expectations, while constraints faced by decision makers will be discussed in the subsequent section covering the empirical approach. Unlike traditional assumptions of independent preferences, identity economics suggests that individual preferences are influenced by social context and expands the utility function to include identity utility alongside standard utility (Akerlof & Kranton, 2000). In the migration context, standard utility is the traditional view that migration is an investment in human capital or a strategy for maximizing wages (Faggian, 2021; Sjaastad, 1962). Identity economics adds an important insight by highlighting that individuals may prioritize identity utility over economic gains, leading them to potentially exclude themselves from economically beneficial activities, such as employment migration. According to identity economics, norms depend on an individual's social group membership, drawing upon social identity theory (Tajfel et al., 1979) which suggests that individuals derive a sense of belonging from group membership and conform to group norms to maintain positive self-image.

More formally, standard utility can be extended by proposing an identity utility function that is comprised of three main elements (Akerlof & Kranton, 2000): *identity* (I) which comprises social groups (G), each individual's (j's) assignment to the group, *group norms* (P), and *identity utility* (U_j) which captures the gains or losses to identity caused by conforming to or deviating from group norms. Suppose that a set of ethnic groups (G) is represented by the ethnic groups used in this paper. Ethnic identity in this case describes both an individual's self-image and assigned ethnic group, where g_j describes j's own assignment as well as j's assignment for everyone else in the population. Suppose that P concerns norms for the migration behavior of g groups, and that there are M possible employment migration alternatives ($m = 1, \ldots, M$) from which individual j can choose. For example, a graduate leaving HE faces two main employment migration alternatives relative to their original place of domicile: they can choose to find work in their home domicile or to find work elsewhere. Following, Faggian et al. (2007a), the utility function of the j-th individual choosing m possible migration alternatives is as follows:

$$U_{\mathrm{jm}} = f\,(A_j, R_{\mathrm{jm}}, I_{\mathrm{jm}}) + \varepsilon_{\mathrm{jm}}, \tag{1}$$

where A_j is a vector of personal and human capital characteristics, R_{jm} represents the expected pecuniary returns to migration for individual j at location m, and I_{jm} is j's ethnic identity in the context of migration alternative m to demonstrate that identity utility can vary from place to place. The random error caused by unexplained effects is represented by $\varepsilon_{\mathrm{jm}}$. With this structure, I_j is formally represented as (Akerlof & Kranton, 2000):

$$I_j = f\,(m_j, m_{j*}, g_j, \epsilon_j, P), \tag{2}$$

where an individual j's identity (I_j) depends first and foremost on j's ethnic group (g_j). Identity depends on the extent to which j's choice of migration alternative (m_j) and the choices of others (m_{j*}) conform to the migration behavior suggested by group norms P. Identity also depends on the match between j's characteristics (ϵ_j) and the ideal of j's ethnic group as suggested by P. A well-known problem with using nonexperimental data in the econometric modeling of social interactions is the poor instrumentation of key concepts (Manski, 2000; Radu, 2008). Bertrand et al. (2015) address this concern by using well-established measures of identity (e.g., such as gender) and gender norms (e.g., such as a wife's preference not to outearn her husband) when applying identity economics to their analysis of secondary survey data, including the *National Survey of Families and Households* and the *American Community Survey*. Similarly, the approach taken here is to use uncontroversial measures of identity and group norms.

Identity (I_j) is measured here by individual j's self-identified ethnicity, while the group norm (P) is the well-documented phenomenon of spatial clustering among EMs in the United Kingdom, which has been demonstrated in terms of the general population (Feng et al., 2015; Johnston et al., 2002; Knies et al., 2016; Longhi, 2014; Zwysen & Demireva, 2020) and among HE students (Donnelly & Gamsu, 2018; Finney, 2011; Gamsu et al., 2019). All else being equal, migration is inherently more psychically costly than nonmigration (Sjaastad, 1962). Additionally, it is reasonable to expect bias for the status quo in migration decisions (Czaika, 2015). Under this model, it is therefore theorized that an EM individual gains identity utility by adhering to group norms of working in an ethnically diverse location (e.g., migrating to an employment location that is highly ethnically diverse) or they lose identity utility by going against group norms (e.g., migrating to a less-diverse employment location).

More formally, utility can be decomposed into an observed deterministic component $[V(A_j, R_{jm}, I_{jm})]$ that is linear in its parameters and an unobserved random component (ε_{jm}) with Gumbel's extreme-value distribution. Therefore, the probability $\Pr(E_{jm})$ that an individual j will choose employment migration alternative m is the probability that the individual will maximize their utility by choosing m rather than any other available alternative m'. Following Faggian et al. (2007a), this can be expressed formally as:

$$\Pr(E_{jm}) = \Pr \quad [U_{jm} = V(A_j, R_{jm}, I_{jm}) + \varepsilon_{jm} > U_{jm'} = V(A_j, R_{jm'}, I_{jm'}) + \varepsilon_{jm'}], m = m'; m, m' \in M. \tag{3}$$

An identity-based model of migration is complimentary to the standard model that suggests that individuals migrate to maximize income, since it indicates that individual j chooses migration alternative m to maximize utility. Relaxing the assumption of individual tastes and preferences introduces the problem of endogenous interactions in migration analyses (see Radu, 2008). Modeling endogenous interactions is common in the economics literature, notably in the form of herd behavior (Bikhchandani et al., 1998) and networked migration (Winters et al., 2001). Radu (2008) suggests that the primary method for reducing endogenous interaction bias in migration modeling is to control for personal and local characteristics, which allows for a more accurate causal inference of why individuals from the same ethnic group tend to make the same migration decisions. Therefore, this paper controls for a rich set of personal characteristics to allow for the reasoned inference that clustering norms among EMs influence individual decisions about where to live and work after leaving HE. Accordingly, an evaluation of identity economics here can be formalized by the hypothesis stated in the introduction:

> Compared with White graduates, EM graduates are more likely to seek work outside of their home domicile in a more ethnically diverse location than in a less diverse location.

The identity economics model can be solved by demonstrating that an identity utility maximizing approach explains the migration patterns of EM graduates more effectively than the standard model alone. With the utility framework formalized, it is now possible to estimate the effect of ethnic identity on graduate migration using regression analysis.

4 | EMPIRICAL APPROACH

This paper uses observational data, and the main sources of potential endogeneity are omitted variables that may impact migration decisions, as well as selection based on heterogeneous returns to human capital investments. Identifying endogeneity in a cross-sectional analysis of this type is difficult (see Longhi, 2014), but this paper follows previous approaches taken in the literature by using only “good controls” (Angrist & Pischke, 2009) that are fixed at the time of the migration decision to account for unobserved factors that influence migration choices. As is common in the literature, local characteristics of the home domicile are treated as personal characteristics since they represent the economic and social information available to the individual before entering HE literature (Faggian et al., 2006).

The empirical approach consists of four steps. First, a generalized linear model (GLM) is used to analyse the relationship between an individual's ethnicity and the overall ethnic diversity level of their post-HE place of employment. The outcome variable measures a lagged population proportion of EMs relative to the total population in each of the UK's 154 administrative areas. Second, a binomial logistic regression (BLR) is used to predict the probability of an individual being a migrant or nonmigrant within the United Kingdom, where migration is indicated by a binary variable that represents employment in the home domicile or elsewhere. Third, an MNL is used to classify graduates into three migration categories based on their movement to more or less diverse areas relative to their home domicile. Finally, an alternative two-level specification is used for the main MNL, employing a generalized structural equation model to control for expected wages at employment location. The expected wages are treated here as *ex-ante* information available to an individual before making the migration decision, but because of concerns due to likely endogeneity, the original MNL remains the preferred model.

Robustness checks reported in appendices examine the potential effects of ethnicity interacting with individual human capital levels and, separately, working in Greater London. Finally, the regressions are accompanied by standard multicollinearity tests to correct for the potential problem of the simultaneous correlation of observed characteristics. The use of regression methods requires strong assumptions about endogeneity to obtain estimates of causal effects. Therefore, the results presented here should not be regarded as causal in nature since bias likely remains due to omitted variables and selection on unobservables like motivation.

5 | DATA

This paper uses data from the GO survey for the 2018/2019 cohort, which collects individual-level data on background characteristics, university and course information, employment outcomes, and postcode information. The GO survey, administered 15 months after respondents have left HE, is a census of all UK graduates for a given year cohort; thus, no sampling is performed. Issues related to data quality include nonresponse and measurement error. HESA claims to have a near-complete sampling frame, which means that the only cause for the nonrepresentativeness of the data set is nonresponse (Lynn & Xena, 2021). The response rate for UK-domiciled graduates from the 2018/2019 cohort is 57% which is lower than that for the DHLE survey; however, HESA reports that no evidence of substantial nonresponse bias exists in the 2018/2019 survey data (Lynn & Xena, 2021). The survey was conducted during the COVID-19 pandemic, but HESA has not found evidence that COVID-19 introduced significant response bias into the data (Essen-Fishman, 2023).

This paper focuses on undergraduates who were domiciled in the United Kingdom before entry to HE, were in full-time employment at the time of the census and received wages in pounds sterling. The data set includes information on students' pre-HE home domicile, place of study, and place of employment. In line with other studies on UK graduate migration, this paper uses the place of employment as a marker for graduate destinations. The location data are provided in the form of the administrative units that correspond to LAUAs in England and Wales, council areas in Scotland, and local government districts in Northern Ireland. Migration is measured by movements across administrative boundaries, which is a common approach in the interregional migration literature (e.g., Iammarino & Marinelli, 2015; Martin & T Lichter, 1983; Siow & Ng, 2013). A listwise deletion approach is adopted with the assumption that HESA data are missing at random (Lynn & Xena, 2021). Data measuring local characteristics are taken from several of the sources listed in Table 2, including the ONS for population, GDP, and life satisfaction measures, home.co.uk for market rent summaries, and GeoHack for coordinate data.

6 | SAMPLE SUMMARY

Table 1 presents summary statistics by major ethnic group which reveal substantial differences in characteristics across ethnic groups. White graduates constitute most graduates in the census at 79.9% and, on average, they come from higher socioeconomic backgrounds as measured by Index of Multiple Deprivation and parental education, have a higher likelihood of reporting a disability, originate from less diverse areas, and migrate longer

TABLE 1 Summary statistics by major ethnic group.

