BETWEEN TWO WORLDS: EDUCATION-OCCUPATION MISMATCH FOR SECOND-GENERATION IMMIGRANTS IN THE UK

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Abstract

This study assesses the quality of occupations that second-generation immigrants are employed in relative to natives in the UK. Based on the concept of education-occupation mismatch, we investigate whether the utilization of workers' skills is commensurate with those required under the job. Using the multinomial logistic regression model to fit data from the Understanding Society: UK Household Longitudinal Study, we show that second-generation immigrants have a higher probability of being over-educated than natives and evaluate the mechanisms driving the results. We further explore the presence of double penalty along the overlap of legal and social identities. The findings direct attention towards the unique context of second-generation immigrants and inform policy efforts.

Key words: Second Generation Immigrants, education-occupation mismatch, UK

I. Introduction

Variations in labour market outcomes exist across economic classes, social groups and geographies. It is well-researched and established in the literature that migrants[1] have inferior positions in the UK employment sector than natives with respect to unemployment rate, wages and job quality (Clark and Drinkwater 2009; Altorjai, 2013; Heath and Li, 2020). To what extent do second-generation immigrants differ in the utilization of their potential as compared to natives? This question follows a unique context resulting from an amalgamation of diverse institutions and has received limited attention despite its relevance to policymakers and wider society. Education-occupation mismatch is used as the indicator to evaluate these circumstances and the factors contributing to it. It marks the divide between the skills attained against those required to effectively perform at a job. A market failure that leads to inefficient allocation of resources, it lowers the national welfare and decelerates social inclusion. In this paper, we investigate the contribution of immigration status to this inconsistency in the UK labour market. There is a particular focus on its intersection with gender and ethnicity identities, a concept that has not been previously explored across generations in this background. We assess the channels of mismatch to inform and direct action.

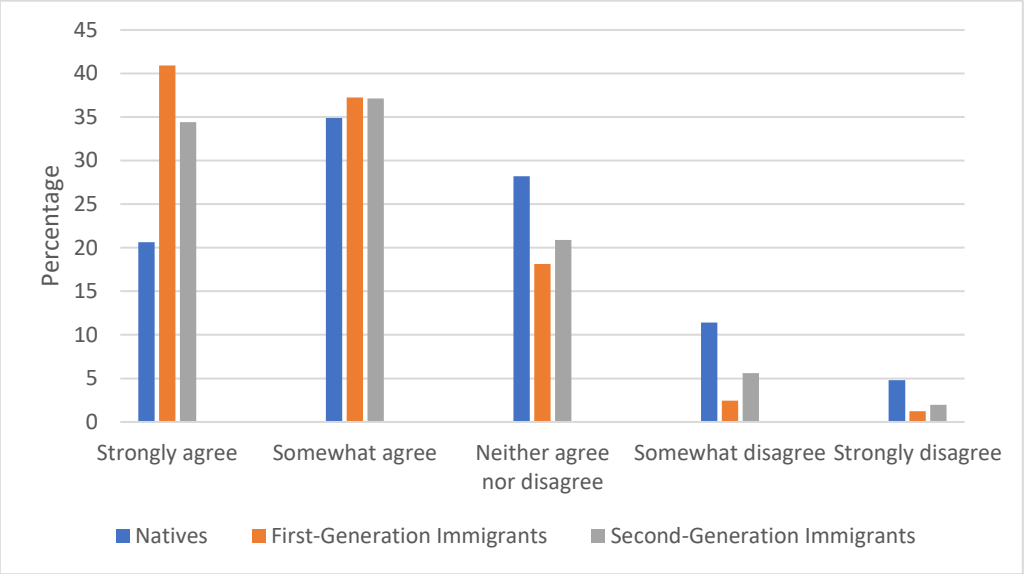
The recent years have witnessed renewed interest and concern about immigration as a political policy in the UK. With the general opposition towards increasing number of immigrants[2], particularly un- or low-skilled workers entering and settling into the country, Britons have consistently voted migration as a 'top issue' between 2001 and 2016[3]. Figure 1a and Figure 1b portray a nationally representative sample's attitudes towards immigrants and their impact in the year 2020. This ultimately factored into the decision to Leave the European Union in the 2016 Referendum, more commonly known as Brexit, and the Government of UK's commitment towards protecting the economic and social interests of the country. The existing merit-based immigration system was solidified to incorporate only the highly skilled, innovative and productive people from around the world[4].

A robust strategy for new entrants, such as the one stated above, does not automatically imply their and their future generations' incorporation into and contribution to the society (Gordon, 1964; Borjas, 1985). The shock of migration lands them in an unfamiliar setting, endowed with qualifications, experiences and qualities shaped in the country of origin. This results in a lower starting point for their offspring and sets in motion a cycle of disadvantage. In a multicultural setting, like that of the UK, failure to adapt to the host country creates social externality, economic costs and welfare reduction owing to lack of economic opportunities or/and exclusion (Akerlof and Kranton, 2000). Thus, integration becomes a relevant point of policy discussions.

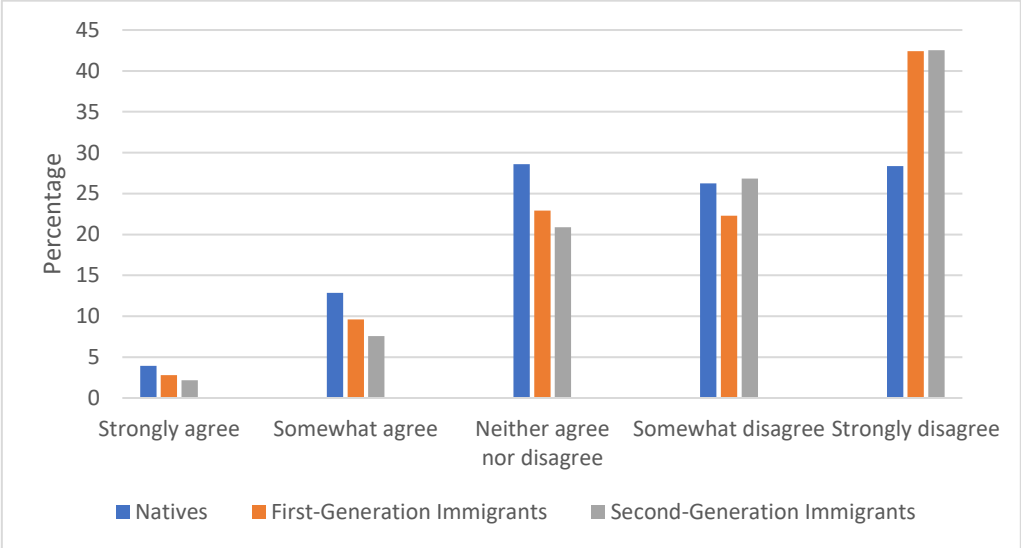
[1] Used interchangeably with first-generation immigrants
[2] Used to refer to the collection of first-generation and second-generation immigrants
[3] *UK Public Opinion Toward Immigration: Overall Attitudes and Level of Concern (2020) Migration Observatory*. Available at: https://migrationobservatory.ox.ac.uk/resources/briefings/uk-public-opinion-toward-immigration-overall-attitudes-and-level-of-concern/
[4] *The UK's future skills-based immigration system (2018) Home Office, Government of UK*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/766672/The-UKs-future-skills-based-immigration-system-accessible-version.pdf

Figure 1: The degree of agreement or disagreement with the given statements by immigration status in 2020

a) "Immigrants are generally good for Britain's economy"



b) "Britain's culture is generally harmed by immigrants"



Source: Author's calculation based on *Understanding Society*: UKHLS dataset (ISER, 2022)

One crucial identifier for assimilation is the consideration of labour market outcomes. Existing social mobility research presents that migrants face hindrances in the UK employment sector in terms of educational and occupational attainment against their native counterparts (Blanden *et al.,* 2004; Goldthorpe and Mills, 2008). Even after they are employed (extensive margin), there is under-utilization of their abilities (intensive margin). Cleavages further exist along the social lines of gender and ethnicity, suggesting cumulative penalty (Heath and Li, 2018).

Do these circumstances persist for their subsequent generations? Specifically, how do second-generation immigrants fare in terms of quality of their current occupation against natives and first-generation immigrants? These are individuals who are brought up in the same economic, social and political institutions as other UK-borns but are also influenced by their parents' foreign characteristics (Fernandez and Fogli, 2009). It becomes imperative to

disentangle this segment from their previous generation and focus on their distinct life trajectories. We attempt to: a.) determine the presence and extent of misalignment of skills and b.) isolate mechanisms governing it to understand employment sector decision-making. This is further investigated along the gender and ethnic dimensions. An overlap of social identities with immigration status reveals a double disadvantage in the labour market in terms of opportunities and barriers (Purdie-Vaughns and Eibach, 2008). The UK houses multiple-cultures with rich history and provides the base for studying their participation in the economy.

To ascertain the same, we consider the concept of education-occupation mismatch (Duncan and Hoffman, 1981) in the contemporary background of intergenerational analysis. Vertical mismatch reveals the deviation, either upward or downward, in attained qualifications from that needed for a job, which is different from horizontal mismatch based on the field of education. It captures the appropriateness of an individual's skills for their occupation.

Mismatch is a serious efficiency concern and welfare reducing scenario. This misallocation of human capital imposes massive socio-economic costs at the individual, firm and national level. Those incorrectly matched to their occupations are unable to advantageously utilize their skills and experience lower job satisfaction (Tsang *et al.*, 1991; Allen and de Weert, 2007), wages (Allen and van der Velden, 2000; McGuinness and Sloane, 2011) and productivity (Haskel and Martin, 1993; Allen and de Weert, 2007) that result in higher turnover rates (Hersch, 1991; Badillo-Amador and Vila, 2013), lower prosperity and greater inequality (Green and Zhu, 2010).

The paper combines two different bodies of literature: intergenerational mobility and occupational matching. It contributes to the knowledge on immigrants' labour market outcomes in three ways. First, using the *Understanding Society*: UK Household Longitudinal Study (UKHLS) data (ISER, 2022), we provide UK-focused evidence on the education-occupation mismatch of immigrants as compared to native borns. Previous studies have covered the USA or Europe as a whole. Second, the dataset allows the use of latest and longest-spanning information collected from 2009 to 2020 in a paper on this theme. This makes it possible to highlight the current conditions and track the evolution of mismatch. Third, and perhaps the most novel attribute of the study is that we extend the existing line of research to include second-generation immigrants in addition to first-generation to conduct intergenerational analysis. The circumstances surrounding second-generation immigrants are different from their previous generation and call for focused attention and comparisons, an element that remains missing from the literature.

Using a multinomial logistic regression model based on pooled and individual cross-section strategy, we demonstrate that immigrants are less likely get opportunities commensurate with their abilities as compared to natives: first-generation immigrants, coming to the UK with their academic and professional endowments, have a higher probability of being over-educated. This feature subsists for their future generation, at a diminished magnitude. The results support a catch-up story for the second-generation, albeit a slow and tough one. The findings for second-generation immigrants in the UK are consistent with the ethnic discrimination theory.

The rest of the paper is organized as follows. Section II presents the literature on education-occupation mismatch and its prevalence among immigrants. Section III delineates and describes the data to motivate the undertaking and Section IV expands on the identification strategy. Section V provides the results of the econometric model and its discussion. The last section concludes with policy relevance.

Literature Review

A. Measuring Mismatch

Education-occupation mismatch occurs when the formal education required to function efficiently at a job differs from the employees' acquired levels. If the acquired level exceeds what is needed for their occupation, the individual is labelled as over-educated, if it is below, the worker is under-educated[5]. These classifications are susceptible to the way the misalignment is measured. In the existing body of knowledge, there are three methods. First, occupation analysis uses official definitions of different job titles and converts it into years of schooling (Rubb, 2003; Flisi *et al.*, 2016). It fails to capture the evolving nature of job structures and is threatened by measurement bias while transforming the data. Second, the self-assessment method relies on the respondent's understanding of the required education level of their job (Chevalier, 2003; Falcke, Meng and Nollen, 2020). While the exercise reveals the current standards, it suffers from subjectivity bias. Third, realized matches considers the distribution of schooling within each occupation and estimates deviations from the mean or modal level (Aleksynska and Tritah, 2013; Pivovarova and Powers, 2022). Having the advantage of being an objective measure, it has been criticised for representing labour market supply and demand rather than the need (Piracha and Vadean, 2012).

B. Empirical Evidence

Imperfect matching has been characteristic of labour markets globally and can even be a temporarily optimal outcome (Freeman, 1976). However, ascriptive factors such as immigration status, sex or race play a role in systematically impeding outcomes of certain segments disproportionately and persistently. There is consistent consensus among researchers that the incidence of over-education is higher for both first-generation and second-generation immigrants than natives in the UK (Aleksynska and Tritah, 2013; Luthra and Platt, 2023). This is driven by the phenomenon of working in jobs for which the quality is lower than their skills demand, resulting in smaller wages, less security and lower derived value (Zwysen and Demireva, 2020).

Aleksynska and Tritah (2013) employ a pooled cross-section based on the European Social Survey to reveal heterogeneities between migrants and natives. First-generation immigrants have a higher probability of being both under- and over-educated based on differing institutions in the origin and destination countries. On average, the incidence of over-education

[5] One critique of measuring mismatch is the argument that the acquisition of education is a norm and is not done keeping in mind a particular job.

reported in existing studies is 13.2%, while the frequency of appearing as under-educated is lower with 5.4% (Piracha and Vadean, 2012). A homogenous sample of graduates in Netherlands eliminates differences due to quality of human capital and reveals that second-generation immigrants are more likely to be incorrectly matched or unfit with respect to their native counterparts (Falcke, Meng and Nollen, 2020). Under the sub-sample analysis of just immigrants, Pivovarova and Powers (2022) specify that the incidence of over-education is higher for first-generation immigrants than second-generation immigrants in the UK. We fill the gap in the literature by collating the three sub-groups of natives, first-generation immigrants and second-generation immigrants in one study to draw valid and comprehensive comparisons.

At the intersection of legal and social identities, existing penalties are further exacerbated for minority groups. These intricate relations unravel marked differences across levels and layers of classifications. While white migrants are comparable to white British-born workers, ethnic minority migrants perform worse in the labour market (Bertrand and Mullainathan, 2004; Demireva and Kesler, 2011). The segment of interest is found to be at a higher risk of being over-educated than the majority workers (Battu and Sloane, 2004; Lindley, 2009). They are less likely to sit in managerial and professional chairs- a dismal evidence that has endured with no improvements (Heath and Li, 2010; Cheung, 2014; ONS, 2021).

