

Muslim Labour Market Penalties in the Context of Contemporary Migrations from Eastern Europe to the UK.

UNIVERSITY of
STIRLING



Scot Hunter

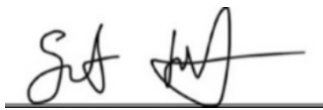
September 2024

University of Stirling

Submitted for the degree of Doctor of Philosophy

Declaration

I declare that I have composed this thesis myself and that it embodies the results of my own research. Where appropriate, I have acknowledged the nature and extent of work carried out in collaboration with others included in the thesis.

A handwritten signature in black ink, appearing to read 'Scot Hunter', is written over a horizontal line.

Scot Hunter

Copyright

The copyright of this thesis belongs to the author under the terms of the United Kingdom Copyright Acts as qualified by the University of Stirling Regulations for Higher Degrees by Research. Due acknowledgement must always be made of the use of any material contained in, or derived from, this thesis.

Acknowledgements

This doctoral research was supported by the Economic and Social Research Council.

A special thank you to my supervisory team for entrusting me with this project. In particular, Prof. Paul Lambert, whose efforts have been instrumental in getting me this far. Over the past five years, Paul has taught me so much about social science and statistics and has always provided helpful feedback on many drafts and applications. I hope the analyses in this thesis make him proud, or at least prouder than he is of my eight-ball skills, as we discovered around that pool table in Colchester.

Furthermore, Dr. Marina Shapira's unmatched knowledge in ethnicity literature and expertise in quantitative methods have been invaluable. All of her additional support beyond the PhD is also acknowledged. This mostly includes advice about research and teaching opportunities, but also reading my fortune in coffee grounds on that first, sleep-deprived morning in Yerevan. Opting out of a press conference on that very hot day to skive off and visit your old stomping ground will remain a core memory of mine.

This doctoral research is the culmination of a decade studying and teaching sociology at the University of Stirling. Many colleagues from the Faculty of Social Sciences are acknowledged for making the last ten years so enjoyable. Maria, Maggie, Sarah, Ashley—to all of you, I owe a huge debt for the life and work skills you've imparted and that I will carry forward with me. This also includes office staff, particularly Tegan, for always keeping me right. Thanks also to the social surveys research group, including the 'Edinburgh lot,' for all the helpful feedback on my presentations. A special thank you is owed to Dr. David Griffiths, who convinced me to apply for the doctoral scholarship in the first place.

If Kate O'Hara hadn't joined the faculty when she did, halfway through my doctorate, I'm genuinely unsure if I would be sitting here writing this today. I know how funny she'll find reading this – but honestly, thanks for helping me get my act together and for always being my biggest champion. Thanks to Dr. Stacey McNicol for being so hilarious and ridiculously optimistic about everything, and especially for lending a listening ear to my rants, usually when it came to essay marking. I am excited to see them both progress in their careers and witness the positive changes they will make in their respective fields.

Of course, I'd like to thank my friends and family for all the love and support. To my sister Leigh, thank you for all the 'brat'-cookie care packages and constant reminders to treat myself. Please never stop sending me videos of my adorable nieces wreaking havoc. Mum, thank you for instilling in me compassion and acceptance from a young age. Thank you for constantly keeping my ego healthily inflated by always over-exaggerating my accomplishments to every person you meet. Your perseverance and resilience have endlessly inspired me, helping me reach this far, especially during difficult times. This wouldn't have been possible without you both; you kept me going.

And to my Dad and Granny Pat, who started this journey with me but departed before its end, this work is dedicated to you.

ABSTRACT

This thesis investigates the impact of contemporary migration patterns on Muslim communities in the UK. Post-war immigration has significantly changed Britain's ethnic composition, with Muslim communities facing inequalities such as lower economic activity, higher unemployment, lower wages, and limited access to advantaged occupations. The 2004 EU accession brought many Eastern Europeans to the UK. These contemporary migration trends sparked public fears about impacts on education, housing, wages, and job competition. Despite research debunking these fears, the effects on earlier established ethnic minorities, particularly Muslims, remain underexplored.

This study encompasses three interrelated empirical analyses to examine the socio-economic inequalities experienced by Muslims and how these might be impacted by contemporary migrations. These analyses entail theoretically informed advanced statistical modelling of data from *Understanding Society* — The UK Household Longitudinal Study (UKHLS). The UKHLS is an ongoing, large scale, nationally representative survey with measures on ethnicity, religion, work and employment which are essential for exploring Muslim circumstances. In addition, macro-level migration data from the Office of National Statistics (ONS) is used to explore the potential impacts of new migrations on Muslim communities.

Informed by intersectionality (the theory that social inequalities have combined effects), the analysis highlights the multidimensional Muslim experience (for example ethnic, gender, religious and generational effects). Contrary to orientalist narratives that suggest Muslims self-exclude due to cultural or religious reasons, this study reveals that even when Muslims are well integrated into British society, they continue to face disadvantages. This ongoing disparity suggests that it is challenging to attribute their poorer outcomes to anything other than discrimination. Furthermore, this research challenges the notion that new migrations disrupt local labour market opportunities for Muslims, demonstrating that disadvantages persist regardless of these demographic changes.

Table of Contents

Abstract	4
1. Introduction	11
1.1. Thesis Overview and Research Questions	15
1.2. Thesis Contributions	19
2. Literature Contextualisation	21
2.1. Overview of British Muslims	21
2.2. Ethnic and Muslim penalties in the labour market	24
2.2.1. International perspectives on ethnic and religious penalties	24
2.2.2. Ethnic penalties in the UK	25
2.3. Ethno-religious penalties	26
2.4. Theories for Muslim economic disadvantage	28
2.4.1. Human capital, personal characteristics and employment features	30
2.4.2. Orientalist narratives	34
2.4.3. Bias and Discrimination	38
2.4.4. Methodological challenges and applications	42
2.4.5. Summary	44
2.5. Intersectional inequalities in the labour market	46
2.5.1. Overview	46
2.5.2. Conceptualising intersectionality	47
2.5.3. Operationalising intersectionality	49
2.6. EU Enlargement Migration in the UK	51
2.6.1. Socio-political context	51
2.6.2. Social and economic circumstances of contemporary migrants	53
2.6.1. Eastern European labour market penalties	63
2.7. Understanding the Labour Market Impacts of Immigration	64
2.7.2. Summary	66
3. Data and Variable Operationalisation	68
3.1. Overview	68
3.2. Data Source	69

3.2.1.	The UK Household Longitudinal Study (UKHLS)	69
3.3.	Outcome Variables	73
3.4.	Explanatory variables	77
3.4.1.	Population characteristics	78
3.4.2.	Human capital	85
3.4.3.	Sociocultural factors	86
4.	<i>Muslim Penalties in the Labour Market</i>	88
4.1.	Introduction	88
4.2.	Sample	88
4.3.	Method	89
4.4.	Findings	91
4.4.1.	Bivariate Results	91
4.4.2.	Regression results	107
4.4.3.	Muslim penalties	117
4.5.	Discussion and conclusions	121
5.	<i>Analysing Intersectionality in Muslim Penalties</i>	124
5.1.	Introduction	124
5.1.1.	Intersectionality's compatibility with quantitative methods	125
5.1.2.	Applications of methods for intersectionality	127
5.1.3.	Application of MAIHDA	130
5.1.4.	Alternative models	131
5.2.	Sample	131
5.2.1.	Dependent variable	132
5.2.2.	Controls	135
5.3.	Method	135
5.4.	Findings	140
5.5.	Discussion	150
5.5.1.	Reflections about the application of MAIHDA	151
6.	<i>Assessing the Impact of Contemporary Migrations Patterns on Muslim Labour Market Outcomes</i>	154
6.1.	Introduction	154

6.2. Macro measures	156
6.2.1. Population statistics from the UK census.	157
6.2.2. Deriving occupation level macro measures	158
6.3. Part 1 – Fixed effects approach and macro measures	160
6.3.1. Sample	160
6.3.2. Method	162
6.3.3. Employment-related outcomes.	170
6.4. Part 2 – Random effects and variations at the SOC10 unit group level.	177
6.4.1. Sample and Method	177
6.4.2. Findings	181
7. Discussion and Conclusions	192
7.1. Overview	192
7.2. Key Findings	193
7.2.1. Ethno-religious Identity and Sociocultural Factors: Persistent Muslim labour Market Disadvantage Suggesting Structural Discrimination.	193
7.2.2. The Value of Intersectional Analysis in Understanding Muslim Labour Market Disadvantage	195
7.2.3. Occupation-Specific Disparities and Structural Discrimination in Muslim Employment Outcomes: Limited Impact of Contemporary Migration.	197
7.3. Recommendations from experiential learning	198
7.4. Closing Remarks	201
References	203
Appendices	220
APPENDIX A: Assigned education score based on average CAMSIS for that age group and qualification combination – sorted by education score from low to high.	220
APPENDIX B: Selected syntax for operationalisation of measures and data management.	222
APPENDIX C Summary of micro and macro data sources used	259

List of Tables

<i>Table 1-1 Labour market characteristics of ethnic minority men and women in the UK.</i>	<i>12</i>
<i>Table 3-1 Distribution of observations by ethno-religious group and ancestry.</i>	<i>82</i>
<i>Table 4-1 Sociodemographic Characteristics by Selected Ethno-Religious Groups</i>	<i>96</i>
<i>Table 4-2 Regional breakdown of ethno-religious groups</i>	<i>97</i>
<i>Table 4-3 Educational attainment, education score, and English language proficiency across ethno-religious groups.....</i>	<i>99</i>
<i>Table 4-4 Labour market participation and reason for not participating by ethno-religious group and gender.</i>	<i>100</i>
<i>Table 4-5 Labour Market outcomes for men participating in the labour market by ethno-religious group.....</i>	<i>102</i>
<i>Table 4-6 Labour Market outcomes for women participating in the labour market by ethno-religious group.....</i>	<i>103</i>
<i>Table 4-7 Socio-cultural variables by gender and ethno-religious group.....</i>	<i>105</i>
<i>Table 4-8 Cluster robust logistic regression of labour market participation for men and women.</i>	<i>109</i>
<i>Table 4-9 Cluster robust logistic regression of avoidance of unemployment for men and women participating in the labour market.....</i>	<i>111</i>
<i>Table 4-10 Cluster robust linear regression of CAMSIS for men and women participating in the labour market.</i>	<i>113</i>
<i>Table 4-11 Cluster robust linear regression of hourly average earnings for men and women participating in the labour market.....</i>	<i>115</i>
<i>Table 4-12 Better or worse outcomes compared to second-generation Muslim Indians after controlling for human capital and socio-cultural factors.....</i>	<i>118</i>
<i>Table 4-13 Better or worse outcomes compared to first-generation Muslim Black after controlling for human capital and socio-cultural factors</i>	<i>120</i>
<i>Table 4-14 Better or worse outcomes compared to second-generation Muslim Pakistani and Bangladeshi after controlling for human capital and socio-cultural factors.....</i>	<i>121</i>
<i>Table 5-1 Sample size of intersectional strata defined by gender, ethnicity, religion, and country of birth.</i>	<i>133</i>
<i>Table 5-2 Descriptive statistics of individual observations (N = 40149) and intersectional strata (n – 384) in the UKHLS pooled sub-sample.....</i>	<i>136</i>
<i>Table 5-3 Parameter estimates for linear models of average log hourly earnings.</i>	<i>141</i>
<i>Table 5-4 Inspection of five highest and lowest ranked strata for predicted average log hourly earnings with main additive effects (Model 1B) and extra controls (Model 1C).....</i>	<i>146</i>
<i>Table 6-1 Pearson’s correlation for bivariate relationships between seeking for and securing employment outcomes and neighbourhood indicators.....</i>	<i>164</i>

<i>Table 6-2 Cluster robust logistic regression of labour market participation and avoidance of unemployment for Muslim men and women.</i>	<i>165</i>
<i>Table 6-3 Pearson’s correlation for bivariate relationships between employment related outcomes and neighbourhood/occupational indicators.</i>	<i>172</i>
<i>Table 6-4 Cluster robust linear regression of labour market outcomes and logistic regression of different job-related outcomes for Muslim men and women</i>	<i>174</i>
<i>Table 6-5 Multilevel linear and logistic regression of labour market outcomes for men with SOC10 unit group at level 2.</i>	<i>179</i>
<i>Table 6-6 Multilevel linear regression of labour market outcomes for women with SOC10 unit group at level 2</i>	<i>180</i>
<i>Table 6-7 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Average Hourly Earnings</i>	<i>182</i>
<i>Table 6-8 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Financial Anxiety</i>	<i>186</i>
<i>Table 6-9 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Job Related Satisfaction.....</i>	<i>188</i>

List of Figures

<i>Figure 2-1 European country membership (as of 2024) to the European Economic Area (EEA) and European Union (EU).</i>	<i>54</i>
<i>Figure 2-2 Bivariate share of Muslim and post-04 EU migrants in LSOA neighbourhoods by Government Office Region.</i>	<i>58</i>
<i>Figure 2-3 Bivariate shares of Muslim and post-04 EU migrants in LSOA neighbourhoods for specific regions.</i>	<i>59</i>
<i>Figure 4-1 Labour market profiles of the biggest religious groups in the UKHLS sample.</i>	<i>94</i>
<i>Figure 4-2 Summary coefficient plots showing regression results for the socio-cultural models for each outcome.</i>	<i>116</i>
<i>Figure 5-1 Visualising distributions - sample mean, grand mean, and precision weighted grand mean.</i>	<i>139</i>
<i>Figure 5-2 predicted values by stratum for all 115 strata, ranked low to high.</i>	<i>143</i>
<i>Figure 5-3 Predicted stratum interaction effects ranked low to high.</i>	<i>149</i>
 <i>Figure 6-1 Scatterplot of share of Muslims and of EU Migrants in SOC10 unit groups</i>	 <i>159</i>
<i>Figure 6-2 Distribution of neighbourhood and occupation measure(s) by quintiles.</i>	<i>161</i>
<i>Figure 6-3 Mean proportions participating and employed by Muslim ethnic group and gender... ..</i>	<i>163</i>
<i>Figure 6-4 Interaction effects of Muslim group and neighbourhood characteristics on participation by gender.</i>	<i>167</i>
<i>Figure 6-5 Interaction effects of Muslim group and neighbourhood characteristics on employment by gender.</i>	<i>168</i>
<i>Figure 6-6 Mean proportions of employment outcome by Muslim ethnic group and gender.</i>	<i>171</i>
<i>Figure 6-7 Interaction effects of post-04 EU migrants in occupations on job-related outcomes by gender.</i>	<i>176</i>
<i>Figure 6-8 predicted occupation effects, ranked low to high.</i>	<i>184</i>
<i>Figure 6-9 Predicted occupation effects on financial anxiety, ranked low to high.</i>	<i>187</i>
<i>Figure 6-10 Predicted occupation effects on job related satisfaction, ranked low to high.</i>	<i>190</i>

1. INTRODUCTION

As the second largest religion in the UK, Islam constitutes a substantial 6.5% of the total population, with nearly four million Muslims according to the 2021 Census (Asaria, 2024). British Muslims, who make up one-third of the Black Asian and Minority Ethnic (BAME) population, are a significant demographic, particularly in urban areas like London where they represent 15% of the populace. This diverse and dynamic community, or perhaps best described as a ‘kaleidoscope of communities’ (Asaria et al., 2024, p8), is structured along varied social, cultural, linguistic, historical, geographical, and generational lines (Shahid et al., 2023). The growing Muslim population and broader developments affecting Muslims in Western Europe have sparked significant interest among academics and policymakers (Abbas, 2010). Economists and sociologists have paid considerable attention to Muslim ‘integration’ into British society and the various social inequalities they encounter (Cheung and Heath, 2007; Khattab, 2009; Khattab and Johnston, 2013; Johnston et al., 2010).

The breadth and scale of labour market inequalities experienced by Muslims since their arrival to the UK is well documented (Berthoud, 2002; Kenway and Palmer, 2007; Li and Heath, 2008; Longhi et al., 2013; Modood et al., 1997; Platt, 2007). Recent data shows that these inequalities are still prevalent and vary across ethnic groups and within groups by gender. It is important to note that many of the studies focus on ethnic groups rather than Muslim status itself. However, some ethnic groups, such as Pakistani and Bangladeshi, are predominately Muslim, and hence these studies inform us of Muslim inequalities. For example, between 2015 – 2018, Pakistani and Bangladeshi men (excluding students) had some of the lowest employment rates (81% and 82%) and average earnings (see Table 1.1). These rates and earnings were even lower for these ethnic minority women, as well as for Indian women (Clark and Shankley, 2020). This disadvantage persists even after controlling for factors typically thought to explain labour market inequalities, such as age and human capital (Khattab and Modood, 2015).

The primary focus of this research is labour market disadvantage. However, growing evidence shows that Muslims also underachieve at school (Asaria et al., 2024), face poor

Table 1-1 Labour market characteristics of ethnic minority men and women in the UK.

	Men				Women			
	Economic Activity	Employment	Employment (No Students)	Mean Earnings	Economic Activity	Employment	Employment (No Students)	Mean Earnings
	%	%	%	(£/week)	%	%	%	(£/week)
White British	82.2	79.9	83.6	651.0	78.8	75.6	78.8	408.2
White Irish	84.7	83.8	85.1	853.5	79.9	76.2	78.7	619.0
Other White	90.9	88.3	92.4	647.2	78.9	74.9	78.5	443.3
Indian	84.2	80.4	87.3	720.4	72.0	67.5	72.0	469.0
Pakistani	77.9	71.5	81.4	507.7	41.1	37.8	41.1	329.0
Bangladeshi	77.8	71.9	81.7	385.6	41.3	34.9	37.1	355.9
Chinese	68.7	66.5	82.2	744.8	61.8	60.1	73.1	531.1
Black African	79.0	71.6	83.0	489.9	69.1	60.2	68.3	377.5
Black Caribbean	81.9	73.7	77.9	505.6	77.0	71.5	76.7	428.0

Notes: Adapted tables 6.1 and 6.2 in Clark and Shankley 2020, p132. Source: Quarter Labour Force Survey (merged data from 14 waves of data, January 2015 to June 2018). Men (ages 16 to 64); Women (ages 16 to 59).

housing conditions and overcrowding (Office for National Statistics, 2020), have poorer health outcomes (Cahoun and Nazroo, 2020; Shadid et al., 2023), and disproportionately suffered during events like the recession (Khattab and Johnston, 2013) and the pandemic (Finney et al., 2023; Neves et al., 2024).

Explanations for this labour market disadvantage have included theories of supply and demand. The former would argue that the low participation and employment rates of Muslims, women in particular, is because of their Islamic religiosity including their associated traditional gender values and ‘segregationist’ beliefs preventing them from entering the public sphere (Inglehart and Norris, 2003; Joppke, 2007; Koopmans, 2016). Some theories relating to the demand side suggest that employers operate with individual biases – preventing ethnic minorities to enter the labour market or progress in their careers either deliberately or because of some subconscious bias (Khattab et al., 2020). Other theories consider that Muslims are structurally disadvantaged due to the everyday (re)production of Islamophobia in and across British institutions (Gilks, 2020; Sweida-Metwally, 2022; Wallace et al., 2016). Through these processes, Muslim identity has

come to represent broader social prejudices and systemic barriers that perpetuate economic inequalities.

Recent developments in the ethnic penalty literature have focused on the interaction of social inequalities in determining outcomes (Johnston et al., 2010; Longhi et al., 2013). Scholars are now examining how factors such as ethnicity, gender, religion, and immigrant status intersect to create advantage and disadvantage. This shift towards an intersectional approach examines how different social identities overlap and interact to shape individual experiences (Crenshaw, 1991; McCall, 2005). It acknowledges that individuals do not experience discrimination or privilege in isolation. Instead, these experiences are shaped by the complex interplay of multiple identities (Evans et al., 2018). For instance, studies have highlighted how Muslim women, particularly those from Pakistani and Bangladeshi backgrounds, face more disadvantages in the labour market due to their gender and religious identity (Khattab and Modood, 2015). The differences between foreign born and second/third generation migrants has also led to studies that account for these generational distinctions (Cheung and Heath, 2007). Methodologically, this has led to more sophisticated statistical techniques that aim to capture these interactions, moving beyond conventional single-axis analyses (Evans et al., 2018; Johnston et al., 2010; Longhi et al., 2013). Given these insights, an objective of this research will be to explore different approaches to using quantitative methods for intersectional analysis, aiming to provide a more comprehensive understanding of Muslim experiences.

The arrival of contemporary economic migrants to the UK after the expansion of the EU in 2004 also garnered much academic and public attention. Concern emerged over the perceived negative impact of these migrations on local labour markets, housing markets and an increase in demands on education (Manley et al., 2019). While there is little empirical evidence of this (Drinkwater et al., 2006; Gilpin *et al.*, 2006), these narratives were characterised by fears of increased job competition and reduced wages amongst the public. In general, the flows of post-04 accession migrants, mainly Poles or other Eastern Europeans, had a marginal impact on employment rates and wages (Lemos and Portes, 2008). However, despite the shortage of evidence, the stoking of public anxieties fuelled a surge of Euroscepticism and broader concerns of immigration, ultimately playing a significant role in the Brexit referendum and the UK's decision to leave the EU (Geddes, 2014; Portes, 2019).

Classical economic theory suggests that the arrival of new migrants can disrupt local labour markets and have a severe impact on the receiving country's population (Borjas, 1995, 2003). Contemporary migration flows are expected to cause shocks to the labour supply, potentially lowering wages for similarly skilled native workers, and potentially displacing them. Moreover, evidence in the UK and across Europe has shown that increased immigration, at least in the short term, is associated with lower social trust and subjective well-being of minority group members in the receiving nation (Li et al., 2021). The precariousness of minority groups is thus potentially further heightened by new migrations to the UK, which could intensify the competition for opportunities and resources in local labour markets.

Whilst there is substantive interest in Muslim disadvantage and the labour market impacts of contemporary migrants, little is known about how these two areas intersect. There is a gap in understanding how contemporary migration patterns from post-04 accession countries affect the earlier established ethnic communities of the UK. Focusing on Muslims is particularly helpful for this study of labour market impacts of new migrations. This is because they represent a large segment of the population characterised by socio-economic disadvantage and demographic characteristics. These factors might, in principle, make Muslims more vulnerable to the impacts of new migrations.¹ This focus allows for a detailed examination of a group that is often at the intersection of multiple forms of disadvantage providing valuable insights that can inform broader discussions on ethnic penalties and intersectionality.

Underpinning all of this are numerous methodological challenges and issues of measurement, particularly concerning contemporary migrants. Shortly after the EU accession, identifying these new migrants was difficult. This is because, at the time, some large data resources amalgamated all "White Others" together. This meant it was difficult to distinguish EU accession migrants from other western Europeans and other migrants from the USA, Canada, and Australia. It is only recently that these groups have been disaggregated by country of origin which has made detailed analysis of their potential impact possible.

¹ Evidence shows that vulnerable workers (including migrants and ethnic minorities) are negatively affected by increased competition from new migrants as they entered Italian labour markets (Boeri et al., 2015).

Additionally, there are challenges in identifying Muslims in data based on a range of different factors, such as self-identification, cultural practices and religious observance. The term ‘Muslim’ is defined in the following research using a combination of ethnic and religious-self-identity markers. This includes individuals who self-identify as Muslim based on their religious beliefs, as well as those who belong to ethnic groups predominately associated with Islam including South Asian, Middle Eastern, African and White groups. This diversity means that Muslim identity is often intertwined with ethnic identity. Consequently, understanding the socio-economic circumstances of Muslims requires considering both their religious affiliation and ethnic background, as these factors collectively shape their experiences and challenges. Insights are drawn on Muslim communities in this research both from religious and ethnicity studies, and it attempts to combine elements from these approaches to accurately represent them using a method that considers all these factors.

A key contribution of this thesis will thus be to develop methodologies for defining measures of contemporary migration and Muslims which aim to accurately represent these groups. Different approaches will be carefully considered, drawing from the existing literature, to address these complexities. The development of large social surveys with detailed ethnic and religious information, along with detailed occupation data and advancements in software, now allows for a more sophisticated analysis of these groups than was previously possible. This research, therefore, draws from these advancements to explore the socio-economic interactions and impacts between new migrants and Muslim communities.

1.1. Thesis Overview and Research Questions

There is a well-established body of research examining ethnic and religious penalties in Western labour markets (Chiswick, 2001; Heath and Cheung, 2007; Model and Lin, 2002; Yemane, 2020), alongside growing attention to the effects of migration on employment opportunities in receiving countries (Portes, 2019). In the UK context, a consistent finding is that individuals belonging to Muslim ethno-religious groups face disproportionately poor labour market outcomes (Khattab, 2009; Khattab and Johnston, 2013; Johnston et al., 2010; Sweida-Metwally, 2022). In addition, classical economic theory has long argued that rising levels of immigration may disrupt local labour markets

by increasing labour supply and displacing native workers (Borjas, 1995, 2003). While these literatures have developed in parallel, relatively few studies have considered how migration dynamics intersect with religious and ethnic disadvantage (particularly for British Muslims) within an integrated analytical framework.

This thesis is structured to provide a comprehensive examination of the economic circumstances and socio-economic inequalities experienced by Muslims in Britain, and whether these inequalities are associated with contemporary migration trends. The main objectives of this research are outlined first, setting the stage for the detailed analyses that follow in each empirical chapter. Within each empirical chapter's overview (chapters 4-6), the research questions to address specific aspects of these objectives are stated. The objectives of this research are:

- To provide a robust empirical characterisation of the economic circumstances of Muslims in contemporary Britain.
- To promote methodological and applied research knowledge on using quantitative methods informed by intersectionality to explore Muslim inequalities.
- To define and evaluate methodologies for measuring local variations in contemporary immigration and link that macro-data with detailed micro-data on Muslim individuals.
- To assess the potential impact of contemporary immigration as an explanatory factor in socio-economic inequalities experienced by Muslims in Britain.

To address specific aspects of these aims, this thesis is organised into seven chapters, including the introduction and conclusion. In **Chapter 2**, relevant theoretical and empirical literature for every chapter is contextualised. This includes a brief overview of Islam in Britain and attention to relevant literature on 'ethnic penalties'. Essentially, there is ample evidence that ethnic penalties exist. This means that, compared to the majority population, minority ethnic groups, particularly Muslims, experience less favourable circumstances net of other variables expected to influence outcomes. How intersectionality has been operationalised in the literature and the socio-demographic and labour market profiles of contemporary migrants in the UK are then discussed in addition to a brief overview of labour market impact theories.