		White	Asian	Black	Other	Mixed
	N	**93,170 (79.9%)**	**11,535 (9.9%)**	**6570 (5.6%)**	**1150 (1.0%)**	**4240 (3.6%)**
Independent variables	AGE					
	24 and below	76,650 (82.3%)	10,130 (87.8%)	3995 (60.8%)	910 (79.1%)	3560 (83.9%)
	25 and over	16,525 (17.7%)	1400(12.2%)	2580 (39.2%)	240 (20.9%)	685 (16.1%)
	DEGREECLASS					
	First-class honours	30,920 (33.2%)	2928 (25.4%)	1212 (18.4%)	900 (26.0%)	1245 (29.3%)
	Upper second-class honours	43,680 (46.9%)	5260 (45.6%)	2990 (45.5%)	480 (41.6%)	2040 (48.0%)
	Lower second-class honours	11,540 (12.4%)	1980 (17.2%)	1740 (26.4%)	220 (19.3%)	660 (15.5%)
	Unclassified other	2990 (3.2%)	185 (1.6%)	120 (1.8%)	30 (2.3%)	65 (1.5%)
	Unclassified medical	2290 (2.5%)	805 (7.0%)	100 (1.5%)	85 (7.5%)	150 (3.5%)
	Third class honours/pass	1750 (1.9%)	380 (3.3%)	415 (6.3%)	40 (3.4%)	90(2.1%)
	DISABILITY					
	No known disability	77,860 (83.6%)	10,480 (90.9%)	5695 (86.6%)	1010 (87.8%)	3535 (83.3%)
	Known disability	15,310 (16.4%)	1050 (9.1%)	880 (13.4%)	140 (12.2%)	710 (16.7%)
	DOM_UNI_DIST	107.388 (106.473)	71.404 (96.274)	75.133 (90.685)	71.509 (105.610)	106.605 (104.447)
	ETARIFF	0.366 (0.073)	0.369 (0.077)	0.330 (0.065)	0.361 (0.078)	0.370 (0.080)
	ETHNICITYDOM	0.128 (0.108)	0.222 (0.143)	0.225 (0.149)	0.224 (0.149)	0.182 (0.136)
	GDPDOM	3.157 (1.011)	3.997 (1.350)	4.492 (1.352)	4.448 (1.353)	3.860 (1.331)
	GDPWORK	3.630 (1.234)	4.148 (1.358)	4.463 (1.340)	4.439 (1.349)	4.185 (1.337)
	LIFESATDOM	7.717 (0.151)	7.614 (0.128)	7.582 (0.109)	7.586 (0.124)	7.648 (0.141)
	PARENTED					
	No	37,230 (45.3%)	5785 (58.2%)	2430 (44.2%)	480 (49.1%)	1440 (38.8%)

(Continues)

TABLE 1 (Continued)

N	White 93,170 (79.9%)	Asian 11,535 (9.9%)	Black 6570 (5.6%)	Other 1150 (1.0%)	Mixed 4240 (3.6%)
Yes	44,925 (54.7%)	4150 (41.8%)	3065 (55.8%)	495 (50.9%)	2270 (61.2%)
POPDOM	1.450 (2.168)	3.947 (3.380)	5.057 (3.494)	4.877 (3.529)	3.279 (3.371)
PVTSCHOOL					
State school	80,610 (90.4%)	9990 (90.9%)	5690 (96.7%)	975 (92.6%)	3580 (89.3%)
Private school	8560 (9.6%)	1000 (9.1%)	195 (3.3%)	80 (7.4%)	430 (10.7%)
RENTDOM	1.169 (0.695)	1.778 (1.076)	2.217 (1.097)	2.201 (1.094)	1.710 (1.031)
RUSSGRP					
Non-Russell Group	67,670 (72.6%)	8035(69.7%)	5635 (85.8%)	845 (73.8%)	2905 (68.5%)
Russell Group	25,500 (27.4%)	3500 (30.3%)	935 (14.2%)	300 (26.2%)	1340 (31.5%)
SESIMD					
Less deprived	51,015 (68.1%)	4210 (38.5%)	1365 (21.4%)	420(38.7%)	2120 (54.1%)
More deprived	23,865 (31.9%)	6740 (61.5%)	5000 (78.6%)	660 (61.3%)	1800 (45.9%)
SESOCCUP					
Groups 3–9	44,295 (50.2%)	7620 (68.2%)	4325 (69.9%)	760 (69.1%)	2065 (50.6%)
Groups 1 and 2	43,930 (49.8%)	3555 (31.8%)	1865 (30.1%)	340 (30.9%)	2015 (49.4%)
SEX					
Female	55,390 (59.5%)	6310 (54.7%)	4310 (65.6%)	640 (55.8%)	2560 (60.4%)
Male	37,735 (40.5%)	5220 (45.3%)	2260 (34.4%)	510 (44.2%)	1680 (39.6%)
SUBJECT					
Arts and humanities	16,920 (18.2%)	865 (7.5%)	505 (7.7%)	140 (12.0%)	845 (19.9%)
Medicine and dentistry	2365 (2.5%)	825 (7.2%)	100 (1.5%)	90 (7.7%)	155 (3.6%)

TABLE 1 (Continued)

		White	Asian	Black	Other	Mixed
	N	**93,170 (79.9%)**	**11,535 (9.9%)**	**6570 (5.6%)**	**1150 (1.0%)**	**4240 (3.6%)**
	STEM	42,750 (45.9%)	5600(48.5%)	3,400 (51.8%)	510 (44.2%)	1760 (41.5%)
	SocSci	10,085 (10.8%)	1285(11.2%)	990 (15.1%)	115 (9.9%)	565 (13.3%)
	Law	2610 (2.8%)	430 (3.7%)	265 (4.0%)	50 (4.4%)	135 (3.1%)
	BusComm	13,010 (14.0%)	2150 (18.7%)	1100 (16.7%)	215 (18.7%)	640 (15.1%)
	Education	4930 (5.3%)	370 (3.2%)	195 (2.9%)	35 (2.9%)	135 (3.2%)
	Combined	500 (0.5%)	10 (0.1%)	20 (0.3%)	/	15 (0.4%)
	UNEMPDOM	0.389 (0.117)	0.480 (0.121)	0.489 (0.102)	0.471 (0.105)	0.438 (0.123)
Outcome variables	POPULATION PROPORTION (GLM)	0.151 (0.140)	0.244 (0.150)	0.271 (0.150)	0.262 (0.154)	0.232 (0.154)
	MIGRATION BINARY (BLR)					
	Nonmigrant	33,760 (40.3%)	6025 (58.4%)	3915 (66.9%)	640 (64.6%)	1880 (49.2%)
	Migrant	49,970 (59.7%)	4285 (41.6%)	1935 (33.1%)	350 (35.4%)	1940 (50.8%)
	MIGRATION CATEGORICAL (MNL)					
	Nonmigrant	33,760 (40.3%)	6025 (58.4%)	3915 (66.9%)	640(64.6%)	1880 (49.2%)
	High diversity migrant	26,080 (31.1%)	2520 (24.5%)	1085 (18.5%)	205 (20.6%)	1220 (32.0%)
	Low diversity migrant	23,900 (28.5%)	1765 (17.1%)	855 (14.6%)	145 (14.8%)	720 (18.8%)

Note: NB: HESA rounding requirements mean figures are rounded to the nearest five, and figures based on seven or fewer individuals are suppressed (/). Totals may not sum to 100, and percentages may not equal 100%. For continuous variables, standard deviations appear in brackets.

distances for HE. Although White graduates are more likely to graduate with first- and upper second-class honours, Asian graduates have higher levels of human capital as measured by Russell Group university attendance and average UCAS entry tariffs.

7 | EXAMINING THE RELATIONSHIP BETWEEN ETHNICITY AND WORKING IN AN ETHNICALLY DIVERSE AREA USING A GLM

A GLM is used to examine the relationship between a graduate's ethnicity and the ethnic composition of their area of work 15 months after they leave HE while controlling for personal characteristics. Longhi (2014) finds that averages taken from both English counties and Government Office Regions are good instruments for the measures of ethnic diversity levels used in this paper. Accordingly, the use of averages from the UK's 154 LAUAs (and equivalents) is appropriate since they resemble the size of the English counties used by Longhi (2014). Therefore, the outcome variable used in this analysis is a lagged population proportion of EMs relative to the total population in each of the 154 administrative areas of the United Kingdom, and the data are taken from the 2011 UK Census provided by the ONS. The population proportion (π_m) can be formally expressed as:

$$\pi_m = \sum_{m=1}^{154} \frac{\text{Pop}_{\text{jm}}}{\text{Pop}_m}, \tag{4}$$

where Pop_{jm} is the population of individuals j who self-report being an EM (i.e., Asian, Black, Mixed, and Other ethnic backgrounds) located in each administrative area m, and Pop_m is the total population of the administrative area m. The lowest recorded level of ethnic diversity levels reported in Table 1 is recorded in Orkney at 0.7%, while the highest level is recorded in Slough at 54.3%.

Proportional data have values that fall between 0 and 1, and a common modeling technique for such data is to use a GLM with a logit link and the binomial family (Dobson & Barnett, 2018). A GLM is a flexible generalization of the linear regression model that allows the dependent variable to be related to the independent variables through a link function and an error distribution that is not necessarily normal. The logit function is defined as:

$$\text{logit}(p) = \log \frac{p}{1-p}, \tag{5}$$

where p is the probability of the response being 1. The GLM equation for the binomial family with a logit link function can be expressed formally as:

$$\text{logit}(p) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_{n,} \tag{6}$$

where p is the probability of the binary response being 1, x_1, x_2, ..., x_n are the independent variables; and β_0, β_1, β_2, ..., β_n are the model coefficients. In this analysis, p is the probability of the proportion of EMs in an administrative area equaling 1; x_1 represents the parameter of interest (ethnicity); and x_2, ..., x_n are the control variables representing personal characteristics. Table 2 lists and describes these characteristics.

A more precise estimation of the association between an individual's ethnicity and their migration behavior can be obtained by controlling for factors that may influence the relationship between the outcome variable and the parameter of interest in the model. Characteristics, such as age (AGE), sex (SEX), and disability (DISABILITY); socioeconomic status measured by parental occupation (SESOOCUP) and Index of Multiple Deprivation (SESIMD); and human capital markers such as degree classification (DEGREECLASS), institutional selectivity as measured by average UCAS entry tariff score (ETRARIFF), whether the institution is in the elite Russell Group (RUSSGRP), and course subject (SUBJECT) may all affect graduate migration behavior (Abreu et al., 2015; Borjas, 1992; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017; Wielgoszewska, 2018). The literature treats degree classification as

TABLE 2 Variables used in the regression analyses.

Variable	Definition	Source
AGE	1 if respondent or parent is 25 years and over; 0 if 24 years and below	GO survey (HESA)
DEGREECLASS	Factor variable based on classification of first degree where 0 = unclassified/third/pass, 1 = first class honours, 2 = upper second class honours, 3 = lower second class honours, 4 = unclassified degrees excluding medical/dentistry degrees, 5 = unclassified degree for medical and dentistry degrees	GO survey (HESA)
DISABILITY	1 if respondent reports known disability; 0 otherwise	GO survey (HESA)
DOM_UNI_DIST	Geodetic distance between the center points of domicile and place of higher education (in km)	Coordinate data taken from GeoHack and provided under an Open Government Licence (OGL)
ETARIFF	A continuous variable of average tariffs per institution is determined by taking the total tariff points of first-year first-degree full-time entrants who were aged under 21 at the start of their course, if the qualifications that they entered with could all be expressed using the tariff system	Guardian University Guide, 2016
ETHNICITYDOM	A proportion measuring the density of ethnic minorities in an area is calculated by dividing the sum of all non-White persons in an area by its total number of inhabitants	2011 Census: Ethnic group, local authorities in the United Kingdom (ONS)
ETHNICITY	Factor variable based on self-reported ethnicity where 0 = White, 1 = Asian, 2 = Black, 3 = Other, 4 = Mixed	GO survey (HESA)
GDPDOM	A continuous variable of the Gross Domestic Product per head at current prices of the pre-HE place of domicile, 2019	Regional gross domestic product: Local authorities (ONS); District Council Area Data (Northern Ireland Department for the Economy)
GDPWORK	A continuous variable of the Gross Domestic Product per head at current prices of the post-HE place of employment, 2019	Regional gross domestic product: Local authorities (ONS); District Council Area Data (Northern Ireland Department for the Economy)
LIFESATDOM	A percentage measure of life satisfaction in local authority areas, 2019	Personal well-being estimates by local authority (ONS)

(Continues)

TABLE 2 (Continued)