Participation in the labour market is highly gendered. Apart from demographic characteristics, cultural factors such as gender attitudes, religiosity and changes in partnerships contribute towards lower rates, both extensively and intensively, for women than men (Khoudja, 2018; Wang, 2019). Falcke, Meng and Nollen (2020) demonstrate a pure gender effect through the conclusion that female migrants are more unfit for their occupations than male migrants. Interestingly, second-generation women experience similar job quality levels including "intrinsic quality, work-life balance, monetary rewards, and employment conditions" as compared to UK born white women (Zwysen and Demireva, 2020).

These results imply structural constraints in the UK labour market that create asymmetrical disadvantages faced by minorities. Various theories have been cultivated in academic literature that seek to explain the differences, some also applying to their British equivalents but at a lesser intensity.

C. Theoretical Background

The immigrants in the UK face the same market conditions as the natives but individual-specific traits, country of origin institutions and host country environment can create systematic hindrances for immigrants with respect in contrast with native borns.

On the home country side, migrants can be positively self-selected to the UK based on their intrinsic abilities such as cognitive skills and motivation as compared to not just the population that remained in the original country but also in the host country (Chiswick, 1978; Beine, Docquier and Rapoport, 2008). Contrastingly, factors such as a common language, colonial past or geographical proximity can negatively affect the selection bias and reduce the probability of over-education by lowering the threshold above which the cost of migration is too high (Altorjai, 2013). Superior quality of educational institutions allows first-generation

immigrants to substitute additional schooling for labour market experience, increasing the likelihood of under-education (Sicherman, 1991).

In the destination country of UK, frictions owing to asymmetric information between the employer and potential worker in the job market are more severe for migrants as they face higher initial search cost in a new recruitment setting (Chiswick and Miller, 2009). Thus, the shock of migration makes them more accepting of jobs that do not match their education level at the beginning and switch to ones that are a better fit as market experience and information stock about the employment prospects increase. Prevalence of over-education is further expected when the skills possessed by workers are in less demand with respect to its supply in the labour market (Dean, 2018) or the Leave to Stay in the UK is contingent on being employed (Anderson and Ruhs, 2010).

Being employed in professions that demand lower capabilities could also result from lower transparency of the quality of foreign qualifications and imperfect transferability of skills in light of different technologies, barriers to entry in regulated occupations and lower language proficiency (Duncan and Hoffman, 1981; Friedberg, 2000; Dustmann and Theodoropoulos 2010). As these facets raise the cost of screening, employers would select those type of sub-population for whom the selection is least expensive. The signalling theory (Spence, 1973) supports that migrants will obtain additional education, perhaps from a country that is perceived to have higher value by the employers, to effectively signal their abilities, especially if they originate from a less developed country.

Aspirational and upward-looking individuals consciously overeducate themselves initially for rapid career progressions in the future (Sicherman and Galor, 1990). Sicherman (1991), however, does not support this conclusion and suggests that workers overeducate themselves to compensate for lower labour market experience. Thus, as the length of stay, and with it, the labour market experience increases, the severity of over-qualification has the possibility of subsiding. The utilization of co-ethnic network or diaspora to land a job result in the concentration of migrants into low quality occupations for which they are over-qualified (Zuccotti and Platt, 2016).

Extending these concepts to second-generation immigrants- they are educated in the destination country's institutions, speak the official language and have an extensive social network. We would expect the quality of their human capital to match the natives (Heath and Li, 2008). However, a lower starting point than natives exposes them to higher downward risks. Evidence indicates that the second-generation have higher education and larger unemployment rates at the same time than their native equivalents. Although, once employed, they undergo upward mobility faster indicating that they are skilled (Heath *et al.*, 2008). Li (2018) proposes that this additional income does not present a compensational edge and provides different mechanisms driving the pursuit of schooling. He coins the term "reinvigorated aspiration" to explain that over-educated parents would push their children towards higher levels of education as a strategy in anticipation of potential barriers. Alternatively, over-skilled parents can underestimate the returns to education based on their experiences and reduce their children's levels.

Even after accounting for these personal and market circumstances if divergence in outcomes emerges, it can be attributed to the residual effect of ethnic penalty in the hiring process (Heath and Cheung, 2007). It claims that ethnic minorities would obtain more education to overcome the discrimination (Battu and Sloane, 2004). There are two aspects to it and the necessary policy response would be different depending on which factor prevails.

Statistical discrimination arises when lack of information[6] in the market surrounding segments of population (here, immigrants) prompts employers to base their decisions on existing knowledge or signals (Arrow, 1973). They use gender or ethnicity as a proxy for unobserved details. As more information narrows the gap, there will be less discrimination against the candidate (Zschirnt and Ruedin, 2016). Alternatively, taste-based penalty reflects personal prejudice against certain gender or ethnic groups irrespective of the completeness of information about them (Becker, 1957). As with the previous theories, statistical discrimination diminishes with consistent participation in the job sector but taste-based remains independent of time. In conclusion, while statistical discrimination results from rational decision-making, taste-based discrimination is based on attitudes. Both correspond to market failure and reduction in the inefficiency of social welfare.

Empirical evidence has been consistent with the human capital theory and ethical discrimination in the UK labour market[7].

II. Data and Motivation

The analysis of this paper builds on the *Understanding Society*: UK Household Longitudinal Study (UKHLS) (University of Essex, 2022), a nationally representative panel survey aimed at capturing the trend in living standards in the UK. All those who were 16+ year olds in the target household at the time of the survey, irrespective of their legal status in the UK, were interviewed. We employ the Mainstage questionnaire and merge twelve Waves spanning across the years 2009-2020 in a long format. The survey provides in-depth information on the origins, education, employment and socio-economic aspects indicative of the population. One advantage of using this data over other datasets is that it has an Immigrant and Ethnic Minority Boost sample that allows us to differentiate between and represent different immigrant groups and conduct focused research on differential lifestyles of gender and ethnic minorities across generations. Additionally, the long timeline outlines the trend in education-occupation mismatch over the twelve years.

We assess the data in a repeated cross-section format. The survey design involves overlapping 24-month long fieldwork period for subsequent Waves, with each respondent being interviewed once every year. The details of interviewees are identified and distributed to their corresponding calendar year. Probability weights are used when estimating the coefficients and standard errors to adjust for disproportionate representation or response in the survey. These cross-sectional weights are scaled twice: first, by converting wave-level weights

[6] It is either not available or is too costly to obtain.
[7] Refer to Piracha & Vadean (2013) for a review

and survey unit information to the year-level and second, by multiplying the weights by a scaling factor such that each year has an equal contribution to the total analysis[8].

A. The Sample

We restrict the sample to all individuals between the age of 18-65 years at the time of the interview who are employed (under an employer or self-employed)[9] and information about their and their parents' country of birth, education and occupation is available. As immigration status is the constraint discussed in the theories under the Literature Review, it is the main independent variable and has three categories. An individual is native to the UK when they and both their parents are born in the UK. The term first-generation immigrant refers to individuals born outside the UK to parents who were also born outside the UK. We distinguish them from a second-generation migrant who are defined as people born in the UK with at least one parent born in another country. Respondents with unidentifiable own or parents' country of birth are dropped. It is important to note that the first-generation immigrants are not necessarily the parents of the second-generation in our sample.

The final data consists of 165,532 observations with 75.07% native born, 10.84% first-generation immigrants and 14.09% second-generation immigrants. Each group's segment size remains stable with no spikes over the survey years of 2009-2020 (Figure A1). The distribution of the three immigration status groups across the defined age brackets is similar (Table A1). This removes the concern of the majority of second-generation immigrants being younger, also known as the life-cycle bias, and allows us to make valid comparisons with natives and migrants.

The migrants in the sample arrive in the UK from 25 countries across the world (Table A2). While the presence of Polish and Irish[10] nationalities is significant, a majority of first-generation immigrants belong to the South Asian countries of India, Pakistan and Bangladesh and Africa, particularly Nigeria. These countries either lie in the UK's geographical vicinity or are former British colonies. The nationalities in question started to grow and become distinct communities in the 1960s. More than three-quarters of first-generation immigrants emigrated between 1980s-2000s, the period that witnessed a revolution in international collaboration and outward-looking trade policies (Figure A2).

B. Dependent Variable

The realized matches technique is employed to measure education-occupation mismatch (Verdugo and Verdugo, 1989; Kiker *et al.,* 1997). It is chosen over the other two methods to avoid subjectivity in estimation and reflect categorizations that are customised to the UK's market structure. We employ two variables- years of schooling and occupation title of a job holder. The highest educational qualification variable from the Mainstage is converted into number of years of education using the Regulated Qualifications Framework (Table 1).

[8] The later years have progressively smaller sample sizes. To ensure that each year gets equal importance, this additional scaling is done by multiplying the weights by the ratio of the average sample size by the weighted sample size of each year.
[9] Identified as being in paid employment in the week before the data collection or were temporarily away from work but revealed a relevant occupational code.
[10] Republic of Ireland

Qualification is a broad indicator of human capital through its coverage of formal education and skills fostered[11] (Quintini, 2011)

For each immigrant status category, the table represents their proportions across five levels of qualifications they graduated with. More than 55% of first-generation immigrants have at least a university degree in comparison with 47% of second-generation immigrants and 37% of natives. Indeed, the percentage of migrants with a Masters or PhD is double than the other two groups' numbers. The rankings are reversed when we consider the lower end of the spectrum. Roughly 38% of the natives left academics with a GCSE or equivalent qualification and another 13.6% give their A levels (a total of 51.55% with school-level qualifications). This is in a striking contrast with 41.3% of second-generation immigrants followed by 32.81% of migrants with only school education. Overall, first-generation immigrants are highly educated, followed by second-generation immigrants and lastly, native.

A 3-digit occupational code (in contrast to 1- or 2-digit codes as employed by other studies) based on the Standard Occupational Classification 2000 (SOC2000) precisely identifies the respondent's profession in the survey. A total of 9 broad groups of occupations offer a thorough and comprehensive categorization along the lines of the kind of tasks performed and core competencies exhibited (Table A3). An underlying assumption is that workers with the same occupational code require similar levels of skills in their jobs. The ratio of shares of first-generation immigrants and second-generation immigrants relative to the share of native borns employed in a particular industry provides an insight into the nature of jobs (use of potential and skills) immigrants are employed under vis-à-vis their native equivalent[12]. A significantly greater number of migrants as compared to natives are a part of the declining service industries with un- or low-skilled work (Figure 2a). Children of migrants, although continuing to be largely restricted to low skilled services, experience a slight improvement by expanding to 'knowledge based' service industries (Figure 2b)[13].

[11] Green and McIntosh (2002) observe a modest correlation between over-education and over-qualification. However, no correlation between under-education and under-qualification could be estimated.
[12] It is calculated as the proportion of first-generation immigrants over proportion of natives working in a particular industry. Similarly, for second-generation immigrants.
[13] Wright, J., Brinkley, I. and Clayton, N. (2010) *Employability and Skills in the UK: Redefining the debate*, *British Library*. Available at: https://www.bl.uk/britishlibrary/~/media/bl/global/business-and-management/pdfs/non-secure/r/e/a/reading-counts-why-english-and-maths-skills-matter-in-tackling-homelessness.pdf

Table 1: Categorization of the highest educational level attained by years of education and immigration status

Highest Education Qualification	Years of Education (1)	Natives (2a)	First-Generation Immigrants (2b)	Second-Generation Immigrants (2c)
GCSE or equivalent	11	37.89	19.78	26.59
A Levels or equivalent	13	13.66	13.03	14.75
Diplomas 1. Diploma in Higher Education 2. Teaching Qualification not PGCE	15	10.96	10.87	11.47
First Degrees 1. Nursing/Other Medical Qualifications 2. First Degree or equivalent	16	23.86	25.69	28.03
Higher Degree[14]	17.5	13.63	30.63	19.16
Total		100.00	100.00	100.00

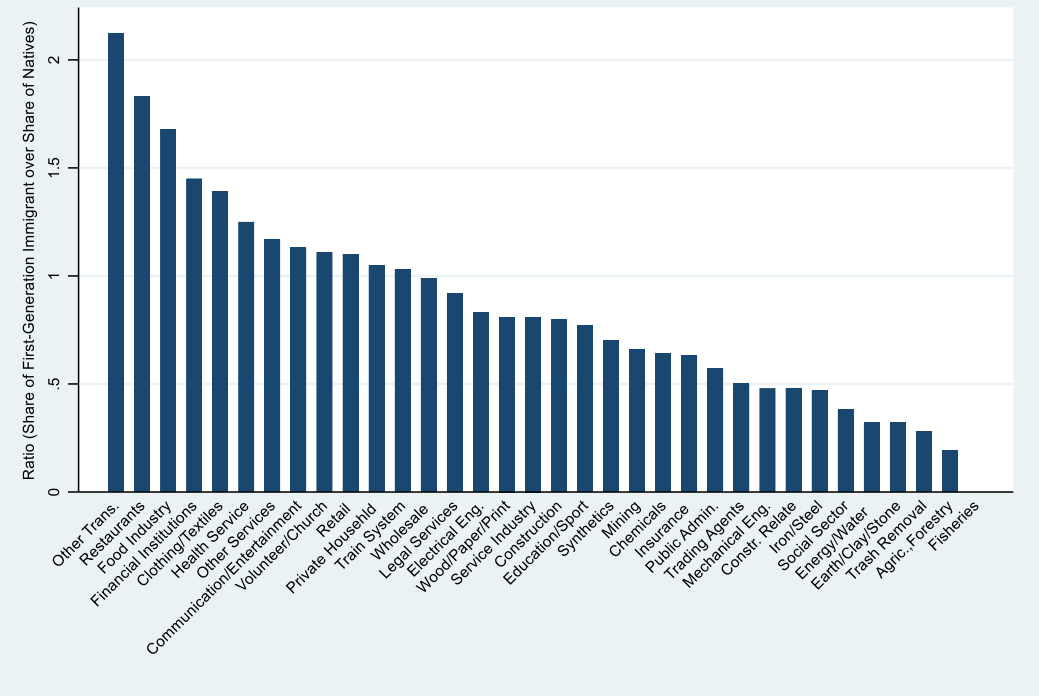
Column (1) converts the education qualification into years of schooling. Columns (2a)-(2c) account for the proportion of respondents within each immigration status group who have that qualification as their highest levels achieved.

We cannot reconcile these figures with their educational backgrounds and are motivated to continue with a formal investigation of the prevalence and relevance of education-occupation mismatch among immigrants. For each occupation in a given year, the average years of education are subtracted from an individual's level working in that profession and year. Respondents with schooling one standard deviation above this mean are overeducated in that occupation and those with one standard deviation below this mean are undereducated. Individuals who lie within the range of one standard deviation above and below the mean are considered fit for their jobs. The selection of one standard deviation is arbitrary and does not have an economic logic behind it.