Chapter 3 includes a methodological discussion of the social survey resource that is analysed in chapters 4-6. *Understanding Society* - the UK Household Longitudinal Study (UKHLS) is currently the most comprehensive large scale, nationally representative data resource that contains suitable labour market measures and boost samples of adults from different ethnic and migrant backgrounds (University of Essex, 2022); thereby making it the most appropriate resource necessary for detailed analysis of Muslim circumstances. Chapter 3 describes the UKHLS sample in addition to the operationalisation of outcome and explanatory variables that are used in the subsequent empirical chapters. **Chapter 4** builds on recent ethnic penalty research indicating that Muslim penalties stem from structural discrimination rather than socio-cultural differences and self-exclusionary actions (cf. Koopmans, 2016; Sweida-Metwally, 2022). The analysis in this chapter involves using a multi-categorical approach when defining and using analytical categories. Essentially, this approach allows for the comparison between different members of Muslim communities, exploring differences between various ethnic groups, generations, and genders. The chapter finishes by exploring an alternative way of comparing penalties between different ethno-religious groups, rather than methods that involve making comparisons to the majority only. The research questions for this chapters are:

1. What is the specific influence of belonging to a Muslim ethno-religious group on labour market outcomes, compared to the majority group?
2. Does any Muslim labour market disadvantage persist after accounting for individuals' circumstances and human capital?
3. Does any Muslim labour market disadvantage persist even after adjusting for sociocultural factors, indicating potential structural discrimination?

Chapter 5 examines a novel quantitative approach for exploring Muslim inequalities within an intersectional framework – the Multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIDHA) (Evans et al., 2018). This chapter makes a methodological contribution to ethnic penalty literature using multilevel models which nest individuals into intersectional contexts (“strata”) based on different combinations of social identities. This method provides insight into how outcomes vary within and between ethnic groups. It shows how different axes of advantage and disadvantage interlock and shape outcomes for different people at different positions of the social structure. The chapter argues that this approach offers some potentially useful

methodological tools for exploring differences within and between ethno-religious groups which could be beneficial to future ethnic penalty research. The research questions for this chapter are:

4. How useful are intersectional strata for exploring Muslim labour market disadvantage?
5. To what extent do complex interactions of gender, ethnicity, religious affiliation, and country of birth contribute to explaining inequalities in the labour market?

Chapter 6 includes analysis on the potential impact of contemporary migration on Muslim groups. The chapter contributes to a burgeoning segment of ethnic penalty research that explores the effects of contextual environments on minority group outcomes (Jivraj and Alao, 2023; Knies et al., 2016; Zwysen and Demireva, 2020). It investigates the association between Muslim disadvantage and derived contemporary migration measures (from ONS sources including census data and the Labour Force Survey) at detailed levels of geography and within specific occupation groups. The chapter concludes by using multilevel models to explore any variation within and between occupations that are populated by more Muslims than on average. Additionally, this chapter highlights how emerging methodologies and technologies, particularly in software, have enabled progress in examining the heterogeneity of labour market circumstances.

6. How is the concentration of post-2004 EU accession migrants and other local area characteristics associated with inequalities in outcomes for Muslims seeking and securing employment?
7. Are post-2004 EU accession migrant worker rates and other occupation factors associated with poorer outcomes for Muslims in employment?
8. How does more detailed occupation information reveal unique patterns and disparities in employment outcomes for Muslims, compared to broader occupational analyses?

The key empirical findings and contributions of the thesis are described in **Chapter 7**. This chapter also presents potential recommendations for future work and ethnic penalty research using secondary data resources. Another feature of this doctoral research is that preparatory data management and analysis materials are made available in Appendix B

and at an [online repository](#).² This approach speaks to growing concerns across a wide range of academic disciplines that empirical results cannot be verified (Connolley et al., 2020). Cross reference will be made throughout the research directing the reader to relevant segments of syntax (computer programming language) or command files which illustrate the Stata code that was used for data management or analysis. The open-source availability of the analysis code and the development of effective visualisations further enhance the accessibility and impact of the research.

1.2. Thesis Contributions

Despite decades of research into ethnic penalties, our understanding of how multiple identities shape labour market disadvantage remains incomplete. Religion, migration background, and ethnicity are often examined in isolation, yet in reality, these characteristics intersect in ways that are not easily captured by conventional analytical models. When studies do attempt to consider them together, the resulting complexity often leads to models that are difficult to interpret or apply meaningfully. There is a pressing need for approaches that can account for these interlocking identities in a more structured and interpretable way. This thesis is motivated by the aim to advance such an approach—one that can offer clearer insights into how multiple forms of disadvantage combine to affect the employment outcomes of minority groups, particularly Muslims in the UK.

At the same time, research on the economic effects of immigration rarely engages with questions of ethno-religious inequality, particularly as it affects minority groups within the receiving society. This thesis is motivated by the need to bridge these scholarly strands and to develop a more integrated understanding of how structural and socio-cultural factors combine to shape labour market outcomes for disadvantaged Muslim groups. By bringing together intersectional analysis and macro-level migration dynamics, the research aims to enrich existing theories of ethnic penalties and extend them in more context-sensitive and empirically robust directions.

² https://github.com/scotphunter/hunter24_thesis_muslimlabourmarketoutcomes

This thesis makes both conceptual and empirical contributions to the ethnic penalty literature. Conceptually, it advances the field by moving beyond conventional models that focus primarily on demographic characteristics and human capital (such as age, sex, and education), incorporating socio-cultural dimensions (particularly religion and migrant generation) that have only recently become analysable due to improved data availability. It also introduces a more refined operationalisation of intersectionality by applying a multilevel framework to examine how identities such as gender, ethnicity, religion, and immigrant generation jointly shape labour market outcomes for Muslims in the UK. This approach enables a deeper understanding of how layered forms of disadvantage operate, moving beyond additive models of inequality.

Empirically, the thesis integrates detailed micro-data from the UK Household Longitudinal Study (UKHLS) with macro-level indicators of EU migration to assess how broader structural trends interact with individual-level characteristics. This enables an investigation of both the overall scale of ethnic and religious penalties and the specific occupational contexts in which they are most pronounced, offering new evidence that can inform policy efforts aimed at reducing labour market inequalities.

2. LITERATURE CONTEXTUALISATION

This chapter provides contextualisation for the following analyses. Section (2.1 – 2.5) contextualises Chapter 4 and 5 by reviewing Muslim penalty literature, presenting several theories thought to explain Muslim disadvantage and discussing how intersectionality has been conceptualised and operationalised in the literature. Section 2.6 and 2.7 situates Chapter 6 by contextualising the social and economic circumstances of Eastern Europeans and reviewing literature on the labour markets impacts of new migrations.

2.1. Overview of British Muslims

Islam has a long history in the UK. Since the 16th century, Muslims have entered the UK labour market in various roles, including traders, bankers, spice merchants, medical students, sailors, and servants (Commission of Racial Equality, 1996). During the colonial era, Muslims from upper-class backgrounds came to the UK to pursue education and employment opportunities (Abbas, 2010). After the end of the second world war³, many South Asians from more disadvantaged regions, like Azad Kashmir in Pakistan, Sylhet in north-west Bangladeshi, and Punjab in India, came to the UK with the aim to help with the post war effort and create wealth. Despite being bolstered by the ‘myth of return’, many ended up settling and establishing communities in industrial areas such as Manchester, Bradford, and Rochdale, with Bangladeshi settling in deprived urban areas like Tower Hamlets (Anwar, 1979; Panyai, 2010).⁴ These immigrants from Pakistan,

³ Prior to the large migrations from commonwealth countries, approximately one million Irish people migrated to the UK between 1800 and 1945. Additionally, around 150,000 Jewish people from Western Europe, fleeing political persecution, settled in London from 1870 onwards, tripling the Jewish population. Despite intermarriage and subsequent immigration patterns reducing their presence in the UK population, these groups shared characteristics like faith and skin colour, which limited perceived differences with the native population. However, they still faced “othering” processes similar to newer migrants. Irish Catholics were seen as a threat to British identity, akin to the experiences of recent Muslim and South Asian migrants post-1945. This recurring “othering” process highlights the persistent prejudice faced by migrants based on their status (Panyai, 2010; Meer, 2013).

⁴ In addition to large South Asian communities arriving in the UK, there was also a significant arrival of Caribbean migrants, mostly ex-servicemen, after the war. By 1958, around 125,000 Caribbean people had settled, primarily in London before spreading to other areas. While their arrival was generally welcomed

India and Bangladesh and their descendants nowadays account for the largest groups of Muslims in the UK (approximately 60%, see Asaria et al., 2024, p8).

The ‘Africanisation’ of former British colonies in the 1960s/1970s led to the arrival of East African Asians, some of which were Muslim (Abbas, 2010, p20). Many were middle class and held professional occupations at the time and pursued similar circumstances after arriving. Many Ugandan refugees sought asylum in the UK and settled in and around Leicester, despite official policy created at the time to try and prevent their settlement near other South Asian communities (Panyai, 2010) – what Abbas (2010) notes were referred to as ‘red zones’ (p20). Other Muslims from Eastern Europe and the Middle East have arrived in the UK more recently due to forced movement and political dislocation. Overall, the Muslim community has a heterogenous ethnic demographic consisting of South Asians, Bosnians, Kosovans, Afghans, Somali and Iraqis, amongst others (Abbas, 2007, 2010).⁵ This ethnic heterogeneity is further evidenced by recent census data showing that Muslims have representation in all the major ethnic groups in the UK, including the gypsy or Irish traveller and Roma communities (Asaria, et al., 2024).

A variety of socio-economic and religious influences have led to unique settlement patterns among South Asian communities in the UK. The religious affiliations of South Asian groups differ considerably. An analysis conducted on the PSI fourth national survey of ethnic minorities in 1994, Modood et al., (1997) show that the ‘overwhelming majority’ of Pakistanis (96%) and Bangladeshis (95%) were Muslims. In contrast, Indians were typically Sikhs (50%) or Hindus (32%) with a small minority (6%) holding the Islamic faith (p17). There is also a considerable amount (15%) of African Asian people who identified in the fourth survey as Muslim (Modood et al., 1997). During the 1990s, Pakistani and Bangladeshi populations, on average, resided in areas where they constituted 13% and 14% of the population, respectively. This percentage was notably lower for Indian populations (Modood et al., 1997). This trend highlights the tendency

due to economic needs, racial tensions arose, notably leading to the 1958 Notting Hill race riots. Despite these challenges, Caribbean migrants positively impacted the economy and contributed to growing ethnic diversity and interracial marriages. Shared Christian faith helped their integration, unlike South Asians who faced different challenges.

⁵ In the 2001 Census over two million people reported of Asian ethnicity in Britain (1,000,000 Indians, 750,000 Pakistanis and 280,000 Bangladeshis) demonstrating the scale of migration to Britain of South Asians since 1945. The growth of South Asian communities was accelerated by family unification in the 1970s and the high fertility rates, which are a common characteristic of migrant groups (Panayi, 2010).

for economically disadvantaged Pakistani and Bangladeshi groups to concentrate in specific urban areas. These concentrations were largely influenced by (1) industry-specific factors, particularly moving to localities close to the once-strong but now declining textile industry (Cheung and Heath, 2007), and (2) housing cooperatives and coordinated renting opportunities. For instance, arrangements where deposits were paid to buy homes using collective savings (Modood et al., 1997). While most Pakistani and Bangladeshi individuals migrated as labourers entering low-skilled jobs, other South Asians, such as Indian doctors, are more dispersed and tend to reside in affluent areas (Cheung and Heath, 2007; Panyai, 2010).

When considering the labour market integration of migrants, ethnic and religious identities are best viewed as distinct yet interconnected aspects of complex social identities (Khattab and Johnston, 2013). Many British Muslims perceive their faith to be central to their identity, leading to a growing desire for 'Islamisation' among second- and third-generation Muslims (Abbas, 2010). British-born South Asians, in particular, are increasingly distinguishing their ethnic from their religious identities (ibid, 2010). This reformation of identities, and focus on being Muslim, has been influenced by inter-generational change, and led to tensions within communities and affected broader social relations.

Varied literature on the relationship between Islam and the nation-state exists. However, Meer and Modood (2009) state that Islamisation and the importance of Islamic faith to Muslims does not amount to anti-British or anti-democratic attitudes, contrary to public discourse. The assumption that British Muslims are not loyal to democratic practices is unfounded and based on several misconceptions. They cite a study from Heath and Roberts (2008), which reports that most British Muslims had no problem identifying as British and believed in similar democratic processes as the majority population (cited in Meer and Modood, 2009). Yet, like other minority collectives, Islam is still viewed as a threat to British identity and Muslims are consequently penalised for this.

The rise in anti-Muslim sentiment and Islamophobia, particularly following the 9/11 and 7/7 events (Meer and Modood, 2009; Parekh, 2008) and the 22/4 attack on Manchester Arena (Gilks, 2020), may have shifted the focus from ethnic background to religious identity. This shift means that people may often be seen as Muslim first, rather than members of specific ethnic groups. For example, Khattab et al., (2020) observe that the

large Pakistani Muslim population in the UK has led to a lay association of Islam with Pakistani ethnicity, resulting in broad generalisations that treat Muslims as a single homogenous group. This generalisation is so pronounced that White converts to Islam have faced similar Islamophobia as Pakistani Muslims (Moosavi, 2015). These factors highlight that religion plays a central role in shaping the identity of ethnic groups and can significantly influence their outcomes, especially if their religion is perceived to conflict with the dominant faith and democratic values of the host country.

This study aims to explore the heterogeneity of the Muslim experience, building on established literature that examines the intersections between different demographics within these groups (Johnston et al., 2010; Longhi et al., 2013). However, fully acknowledging the complexities and nuances of various Muslim identities is challenging due to data limitations. Therefore, the focus will primarily be on the differences between the largest Muslim communities (i.e Indian, Pakistani, Bangladeshi, Black, and White British⁶), as that is where the most substantial data is available. Nevertheless, care will be taken to respect the diversity within the Muslim community and to employ methods that can help best represent this heterogeneity.

2.2. Ethnic and Muslim penalties in the labour market

2.2.1. INTERNATIONAL PERSPECTIVES ON ETHNIC AND RELIGIOUS PENALTIES

This analysis is informed by a growing international literature on ethnic and religious penalties in Western labour markets (Chiswick, 2001; Foner and Alba, 2008; Model and Lin, 2002; Yemane, 2020). In the US, for example, research has demonstrated how racial and religious minorities, particularly Muslim Americans, face both economic and social exclusion (Yemane, 2020), exacerbated by securitisation and surveillance post-9/11 (Kaushal et al., 2007; Seold and Embrick, 2013; Shams, 2020). Chiswick and Miller

⁶ The operationalisation of these groups is discussed in detail in Chapter 3. The Black group mentioned here consists of mostly Africans but also include Caribbean and those from other Black backgrounds who identified as Muslim. The 'Other' category consists of people who identified as Muslim but not in any of the above ethnic groups.

(2003) have shown the role of language proficiency in shaping employment outcomes, while Maskileyson and Semyonov (2017) find that racial and ethnic penalties are especially pronounced for first-generation migrants. Evidence of Muslim labour market disadvantage—particularly among women—emerges across multiple national contexts, including Europe (Connor and Koenig, 2015), Canada (Akbar, 2019; Khattab et al., 2020a), the United States (Abdelhadi, 2017), and Australia (Khattab et al., 2020b). Comparative European research (e.g., Alba, 2005 on France; Connor and Koenig, 2015) also identifies persistent exclusion, though institutional and policy variations shape national trajectories.

These works provide useful theoretical frameworks and comparative insights into how racial, religious, and migration-related disadvantages manifest globally. However, this thesis focuses specifically on British Muslims, whose experiences are shaped by a distinct socio-political and post-colonial context. The majority are descendants of post-war migrations from South Asia and, to a lesser extent, East Africa and African countries—movements deeply rooted in Britain’s imperial past and evolving immigration regimes. These historical legacies have influenced not only settlement patterns but also the racialisation and socio-economic positioning of Muslim communities within the UK. As such, while international literature offers valuable reference points, its findings are not always directly transferable. This research therefore centres on the British case to explore the interplay between structural inequalities and intersectional identities in a context shaped by the UK’s unique history of race, religion, and migration.

2.2.2. ETHNIC PENALTIES IN THE UK

Ethnic penalties are the remaining disparities in employment outcomes between ethnic minorities and the majority, even after accounting for factors like age, education, and migration status (Berthoud, 2000; Cheung and Heath, 2007; Heath and Martin, 2013). These studies show that commonwealth migrants have experienced persistent discrimination and disadvantage since their arrival in the UK (Berthoud, 2000, Berthoud 2002; Heath and Cheung, 2006; Kenway and Palmer, 2007; Li and Heath, 2008; Modood et al., 1997; Platt, 2007). Black African, Black Caribbean, Pakistani and Bangladeshi individuals, face heightened barriers to the labour market and tend to earn less than their

White counterparts across the life course (Li and Heath, 2020). Pakistanis and Bangladeshis are the most disadvantaged. They are more likely to occupy manual jobs, have higher unemployment, lower household incomes, and poorer living conditions (Brynin and Longhi, 2015; Heath and Cheung, 2006; Modood et al., 1997). Chinese and Indians also face disadvantages, though to a lesser extent. They occupy a ‘middle position,’ with circumstances better than Pakistanis and Bangladeshis but not as favourable as the majority population (Li and Heath, 2008; Modood et al., 1997, p. 334). However, Berthoud (2000) and Heath and Cheung (2006) note that Indians improved their circumstances, approaching parity with the White majority.

Ethnic groups are more likely to be concentrated in the public sector and underrepresented in advantaged private sector occupations. Visible migrants, compared to White migrants, experience significant ethnic penalties, and second-generation migrants tend to have more favourable outcomes than their first-generation counterparts (Aradhya et al., 2023; Cheung and Heath, 2007; Heath and Cheung, 2006; Li and Heath, 2016; Zschirnt and Ruedin, 2016). Although, Cheung (2014) and Daoud and Khattab (2022) failed to detect any generational progress across employment outcomes. Karlsen et al., (2020) do find evidence of downward mobility and less generational progress among Black Caribbean, Pakistani and Bangladeshi women and men. The most recent evidence suggests disadvantage persists for Black African, Black Caribbean, Pakistani and Bangladeshi individuals (Byrne et al., 2020). These groups also tend to experience additional disadvantage during times of crises above the regular penalty (Finney et al., 2023; Neves et al., 2024). Overall, ethnic minority women face similar disadvantages to men but there are some exceptions. Pakistani and Bangladeshi women have particularly low employment rates, and the non-employed women of these ethnic groups have strikingly low levels of labour market participation (Berthoud and Blekesaune, 2007) and experience significant labour market penalties across multiple outcomes (Cheung, 2014) including lower pay (Breach and Li, 2017).

2.3. Ethno-religious penalties

Complementary research has explored how cultural and religious factors contribute to perpetuating disadvantage (Khattab, 2009). The labour market performance of South

Asians varies largely by gender, religion, and generation. Hindu Indians generally outperform Sikhs, who encounter similar levels of disadvantage as Muslims. However, Indian Muslims exhibit distinct economic patterns compared to Pakistani and Bangladeshi Muslims, showing significantly higher rates of economic activity and earnings (Brown, 2000; Heath and Martin, 2013; Lindley, 2002). Muslim and Hindu Indians are more likely to attain advantaged occupations than their Sikh counterparts and compared to Pakistani and Bangladeshi Muslims (Khattab, 2009). Additionally, non-White women, particularly Muslims, tend to participate less in the labour market (Lindley, 2002). Heath and Martin (2013) and Cheung (2014) find evidence of substantial ethno-religious penalties across multiple employment measures and suggests cultural markers such as religion are more salient than ethnic identity in determining poorer outcomes. According to Daoud and Khattab (2022), while there is some evidence that the proportion of Muslim women in higher occupations is comparable to that of White women, Muslim women overall face the most significant challenges in economic activity, avoiding unemployment, and securing salaried positions.

Johnston et al., (2010) also found that all ethno-religious men were overqualified compared to the White British Christian charter population. Among Indians, Sikhs received less occupational returns on their education than Hindus, and there are noted differences in circumstances among Indian, Pakistani, and Bangladeshi Muslim men. These studies represent a step change in ethnic penalty literature, as the authors employ analytical categories that represent various combinations of ethnicity and religion (Khattab, 2009; Johnston et al., 2010). The influence of this approach on this research will be returned to in the methodology discussion (see Chapter 3).

Literature adopting this multicategory ‘ethno-religious’ approach to explore Muslim circumstances burgeoned. For example, Khattab and Modood (2015) found evidence of Muslim Pakistani and Bangladeshi having poor employment probabilities than other ethno-religious groups. Muslims, in particular, are also found to have suffered additional disadvantage, over and above the usual penalty, during the recession (Khattab and Johnston, 2013). However, Khattab (2016) finds little evidence of a Muslim earnings penalty among the British Salaried Class (the two highest NS-SEC codes), which suggests other mechanisms other than ethnicity and race may be more important in determining outcomes.

Longhi et al., (2013) and Khattab and Hussein (2018) extend the multicategory approach by incorporating generation into the analytical categories, rather than just controlling for it like other studies. This approach essentially uses analytical groups that represent three-way interactions between ethnicity, religion and immigrant status. They find Hindu Indian men tend to earn more than their Muslim counterparts, and Pakistani and Bangladeshi have the lowest earnings. Among all these groups, the second-generation ethno-religious have slightly more favourable outcomes compared to the first (Longhi et al., 2013). Khattab and Hussein (2018) found that all Muslim women, regardless of ethnicity, religion, and generation earn less, experience higher unemployment and are less represented in salariat classes. These effects are more pronounced for Pakistani, Bangladeshi and Black-Muslim women than for Indian and White Muslim women. In general, the second generation did slightly better. Even White Muslim women experience disadvantage compared to their White British Christian counterparts, evidencing the saliency of Islam in driving labour market performance even among majority ethnic groups (Manley et al., 2019; Sweida-Metwally, 2022).

2.4. Theories for Muslim economic disadvantage

Explanations for this persistent disadvantage are inconclusive, with two main camps of thought long-standing: (1) the self-exclusionary actions of British Muslims inspired by their faith, and (2) discriminatory mechanisms preventing them from getting in and on in the labour market. Traditional studies were seldom able to take these analyses further, as the data resources used to obtain ethnic penalties were limited to human capital and socio-demographic measures. Recent developments in the literature and social surveys, however, have allowed researchers to explore self-exclusionary theories more rigorously (Sweida-Metwally, 2022). This section situates the analysis within the viewpoint that self-exclusionary and individualised theories are often based on damaging stereotypes. These stereotypes are rooted in orientalist theories and colonial-era evidence about Muslims (Shadid et al., 2023).

After accounting for differences in human capital, population characteristics, and job-related factors thought to broadly influence entry into or progression in the labour market, theories for Muslim disadvantage can also be organised into supply- and demand-side

issues. Supply-side issues refer to behaviours of individuals that might influence their participation or career development. For example, religion, might drive decisions about where and the ways in which people want to work. Some have argued that supposed ‘social isolationist’ customs associated with Islam, for example, is associated with their reluctance to enter the British Labour market or to select into certain jobs (Inglehart and Norris, 2003; Joppke, 2009).

Demand-side issues involve discriminatory employer practices that can hinder individuals from entering or advancing in certain occupations due to specific characteristics. Discrimination against visible minority groups, such as Muslims in the UK, who occupy lower positions within the ethnic-religious hierarchy (Khattab et al., 2020a), may prevent them from securing employment or progressing in their careers. Both of these will be discussed in more detail below, but first the main human capital and population variables that are usually controlled for in ethnic penalty research, and how they are relevant to Muslims, will be discussed.

It is worth noting, however, that the historical literature on culture and discrimination is more nuanced than a simple binary might suggest. Foundational studies such as those by Modood et al. (1997) and Heath and Cheung (2006) recognised that cultural practices and experiences of discrimination are often deeply intertwined rather than mutually exclusive. For example, what might appear as cultural resistance or isolationism may actually reflect adaptive responses to marginalisation, or structural constraints misinterpreted as personal choice. These dynamics complicate efforts to neatly categorise causes of disadvantage. However, while this thesis acknowledges the complexity of the culture-discrimination debate, it necessarily focuses on specific aspects—namely, the measurable factors that can be captured using quantitative survey data. As such, there is a trade-off: although the analysis offers empirical insights using large-scale data, it cannot fully unpack the deeper processes and meanings that underpin cultural behaviour or discrimination. These would require more interpretive or qualitative approaches. This thesis therefore does not attempt to offer a comprehensive account of all possible influences but rather seeks to shed light on observable patterns and disparities through the tools available in quantitative social science.

2.4.1. HUMAN CAPITAL, PERSONAL CHARACTERISTICS AND EMPLOYMENT FEATURES

The logic of ethno-religious penalty literature is that any remaining disadvantage between minority groups and the majority should be considered ethnic penalties. This holds true even after accounting for equivalent human capital and socio-demographic characteristics. It is common, then, to adjust analysis to account for any other determinants of a labour market outcome. As shown in the previous sections, there is well-established evidence of prevailing disadvantage among Muslims, net of these other characteristics in the analysis.

2.4.1.1. Human and Social Capital

Classical approaches to measuring human capital focus on formal educational credentials and labour market experience (Becker, 1975; Mincer, 1974), but in the case of ethnic and religious minority groups, a third factor, linguistic skills, is also associated with inequalities in outcomes.

Proficiency in the host country language is important for immigrants' economic and social integration (Dustmann and Fabbri, 2003; Miaari, 2019; Khattab et al., 2020) with evidence suggesting it can double the employment level of new arrivals (Schmid, 2023). Being proficient in the majority language is linked to better labour market outcomes as it enhances communication skills, expands job opportunities, and facilitates integration into broader society. Research indicates that migrant groups who possess fluency in the dominant language tend to experience more positive outcomes (Constant and Massey, 2003; Dustmann and Fabbri, 2003; Heath and Cheung, 2007). In the 2021 census, 91% of the Muslim population in Britain reported either that their main language is English or that it is spoken very well or well (Asaria et al., 2024). The poorer English language proficiency of the remaining 9% might explain their disadvantaged economic outcomes.

Education is a compelling explanatory factor in predicting participation and progress in the labour market (Connelly et al., 2016; Hartog, 2000; Jenkins and Siedler, 2007). Education provides employers with a clear indication of a candidate's skills, knowledge,

and suitability for the job. Individuals with lower-level qualifications may be viewed by employers as less employable. Poorer economic circumstances of Muslims may, therefore, be due to their distinct education profiles (Alexander and Shankley, 2020; Asaria et al., 2024). For example, between 2012 and 2018 in England and Wales, Muslims were more likely to report having no qualifications than most other religious groups (Office for National Statistics, 2020).