Variable	Definition	Source
PARENTED	1 if respondent's parents have higher education qualifications; 0 if otherwise	GO survey (HESA)
POPDOM	A continuous variable of an area's total population, 2011	2011 Census: Ethnic group, local authorities in the United Kingdom (ONS)
PVTSCHOOL	1 if attended private school; 0 if state school	GO survey (HESA)
RENTDOM	A continuous variable of median monthly rent for an area's administrative headquarters	Market rent summary (www.home.co.uk)
RUSSGRP	1 if attended a Russell Group university; 0 if otherwise	GO survey (HESA)
SALARY	A continuous variable based on annual pay (before tax) of the graduate's main employment during census week, measured in British pounds and excludes salary outliers. Rounded to the nearest thousand.	GO survey (HESA)
SESIMD	1 if respondent is classified in the lowest five IMD deciles; 0 if classified in the highest five IMD deciles	GO survey (HESA)
SESOCCUP	1 if respondent or parent is classified in National Statistics Socioeconomic Classification groups 1 and 2; 0 if groups 3–9	GO survey (HESA)
SEX	1 if responded male; 0 if responded female	GO survey (HESA)
SUBJECT	Factor variable based on JACS subject area where 0 = Arts and Humanities, 1 = Medicine and dentistry, 2 = STEM, 3 = Social Science (SocSci),), 4 = Law, 5 = Business/Communications (BusComms), 6 = education, 7 = Combined	GO survey (HESA)
UNEMPDOM	A percentage measure of unemployment rates in local and unitary authorities and District Council Area of Northern Ireland	Unemployment rates in local and unitary authorities (ONS), District Council Area Data (economy-ni.gov.uk)

the preferred measure of individual human capital endowments (Faggian & McCann, 2009; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017). The categorical variable for degree classification (DEGREECLASS) uses the third-class degree/pass degree group as the base outcome. It distinguishes between unclassified medical degrees and other unclassified degrees because medical degrees in the United Kingdom are typically unclassified, while unclassified degrees in other subjects may indicate insufficient credits for a third-class degree. Additional personal characteristics included in the model are a parental education marker (PARENTED) and whether the graduate attended private school (PVTSCHOOL), since graduates who are privately educated and have graduate parents may have more complete information about employment opportunities across longer distances (Borjas, 1992; Green et al., 2017).

The selection of EMs into employment locations may exhibit endogeneity due to unobserved characteristics that could be correlated with migration. This issue can be partly addressed by including the following control variables for domicile characteristics that are known to influence the choice of location (Faggian et al., 2006, 2007a, 2007b; Florida, 2014): cost of housing (RENTDOM), average life satisfaction (LIFESATDOM), total population (POPDOM), wages (GDPDOM), unemployment rates (UNEMPDOM), and ethnic diversity level (ETHNICITYDOM). This model controls for evidence of previous migration by including the distance traveled from the home domicile to the place of employment (DOM_UNI_DIST), a variable that captures some of the unobserved heterogeneity in the propensity to migrate for employment (DaVanzo, 1983). The size of the effects of ethnicity on the probability of working in an ethnically diverse administrative area is estimated using marginal effects while all other covariates are held at their mean values (see Williams, 2012), which is an intuitive way to compare the "average" graduate from one major ethnic group to the reference White group.

Table 3 presents the results of the GLM, where robust standard errors are provided. The results indicate that, for graduates from all EM groups, there is a positive and statistically significant relationship between ethnicity and being employed in an ethnically diverse area 15 months after leaving HE compared with White graduates. Table 3 reports the marginal effects of ethnicity in the GLM, which show that the effect sizes range between 4.4 percentage points (pps) for Black graduates and 2.5 pps for Mixed graduates.

These findings are in keeping with the well-documented phenomenon of spatial clustering among EMs in the United Kingdom, both in terms of the general population (Dustmann & Preston, 2001; Feng et al., 2015; Johnston et al., 2002; Knies et al., 2016; Longhi, 2014; Zwysen & Demireva, 2020) and among HE students (Donnelly & Gamsu, 2018; Finney, 2011; Gamsu et al., 2019). However, because of the novelty of using the LAUA level (and equivalents), the spatial clustering of EM graduates in localities throughout the UK has not been previously described in the literature.

8 | MODELING THE EFFECT OF ETHNICITY ON THE PROBABILITY OF LEAVING THE HOME DOMICILE FOR EMPLOYMENT USING BLR

Migration decisions are a classic case of the decision maker's set of alternatives being qualitative and lumpy (McFadden, 1973), and a common approach for modeling graduate migration behavior under these conditions is logistic regression (e.g., Faggian et al., 2007b). This step seeks to understand the effect of ethnicity on the probability that an individual will be working in their pre-university domicile 15 months after graduating from HE. For a given area, let a *nonmigrant* be a graduate who is domiciled in an area before entering HE and who is then employed in that same area 15 months after leaving HE. Thus, a *migrant* is a graduate employed in a local area other than their pre-HE home domicile 15 months after graduation. This assumes that the decision of whether to migrate for employment has only two choices available ($y = 0$ = work in domicile of origin = nonmigrant; and $y = 1$ = work in any other UK administrative area = migrant). When the identity utility framework is used to describe migration choice behavior, the alternative that is chosen is the alternative with the highest utility. Therefore, estimating the

TABLE 3 Estimation results and marginal effects of ethnicity: GLM (y = ethnic diversity level of post-HE place of employment) and BLR (y = probability of migrating away from home domicile, (n = 70,005).

Variables	GLM Coeff.[a]	GLM Marg. Eff.[b]	BLR Coeff.[a]	BLR Marg. Eff.[b]
ETHNICITY				
Asian	0.200***	0.0302***	−0.0299	−0.00740
	(0.0101)	(0.00159)	(0.0307)	(0.00761)
Black	0.282***	0.0436***	0.220***	0.0535***
	(0.0128)	(0.00212)	(0.0425)	(0.0102)
Other	0.201***	0.0302***	−0.104	−0.0257
	(0.0265)	(0.00424)	(0.0974)	(0.0243)
Mixed	0.165***	0.0246***	0.0845*	0.0208*
	(0.0151)	(0.00235)	(0.0449)	(0.0110)
DEGREECLASS				
First-class	0.136***		0.439***	
	(0.0234)		(0.0665)	
Upper second-class	0.0511**		0.211***	
	(0.0232)		(0.0661)	
Lower second-class	−0.0134		0.0299	
	(0.0241)		(0.0690)	
Unclassified other	−0.202***		0.383***	
	(0.0415)		(0.108)	
Unclassified medical	−0.0899		0.830**	
	(0.141)		(0.361)	
SEX	0.0247***		0.204***	
	(0.00684)		(0.0179)	
AGEOVER25	−0.0579***		−0.260***	
	(0.0107)		(0.0278)	
DISABILITY	0.00622		0.120***	
	(0.00919)		(0.0235)	
SESOCCUP	0.0313***		0.0786***	
	(0.00738)		(0.0190)	
SESIMD	−0.0668***		−0.159***	
	(0.00755)		(0.0196)	
PARENTED	0.0158**		0.129***	
	(0.00732)		(0.0189)	
PVTSCHOOL	0.189***		0.0872***	
	(0.0111)		(0.0304)	

TABLE 3 (Continued)

Variables	GLM Coeff.[a]	GLM Marg. Eff.[b]	BLR Coeff.[a]	BLR Marg. Eff.[b]
SUBJECT				
Medicine and dentistry	−0.418***		0.905***	
	(0.138)		(0.350)	
STEM	−0.203***		0.196***	
	(0.00964)		(0.0249)	
SocSci	0.0118		−0.00150	
	(0.0118)		(0.0316)	
Law	−0.0290		0.0106	
	(0.0191)		(0.0525)	
BusComms	0.0419***		0.180***	
	(0.0118)		(0.0308)	
Education	−0.241***		−0.488***	
	(0.0170)		(0.0463)	
Combined	0.00342		−0.150	
	(0.0670)		(0.171)	
RUSSGRP	0.0826***		0.127***	
	(0.0106)		(0.0274)	
ETARIFF	1.249***		2.249***	
	(0.0685)		(0.173)	
POPDOM	0.0156***		−0.208***	
	(0.00323)		(0.00826)	
ETHNICITYDOM	2.443***		0.388**	
	(0.0633)		(0.153)	
RENTDOM	0.0687***		−0.246***	
	(0.0112)		(0.0286)	
GDPDOM	0.00781		0.0662***	
	(0.00707)		(0.0172)	
UNEMPDOM	−0.780***		−0.397***	
	(0.0517)		(0.122)	
LIFESATDOM	0.000281		1.611***	
	(0.0349)		(0.0902)	
DOM_UNI_DIST	0.000343***		0.00334***	
	(3.53e−05)		(0.000103)	

(Continues)

TABLE 3 (Continued)

Variables	GLM Coeff.[a]	GLM Marg. Eff.[b]		BLR Coeff.[a]	BLR Marg. Eff.[b]
Constant	−2.253***			−13.22***	
	(0.281)			(0.726)	
Log pseudolikelihood =	−23486.17897		Log pseudolikelihood=	−40324.788	
(1/*df*) Pearson=	0.1091545		Wald X^2 (32)=	10486.92	
AIC=	0.6719285		Prob > X^2=	0.0000	
BIC=	−773247.9		Pseudo R^2	0.1622	

[a]Robust standard errors in parentheses.
[b]Marginal effects are the discrete change from the reference White category. All predictors are at their mean value.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

probability that a decision maker *j* will be classified as a migrant can be modeled using BLR, which can be expressed formally as follows (Faggian et al., 2007b)

$$P_{j(y=1)} = \frac{1}{1 + e^{-X_j\beta}}, \quad (7)$$

where X_j includes personal characteristics and β is a vector of the parameters to be estimated. The parameter of interest in this model is ethnicity, and the same variables are controlled for as in the GLM.

The results of the BLR are provided in Table 3 with robust standard errors, where the pseudo-R^2 value of 0.1622 indicates a good model fit for a logit model using microdata (Faggian et al., 2007b; Louviere et al., 2000). The BLR results reveal that, compared to White graduates, there is a statistically significant probability that graduates from Black and Mixed backgrounds are, on average, more likely to find work outside of their home domicile. The results for individuals from Asian and Other backgrounds are not significant. The marginal effects in Table 3 indicate that Black graduates are, on average, 5.4 pps more likely than White graduates to migrate for employment, whereas the difference is 2.1 pps for Mixed background graduates. The present findings contradict-previous evidence that has found that Black graduates are less mobile than their White counterparts (Abreu et al., 2015; Faggian et al., 2006). Several explanations may account for this difference.

First, this paper uses a new data set that allows the regression to control for more detailed background characteristics that are known to have an important impact on human capital accumulation and migration, factors such as parental HE attainment (Borjas, 1992), private school attendance (Green et al., 2017), and multiple measures of socioeconomic status (Wielgoszewska, 2018). Second, the use of different ethnic categories across studies may contribute to the differences reported here. Faggian et al. (2006) use White, Asian, and Black categories in their model, while Abreu et al. (2015) employ White, Asian, Black, and Other categories. Kidd et al. (2017) and Mosca and Wright (2010) create dummy variables by grouping all non-White ethnic groups together. Additionally, while this paper measures migration based on administrative boundary changes, Faggian et al. (2006), Abreu et al. (2015), and Kidd et al. (2017) employ distance thresholds. Faggian et al.'s (2006) data covers 1998–2001, while Abreu et al. (2015) data covers the 2002/2003 year cohort. Furthermore, Black graduates may have become more migratory over the past 20 years. The results also reveal a positive relationship between the probability of migration and the following three markers of individual human capital levels: degree classification, Russell Group university attendance, and UCAS entry tariff score. This is broadly in line with the predictions of human capital theory (Sjaastad, 1962) and the empirical tests of it using HESA data (Faggian & McCann, 2009; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017).