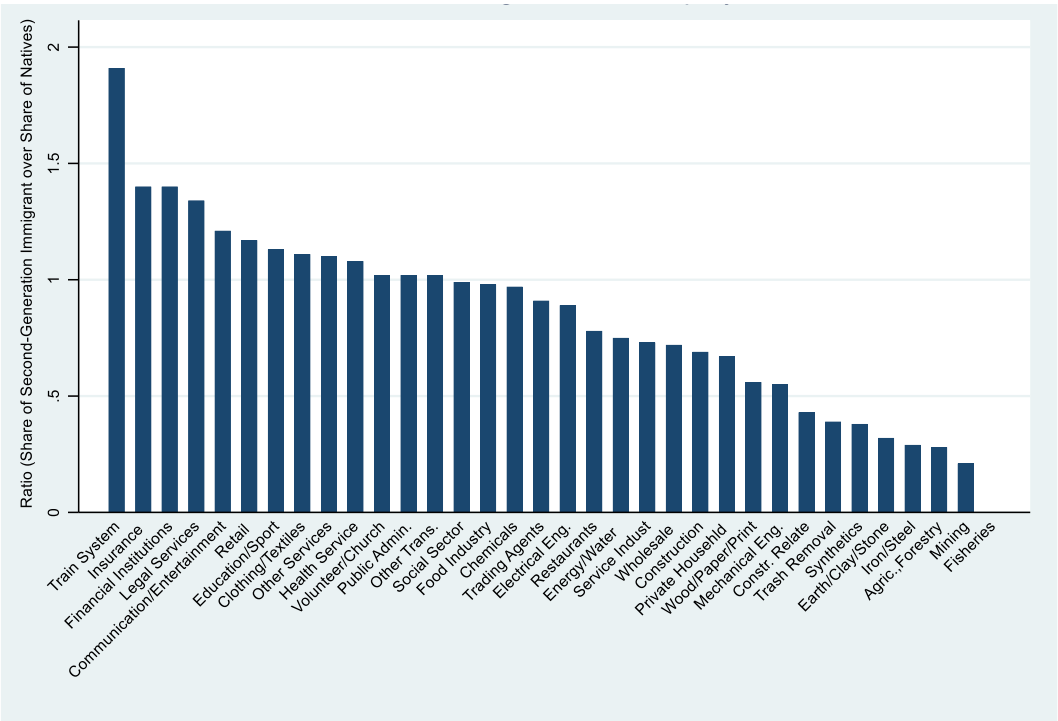
Figure 2: Industries immigrants are employed in relative to natives

a) First-generation immigrants

[14] Higher degree includes Masters and PhDs. The corresponding years of education is weighted by the proportion of Postgraduates and PhD students in their sum over 2009-2020



b) Second-generation immigrants



C. Independent Variables

Immigration status is the main independent variable, taking three discrete values to identify a native, first-generation immigrant or second-generation immigrant. For heterogeneity analysis, two indicator dummy variables are created: gender, identifying the individual as male or female and race[15], categorizing respondents as white or non-white (Table A4). Mixed-race members

[15] As per the recommendations of the Commission on Race and Ethnic Disparities in march 2021, the Government of UK has ceased the use of BAME (Black, Asian and Minority Ethnic) to refer to ethnic minorities. An alternate terminology suggested was the use of white or non-white classification.

are excluded from the categorization to prevent wrongful classifications. Within the native sub-group, non-whites account for a miniscule 0.36% while whites make up the remaining share of 99.64%. Any comparisons between the two would not be able to capture the unbiased incidence of mismatch, prompting us to restrict the analysis to first-generation and second-generation immigrants when race is concerned.

Theoretical models uncover the factors that contribute to labour market participation and subsequently, education-occupation mismatch in the labour market. These variables broadly fall under the socio-economic background, employment circumstances, parental human capital and immigrant-specific characteristics themes. Age, along with its non-linear form, and gender dummy standing for females are involved.

Additional variables include measures that indicate if the respondent is married, divorced, has children and resides in an urban area. Logged personal income per month, any past unemployment spells and the number of hours worked per week impact their employment profile in the destination economy. Parental education levels are instrumental in the generation and quality of their offspring's human capital. Thus, fathers and mothers with at least school level qualifications are accounted for in the regression equation. For the immigrant sub-sample analysis, assimilation variables such as English language proficiency (measured by if they speak the language at home) and length of stay in the UK are factored in.

Citizenship and years of labour market experience were considered as additional covariates but could not be included due to inability to credibly construct them with the available data. Furthermore, given the target participants and objective of the study, we cannot trace the labour market experiences of first-generation immigrants before migration. An assumption ensues that the skills of these individuals were suitable for their occupations (if they were in one) in their origin countries.

III. Empirical Strategy

To ascertain the extent of education-occupation mismatch for second-generation immigrants and the factors driving it, we fit a multinomial logit regression model. The choice of identification strategy accounts for the dependent variable with three categories and is based on the maximum likelihood method (MLE) of estimating coefficients. The *svyset* command in Stata for survey design reports the robust (linearized) standard errors at the Primary Sampling Unit (PSU) level.

We follow Pivovarova and Powers (2022) to construct the primary econometric equation over two models. Model 1 represents a pooled cohort and Model 2 separates individual cross-sections.

$$Probability(Mismatch_{it} = m|X_{it}) = F(\beta_0 + \beta_1 ImmStat_i + \beta_2 X_{it} + \varepsilon_{it})$$

$$\text{where } F(x) = \frac{1}{1 + e^{-x}}$$

(Equation 1)

Here, m denotes the three outcomes of the education-occupation mismatch variable (under-educated = 2, fit = 1 and over-educated = 3); $ImmStat_i$ classifies an individual i as a native, first-generation immigrant or second-generation immigrant; X_{it} is a vector of controls that affect the outcome variable and ε_{it} is the error term. β_1 is our coefficient of interest. The results present average marginal effects for a comprehensible interpretation[16], with the standard log odds ratio attached in the Appendix. With natives as the base, it is expected that the sign on the marginal effect coefficient for over-educated category is negative for both first-generation and second-generation immigrants, with a lower frequency for the latter. This exercise is carried out for the sub-sample of immigrants with first-generation immigrants as the reference category. In this case, the coefficients on under- and over-education are expected to be statistically positive and negative, respectively.

Further penalty along the gender and race dimension can be revealed through the following specification under Model 1:

$$Probability(Mismatch_{it} = m|X_{it}) = F(\beta_0 + \beta_1 ImmStat_i + \beta_2 Sex_i + \beta_3 ImmStat_i * Sex_i + \beta_4 X_{it} + \varepsilon_{it})$$

(Equation 2a)

$$Probability(Mismatch_{it} = m|X_{it}) = F(\beta_0 + \beta_1 ImmStat_i + \beta_2 Race_i + \beta_3 ImmStat_i * Race_i + \beta_4 X_{it} + \varepsilon_{it})$$

(Equation 2b)

Log odds ratio are presented since it is mathematically not possible to calculate the derivative for an interaction term. If the coefficient β_3 are statistically significant, we can suggest the presence of taste-based discrimination, otherwise, the penalty is more information-based.

We follow existing studies (Chiswick and Miller, 2009; Falcke, Meng and Nollen, 2020; Akgüç and Parasnis, 2023) to conduct a pooled analysis by compiling the twelve waves of the survey. This would imply treating the respondents as separate units in successive years, thereby increasing the sample size, accuracy of the estimates and the power of the study. It ensures enough variation in education-occupation mismatch across the immigration status groups in a sufficiently large sample (Table 2). The test for pair-wise independence using under the Pearson's Chi2 test amounts for p-values less than the critical level of 5%. We can reject the null hypothesis of no statistical difference in the dependent variable through the exploratory variable, enforcing our ability to conduct regressions. Additionally, information for each respondent is derived from the corresponding year and not from previous years, eliminating the need for the panel dimension of the dataset.

Table 2: Pearson's Chi2 test for pair-wise independence

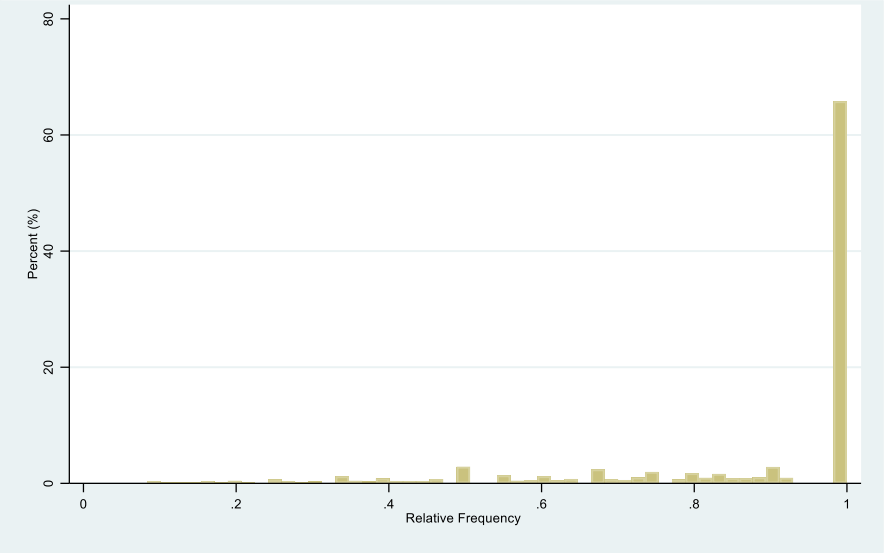
Immigration Status	Mismatch	
	Pearson's Chi2	p-value
Natives	2607.81	0.0000
First-Generation Immigrants	3467.05	0.0000
Second-Generation Immigrants	118.90	0.0000

[16] It captures the effect of the change in an independent variable on the probability of observing an outcome *MLOGIT Postestimation Manual Stata*. Available at: https://www.stata.com/manuals13/rmlogitpostestimation.pdf

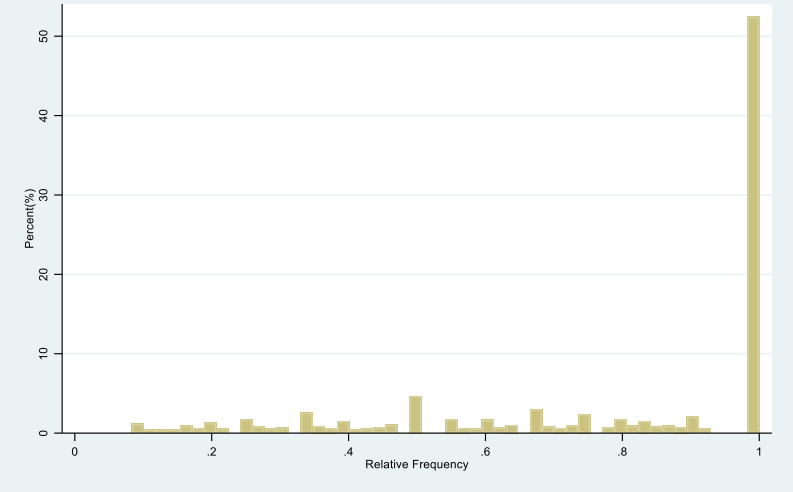
In the sample, we find that the assignment of the mismatch status (fit, under-educated or over-educated) rarely changes for an individual and depict it in Figure 3a. Indeed, it does not change even once across the study duration for more than 65% of the sample[17]. It is driven by these respondents continuing in their respective occupations throughout the survey timeline, the average years of education for which do not change enough to alter the mismatch categorization of the individual (Figure 3b). This revelation is expected in the population and reflects reality. Thus, while we cannot omit unobserved time-invariant heterogeneity, the cross-sectional specification can be utilized and remains consistent.

Figure 3: Relative frequency plot for changes in

a) Mismatch status



b) Occupation



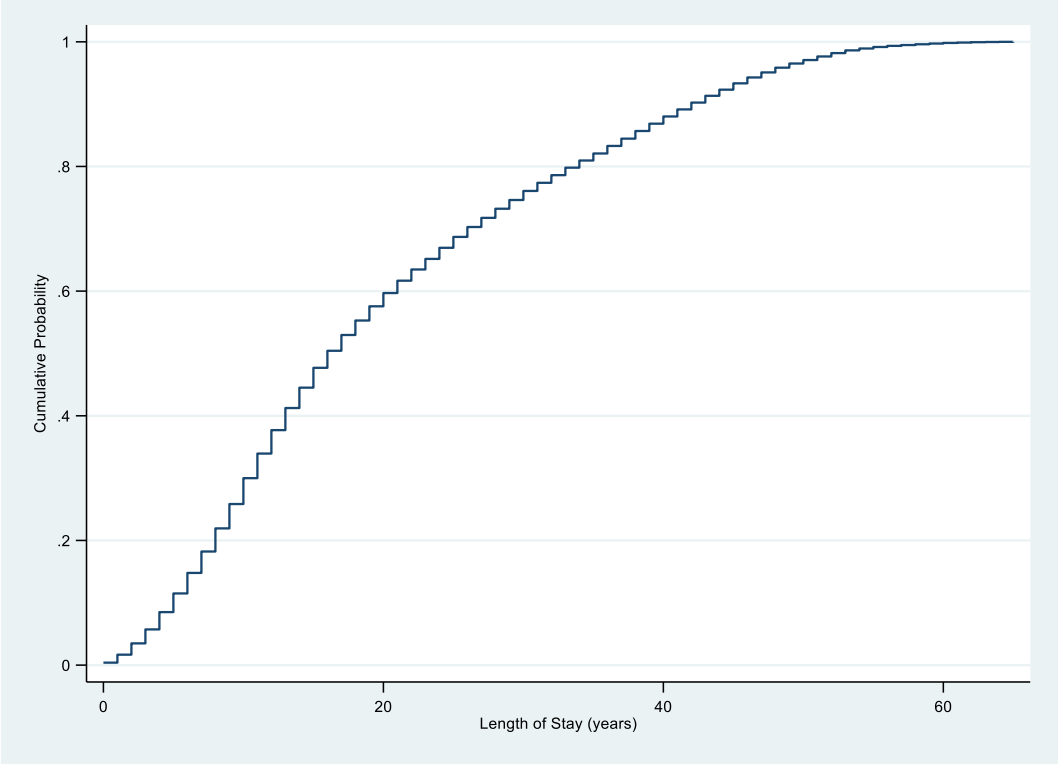
Another aspect of the econometric setup that needs to be addressed is that of the endogeneity of the immigration status. For natives and second-generation immigrants, by virtue of being born in the UK, the immigration status assigned to them is pre-determined and orthogonal to the education-occupation mismatch variable. The first-generation immigrants were either pushed out of their country of origin in light of negative circumstances, such as

[17] The interpretation of the ratio corresponding to 1 is that throughout the survey timeline, the individual does not experience any change in the outcome of interest.

political unrest and natural disasters or pulled towards the destination country in hopes of better employment opportunities and standard of living. Migration choice based on pull factors is not random, they self-select themselves into the host country. Variations in the decade of emigration and the reason for undertaking it[18] cannot allow us to conclusively make claims for the entire migrant sub-sample. For instance, the Bangladeshi diaspora established itself in the 1950s and 1960s in the UK to escape conflict. Following the Independence from west Pakistan in 1971, changes in the immigration laws enhanced the flow of trade and people driven by economic interests.