Migrants often rely on interethnic ties and their social networks to learn about job openings, receive referrals, and secure employment (Granovetter, 1983, Ryan, 2022). Interactions between migrants and the majority group, known as bridging social capital (weak ties) (Granovetter, 1983; Putnam, 2007), are valuable in providing information. This is due to the majority group's control over limited societal resources and their understanding of majority cultural norms. On the other hand, bonding social capital (strong ties) with family members are not as useful for people trying to find employment, as summarised by Mustafa (2016, p2):

‘immigrant parents or family members may not be helpful at guiding their second-generation offspring in the best methods of gaining employment, where to search and how to search for jobs. If the second generation are also in residentially segregated areas, then they may have less access to and knowledge of the mainstream social and civic organisations.’

Empirical findings (Bunglawala, 2008; Reynolds and Birdwell, 2015) suggest that lack of interethnic connections (weak ties) with members of the host society and strong ethnic concentration of Muslims in neighbourhoods (Zuccotti and Platt, 2017) is detrimental to Muslims finding employment. The more weaker ties Muslims obtain, the more they might be able to secure opportunities (Sweida-Metwally, 2022).

2.4.1.2. Population characteristics

Women often exhibit distinct patterns in the labour market compared to men. Several unique factors influence women's participation rates and hours worked (Hakim, 2003). One significant factor is the presence of children in the home, which strongly predicts their working arrangements (Crompton and Lyonette, 2005; England, 2010). Having

children is also associated with women spending more time on unpaid housework (Glauber, 2008) and are they more likely to work part-time (Gregory and Connolly, 2008). With this in mind, gender is expected to have a large effect on economic circumstances. However, it is important to recognise that these gendered patterns are not uniform across all groups. There is empirical evidence showing that inequalities related to gender differ among various ethnic and religious groups (Daoud and Khattab, 2022; Lindley, 2002). These variations may be influenced by a range of factors, including diverse cultural practices and societal norms, which can affect approaches to childcare and women's employment.

Younger generations are more likely to have poorer economic outcomes including more unemployment, less earnings and are less likely to obtain advantaged jobs (Scarpetta et al., 2010). The younger age profiles of migrants, and Muslims in particular, might explain their economic circumstances. For example, Pakistani and Bangladeshi have some of the youngest age profiles, with many concentrated within the 16-64 age range (Shankley, et al., 2020).

Matters of family structure such as marital status and number of children have a bearing on economic outcomes. Studies indicate that married individuals tend to have better job prospects, with lower rates of unemployment and inactivity (Ribar, 2004; van Damme et al., 2008). Having dependents typically means additional financial responsibilities for necessities such as food, clothing, education and healthcare. This often leads to a need for increased income, driving individuals to seek higher-paying jobs or additional work hours. The presence of dependents can also affect job choices. Parents might prefer more stable employment or jobs with health benefits over higher paying but less secure positions. Childcare responsibilities often fall more heavily on women, potentially affecting their job prospects and how much time they can spend in the labour market. This might lead to career breaks or part-time work, which may impact long-term earnings and career progression. The high fertility rates of Muslims in the UK (Coleman and Dubuc, 2010; Shankley et al., 2020) suggests dependents in the household is an important control to adjust for in ethno-religious penalty analysis.

Immigrant status and country of birth is likely to affect labour market processes. First generation migrants might lack the types of human capital essential to succeed in the country of destination, especially if they are from less-developed countries with limited

educational provision (Heath and Cheung, 2006). Brown (2000) suggests that the religious affiliation and ethnicity of first-generation migrants could potentially be a proxy for the effects of the socio-economic conditions they originate from. For example, Indian Muslims have more favourable outcomes as they originate from more middle-class backgrounds and affluent regions of South Asia, which is the opposite for many Pakistani and Bangladeshi (Abbas, 2010). First generation may also struggle with the language of the receiving country and the qualifications they obtained before arriving may cause uncertainty among employers (Heath and Cheung, 2006).

Living in a more deprived area with less employment opportunities and poorer formal local institutions are thought to affect an individual's likelihood of employment (Brattbakk & Wessel, 2012; Dujardin & Goffette-Nagot, 2010; van Ham and Manley, 2010; Platt, 2019; Plum & Knies, 2019). Higher unemployment rates in an area might lead to higher competition among individuals in that area. When residents in an area share similar skillsets, it can exacerbate employment competition. For instance, the collapse of the textile industry in the 1980s left many similarly skilled workers in Oldham and Bradford unemployed (Portes, 2019). These areas have high Pakistani populations who were adversely affected. These factors can lead to different economic outcomes in various regions. London, with its unique economic position, higher job creation, better transport, and diverse population, requires special consideration in labour market analysis (Sweida-Metwally, 2022).

Health status and concerns can serve as important confounders in reducing employment opportunities or determining poorer outcomes. For example, a long-standing health concern could prevent someone from entering the labour market in the first place or hold back those who are employed from promotions and earning more. Stigma could also prevent employers from hiring people with health conditions. This could be especially impactful for ethnic minority groups who may be less educated, living in more deprived areas, and have less access to health services (Li and Heath, 2020). This is an important issue for Muslims who have some of the worst health outcomes in the UK (Chouhan and Nazroo, 2020), which are particularly pronounced among women (Shadid et al., 2023). Individuals with care giving responsibilities might also work less as a considerable amount of their time is dedicated to looking after others.

2.4.1.3. Employment features

Different employment features can influence the economic circumstances and other job-related outcomes of ethnic groups in employment. In contemporary Britain, Muslims are overrepresented in many lower-paying industries, such as retail or hospitality. Consequently, their average earnings might be lower compared to those in higher-paying sectors like technology or finance (Khattab and Modood, 2015). The public sector often has different pay scales and benefits compared to the private sector. According to official statistics cited by Clark and Shankley (2020), most non-White groups in the UK are marginally more likely to be employed in the public sector compared to their White counterparts. Black African and Caribbean are the exception, with 43% of its workforce in this sector, compared to 30% overall (Clark and Shankley, 2020). Conversely, Pakistanis and Bangladeshis are more likely to secure jobs in the private sector, particularly within retail, hotel and restaurant industries (ibid). The number of hours worked, and work orientation are also important factors influencing earnings. According to Akbar (2019), immigrant women are disproportionately represented in part time employment. For instance, Bangladeshi women are twice as likely to be employed part-time compared to their male counterparts. Without accounting for these variables, any analysis of earnings disparities might be misleading; lower average earnings could be attributed to the nature of their employment rather than other factors.

2.4.2. ORIENTALIST NARRATIVES

“an Islamic religious heritage is one of the most powerful barriers to the rising tide of gender equality”

(Inglehart and Norris, 2003, p49).

The above quote underscores a significant perspective in the debate on whether Muslim religiosity deters women’s participation in paid work, which is considered a key aspect of the relationship between Islam and gender inequality (cf. Abdelhadi, 2017). This remains a contentious topic in both scholarly and public discussions, with the role of

religion and cultural backgrounds, particularly Islam, being a central point of contention. Religion can guide and provide meaning for the actions, values, norms and beliefs of individuals (Durkheim, 1961; Weber, 1930), and it is argued that religion is instrumental in establishing guidelines for people's actions. This encompasses setting guidelines for both men and women's attire, dietary regulations, and various other behaviours. For instance, Sikh men often follow specific guidelines that involve wearing a turban, maintaining uncut hair, and adhering to a vegetarian diet. Moreover, many Muslims do not eat pork and women wear the hijab as guided by Islam (Khattab et al., 2020a). Therefore, religion could influence the supply side of the labour market as it shapes people's norms and preferences in relation to paid labour and the types of jobs they can do without compromising their faith (Lindley, 2002). For example, although Islam does not prevent Muslim women from working (Abdelhadi, 2017), Muslims do select into particular occupations or work certain hours as guided by their faith (Khattab, et al., 2020a; Spierings, 2014). Moreover, for example, for many Muslims, consuming alcohol is prohibited by their religious beliefs, so a job that requires handling or serving alcohol would conflict with their faith.

However, it is important to distinguish between the influence of community religion and personal religious values. Community religion refers to the collective religious practices and norms of an ethnic group, which can influence behaviours and expectations within that community. For example, Pakistani and Bangladeshi communities in the UK might collectively follow certain Islamic practices that influence women's participation in the labour market. These community norms can exert significant pressure on individuals to conform to certain behaviours (Khattab et al., 2020). On the other hand, personal religious values are the individual beliefs and practices of a person, which can vary widely even within the same ethnic group. While some Muslim women might personally choose to work in jobs that align with their religious beliefs (Spierings, 2014), others might prioritise different aspects of their faith or personal circumstances.

It is feasible that religious practices described above could influence individual's choices and behaviours, including where to enter the labour market and how long to spend in it. Religiosity refers to the extent an individual's beliefs, practices, and commitment (Abdelhadi, 2017) and is conventionally defined through measures of beliefs, knowledge, experience, practice and the associated consequences (Glock, 1962). Religiosity can also be an ideological commitment which can be quantified by attendance at church or

frequency of prayer (see Abdelhadi 2017). Due to limited data availability and the absence of standardised questions addressing these various dimensions, there is no uniform method for measuring religiosity and studies often use one or more of these measures to represent the different aspects (Voas et al., 2007). It should be noted that conventional measures of religiosity, such as frequency of prayer, have been developed in studies that focused on Christian religiosity and thus may not be appropriate when looking at Muslim religiosity. For example, Sweida-Metwally (2022) states that compared to men, there is no obligation of Muslim women to attend mosques, so other measures such as importance of religion to life should be used.

Migrants tend to have higher religiosity than their native counterparts (Guveli and Platt, 2023). If adherence to religious customs did impact circumstances, we would expect religiosity to be negatively associated with labour market outcomes (Abdelhadi, 2017). Put otherwise, if religion was to impinge on individual outcomes and deter entry into the labour market, the effect should be stronger for those who participate in religious activities more often – alas, something that Abdelhadi (2017) and Sweida-Metwally (2023) find little evidence of.

Studies that follow the logic of religiosity equating to disadvantage, without properly disentangling these effects from other structural factors, inadvertently imply that the disadvantages faced by religious minorities are due to their own behaviours. This overlooks the systemic barriers and discrimination that these groups encounter. Shadid et al., (2023) argue that biased academic narratives have portrayed British Muslim women through orientalist and colonial perspectives, often generalising the experiences of first-generation women to younger generations. They stress the importance of recognising the diverse and evolving experiences of different generations and advocate for intersectional approaches to better understand the circumstances of Muslims.

A strand of literature suggests that Muslim penalties should not automatically be viewed as discriminatory or solely the result of structural factors, but rather as stemming from cultural and gender norms inherent to Islam (Blackaby et al., 1999; Inglehart and Norris, 2003; Joppke, 2009; Koopmans, 2016). For example, stereotypes such as women being forbidden to work because their husbands told them not to, or due to religious teachings, are rooted in colonial perspectives. These views, which misrepresented the practices of Muslim-majority countries under British rule, have persisted and continue to be applied

to Muslims today in the UK (Joppke, 2009) and internationally (Inglehart and Norris, 2003; see Abdelhadi, 2017).

These studies suggest that “self-segregation” inherent to Islam implies individuals prefer to form relationships with those who share their religion or ethnicity rather than with members of other groups, and especially the majority (Blackaby et al., 1999, 2002; Joppke, 2009). This leads ethno-religious minorities to develop strong ties (bonding capital) which is less advantageous in terms of securing employment. Weak ties (bridging capital), that is connections with the majority who generally have higher occupational attainment, can provide better opportunities (Granovetter, 1983; Putnam, 2001). The implication across these studies is that if Muslims did not hold ‘isolationist values’ and ‘tastes of isolation’ (Blackaby et al., 1999, p3), they would be able to integrate into the British labour market more successfully (Sweida-Metwally, 2023). More broadly, conservative gender values have been associated with women’s labour market participation (Petti et al., 2009). It has been suggested then, that Muslim women’s non-participation in the labour market due to their traditional gender values guides them to prioritise childbearing and domestic responsibilities.

Koopmans (2016) argues that scholars have been too quick to interpret differences in labour market outcomes between the host population and migrants as ‘ethnic penalties’ resulting from discrimination. Instead, Koopmans attributes this remaining gap to differences in values supposedly influenced by differences in culture, which in turn impacts their labour market participation. For example, Connor and Koenig (2015), found that cultural values held by members of ethno-religious minority groups – such as women upkeeping traditional views and prioritising looking after families over paid employment - influence decisions about entering the labour market. Whilst Islamic religiosity and traditional values may be influential, it is important to note the acculturation of migrants, Muslims in particular, into receiving countries usually leads to dissimilation from the origin society that results in more and “progressive” gender views (Röder, 2014; van Klingeren and Spierings, 2020).

2.4.3. BIAS AND DISCRIMINATION

2.4.3.1. Individual Theories

In ethnic penalty research, unexplained disadvantage that remains after adjusting analysis for covariates is usually attributed to discrimination. Individual biases within the labour market can influence a person's chances of finding employment or progressing within their career. Visibility can lead to discrimination, not on just an individual level but as a broader societal problem (Khattab et al., 2020a). Discrimination means treating people differently based on certain characteristics and, especially in labour market studies, it usually has 'pejorative' connotations (Oaxaca, 2001). Ethnic labour market discrimination implies the disadvantaged circumstances of minority groups is based on their characteristics (Lippens et al., 2022). Employers or employees might harbour negative stereotypes against certain ethnic or religious groups as they stand out from the mainstream, leading to biased hiring practices and differential workplace treatment. Ethnic minorities frequently face differential treatment, often rendered inferior to the majority population during the recruitment process (Lippens et al., 2022). This results in lower job satisfaction, commitment to the company, and poorer relationships between the employee and employer. Differential treatment can also impact the mental and physical health of ethnic minorities as they are constantly undermined (Paradies et al., 2015). Individual labour market discrimination can be explained by two leading mechanisms: taste based and statistical, both affecting groups rather than just individuals (Lippens et al., 2022; Neumark, 2018).

2.4.3.1.1. TASTE DISCRIMINATION

Becker (1971) suggests that employers may have a "taste" or preference against working with certain groups based on characteristics that differ from the majority. This bias can manifest in discriminatory practices within the workplace. Employers may have these specific tastes themselves or hire individuals on concerns about the tastes of employees or clients/customers (Khattab and Modood, 2015; Oaxaca, 2001). Evidence of taste discrimination is usually presented in field experiments that simulate hiring processes. These experiments often involve sending out identical resumes with only the names

changed to reflect different ethnic or religious backgrounds (Lippens et al, 2022). The results typically show that candidates from minority groups are invited to interviews less than their majority counterparts, signalling the presence of discriminatory tastes among employers. An expanding literature demonstrates alarming levels of hiring discrimination, especially towards Muslim applicants and other visible groups in the UK (Bartkoski et al., 2018; Larsen and Di Satsio, 2021; Stasio, et al 2021; Zschirnt and Ruedin, 2016).

There is also evidence that preferences can work in the opposite direction, with employers favouring candidates who resemble themselves in terms of social class or educational background (Friedman and Laurison, 2020). For instance, studies have documented homophilous hiring practices, where recruiters with European-sounding names were more likely to respond positively to applicants with similar names (Edo et al., 2019). Homophily—the tendency for individuals to associate more closely with those who share similar characteristics—can shape not only hiring decisions but also social connections more broadly (McPherson et al., 2001). This principle suggests that ethnic minorities may be more likely to form networks with others from the same ethnic or racial background, which can further influence labour market outcomes.

2.4.3.1.2. STATISTICAL DISCRIMINATION

The statistical mechanism of discrimination is centred around the ‘economically rational, objective reaction of employers to information asymmetry’ (Lippens et al., 2022, p4244). Put otherwise, this means that discrimination can happen because, in order to maximise profit, employers make decisions based on incomplete or unreliable information (Small and Pager, 2020). They might treat people differently because they do not have all the facts and are trying to make the best decision with the information they do have. When employers do not have complete information about how productive an individual employee is, they use information about the average productivity of the group that employee belongs to as a reference. This helps them make decisions, even though it might not be entirely fair to the individual (Lippens et al., 2022; Neumark, 2018). Employers may apply negative stereotypes associated with a group to individual minority candidates, resulting in less favourable employment opportunities. Such stereotypes can

pertain to assumed deficiencies in language skills, educational profile, or personality traits perceived as unproductive (Carlsson, 2010; Lippens et al., 2022) .

2.4.3.2. Structural theory

2.4.3.2.1. INSTITUTIONAL ISLAMOPHOBIA

“...limiting the study of discrimination to the actions of potentially prejudiced individuals dramatically understates the extent to which people experience discrimination; understates the extent to which discrimination may account for social inequality; and understates the extent to which discrimination may play a role in markets for labour, credit, and housing, as well as in other contexts”

(Small and Pager, 2020, p51).

The concept of race originated with European colonisers who encountered people with different physical traits, leading to the categorisation of populations based on physical differences such as skin colour and head shape (Ansell, 2013). This categorisation aimed to explain behavioural differences and justify the subjugation of enslaved and colonized populations, deeming them inferior to White Europeans. Racial categorisation has persisted as a reflection of power relations, with scientific fields historically attempting to justify these differences (Meer, 2013). Despite being debunked as a biological concept, race remains a social construct with significant cultural and social implications (Fenton, 2010). Cultural meanings attached to physical traits have maintained hierarchies that benefit White populations, perpetuating privilege and dominance (Winant, 1997). Racism, as defined operates at both micro and macro levels to disenfranchise groups based on physical or cultural differences. Du Bois ([1899] 2007) highlighted how racism systematically affects economic and social structures, emphasising that race’s power lies in societal meaning rather than inherent characteristics (Bobo, 2001). Although race is a social construct, it continues to shape identities and social actions, evidenced by ongoing racism and discrimination in Western countries (Ansell, 2013). Racism has evolved to focus on cultural and ethnic differences, affecting groups beyond physical traits, including European migrants and Muslim individuals. This shift underscores the

intertwined nature of race and ethnicity, which, despite their differences, both influence social hierarchies and experiences of discrimination (Fenton, 2010).

Institutional racism highlights that discrimination towards ethnic and religious minorities can be embedded in organisational rules or laws, not just individual actions. This broader sociological view suggests that focusing only on individual prejudice (taste and statistical discrimination) underestimates the extent and impact of discrimination in society (Small and Pager, 2020). Ethnic disadvantages can be reinforced, both intentionally and unintentionally, through institutional, cultural, and historical structures that maintain White privilege. Institutional Islamophobia, a form of institutional racism, is perpetuated through various mechanisms that lead to the marginalisation and unequal treatment of Muslims in the labour market (Abbas, 2010). Central to Islamophobia is the securitization of Muslims, which refers to the process by which Muslims and Islam are framed as security threats (Gilks, 2020). This process is often reinforced by institutions and driven by political actors, media representations, and public discourse that link Islam to terrorism and extremism (Abbas, 2010). For example, after an extremist attack, media coverage and political rhetoric may emphasise the Muslim identity of the perpetrators, which further stigmatises Muslim communities as security threats.

This institutional securitization is (re)produced in several ways across many different domains in society. Concerns and perceptions of security might influence hiring protocols, leading to the profiling of individuals based on popularly understood signifiers of their identity (skin colour, beard, hijab) or names, which disproportionately targets Muslims in the context of anti-terrorism efforts (Bonino, 2013). Workplace policies may fail to accommodate religious practices, such as prayer times, creating additional barriers and singling out Muslims from the majority (Lindley, 2000). Educational curricula that lack religious literacy and diversity or present biased content can reinforce stereotypes from a young age, influencing employers' (and society more broadly) views and expectations (Guest et al., 2020). Media representation often perpetuates negative stereotypes which facilitates the '(re)production' of widespread Islamophobia that 'penetrates the social fabric and reinforces a popular image of Muslims as folk devils of late modernity' (Bonino, p385). These media portrayals shape public perceptions and reinforce biases that affect broader processes, such as hiring and workplace treatment (Sian et al., 2012).

Furthermore, public responses towards “Islamist” terrorist events from political elites and governance institutions also reinforce stigmatisation and securitization of Muslims (Gilks, 2020). Law enforcement practices, such as racial profiling, can lead to unequal treatment and outcomes for Muslim communities, further entrenching negative stereotypes (Alotaibi, 2016). Additionally, disparities in healthcare provision based on ethnicity or socioeconomic status can drive health inequalities, which may be perceived by employers as a lack of reliability or productivity (Shadid et al., 2023). The structural emergence of Islamophobia is thus seen at the intersection of individual and institutional actions, where each institution’s incentives and biases are shaped by a broader securitized context. This dynamic exacerbates the marginalisation of Muslims, influencing employers’ views and hiring decisions, and perpetuating a cycle of discrimination and inequality.

2.4.4. METHODOLOGICAL CHALLENGES AND APPLICATIONS

Now that the theories of explanation have been discussed, it is also worth considering the methodological implications of ethnic penalty literature. The choice of data resources significantly impacts the scope and depth of research on Muslim circumstances. One of the main challenges in ethnic penalty research is obtaining ample data to explore the experience of different groups. This challenge becomes even more pronounced when considering subgroups within these populations, such as across generations or different religious affiliations (Johnston et al., 2010). With this challenge in mind, four types of data are commonly used: census data, large cross-sectional government data, social surveys that are either cross sectional or include repeated contacts and smaller scale specialised surveys.

Developments in recent census data collection have resulted in better ethnic and religious coverage which now allows for detailed demographic analysis (Karlsen et al., 2020; Khattab, 2009; Khattab et al., 2020; Miaari et al., 2019). However, census data are limited by the infrequency of data collection and limited in their topic coverage (Chen et al., 2004). Over the last two decades, cross-sectional data resources from the Office of National Statistics such as the Annual Population and the Labour Force Survey have been popular amongst ethnic penalty scholars (Berthoud, 2000; Daoud and Khattab, 2022;

Dobson, 2009; Fratinni, 2017; Heath et al., 2000; Johnston et al., 2015; Khattab and Hussein, 2018; Manley et al., 2019; Zwysen et al., 2021). These studies are collected on a more frequent basis and have a mixture of detailed ethnicity and economic measures that are appropriate for ethnic penalty research. However, Koopmans (2016) and Sweida-Metwally (2022) note, that important controls such as health concerns and cultural factors are usually absent from these sources. Furthermore, the cross-sectional nature of these data mean they are limited to a single point in time rather than over a period which can limit the ability to observe changes and trends (Gayle and Lambert, 2018). Although these data may have relevant measures, the key challenge of sample size remains and sometimes there is not sufficient data in a single wave or year for detailed analysis of ethnic groups.

In response, pooling multiple waves of comparable cross-sectional data is common approach to obtaining ample sample sizes for robust analysis of ethno-religious groups (Cheung and Heath, 2007; Daoud and Khattab, 2022; Heath and Martin, 2013; Khattab, 2016; Khattab and Hussein, 2018; Li and Heath, 2008; Longhi et al., 2013; Manley et al., 2019). Longitudinal and repeated contacts data such as the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), are invaluable for exploring the dynamics of socio-economic outcomes and the long-term impacts of various factors on ethnic minorities (Karlsen et al., 2020; Khattab and Johnston, 2013; Khattab and Modood, 2015; Li and Heath, 2016; Li and Heath, 2020). These resources allow researchers to examine trends over time and identify patterns that might not be apparent in single wave studies. Additionally, both the BHPS and UKHLS have the added benefit of including very detailed measures on different socio-economic circumstances that are not available in the LFS or APS (Platt and Nandi, 2020; Jivraj and Alao, 2023; Neves, 2024). The UKHLS has the added benefit of boost samples which overrepresent ethnic minorities, allowing for a richer analysis of their socio-economic outcomes (University of Essex, 2022). These data can also be treated as cross-sectional if appropriately analysed to account for the repeated contact structure. When pooled (i.e combining different waves together), they can offer a substantial amount of data about ethnic minorities on a wide array of detailed measures.

There are also specialist data resources on ethnic minorities which offer more targeted insights but are used less frequently (Cheung, 2014; Finney et al., 2023; Modood et al., 1997). The Evidence for Equality National Survey (EVENS) is a recent example of

unique data set that has been designed to collect detailed information on the experiences of ethnic and religious minorities in the UK (Finney et al., 2023). EVENS includes a wide range of variables, such as economic status, health, and cultural practices, which are usually missing from government data sources. However, these surveys typically use non-probability sampling methods, which means they are not representative of the entire population. This approach can lead to challenges in generalising findings to the broader population, and the weighting structure used to adjust for this can be complex. Researchers using the UKHLS also need to be mindful of the challenges posed by non-probability sampling. This can be addressed through the use of weights, which help to adjust for any biases and ensure the sample more accurately represents the population (Gayle and Lambert, 2018).

In summary, there are ways to address the challenges of obtaining sufficient data for detailed ethnic minority analysis, but these come with compromises. Researchers may need to engage with complex weighting structures to adjust for biases, or they might have to select data sources that are collected less frequently or have less detailed measures. Each approach has its trade-offs, and the choice depends on the specific research goals and the available resources.

2.4.5. SUMMARY

Sections 2.1 to 2.3 have demonstrated that Muslim communities in the UK are diverse, comprising individuals from various ethnic backgrounds and with diverse socio-demographic profiles. The literature on ethnic penalties of British Muslims highlights several key areas of disadvantage across multiple outcomes. In particular, while there are variations between studies, Pakistani and Bangladeshi face significant barriers in the labour market, with Muslim women being much less likely to participate or to be employed. These disadvantages persist even after accounting for various population characteristics and human capital factors that typically influence labour market performance. Several theories have been proposed to explain these enduring gaps:

- **Cultural and Religious Factors:** High levels of Islamic religiosity, “social isolationist tendencies”, and traditional gender roles held by members of Muslim communities may hinder labour market participation.

- **Discrimination:** Taste-based discrimination, statistical discrimination, and institutional Islamophobia may prevent Muslims from obtaining employment and progressing in jobs.

The structural reinforcement of Islamophobia presents a more compelling argument compared to individual economic theories and cultural/religious explanations of ethnic penalties. This perspective moves beyond biased explanations for Muslim disadvantage, which often stigmatise individuals through an orientalist lens and blame them for their circumstances (Shadid et al., 2023). Instead, it focuses on how broader systemic processes contribute to their disadvantage. Relevant empirical and theoretical literature about contemporary migrations, and their potential impact on Muslim circumstances, will feature next. While these explanations are often framed in opposition, they are not necessarily mutually exclusive, and disentangling their relative contributions remains challenging—particularly within the limits of quantitative research—yet this thesis aims to make a meaningful contribution by engaging critically with measurable dimensions of these broader processes.