9 | EXPLORING THE IDENTITY ECONOMICS THESIS USING MNL

If the migration choice sets available to a graduate are mutually exclusive or are neither substitutes nor complements, then the probability of migration can be estimated consistently using the MNL approach that is common in the graduate migration literature. Following Faggian et al. (2007b), in the case of more than two migration categories ($k = 1,\ldots, K$) where the focus is on the personal characteristics of the decision maker j only, the MNL can be expressed formally as:

$$P_j(k) = \frac{e^{\beta_k X_j}}{\sum_h e^{\beta_h X_j}}, \tag{8}$$

where X_n includes personal characteristics and β_k is a vector of the parameters to be estimated relative to a reference category. Based on the identity economics thesis, it is argued that EM graduates are comparatively more likely to seek employment outside of their home domicile in a more ethnically diverse location than in a less diverse location. To evaluate this hypothesis, a composite outcome variable is created by combining the prior outcome variables used in the GLM and BLR models. This composite variable is created as follows. First, a dichotomous variable is generated using the population proportions used in the GLM (Equation 5). In this binary coding scheme, areas falling within the lowest four ethnic diversity quintiles are coded 0, while those in the highest diversity quintile areas are coded 1. Then, this dichotomous quintile-based variable is combined with another dichotomous variable, coded as 0 for nonmigrants and 1 for migrants. This combination leads to the creation of a composite categorical variable with four distinct categories, representing all possible joint values. For clarity and ease of interpretation, the two categories pertaining to nonmigrants are collapsed into a single category. This results in the outcome variable used here, which classifies individuals into one of the following:

- Nonmigrant (NM)—if they are employed in their pre-HE domicile of origin.
- High diversity migrant (HDM)—if they migrate to an employment location that is in the highest ethnic diversity quintile.
- Low diversity migrant (LDM)—if they migrate to an employment location that is in the lowest four ethnic diversity quintiles.

Negative results of the Hausman and Small–Hsiao tests indicate that the outcomes are different and mutually exclusive, which satisfies the assumption of the independence of irrelevant alternative (IIA). The parameter of interest in this model is ethnicity, and the same variables are controlled for as in the previous GLM and BLR. The reference category used here is NM because this allows for a direct comparison of results between those who migrate to more diverse places (i.e., *HDMs*) and those who migrate to less diverse places (i.e., *LDMs*). The results of the MNL model in Table 4 are provided with robust standard errors, and the pseudo-R^2 value of 0.1252 indicates a reasonable model fit.

The results indicate a positive and statistically significant likelihood that graduates from Asian, Black, and Mixed groups fall into the *HDM* category compared with their White counterparts. The results for the Other group are not significant. Furthermore, a negative and statistically significant result exists that graduates from Asian, Other, and Mixed groups fall into the *LDM* category compared with their White peers. The results for the Black group are not significant. Interestingly, most estimation coefficients have a similar direction and statistical significance when *HDMs* and *LDMs* are compared, which means ethnicity is one of the few factors that distinguishes *HDMs* and *LDMs* from *NMs*.

The marginal effects presented in Table 5 reveal that Black graduates have, on average, a 11.2 pp higher probability of being an *HDM* compared to their White counterparts. The difference is 6.8 for Mixed graduates and 6.2 pp for Asian graduates. Asian graduates have, on average, a 6.6 pp lower probability of being classified as *LDMs* compared to White graduates. The difference is 5.2 pp for Black graduates, 4.8 pp for Other, and 4.7 pp for Mixed

TABLE 4 MNL results: Ethnicity and migration to ethnically diverse areas (n = 70,005).

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
ETHNICITY		
Asian	0.187***	−0.299***
	(0.0359)	(0.0389)
Black	0.473***	−0.0796
	(0.0511)	(0.0536)
Other	0.0126	−0.264**
	(0.112)	(0.121)
Mixed	0.260***	−0.150***
	(0.0512)	(0.0573)
DEGREECLASS		
First-class	0.599***	0.277***
	(0.0817)	(0.0789)
Upper second-class	0.313***	0.121
	(0.0812)	(0.0784)
Lower second-class	0.0677	0.00566
	(0.0849)	(0.0817)
Unclassified other	0.199	0.533***
	(0.133)	(0.119)
Unclassified medical	0.876**	0.747*
	(0.402)	(0.394)
SEX	0.211***	0.198***
	(0.0204)	(0.0215)
AGEOVER25	−0.311***	−0.228***
	(0.0339)	(0.0328)
DISABILITY	0.128***	0.114***
	(0.0269)	(0.0281)
SESOCCUP	0.0941***	0.0608***
	(0.0218)	(0.0230)
SESIMD	−0.235***	−0.0741***
	(0.0229)	(0.0236)
PARENTED	0.133***	0.124***
	(0.0218)	(0.0228)
PVTSCHOOL	0.205***	−0.122***
	(0.0331)	(0.0389)

TABLE 4 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
SUBJECT		
Medicine and dentistry	0.473	1.480***
	(0.388)	(0.382)
STEM	−0.0642**	0.519***
	(0.0282)	(0.0311)
SocSci	0.0159	−0.0317
	(0.0351)	(0.0420)
Law	0.00655	0.0257
	(0.0594)	(0.0687)
BusComms	0.222***	0.131***
	(0.0345)	(0.0399)
Education	−0.810***	−0.133**
	(0.0597)	(0.0558)
Combined	−0.279	0.0416
	(0.189)	(0.221)
RUSSGRP	0.289***	−0.0939***
	(0.0308)	(0.0335)
ETARIFF	2.853***	1.434***
	(0.196)	(0.212)
POPDOM	−0.248***	−0.167***
	(0.00969)	(0.00997)
ETHNICITYDOM	0.482***	0.362*
	(0.176)	(0.191)
RENTDOM	−0.252***	−0.216***
	(0.0321)	(0.0342)
GDPDOM	0.0713***	0.0421**
	(0.0189)	(0.0213)
UNEMPDOM	−1.284***	0.508***
	(0.141)	(0.150)
LIFESATDOM	1.540***	1.615***
	(0.104)	(0.110)
DOM_UNI_DIST	0.00341***	0.00325***
	(0.000112)	(0.000119)

(Continues)

TABLE 4 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
Constant	−13.15***	−14.15***
	(0.838)	(0.887)
Log pseudolikelihood=	−65142.55	
Wald X^2 (64)=	12981.93	
Prob > X^2=	0.0000	
Pseudo R^2	0.1252	

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE 5 MLR: Marginal effects of ethnicity at mean values (n = 70,005).

Variables	Asian Marg. eff.	Black Marg. eff.	Other Marg. eff.	Mixed Marg. eff.
Nonmigrant	0.00383	−0.0603***	0.0273	−0.0210*
	(0.00770)	(0.0103)	(0.0242)	(0.0111)
High diversity migrant	0.0616***	0.112***	0.0209	0.0675***
	(0.00743)	(0.0114)	(0.0221)	(0.0106)
Low diversity migrant	−0.0655***	−0.0516***	−0.0483***	−0.0465***
	(0.00580)	(0.00853)	(0.0187)	(0.00882)

Note: Standard errors in parentheses. Marginal effects are the discrete change from the reference White category. All predictors at their mean value.
***$p < 0.01$; *$p < 0.1$.

graduates. These results support this paper's hypothesis, suggesting that when graduates from Asian, Black, and Mixed backgrounds migrate for work, they tend to, on average, select more diverse areas over less diverse areas. Using this approach, however, it is difficult to disentangle the effects of identity-related motivations for migration and motivations related to the quantity and quality of job opportunities at the destination.

Therefore, an alternative MNL specification is used for the main model using a two-level multinomial logistic regression with a generalized structural equation model after the method described by Skrondal and Rabe-Hesketh (2003). This model estimates the probability of individuals falling into the previously discussed three migration categories using the same controls as the original MNL, while also controlling for the expected wages at the employment destination (GDPWORK). The estimation results in Table A1, Appendix 1 are qualitatively similar to the previous MNL: Asian, Black, and Mixed groups are more likely to fall into the *HDM* category, with statistically significant results. However, the original MNL remains the preferred model because GDPWORK is likely endogenous (i.e., determined simultaneously along with the migration decision).

Comparing these results with those of existing literature is difficult due to the unique migration categories developed in this paper. However, the novel findings to emerge from this analysis are that, on average, graduates from Asian, Black, and Mixed backgrounds are comparatively more likely to migrate to highly ethnically diverse employment locations. This is consistent with evidence from Gamsu et al. (2019), who demonstrate that EM students are more likely to migrate for HE to areas with similar or higher levels of ethnic diversity compared with their home domicile. Taken together, these findings provide some tentative support for the identity economics thesis, suggesting that EM graduates may seek to maximize identity utility alongside standard utility when selecting employment locations.

10 | ROBUSTNESS CHECKS

The literature often treats a positive relationship between migration and individual human capital endowments as support for human capital theory. Furthermore, long-standing evidence exists for ethnic disparities in human capital levels among UK graduates. The results of the robustness checks presented in Appendix 2 indicate that controlling for the interaction between ethnicity and the three markers of human capital levels (degree classification, Russell Group attendance, and UCAS entry tariff) does not significantly impact this paper's findings. The literature has also evidenced a London effect, where highly qualified graduates are less likely to migrate because of better job access in the capital, as predicted by job search theory. Therefore, a second robustness check is performed to assess the strength of the findings against the outsized role played by Greater London in the UK labor market. The findings in Appendix 3 demonstrate that excluding Greater London employment observations has several noteworthy implications. For the alternative BLR specification, the Black group loses statistical significance while the coefficient for the Mixed group turns negative, which indicates that Greater London observations contribute substantially to the main findings that Black and Other background graduates are more mobile than their White peers. When Greater London observations are dropped from the MNL, the sign of the Asian and Other coefficients turns negative for the HDM category. Overall, these results suggest that Greater London observations drive much of the observed migration to diverse areas, which is unsurprising given that Greater London is the most populous LAUA and one of the most ethnically diverse areas of the United Kingdom.

11 | DISCUSSION AND CONCLUSION

A limited number of studies have specifically examined ethnic differences in graduate migration behavior in the United Kingdom, with the extant literature being focused on ethnic differences in sequential migration behavior, sector-based migration, and earnings. Therefore, research has not considered whether the preference for working in ethnically diverse areas may account for some of the differences in graduate migration patterns among ethnic groups. This paper has specifically addressed this gap by using the GO survey for the first time, which contains more detailed background information on graduates than previous studies have been able to use. This paper has revealed three new findings that have important implications for the study of UK graduate migration. First, a focus on LAUA and equivalents across the United Kingdom reveals that EM graduates are more likely than their White peers to find work in more ethnically diverse areas, which has not been previously reported in the literature. This finding corroborates existing research on the spatial clustering of EMs in the United Kingdom (Feng et al., 2015; Johnston et al., 2002; Knies et al., 2016; Longhi, 2014; Zwysen & Demireva, 2020; Zwysen & Longhi, 2018). However, the approach adopted here differs insofar as it focuses on overall ethnic diversity levels rather than on the concentration of co-ethnics.

Second, an analysis of the relationship between ethnicity and the probability of leaving the home domicile for employment has revealed that Black and Mixed-background graduates are more mobile than their White peers. Moreover, robustness checks have revealed that this difference is substantially driven by employment migration to Greater London. The evidence on Black migration presented here contradicts previous findings from Abreu et al. (2015) and Faggian et al. (2006), but their evidence on Black mobility rates may be outdated since the data underpinning their studies are over 20-year-old. The migration patterns of Black graduates may have changed over time, and more recent evidence suggests that Black and White students exhibit similar migration rates upon entry to HE (Donnelly & Gamsu, 2018). It is also possible that controlling for more detailed background characteristics and the different methods of measuring migration used in this study may have influenced the present findings. On the other hand, the results confirm previous research that has indicated that graduates from Asian and Other backgrounds are less likely to migrate for work than their White counterparts (Abreu et al., 2015; Faggian et al., 2006).