Migrants can be argued to be broadly endogenous if they arrived into the UK in the recent times. Then, the factors that contributed to the decision to emigrate are likely to influence their current labour market decisions. These unobserved characteristics are formed in the country of origin and persist in the destination country. However, if a large proportion of first-generation immigrants migrated a satisfactory number of years back, the factors are roughly extraneous to present-day choices. The two differ distinctively in time and space and less likely to invalidate orthogonality. A cumulative density function plot in Figure 4 based on the length of stay depicts that 75 percent of the first-generation immigrant sample has resided in the UK for more than 9 years, 50 percent correspond to greater than 16 years and the proportion that has been in the UK for 30+ years is 25 percent. The unobserved heterogeneities that influence the choice to migrate and participate in the labour market are time span wise apart from each other, ensuring the MLE minimizes sum of absolute deviations.

Figure 4: Cumulative density function over the number of years stayed in the UK by first-generation immigrants



[18] The question "reason for moving to the UK" is asked in the Waves 6 and 7 of the *Understanding Society*: UKHLS dataset but not all.

Table 3: Detailed summary of length of stay of first-generation immigrants in the UK

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew	Kurt
Length of Stay	15640	20.322	13.994	0	65	.753	2.614

Percentiles	Length of stay (years)
1%	1
5%	3
10%	5
25%	9
50%	16
75%	30
90%	42
95%	47
99%	55

IV. Results and Discussion

A. Exploratory Results

Table 4 registers the quality of occupations natives and immigrants are employed in. The probability of being mismatched in the labour market differs by immigration status. The percentage of natives who are over-educated and under-educated is roughly same and exhibits a normal distribution pattern (Hartog, 2000). However, these statistics remain skewed towards over-qualification for the immigrants. The substantial tendency of immigrants to be over-educated as compared to natives coincides with the low proportions for the under-educated group, although these figures are less pronounced for second-generation immigrants.

A further clustering of respondents under gender and ethnic classifications in Table 5 reveals the similar pattern of bell-shape for native borns and asymmetry for immigrants. There does not seem to exist any notable variations within these social groups. Namely, males and females account for comparable portions in the mismatch types for both natives and immigrants and likewise for whites and non-whites. A pure disadvantage effect based on sex and race of the respondent does not reveal itself. The figures for second-generation immigrants remain in-between natives and first-generation immigrants, hinting at a partial convergence.

Tabel 4: Distribution of workers by immigration status and education-occupation mismatch

Immigration Status	Mismatch			
	Under-educated	Fit	Over-educated	Total
Natives	15.90	67.27	16.83	100.00
First-Generation Immigrants	6.05	59.50	34.45	100.00
Second-Generation Immigrants	12.99	65.11	21.90	100.00

The column has *row percentages*

Tabel 5: Distribution of workers by social identity, immigration status and education-occupation mismatch

	Immigration Status								
	Natives			*First-Generation Immigrants*			*Second-Generation Immigrants*		
	Under-	Fit	Over-	Under-	Fit	Over-	Under-	Fit	Over-
Gender									
Males	15.02	68.18	16.80	5.05	59.23	35.72	11.89	67.35	20.76
Females	16.69	66.46	16.85	7.21	59.80	32.99	13.89	63.28	22.83
Race									
Whites				5.55	61.30	33.16	15.56	63.56	20.88
Non-Whites				5.99	58.60	35.41	10.98	66.38	22.64

Rows within each immigration status group have *row percentages*

Note: under- and over- stand for under-educated and over-educated, respectively

In Table 6, we tabulate the distribution of workers by their education level, the degree of mismatch variable based on that level and immigration status. Compared to first-generation immigrants, second-generation immigrants with more than school-level qualifications appear more fit and less over-educated. For university-educated second-generation immigrants, the incidence of being correctly matched is lower and that of being over-educated is higher against natives. Second-generation immigrants with at most school-level achievements are more under-educated for their current jobs than migrants.

Tabel 6: Cross-tabulation of highest education qualification, education-occupation mismatch and immigration status

Highest Educational Qualification	Immigration Status		
	Natives	First-Generation Immigrants	Second-Generation Immigrants
GCSE equivalent			
Fit	62.04	73.99	57.88
Under-educated	37.96	26.01	42.12
Over-educated	0.00	0.00	0.00
A level equivalent			
Fit	90.08	93.76	89.22
Under-educated	9.82	6.16	10.78
Over-educated	0.10	0.09	0.00
Diplomas			
Fit	80.15	73.14	84.34
Under-educated	0.59	0.51	0.67
Over-educated	19.26	26.35	14.99
First Degree			
Fit	77.81	60.69	73.68
Under-educated	0.00	0.00	0.00
Over-educated	22.19	39.31	26.32
Higher Degree			
Fit	33.01	30.90	35.43
Under-educated	0.00	0.00	0.00
Over-educated	66.99	69.10	64.57

Columns within each education level have *column percentages*

Disparities in demographic characteristics across the immigration status groups could explain some of the differences in the education-occupation mismatch. Table 7 provides the means and standard deviations for a selection of independent variables by immigration status. On average, second-generation immigrants are about 2 years younger than natives and migrants. Female migrants are underrepresented, perhaps evidencing towards gender inequality in international migration. 72.6% of first-generation immigrants are non-white against 27.4% of whites, while these figures for second-generation immigrants are slightly more balanced (53.7% vs 46.3%).

In terms of civil status and presence of children, natives and second-generation immigrants see a similar trend while migrants are significantly more likely to be married and have children and less likely to be divorced. This fact exposes the variations in social institutions and culture in the UK and other countries. Second-generation immigrants, being born and brought up in the UK, follow the norms of the country. Most of the immigrants settle in urban areas (over 90%). As expected, the geographical spread of second-generation immigrants accompanies that of first-generation immigrants. Immigrants tend to be concentrated in or near the economic hub- London, while the layout of natives is approximately uniform (Figure A3).

Employment outcomes for migrants are weaker in terms of the number of hours worked and the compensation as compared to British borns. Strikingly, second-generation immigrants in the sample have a higher incidence of being unemployed in the previous year than both the other two groups. Looking at parental educational background, more immigrants have mothers with no qualifications (including school certificates) than mothers of natives. The proportion of second-generation immigrants with fathers having some qualifications is lower at 63.3% (70.1% for natives and 74.4% for first-generation immigrants).

While focusing on assimilation factors, we observe that roughly three-fourths of the migrants do not speak English at home, while the opposite is true for second-generation immigrants. In a sample of individuals who are 18 years or over, most immigrants have been in the UK for more than 10 years[19].

[19] Roughly 75%

Tabel 7: Descriptive statistics of selected independent variables by immigration status

Variable	Immigration Status					
	Natives		First-Generation Immigrants		Second-Generation Immigrants	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	41.991	11.888	41.352	10.578	39.05	11.59
Female	.529	.499	.464	.499	.549	.498
Race						
White			.274	.446	.463	.499
Non-white			.726	.446	.537	.499
Married	.554	.497	.712	.453	.495	.5
Divorced	.057	.232	.038	.191	.05	.217
Has children	.376	.485	.506	.5	.38	.485
Urban	.735	.442	.942	.233	.903	.295
Log Monthly Income	7.519	.878	7.468	.946	7.517	.924
Unemployed in the last year	.018	.135	.026	.159	.029	.167
Hours worked per week	33.684	11.893	33.807	11.712	33.154	11.451
Father's Highest Education						
No education qualifications	.299	.458	.256	.436	.367	.482
Some education qualifications	.701	.458	.744	.436	.633	.482
Mother's Highest Education						
No education qualifications	.292	.455	.382	.486	.383	.486
Some education qualifications	.708	.455	.618	.486	.617	.486
English Proficiency						
Does not speak English at home			.741	.438	.32	.466
Speaks English at home			.259	.438	.68	.466
Length of stay						
0 to 5 years			.1	.3	0	0
6 to 10 years			.161	.368	0	0
11 to 20 years			.259	.438	.034	.181
21 to 30 years			.143	.35	.248	.432
more than 30 years			.337	.473	.718	.45

B. Confirmatory Analysis

The average marginal effects from the multinomial logit regression from Equation 1 are presented in Table 8. Model 1 based on the entire cohort of workers is utilized. With natives as the base category, these coefficients can be interpreted as the likelihood of a worker being mismatched[20] (fit, under- and over-educated) to their occupation. The corresponding tables depicting the log odds ratio appear in the Appendix. Columns (1)-(3) produce the results from the equation when the covariates are not involved, while columns (4)-(5) include covariates.

We show that immigration status is relevant while assessing the quality of jobs workers are employed in. Even after accounting for demographic characteristics and labour market conditions, immigrants are less likely to be correctly matched to their occupations than their native counterparts in the UK labour market. The magnitude and significance of coefficients does not change considerably in the full specification. The probability of observing an individual as fit in terms of the competency needed for their job is less for first-generation and second-generation immigrants than natives by 8.6 and 3.5 percentage points (pp), respectively. This segment also has lower probability to the extent of 11.6 and 1.9 pp in comparison to their native counterparts in respect of appearing as under-educated in the labour market.

[20] Mathematically, it is calculated by taking the derivative of the outcome variable, m with respect to the choice of independent variable.

Simultaneously, immigrants are more likely to be over-educated against natives (20.1 and 5.4 pp). Evidently, this degree of mismatch is lower for second-generation than that of first-generation immigrants across the three categories of fit, under- and over-educated. Subsequent generation of immigrants appear to be catching-up with their native counterparts.

In addition to this general story, we also look at the trend in education-occupation mismatch over the survey timeline. It roughly identifies the presence of structural change that contribute to the mismatch of immigrants with respect to natives over time. Figures 5a-c plot the marginal effect coefficients based on Model 2 of individual cross-sections at the 95% level. For each year under the survey years of 2009-20, we track the degree of mismatch by immigration status. The probability of being observed as unfit is falling for first-generation and second-generation immigrants against natives; we cannot claim this with confidence post the year 2012 as the estimates become insignificant at the 95% level. Contrastingly, the extent of under-education experienced by first-generation immigrants keeps rising over the years. There is no perceptible story for second-generation immigrants for this aspect of mismatch. The immigrants statistically significantly remain over-educated throughout the years with marginal downwards trend. Thus, the category of concern for second-generation immigrants is over-education. This residual effect can be attributed to ethnic discrimination. Over-education is undertaken to overcome this penalty and positively signal their skills to employers.

able 8: Average marginal effects, entire cohort

	Fit	Under-	Over-	Fit	Under-	Over-
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration Status						
First-Generation Immigrant	-0.0863***	-0.109***	0.195***	-0.086***	-0.116***	0.201***
	(0.0134)	(0.00583)	(0.0135)	(0.018)	(0.008)	(0.018)
Second-Generation Immigrant	-0.0267***	-0.0242***	0.0509***	-0.035**	-0.019**	0.054***
(Ref. Natives)						
	(0.0100)	(0.00812)	(0.00884)	(0.014)	(0.012)	(0.013)
Age				-0.0135***	0.0156***	-0.00209
				(0.00270)	(0.00236)	(0.00203)
Female				0.0156***	0.0172**	-0.00524
				(0.00236)	(0.00698)	(0.00714)
Married				0.0125	-0.00961	-0.00287
				(0.00985)	(0.00770)	(0.00813)
Divorced				0.00865	0.00264	-0.0113
				(0.0164)	(0.0124)	(0.0146)
Has Children				0.00549	0.00342	-0.00891
				(0.00862)	(0.00732)	(0.00698)
Urban				-0.000630	0.0114	-0.0107
				(0.00947)	(0.00768)	(0.00835)
Log Monthly Income				-0.00423	-0.0138***	0.0180***
				(0.00431)	(0.00252)	(0.00439)
Unemployed in the last year				-0.0126	-0.0159	0.0284**
				(0.0193)	(0.0163)	(0.0141)
Hours worked per week				-.0000377	0.00115***	-0.00111***
				(0.000327)	(0.000239)	(0.000290)
Parental educational levels						
Father has some education qualifications				-0.0109	-0.0217**	0.0327***
(Ref. Father has no education qualifications)				(0.0106)	(0.00853)	(0.00832)
Mother has some education qualifications				-0.0140	-0.0165*	0.0305***
(Ref. Mother has no education qualifications)				(0.0109)	(0.00850)	(0.00868)

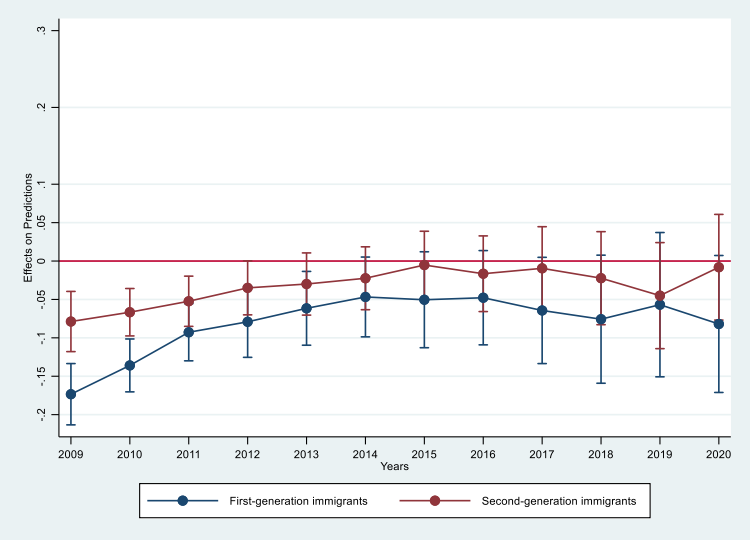
Columns (1)-(3) represent the coefficients of the multinomial regression without covariates and columns (4)-(5) are the estimates from the regression with covariates

*** p<.01, ** p<.05, * p<.1

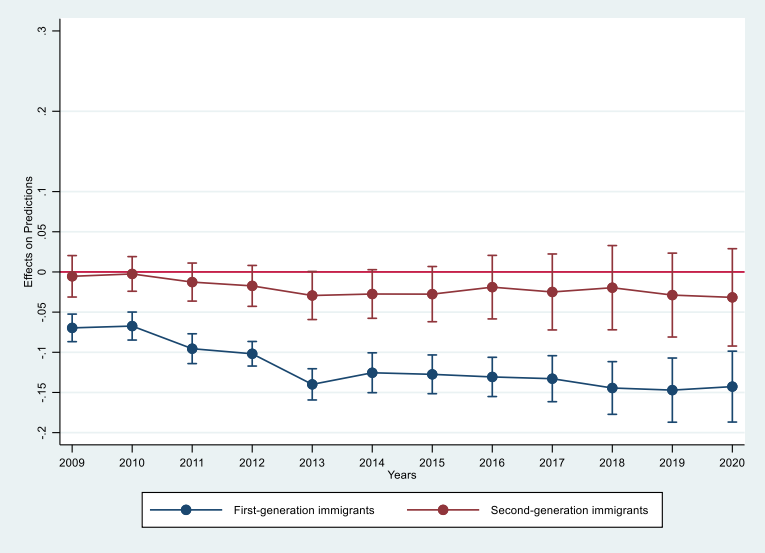
Note: under- and over- stand for under-educated and over-educated, respectively