These complexities directly inform the first objective and set of research questions guiding this thesis. First, by examining the specific influence of belonging to a Muslim ethno-religious group on labour market outcomes (RQ1), the study aims to isolate the role of religion and ethnicity in shaping disadvantage. Second, by assessing whether disparities persist after controlling for human capital and individual-level characteristics (RQ2), it tests the extent to which disadvantage can be explained by measurable population variables. Finally, by incorporating sociocultural factors and still observing penalties (RQ3), the analysis interrogates whether structural and institutional forms of discrimination are at play. Together, these questions reflect an attempt to engage critically and empirically with the cultural–discrimination debate, recognising its historical nuance while working within the boundaries of quantitative data.

2.5. Intersectional inequalities in the labour market

2.5.1. OVERVIEW

Intersectionality is a critical theoretical framework that considers the complex ways in which various social divisions, such as race, gender, class, religion, and migrant background, intersect and interact to shape social structures and influence individual and group outcomes (Evans et al., 2024). By examining how these multiple axes of identity converge, intersectionality provides insight into the compounded forms of oppression and discrimination that individuals face, which cannot be fully understood by isolating each dimension of identity. For example, a Black woman may experience a distinct form of oppression due to the combined effects of both her race and gender, which cannot be fully captured by examining her race alone (Crenshaw, 1991). This framework highlights how specific identities intersect to create unique experiences of inequality, demonstrating that social structures and systems of power are not neutral but are shaped by the interrelationship of these intersecting categories (Hancock, 2007; McCall, 2005).

Originating in feminist gender studies, intersectionality has since been adopted across various disciplines, including sociology, political science, and anthropology, to explore social phenomena in a more nuanced and inclusive way. While traditionally aligned with qualitative research methods, particularly those that aim to capture the lived experiences of marginalised groups, the framework has increasingly been applied to quantitative analyses as well (Evans et al., 2018). Scholars have sought to operationalise intersectionality in ways that allow for the measurement and empirical analysis of how multiple forms of social identity intersect to produce distinct patterns of inequality, often revealing complexities that are overlooked when these categories are studied in isolation (Dubrow, 2013). This approach is particularly useful for understanding the experiences of Muslim communities, where ethnicity, religion, and migrant background interact in multifaceted ways to shape labour market outcomes and other dimensions of social disadvantage.

To fully understand the labour market inequalities experienced by Muslims in Britain, it is essential to consider how intersecting social categories —such as ethnicity, religion, and migrant background—combine to shape individuals' experiences and outcomes. As

the previous section has shown, explaining these disadvantages requires careful attention to a range of overlapping factors, and recognising their interaction is crucial for developing a more accurate and meaningful account of ethnic minority disadvantage in the labour market. The remainder of this section explores how the literature has conceptualised and operationalised intersectionality, examining whether these dimensions of identity are treated as distinct or overlapping, and what is gained analytically and empirically by adopting an intersectional approach.

2.5.2. CONCEPTUALISING INTERSECTIONALITY

In much of the existing literature, ethnicity, religion, and migrant background are sometimes treated as separate categories, each contributing independently to socio-economic outcomes. Ethnicity, for instance, has traditionally been viewed as a key determinant of labour market disparities, with certain ethnic groups facing higher levels of discrimination and exclusion (Khattab et al., 2020a). Religion, similarly, has been studied in isolation, particularly in relation to the unique challenges faced by Muslim communities, such as Islamophobia and religious discrimination (Shadid et al., 2023). Finally, migrant background has been considered a significant factor in explaining the socio-economic outcomes of immigrant groups, with both first-generation migrants and their descendants experiencing differing levels of integration (Chiswick, 2001).

However, an intersectional approach challenges the notion that these categories can be neatly separated. Instead, it emphasises that the experience of disadvantage cannot be fully understood by considering ethnicity, religion, or migrant background in isolation. This approach, developed through the work of scholars like Crenshaw (1989), argues that individuals' experiences of oppression and inequality are shaped by the interconnectedness of multiple social identities. For example, a Muslim woman from a South Asian background may face compounded discrimination that cannot be explained solely by her ethnicity, her religion, or her migrant status, but rather by how these identities intersect. By adopting an intersectional lens, we can more accurately capture the complexity of socio-economic inequalities and the ways in which these categories interact to produce unique forms of disadvantage.

To understand how intersectionality has been conceptualised and operationalised in the quantitative literature on ethnic penalties, it is important to first consider the three primary orientations that McCall (2005) outlines: the anti-categorical, intra-categorical, and inter-categorical approaches. Each of these orientations serves different research goals and can be adapted to different research methods, including both qualitative and quantitative techniques.

The anti-categorical approach deconstructs analytical categories altogether, arguing that social categories are not natural or inherent but are socially constructed and serve to perpetuate inequalities. It views the complexity of social life as too nuanced to be captured by fixed categories. In this approach, social categories, rather than reflecting objective reality, are seen as tools that create differences and inequalities. For quantitative research, this approach poses a challenge, as it requires questioning and possibly abandoning traditional categories used to measure outcomes, such as ethnicity or religion. However, its critical stance has pushed scholars to reflect on how these categories may obscure deeper, more nuanced understandings of social inequality (McCall, 2005).

The intra-categorical approach challenges the homogeneity of traditional social categories and focuses on examining individuals at the intersections of these categories, especially those who are often overlooked in mainstream research. It is critical of the way categories like gender or ethnicity are typically used to generalise across groups, and instead centres on the lived experiences of individuals whose identities cross multiple, often marginalised, categories. While this approach is typically associated with qualitative research, it has also influenced quantitative studies by pushing scholars to refine or adapt the measures of identity to account for complexity and diversity within groups. For example, in studies of Muslim disadvantage in the UK, researchers might focus on the experiences of Muslim women of different ethnic backgrounds, examining how their intersecting identities shape their labour market outcomes.

The inter-categorical approach offers a more pragmatic stance, acknowledging that, while social categories are imperfect and fluid, they reflect empirical realities that can be useful for analysis. This approach focuses on comparing multiple social categories — for example, comparing the experiences of Muslims and non-Muslims, or Pakistani and Bangladeshi Muslims — to understand patterns of inequality across different groups.

While it recognises that categories like ethnicity, religion, and migrant background are not fixed, it allows for these categories to be used in a provisional and comparative way. This approach is particularly useful in quantitative research, where large-scale data allows for the comparison of multiple categories and the examination of how their intersections influence outcomes like employment, income, and educational attainment (Evans et al., 2018). Studies using this approach often focus on understanding the relative disadvantages of different groups, as well as the potential benefits of being positioned within certain social categories.

2.5.3. OPERATIONALISING INTERSECTIONALITY

Inter-categorical intersectionality has been increasingly operationalised in quantitative research across fields such as education, social stratification, and, most notably, in the ethnic penalty literature. This body of research has grown substantially since the late 1990s, following the inclusion of detailed ethnicity variables in large-scale labour market datasets in Western countries (Heath and McMahon, 2000; Heath and Cheung, 2007). These data have enabled robust statistical analyses of employment disparities between ethnic minorities and majority populations. As discussed in the previous section, ethnic penalty models assess gaps in outcomes such as unemployment or occupational attainment, controlling for human capital, language proficiency, and other individual characteristics. When disparities persist despite these controls, they are commonly referred to as “ethnic penalties” (Heath and McMahon, 2000), often interpreted as evidence of discrimination.

The inter-categorical intersectional framework has become especially influential in this field through the development of multi-category or ‘ethno-religious’ approaches. These combine ethnicity, religion, and migrant background into intersecting analytical groups. For example, Johnston et al. (2010) and Khattab (2009) examined the combined effects of ethnicity and religion on labour market outcomes, marking an important shift toward more nuanced modelling of disadvantage. Subsequent studies extended this by incorporating generational status to enable three-way interactions between ethnicity, religion, and migrant background (e.g., Longhi et al., 2013; Khattab and Modood, 2015; Khattab and Hussein, 2018). This approach allows researchers to capture group-specific

inequalities that would be obscured if these categories were treated in isolation (Khattab, 2016; Manley et al., 2019; Sweida-Metwally, 2022).

Ethnic penalty research thus reflects two key features of intersectional thinking. First, it recognises ethnicity as a complex, multifaceted category that must be disaggregated and contextualised to understand the full scope of disadvantage. Second, it employs statistical models that often include interaction terms between multiple social categories, allowing for the exploration of how their combined effects shape outcomes. For example, a regression model on labour market participation might include main effects for ethnicity and sex, alongside an interaction term to test whether ethnic disparities differ by gender. If Pakistani individuals and women both show lower participation, and the interaction term for Pakistani women is significantly negative, this suggests compounded disadvantage beyond additive effects. With large datasets, such models can be extended to include three-way interactions, enabling comprehensive analyses of intersecting inequalities.

As interest in intersectionality has grown alongside developments in data infrastructure, quantitative researchers have continued to refine these approaches. Increasingly, intersectional frameworks are being used not only to test for disparities, but also to examine how multiple social identities interact to produce complex and specific patterns of labour market stratification.

While this traditional single-level regression approach has been widely used, it has increasingly come under criticism for its limited scalability when applied to intersectional analyses (Evans et al., 2018; Merlo, 2018). That is, single-level models often struggle to accommodate the hierarchical and context-dependent nature of social categories, particularly when multiple interactions are introduced. As the number of intersecting categories increases, models can become statistically inefficient or unstable, especially when some groups are small or unevenly distributed. In response, multilevel approaches have been proposed as a way to address these limitations (Evans et al., 2024). Such models allow for individuals to be nested within analytically meaningful groups, enabling the estimation of group-level effects while retaining individual-level variation. This approach offers a more flexible and robust way to analyse the complex, overlapping social identities central to intersectionality. While the proposed multilevel methods employed in this thesis — particularly Multilevel Analysis of Individual Heterogeneity

and Discriminatory Accuracy (MAIHDA) — will be discussed fully in Chapter 5 which addresses research questions 4 and 5. The main objective of this section is to situate intersectionality within the wider literature and laying the groundwork for the analytical strategies that follow.

2.6. EU Enlargement Migration in the UK

So far, this chapter has focused on Muslim and other commonwealth migrants who entered the UK during the post war period. The remainder considers contemporary migration patterns driven by the recent European Union (EU) enlargements.

Migration generally refers to the movement of people from one area to another, with migrants seeking better social and economic opportunities in a new country (Portes, 2019). However, this definition is complex. Migrants can also include those who temporarily stay in a country, like seasonal workers (Portes, 2019). There is also debate about whether the descendants of migrants (second/third generation) should be included in this definition (Nandi and Platt, 2020). Additionally, the terms “immigrant” and “migrant” are often conflated. According to Anderson and Blinder (2015), “immigrant” refers to people who intend to settle in their new country, while “migrant” can refer to those temporarily residing in the host nation or even those moving within their country’s borders.

2.6.1. SOCIO-POLITICAL CONTEXT

The EU expansions of 2004, 2007 and 2013 were expected to have significant implications for the UK’s labour market, education system, housing demand and culture (Frattoni, 2017; Shankley and Byrne, 2020). Beginning in 2004, eight central and eastern European countries⁷ as well as Cyprus and Malta⁸ joined the EU and were given the right of free movement to gain employment in established member states (Portes and French, 2005). In anticipation of this and concerned about the possible impact an influx of

⁷ Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovenia, Slovakia.

⁸ Cyprus and Malta already had access to the EU labour market before they joined which is reflected in the UK already having well established Cypriot and Maltese populations (Gilpin *et al.*, 2006).

immigrants may have on the labour market, most existing member states delayed the free movement to work for several years. Britain, Ireland and Sweden, however, did not take the same precautions and provided these new members full access to their labour markets from day one, albeit with some transitional measures applied (Drinkwater et al., 2006; Gilpin et al., 2006). Similar processes then occurred as Bulgaria and Romania joined in 2007, followed by Croatia in 2013, resulting in a ‘large’ and ‘unexpected’ growth in EU migration to the UK (Shankley and Byrne, 2020, p40). Portes (2019, p23) asserts that between 2004 and 2019 ‘the number of UK residents who were born elsewhere in the EU has risen from 1.5 million to 3.7 million’.

The initial migration inflow in 2004 is considered as one of the largest in the history of the UK⁹, with the Worker Registration Scheme suggesting that approx. 560,000 accession migrants joined the UK labour market between 2004 and 2006, therefore, comprising a substantial 2% of total employment (Salt and Miller, 2006). Most of the public narratives about this group of migrants have therefore focused on the potential impact that this ‘rapid migration shock’ had on labour markets in the UK (Lemos and Portes, 2008, p2).

⁹ The societal response to EU accession can be demonstrated in the public discourses and immigration policies which have emerged over the last two decades. Anti-immigrant rhetoric has developed following rising concern over the labour participation of EU migrants (Geddes, 2014). Arguably, these concerns have been central to the rising anti-immigrant sentiment and Euroscepticism that has developed in the last decade and led to many political consequences (Geddes, 2014). The rise of the UK Independence Party (UKIP) and other far-right parties which prioritise immigration control and the Brexit vote of 2016 is symbolic of the swelling concern (Portes, 2019). Since 2010, to deal with the migrant “problem”, the Conservative party have been devoted to creating a ‘hostile environment’ for migrants (Shankley and Byrne, 2020, p43). The aim was to make the UK an unappealing destination to dissuade migrants from coming and deport any of those who arrived illegally (ibid, 2020). This included a battery of policies which allowed landlords to check the immigration status of occupants, eligibility checks for patients in the NHS, and identification checks enforced by employers and educational institutions (ibid, 2020). In policy, the 2014 and 2016 Immigration Acts demonstrate the demand for tighter immigration control as the acts enforced stricter criteria and fewer opportunities to EU citizens. All the above has notably shifted the language used when discussing migration and had consequences of migrant minority groups, making them vulnerable to forms of racism across different social domains. Therefore, European migrants, mostly Polish, have gone under processes of racialisation – despite being White – and experience discrimination. The conceptualisation of what constitutes a “migrant” has thus shifted in line with the growing concern – ‘semantic difference does not get in the way of xenophobic racism; it turns our racialised difference can be invented in situ’ (Fox et al., 2012, p681). In other words, similar othering processes which occurred with racially diverse migrants (Caribbean and South Asian) has occurred with EU accession migrants, despite them also being White.

2.6.2. SOCIAL AND ECONOMIC CIRCUMSTANCES OF CONTEMPORARY MIGRANTS

A range of terms are used in the literature and policy to describe different groups of foreign-born people who arrived in the UK between 2000 and 2016. This following analysis focuses only on economic migrants (and their families) from Eastern European countries who entered the UK for employment and thus will not include people moving for asylum. While there are some differences between sources, the following terms will be used to represent the following groups of migrants:

- **EU14 migrants:** People from member states who were a part of the EU prior to the enlargement in 2004. This includes the founders (Belgium, France, Germany, Italy, Luxembourg and Netherlands) and those who joined between 1973 and 1995 (Denmark, Ireland, Greece, Portugal, Spain, Austria, Finland and Sweden).
- **A8 / EU8 migrants:** People from member states who joined in 2004 who already did not have access to the EU labour market: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia. The UK put transitional measures in place that meant A8 nationals were required to register with the Worker Registration Scheme (WRS) to take up employment.
- **EU10 migrants:** People from A8 / EU8 countries + Malta and Cyprus. Unlike the other A8 members, people from Malta and Cyprus were granted full free movement rights and rights to work in the UK.
- **A2/ EU2 migrants:** People from Romania and Bulgaria who joined in 2007. Similar to the A8, A2 nationals who want to take up employment had to apply for worker cards under the Workers Authorisation Scheme.
- **Post-04 accession migrants:** people from A8/EU8 countries + A2/EU2 countries + Croatia, Malta, and Cyprus.

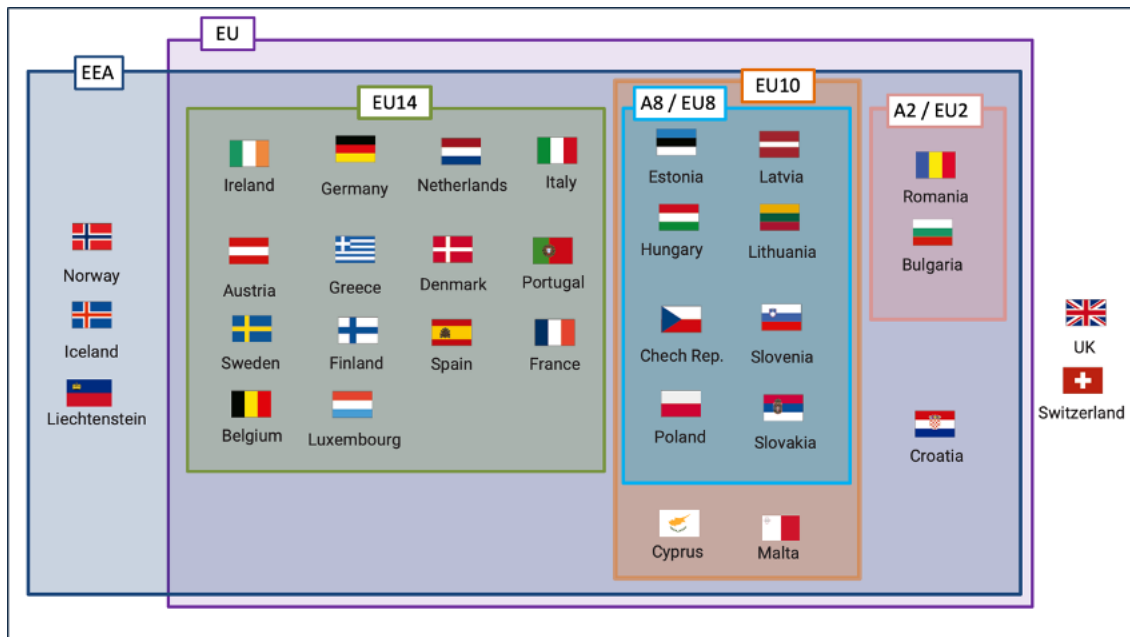


Figure 2-1 European country membership (as of 2024) to the European Economic Area (EEA) and European Union (EU).

Note: EU 14 (joined prior to 2004), A8 (joined in 2004), A2 (Joined in 2008) and Croatia who joined in 2013. Cyprus and Malta did join the EU in 2004 alongside the A8 countries, however they already had access to the EU labour market before joining so are not included with 'A8' accession migrants.

Around 60% of A8 migrants came from Poland – a country which, at the time, had a high unemployment rate (20%) and poorly performing labour market (Drinkwater et al., 2006). An established Polish diaspora in the UK further influenced migration from Poland, whereas there were relatively small amounts of residents in the UK from other A8 countries (ibid). While all post-04 accession migrants will be included in the following analysis, it should be noted that most of these people are Polish. For example, in pooled Labour Force Survey data from the last ten years, 70% of all post-04 accession migrants were born in Poland (for more see section 6.2). Evidence about Eastern European migrants and their economic and social circumstances tends to be based on broad statistical analysis from the likes of Migration Observatory (Fernandez-Reino and Reinzo, 2021) and include descriptive analyses comparing outcomes based on country of birth (Portes, 2019; Shankley and Byrne, 2020).

Between 2000 – 2012, Frattini (2017) finds that new arrivals from EU10 countries tended to be on average 10 years younger, than their receiving country counterparts. They also had the lowest average age amongst all migrant groups in the study (other EEA and non-EEA migrants). The EU10 Migrants had poorer education outcomes in comparison to

other ethnic groups. LFS data from 2001 – 2006 show that around 19% of Poles chose to reside in London, while 20% found their homes in the East/South East regions. The remaining 62% settled elsewhere in the UK. Other A8 migrants followed a similar distribution pattern, with 23% in London, 12% in East/South East and 65% elsewhere. In terms of economic outcomes, Polish migrants had a higher employment rate compared to other A8 nationals, but self-employment rates are around the same (3%).

Eastern Europeans from both affluent and poorer backgrounds are attracted by the economic opportunities in the West (Dobson, 2009). Migration is mostly viewed by these individuals as a temporary arrangement, motivated to gain as much wealth as possible before returning home. Evidence shows that Poles and Romanians in particular appear to have accepted ‘sharp downward mobility’ on arrival to the UK (Favell, 2008, p771). They take on lower-status jobs that are not matched to their qualifications in order to support their families back home, even though these jobs are not ideal for their level of human capital (Favell, 2008). For example, while older arrivals from EU14 countries tend to select into professional occupations (e.g health actioners and academics), post-04 arrivals concentrate in elementary occupations like farm workers, cleaners, and packers/bottlers (Vargas-Silva, 2014).

Fernandez-Reino and Reinzo, (2021) compare male and female unemployment rates for different groups of working age people in the UK based on country of birth. Both EU8 men (3.1%) and women (5.7%) had lower employment rates than their UK-born counterparts (3.8% and 6%, respectively). Unemployment rates for EU2 were higher than both EU8 and the UK born, suggesting they have potentially not integrated into the labour market as successfully. Pakistani and other South Asian born people had the highest unemployment rates (Male = 6% and female = 13%) whereas the rate for Indian men was around the same as for EU8 men (3%), but higher for Indian women (7%). This evidence suggests post-04 migrants, A8 migrants in particular, have better integrated into the UK labour market better when it comes to avoiding unemployment than Pakistani- and Bangladeshi-born people in the UK.

In 2020, Indian born workers (47%) and EU14 migrants (45%) were most likely to be in high skilled occupations in comparison to the majority White UK-born population (30%). Twenty-three percent of Pakistani and other South Asians were in high skilled jobs, followed by 18% of EU2 and EU8 nationals having the lowest (17%). Given that these

groups have the lowest percentages in high-skilled jobs, it suggests they are more concentrated in medium-low skill occupations. In terms of industry, EU2 and EU8 nationals, as well as Pakistanis and other south Asians, were overrepresented in retail occupations. Twenty percent of the health and social work industry comprised of Indian migrant workers, whereas the 14% of EU14 nationals worked in education. These data suggest that post-2004 accession migrants and Muslim migrant workers (specifically Pakistani and other South Asian individuals) may be concentrated within the same industry, potentially competing for opportunities. However, it is important to consider that these figures do not account for second-generation migrants, and the category of “other South Asian” may include nationals with varying faiths beyond just Muslim individuals.

2.6.2.1. Geographical distributions in areas highly populated by Muslims

Figures 2-2 show the distribution of EU migrants in different neighbourhoods in the Government Office Regions across the UK.¹⁰ The increase in gradient from light pink to blue suggests an increase in the Muslim population, an increase from pink to red suggests an increase in the post-04 population, while an increase in gradient from pink to dark red/purple suggests an increase in both populations. In addition to the bivariate map, the percentage of each group is listed next to the plots. Of all 12 regions in the UK, Northwest, Yorkshire and the Humber, the Region of London and West Midlands had the highest share of Muslims.

Figure 2-3 shows the further breakdown of both migrant groups in neighbourhoods in relation to the total population in each Local Authority District (LADs), categorised within the four regions of the UK with the highest Muslim shares as listed above. Local Authority Districts with a lot of purple shading, and therefore a high concentration of both groups includes places like Newham, Waltham Forest, and Brent (London); Sandwell and Birmingham (West Midlands); Bradford and Leeds (Yorkshire); and

¹⁰ Stata do files for the creation of these heatmaps can be found at [ch2a1 bivariate heatmaps hunter24.do](https://github.com/scotphunter/hunter24_thesis_muslimlabourmarketoutcomes) or https://github.com/scotphunter/hunter24_thesis_muslimlabourmarketoutcomes

Manchester and Salford (North West). Showing the distribution of EU migrants in areas highly populated by Muslims provides valuable context on how these groups are concentrated in similar regions. This overlap can highlight the social, economic, and cultural factors that attract both groups to the same areas, such as employment opportunities, affordable housing, and community support networks (Panyai, 2010; Portes, 2019).

Government Office Regions

1 North East (2.7% / 1.6%)

2 North West (5.5% / 2.2%)

3 Yorkshire and the Humber (6.6% / 2.5%)

4 East Midlands (3.9% / 3.1%)

5 West Midlands (7.1% / 2.6%)

6 East of England (3.4% / 3.1%)

7 London (13% / 5.2%)

8 South West (1.9% / 2.5%)

9 South East (3.2% / 2.7%)

10 Wales (2.4% / 2%)

11 Scotland (2.4% / 2.7%)

12 Northern Ireland (1.1% / 3.3%)

(Muslim share/post-04 EU Migrant share in GORs)

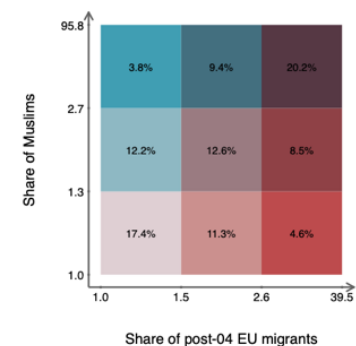
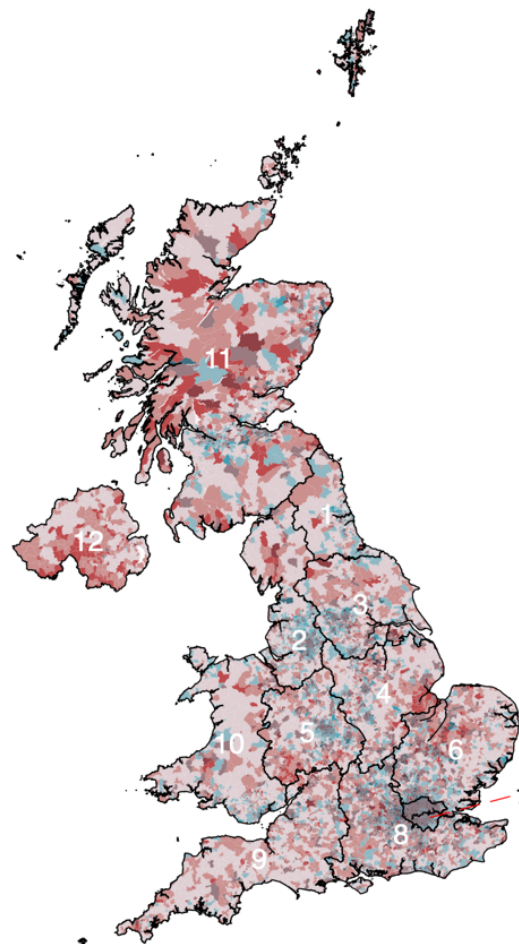


Figure 2-2 Bivariate share of Muslim and post-04 EU migrants in LSOA neighbourhoods by Government Office Region.