Finally, few studies have considered the possibility that an individual's ethnic identity may play a causal role in their decisions about where to live and work after leaving HE. Accordingly, this paper has formalized a utility function that combines the traditional approaches of human capital theory and job search theory (Faggian et al., 2007b) with identity economics (Akerlof & Kranton, 2000). This paper has evaluated the identity economic thesis by testing the hypothesis that EMs are more likely to leave their home domicile for work in a more ethnically diverse place than in a less diverse place. The rich controls used in regressions follow guidance in the literature on reducing endogenous interaction bias in migration modeling (Radu, 2008), which allows for a better understanding of the effect of ethnicity on migration. The findings show that graduates from Asian, Black, and Mixed backgrounds are, on average, more likely than their White counterparts to leave their home domicile for employment locations with higher levels of ethnic diversity. Because EM graduates tend to originate from more ethnically diverse areas, this new evidence may help explain why previous studies (Abreu et al., 2015; Faggian et al., 2006; Kidd et al., 2017; Mosca & Wright, 2010) have reported lower rates of employment migration among EMs. Additionally, this suggests that the migration patterns of EM graduates as they enter the labor market are similar to the migration patterns of EMs upon entering HE, as described by Gamsu et al. (2019).

Apart from ethnicity, the characteristics of graduates who migrate to equally or more diverse places and the characteristics of graduates who migrate to less diverse places are surprisingly similar. Compared with nonmigrants, both are more likely to be male, to be under the age of 25 years, to come from similar socioeconomic backgrounds, to have parents who are graduates, to have similar human capital characteristics as measured by degree classification, and to migrate similar distances for HE. The standard explanations based on human capital theory and job search theory alone cannot satisfactorily explain why otherwise similar Asian, Black, and Mixed graduates might prefer working in ethnically diverse areas. The identity economics thesis, however, offers a parsimonious explanation: They gain psychic satisfaction from working in ethnically diverse areas because going against group norms is inherently costly. Norms in this study were defined as the well-evidenced phenomenon of spatial clustering among EMs, the root cause of which may be varied. The literature cites explanations such as the cost and availability of housing, discrimination, access to ethnic goods, and the maintenance of positive social connections (Johnston et al., 2002; Zwysen & Demireva, 2020).

Additionally, this study broadly supports the predictions of human capital theory (Sjaastad, 1962) by demonstrating a positive relationship between the probability of migration and three different markers of individual human capital levels. The descriptive statistics accord with existing studies that have demonstrated that EMs tend to originate from ethnically diverse areas, which may have crucial implications for nonmigrants' access to graduate jobs (Feng et al., 2015; Zwysen & Longhi, 2018). This highlights a potential tension between maximizing individual financial returns on the one hand and identity returns on the other hand, with the implication that individuals from EM backgrounds may sometimes forgo the financial benefits of employment migration because they enjoy living in their ethnically diverse domiciles. Finally, robustness checks have shown that this paper's findings are largely robust when considering the interaction of ethnicity and individual human capital levels.

While these findings are interesting, this study represents an early attempt at analysing the role played by ethnic identity in employment migration decisions. However, the present study is limited by the empirical challenge of using outcomes data to distinguish between identity-related motivations and those associated with the quantity and quality of job opportunities at the destination. Future research using experimental or survey methods could explore how motivations related to identity impact decisions about where to live and work after leaving higher education. Additionally, causal estimates assume that all relevant factors that affect employment migration are observable, but selection bias likely remains due to unobserved factors like motivation. Additionally, bias due to omitted variables remains a potential source of concern, and therefore, the results cannot be claimed to be causal in nature. An additional uncontrolled factor is the possibility that lockdowns in response to the COVID-19 pandemic introduced response bias into the data, while ethnic group differences in the effects of COVID-19 on interregional employment migration are also possible.

Since the beginning of labor migration research, economists have understood that migration has both financial and nonfinancial motivations. Before this study, there had been no attempts to formalize an economic understanding of ethnic identity in the study of graduate migration. By combining pioneering work from Akerlof and Kranton (2000) and Faggian et al. (2007a), this study has established an identity utility framework that can be used in future research. Furthermore, the findings should be interpreted with some caution due to the heterogeneity within the major ethnic classifications used in this study. A focus on more detailed ethnic classifications, such as the ONS's list of 20 classifications, could lead to interesting findings that better account for the heterogeneity within various ethnic groups. Obtaining statistically significant results may prove challenging, however, when using more granular ethnic categories. Furthermore, future work might consider whether the present findings hold when migration patterns and co-ethnic concentrations in employment destinations are considered.

In closing, migration allows graduates to flow to areas where their human capital can be used most productively. Thus, findings suggesting that ethnic identity may play a part in this process have important practical implications. Foremost among them is the need to re-evaluate the framing of graduate migration as solely an investment in human capital or a strategy for maximizing wages.

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CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

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APPENDIX 1

(Table A1)

The main MNL model is a limited test of the identity economics thesis because it does not control for the expected returns to migration that an individual may expect in a particular location, as suggested by human capital theory and job search theory (Faggian, 2021; Sjaastad, 1962). Therefore, an alternative MNL specification is used for the main model using a two-level multinomial logistic regression with a generalized structural equation model (see Skrondal & Rabe-Hesketh, 2003). This model estimates the probability of individuals falling into the previously used migration categories, while also controlling for the expected wages nested in the employment destination (GDPWORK).

Convergence was achieved using the Laplacian approximation, which means the estimation results should be interpreted with caution because they may be less accurate than estimations using other integration methods. Additionally, the original MNL remains the preferred model because GDPWORK is likely endogenous, that is, determined simultaneously along with the outcome variable.

TABLE A1 Two-level MNL results (n = 70,005).

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
ETHNICITY		
Asian	0.554***	−0.385***
	(0.0731)	(0.0531)
Black	0.531***	0.0426
	(0.0884)	(0.0732)
Other	0.111	−0.423***
	(0.201)	(0.163)
Mixed	0.515***	−0.0602
	(0.102)	(0.0751)
DEGREECLASS		
First-class	1.402***	0.416***
	(0.241)	(0.0929)

TABLE A1 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
Upper second-class	1.256***	0.157*
	(0.240)	(0.0920)
Lower second-class	0.848***	0.0147
	(0.247)	(0.0961)
Unclassified other	1.925***	0.592***
	(0.346)	(0.149)
Unclassified medical	8.377***	0.575
	(0.762)	(0.547)
SEX	0.282***	0.186***
	(0.0514)	(0.0263)
AGEOVER25	−0.953***	−0.302***
	(0.0961)	(0.0386)
DISABILITY	0.147**	0.151***
	(0.0686)	(0.0340)
SESOCCUP	0.0258	0.0780***
	(0.0558)	(0.0278)
SESIMD	−0.913***	−0.0542*
	(0.0570)	(0.0286)
PARENTED	0.334***	0.120***
	(0.0561)	(0.0276)
PVTSCHOOL	−0.755***	0.0380
	(0.0864)	(0.0514)
SUBJECT		
Medicine and dentistry	2.205***	1.327**
	(0.679)	(0.534)
STEM	0.380***	0.419***
	(0.0723)	(0.0375)
SocSci	−0.171*	0.0226
	(0.0909)	(0.0504)
Law	−0.749***	0.156*
	(0.186)	(0.0833)
BusComms	0.187**	0.175***
	(0.0896)	(0.0483)
Education	−1.566***	−0.196***

(Continues)

TABLE A1 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
	(0.185)	(0.0640)
Combined	−3.803***	0.236
	(0.864)	(0.274)
RUSSGRP	0.273***	0.0143
	(0.0760)	(0.0420)
ETARIFF	−3.384***	2.319***
	(0.484)	(0.272)
POPDOM	−54.64***	0.265***
	(0.0428)	(0.0127)
ETHNICITYDOM	−61.09***	4.232***
	(0.680)	(0.225)
RENTDOM	−17.36***	−0.855***
	(0.170)	(0.0402)
GDPDOM	−5.849***	−0.0223
	(0.0687)	(0.0235)
UNEMPDOM	−40.05***	−0.130
	(0.532)	(0.175)
LIFESATDOM	38.44***	−0.247*
	(0.485)	(0.138)
DOM_UNI_DIST	0.00408***	0.00240***
	(0.000240)	(0.000142)
M1[GDPDOM]	1	−0.116***
	(0)	(0.00169)
Constant	−244.3***	2.231**
	(3.865)	(1.116)
var(M1[GDPDOM])	2438***	
	(285.8)	
Log-likelihood=	−107901.3	
Df=	34	
AIC=	215870.6	
BIC=	216195.6	

Note: Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

APPENDIX 2

The literature (Faggian & McCann, 2009; Faggian et al., 2006, 2007a, 2007b; Kidd et al., 2017) treats a positive relationship between migration and measures of individual human capital levels as evidence in support of the human capital theory of migration. Therefore, Appendix 1 seeks to understand if controlling for the confounding interaction effect of ethnicity and human capital levels changes the results reported in the main analysis. Measures of human capital used in the literature (Faggian et al., 2007b; Kidd et al., 2017) include degree classification, the type of university attended (e.g., Russell Group) and selectivity in the form of rankings such as the Research Assessment Exercise. Therefore, three additional specifications are developed for the main GLM, BLR, and MNL that control for the interaction of ethnicity and three alternative measures of individual human capital levels:

1. Model 1: Controls for the interaction of ethnicity and degree classification
2. Model 2: Controls for the interaction of ethnicity and Russell Group attendance
3. Model 3: Controls for the interaction of ethnicity and average UCAS entry tariff for the HEI.

When controlling for the interaction of ethnicity and degree classification in Model 1, the results presented in Table B1 are qualitatively similar to the main GLM model, except the results for the Mixed group lose significance.

TABLE B1 GLM controlling for the interaction of ethnicity and human capital markers (n = 70,005).