Figure 5: Average marginal plot for each cross-section with 95% confidence intervals, entire cohort

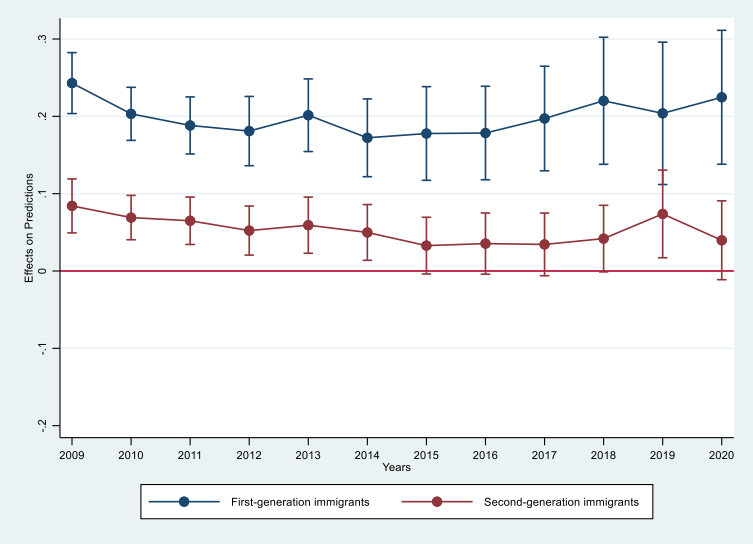
a) Fit



b) Under-educated



c) Over-educated



Considering the sub-sample, the results are presented in Table 8. Second-generation immigrants appear to have a higher probability of over-reaching for jobs in terms of their qualifications and a correspondingly lower likelihood of being over-qualified than first-generation immigrants. The fully saturated model caters for the systematic variations in over-education. The incidence of under-education still prevails, albeit with a lower magnitude. In the year-on-year analysis, we cannot find evidence of statistical differences between first-generation and second-generation immigrants. Between 2011 and 2014, the lower likelihood of under-education for second-generation immigrants against migrants is significant. As noted by Aleksynska and Tritah (2013), the extent of appearing as under-educated in the labour market is characteristic of home country, rather than the destination country, making this result consistent with theory.

Females perform better in the labour market as they are more likely to be fit under their occupations with respect to males. Assuming that as individuals age, they gain more

employment experience, they have a higher probability of being under-educated and are less likely to be categorised as fit. On average, higher income is positively correlated with the incidence of over-education. Any unemployment spells in the previous year prompts workers to accept jobs which demand lower abilities. The qualifications of father and mother contribute to the acquisition of qualifications by their offspring, as evidenced by an increase in the probability of being over-educated and decrease in the likelihood of being under-educated at the same time. Furthermore, an immigrant proficient in the English language is more likely to be fit and less likely to be over-educated as they do not need to compensate for the lack of. As the duration of their residence in the UK increases, immigrants are assumed to have adjusted to the UK labour market and appear more fit.

Table 9: Average marginal effects, first-generation immigrants as base

	Fit	Under-	Over-	Fit	Under-	Over-
Immigration Status						
Second-Generation Immigrant	0.0595***	0.0849***	-0.144***	-0.0130	0.0622***	-0.0492*
	(0.0169)	(0.00906)	(0.0161)	(0.0291)	(0.0153)	(0.0278)
(Ref. First-Generation Immigrant)						
Age				-0.0161**	0.000420	0.0156**
				(0.00700)	(0.00493)	(0.00613)
Female				-0.0307	0.0263*	0.00446
				(0.0207)	(0.0134)	(0.0183)
Married				0.00628	0.00733	-0.0136
				(0.0242)	(0.0148)	(0.0225)
Divorced				0.0251	0.0264	-0.0515
				(0.0446)	(0.0205)	(0.0451)
Has Children				0.0183	0.0107	-0.0290
				(0.0198)	(0.0126)	(0.0183)
Urban				0.0267	0.00119	-0.0279
				(0.0330)	(0.0163)	(0.0329)
Log Monthly Income				0.00947	-0.0181***	0.00867
				(0.00890)	(0.00454)	(0.00891)
Unemployed in the last year				-0.0661	0.0254	-0.0661
				(0.0443)	(0.0294)	(0.0443)
Hours worked per week				0.000915	0.00137***	-0.00229***
				(0.000771)	(0.000418)	(0.000719)
Parental educational levels						
Father has some education qualifications				-0.0321	-0.00428	0.0364
(Ref. Father has no education qualifications)				(0.0247)	(0.0144)	(0.0226)
Mother has some education qualifications				-0.0345	-0.0294*	0.0639***
(Ref. Mother has no education qualifications)				(0.0239)	(0.0156)	(0.0216)
Speaks English at home				0.0422*	0.0101	-0.0523***
(Ref. Does not speak English at home)				(0.0224)	(0.0167)	(0.0195)
Length of stay						
6 to 10 years				0.0937**	-0.0863**	-0.00737
				(0.0371)	(0.0348)	(0.0395)
11 to 20 years				0.119***	-0.118***	-0.00100
				(0.0411)	(0.0393)	(0.0433)
21 to 30 years				0.105**	-0.172***	0.0664
				(0.0454)	(0.0431)	(0.0421)
more than 30 years				0.139***	-0.194***	0.0553
				(0.0488)	(0.0480)	(0.0430)
(Ref. 0 to 5 years)						

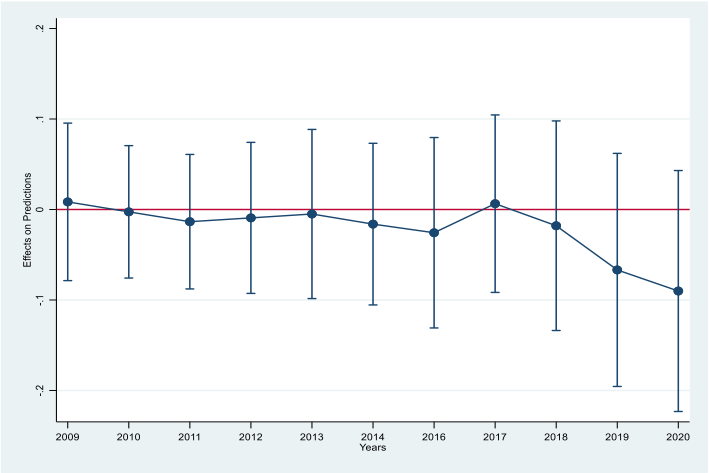
Columns (1)-(3) represent the coefficients of the multinomial regression without covariates and columns (4)-(5) are the estimates from the regression with covariates

*** p<.01, ** p<.05, * p<.1*

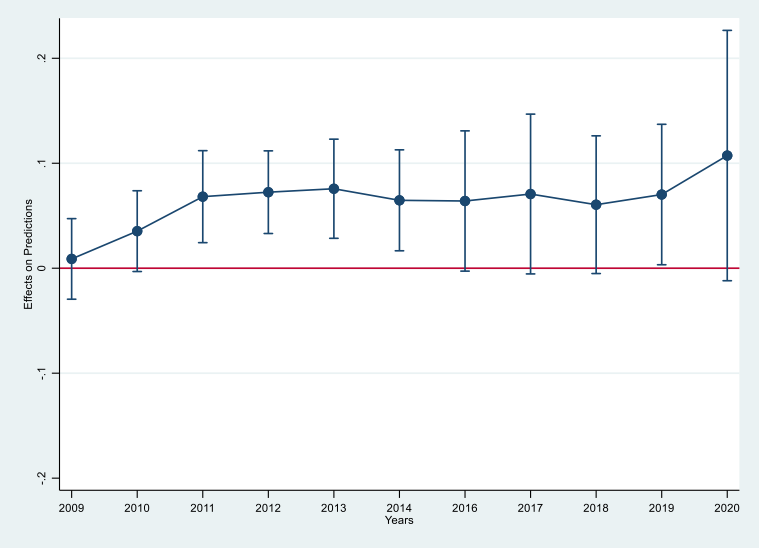
Note: under- and over- stand for under-educated and over-educated, respectively

Figure 6: Average marginal plot for each cross-section with 95% confidence intervals, first-generation immigrants as base

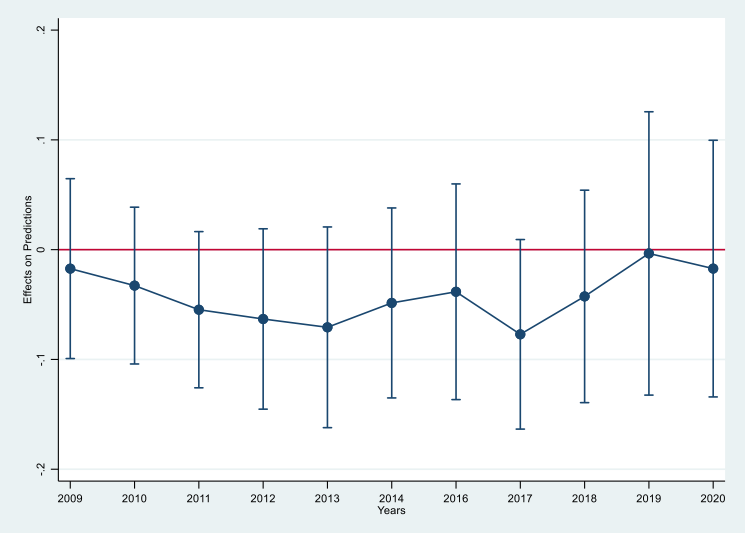
a) Fit



b) Under-educated



c) Over-educated



In conclusion, immigrants are at a higher risk of being over-educated than natives, while no statistical significant can be deduced in this regard. These results for the over-educated category are consistent with the theory of ethnic discrimination. Second-generation immigrants differ from natives on the lines of race but are similar when the quality of educational institutions is concerned. The divergence in the probability of observing them as over-educated can be attributed to ethnic discrimination after controlling for appropriate characteristics that affect the outcome variable. This is reinforced by the results that first-generation immigrants are more likely to be statistically significantly over-educated than natives but are not recognizably different than second-generation immigrants, with whom they are similar in terms of the ethnicity factor. For first-generation immigrants, human capital and ethnic discrimination theories are most relevant. Thus, employers are sensitive to their endowment of information regarding certain social groups and discount the qualifications of workers accordingly. The immigrant segment acquires additional education to compensate for this ethnic penalty.

In order to unmask the cleavages that further exist along social identity in the UK labour market, we borrow the concept of intersectionality from sociology. The regression results from Equation 2a and Equation 2b are organized in Table 10 and Table 11, respectively. All reported estimates are log odds. For second generation immigrants, gender and race differences in the incidence of education-occupation mismatch are not meaningful, as indicated by the statistically insignificant estimates. In other words, the minority groups of women and non-whites do not face differential outcomes (extent of under- and over-education) as compared to the majority groups of men and whites among second generation immigrants. There is no effect of being a female or non-white immigrant on the mismatch. This finding casts doubt on taste-based discrimination as the path to ethnic penalty and causes us to accept statistical discrimination as the possible mechanism that drives, at least partially, the phenomenon of over-education among first- and second-generation immigrants.

Table 10: Interaction of immigration status with gender

Mismatch	Coef.	st.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Immigration Status						
First-Generation Immigrant	-1.417	.204	-6.94	0	-1.818	-1.017
Second-Generation Immigrant	-.117	.148	-0.79	.428	-.407	.173
(Ref. Natives)						
Female	.109	.059	1.85	.065	-.007	.225
First-generation immigrant * Female	.576	.266	2.17	.03	.055	1.097
Second-generation immigrant * Female	.085	.182	0.47	.641	-.272	.441
Age	.124	.019	6.66	0	.087	.16
Age square	-.001	0	-5.45	0	-.002	-.001
Married	-.081	.061	-1.32	.187	-.201	.039
Divorced	.007	.097	0.08	.94	-.184	.198
Has children	.017	.058	0.29	.771	-.096	.13
Urban	.077	.06	1.29	.196	-.04	.195
Log Monthly Income	-.087	.019	-4.50	0	-.126	-.049
Unemployed in the last year	-.091	.13	-0.70	.485	-.346	.164
Hours worked per week	.008	.002	4.10	0	.004	.011
Parental educational levels						
Father has some education qualifications	-.127	.065	-1.96	.05	-.254	0
(Ref. Father has no education qualifications)						
Mother has some education qualifications	-.09	.065	-1.38	.169	-.218	.038
(Ref. Mother has no education qualifications)						
Constant	-4.055	.397	-10.22	0	-4.833	-3.277
Over-educated						
Immigration Status						
First-Generation Immigrant	.933	.113	8.29	0	.713	1.154
Second-Generation Immigrant	.239	.117	2.05	.041	.01	.467
Female	-.041	.058	-0.72	.472	-.155	.072
First-generation immigrant * Female	.058	.136	0.43	.667	-.208	.324
Second-generation immigrant * Female	.209	.145	1.45	.148	-.074	.493
Age	.007	.014	0.48	.629	-.021	.035
Age square	0	0	-0.87	.383	0	0
Married	-.033	.057	-0.57	.566	-.145	.079
Divorced	-.075	.102	-0.73	.463	-.274	.125
Has children	-.059	.048	-1.23	.22	-.154	.035
Urban	-.062	.058	-1.07	.286	-.175	.052
Log Monthly Income	.11	.03	3.61	0	.05	.17
Unemployed in the last year	.181	.1	1.81	.07	-.015	.376
Hours worked per week	-.006	.002	-3.14	.002	-.01	-.002
Parental educational levels						
Father has some education qualifications	.212	.062	3.39	.001	.089	.334
(Ref. Father has no education qualifications)						
Mother has some education qualifications	.203	.065	3.13	.002	.076	.329
(Ref. Mother has no education qualifications)						
Constant	-2.262	.318	-7.10	0	-2.887	-1.638
Mean dependent var	1.478	SD dependent var				0.732
Number of obs	104345	F-test				16.828