Note: Source: 2011 Census data (Office of National Statistics). Map displays the share of Muslims and post-04 EU migrants in neighbourhoods (Lower Super Output Areas) across the UK. The legend displays a range of colours, each corresponding to a specific value or percentile. These colours represent the intensity of the data being visualised (in this case, the share of Muslims and EU migrants). The percentages displayed in the legend represent the percent of neighbourhoods (LSOAs) falling within specific ranges. The legend helps interpret the heatmap by associating colours with these percentile ranges. The legend also provides aggregated neighbourhood percentages for each Government Office Region.

**London Local Authority Districts
sorted by share of Muslims
(from high to low)**

323 Tower Hamlets (36% / 3.3%)
318 Newham (33% / 9.9%)
319 Redbridge (24% / 4.9%)
324 Waltham Forest (23% / 10%)
298 Brent (20% / 9.3%)
326 Westminster (19% / 2.8%)
303 Enfield (18% / 5.2%)
302 Ealing (17% / 11%)
307 Haringey (15% / 8.9%)
305 Hackney (15% / 4%)
311 Hounslow (15% / 8%)
295 Barking and Dagenham (15% / 7%)
308 Harrow (13% / 6.8%)
300 Camden (13% / 2.8%)
310 Hillingdon (12% / 4.3%)
296 Barnet (11% / 7%)
306 Hammersmith and Fulham (11% / 3.9%)
313 Kensington and Chelsea (11% / 2.6%)
312 Islington (10% / 2.5%)
321 Southwark (9.5% / 3.4%)
317 Merton (9.1% / 7%)
301 Croydon (9.1% / 3.9%)
325 Wandsworth (9.1% / 4.5%)
315 Lambeth (8.1% / 4.7%)
304 Greenwich (7.8% / 4.1%)
316 Lewisham (7.4% / 4.4%)
314 Kingston upon Thames (6.9% / 3.6%)
294 City of London (6.5% / 2.3%)
322 Sutton (5.1% / 3.2%)
320 Richmond upon Thames (4.3% / 3%)
299 Bromley (3.5% / 2.5%)
297 Bexley (3.4% / 2.3%)
309 Havering (3% / 2.6%)

(Muslim share/post-04 EU Migrant share in LADs)

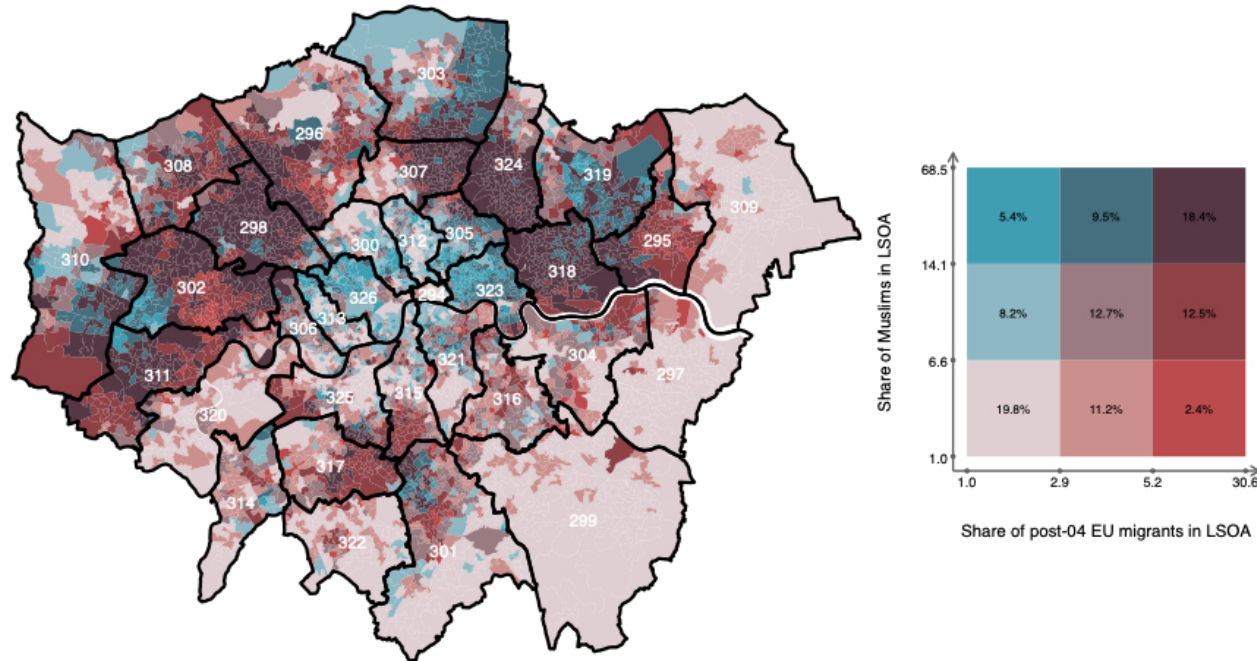
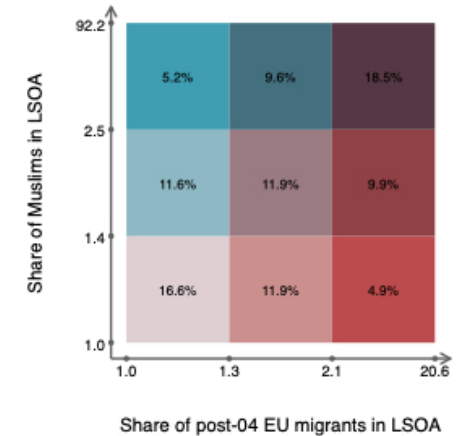
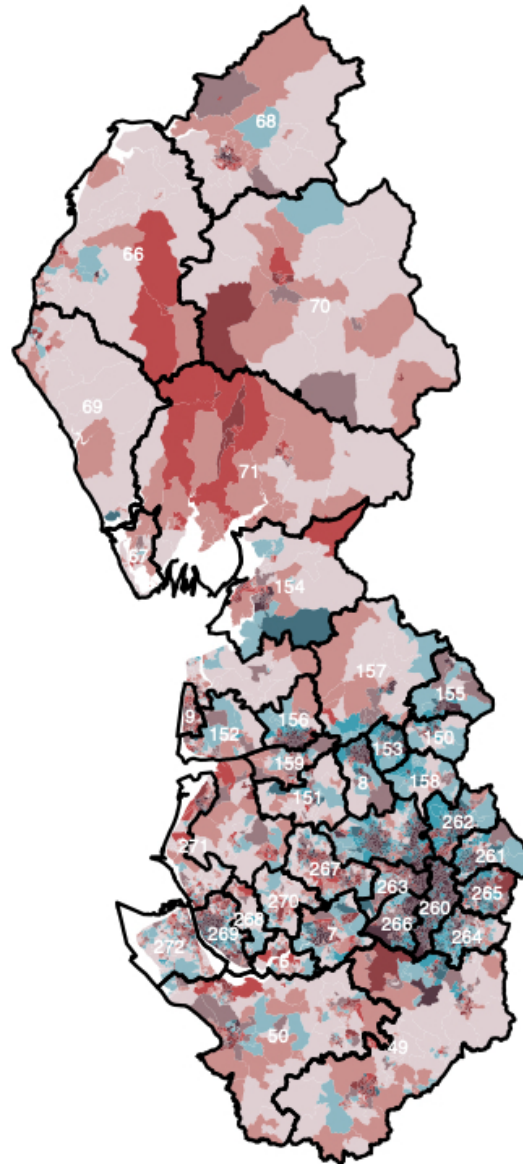


Figure 2-3 Bivariate shares of Muslim and post-04 EU migrants in LSOA neighbourhoods for specific regions.

Note: Source: 2011 Census data (Office of National Statistics). Each bivariate map displays the share of Muslims and post-04 EU migrants in neighbourhoods (Lower Super Output Areas) across the UK. The legend displays a range of colours, each corresponding to a specific value or percentile.

**North West Local Authority Districts
sorted by share of Muslims
(from high to low)**

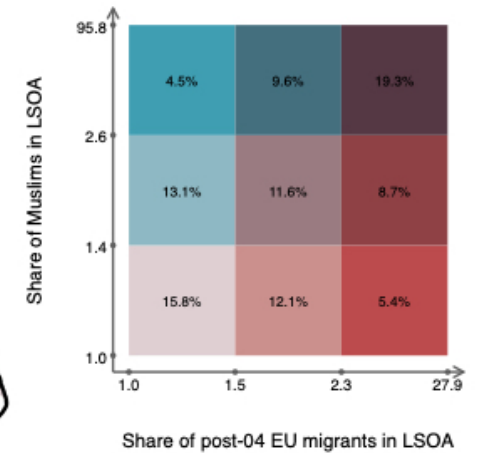
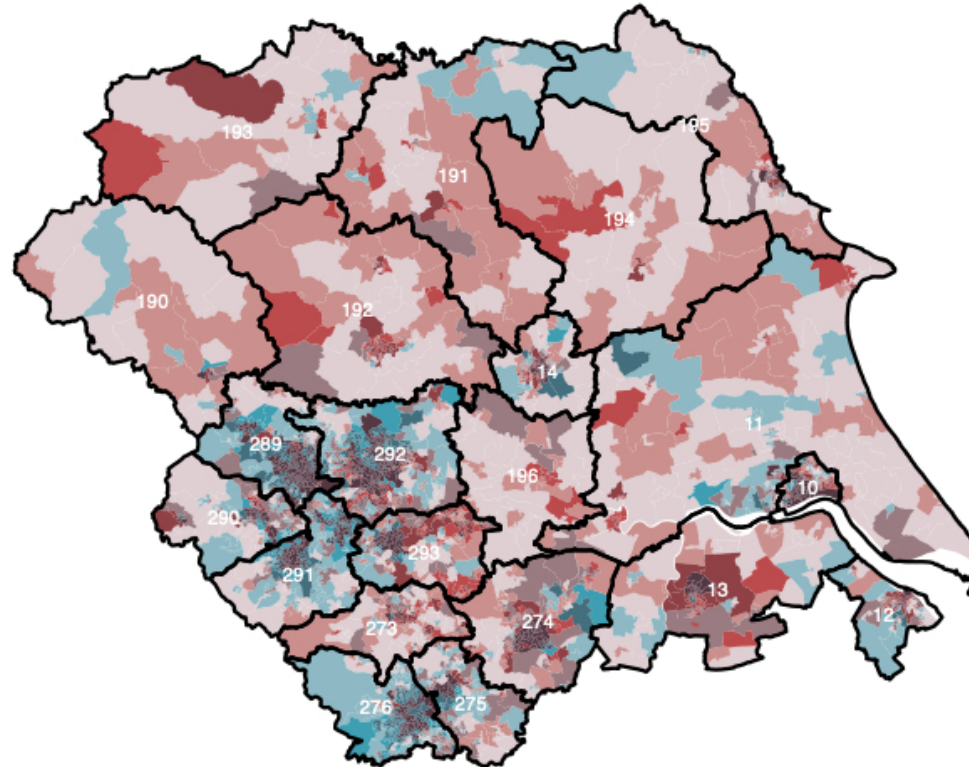
8 Blackburn with Darwen (28% / 2.8%)
 261 Oldham (19% / 1.8%)
 155 Pendle (18% / 3.1%)
 260 Manchester (17% / 3.4%)
 262 Rochdale (15% / 2.6%)
 266 Trafford (6.7% / 2.4%)
 265 Tameside (5.4% / 2.3%)
 158 Rossendale (4.8% / 1.4%)
 264 Stockport (4.3% / 1.6%)
 269 Liverpool (4.3% / 2.3%)
 263 Salford (3.6% / 3.6%)
 154 Lancaster (2.3% / 3.1%)
 151 Chorley (2.1% / 1.7%)
 7 Warrington (2% / 2.5%)
 9 Blackpool (1.7% / 2.9%)
 157 Ribble Valley (1.7% / 1.7%)
 267 Wigan (1.7% / 1.9%)
 49 Cheshire East (1.7% / 2.7%)
 272 Wirral (1.6% / 1.5%)
 159 South Ribble (1.5% / 1.7%)
 50 Cheshire West and Chester (1.5% / 2.1%)
 152 Fylde (1.5% / 1.6%)
 271 Sefton (1.4% / 2.2%)
 68 Carlisle (1.4% / 2.9%)
 270 St. Helens (1.3% / 1.4%)
 69 Copeland (1.3% / 1.4%)
 268 Knowsley (1.3% / 1.3%)
 161 Wyre (1.3% / 1.3%)
 160 West Lancashire (1.2% / 1.9%)
 67 Barrow-in-Furness (1.2% / 1.5%)
 70 Eden (1.2% / 2.3%)
 6 Halton (1.2% / 1.5%)
 66 Allerdale (1.2% / 1.5%)
 71 South Lakeland (1.2% / 2.4%)
 Barrow-in-Furness (1.2% / 1.5%)
 70 Eden (1.2% / 2.3%)
 6 Halton (1.2% / 1.5%)
 66 Allerdale (1.2% / 1.5%)
 71 South Lakeland (1.2% / 2.4%)
 Barrow-in-Furness (1.2% / 1.5%)
 (Muslim share/post-04 EU Migrant share in LADs)



**Yorkshire and the Humber
Local Authority Districts
sorted by share of Muslims
(from high to low)**

289	Bradford	(26% / 3%)
291	Kirklees	(16% / 2.3%)
276	Sheffield	(8.7% / 1.9%)
290	Calderdale	(8.3% / 2.3%)
292	Leeds	(6.4% / 2.7%)
275	Rotherham	(4.7% / 1.8%)
10	Kingston upon Hull, City of	(3.1% / 4.4%)
293	Wakefield	(3% / 3.2%)
13	North Lincolnshire	(2.8% / 4.3%)
274	Doncaster	(2.7% / 3.7%)
14	York	(2% / 2.5%)
190	Craven	(1.9% / 1.8%)
12	North East Lincolnshire	(1.8% / 2.3%)
195	Scarborough	(1.5% / 2.4%)
273	Barnsley	(1.4% / 2.2%)
11	East Riding of Yorkshire	(1.4% / 1.8%)
192	Harrogate	(1.4% / 2.7%)
191	Hambleton	(1.3% / 1.8%)
193	Richmondshire	(1.3% / 1.7%)
196	Selby	(1.1% / 2.8%)
194	Ryedale	(1.1% / 1.8%)

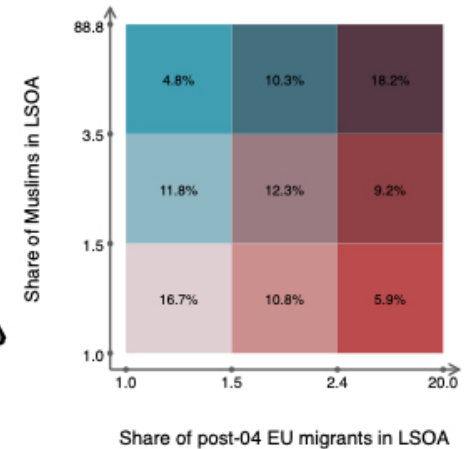
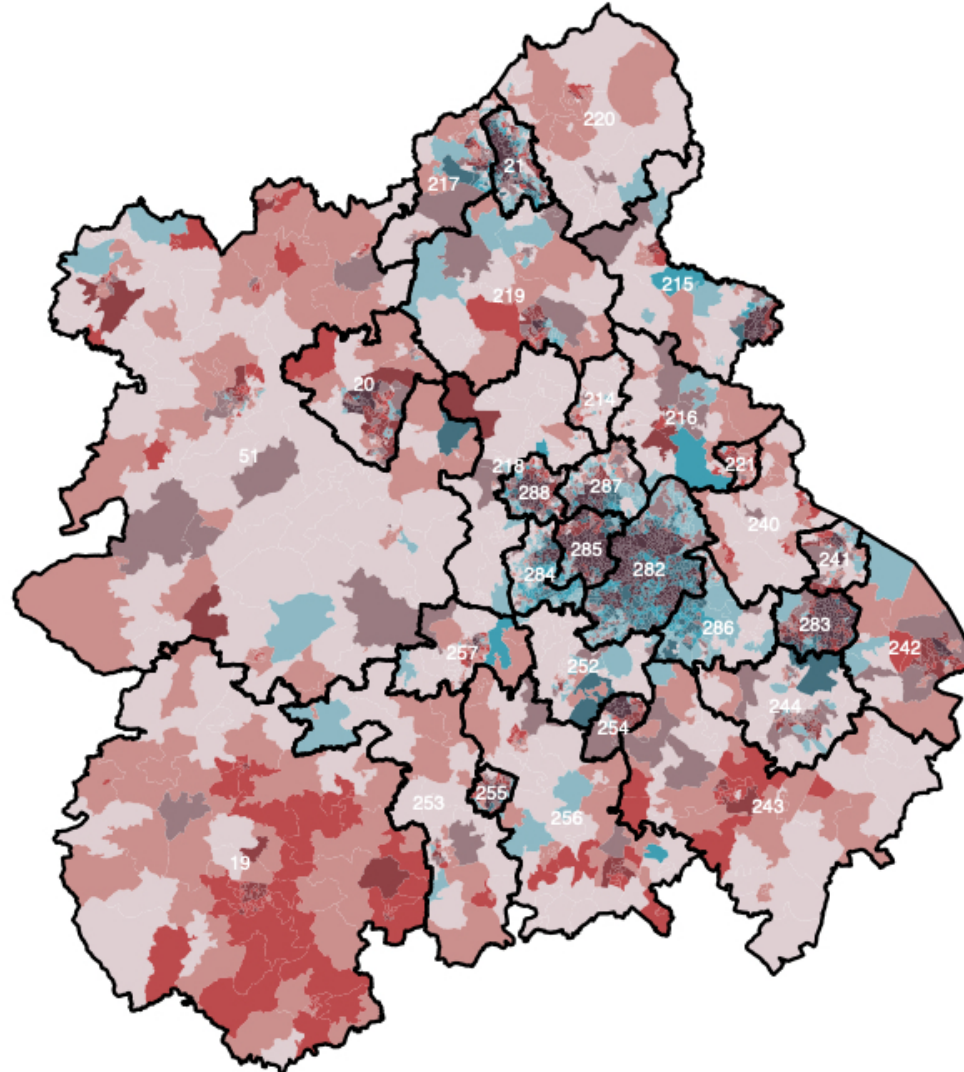
(Muslim share/post-04 EU Migrant share in LADs)



**West Midlands Local Authority Districts
sorted by share of Muslims
(from high to low)**

282 Birmingham (23% / 2.7%)
 287 Walsall (9.2% / 2.1%)
 285 Sandwell (9.2% / 4.3%)
 283 Coventry (8.5% / 4.7%)
 21 Stoke-on-Trent (7% / 2.3%)
 215 East Staffordshire (7% / 4%)
 284 Dudley (5.1% / 1.5%)
 288 Wolverhampton (4.6% / 3.3%)
 254 Redditch (4.4% / 4.6%)
 255 Worcester (3.9% / 3.3%)
 286 Solihull (3.5% / 1.5%)
 241 Nuneaton and Bedworth (3.3% / 2.5%)
 20 Telford and Wrekin (2.8% / 3.2%)
 242 Rugby (2.2% / 5%)
 217 Newcastle-under-Lyme (2.1% / 1.7%)
 244 Warwick (1.9% / 2.3%)
 219 Stafford (1.9% / 2.1%)
 257 Wyre Forest (1.7% / 2.1%)
 252 Bromsgrove (1.5% / 1.3%)
 216 Lichfield (1.4% / 1.8%)
 218 South Staffordshire (1.3% / 1.2%)
 51 Shropshire (1.3% / 2%)
 256 Wychavon (1.3% / 3.5%)
 221 Tamworth (1.3% / 2.3%)
 253 Malvern Hills (1.3% / 1.6%)
 243 Stratford-on-Avon (1.2% / 2.8%)
 214 Cannock Chase (1.2% / 1.5%)
 19 Herefordshire, County of (1.2% / 4.3%)
 220 Staffordshire Moorlands (1.2% / 1.6%)
 240 North Warwickshire (1.2% / 1.7%)

(Muslim share/post-04 EU Migrant share in LADs)



2.6.1. EASTERN EUROPEAN LABOUR MARKET PENALTIES

Discussions of labour market penalties has usually focused on waves of commonwealth migrants and their descendants who identify as a minority ethnic. These studies usually compare minority outcomes to a homogenous 'White' charter category, thus obscuring experiences of other White contemporary migrant groups like Western or Eastern Europeans. While some studies do use analytical categories that separate White British people from others (for example Johnston et al., 2010), categories for other White groups are usually not included. Nevertheless, there is an expanding literature providing evidence of heterogenous experiences within the White population in the UK, with circumstances varying across people with different religions and social origins (Fox, 2013; Manley et al., 2019). White Muslim women, for example, reported experiencing discrimination for wearing the hijab despite belonging to the dominant ethnic group (Franks, 2000).

More recent studies have considered the economic circumstances of Eastern Europeans. There is evidence that this group tend to have higher employment rates and are less likely to work part-time. This is expected as they have specifically come to the UK in search for work, and if they were not able to find it, they would most likely return home. However, on average, Eastern Europeans (in comparison to other Western European or White migrants) are overqualified and earn less in excess of their education in the UK (Ciupijus, 2011; Johnston et al 2015). Considering religion, there is evidence of statistically significant differences between Christian White Eastern European migrants and the Christian White British majority. In general, Christian White Eastern Europeans were more likely to be represented in less advantaged occupations and overqualified (Manley et al., 2019). This could potentially be because, as first-generation migrants, their qualifications are ambiguous to British employers. Another reason could be that they experience similar discriminatory practices as other ethnic groups. That is, they have undergone processes of racialisation (Fox et al., 2012) (described in footnote 14) and are impacted by discriminatory hiring processes, despite being White and Christian. When considering labour market penalties of EU nationals, it is important to consider their diverse motivations for coming to the UK. These motivations can considerably

influence their experiences and outcomes in the labour market, like downward mobility and low pay. Many Eastern Europeans are circular migrants, taking low-skilled and low-paid jobs with short-term goals. Some stay longer to accumulate wealth before returning home. Others intend to stay long-term, progressing in the UK labour market, with some keeping their options open for return and others staying permanently (Manley, et al., 2019).

2.7. Understanding the Labour Market Impacts of Immigration

There are multiple factors that shape both micro and macro labour market conditions and social changes in the context of migration. These factors include the size of the immigrant community, the extent of its distribution, the nature of the host country (such as urban or rural settings), the aspirations and plans of migrants, and the broader socio-cultural, religious, legal, and political environment of the receiving country (Pędziwiatr, 2017). This section considers the evidence for the potential impacts of immigration on native and ethnic minority workers in the UK. While most evidence focuses on British workers, there is also some evidence of how new migrations effect earlier established ethnic minorities (Shaginyan-Shapira, 2010).

2.7.1.1. Classical economic theory

Research on the effects of immigration on the labour market is often rooted in classical economic theory. This theory suggest that an influx of immigrant workers causes a labour supply shock, potentially lowering wages for similarly skilled native workers, and potentially displacing them (Borjas, 2003). Immigration flows are theorised to affect the skill composition of the receiving country's labour force. That is, if the skillsets of new arrivals do not match those of natives, this will lead to 'disequilibrium between supply and cost-minimising demand for different labour types at existing wages and output levels' (Dustmann et al., 2005, p325).

Restoring this equilibrium might lead to significant changes in order to adjust, thus impacting the overall labour market dynamics. These changes could manifest in: (1) a lack of opportunities and increased competition between the migrant and native populations over jobs; (2) displacement or redundancies of native workers, replaced by migrants, and ultimately contributing to higher unemployment of the native population; (3) a reduction in wages for native workers influenced by a higher supply of labour that employers can draw from, and; (4) increased labour supply may lead to higher levels of output and employment, enabling companies to develop and not improve wages or conditions for current workers (Borjas, 1995; Gilpin et al., 2006; Portes and French, 2005). However, despite the prevalence of this theoretical assumption in the immigration literature (Borjas, 2003), there is little evidence to support it. Studies have found little evidence that immigration has overall effects on aggregate employment, participation, unemployment and wages in the US and the UK (Dustmann et al., 2005; (Shaginyan-Shapira, 2010).

2.7.1.1. Opportunity structure and spatial inequality

While foundational in understanding many aspects of the labour market, this classical theory is based on broad labour market impacts of everyone in a receiving country. Classical theory falls short in fully exploring the labour market outcomes of ethnic minorities on several accounts. First, these theories often assume a perfectly competitive market where all workers have equal access to opportunities and information, thus ignoring structural racism and other barriers that people may face. Second, these theories also do not adequately consider the geographic and spatial constraints experienced by ethnic minorities based on where they live. Ethnic minorities tend to concentrate in areas with fewer job opportunities and formal institutions to help find work (Jivraj and Alao, 2023; Zwysen and Demireva, 2020). Ethnic minority individuals also tend to have limited commuting capacity and therefore depend on local jobs (van Ham and Manley, 2010). Third, these models often ignore the social and cultural factors that influence labour market outcomes. For instance, ethnic minorities might have different social networks, cultural expectations, and family responsibilities that affect their job search and employment stability, and these networks might vary based on where ethnic minorities

are concentrated. Therefore, it is essential to control for differences in opportunities across local labour markets, especially when considering the impacts on ethnic minority groups (Shaginyan-Shapira, 2010).

For example, Lieberman (1980) states that immigrants tend to enter local labour markets which are already ethnically diverse, with their success dependent on how they are perceived in relation to other ethnic groups. Their arrival could have either negative or positive consequences on different types of workers. For example, just as immigrants enter ethnically diverse labour markets, Eastern Europeans may join areas with established Muslim communities. The impact on the labour market will be dependent on the relative prestige and reputation of these groups among employers. If employers prefer hiring Eastern Europeans over Muslims due to ‘taste’, statistical discrimination, or influenced by broader institutionalised Islamophobia (see section 2.4.3), this could lead to the displacement of Muslim workers in certain industries. Conversely, if Muslims are seen as more employable, Eastern Europeans might take less desirable jobs, potentially aiding the mobility of Muslims. The relative size of the Muslim community in a given area will also play a role. In areas where Muslims are a smaller minority, the arrival of Eastern Europeans might open up higher-status job opportunities for Muslims as the newcomers take on less advantaged occupations. Overall, this suggests that the labour market impact of new migrations will be influenced by the size and composition of the ethnic minority population in local areas and local labour markets.