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
ETHNICITY			
Asian	0.373***	0.267***	0.743***
	(0.0565)	(0.0118)	(0.0438)
Black	0.408***	0.336***	0.986***
	(0.0562)	(0.0139)	(0.0559)
Other	0.322*	0.261***	0.720***
	(0.194)	(0.0297)	(0.132)
Mixed	0.137	0.234***	0.565***
	(0.112)	(0.0186)	(0.0689)
DEGREECLASS			
First-class	0.209***	0.140***	0.145***
	(0.0341)	(0.0234)	(0.0234)
Upper second-class	0.115***	0.0560**	0.0610***
	(0.0340)	(0.0231)	(0.0231)
Lower second-class	0.00264	−0.0108	−0.00702
	(0.0354)	(0.0241)	(0.0241)
Unclassified other	−0.160***	−0.206***	−0.199***
	(0.0531)	(0.0416)	(0.0416)
Unclassified medical	0.0821	−0.0905	−0.0691

(Continues)

TABLE B1 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
	(0.146)	(0.138)	(0.139)
SEX	0.0250***	0.0261***	0.0263***
	(0.00684)	(0.00684)	(0.00683)
AGEOVER25	−0.0596***	−0.0602***	−0.0676***
	(0.0106)	(0.0107)	(0.0107)
DISABILITY	0.00792	0.00804	0.00802
	(0.00919)	(0.00920)	(0.00919)
SESOCCUP	0.0312***	0.0315***	0.0315***
	(0.00738)	(0.00738)	(0.00738)
SESIMD	−0.0667***	−0.0689***	−0.0689***
	(0.00755)	(0.00755)	(0.00756)
PARENTED	0.0155**	0.0147**	0.0149**
	(0.00732)	(0.00731)	(0.00731)
PVTSCHOOL	0.190***	0.187***	0.183***
	(0.0111)	(0.0111)	(0.0111)
SUBJECT			
Medicine and dentistry	−0.423***	−0.394***	−0.405***
	(0.139)	(0.135)	(0.135)
STEM	−0.203***	−0.202***	−0.203***
	(0.00965)	(0.00963)	(0.00964)
SocSci	0.0119	0.0117	0.0139
	(0.0118)	(0.0118)	(0.0118)
Law	−0.0322*	−0.0295	−0.0286
	(0.0191)	(0.0190)	(0.0190)
BusComms	0.0404***	0.0404***	0.0412***
	(0.0118)	(0.0118)	(0.0118)
Education	−0.241***	−0.235***	−0.233***
	(0.0170)	(0.0170)	(0.0170)
Combined	0.000952	−0.00499	−0.405***
	(0.0670)	(0.0667)	(0.135)
RUSSGRP	0.0816***	0.129***	0.0790***
	(0.0106)	(0.0114)	(0.0106)
ETARIFF	1.252***	1.269***	1.664***
	(0.0684)	(0.0683)	(0.0753)

TABLE B1 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
POPDOM	0.0156***	0.0158***	0.0162***
	(0.00323)	(0.00323)	(0.00323)
ETHNICITYDOM	2.441***	2.409***	2.397***
	(0.0632)	(0.0631)	(0.0630)
RENTDOM	0.0682***	0.0707***	0.0700***
	(0.0112)	(0.0112)	(0.0112)
GDPDOM	0.00823	0.00888	0.00917
	(0.00707)	(0.00707)	(0.00706)
UNEMPDOM	−0.780***	−0.777***	−0.781***
	(0.0517)	(0.0517)	(0.0517)
LIFESATDOM	−0.00319	−0.00757	−0.0147
	(0.0349)	(0.0349)	(0.0349)
DOM_UNI_DIST	0.000338***	0.000329***	0.000320***
	(3.53e−05)	(3.53e−05)	(3.53e−05)
Constant	−2.291***	−2.223***	−2.299***
	(0.283)	(0.282)	(0.281)
ETHNICTY#DEGREECLASS			
Asian#first	−0.214***		
	(0.0586)		
Asian#upper second	−0.173***		
	(0.0577)		
Asian#lower second	−0.0437		
	(0.0604)		
Asian#unclassified other	−0.00163		
	(0.104)		
Asian#unclassified medical	−0.409***		
	(0.0778)		
Black#first	−0.198***		
	(0.0613)		
Black#upper second	−0.137**		
	(0.0582)		
Black#lower second	−0.0114		
	(0.0606)		

(Continues)

TABLE B1 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
Black#unclassified other	−0.134		
	(0.162)		
Black#unclassified medical	−0.350**		
	(0.139)		
Other#first	−0.201		
	(0.201)		
Other#upper second	−0.137		
	(0.198)		
Other#lower second	0.0591		
	(0.201)		
Other#unclassified other	0.262		
	(0.282)		
Other#unclassified medical	−0.298		
	(0.243)		
Mixed#first	0.0106		
	(0.115)		
Mixed#upper second	0.0446		
	(0.114)		
Mixed#lower second	0.106		
	(0.119)		
Mixed#unclassified other	−0.106		
	(0.185)		
Mixed#unclassified medical	−0.352**		
	(0.167)		
ETHNICITY#RUSSGRP			
Asian#Russell Group		−0.185***	
		(0.0188)	
Black#Russell Group		−0.239***	
		(0.0285)	
Other#Russell Group		−0.189***	
		(0.0598)	
Mixed#Russell Group		−0.182***	
		(0.0306)	

TABLE B1 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
ETHNICITY#ETARIFF			
Asian#ETARIFF			−1.442***
			(0.115)
Black#ETARIFF			−2.036***
			(0.160)
Other#ETARIFF			−1.416***
			(0.369)
Mixed#ETARIFF			−1.058***
			(0.180)
Log pseudolikelihood=	−23480.26588	−23477.98684	−23472.21848
(1/*df*) Pearson=	0.1090336	0.1090092	0.1088643
AIC	0.672331	0.6718088	0.671644
BIC	−773036.6	−773219.6	−773231.2

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE B2 Gat the LM: Marginal effects of ethnicity at mean values ($n = 70{,}005$).

Variables	Model 1 *dy/dx*	Model 2 *dy/dx*	Model 3 *dy/dx*
Asian	0.0301***	0.0316***	0.0326***
	(0.00159)	(0.00159)	(0.00159)
Black	0.0403***	0.0402***	0.0369***
	(0.00228)	(0.00216)	(0.00217)
Other	0.0286***	0.0305***	0.0304***
	(0.00421)	(0.00421)	(0.00421)
Mixed	0.0244***	0.0266***	0.0266***
	(0.00236)	(0.00236)	(0.00236)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.
***$p < 0.01$.

Only one-fourth of the interaction terms are statistically significant, which could be due to the sample sizes. The interaction terms in Models 2 and 3 are statistically significant, and the results are similar to the original GLM model. Marginal effects presented in Table B2 show that the effect of ethnicity does not vary significantly across models and the effects are similar to the original GLM specification.

The results of the alternative BLR estimations are presented in Table B3. Model 1 does not serve as a meaningful robustness check since none of the interaction terms for ethnicity and degree classification are statistically significant. The insignificant interaction effects may be due to the sample sizes. The interaction terms for Black graduates in Models 2 and 3 are statistically significant, and the overall results are qualitatively similar to the original BLR. Marginal effects presented in Table B4 do not vary significantly across the three models, and the marginal effects are similar to the original BLR.

TABLE B3 BLR controlling for the interaction of ethnicity and human capital markers (n = 70,005).

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
ETHNICITY			
Asian	0.117	−0.0339	−0.161
	(0.175)	(0.0369)	(0.136)
Black	0.223	0.299***	1.036***
	(0.189)	(0.0468)	(0.196)
Other	−0.00683	−0.143	0.0732
	(0.706)	(0.119)	(0.452)
Mixed	0.129	0.0997*	0.229
	(0.354)	(0.0556)	(0.206)
DEGREECLASS			
First-class	0.477***	0.440***	0.440***
	(0.0818)	(0.0665)	(0.0665)
Upper second-class	0.229***	0.213***	0.213***
	(0.0814)	(0.0660)	(0.0661)
Lower second-class	0.0442	0.0311	0.0313
	(0.0849)	(0.0689)	(0.0690)
Unclassified other	0.454***	0.381***	0.385***
	(0.127)	(0.108)	(0.108)
Unclassified medical	0.863**	0.824**	0.829**
	(0.371)	(0.361)	(0.361)
SEX	0.203***	0.204***	0.204***
	(0.0179)	(0.0179)	(0.0179)
AGEOVER25	−0.261***	−0.264***	−0.268***
	(0.0278)	(0.0278)	(0.0278)
DISABILITY	0.121***	0.121***	0.120***
	(0.0235)	(0.0235)	(0.0235)
SESOCCUP	0.0791***	0.0782***	0.0781***
	(0.0190)	(0.0190)	(0.0190)
SESIMD	−0.159***	−0.159***	−0.158***

TABLE B3 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
	(0.0196)	(0.0196)	(0.0196)
PARENTED	0.129***	0.129***	0.129***
	(0.0189)	(0.0189)	(0.0189)
PVTSCHOOL	0.0883***	0.0846***	0.0837***
	(0.0304)	(0.0304)	(0.0304)
SUBJECT			
Medicine and dentistry	0.889**	0.911***	0.909***
	(0.353)	(0.350)	(0.350)
STEM	0.195***	0.196***	0.196***
	(0.0249)	(0.0249)	(0.0249)
SocSci	−0.00199	−0.00100	−0.00111
	(0.0316)	(0.0316)	(0.0316)
Law	0.00937	0.0118	0.0135
	(0.0525)	(0.0526)	(0.0525)
BusComms	0.179***	0.180***	0.181***
	(0.0308)	(0.0308)	(0.0308)
Education	−0.488***	−0.484***	−0.484***
	(0.0463)	(0.0463)	(0.0463)
Combined	−0.152	−0.148	−0.151
	(0.171)	(0.172)	(0.171)
RUSSGRP	0.127***	0.143***	0.125***
	(0.0275)	(0.0288)	(0.0275)
ETARIFF	2.250***	2.255***	2.346***
	(0.173)	(0.173)	(0.185)
POPDOM	−0.209***	−0.208***	−0.208***
	(0.00826)	(0.00826)	(0.00826)
ETHNICITYDOM	0.385**	0.380**	0.388**
	(0.153)	(0.154)	(0.154)
RENTDOM	−0.247***	−0.244***	−0.246***
	(0.0286)	(0.0286)	(0.0286)
GDPDOM	0.0668***	0.0663***	0.0657***
	(0.0172)	(0.0172)	(0.0172)
UNEMPDOM	−0.395***	−0.397***	−0.402***
	(0.122)	(0.122)	(0.122)

(Continues)

TABLE B3 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
LIFESATDOM	1.610***	1.612***	1.609***
	(0.0903)	(0.0903)	(0.0903)
DOM_UNI_DIST	0.00333***	0.00334***	0.00334***
	(0.000103)	(0.000103)	(0.000103)
Constant	−13.23***	−13.23***	−13.23***
	(0.728)	(0.726)	(0.726)
ETHNICTY#DEGREECLASS			
Asian#first	−0.212		
	(0.182)		
Asian#upper second	−0.0822		
	(0.180)		
Asian#lower second	−0.187		
	(0.190)		
Asian#unclassified other	−0.558		
	(0.341)		
Asian#unclassified medical	−0.209		
	(0.232)		
Black#first	−0.0835		
	(0.207)		
Black#upper second	−0.0265		
	(0.197)		
Black#lower second	0.0978		
	(0.205)		
Black#unclassified other	0.343		
	(0.432)		
Black#unclassified medical	0.307		
	(0.396)		
Other#first	−0.0932		
	(0.727)		
Other#upper second	0.0118		
	(0.720)		
Other#lower second	−0.180		
	(0.747)		
Other#unclassified other	−1.113		
	(0.947)		

TABLE B3 (Continued)

Variables	Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.
Other#unclassified medical	−0.262		
	(0.799)		
Mixed#first	−0.187		
	(0.362)		
Mixed#upper second	−0.0212		
	(0.360)		
Mixed#lower second	0.132		
	(0.375)		
Mixed#unclassified other	−0.265		
	(0.526)		
Mixed#unclassified medical	0.490		
	(0.509)		
ETHNICITY#RUSSGRP			
Asian#Russell Group		0.00908	
		(0.0594)	
Black#Russell Group		−0.423***	
		(0.0960)	
Other#Russell Group		0.120	
		(0.208)	
Mixed#Russell Group		−0.0485	
		(0.0922)	
ETHNICITY#ETARIFF			
Asian#ETARIFF			0.349
			(0.353)
Black#ETARIFF			−2.406***
			(0.556)
Other#ETARIFF			−0.485
			(1.194)
Mixed#ETARIFF			−0.396
			(0.536)
LR X^2	(52) = 10517.42	(36) = 10535.55	(36) = 10554.71
Prob > X^2=	0.0000	0.0000	0.0000
Pseudo R^2	0.1625	0.1624	0.1624

Note: Robust standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE B4 BLR: Marginal effects of ethnicity at mean values (n = 70,005).