Table 11: Interaction of immigration status with race

Mismatch	Coef.	st.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Second-generation immigrant	.928	.239	3.89	0	.46	1.396
Non-white	-.135	.3	-0.45	.653	-.724	.454
Second-generation immigrant * Non-white	-.232	.338	-0.69	.492	-.894	.43
Age	.007	.059	0.11	.912	-.109	.122
Age square	0	.001	0.13	.894	-.001	.001
Married	.317	.163	1.94	.052	-.003	.636
Divorced	.045	.18	0.25	.801	-.307	.398
Has children	.272	.246	1.10	.269	-.211	.755
Urban	.119	.151	0.79	.428	-.176	.415
Log Monthly Income	-.024	.195	-0.12	.901	-.407	.359
Unemployed in the last year	-.218	.055	-3.98	0	-.326	-.111
Hours worked per week	.498	.347	1.43	.152	-.183	1.178
Parental educational levels	.016	.005	3.31	.001	.007	.026
Father has some education qualifications	.021	.171	0.12	.904	-.315	.357
(Ref. Father has no education qualifications)						
Mother has some education qualifications	-.245	.175	-1.40	.162	-.589	.099
(Ref. Mother has no education qualifications)						
Speaks English at home	-.131	.204	-0.64	.52	-.531	.268
(Ref. Does not speak English at home)						
Length of stay						
11 to 20 years	11.86	1.665	7.12	0	8.595	15.125
21 to 30 years	12.321	1.654	7.45	0	9.079	15.563
more than 30 years	12.509	1.659	7.54	0	9.257	15.761
(Ref. 6 to 10 years)						
Constant	-14.14	1.994	-7.09	0	-18.049	-10.231
Over-educated						
Second-generation immigrant	-.077	.166	-0.46	.643	-.402	.248
Non-white	.112	.163	0.69	.489	-.206	.431
Second-generation immigrant * Non-white	-.312	.202	-1.54	.123	-.709	.085
Age	.085	.033	2.54	.011	.019	.151
Female	-.001	0	-2.81	.005	-.002	0
Age square	.059	.101	0.59	.558	-.139	.257
Married	-.081	.125	-0.65	.518	-.327	.165
Divorced	-.163	.249	-0.65	.513	-.652	.325
Has children	-.106	.099	-1.07	.284	-.299	.088
Urban	-.124	.178	-0.70	.486	-.473	.225
Log Monthly Income	.026	.049	0.52	.601	-.071	.122
Unemployed in the last year	.234	.224	1.05	.296	-.205	.673
Hours worked per week	-.01	.004	-2.58	.01	-.018	-.002
Parental educational levels						
Father has some education qualifications	.211	.13	1.63	.104	-.043	.465
(Ref. Father has no education qualifications)						
Mother has some education qualifications	.304	.126	2.40	.016	.056	.552
(Ref. Mother has no education qualifications)						
Speaks English at home	-.306	.118	-2.59	.01	-.538	-.074
(Ref. Does not speak English at home)						
Length of stay						
11 to 20 years	-.451	.607	-0.74	.457	-1.641	.739
21 to 30 years	-.704	.612	-1.15	.25	-1.904	.496
more than 30 years	-.891	.617	-1.44	.149	-2.101	.319
(Ref. 6 to 10 years)						
Constant	-1.346	.904	-1.49	.136	-3.117	.426
Mean dependent var	1.461	SD dependent var			0.668	
Number of obs	27755	F-test			8.146	

Conclusion

In this paper, we demonstrated that relative education-occupation mismatch is important and pervasive for second-generation immigrants in the UK. On average, immigrant workers were more likely to be over-educated than natives in the UK labour market, the severity of which was stronger for first-generation immigrants than second-generation immigrants. Within the segment of immigrants, there do not exist statistically significant differences between first- and second-generation immigrants in terms of being fit and over-educated after demographic, employment and assimilation factors have been accounted for. The probability of observing a second-generation immigrant worker as under-educated is less than that for migrants. This implies that first-generation immigrants have lower years of work experience, which they compensate for by acquiring additional educational. Unfamiliarity with the UK job sector and under-recognition of country of origin qualifications emerge as the mechanism driving these differences. These factors are expected to influence second-generation immigrants at a lesser extent. Extending the results to segment of interest, they are consistent with the theory of ethnic discrimination.

We paid particular attention to the intersection of immigration status and these social indicators and did not find evidence of persisting inequality over generations. This lack of significance leads to confirm the role of statistical discrimination, similar to Longhi (2020). When sub-populations unknown to employers enter the labour force, information regarding the quality of their education and skills is not readily available. To bridge this gap, they depend on the incorrect indicators of gender and ethnicity, and the prejudice associated with them. This systematic marginalization sustains and reinforces itself over the years and across generations. Additional variables also affect the incidence of mismatch. Higher English proficiency levels are correlated with lower probability of over-education. Workers with parents having at least school-level qualifications are more likely to be over-educated and less likely to be under-educated. With increasing number of years resided in the UK, second-generation immigrants are expected to be more correctly matched to their jobs. Unfavourable visa status might diminish this effect and the inability to include it in our analysis remains a data constraint. Thus, while second-generation immigrants have experienced improvements in their outcomes, there still remains a long way to convergence with the natives.

Pooled and cross-section study confirms the degree of education-occupation mismatch for immigrations relative to natives. Because we do not employ the panel dimension of the dataset, we cannot claim dynamical views that might expose convergence or divergence in outcomes. Expressed differently, variations in the probability of appearing as mismatched at a given point in time could be due to unobserved heterogeneity. The way forward is to capture the transitions in education-occupation mismatch for second-generation immigrants in the UK by exploiting the longitudinal dataset of *Understanding Society*: UKHLS. Another aspect that the paper does not address selection into employment. The sample consists of respondents who are employed in paid work and does not take into account the disproportionately higher rates of unemployment for immigrants as compared to natives. This non-randomness in selection could introduce a bias in the measurement of the estimates. Zwysen and Demirera (2020) employ a Heckman selection model on the nature of the job in order to tackle the issue.

Our results warrant policy attention and action. The Government must focus on this segment to reduce the incidence of over-education, not by reducing the education levels but by

introducing reforms in the labour market. Since the labour market outcome of first-generation immigrants determine the starting point for second-generation immigrants, both the groups have to be targeted. This will pave the way for social inclusion and national well-being. First, it must create a conducive environment that allows immigrants to effectively signal the appropriateness of their qualifications and skills and secure the most relevant jobs. Second, no tolerance policy against prejudice and discrimination must be incentivised and not simply enforced. Third, guidance regarding access to opportunities, practical training and on-the-job learning would imply mainstreaming of immigrants in the society. Increased interactions with the employer will improve the quality of information available surrounding immigrants and reduce the incidence of statistical ethnic discrimination.

As noted, education-occupation mismatch has serious implications for the worker, firm and the society as a whole. It represents a 'wastage' of human potential, imposes efficiency loses on the society, prevents social inclusion and hinders well-being. It is particularly pertinent to second-generation immigrants in the UK, who despite being brough up in the same economic, political, and social institutions as natives, find it difficult to assimilate into the country.

References

Akerlof, G.A. and Kranton, R.E. (2000) 'Economics and Identity', *Quarterly Journal of Economics*, 115(3), pp. 715–753. doi:10.1162/003355300554881.

Akgüç, M. and Parasnis, J. (2023) 'Occupation–education mismatch of immigrant women in Europe', *Social Indicators Research*. doi:10.1007/s11205-023-03066-0.

Aleksynska, M. and Kolev, A. (2021) 'Education-occupation mismatch in the context of informality and development', *OECD Development Centre Working Papers No. 346*. doi:10.1787/3291e65c-en.

Aleksynska, M. and Tritah, A. (2011) *Occupation-Education Mismatch of Immigrant Workers in Europe: Context and Policies*, Centre d'Etudes Prospectives et d'Informations Internationales Working paper No. 2011-16. Available at http://www2.cepii.fr/PDF_PUB/wp/2011/wp2011-16.pdf

Allen, J. and De Weert, E. (2007) 'What Do Educational Mismatches Tell Us About Skill Mismatches? A Cross-Country Analysis', *European Journal of Education*, 42(1), pp. 59–73. doi:10.1111/j.1465-3435.2007.00283.x.

Allen, J. and van der Velden, R. (2001) 'Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction, and On-the-Job Search', *Oxford Economic Papers*, 53(3), pp. 434–452. doi:10.1093/oep/53.3.434.

Altorjai, S. (2013) 'Over-Qualification of Immigrants in the UK', ISER Working Paper Series 2013-11, *Institute for Social and Economic Research*

Anderson, B. and Ruhs, M. (2010) 'Migrant workers: Who needs them? A framework for the analysis of staff shortages, immigration, and public policy', *Who Needs Migrant Workers?*, pp. 15–53. doi:10.1093/acprof:oso/9780199580590.003.0002.

Arrow, K.J. (1973) 'Higher Education as a filter', *Journal of Public Economics*, 2(3), pp. 193–216. doi:10.1016/0047-2727(73)90013-3.

Badillo-Amador, L. and Vila, L.E. (2013) 'Education and Skill Mismatches: Wage and Job Satisfaction Consequences', *International Journal of Manpower*, 34(5), pp. 416–428. doi:10.1108/ijm-05-2013-0116.

Battu, H. and Sloane, P.J. (2004) 'Over-Education and Ethnic Minorities in Britain', *The Manchester School*, 72(4), pp. 535–559. doi:10.1111/j.1467-9957.2004.00407.x.

Battu, H., Belfield, C.R. and Sloane, P.J. (2000) 'How well can we measure graduate over- education and its effects?', *National Institute Economic Review*, 171, pp. 82–93. doi:10.1177/002795010017100107.

Becker, G.S. (1957) *The Economics of Discrimination: An Economic View of Racial Discrimination*. Chicago, IL: University of Chicago.

Beine, M., Docquier, F. and Rapoport, H. (2008) 'Brain Drain and Human Capital Formation in Developing Countries: Winners and Losers', *The Economic Journal*, 118(528), pp. 631–652. doi:10.1111/j.1468-0297.2008.02135.x.

Bertrand, M. and Mullainathan, S. (2003) 'Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination', *American Economic Review*, 94(4), pp. 991–1013. doi:10.3386/w9873.

Blanden, J. et al. (2004) 'Changes in Intergenerational Mobility in Britain', *Generational Income Mobility in North America and Europe*, pp. 122–146. doi:10.1017/cbo9780511492549.007.

Borjas, G.J. (1985) 'Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants', *Journal of Labor Economics*, 3(4), pp. 463–489. doi:10.1086/298065.

Chevalier, A. (2003) 'Measuring over-education', *Economica*, 70(279), pp. 509–531. doi:10.1111/1468-0335.t01-1-00296.

Chiswick, B.R. (1978) 'The Effect of Americanization on the Earnings of Foreign-born Men', *Journal of Political Economy*, 86(5), pp. 897–921. doi:10.1086/260717.

Chiswick, B.R. and Miller, P.W. (2009) 'The International Transferability of Immigrants' Human Capital', *Economics of Education Review*, 28(2), pp. 162–169. doi:10.1016/j.econedurev.2008.07.002.

Clark, K. and Drinkwater, S. (2009) 'Dynamics and diversity: Ethnic employment differences in England and Wales, 1991–2001', *Research in Labor Economics*, pp. 299–333. doi:10.1108/s0147-9121(2009)0000029014.

Clark, K. and Lindley, J. (2008) 'Immigrant Labour Market Assimilation and Arrival Effects: Evidence from the UK Labour Force Survey', *Journal of Population Economics*, 22(1), pp. 175–198. doi:10.1007/s00148-007-0173-4.

Dean, J. (2018) 'Does it matter if immigrants work in jobs related to their education?', *IZA Journal of Development and Migration*, 8(1). doi:10.1186/s40176-017-0114-2.

Duncan, G.J. and Hoffman, S.D. (1981) 'The Incidence and Wage Effects of Overeducation', *Economics of Education Review*, 1(1), pp. 75–86. doi:10.1016/0272-7757(81)90028-5.

Dustmann, C. and Theodoropoulos, N. (2010) 'Ethnic minority immigrants and their children in Britain', *Oxford Economic Papers*, 62(2), pp. 209–233. doi:10.1093/oep/gpq004.

Falcke, S., Meng, C. and Nollen, R. (2020) 'Educational Mismatches for Second Generation Migrants. An Analysis ff Applied Science Graduates in the Netherlands', *Journal of Ethnic and Migration Studies*, 46(15), pp. 3235–3251. doi:10.1080/1369183x.2020.1738211.

Fernández, R. and Fogli, A. (2009) 'Culture: An empirical investigation of beliefs, work, and fertility', *American Economic Journal: Macroeconomics*, 1(1), pp. 146–177. doi:10.1257/mac.1.1.146.

Flisi, S., Meroni, E. and Vera Toscano, M. (2016) *Educational outcomes and immigrant background*. rep. Publications Office of the European Union. Available at: https://publications.jrc.ec.europa.eu/repository/handle/JRC102629.

Freeman, R. (1976) 'The Overeducated American', in *Readings in Labor Economics and Labor Relations*. New York: Academic Press.

Friedberg, R.M. (2000) 'You can't take it with you? immigrant assimilation and the portability of human capital', *Journal of Labor Economics*, 18(2), pp. 221–251. doi:10.1086/209957.

Goldthorpe, J.H. and Mills, C. (2008) 'Trends in Intergenerational Class Mobility in Modern Britain: Evidence from National Surveys, 1972—2005', *National Institute Economic Review*, 205, pp. 83–100. doi:10.1177/0027950108096591.

Gordon, M.M. (1964) *Assimilation in American life the Role of Race, Religion and National Origins*. New York: Oxford University Press.

Green, C., Kler, P. and Leeves, G. (2007) 'Immigrant Overeducation: Evidence from Recent Arrivals to Australia', *Economics of Education Review*, 26(4), pp. 420–432. doi:10.1016/j.econedurev.2006.02.005.

Green, F. and Zhu, Y. (2008) 'Overqualification, Job Dissatisfaction, and Increasing Dispersion in the Returns to Graduate Education', *SSRN Electronic Journal*, 62(4), pp. 740–763. doi:10.2139/ssrn.1143459.

Hartog, J. (2000) 'Over-education and earnings: Where are we, where should we go?', *Economics of Education Review*, 19(2), pp. 131–147. doi:10.1016/s0272-7757(99)00050-3.

Haskel, J. and Martin, C. (1993) 'Do Skill Shortages Reduce Productivity? Theory and Evidence from the United Kingdom', *The Economic Journal*, 103(417), p. 386. doi:10.2307/2234777.

Heath, A. and Li, Y. (2010) 'Struggling onto the Ladder, Climbing the Rungs: Employment and Class Position of Minority Ethnic Groups in Britain', In: Stillwell, J., Norman, P., Thomas, C., Surridge, P. (eds) *Spatial and Social Disparities*. Dordrecht: Springer.

Heath, A. and Cheung, S.Y. (2007) 'The comparative study of ethnic minority disadvantage', *Unequal Chances*. doi:10.5871/bacad/9780197263860.003.0001.