2.7.2. SUMMARY

Shortly after the expansion of the EU in 2004, claims emerged that Eastern Europeans had been responsible for the rise in Jobseeker’s Allowance and unemployment following their arrival, as well as causing the depression of wages (Blanchflower et al., 2007; Telegraph 2004; The Economist 2006). Concerns also emerged over demands on education and the housing market (Manley et al., 2019). These studies and the public discourse around them are arguably guided by classical economic theory. However, little empirical evidence supporting these claims have been found, with studies suggesting modest effects on labour markets and no basis to suggest wages fell or unemployment grew (Drinkwater et al., 2006; Dustmann et al., 2005; Dustmann and Theodoropoulos,

2010; Lemos and Portes, 2008). There is even some evidence to suggest that new migrations from 2004 onwards had a small positive impact on labour markets in areas with high levels of ethnic diversity (Shaginyan-Shapira, 2010).

To the best of the author's knowledge, no studies have specifically examined the impact of recent Eastern European migration on Muslim communities in the UK. Given the potential overlap between Eastern European and Muslim communities in urban areas, where they may compete for similar employment opportunities, this research seeks to investigate how the concentration of post-2004 EU accession migrants might relate to inequalities in labour market outcomes for Muslims (RQ6). The presence of Eastern Europeans could disrupt opportunities for Muslims, particularly when considering factors such as worker rates and local occupation structures.

Additionally, while Eastern Europeans' participation in the labour market is often discussed in relation to job availability, this thesis explores whether their employment rates and associated occupation factors could contribute to poorer outcomes for Muslims in employment (RQ7). This is especially relevant when examining specific employment sectors where both groups may compete for positions. By focusing on detailed occupation data, the analysis aims to identify whether nuanced patterns and disparities in employment outcomes for Muslims emerge, particularly in occupations where broader occupational categories might mask structural inequalities (RQ8).

Once accounting for the various factors that typically shape labour market outcomes, this research will examine if any remaining disadvantage for Muslims can be linked to the presence of Eastern Europeans in local labour markets. Previous data limitations hindered such analyses, but this research seeks to overcome them by leveraging a large social survey that includes detailed migration measures and economic variables. The integration of macro-level migration data within individual-level data allows for a more refined analysis of how new migrations—particularly from Eastern Europe—may have influenced the labour market circumstances of Muslim communities in the UK. The detailed linkage of macro and micro-level data as part of this research also addresses Research Objective 3, defining and evaluating methodologies for measuring local variations in contemporary immigration and linking macro-data with detailed micro-data on Muslim individuals.

3. DATA AND VARIABLE OPERATIONALISATION

3.1. Overview

This thesis is structured around three empirical analysis chapters, each primarily using data from *Understanding Society* - The UK Household Longitudinal Study (UKHLS). In each chapter, data is pooled from 12 waves of the UKHLS, and selected variables are operationalised consistently across the analysis chapter. Each chapter will introduce any unique aspects and variations in how the data is specified and how variables are operationalised in the analysis. In Chapter 6, the process of deriving measures from the Labour Force Survey (2023) and Office of National Statistics (ONS, 2020), and their linkage to the UKHLS, is described.

Selected Stata syntax that documents the various processes involved in this research, such as variable operationalisation and data cleaning, are available in Appendix B. In addition, complete Stata do files that were used for the analysis are available at the online repository [here](#).¹¹ A range of these command files serve as a detailed record of the steps taken to conduct the analysis. By sharing these files, the aim is to promote transparency and facilitate the verification and extension of the research findings. This approach is guided by increasing concerns that empirical results are not transparent and cannot be reproduced (see Connelly et al., 2020; Gayle and Connelly, 2022). Replicability and transparency are fundamental principles in scientific research, ensuring that findings are reliable, credible, and can be independently verified. This openness not only facilitates replication but also enables other researchers to understand, evaluate, and build upon the work. By promoting replicability and transparency, this doctoral research contributes to a more robust and trustworthy scientific environment, where knowledge can be accurately shared and expanded.

¹¹ https://github.com/scotphunter/hunter24_thesis_muslimlabourmarketoutcomes

3.2. Data Source

3.2.1. THE UK HOUSEHOLD LONGITUDINAL STUDY (UKHLS)

First collected in 2009, the UKHLS is a nationally representative annual household panel survey that collects information over 24-month periods on a range of broad, multi-disciplinary topics. Overall, the survey includes a general population sample of approximately 120,000 individuals from 40,000 households (University of Essex, 2022). It also includes an ethnic minority boost sample (EMBS) of around 4000 households (from wave 1 - 2009/2011) and an additional immigrant and ethnic minority boost sample (IEMBS) of 2500 households (from wave 6 - 2014/2016). These boost samples inflate the number of participants from ethnic minority and migrant backgrounds (and their descendants) allowing for in-depth analyses of their experiences that is not routinely possible with other UK survey data (Platt and Nandi, 2020).

The UKHLS is particularly useful for investigating outcomes within the Muslim community, given that several ethnic groups comprising many Muslims (namely Indian, Pakistani, Bangladeshi and black African) were intentionally oversampled in the EMBS in wave 1. The subsequent IEMBS in wave 6 was intended to inflate these groups further, but also boosted participants from other groups with migrant backgrounds.¹² Another attraction of the UKHLS is that its household focus allows researchers to examine the role of other family (or household) members (including children and non-respondents) on individual's outcomes. In this analysis, for example, household information such as parent's country of birth has been used when establishing the ethnic group membership of individuals.

In addition to the rich information about ethnic minority households, the UKHLS also has detailed information on labour market outcomes, occupational position, and other social inequalities. A special license was obtained through the UK Data Service to receive two secure-access versions of the data. The first version (SN 6931) included more detailed occupational information such as 4-digit codes for SOC2000, SOC2010 (Standard Occupational Classification) that were not included in the general version

¹² The general population sample was selected from across the United Kingdom (UK), but the EMBS and IEMBS were drawn from only England, Wales and Scotland.

(University of Essex, 2022). Access to the detailed occupational positions of UKHLS respondents will allow for more detailed analysis of the distinct patterns of ethnic segregation by occupations in the UK. The second secure version of the UKHLS (SN 7248) included micro-level geocodes at the level of Lower Layer Super Output Area (LSOA) (University of Essex, 2022).¹³

Information on main adult respondents for all 12 waves (2009-2022) of the special versions of the UKHLS were pooled together (see Appendix B2). Pooling together comparable data from different years to boost sampling power is a common approach in exploring ethnic minority outcomes (Cheung and Heath, 2007) and especially when concerning Muslims in which data is usually sparse (Connor and Koeing 2015; Khattab and Hussein 2018; Khattab and Modood 2015; Khattab and Modood 2018; Khattab et al., 2016; Longhi 2020; Sweida-Metwally 2022). Although the UKHLS is a panel survey which includes repeated responses from individuals, improved sampling power can still be achieved by combining different waves of data. However, it is important that methods that account for the clustering of responses within individuals and the impact this will have on results are used in conjunction.

A couple of alternative data resources were considered for exploring Muslim outcomes in this thesis. For example, safe-guarded micro-Census data includes detailed ethnicity, country of birth, religion, and some relevant labour market measures. In addition, the large population size of this resource would result in less concern about statistical power and the robustness of any inferential analysis. Furthermore, the annual population and labour force surveys were also considered for their comprehensive coverage and large sample sizes.

However, the UKHLS was selected due to several distinct advantages that are particularly well-suited to addressing the research questions. First, the UKHLS includes a range of detailed measures that are not routinely available in other data resources. These

13 LSOAs are a geographical statistical unit used in the UK for reporting small-area statistics. They are designed to provide a consistent framework for the reporting of statistics across the country, ensuring that data can be compared across different regions. LSOAs are a part of a hierarchy of geographical units, including (from smallest to largest): Output Areas (OAs) – the smallest level inc. approx. 125 households [not included in analysis]; Lower Layer Super Output Areas (LSOAs) – larger aggregations of OAs ; Middle Layer Super Output Areas (MSOAs) – larger geographical areas comprising groups of LSOAs; and Local Authority Districts (LADs) – administrative regions (local councils or boroughs) that encompass multiple LSOAs and MSOAs
www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/2011censusgeographies.

include variables related to social and cultural integration, such as measures of religiosity, ethnic composition of networks, and liberal attitudes. This is particularly relevant to research question 3 that aims to examine whether discrimination persists even for those who are well integrated into British society. Additionally, the UKHLS provides a range of detailed work-related variables. These measures were used to design a composite measure of job quality, as featured in Chapter 6, allowing for a more nuanced analysis of labour market outcomes. The linkage facilities available with the secure versions of the UKHLS also allowed for the linking of micro data to other macro resources, enhancing the richness of the dataset. This was particularly useful for research question ____ on the impact of contemporary migration on Muslim disadvantage. Furthermore, the ethnic and immigrant minority boost samples enhance representation across all four nations of the UK, leading to more accurate and detailed analysis even when weights are applied (Kaminska and Lynn, 2019). The robust weighting and sampling design of the UKHLS provided confidence in the representativeness and reliability of the data used in the analysis. How the complex survey design was addressed in the following analysis will be discussed next.

3.2.1.1. Weights

The UKHLS sample design incorporates clustering and stratification, which can introduce biases related to ethnic and religious groups as well as geographic regions. Clustering is determined by postcodes to save on survey costs, while stratification is based on 12 regions (10 in England, 1 in Scotland, and 1 in Wales) and then creating sub-groups within these regions based on factors like the type of workers in households, population density, and ethnic minority density, all aimed at enhancing the survey's representativeness. The oversampling of ethnic minorities, while beneficial for studying these groups in detail, can lead to an overrepresentation of certain demographics if not properly weighted (Kaminska and Lynn, 2019). Additionally, geographic biases may arise due to the clustering of samples in specific areas potentially skewing results if certain regions are over- or under-represented.

Ethnic and religious biases are particularly relevant in the UKHLS due to the deliberate inclusion of more ethnic minority participants via the ethnic and immigrant boost

samples. These boost samples aim to provide robust data on these groups but requires careful weighting to ensure that the overall sample remains representation of the broader population. Geographical biases can also impact the representativeness of certain geographic areas, which can affect the generalisability of the findings. Applying weights helps to mitigate these biases by adjusting for the survey design and ensuring that the sample accurately represents the population distribution across the different regions.

However, the UKHLS can still be treated as nationally representative as long as appropriate weights are used (Kaminska and Lynn, 2019). Unweighted analysis risks providing biased estimates that do not accurately represent the population structure. Weights provided by the UKHLS also correct for variations in response rates at wave 1 and attrition in subsequent waves, ensuring more accurate and representative results. Due to the specific conditions inherent in the pooled sample used in the following analysis (discussed in the previous section), appropriate weights needed to be designed for representative analysis. The pooled panel data sample is unbalanced, meaning some entities are not observed at every time point, leading to missing observations for certain individuals in some waves. Unbalanced data was chosen because employing a balanced panel dataset would result in the loss of a considerable number of observations overall. Given the interest in small minority groups, this reduction would lead to an insufficient number of observations and a reduction in statistical power. The rationale behind proceeding with an unbalanced dataset was to retain as many observations as possible to ensure more reliable and accurate results.

Additionally, the complex survey design and oversampling of ethnic minorities make it challenging to achieve representativeness without applying weights provided in the data (Kaminska and Lynn, 2019). These weights are necessary to correct for the survey design and ensure that analysis accurately reflects the population structure. However, the UKHLS only includes weights for one wave at a time or for longitudinal analysis. Because this analysis is cross-sectional of pooled data, an aggregate weight variable that extracted weights for each wave had to be created and applied to individuals. . For example, wave 1 weights apply to responses from wave 1 and wave 2 weights apply to responses from wave 2 and so on. To implement this in Stata, a program was created to apply each year's wave-specific weight to each individual. The Stata code used to define this program is provided in appendix B1. This approach follows the official guidance from UKHLS user forum on weighting cross-sectional pooled data. To ensure results can

be inferred to the broader British population, the majority of the following analyses will be weighted unless stated otherwise.

3.2.1.2. Missing data

The panel design of the UKHLS means that data is collected from the same individuals and households over time. Although most of the same questions are asked on a yearly basis, it is possible that respondents may have missing data on certain variables in some waves. Any records with missing data on any analytical variables were excluded from the following analysis. However, missing data on core time-invariant variables for individuals (such as ethnicity and religion) was imputed by using a valid response from the nearest wave available. Although this procedure runs the risk of misrepresenting any changes between values of variables across different years for individuals, the variables are considered stable and unlikely to change in most instances, and the imputation increases sample size. Carrying responses forward/backward to other waves for UKHLS respondents has been successfully implemented in previous ethnic minorities studies that uses pooled data (Sweida-Metwally, 2022; Zwysen and Demireva, 2020).

3.3. Outcome Variables

There are eight labour market outcomes explored throughout the following empirical chapters. The first four, participation, avoidance of unemployment, average earnings and occupational attainment, are explored in Chapter 4. While the former three of these outcomes usually feature in ethnic penalty literature, analysis of occupational attainment (average CASMSIS scores) as it is operationalised here is less common. To extend the story, three more outcomes (in addition to the former) are explored in Chapter 6: financial anxiety, job related satisfaction, and a composite measure of job quality based on different workplace indicators. The outcome variables and how they are operationalised will now be described in turn.

Labour force participation (economic activity): labour force participation can reflect the extent to which individuals have access to employment opportunities which can

determine equality disparities. A variable on the labour market participation of individuals in the UKHLS was used to derive a measure of economic activity. Those outside the labour market, such as full-time students, doing family care or working at home, the long-term sick or disabled, the retired, unpaid family business workers, and those ‘doing something else’ were given the value 0 (inactive). Everyone else, such as those who are self-employed, an employee (full or part time), unemployed but looking for work, and on maternity leave were given the value of 1 (active).

Avoidance of unemployment: lower employment rates of Muslim ethno-religious groups compared to the majority group can serve as an indicator of additional disparities in terms of access employment opportunities and social inequality patterns. This variable is a subset of the labour force participation variable and only includes those who are economically active.¹⁴ An avoidance of unemployment variable was derived with people who were self-employed or in paid employment (ft/pt), or on maternity leave were given the value 1 ‘employed – avoiding unemployment’, whereas those who were unemployed but searching for a job were given the value 0 ‘unemployed but looking for work’.

Occupational attainment (access to social and material resources): Occupational attainment is widely regarded as a valuable indicator of social inequalities as it reflects an individual’s circumstances within the societal structure, as well as their access to resources (Lambert and Griffiths, 2018). The occupation one holds can be influenced by various factors, including education, social background, and available opportunities. Consequently, differences in occupational attainment often shed light on the unequal distribution of social and economic opportunities, contributing to the understanding of social inequalities. While descriptive analysis is carried out on the representation of British Muslims in top professions – based on National Statistics Socio-Economic Classifications (NS-SEC) - the main measure of occupational advantage used in the following analysis is the Cambridge Social Interaction and Stratification Scale (CAMSIS).

The CAMSIS scale is a tool used in the field of social stratification and inequality and is based on the exploration of different interaction patterns exhibited by individuals within

¹⁴ Students, unpaid family care or home workers, long term sick or disabled, retired, unpaid family business workers, and those doing something else were excluded from the analysis.

and between specific occupations, which serve as indicators of both social and material advantages. The underlying premise of CAMSIS is that individuals who share similar social characteristics are more likely to interact with one another (Prandy and Lambert, 2003). This approach allows for deeper understanding of how social dynamics and relationships shape the distribution of resources and opportunities within society. A higher CAMSIS score generally indicates that an individual occupies a position associated with greater social and material advantages. This includes higher levels of education, income, and economic security. Occupations with higher CAMSIS scores often require advanced skills and education, such as medical doctors, university professors or medical professionals (Lambert and Griffiths, 2018). In the following analyses, CAMSIS score – based on 2010 SOC codes attached to individuals - is fit as a continuous outcome.

Log of average hourly earnings: personal earnings can reflect the unequal distribution of income within society which leads to disadvantage. Higher hourly earnings indicate greater financial resources and economic well-being, while lower earnings imply limited financial means. A log transformed average earnings per hours worked¹⁵ (including both self-employed hours and hours worked as an employee) variable served as the third labour market outcome that is explored. It is important to note that these earnings have not been adjusted for inflation despite the data covering multiple years. Sensitivity analysis was conducted to check for any significant differences, and the results indicated that there were no important differences in findings when adjusting for inflation (see corresponding log file 'sa2_earnings_hunter24' available at the [online repository](#)).

Financial anxiety: subjective perceptions of current financial situation can give insight into other inequalities aside from labour market performance. This is measured using a variable that asks respondents to rank their current financial situation using a five-point scale that runs from 1 “finding it very difficult” to 5 “living comfortably”.

Job related satisfaction: Ethnic minority groups tend to report lower levels of satisfaction compared to their majority counterparts (Bartram, 2011; Safi, 2010; Sirgy and Cornwell, 2002) or across country of birth (Frank et al., 2015) and generational groups (Amit,

¹⁵ After removing extreme outliers (cases below the 1 percentile or above the 99 percentile) the distribution of the original earnings variable was skewed to the right, the log transformation compressed the upper end of this distribution while stretching out the lower end making it more symmetric.

2010). Following Knies et al.'s (2016) approach, job related satisfaction is measured in the following analyses using a composite measure available in the UKHLS based on questions that asked participants how satisfied they were with their amount of leisure time, income and health, choosing from a scale from 1 "completely dissatisfied" to 7 "completely satisfied". Sensitivity analysis comparing religious variations in other available satisfaction questions (about amount of leisure time, income and health) yielded similar patterns to the overall measure – on average, Muslim and Other religion participants have the poorest outcomes. It was decided to proceed with just the overall job-related satisfaction measure as a summary of these different processes (supported with a Cronbach's alpha score of 0.80 among all the measures).

Job quality is important when examining the Muslim experience and broader job outcomes. Literature highlights that factors beyond job satisfaction and monetary rewards, such as access to pension schemes and flexible workplace conditions, significantly impact job satisfaction and overall well-being (Muñoz de Bustillo et al., 2011; Li and Heath, 2016). Understanding these dimensions helps address disparities and improve employment experiences of ethnic minorities.

Inspired by these recent studies, particularly Zwysen and Demireva (2020), information from fifteen different employment-related indicators across four domains (monetary rewards, work-life balance, intrinsic quality of work, and employment security/quality) is used to estimate a measure of belonging to a high-quality job. First, monetary rewards are measured with a variable indicating whether respondents are in the top quartile of earners (hourly), whether they are paid per hour or have a salary, whether their pay includes bonuses or profit shares, and whether a pension scheme is offered by their employer. Second, work-life balance is measured via a variable indicating whether people mainly work standard hours (in the day), whether people sometimes or mainly work non-standard hours (such as evenings and weekends), whether they are able to vary their working hours on an informal basis, and whether their employer offers them at least two or more flexibility schemes.¹⁶

¹⁶ Including working part-time, working term-time only, job sharing, flexi-time, working a compressed week, working annualised hours, working from home on a regular basis, or other flexible working arrangements.

Third, intrinsic quality of work measures includes a variable indicating individuals in the highest quartile of a multi-item scale who report having significant autonomy over various job aspects, such as tasks, work pace, manner, task order, and working hours. It also includes a variable indicating job dissatisfaction and another for those in the highest quartile of a multi-item scale measuring job-related anxiety, including feelings of tension, unease, worry, depression, gloominess, or misery due to work. Fourth, employment quality is captured by a variable indicating job security (higher values mean more security), whether individuals have a temporary contract, and the potential for career advancement. This is measured by whether respondents believe it is likely they will get a better job with the same employer or access to training in the next year.

Following Zwysen and Demireva's (2020) novel method for exploring job quality among ethnic minorities, latent class analysis (LCA) is used to combine all indicators in order to estimate a measure of job-quality. Through LCA, posterior probabilities are used to group individuals into different job types ('classes') based on their responses to the 15 indicators. The underlying assumption of LCA assumes that an individual's scores on the indicators are influenced by their class membership. For example, people with high scores on favourable variables will be in higher quality jobs. While Zwysen and Demireva (2020) identify five different job types (ranging from 'bad jobs' to 'high quality'), the following analysis only focuses on the latent class with the most favourable scores across all indicators. Referred to as having 'high quality jobs', people who belong in this class have high wages, are salaried, receive bonuses and have other positive outcomes on the variables listed above. The probabilities of belonging to this class of jobs are then stored for each individual and fit as a dichotomous outcome in a logistic regression model. For corresponding data management and analysis code, see [ch3_jobquality_indicators_hunter24.do](#) available at the [online repository](#)).

3.4. Explanatory variables

In almost all of ethnic penalty studies, circumstances of ethnic and ethno-religious minorities are compared to a White British or White British Christian reference category. The following controls are frequently used: age, age squared, highest qualification held, born in the UK or some measure of immigrant status, and region (Khattab, 2009) plus

marital status (Johnston et al., 2010), in addition to a dependent children or family structure measure (Berthoud, 2000; Daoud and Khattab, 2022; Heath and Martin, 2013; Khattab and Hussein, 2018; Khattab and Johnston, 2013; Khattab et al., 2020b; Li and Heath, 2008; Manley, Khattab, Johnston, 2019). Some include occupational controls to account for clustering of ethnic minorities in manual occupations (Khattab and Modood, 2015) and parents' circumstances when exploring social mobility of groups (Connor and Koeing, 2015; Li and Heath, 2016; Karlsen et al., 2020). However, parent's circumstances will not be considered in the subsequent analysis. When modelling earnings, controls for work hours, public-sector, part-time orientation, and occupation category are routinely adjusted for (Khattab, 2016, Longhi et al., 2013).

Fewer studies adjust analysis for language fluency (Lindley, 2002; Sweida-Metwally, 2022) or health conditions (see Li and Heath, 2020; Sweida-Metwally, 2022) and immigrant wellbeing studies more broadly (Knies et al., 2016). Other socio-cultural variables representing the different networks of migrant groups are absent from most of the studies. These shortcomings are most likely due to studies using Census or Labour Force Survey type data which lack appropriate measures. Cheung (2014), using a specialist survey on ethnic minority experience and Sweida-Metwally (2022) using the UKHLS, do however, control for cultural factors that represent bonding and bridging capital and cultural values. Most importantly to Sweida-Metwally (2022), most studies, apart from Connor and Koeing, (2015) do not adjust for religiosity. The remainder of this section will explain in detail which explanatory variables are used (and their operationalisation) throughout this doctoral research.

3.4.1. POPULATION CHARACTERISTICS

3.4.1.1. Ethnicity, religion, migration and ethno-religious groups.

Ethnic group membership is measured with a variable in the UKHLS derived from multiple sources, with priority given to self-reported information (See Appendix B7). The original ethnicity variable has 18 categories which was reduced to eight to focus on ethnic groups with Muslim respondents and to increase the sample size of these groups

when possible. Five categories which represent different ‘mixed’ ethnic background combinations (White and Black African, White and Black Caribbean; White and Asian; other mixed background) were recoded into one ‘mixed’ ethnic group and these were grouped with Asian Other and Arab into the ‘Other’ category due to small sample size. In order to focus on comparing outcomes between Muslims and the White British ethnic majority, other White ethnic groups, such as White Other and White Irish were excluded from the following analysis as these groups had very little number of Muslim respondents.

A small number of respondents did not identify with either the ‘Black Caribbean’ or ‘Black African’ ethnic group categorisation, but instead chose ‘any other Black background’. In their analysis on ethnic equalities, Heath and Martin (2013) suggest that in the ‘Other Black’ category in their data (the Annual Population Survey) consisted overwhelmingly of second-generation Caribbean origin migrants who ‘rejected’ the Caribbean label. The UKHLS has data on both mother and father’s country of birth which revealed that most respondents who identified as ‘Other Black Background’ had parents from African or Caribbean countries, and on this basis most cases were assigned to either the Black African or Black Caribbean categories (See Appendix B6). The few with both parents coming from neither an-African nor Caribbean country were put with the broader ‘other’ ethnic group, and the those who had the combination of one African parent and one Caribbean parent were recoded into the broader ‘mixed’ category. A similar procedure was carried out for the few ‘Other Asians’ whose both parents came from India, Pakistan, and Bangladesh respectively. The final measure of ethnic group membership thus included: White British, Indian, Pakistani, Bangladeshi, Other Asian, Black Caribbean, Black African, and Other (comprising mixed groups, Arabs and other Asians).

Religious affiliation: Information was taken from self-reported religious affiliation (see Appendix B4). All 11 of the Christian denominations in the original variable were amalgamated together into one group, leaving eight categories: Christian, Muslim, Hindu, Jewish, Sikh, Buddhist and Other and one category for those with no religion that draws from another measure asking respondents whether they adhere to a religion or not (See Appendix B4). Due to the data being pooled and respondents not always reporting their religion every year, any missing data were filled by using information about their parents religion or the closest neighbouring year with valid data (see Appendix B5).

Therefore, for the purposes of this analysis, religious affiliation is treated as ‘religion of family background’ rather than ‘personal religious orientation.’ This distinction is important because it acknowledges that the reported religious affiliation may reflect the cultural and familial context in which individuals were raised, rather than their current personal beliefs or practices. This approach is particularly relevant when examining ethno-religious disadvantage and comparing socio-economic outcomes across different religious groups. Instead of categorising individuals who identify as having ‘no religion’ into distinct categories, they were merged with Christian respondents into their respective ethno-religious groups. For instance, White British Christians and White British individuals who reported no religious affiliation are combined together. Likewise, Black African Christians, and Black Africans with no religion are merged and so on. This decision was made based on the expectation that the two categories have similar implications in the current context. For instance, in the UK, where Christian categories have been the historical majority and have shaped mainstream institutions, many people who describe themselves as having ‘no religion’ may well have a Christian family background and are very likely to have experienced educational and other institutions that are grounded in Christian traditions. Under this assumption, it is more parsimonious to treat the Christian and no-religion categories as comparable and focus only on other religions when they have been explicitly identified.

Studies have illustrated that country of birth and migration status has an important influence on outcomes (Cheung, 2014). Therefore, in addition to organising individuals based on their ethnicity and religious identity, migration background is also factored into the creation of groups. This approach aligns with Cheung and Heath (2007) who include different combinations of ethnicity and generation as units of analysis. For example, they distinguish between first generation and second generation Pakistani and Bangladeshi and use these as analytical categories.

Migration background: first generation migrants born outside the UK were coded as 1, second generation migrants with at least one parent not born in the UK are coded as 2, third generation migrants with at least one grandparent born outside the UK were dropped from the analysis due to there being very little ethnic minorities in this category. Everyone else (people with both parents and all grandparents born in the UK) were coded as 4 representing the ‘no migrant background’ group.