Variables	Model 1 *dy/dx*	Model 2 *dy/dx*	Model 3 *dy/dx*
Asian	−0.00725	−0.00768	−0.00830
	(0.00761)	(0.00763)	(0.00766)
Black	0.0505***	0.0410***	0.0383***
	(0.0109)	(0.0105)	(0.0106)
Other	−0.0186	−0.0264	−0.0258
	(0.0244)	(0.0244)	(0.0242)
Mixed	0.0207*	0.0208*	0.0209*
	(0.0110)	(0.0110)	(0.0110)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.

***$p < 0.01$; *$p < 0.1$.

TABLE B5 MNL controlling for the interaction of ethnicity and human capital markers (n = 70,005).

	Model 1 (Coeff.)		Model 2 (Coeff.)		Model 3 (Coeff.)	
Variables	HDM	LDM	HDM	LDM	HDM	LDM
ETHNICITY						
Asian	0.469**	−0.257	0.198***	−0.316***	0.202	−0.575***
	(0.216)	(0.223)	(0.0439)	(0.0464)	(0.159)	(0.176)
Black	0.439*	−0.0254	0.552***	−0.00136	1.286***	0.763***
	(0.240)	(0.225)	(0.0572)	(0.0578)	(0.235)	(0.259)
Other	−0.120	−0.0325	−0.189	−0.183	−0.275	0.337
	(1.080)	(0.817)	(0.152)	(0.140)	(0.543)	(0.566)
Mixed	0.517	−0.282	0.321***	−0.177**	0.648***	−0.238
	(0.405)	(0.493)	(0.0640)	(0.0710)	(0.235)	(0.266)
DEGREECLASS						
First-class	0.664***	0.304***	0.601***	0.278***	0.601***	0.278***
	(0.100)	(0.0945)	(0.0816)	(0.0789)	(0.0816)	(0.0789)
Upper second-class	0.354***	0.134	0.316***	0.123	0.316***	0.123
	(0.100)	(0.0941)	(0.0812)	(0.0784)	(0.0812)	(0.0784)
Lower second class	0.111	0.00241	0.0691	0.00661	0.0695	0.00666
	(0.105)	(0.0981)	(0.0848)	(0.0817)	(0.0849)	(0.0817)
Unclassified other	0.260*	0.607***	0.195	0.530***	0.199	0.535***
	(0.155)	(0.138)	(0.133)	(0.119)	(0.133)	(0.119)
Unclassified medical	0.952**	0.732*	0.868**	0.743*	0.875**	0.745*

TABLE B5 (Continued)

Variables	Model 1 (Coeff.)		Model 2 (Coeff.)		Model 3 (Coeff.)	
	HDM	LDM	HDM	LDM	HDM	LDM
	(0.412)	(0.405)	(0.402)	(0.396)	(0.401)	(0.396)
SEX	0.210***	0.198***	0.211***	0.199***	0.211***	0.198***
	(0.0204)	(0.0215)	(0.0204)	(0.0215)	(0.0204)	(0.0215)
OVER25	−0.313***	−0.230***	−0.314***	−0.233***	−0.319***	−0.237***
	(0.0339)	(0.0329)	(0.0339)	(0.0328)	(0.0340)	(0.0329)
DISABILITY	0.129***	0.115***	0.129***	0.114***	0.128***	0.114***
	(0.0269)	(0.0281)	(0.0269)	(0.0281)	(0.0269)	(0.0281)
SESOCCUP	0.0943***	0.0617***	0.0939***	0.0605***	0.0938***	0.0602***
	(0.0218)	(0.0230)	(0.0218)	(0.0230)	(0.0218)	(0.0230)
SESIMD	−0.236***	−0.0732***	−0.235***	−0.0737***	−0.234***	−0.0725***
	(0.0229)	(0.0236)	(0.0229)	(0.0236)	(0.0229)	(0.0236)
PARENTED	0.133***	0.123***	0.132***	0.123***	0.133***	0.124***
	(0.0218)	(0.0228)	(0.0218)	(0.0227)	(0.0218)	(0.0227)
PVTSCHOOL	0.206***	−0.121***	0.203***	−0.125***	0.202***	−0.125***
	(0.0331)	(0.0389)	(0.0331)	(0.0389)	(0.0331)	(0.0389)
SUBJECT						
Medicine and dentistry	0.454	1.468***	0.481	1.486***	0.479	1.482***
	(0.390)	(0.386)	(0.388)	(0.384)	(0.387)	(0.384)
STEM	−0.0646**	0.518***	−0.0638**	0.519***	−0.0642**	0.519***
	(0.0283)	(0.0311)	(0.0283)	(0.0311)	(0.0283)	(0.0311)
SocSci	0.0154	−0.0318	0.0161	−0.0311	0.0163	−0.0312
	(0.0351)	(0.0420)	(0.0351)	(0.0420)	(0.0352)	(0.0420)
Law	0.00436	0.0252	0.00702	0.0271	0.00875	0.0288
	(0.0594)	(0.0687)	(0.0594)	(0.0687)	(0.0594)	(0.0687)
BusComms	0.220***	0.130***	0.221***	0.131***	0.222***	0.132***
	(0.0345)	(0.0399)	(0.0345)	(0.0399)	(0.0345)	(0.0399)
Education	−0.810***	−0.134**	−0.807***	−0.130**	−0.806***	−0.131**
	(0.0597)	(0.0558)	(0.0597)	(0.0558)	(0.0597)	(0.0558)
Combined	−0.280	0.0387	−0.279	0.0443	−0.282	0.0426
	(0.189)	(0.221)	(0.189)	(0.222)	(0.189)	(0.221)
RUSSGRP	0.289***	−0.0944***	2.862***	1.439***	0.286***	−0.0969***
	(0.0308)	(0.0336)	(0.196)	(0.212)	(0.0308)	(0.0336)
ETARIFF	2.852***	1.434***	−0.247***	−0.167***	−0.246***	−0.167***
	(0.196)	(0.212)	(0.00970)	(0.00997)	(0.00970)	(0.00998)

(Continues)

TABLE B5 (Continued)

Variables	Model 1 (Coeff.) HDM	Model 1 (Coeff.) LDM	Model 2 (Coeff.) HDM	Model 2 (Coeff.) LDM	Model 3 (Coeff.) HDM	Model 3 (Coeff.) LDM
POPDOM	−0.248***	−0.168***	0.468***	0.361*	0.469***	0.372*
	(0.00969)	(0.00998)	(0.177)	(0.191)	(0.177)	(0.192)
ETHNICITYDOM	0.474***	0.364*	−0.250***	−0.215***	−0.251***	−0.217***
	(0.176)	(0.191)	(0.0321)	(0.0342)	(0.0321)	(0.0342)
RENTDOM	−0.252***	−0.217***	0.0716***	0.0419**	0.0713***	0.0411*
	(0.0321)	(0.0342)	(0.0189)	(0.0213)	(0.0189)	(0.0213)
GDPDOM	0.0723***	0.0423**	−1.285***	0.508***	−1.289***	0.503***
	(0.0189)	(0.0213)	(0.141)	(0.150)	(0.141)	(0.150)
UNEMPDOM	−1.281***	0.510***	1.540***	1.616***	1.536***	1.614***
	(0.141)	(0.150)	(0.104)	(0.110)	(0.104)	(0.110)
LIFESATDOM	1.536***	1.616***	0.00341***	0.00325***	0.00341***	0.00326***
	(0.104)	(0.110)	(0.000112)	(0.000119)	(0.000112)	(0.000119)
DOM_UNI_DIST	0.00340***	0.00325***	−13.16***	−14.16***	−13.18***	−14.15***
	(0.000112)	(0.000119)	(0.838)	(0.888)	(0.838)	(0.888)
Constant	−13.18***	−14.17***	0.481	1.486***	0.479	1.482***
	(0.840)	(0.889)	(0.388)	(0.384)	(0.387)	(0.384)
INTERACTION ETHNICITY #DEGREECLASS						
Asian#first	−0.361	−0.102				
	(0.223)	(0.233)				
Asian#upper second	−0.212	0.00694				
	(0.220)	(0.229)				
Asian#lower second	−0.331	−0.0469				
	(0.233)	(0.241)				
Asian#unclassified other	−0.252	−0.847*				
	(0.408)	(0.440)				
Asian#unclassified medical	−0.386	−0.0107				
	(0.275)	(0.273)				
Black#first	−0.0894	−0.0807				
	(0.260)	(0.250)				
Black#upper second	0.0271	−0.101				
	(0.249)	(0.237)				
Black#lower second	0.129	0.0540				
	(0.260)	(0.246)				

TABLE B5 (Continued)

Variables	Model 1 (Coeff.) HDM	LDM	Model 2 (Coeff.) HDM	LDM	Model 3 (Coeff.) HDM	LDM
Black#unclassified other	0.598	0.111				
	(0.536)	(0.476)				
Black#unclassified medical	0.546	0.102				
	(0.461)	(0.444)				
Other#first	0.172	−0.275				
	(1.098)	(0.851)				
Other#upper second	0.264	−0.149				
	(1.092)	(0.838)				
Other#lower second	−0.0932	−0.217				
	(1.129)	(0.867)				
Other#unclassified other	−0.238	−1.991				
	(1.337)	(1.322)				
Other#unclassified medical	−0.175	−0.260				
	(1.149)	(0.905)				
Mixed#first	−0.406	−0.0231				
	(0.414)	(0.504)				
Mixed#upper second	−0.195	0.0832				
	(0.411)	(0.500)				
Mixed#lower second	−0.119	0.380				
	(0.431)	(0.515)				
Mixed#unclassified other	−1.083	0.347				
	(0.716)	(0.652)				
Mixed#unclassified medical	0.0437	0.872				
	(0.570)	(0.611)				
ETHNICITY#RUSSGRP						
Asian#Russell Group			−0.0272	0.0465		
			(0.0680)	(0.0771)		
Black#Russell Group			−0.391***	−0.490***		
			(0.110)	(0.140)		
Other#Russell Group			0.447*	−0.226		
			(0.238)	(0.267)		
Mixed#Russell Group			−0.156	0.0657		
			(0.104)	(0.119)		

(Continues)

TABLE B5 (Continued)

Variables	Model 1 (Coeff.) HDM	Model 1 (Coeff.) LDM	Model 2 (Coeff.) HDM	Model 2 (Coeff.) LDM	Model 3 (Coeff.) HDM	Model 3 (Coeff.) LDM
ETHNICITY#ETARIFF						
Asian#ETARIFF					−0.0327	0.738
					(0.408)	(0.461)
Black#ETARIFF					−2.376***	−2.518***
					(0.659)	(0.754)
Other#ETARIFF					0.700	−1.629
					(1.387)	(1.533)
Mixed#ETARIFF					−1.030*	0.224
					(0.605)	(0.696)
LR X^2	(104) = 13033.12		(72 = 13046.49		(72) = 13058-.98	
Prob > X^2=	0.0000		0.0000		0.0000	
Pseudo R^2	0.1256		0.1254		0.1254	

Note: Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

The results of the alternative MNL specifications are presented in Table B5, which show that few of the interaction terms between ethnicity and degree classification, Russell Group attendance, or average UCA entry tariff points are statistically significant. These results are likely due to the sample sizes rather than the real effects of the interactions. The marginal effects presented in Table B6 show that the marginal effects of ethnicity do not differ substantially across models, and there is little difference between these results and the original MNL estimation.

TABLE B6 MLR: Marginal effects of ethnicity at mean values (n = 70,005).