Heath, A. and Li, Y. (2018) 'Persisting disadvantages: A study of labour market dynamics of ethnic unemployment and earnings in the UK (2009–2015)', *Journal of Ethnic and Migration Studies*, 46(5), pp. 857–878. doi:10.1080/1369183x.2018.1539241.

Hersch, J. (1991) 'Education Match and Job Match', *The Review of Economics and Statistics*, 73(1), pp. 140–144. doi:10.2307/2109696.

Kiker, B.F., Santos, M.C. and de Oliveira, M.M. (1997) 'Overeducation and undereducation: Evidence for Portugal', *Economics of Education Review*, 16(2), pp. 111–125. doi:10.1016/s0272-7757(96)00040-4.

Li, Y. (2018) 'Against the Odds? – A Study of Educational Attainment and Labour Market Position of The Second-Generation Ethnic Minority Members In The UK', *Ethnicities*, 18(4), pp. 471–495. doi:10.1177/1468796818777546.

Lindley, J. (2009) 'The over-education of UK immigrants and minority ethnic groups: Evidence from the Labour Force Survey', *Economics of Education Review*, 28(1), pp. 80–89. doi:10.1016/j.econedurev.2007.11.003.

Luthra, R.R. and Platt, L. (2023) 'Do immigrants benefit from selection? migrant educational selectivity and its association with social networks, skills and health', *Social Science Research*, 113, p. 102887. doi:10.1016/j.ssresearch.2023.102887.

Mayhew, M. and Lindo, S. (2023) *Migration and the labour market, England and Wales: Census 2021*, *Migration and the labour market, England and Wales - Office for National Statistics*. Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/migrationandthelabourmarketenglandandwales/census2021

McGuinness, S. and Sloane, P.J. (2011) 'Labour Market Mismatch among UK Graduates: An Analysis using REFLEX data', *Economics of Education Review*, 30(1), pp. 130–145. doi:10.1016/j.econedurev.2010.07.006.

Piracha, M. and Vadean, F. (2012) 'Migrant Educational Mismatch and the Labour Market', in *International Handbook on the Economics of Migration*. Cheltenham: Edward Elgar, pp. 176–192.

Pivovarova, M. and Powers, J.M. (2022) 'Do immigrants experience labor market mismatch? new evidence from the US PIAAC', *Large-scale Assessments in Education*, 10(1). doi:10.1186/s40536-022-00127-7.

Platt, L. (2007) 'Poverty and ethnicity: The evidence', *Poverty and ethnicity in the UK*, pp. 37–58. doi:10.51952/9781447366829.ch004.

Purdie-Vaughns, V. and Eibach, R.P. (2008) 'Intersectional invisibility: The distinctive advantages and disadvantages of multiple subordinate-group identities', *Sex Roles*, 59(5–6), pp. 377–391. doi:10.1007/s11199-008-9424-4.

Quintini, G. (2011) *Right for the job*, *OECD iLibrary*. Available at: https://www.oecd-ilibrary.org/social-issues-migration-health/right-for-the-job_5kg59fcz3tkd-en (Accessed: 17 September 2023).

Rubb, S. (2003) 'Overeducation in the labor market: A comment and re-analysis of a meta-analysis', Economics of Education Review, 22(6), pp. 621–629. doi:10.1016/s0272-7757(02)00077-8.

Sanroma, E., Ramos, R. and Simon, H. (2008) *The Portability of Human Capital and Immigrant Assimilation: Evidence for Spain,* IZA Discussion Paper No. 3649. Available at https://docs.iza.org/dp3649.pdf

Sicherman, N. (1991) '"Overeducation" in the Labor Market', *Journal of Labor Economics*, 9(2), pp. 101–122. doi:10.1086/298261.

Sicherman, N. and Galor, O. (1990) 'A theory of career mobility', *Journal of Political Economy*, 98(1), pp. 169–192. doi:10.1086/261674.

Sloane, P.J., Battu, H. and Seaman, P.T. (1999) 'Overeducation, undereducation and the British Labour Market', *Applied Economics*, 31(11), pp. 1437–1453. doi:10.1080/000368499323319.

Spence, M. (1973) 'Job Market Signaling', *The Quarterly Journal of Economics*, 87(3), p. 355. doi:10.2307/1882010.

Tsang, M.C., Rumberger, R.W. and Levin, H.M. (1991) 'The Impact of Surplus Schooling on Worker Productivity', *Industrial Relations*, 30(2), pp. 209–228. doi:10.1111/j.1468-232x.1991.tb00786.x.

University of Essex, Institute for Social and Economic Research. (2022). Understanding Society: Waves 1-12, 2009-2021 [data collection]. 17th Edition. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-18.

Verdugo, R.R. and Verdugo, N.T. (1989) 'The impact of surplus schooling on earnings: Some additional findings', *The Journal of Human Resources*, 24(4), p. 629. doi:10.2307/145998.

Zschirnt, E. and Ruedin, D. (2016) 'Ethnic discrimination in hiring decisions: A meta-analysis of correspondence tests 1990–2015', *Journal of Ethnic and Migration Studies*, 42(7), pp. 1115–1134. doi:10.1080/1369183x.2015.1133279.

Zuccotti, C.V. and Platt, L. (2016) 'Does neighbourhood ethnic concentration in early life affect subsequent labour market outcomes? A study across ethnic groups in England and Wales', *Population, Space and Place*, 23(6). doi:10.1002/psp.2041.

Zwysen, W. and Demireva, N. (2020) 'Who benefits from host country skills? Evidence of heterogeneous labour market returns to host country skills by migrant motivation', *Journal of Ethnic and Migration Studies*, 46(1), pp. 200–221.

Appendix

Figure A1: Proportion of immigration status groups within each year of the sample timeline

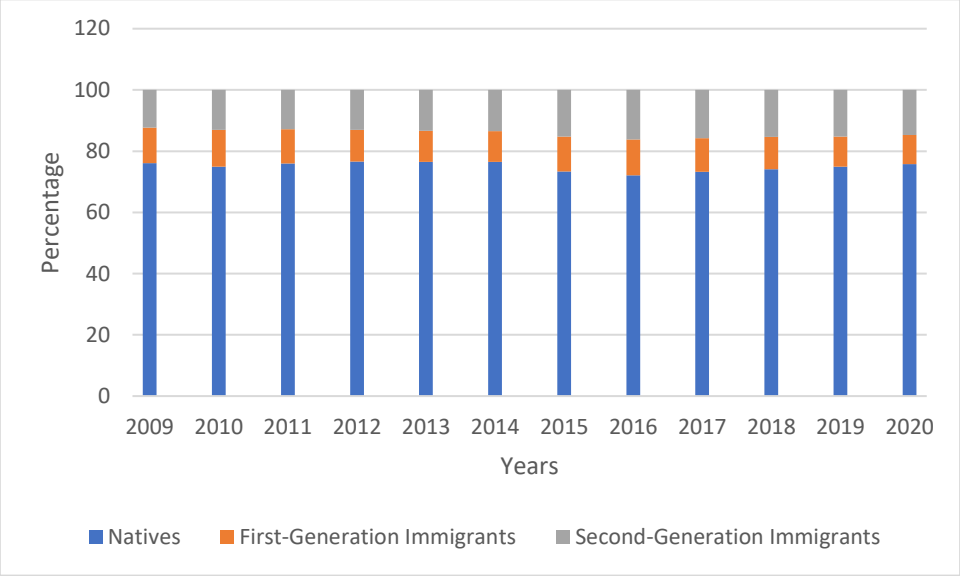


Table A1: The distribution of respondents within each immigration status group across age brackets

Age Bracket (years)	Immigration Status			
	Natives	First-Generation Immigrants	Second-Generation Immigrants	Total
18-25	10.72	6.39	15.26	10.89
26-35	21.02	25.88	26.01	22.25
36-45	26.14	32.50	26.37	26.87
46-55	27.48	24.03	23.51	26.55
56-65	14.63	11.19	8.85	13.45
Total	100.00	100.00	100.00	100.00

The rows have *column percentages*

Table A2: Origins of first-generation immigrants in the UK

Country of Birth	Percentage
Republic of Ireland	4.53
France	1.77
Germany	2.50
Italy	1.31
Spain	0.99
Poland	7.50
Cyprus	0.38
Turkey	1.18
Australia	0.92
New Zealand	1.13
Canada	0.71
U.S.A	2.74
China/Hong Kong	3.47
India	20.27
Pakistan	12.40
Bangladesh	9.04
Sri Lanka	5.19
Kenya	3.67
Ghana	4.23
Nigeria	6.98
Uganda	2.01
South Africa	3.32
Jamaica	3.62
Portugal	0.09
Brazil	0.08
Total	100.00

The rows have *column percentages*

Figure A2: Decade first-generation immigrants migrated to the UK (%)

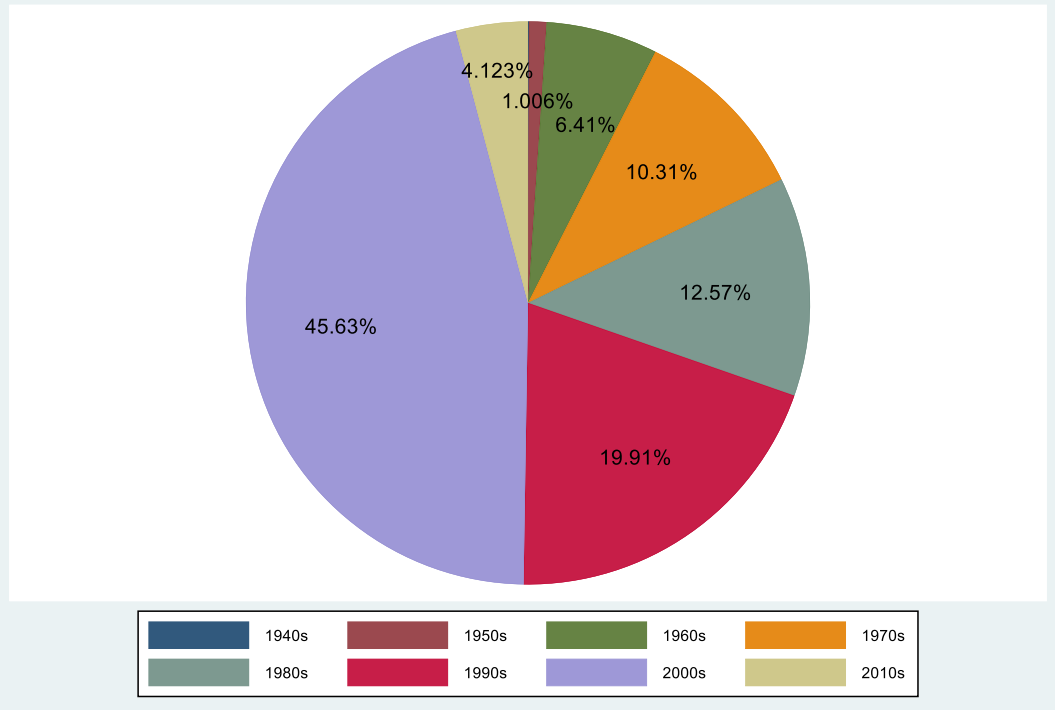


Table A3: Broad classification of occupation titles

S. No.	SOC 2000 Major Groups
1	Managers and senior officials
2	Professional occupations
3	Associate professional and technical occupations
4	Administrative and secretarial occupations
5	Skilled trades occupations
6	Personal service occupations
7	Sales and customer service occupations
8	Process, plant and machine operatives
9	Elementary occupations

Table A4: List of racial (ethnic) groups

White	Non-white
British/English/Scottish/Welsh/Northern Irish	Indian
Irish	Pakistani
Gypsy or Irish Traveller	Bangladeshi
Any Other White Background	Chinese
	Any Other Asian Background
	Caribbean
	African
	Any Other Black Background

Figure A3: Region-wise spread of the workers by immigration status

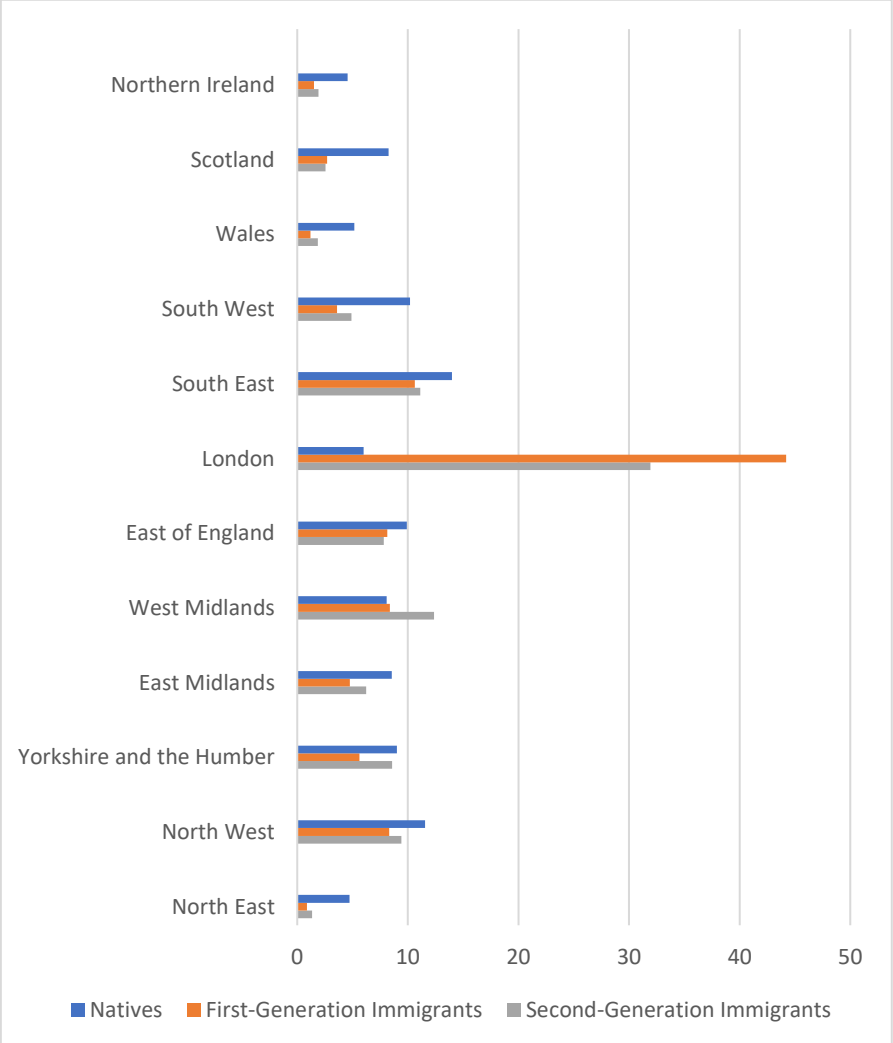


Table A5: Log odds ratio from the multinomial logistic regression over the pooled sample of workers
Base: Natives