Ethno/generational-religious group: Information from (1) ethnic group membership, (2) religious affiliation, and (3) migration background was used to organise individuals in the UKHLS into empirical groups based on the combinations of these three variables (See Appendix B7). Creating groups based on major permutations of ethnic group membership and religious affiliation is common in research on Muslim labour market outcomes (Longhi et al., 2013). However, in these studies' migration background is usually controlled for as a separate term in the analysis. Instead of fitting migrant background as a separate term in the following analysis, it is integrated into the ethnicity measure, as is done by Cheung and Heath (2007). This approach offers two advantages: first, it facilitates a more straightforward comparison between first- and second-generation migrant groups and the reference category, and second, it enables comparisons with other ethno-religious groups in the UK that have no migration backgrounds, such as a group frequently overlooked in the literature, Muslim White British individuals.

Overall, 11 ethno/generational-religious groups (hereinafter referred to as 'ethno-religious groups'), representing the major permutations of religion, ethnicity and migration background that exist for Muslims in the UKHLS were created as shown in table 3-1. Dummy variables for each permutation were included in the analysis, with the reference category being Christian/Agnostic White British. This approach is also inspired by recent efforts in using quantitative methods to explore the wider diversity of ethnic and religious group experiences (Rahouni, 2014; Spierings, 2023). For example, while earlier literature predominately centred on South Asian members of the Muslim community, recent advancements in data availability have enabled researchers to explore the outcomes of groups within the community. For instance, Khattab and Modood (2015) and Sweida-Metwally (2022) have examined the intersection of ethnicity and religion. They investigate whether individuals from religious minorities who belong to the majority ethnic group, such as White British people who practice Islam, experience more favourable outcomes compared to their ethnic-minority counterparts. The inclusion of the ethnic minority boost sample in the UKHLS makes it an appropriate and valuable data source to further investigate such diverse identities.

Table 3-1 Distribution of observations by ethno-religious group and ancestry.

	Unweighted		Weighted	
	N	%	N	%
British Ancestry				
Christian White British	270,574	89.8	268,875	96.0
White Muslim British	1,150	0.4	828	0.3
First generation				
Muslim Indian	1,536	0.5	612	0.2
Muslim Pakistani	7,105	2.4	2,385	0.9
Muslim Bangladeshi	5,181	1.7	1,153	0.4
Muslim Black	2,035	0.7	848	0.3
Muslim Other	1,211	0.4	774	0.3
Second generation				
Muslim Indian	1,307	0.4	504	0.2
Muslim Pakistani	6,059	2.0	2,221	0.8
Muslim Bangladeshi	3,238	1.1	838	0.3
Muslim Other	1,789	0.6	960	0.3
Total	301,185	100	279,997	100

Data source: N = number observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weighted and unweighted figures presented.

3.4.1.2. Other Population characteristics

Sex: In the ethno-religious penalty literature, sex is sometimes fit as a control (Khattab and Modood, 2015; Khattab, 2016). However, it is far more common that analysis is specifically focused on women (Daoud and Khattab, 2022; Khattab and Hussein, 2018; Khattab et al., 2020b) or that analysis is split by sex in order to properly account for women’s unique labour market profiles (Cheung, 2014; Connor and Koeing, 2015; Karlsen et al., 2020; Khattab, 2009; Li and Heath, 2016; Lindley, 2002; Sweida-Metwally, 2022). To explore the intersection of gender and ethnoreligious identity on outcomes, separate models are run and presented for men and women throughout all the analyses.

Age and age squared: a continuous measure of age in years was included in addition to an age-squared variable to allow for curvilinear effects. The sample was restricted to participants between the age of 16 and 65 as to include only those within the working population. There are several ways to model age patterns in statistical analysis. Another common approach is to use categorical groups (Akbar, 2019), which can capture non-linear effects but may lose some granularity and statistical power. In this research, the use of age and age squared is deemed sufficient as it allows for the modelling of

curvilinear effects, capturing the potential non-linear relationship between age and labour market outcomes. For example, while earnings might increase as you age, it could potentially start declining for people approaching retirement in certain occupations. While other options could have been explored, such as including a term for age cubed, using age squared is sufficient for capturing the essential non-linear effects without adding unnecessary complexity to the model.

Government Office Region: Different dummy variables for each of the most Muslim-populated government office regions of interest were fit including the values (1) London (2) Yorkshire and the Humber, (3) North West (4) West Midlands, (5) Rest of England – East Midlands, East of England, North East, North West, South East, (6) Rest of UK-Scotland, Wales, and Northern Ireland. For information on UK level geographical distributions by ethnicity and religion the ONS census reports are widely cited, and these are likely to show small differences in patterns of concentration compared to the UKHLS unweighted data. However, while these regional variables provide a broad overview of geographical distributions, they may not capture the fine-grained locality concentrations of Muslim or other ethnic minority populations. For example, research has shown that ethnic and religious minorities often concentrate in specific localities within and across regions, leading to variations in social economic conditions and integration (Jivraj and Alao, 2024; Zwysen and Demireva, 2020). While broad government office regions are used initially in Chapters 4 and 5 to provide an overview of Muslim circumstances, these fine-grained locality concentrations are returned to in Chapter 6.

Legal marital status: measures of family structure, such as marital status, are commonly controlled for in labour market analysis (Ribar, 2004). A dummy variable was fit with those who were single, never married or separated/divorced/widowed coded as 0 and those legally married or in a same sex civil partnership coded as 1. It is expected those who are cohabitating but not legally married will be in the single or never married category (0).

Number of children (under the age of 16): 0 = none, 1 = responsible for one child, 2 = responsible for two children, 3 = responsible for three or more children. The number of dependent children in the household is also an important measure of family structure that frequently features in this type of analyses (Akbar, 2019). For a more comprehensive discussion of the influence of these family structure measures see section 2.4.1.2.

Health Status: Health conditions and related issues can act as significant confounding factors that limit employment opportunities or lead to less favourable outcomes. This is particularly relevant for ethnic minority groups who might have lower educational attainment, reside in more disadvantaged areas, and face barriers to accessing healthcare services (Li and Heath, 2020; Chouhan and Nazroo, 2020). A control for health status is thus usually included in recent analysis of ethnic minority studies of employment opportunities and unemployment persistence (see Li and Heath, 2020 and Aradhya et al., 2023; Sweida-Metwally, 2022) and immigrant wellbeing studies more broadly (Knies et al., 2016). For the following analyses, a dichotomous variable where 1 = respondent reported having a long standing¹⁷ physical or mental impairment, illness, or disability, and 0 = no-health concern reported, was included.

Caring responsibilities: Other variables on family structure might help shed light on reasons for non-participation in the labour market. For example, individuals who live with extended families may have to take on additional caring responsibilities which prevent them from seeking employment, or impact how much work and the type of jobs they can do. A composite variable combining responses from two questions about care responsibilities was created with value (1) representing those who care for ‘handicapped’/others in the household, care for non-residents, or care for both the former and latter, whereas (0) representing those with no care responsibilities.

Year of survey response: Period effects consider how variation over time may lead to ‘shifts in social, cultural, economic, or physical environments’ of the respondents in cross sectional surveys (Khattab and Hussein, 2018, p1026). As the pooled sample used in the following analyses will be treated as cross-sectional, dummy variables for each of the waves of the survey was fit to account for periodical effects. While the survey wave modal year is not the most accurate record of the time of interview, and more precise measures such as ‘interview month’ might often be preferred, ‘survey wave’ dummies have been used. Survey wave dummies not only capture period effects but also account for any non-period influences, such as changes to survey delivery arrangements. To ensure robustness of this approach, a sensitivity analysis was conducted comparing the results using survey wave dummies versus interview year. The analysis indicated that

¹⁷ ‘Long-standing’ is defined by UKHLS documentation as ‘anything that has troubled the participant over a period of at least 12 months or that is likely to trouble them over a period of at least 12 months.’

while there were slight changes in the magnitude of coefficients, the overall findings (sign and significance) remained consistent (see ‘sal_interview_year_hunter24.log’ available at the [online repository](#)). This suggests that using survey wave dummies does not introduce significant bias.

When exploring the circumstances of people in employment, there are a range of confounders which can significantly influence labour market outcomes that are usually controlled for (see section 2.4.1.3). These controls are used in the following analyses of earnings for ensuring the accuracy and reliability.

Work Orientation: This is a dichotomous variable where 1 indicates the respondent reported working part-time, and 0 indicates the respondent reported working full-time. This control is important because part-time and full-time workers often have different earnings, benefits, and job stability. By controlling for work orientation, we can more accurately assess the impact of other variables on average earnings among economically active respondents.

Public Sector: This is a dichotomous variable where 1 indicates the respondent reported working in the public sector, and 0 indicates the respondent reported working in the private sector. This control is essential because public sector jobs often have different pay scales, job security, and benefits compared to private sector jobs. By including this variable, we can better understand how sectoral differences influence average hourly earnings.

3.4.2. HUMAN CAPITAL

English language proficiency: Although Koopmans (2016) labels host country language proficiency as a sociocultural variable in his own research, it has been decided here to use it as a measure of human capital as is done in Miaari et al., (2019), Khattab and Modood, (2015) and Khattab et al., (2020). Similar to Sweida-Metwally (2022), English language proficiency is measured by generating a summary score of three variables where respondents reported being confident: (1) speaking English in person or over the phone, (2) reading English and, (3) completing official forms in English. Where a response on any of these questions were not available, information on whether the survey

interview has been conducted in English was used as a proxy for English language proficiency as was done by Sweida-Metwally (2022).

Educational advantage score: This was derived from a variable measuring respondent's highest qualification. The variable consists of five values (1) degree (2) A-level etc, (3) GCSE etc, (4) Other qualifications, and (5) no qualification which were then assigned a score based on the mean male CAMSIS score for each qualification group in the population (See Appendix B3 for operationalisation). These scores were also standardised within nine 10-year birth cohorts to account for any cohort effects on the value of educational qualifications over time. A sensitivity analysis comparing the single measure and different dummy variables for each qualification category revealed identical results in terms of the sign and significance, however the magnitude of coefficients slightly changed – in most instances, slightly reducing. It was decided to go with the educational attainment score measure as this had the added benefit of being standardised by age and also improved the model fit in all but one of the models run. See Appendix A for a table displaying the educational categories and to see their assigned scores.

3.4.3. SOCIOCULTURAL FACTORS

Ties to the majority: Rather than using civic participation rate as a proxy for interethnic ties (Sweida-Metwally, 2022), the UKHLS has questions about the ethnicity of a respondent's closest friends. Every respondent who reported having either a first, second, or third 'best friend' with a majority ethnic background (White British) were coded as 1. People who only reported friends from ethnic minority groups were coded 0. This approach is influenced by Koopmans' (2016) measures of host-country friendships. Ideally, as Koopmans (2016) suggests, these controls should have been continuous measures of the number of majority friends that respondents reported having. However, the friendship measure used here was derived from three questions, each asking about one friend at a time in the first, second, and third position, rather than frequency of friends. While it was possible to sum the total number of friends, it was decided to dichotomise the variable into 'has majority friend' or 'no friend' by amalgamating all three variables. This simplified the analysis and ensured consistency across the other socio-cultural measures which were also dichotomised.

Liberal gender attitudes: Similar to Sweida-Metwally (2022), an opinion question on gender and the workplace was used to derive a measure of liberal gender attitudes. Those who strongly disagreed or disagreed with the statement: ‘the husband should earn wife should stay at home’ were coded 1, everyone else was coded 0.

Low Religiosity: Connor and Koeing (2015) use three distinct measures of religiosity in their study on Muslims in western labour markets. For efficiency, in this study, a composite variable was derived using information from three similar variables that asked about different elements of religious activity. The internal consistency of these variables was confirmed with a Cronbach’s alpha score of 0.85 suggesting each of the variables measure the same concept. The variables and their values include:

- Frequency of prayer: 1 = a great difference, 2 = some difference, 3 = a little difference, 4 = no difference.
- Attendance at religious services: were 1 = once a week, 2 = at least once a month, 3 = at least once a year, 4 = (practically) never, 5 = only at weddings, funerals etc.
- Importance of religion (religion makes a difference to life): 1 = a great difference, 2 = some difference, 3 = a little difference, 4 = no difference.

After the variables were combined into one measure, all of respondents who reported high frequency of prayer/attendance and higher importance were coded as 0 where everyone else was coded at 1 suggesting they had lower religiosity. The composite multi-item scale was reduced to a dichotomy to be consistent with the format of other socio-cultural variables. In the subsequent analysis chapters, any deviations from the operationalisation described thus far will be noted. Each chapter will provide a detailed description of the specific sample and methodology employed for the respective analyses.

4. MUSLIM PENALTIES IN THE LABOUR MARKET

4.1. Introduction

This chapter contributes to the literature on the economic position of Muslims in Britain by using pooled UKHLS data from 2009 to 2022 to offer contemporary insights into labour market participation, unemployment, earnings, and access to material and social resources. It addresses the first research question by comparing the labour market outcomes of Muslim ethno-religious groups with those of the majority group, using a multicategory framework that accounts for the intersection of ethnicity, religion, and migrant generation—an approach established by Johnston et al. (2010) and Longhi et al. (2013). By estimating separate models for men and women, the analysis incorporates four-way interactions that capture the compounding effects of gendered and ethno-religious identities.

To address the second research question, the chapter introduces controls for individual-level circumstances and human capital (such as education, age, and region), assessing whether labour market disadvantages remain once these are taken into account. The third research question is explored by including additional controls for sociocultural variables, including language proficiency and friendship networks. In doing so, the analysis builds on and extends recent work by Sweida-Metwally (2022), which challenges claims—such as those made by Koopmans (2016)—that cultural and religious factors explain away Muslim disadvantage. Ultimately, this chapter aims to evaluate whether persistent disparities can be attributed to structural discrimination, thereby setting the stage for the subsequent analysis of new migration impacts in Chapter 6.

4.2. Sample

In the unweighted pooled dataset, a total of 76263 respondents (aged 16 and above) provided data, contributing to 397915 observations across all 12 waves. When weighted,

this corresponds to 67,471 adults contributing 368962 weighted observations. While some data from the UKHLS household grid file ('indall') and the household file ('hhresp'), including information about children and non-respondents, have been linked to the main respondents, analysis will only focus on full interview responses as these include detailed information on labour market outcomes.

4.3. Method

The analysis is divided into two parts. In the first part the focus is on comparing outcomes between groups within the Muslim community and the Christian White majority. Non-Muslim minority groups have intentionally been excluded from this section and this decision was driven by the challenges encountered during prior sensitivity analysis, which required fitting 28 separate controls for each ethno-group across different generations. While the original approach provided valuable insights into how religious affiliation and ethnicity interact in determining overall outcomes, it also complicated interpretation due to having so many parameters. As the primary objective of this chapter is to explore the labour market disadvantage experienced by Muslims in comparison to the majority, it was decided to just focus on Muslims in the first stage of analysis. For command files for all of the analysis, see [ch4a1_desc_models_hunter24.do](#) available at the [online repository](#).

In the second part, subsequent analysis directly compares outcomes by removing the Christian White majority from the analysis and changing the reference categories to Muslim groups. The intention here is to explore whether Muslims experience worse outcomes than their non-Muslim ethnic minority counterparts (see [ch4a2_ethnic_focus_hunter24.do](#) available at the [online repository](#)).

Descriptive techniques are employed to first examine the overall disadvantage experienced by the Muslim community and in Britain. This includes an analysis of various socio-demographic variables and how they are distributed among different ethno-religious groups, by generation. Cross tabulations and tables of means comparing the relationship between ethno-religious identity and explanatory variables and several outcomes of interest are then presented.

While looking at gross differentials between distinct ethno-religious groups can provide a valuable overview, ignoring the influence of variables that may explain some of the variation in the outcome will lead to unreliable results. For example, it is expected that the number of hours worked by individuals will heavily influence their income and people with high levels of education will have access to higher occupational groups. The next stage of analysis will, therefore, employ modelling techniques to explore any remaining disadvantage experienced by different Muslim groups in comparison to the majority (Christian/agnostic White British), once human capital and other important covariates have been controlled for. Further models will then be run accounting for any ‘socio-cultural’ differences between ethno-religious groups.

To examine this net disadvantage, cluster robust linear and logistic models (Gayle and Lambert, 2018) will be used to model outcomes. Models with robust standard errors account for the clustering of observations around individuals across waves. Separate models will be run for men and women as this is commonly done in the literature to account for the differing impact that gender has on economic outcomes, especially for Muslim groups (Sweida-Metwally 2022). Models exploring employment, occupational advantage and average earnings are limited to only those who are currently participating in the labour market. To account for potential selection bias, the predicted probabilities for men and women participating, once controlling for other factors, are fit as explanatory variables in the corresponding models. This procedure is a slight variation of a full selection model, which typically involves a two-step process to correct for selection bias (though it is likely to lead to the same conclusions) (Robins et al., 2001). Sensitivity analysis shows that while controlling for selection slightly changes the magnitude of coefficients, broadly the same findings (sign and significance) appear, suggesting a weak selection bias in models that ignore selection processes.

Models also include interactions between the Muslim ethno/generational groups and three core variables: education score, health and low religiosity. Muslim groups, particularly Bangladeshi, have an increased risk of poor health compared with the majority population (Chouhan and Nazroo, 2020) and more first-generation Muslim groups in the UKHLS tended to report having a health concern in comparison to the second generation. Moreover, it is commonly argued that ethnic minorities typically receive lower returns for their educational achievements in comparison to majority groups (Heath and Cheung, 2012), and this may differ by generation. For example, the

qualifications held by first generation groups that were not obtained in the UK may not be respected/recognised by employers and hinder participation efforts. For these reasons, models were fit (omitted from outputs) including interaction terms which represent all of the possible interaction between these variables and different Muslim sub-groups. Significant interaction terms were then carried over into the final models and displayed in the outputs.

The second part of this analysis extends the above analysis by refitting similar models but on sub-samples of different ethnic groups. The intention here is to attempt separating out ethnic and religious penalties to test whether Muslim respondents fare better or worse to their ethnic counterparts with different religions, and thus exploring whether they experience a double penalty on account of their ethnicity *and* religion (Khattab and Modood, 2015; Heath and Martin, 2013, Cheung, 2014). For example, each model is run again but only for Indian, Black Caribbean and Black African, and Pakistani and Bangladeshi respondents. White Christian British are removed from the analysis and respective Muslim groups are used as reference categories. Comparisons can thus be made between members of the same ethnic group from different religious backgrounds and their Muslim counterparts in order to determine whether Islam in addition to ethnicity has an overall effect.

4.4. Findings

4.4.1. BIVARIATE RESULTS

Among women, Graph 4-1a shows that Muslims are significantly less likely to be participating in the labour market compared to all other groups - Men tend to perform better here, outranking Sikh and Buddhists, but still having a lower proportion of participating than their Christian/no religion counterparts. The highest gender gap among religious groups in terms of participation exists between Muslim men and women - with a difference of 30% between them. Figure 4-1b shows that over 30% of Muslim women said they were not participating in the labour market due to looking after family or home responsibilities – significantly more than any other group. This was a more common reason than being a student, having an illness or disability, or citing other reasons. Retired people are excluded from this analysis due to the age range of the sample. Hardly any

men were inactive due to home or family care. Of those who are actively looking for work (Figure 4-1c), again Muslim women had the lowest proportion of those in employment. Muslim men had a slightly higher proportion rate, but one that is still significantly lower than their male Christian/no religion counterparts.

Among those in employment, Muslim men are the most under-represented group in top professions (as per Figure 4-1d). However, while there was a significant difference between male Christians/no religion and Muslims, confidence intervals of the Buddhist and Other groups overlap suggesting these groups could be the most under represented. Figure 4-1e shows that although Muslim men have significantly lower average CAMSIS score compared to Christian/no religion, there is ambiguity whether they have the lowest mean score overall due to overlapping uncertainty with Sikhs, Buddhists, and the other groups. There is more ambiguity with the average CAMSIS score for female Muslims - this might not be different from Christian/no religious equivalents. It is clear, however, that Jewish women appear to outrank all other groups in this regard. Finally, Figure 4-1f shows that Muslim men earn less on average compared to the Christian/non-religious, Hindu, Jewish, Buddhist and other groups - however there is no statistical difference in earnings between them and Sikhs. For women, the picture is less clear – Muslim women only show a statistically significant earnings gap when compared to Jewish women, who earn more. Overall, this analysis partly supports existing empirical literature (Reynolds and Birdwell, 2015), demonstrating that Muslim men and women tend to fare worse in labour market outcomes compared to their Christian and non-religious counterparts – especially when it comes to female participation and employment. Moreover, it confirms that Muslim women are far more likely than any other religious group in the UK to not participate in the labour market due to family or home care than any other group (Reynolds and Birdwell, 2015). While this analysis serves as a valuable starting point, it also underscores the necessity for analytical methods that explore how different intersections shape these observations. The subsequent analysis of Muslim outcomes is therefore aggregated by generation and ethnicity.

4.4.1.1. Sociodemographic characteristics

Proportions for the socio-demographic variables used in the analysis are reported in Table 4-1. These statistics reveal notable differences in the demographic composition of Muslim groups (separated by generation) compared to the majority Christian White British. Minority groups that are statistically different to the majority are denoted with an emboldened star. Among the first-generation, Pakistani participants exhibit an equal gender distribution whereas Indians and Bangladeshis have a higher proportion of men and Other and Black groups have more women. For second generation participants the gender distributions are more balanced across all groups. White Muslim Brits in the sample are predominately men. The prevalence of males amongst first-generation migrants might reflect typical migration strategies that involve sending a young male to work and remit funds home before settling down and getting married.

First generation South-Asian groups all have a similar mean age to the majority, with Black and Others being younger. As expected, the average age of second-generation groups is lower with Bangladeshi the youngest. White Muslim Brits are slightly younger than their Christian counterparts.

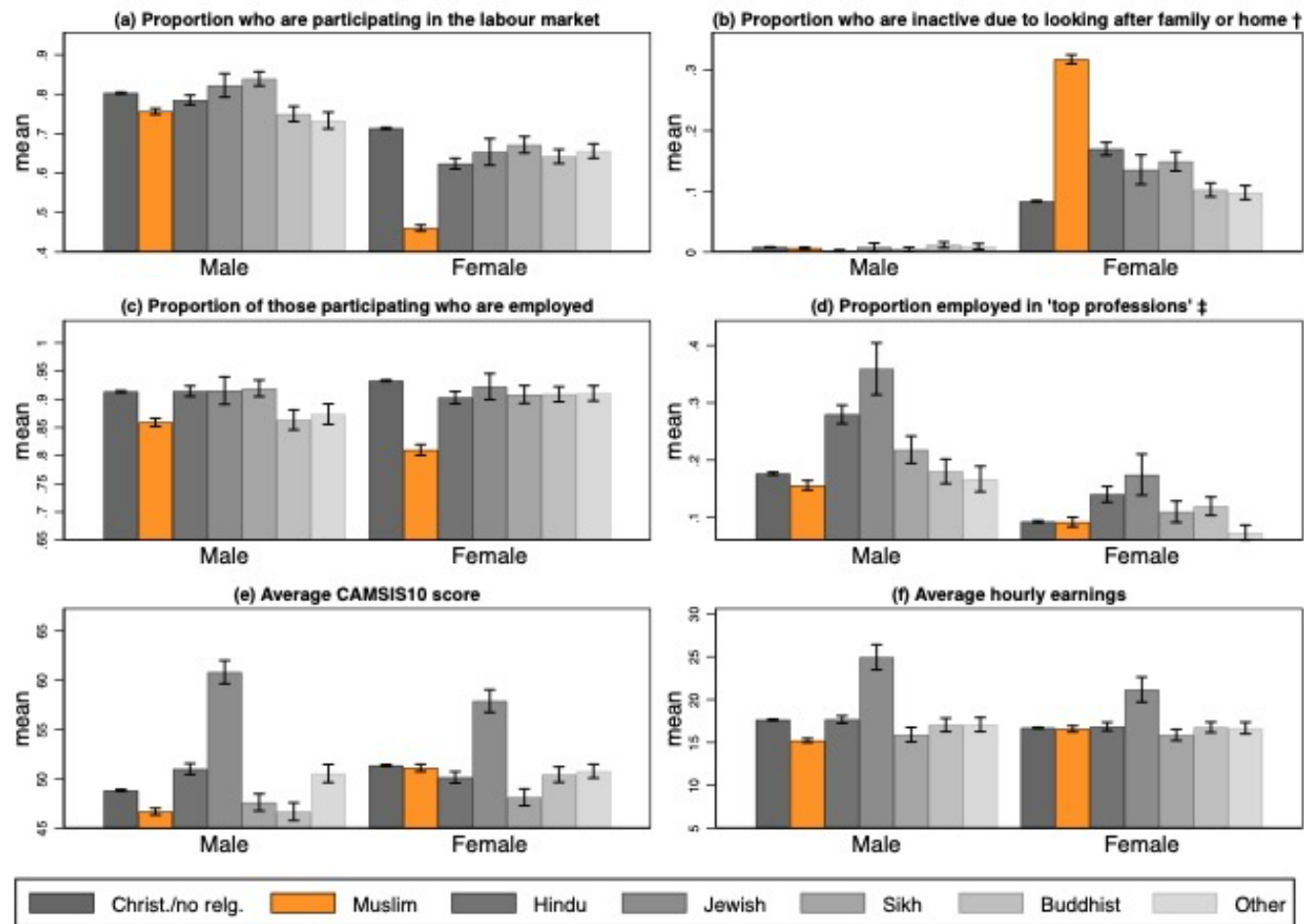


Figure 4-1 Labour market profiles of the biggest religious groups in the UKHLS sample.

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied and errors bars with 95% confidence intervals presented. † Remaining proportion includes students, long term ill or disability, and other. ‡ Top professions includes 1.1 'large employers and higher management' and 1.2 'higher professional' of the NS-SEC scheme.

All first-generation groups, apart from Black, exhibit higher proportions of legally married individuals than the majority. Second-generation Pakistani and Other Muslims have higher married proportions compared to Bangladeshi. The legal marriage rate for second-generation Indians and White Muslim Brits is not statistically different to that of the majority population. With the exception of White Muslim British and second-generation Bangladeshi, each group exhibits a higher mean number of children compared to the majority. This is especially pronounced for first-generation Pakistani and Bangladeshi. The lower marriage rates of the second generation groups might be influenced by factors such as cultural adaptation, socio-economic changes, and evolving demographic patterns among succeeding generations.