	Asian *dy/dx*			Black *dy/dx*			Other *dy/dx*			Mixed *dy/dx*		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
NMs	0.00386	0.00369	0.00395	−0.0575***	−0.0475***	−0.0451***	0.0216	0.0354	0.0314	−0.0193*	−0.0223**	−0.0223**
	(0.00771)	(0.00772)	(0.00775)	(0.0110)	(0.0107)	(0.0108)	(0.0246)	(0.0247)	(0.0245)	(0.0112)	(0.0112)	(0.0112)
MDMs	0.0625***	0.0624***	0.0627***	0.110***	0.108***	0.105***	0.0269	0.00694	0.0140	0.0696***	0.0708***	0.0708***
	(0.00750)	(0.00751)	(0.00756)	(0.0120)	(0.0115)	(0.0116)	(0.0235)	(0.0232)	(0.0231)	(0.0107)	(0.0107)	(0.0107)
LDMs	−0.0663***	−0.0661***	−0.0666***	−0.0522***	−0.0601***	−0.0598***	−0.0485**	−0.0423**	−0.0453**	−0.0503***	−0.0486***	−0.0486***
	(0.00595)	(0.00582)	(0.00583)	(0.00904)	(0.00895)	(0.00900)	(0.0203)	(0.0193)	(0.0190)	(0.00895)	(0.00883)	(0.00884)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

APPENDIX 3

(Table C6)

There is strong evidence that Greater London plays an outsized role in the UK graduate labor market, and Faggian and McCann (2009) have observed a "London effect" where graduates with better quality degrees are less likely to migrate for employment when Greater London observations were included in their analysis. Additionally, Greater London is the most ethnically diverse region in the United Kingdom with over 40% of residents identifying as coming from Asian, Black, Mixed, or Other ethnic backgrounds (ONS, 2019). Considering this evidence, there is a need to include a second robustness check in Appendix 2 to evaluate whether the inclusion of Greater London employment observations changes the results.

Table C1 presents the results of the alternative GLM with Greater London employment observations dropped. When comparing these results to the original specification, the most relevant difference is that the

TABLE C1 GLM with Greater London employment observations dropped (*n* = 50,766).

Variables	Coeff.
ETHNICITY	
Asian	0.176***
	(0.0132)
Black	0.181***
	(0.0196)
Other	0.0201
	(0.0464)
Mixed	0.107***
	(0.0188)
DEGREECLASS	
First-class	0.0650***
	(0.0241)
Upper second-class	0.0174
	(0.0239)
Lower second-class	0.000547
	(0.0249)
Unclassified other	−0.0365
	(0.0381)
Unclassified medical	0.347***
	(0.120)
SEX	−0.0190**
	(0.00742)
AGEOVER25	−0.0500***

TABLE C1 (Continued)

Variables	Coeff.
	(0.0110)
DISABILITY	0.0297***
	(0.00988)
SESOCCUP	0.000918
	(0.00785)
SESIMD	−0.0659***
	(0.00798)
PARENTED	0.00926
	(0.00780)
PVTSCHOOL	0.0220
	(0.0142)
SUBJECT	
Medicine and dentistry	−0.340***
	(0.116)
STEM	−0.0445***
	(0.0104)
SocSci	0.00478
	(0.0139)
Law	0.0280
	(0.0219)
BusComms	0.0342***
	(0.0130)
Education	−0.0600***
	(0.0172)
Combined	−0.138**
	(0.0692)
RUSSGRP	0.123***
	(0.0125)
ETARIFF	−0.519***
	(0.0833)
POPDOM	0.0121***
	(0.00336)
ETHNICITYDOM	3.323***
	(0.0703)

(Continues)

TABLE C1 (Continued)

Variables	Coeff.
RENTDOM	−0.382***
	(0.0116)
GDPDOM	0.0310***
	(0.00738)
UNEMPDOM	−0.435***
	(0.0483)
LIFESATDOM	−0.00277
	(0.0321)
DOM_UNI_DIST	−0.000214***
	(3.98e-05)
Constant	−1.832***
	(0.261)
Log pseudolikelihood=	−12578.03361
(1/*df*) Pearson=	0.1091545
AIC=	0.4968299
BIC=	−547146.6

Note: Robust standard errors in parentheses.
****p* < 0.01; ***p* < 0.05.

TABLE C2 GLM: Marginal effects of ethnicity at mean values (n = 50,766).

Variables	*dy/dx*
Asian	0.0172***
	(0.00136)
Black	0.0177***
	(0.00204)
Other	0.00185
	(0.00429)
Mixed	0.0102***
	(0.00185)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.
****p*< 0.01.

Other group loses statistical significance in the alternative GLM specification. A reasonable explanation of this finding is that members of the Other ethnic category are concentrated in Greater London. The marginal effects presented in Table C2 are qualitatively similar to the marginal effects of ethnicity in the original estimation.

Table C3 presents an alternative BLR estimation with Greater London employment observations dropped. Notably, the Black category loses statistical significance, and the Mixed coefficient becomes negative, which means that Greater London observations are driving much of the main findings that Black and Mixed graduates are more mobile than their White peers. The marginal effects presented in Table C4 are qualitatively similar to the marginal effects of the original BLR.

TABLE C3 BLR with Greater London employment observations dropped (*n* = 50,766).

Variables	Coeff.
ETHNICITY	
Asian	−0.324***
	(0.0353)
Black	0.0775
	(0.0510)
Other	−0.334***
	(0.113)
Mixed	−0.0695
	(0.0548)
DEGREECLASS	
First-class	0.429***
	(0.0689)
Upper second-class	0.217***
	(0.0683)
Lower second-class	0.0995
	(0.0714)
Unclassified other	0.432***
	(0.109)
Unclassified medical	0.619
	(0.467)
SEX	0.178***
	(0.0200)
AGEOVER25	−0.227***
	(0.0290)
DISABILITY	0.117***
	(0.0260)
SESOCCUP	0.0193
	(0.0212)

(Continues)

TABLE C3 (Continued)

Variables	Coeff.
SESIMD	−0.0890***
	(0.0215)
PARENTED	0.125***
	(0.0209)
PVTSCHOOL	0.0388
	(0.0412)
SUBJECT	
Medicine and dentistry	1.116**
	(0.459)
STEM	0.355***
	(0.0287)
SocSci	−0.0135
	(0.0383)
Law	0.122**
	(0.0603)
BusComms	0.178***
	(0.0360)
Education	−0.273***
	(0.0491)
Combined	−0.160
	(0.229)
RUSSGRP	0.146***
	(0.0318)
ETARIFF	1.478***
	(0.215)
POPDOM	0.0265***
	(0.00926)
ETHNICITYDOM	1.678***
	(0.172)
RENTDOM	0.155***
	(0.0323)
GDPDOM	0.113***
	(0.0188)
UNEMPDOM	−1.051***
	(0.134)

TABLE C3 (Continued)

Variables	Coeff.
LIFESATDOM	1.780***
	(0.0966)
DOM_UNI_DIST	0.00316***
	(0.000123)
Constant	−15.22***
	(0.780)
Log pseudolikelihood=	−31842.171
Wald X^2 (32)=	5107.12
Prob > X^2=	0.0000
Pseudo R^2	0.0873

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$.

TABLE C4 BLR: Marginal effects of ethnicity at mean values (n = 50,766).

Variables	*dy/dx*
Asian	−0.0805***
	(0.00880)
Black	0.0188
	(0.0123)
Other	−0.0829***
	(0.0281)
Mixed	−0.0171
	(0.0135)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.
***$p < 0.01$.

The results of the alternative MNL in Table C5 show that dropping London observation results in a change of the sign for Asian and Other groups in the HDM category. This suggests that Greater London observations drive much of the migration to diverse areas for these two groups, which is not surprising considering Greater London is the UK's most populous LAUA and one of the most ethnically diverse areas. However, the coefficient for the Black group remains positive for the HDM category.

TABLE C5 MNL with Greater London employment observations dropped (n = 50,766).

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
ETHNICITY		
Asian	−0.177***	−0.428***
	(0.0450)	(0.0409)
Black	0.265***	−0.0538
	(0.0641)	(0.0587)
Other	−0.323**	−0.347***
	(0.146)	(0.129)
Mixed	0.0624	−0.169***
	(0.0672)	(0.0625)
DEGREECLASS		
First-class	0.556***	0.346***
	(0.0942)	(0.0786)
Upper second-class	0.302***	0.164**
	(0.0936)	(0.0780)
Lower second-class	0.180*	0.0484
	(0.0975)	(0.0815)
Unclassified other	0.381***	0.454***
	(0.145)	(0.120)
Unclassified medical	0.917*	0.420
	(0.527)	(0.499)
SEX	0.148***	0.200***
	(0.0249)	(0.0225)
AGEOVER25	−0.265***	−0.205***
	(0.0382)	(0.0331)
DISABILITY	0.142***	0.100***
	(0.0323)	(0.0293)
SESOCCUP	−0.00850	0.0387
	(0.0265)	(0.0240)
SESIMD	−0.147***	−0.0490**
	(0.0275)	(0.0245)
PARENTED	0.126***	0.124***
	(0.0263)	(0.0237)
PVTSCHOOL	0.0262	0.0470
	(0.0489)	(0.0452)

TABLE C5 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
SUBJECT		
Medicine and dentistry	0.718	1.400***
	(0.514)	(0.490)
STEM	0.191***	0.473***
	(0.0355)	(0.0329)
SocSci	−0.0322	0.00162
	(0.0474)	(0.0447)
Law	0.193***	0.0614
	(0.0738)	(0.0720)
BusComms	0.227***	0.139***
	(0.0441)	(0.0421)
Education	−0.463***	−0.136**
	(0.0669)	(0.0571)
Combined	−0.557*	0.101
	(0.308)	(0.251)
RUSSGRP	0.435***	−0.0685*
	(0.0387)	(0.0360)
ETARIFF	0.382	2.262***
	(0.260)	(0.243)
POPDOM	0.0704***	−0.000903
	(0.0118)	(0.0104)
ETHNICITYDOM	2.199***	1.365***
	(0.216)	(0.198)
RENTDOM	−0.00767	0.272***
	(0.0386)	(0.0356)
GDPDOM	0.136***	0.0888***
	(0.0225)	(0.0214)
UNEMPDOM	−2.451***	−0.148
	(0.177)	(0.152)
LIFESATDOM	2.151***	1.515***
	(0.123)	(0.109)
DOM_UNI_DIST	0.00288***	0.00336***
	(0.000142)	(0.000133)

(Continues)

TABLE C5 (Continued)

Variables	High diversity migrant Coeff.	Low diversity migrant Coeff.
Constant	−18.04***	−14.33***
	(0.988)	(0.879)
Log pseudolikelihood=	−50566.592	
Wald X^2 (64)=	5953.61	
Prob > X^2=	0.0000	
Pseudo R^2	0.0644	

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE C6 MLR: Marginal effects of ethnicity at mean values (n = 50,766).

Variables	Asian *dy/dx*	Black *dy/dx*	Other *dy/dx*	Mixed *dy/dx*
Nonmigrant	0.0796***	−0.0210*	0.0839***	0.0172
	(0.00881)	(0.0124)	(0.0281)	(0.0136)
High diversity migrant	−0.00181	0.0545***	−0.0307	0.0243**
	(0.00733)	(0.0119)	(0.0216)	(0.0114)
Low diversity migrant	−0.0778***	−0.0336***	−0.0532**	−0.0416***
	(0.00750)	(0.0115)	(0.0248)	(0.0118)

Note: Standard errors in parentheses. *dy/dx* is the discrete change from the reference White category. All predictors at their mean value.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.