a) Without covariates

Mismatch	Coef.	st.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Immigration Status						
First-Generation Immigrant	-.96	.098	-9.77	0.00	-1.153	-.767
Second-Generation Immigrant	-.119	.067	-1.79	.073	-.25	.011
Constant	-1.417	.022	-63.41	0.00	-1.461	-1.373
Over-educated						
Immigration Status						
First-Generation Immigrant	.932	.062	15.11	0.00	.811	1.053
Second-Generation Immigrant	.316	.054	5.82	0.00	.209	.422
Constant	-1.435	.022	-65.70	0.00	-1.478	-1.393
Mean dependent var			1.478	SD dependent var		0.732
Number of obs			165521	F-test		94.882

b) With covariates

Mismatch	Coef.	st.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Immigration Status						
First-Generation Immigrant	-1.109	.144	-7.70	0	-1.391	-.827
Second-Generation Immigrant	-.073	.096	-0.76	.447	-.262	.115
Age	.124	.019	6.67	0	.087	.16
Age Square	-.001	0	-5.45	0	-.002	-.001
Female	.132	.056	2.37	.018	.023	.242
Married	-.082	.061	-1.34	.179	-.202	.038
Divorced	.006	.098	0.06	.954	-.186	.197
Has Children	.015	.058	0.26	.791	-.098	.128
Urban	.077	.06	1.29	.197	-.04	.194
Log Monthly Income	-.087	.019	-4.47	0	-.125	-.049
Unemployed in the last year	-.089	.13	-0.69	.493	-.344	.166
Hours worked per week	.008	.002	4.12	0	.004	.011
Parental educational levels						
Father has some education qualifications	-.126	.065	-1.95	.051	-.254	.001
(Ref. Father has no education qualifications)						
Mother has some education qualifications	-.089	.065	-1.36	.175	-.217	.04
(Ref. Mother has no education qualifications)						
Constant	-4.075	.398	-10.24	0	-4.855	-3.295
Over-educated						
Immigration Status						
First-Generation Immigrant	.961	.085	11.37	0	.795	1.127
Second-Generation Immigrant	.347	.078	4.47	0	.195	.499
Age	.007	.014	0.48	.628	-.021	.035
Age Square	0	0	-0.87	.387	0	0
Female	-.014	.05	-0.27	.788	-.112	.085
Married	-.034	.057	-0.60	.549	-.146	.078
Divorced	-.077	.102	-0.76	.446	-.277	.122
Has Children	-.059	.048	-1.22	.221	-.154	.036
Urban	-.061	.058	-1.06	.29	-.174	.052
Log Monthly Income	.11	.03	3.62	0	.051	.17
Unemployed in the last year	.182	.1	1.83	.067	-.013	.377
Hours worked per week	-.006	.002	-3.14	.002	-.01	-.002
Parental educational levels						
Father has some education qualifications	.212	.062	3.40	.001	.09	.334
(Ref. Father has no education qualifications)						
Mother has some education qualifications	.203	.065	3.14	.002	.076	.33
(Ref. Mother has no education qualifications)						
Constant	-2.282	.316	-7.22	0	-2.901	-1.662
Mean dependent var	1.478	SD dependent var				0.732
Number of obs	104345	F-test				19.084

Table A6: Average marginal effects for individual cross-section, entire cohort

Year	Marginal Effects (SE)					
	Fit	Under-	Over-	Fit	Under-	Over-
	(1)	(2)	(3)	(4)	(5)	(6)
2009	-0.166***	-0.0688***	0.235***	-0.173***	-0.070***	0.243***
	(0.0177)	(0.00754)	(0.0177)	(0.020)	(0.009)	(0.020)
	-0.0514***	-0.0155	0.0669***	-0.079***	-0.005	0.084***
	(0.0162)	(0.0101)	(0.0144)	(0.020)	(0.013)	(0.018)
2010	-0.147***	-0.0663***	0.213***	-0.136***	-0.067***	0.203***
	(0.0144)	(0.00676)	(0.0143)	(0.018)	(0.009)	(0.017)
	-0.0744***	-0.00462	0.0790***	-0.067***	-0.002	0.069***
	(0.0130)	(0.00864)	(0.0122)	(0.016)	(0.011)	(0.015)
2011	-0.114***	-0.0963***	0.211***	-0.093***	-0.096***	0.188***
	(0.0162)	(0.00736)	(0.0160)	(0.019)	(0.009)	(0.019)
	-0.0408***	-0.0155	0.0563***	-0.052***	-0.013	0.065***
	(0.0138)	(0.00997)	(0.0129)	(0.017)	(0.012)	(0.016)
2012	-0.0973***	-0.0919***	0.189***	-0.079***	-0.102***	0.181***
	(0.0193)	(0.00721)	(0.0185)	(0.024)	(0.008)	(0.023)
	-0.0276*	-0.0208**	0.0483***	-0.035*	-0.017	0.052***
	(0.0142)	(0.00967)	(0.0128)	(0.018)	(0.013)	(0.016)
2013	-0.0595***	-0.131***	0.191***	-0.062**	-0.140***	0.201***
	(0.0193)	(0.00842)	(0.0189)	(0.024)	(0.010)	(0.024)
	-0.0239	-0.0289**	0.0528***	-0.030	-0.029*	0.059***
	(0.0148)	(0.0115)	(0.0131)	(0.021)	(0.015)	(0.019)
2014	-0.0729***	-0.107***	0.180***	-0.047*	-0.125***	0.172***
	(0.0206)	(0.0104)	(0.0198)	(0.026)	(0.013)	(0.026)
	-0.0155	-0.0302***	0.0457***	-0.022	-0.027*	0.050***
	(0.0152)	(0.0108)	(0.0134)	(0.021)	(0.015)	(0.018)
2015	-0.0621***	-0.103***	0.165***	-0.050	-0.127***	0.178***
	(0.0228)	(0.0108)	(0.0220)	(0.032)	(0.012)	(0.031)
	0.00260	-0.0314**	0.0288**	-0.005	-0.028	0.033*
	(0.0163)	(0.0123)	(0.0138)	(0.022)	(0.018)	(0.019)
2016	-0.0582***	-0.111***	0.169***	-0.048	-0.131***	0.178***
	(0.0219)	(0.0104)	(0.0212)	(0.031)	(0.012)	(0.031)
	-0.0204	-0.0218*	0.0422***	-0.017	-0.019	0.035*
	(0.0167)	(0.0130)	(0.0140)	(0.025)	(0.020)	(0.020)
2017	-0.0622***	-0.121***	0.183***	-0.064*	-0.133***	0.197***
	(0.0237)	(0.00997)	(0.0233)	(0.035)	(0.015)	(0.034)
	-0.0204	-0.0224	0.0427***	-0.010	-0.025	0.034*
	(0.0179)	(0.0151)	(0.0147)	(0.028)	(0.024)	(0.021)
2018	-0.0655**	-0.130***	0.196***	-0.076*	-0.144***	0.220***
	(0.0266)	(0.0120)	(0.0263)	(0.042)	(0.017)	(0.042)
	-0.00771	-0.0274*	0.0351**	-0.022**	-0.020	0.042*
	(0.0196)	(0.0158)	(0.0153)	(0.031)	(0.027)	(0.022)
2019	-0.0601**	-0.134***	0.194***	-0.057	-0.147***	0.204***
	(0.0290)	(0.0134)	(0.0284)	(0.048)	(0.020)	(0.047)
	-0.0242	-0.0426***	0.0668***	-0.045	-0.029	0.074**
	(0.0205)	(0.0155)	(0.0173)	(0.035)	(0.027)	(0.029)
2020	-0.0507*	-0.140***	0.191***	-0.082*	-0.143***	0.225***

(0.0284)	(0.0139)	(0.0284)	(0.045)	(0.022)	(0.044)
-0.00822	-0.0393**	0.0476**	-0.008	-0.032	0.040
(0.0222)	(0.0176)	(0.0185)	(0.035)	(0.031)	(0.026)

Columns (1)-(3) represent the coefficients of the multinomial regression without covariates and columns (4)-(5) are the estimates from the regression with covariates

*** p<.01, ** p<.05, * p<.1*

Note: under- and over- stand for under-educated and over-educated, respectively

Table A6: Log odds ratio from the multinomial logistic regression over the pooled sample of workers
Base: First-Generation Immigrants

a) Without covariates

Mismatch	Coef.	St.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Second-Generation Immigrant	.841	.111	7.55	0	.622	1.059
Constant	-2.377	.088	-26.87	0	-2.551	-2.204
Over-educated						
Second-Generation Immigrant	-.616	.08	-7.72	0	-.773	-.46
Constant	-.504	.061	-8.31	0	-.622	-.385
Mean dependent var		1.466	SD dependent var			0.674
Number of obs		46913	F-test			70.426

b) With covariates

Mismatch	Coef.	St.err.	t-value	p-value	[95% Conf	Interval]
Fit	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Under-educated						
Immigration Status						
Second-Generation Immigrant	.74	.2	3.70	0	.348	1.186
Age	.027	.057	0.47	.636	-.084	.105
Age Square	0	.001	-0.16	.872	-.001	.001
Female	.314	.156	2.02	.044	.009	.619
Married	.067	.169	0.39	.693	-.265	.389
Divorced	.238	.233	1.02	.309	-.22	.689
Has Children	.084	.144	0.59	.558	-.198	.345
Urban	-.025	.186	-0.14	.893	-.389	.341
Log Monthly Income	-.201	.051	-3.95	0	-.3	-.101
Unemployed in the last year	.355	.335	1.06	.29	-.303	1.022
Hours worked per week	.013	.005	2.75	.006	.004	.022
Parental educational levels						
Father has some education qualifications	.001	.164	0.01	.996	-.321	.322
(Ref. Father has no education qualifications)						
Mother has some education qualifications	-.242	.167	-1.45	.148	-.57	.086
(Ref. Mother has no education qualifications)						
Speaks English at home	.045	.19	0.24	.812	-.328	.418
(Ref. Does not speak English at home)						
Length of stay						
6 to 10 years	-.303	.767	-0.40	.693	-1.807	1.2
11 to 20 years	-.216	.835	-0.26	.796	-1.854	1.421
21 to 30 years	.631	.784	0.80	.421	-.907	2.169
more than 30 years	.482	.806	0.60	.55	-1.099	2.064
(Ref. 0 to 5 years)						
Constant	-2.727	1.259	-2.17	.03	-5.195	-.259
Over-educated						
Immigration Status						
Second-Generation Immigrant	-.173	.144	-1.20	.231	-.456	.11
Age	.086	.033	2.64	.008	.022	.15
Age Square	-.001	0	-2.91	.004	-.002	0
Female	.061	.099	0.62	.536	-.132	.255
Married	-.064	.121	-0.53	.594	-.301	.172
Divorced	-.245	.241	-1.01	.311	-.718	.228
Has Children	-.144	.098	-1.47	.143	-.335	.048
Urban	-.151	.176	-0.86	.391	-.496	.194
Log Monthly Income	.022	.047	0.47	.641	-.071	.115
Unemployed in the last year	.258	.209	1.24	.216	-.151	.668
Hours worked per week	-.011	.004	-2.77	.006	-.018	-.003
Parental educational levels						
Father has some education qualifications	.196	.126	1.56	.119	-.051	.443
(Ref. Father has no education qualifications)						
Mother has some education qualifications	.317	.121	2.62	.009	.08	.555
(Ref. Mother has no education qualifications)						
Speaks English at home	-.272	.105	-2.58	.01	-.478	-.066
(Ref. Does not speak English at home)						
Length of stay						
6 to 10 years	-.399	.134	-2.99	.003	-.662	-.137
11 to 20 years	-.54	.152	-3.55	0	-.839	-.242
21 to 30 years	-.716	.174	-4.11	0	-1.057	-.375
more than 30 years	-.858	.197	-4.34	0	-1.245	-.47
(Ref. 0 to 5 years)						
Constant	-1.335	.665	-2.01	.045	-2.639	-.031

Mean dependent var	1.461	SD dependent var	0.671
Number of obs	29508	F-test	8.699

Table A7: Average marginal effects for individual cross-section, first-generation immigrants as base

Year	Marginal Effects (SE)					
	Fit	Under-	Over-	Fit	Under-	Over-
	(1)	(2)	(3)	(4)	(5)	(6)
2009	0.115***	0.0533***	-0.168***	-0.00844	0.00885	-0.0173
	(0.0232)	(0.0115)	(0.0221)	(0.0444)	(0.0196)	(0.0418)
2010	0.0724***	0.0617***	-0.134***	-0.00259	0.0353*	-0.0327
	(0.0201)	(0.0100)	(0.0199)	(0.0373)	(0.0196)	(0.0364)
2011	0.0734***	0.0808***	-0.154***	-0.0135	0.0682***	-0.0547
	(0.0206)	(0.0112)	(0.0195)	(0.0379)	(0.0223)	(0.0363)
2012	0.0697***	0.0712***	-0.141***	-0.00927	0.0724***	-0.0632
	(0.0246)	(0.0108)	(0.0225)	(0.0425)	(0.0201)	(0.0419)
2013	0.0356	0.103***	-0.138***	-0.00498	0.0757***	-0.0707
	(0.0247)	(0.0130)	(0.0239)	(0.0476)	(0.0241)	(0.0466)
2014	0.0574**	0.0765***	-0.134***	-0.0161	0.0647***	-0.0485
	(0.0262)	(0.0133)	(0.0253)	(0.0455)	(0.0245)	(0.0441)
2015	0.0647**	0.0718***	-0.137***	Convergence not achieved		
	(0.0273)	(0.0145)	(0.0256)			
2016	0.0378	0.0892***	-0.127***	-0.0257	0.0640*	-0.0384
	(0.0274)	(0.0147)	(0.0264)	(0.0536)	(0.0340)	(0.0500)
2017	0.0418	0.0987***	-0.140***	0.00644	0.0707*	-0.0771*
	(0.0305)	(0.0171)	(0.0292)	(0.0499)	(0.0387)	(0.0439)
2018	0.0578	0.103***	-0.161***	-0.0179	0.0605*	-0.0426
	(0.0361)	(0.0181)	(0.0345)	(0.0589)	(0.0334)	(0.0492)
2019	0.0358	0.0918***	-0.128***	-0.0668	0.0702**	-0.00344
	(0.0383)	(0.0195)	(0.0373)	(0.0655)	(0.0340)	(0.0656)
2020	0.0425	0.101***	-0.143***	-0.0901	0.107*	-0.0173
	(0.0397)	(0.0209)	(0.0387)	(0.0676)	(0.0606)	(0.0594)

Columns (1)-(3) represent the coefficients of the multinomial regression without covariates and columns (4)-(5) are the estimates from the regression with covariates

**** p<.01, ** p<.05, * p<.1*

Note: under- and over- stand for under-educated and over-educated, respectively