Notably, all Muslim groups report fewer long-standing physical or mental impairments, illnesses, or disabilities ('health concerns'). While this pattern aligns with the lower age profiles of the second-generation, it is important to note that for groups with similar mean ages (such as first-generation South Asians), the reporting of fewer concerns may not be attributed to age differences in this instance. This finding is surprising, given that literature often indicates that South Asian groups are more likely to report worse health than the majority, an association which is often attributed to social and economic inequalities and discrimination (Chouhan and Nazroo, 2020). These findings might result from the specific wording of the questions of the analytical variable, however sensitivity analysis of different health conditions revealed similar outcomes - in most cases the White majority would fare worse even when controlling for age.¹⁸ In this context the 'health concerns' variable is a convenient measure as it was available for every wave and provides a parsimonious summary. White Muslim Brits and all first-generation groups, except for Pakistani, had fewer caring responsibilities than the majority. However, the proportions were higher for second-generation Pakistani and Bangladeshi individuals. There was no statistical difference between second-generation Indians and the majority.

¹⁸ Using the pooled sample described above and linked health data from waves 1, 3-12 of the UKHLS, I conducted multiple linear regressions for 16 different health conditions (such as diabetes, asthma, cancer, etc.). These regressions compared parameters between ethno-religious minority groups and the Christian White British population, adjusting for age ([sa3_health_outcomes_hunter24.log](#))

Table 4-1 Sociodemographic Characteristics by Selected Ethno-Religious Groups

	Female	Age	Legally Married	No. of Children under 16†	Health Concern	Caring responsibilities	Total
	Pro.	Mean	Pro.	Mean	Pro.	Pro.	N
British Ancestry							
Christian White	0.51	42	0.47	0.26	0.31	0.18	268,875
Muslim White British	0.43*	37*	0.44	0.30	0.23*	0.11*	828
First generation.							
Muslim Indian	0.46*	42	0.80*	0.36*	0.21*	0.12*	612
Muslim Pakistani	0.50	41*	0.77*	0.59*	0.25*	0.18	2,385
Muslim Bangladeshi	0.46*	40*	0.80*	0.58*	0.26*	0.15*	1,153
Muslim Black	0.57*	36*	0.47	0.77*	0.17*	0.12*	848
Muslim Other	0.55	34*	0.56*	0.43*	0.16*	0.08*	774
Second generation							
Muslim Indian	0.44*	29*	0.47	0.43*	0.15*	0.17	504
Muslim Pakistani	0.52	28*	0.41*	0.40*	0.15*	0.20*	2,221
Muslim Bangladeshi	0.51	25*	0.25*	0.19*	0.13*	0.21*	838
Muslim Other	0.49	30*	0.38*	0.33*	0.16*	0.12*	960
Total	0.51	41	0.48	0.27	0.30	0.18	279,997

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. *indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals) † Variable comprises four values 0 = none, 1 = one, 2 = two, 3 = three or more.

Pro = proportion.

4.4.1.2. Government office regions

Weighted distributions of each group across the four most Muslim populated regions in the UK in addition to the rest of England and other nations are reported in Table 4-2. All groups have notably larger proportions of people residing in London compared to the majority. First-generation Bangladeshi and Black and second-generation Bangladeshi have the highest shares and are predominately concentrated in this region. A larger proportion of Pakistanis from both generations and second-generation Indians reside in the Yorkshire and the Humber and the North West. There also appears to be a larger proportion of second-generation Pakistanis in the West Midlands.

Table 4-2 Regional breakdown of ethno-religious groups

	London	Yorkshire and the Humber	North West	West Midlands	Rest of England	Scotland, Wales. & N.Ireland	Total
	Proportion						N
British Ancestry							
Christian White	0.07	0.09	0.12	0.09	0.47	0.17	268,875
Muslim White	0.19*	0.10	0.14	0.08*	0.25*	0.25*	828
British First generation							
Muslim Indian	0.43*	0.07*	0.17*	0.06*	0.23*	0.04*	612
Muslim Pakistani	0.25*	0.18*	0.18*	0.16*	0.19*	0.04*	2,385
Muslim Bangladeshi	0.66*	0.04*	0.05*	0.09	0.15*	0.01*	1,153
Muslim Black	0.62*	0.06*	0.07*	0.05*	0.17*	0.03*	848
Muslim Other	0.50*	0.06*	0.07*	0.02*	0.21*	0.14	774
British Second generation							
Muslim Indian	0.35*	0.22*	0.22*	0.10	0.12*	0.00*	504
Muslim Pakistani	0.17*	0.21*	0.18*	0.22*	0.18*	0.04*	2,221
Muslim Bangladeshi	0.63*	0.05*	0.04*	0.13*	0.14*	0.01*	838
Muslim Other	0.53*	0.08	0.07*	0.04*	0.23*	0.04*	960
Total	0.08	0.09	0.12	0.08	0.45	0.16	279,997

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. * indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals).

All Muslim groups appear to be more evenly dispersed throughout the rest of England, but still have lower proportions than Christian White British overall. There are low proportions of all Muslim groups in Scotland, Wales and Northern Ireland. Overall, Bangladeshis tend to live in London whereas the other Muslim groups are more spread around across the regions

4.4.1.3. Human capital

Table 4-3 shows the distribution of highest qualification held by Muslim groups and their relative education score. A higher proportion of Indians, Pakistanis and Muslim Others from both generations held more degrees than the majority. Apart from second-generation Pakistani, all groups held less ‘other higher’ qualifications compared to their Christian White counterparts. Among first-generation groups, all held fewer A levels

except for Muslim Others, who were not statistically different from the majority. However, a higher proportion of second-generation Pakistani and Bangladeshi individuals held A levels (or equivalent). As expected, all first-generation groups (bar Indian and Other) held more ‘other quals’, arguably due to their overseas qualifications most likely not being classified within the British system. The proportions for second generation groups were much smaller. Among first-generation groups, a significant proportion had no qualifications. Specifically, Pakistani individuals had more than three times the majority proportion, and Bangladeshi individuals had even higher rates. Second-generation tended to fare better when it came to having no qualifications with low proportions. Overall, educational attainment is diverse, with some Muslim groups achieving impressive qualifications, while others share higher rates of lower education.

Each group’s education score¹⁹ can provide an overview: Among all the groups, only first-generation Indians have a higher average score compared to the majority. Both first- and second-generation Bangladeshi have the lowest scores amongst their generational counterparts. Nearly all second-generation groups demonstrate high proficiency in English which is understandable because they were born and brought up in the UK. However, among some first-generation groups (specifically Pakistani and Bangladeshi), only two-thirds are proficient. Other first-generation groups have higher proportions, although none reach the proficiency levels of the second generation.

4.4.1.4. Labour market participation and other socio-economic variables

Labour market participation proportions of each Muslim group by generation and gender are given in table 4-4. Among males, more Muslims with British ancestry, first-generation Indians and Bangladeshi were participating compared to the majority - all other groups apart from first generation Pakistani (no significant difference) had smaller proportions, with second-generation Bangladeshi and Others having the lowest. Overall, for men, there seems to be a significant generational gap. Specifically, the first generation exhibits greater participation compared to the second generation. For

¹⁹ which is the average CAMSIS score for each group standardised by 10-year birth cohorts

instance, approximately a quarter of second-generation Indians do not participate, in contrast to the first generation.

Table 4-3 Educational attainment, education score, and English language proficiency across ethno-religious groups

	Degree	Other Higher	A level etc	GCSE etc	Other quals	No quals	Education score	English prof.	Total
	Pro.	Pro.	Pro.	Pro.	Pro.	Pro.	Mean	Pro.	N
British Ancestry									
Christian White	0.25	0.12	0.25	0.24	0.08	0.07	48.5	100	268,875
Muslim White British	0.24	0.11	0.26	0.26	0.04*	0.10*	47.9*	0.94*	828
First generation									
Muslim Indian	0.37*	0.1	0.15*	0.13*	0.09	0.15*	49.7*	0.79*	612
Muslim Pakistani	0.31*	0.06*	0.13*	0.16*	0.11*	0.23*	47.5*	0.68*	2,385
Muslim Bangladeshi	0.25	0.06*	0.15*	0.17*	0.10*	0.28*	46.4*	0.63*	1,153
Muslim Black	0.23	0.13	0.21*	0.16*	0.11*	0.15*	47.2*	0.82*	848
Muslim Other	0.33*	0.09*	0.24	0.17*	0.08	0.1	48.5	0.78*	774
Second generation									
Muslim Indian	0.30*	0.11	0.25	0.29*	0.01*	0.05	47.9	0.99*	504
Muslim Pakistani	0.28*	0.10*	0.29*	0.26*	0.03*	0.05*	47.5*	0.96*	2,221
Muslim Bangladeshi	0.25	0.04*	0.39*	0.27*	0.02*	0.03*	46.1*	0.96*	838
Muslim Other	0.44*	0.05*	0.27	0.15*	0.03*	0.06	49.6*	0.91*	960
Total	0.25	0.12	0.25	0.24	0.08	0.07	48.46	0.99	279,997

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied.

* indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals).

All of the participation rates are lower for women, with both first- and second-generation Indians having the highest rates within their generational groups. Notably, first-generation Pakistani and Bangladeshi women had substantially lower proportions - about two-fifths less than the majority. Things seem to improve for the second-generation, but there remains a gap of about one-fifth between them and the majority. There is no statistical difference between White Muslims and Christians. Hardly any men reported not participating in the labour market due to caring for the home or family whereas all female ethno-religious groups had significantly higher proportions of this in comparison

to the majority. Strikingly, over half of the first-generation Pakistani and Bangladeshi women said they were not in the labour market due to family or home care. Tables 4-5 and 4-6 report on more labour market outcomes for men and women.²⁰ For men participating, there is no statistical difference in employment rates between first-generation Indian and Pakistani and the majority. However, the remaining groups have lower proportions of employed. Second-generation Pakistani, Bangladeshi and Other tend to fare worse than with lower employment rates than the majority. All male groups

Table 4-4 Labour market participation and reason for not participating by ethno-religious group and gender.

	Men		Women		Total	
	Participating	Reason for not participating = home or family care	Participating	Reason for not participating = home or family care	Participating	Reason for not participating = home or family care
	Pro.	Pro.	Pro.	Pro.	Pro.	Pro.
British Ancestry						
Christian White British	0.80	0.01	0.71	0.08	0.75	0.05
Muslim White British	0.85*	0.01	0.69	0.14*	0.79*	0.06
First generation						
Muslim Indian	0.90*	0*	0.50*	0.36*	0.72	0.17*
Muslim Pakistani	0.82	0.01	0.34*	0.54*	0.58*	0.27*
Muslim Bangladeshi	0.84*	0.02*	0.36*	0.56*	0.62*	0.26*
Muslim Black	0.74*	0.01	0.51*	0.28*	0.61*	0.16*
Muslim Other	0.71*	0	0.45*	0.26*	0.57*	0.15*
Second generation						
Muslim Indian	0.69*	0*	0.59*	0.22*	0.64*	0.09*
Muslim Pakistani	0.70*	0*	0.50*	0.20*	0.60*	0.11*
Muslim Bangladeshi	0.63*	0.01	0.57*	0.11*	0.60*	0.06*
Muslim Other	0.61*	0.01	0.44*	0.23*	0.53*	0.12*
Total	0.80	0.01	0.7	0.09	0.75	0.05

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied.

* indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals).

(limited to those with jobs) have higher proportions than the majority of working part time - especially first generation Bangladeshi and Black exhibit an approx. 25% higher

²⁰ Apart from average earnings, there are no statical differences of labour market outcomes between Muslim White British and Christian White British men.

part-time orientation rate. Apart from second-generation Bangladeshi, some groups are more likely to work in the private sector than the majority - however statistical differences are minimal (see table 4-6). Looking at average CAMSIS, both first- and second-generation Indian and second-generation Others outperform the majority. The higher average CAMSIS of these second-generation groups contrast notably lower average scores of the first generation suggesting generational progress has been made. Both generations of Indian men were more likely than the Christian/no religion majority to be occupied in top positions. First-generation Pakistani men were underrepresented with only 13% compared to 17% for the majority. Second-generation Muslim others had a notably high proportion occupied in top positions, although this is most likely due to small sample size associated with this group. First generation Indian, Black, Other, and second-generation Bangladeshi women were underrepresented in top positions compared to the majority. Muslim Pakistani women and Muslim Other, however, had a higher proportion of people in top positions. There are no differences between Indian and majority earnings, however, both generation Pakistani and Bangladeshi earn significantly less on average than majority.

Apart from first-generation Indians, female employment rates are lower for all generational groups in comparison to the majority. Apart from Others, all second-generation groups out-perform their first-generation equivalents. More Indian women are employed across both generational groups. Proportions of part-time working are higher for first-generation Bangladeshi women, however there are no statistical differences for the other groups. While more second-generation Indian women are in part-time work than the majority, the opposite is true for Pakistani and Bangladeshi (but proportions are still relatively high). Overall, more women than men work in the public sector. However, similar to male patterns, most groups have lower proportions than the majority – the difference is not significant for first generation Indians.

Table 4-5 Labour Market outcomes for men participating in the labour market by ethno-religious group.

	Employed	Part Time	Public Sector	CAMSIS	Employed in 'top positions'	Weekly work hours	Average hourly earnings
	Pro.	Pro.	Pro.	Mean	Pro.	Mean	Mean
British Ancestry							
Christian White British	0.91	0.08	0.18	48.75	0.17	37.73	17.55
Muslim White British	0.87	0.13	0.16	44.72*	0.08*	36.26	15.82*
First generation							
Muslim Indian	0.94*	0.13*	0.11*	48.83*	0.25*	35.56*	17.23
Muslim Pakistani	0.92	0.16*	0.09*	43.99*	0.13*	35.53*	12.92*
Muslim Bangladeshi	0.81*	0.26*	0.13*	43.99*	0.11	31.29*	14.97*
Muslim Black	0.81*	0.21*	0.16	44.38*	0.13	34.07*	18.63
Muslim Other	0.85	0.14*	0.13	44.46*	0.14	36.07	16.18
Second generation							
Muslim Indian	0.91	0.09	0.21	54.01*	0.25*	36.08*	17.9
Muslim Pakistani	0.84*	0.13*	0.18	49.17	0.18	35.44*	14.56*
Muslim Bangladeshi	0.85*	0.16*	0.23*	48.61	0.14	33.32*	14.39*
Muslim Other	0.75*	0.13*	0.22	54.59*	0.30*	36.46	19.25*
Total	0.91	0.09	0.18	48.68	0.17	37.63	17.47
Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. Data limited to only those participating in the labour market.							
* indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals).							

There are minimal statistical differences in CAMSIS scores between first-generation groups and the majority, apart from Blacks having a lower proportion. Second-generation Indian, Other and Pakistani do, however, outperform their majority equivalents with higher average scores. Most groups work on average less hours, but it appears that first-generation Bangladeshi and Black earn on average more than the majority. Second-generation Pakistani and Bangladeshi women are noticeably paid less.

Table 4-6 Labour Market outcomes for women participating in the labour market by ethno-religious group.

	Employed	Part Time	Public Sector	CAMSIS	Employed in 'top positions'	Weekly work hours	Average hourly earnings
	Pro.	Pro.	Pro.	Mean	Pro.	Mean	Mean
British Ancestry							
Christian White British	0.93	0.34	0.37	51.28	0.09	29.51	16.51
Muslim White British	0.94	0.44*	0.38	50.27	0.08	27.08*	16.09
First generation							
Muslim Indian	0.89*	0.35	0.31*	50.18	0.04*	29.3	15.22
Muslim Pakistani	0.74*	0.36	0.25*	50.99	0.14*	26.22*	15.95
Muslim Bangladeshi	0.77*	0.43*	0.30	50.55	0.11	24.47*	18.46*
Muslim Black	0.74*	0.36	0.16*	44.13*	0.06*	27.77*	19.45*
Muslim Other	0.83*	0.33	0.15*	47.88*	0.01*	28.23	18.41
Second generation							
Muslim Indian	0.87*	0.41*	0.33	54.32*	0.08	27.18*	15.78*
Muslim Pakistani	0.80*	0.27*	0.30*	52.79*	0.08	29.39	15.17*
Muslim Bangladeshi	0.84*	0.26*	0.35*	51.02	0.06*	29.75	13.69*
Muslim Other	0.80*	0.31	0.29*	58.2*	0.30*	29.04	20.77*
Total	0.93	0.34	0.37	51.28	0.09	29.48	16.51
Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied.							
* indicates significant differences between Muslim minority groups and Christian White British (non-overlapping 95% confidence intervals).							
Pro = proportion.							

4.4.1.5. Socio-cultural factors

Table 4-7 includes group proportions across different socio-cultural analytical variables by gender. All of the proportions were statistically different to that of majority population. Understandably, Muslim men and women with British ancestry had the highest proportions of close ties to the majority. Proportions among the first-generation were the lowest. Proportions for the second-generation groups were higher as anticipated as these groups have had chances to develop networks with majority population through education and growing up in the country. Men either had marginally higher or similar proportions of close ties compared to women in each group.

British ancestry and second-generation groups had the highest proportions of liberal gender values. Specifically, second-generation Indian men and women demonstrate the highest proportions, suggesting that they are more similar to the majority in terms of liberal attitudes than other groups. With the exception of Muslim Other, all first-generation groups have lower proportions of liberal gender attitudes. In every instance, women held more positive views than men, except for White British Muslims and first-generation Muslim Other (marginal difference).

Low religiosity serves as another measure of how similar these groups are to the majority population. When religiosity is low, it often indicates a more open-minded or acculturated perspective. Muslims with British Ancestry exhibit the highest proportion of low religiosity. Across all second-generation groups, there are higher proportions of low religiosity, and this suggests alignment of this group with broader societal trends. Interestingly, despite their more liberal gender views and similarities in demographic and economic outcomes with the majority population, Indian men and women have the lowest proportion of low religiosity among their generational peers and respective genders. Except for Muslim Other, all first-generation groups have lower proportions of low religiosity. This further underscores generational shifts and the younger cohort's alignment. While all proportions remain below the majority population levels, it is essential to recognise that these groups, on average, still have more religiosity in comparison to Christian White British.

Table 4-7 Socio-cultural variables by gender and ethno-religious group

	Close ties to the majority			Liberal gender values			Low Religiosity			Total
	M Pro.	F Pro.	Tot. Pro.	M Pro.	F Pro.	Tot. Pro.	M Pro.	F Pro.	Tot. Pro.	Tot. N
British Ancestry										
Christian White	0.83	0.87	0.85	0.90	0.91	0.91	0.93	0.90	0.91	252834
Muslim White British	0.57	0.63	0.6	0.83	0.78	0.81	0.67	0.58	0.63	892
First generation										
Muslim Indian	0.12	0.06	0.09	0.58	0.67	0.62	0.12	0.11	0.11	1455
Muslim Pakistani	0.00	0.07	0.03	0.46	0.55	0.50	0.13	0.12	0.13	6271
Muslim Bangladeshi	0.11	0.07	0.09	0.59	0.62	0.60	0.15	0.17	0.16	4498
Muslim Black	0.08	0.08	0.08	0.63	0.64	0.63	0.19	0.16	0.17	1899
Muslim Other	0.12	0.11	0.12	0.72	0.71	0.72	0.39	0.35	0.37	1040
Second generation										
Muslim Indian	0.23	0.16	0.20	0.83	0.86	0.85	0.19	0.23	0.21	1228
Muslim Pakistani	0.22	0.16	0.19	0.70	0.76	0.73	0.24	0.27	0.26	5469
Muslim Bangladeshi	0.13	0.14	0.14	0.68	0.83	0.76	0.22	0.24	0.23	2795
Muslim Other	0.16	0.13	0.15	0.67	0.79	0.73	0.29	0.31	0.30	1616
Total	0.80	0.84	0.82	0.89	0.91	0.90	0.90	0.87	0.88	279997

Data source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. All results for Muslim minority groups were significantly different to the value for Christian White British for both men and women (non-overlapping 95% confidence intervals).

Pro = proportion.

4.4.1.6. Overview

The main observations from this analysis so far can be summarised as follows:

- In most instances, White Muslims with British ancestry had largely similar outcomes to Christian Whites. They were hardly any instances where this group experienced negative outcomes on the same magnitude as first- or second-generation Muslim groups.
- Across multiple domains, both first- and second-generation Indians have either similar (not statistically different) or more favourable outcomes compared to

Christian White British. These favourable outcomes are mostly seen when comparing educational attainment and labour market outcomes. When observations for both men and women are available, Indian men usually had better outcomes than female equivalents – for example, second-generation Indian men had higher average CAMSIS scores. These results also suggest that Indian respondents do better than members of other Muslim groups. Pakistani and Bangladeshi repeatedly came out as faring worse in a range of outcomes. However, it is important to view this with a caveat that the analysis only considered differences between minority groups and the majority. Thus, these differences between Muslim groups themselves may not be statistically significant and should be interpreted as descriptive observations. Overall, these findings support the claim made at the beginning of the section that good performance of Indians in these domains might be skewing the results when looking at Muslim outcomes more broadly. This is supported in the empirical literature where Indians are cited as outperforming or being similar to British groups (Khattab and Modood, 2015; Cheung, 2014).

- In most instances it could be argued that generational progress is being made between first- and second-generation groups. This observation is made based on findings about educational attainment and economic outcomes of people who are in the labour market. Second-generation groups also appear in line with the majority in terms of socio-cultural factors than the first generation.
- There are some major gender differences in outcomes within Muslim groups. Muslim women (especially first generation) were less likely to be participating in the first place. When looking at those within the labour market, more women than men tended to work part time or in the public sector. These women also had lower CAMSIS scores and less average earnings. In terms of socio-cultural factors, women had less strong ties to the majority population, but they did have higher proportions of gender liberal attitudes and second-generation women had more low religiosity.

Overall, this analysis has demonstrated why it is important to consider how ethnicity, generation - and to some extent gender - work together in shaping outcomes for Muslim groups. These observations have informed the next stage of analysis which is separated

by gender and includes analytical categories which involve ancestry and ethnicity intersections. It also improves on this analysis by controlling for other factors that might be influencing the outcomes.

4.4.2. REGRESSION RESULTS

Four models across each outcome are presented for each gender. First, a basic model that focuses solely on the impact of belonging in a Muslim group in comparison to the reference category without incorporating control variables other than the year of survey (not shown). Second, a 'Human Capital' model introduces control variables representing different social demographic characteristics and human capital variables (education and English language proficiency) - negative parameters in these models indicate members of ethno-religious groups have negative outcomes compared to the reference category. These negative coefficients imply the existence of ethno-religious penalties, indicating a disparity relative to the majority group even after accounting for socio-demographic and human capital factors (Cheung and Heath, 2007). Third, a 'Socio-Cultural' model is fit. In line with Koopman's (2016) critique of ethnic-penalty literature, the model incorporating socio-cultural factors such as ties to the host majority, low religiosity, and liberal traditional gender values aims to discern whether the remaining disadvantage, after accounting for human capital factors, should be interpreted as 'penalties.' The anticipation is that these socio-cultural factors may offer explanations for the observed disparities, challenging the straightforward classification of the remaining differences as penalties, as they could be intricately linked to diverse socio-cultural contexts rather than solely reflecting inherent disadvantages. If coefficients remain negative once socio-cultural differences are controlled for, it can be implied that certain religious groups still experience penalties despite being socially-culturally 'assimilated'. Fourth, a final model is fit which includes interaction terms between ethno-religious group and Education score, health condition and low religiosity, but only the statistically significant interactions are shown in the following outputs.

4.4.2.1. Participation in the labour market

As per the descriptive results, model 1B in table 4-8 shows that first-generation Indian and Bangladeshi men are more likely to participate in the labour market in comparison to the Christian White British reference. Conversely, all second-generation men are less likely to participate. Among women, except for Muslims with British ancestry, participation rates are lower overall. In model 2HC, controlling for English proficiency and living in some regions (apart from N.West and Rest of UK) does not significantly impact participation for men. However, proficiency does significantly increase participation for women, but region does not make a difference. Having a health concern, caring responsibilities, or any number of children significantly decreases participation for both genders. An increase in age, being married, and having a higher education score significantly increases participation. Except for White British and first-generation Indian men, belonging to any other Muslim group significantly decreases the likelihood of participation.

Model 3SC shows that having strong ties to the majority and low religiosity increases the chances of participating for both men and women, whereas liberal gender attitudes only make a difference for women. Among men, the negative effect of group membership only persists for first-generation Blacks, first- and second-generation Others, and second-generation Pakistanis. Negative parameters also persist for all Muslim women, apart from White British, first-generation Black, second-generation Indians and Bangladeshis. These negative parameters may be indicative that these groups are vulnerable to ethno-religious penalties despite being socio-culturally assimilated. A full interaction model was fit (not shown) including all interactions between the Muslim subgroups and education, health, and low religiosity. Model 4F includes only the significant interaction terms and shows that education score can boost the participation for some second-generation whereas having a health concern may decrease participation for some first-generation women and men. Low Religiosity can decrease participation for some groups across generations.

Table 4-8 Cluster robust logistic regression of labour market participation for men and women.

	Men				Women			
	1B †	2HC	3SC	4F	1B ‡	2HC	3SC	4F
British ancestry								
Christ. White (ref.)								
Muslim White British	0.59*	0.54	0.62*	0.62*	0.02	-0.1	0.12	-3.53
First generation								
Muslim Indian	0.85*	-0.12	0.25	0.26	-0.85*	-1.08*	-0.61*	-0.62*
Muslim Pakistani	0.06	-0.59*	-0.21	-1.4*	-1.43*	-1.49*	-1*	-1.02*
Muslim Bangladeshi	0.43*	-0.58*	-0.23	-0.23	-1.27*	-1.26*	-0.84*	-3.41*
Muslim Black	-0.25	-0.94*	-0.57*	2.92*	-0.78*	-0.53*	-0.05	-0.06
Muslim Other	-0.55	-1.02*	-0.75*	-0.74*	-1.24*	-1.49*	-1.13*	-1.13*
Second generation								
Muslim Indian	-0.61*	-0.58*	-0.27	-6.1*	-0.64*	-0.73*	-0.4	-0.4
Muslim Pakistani	-0.45*	-0.61*	-0.27*	-2.25*	-0.86*	-0.93*	-0.54*	-0.55*
Muslim Bangladeshi	-0.78*	-0.56*	-0.22	-6.29*	-0.51*	-0.45*	-0.09	-0.09
Muslim Other	-0.83*	-1.13*	-0.83*	-0.82*	-0.99*	-1.2*	-0.86*	-0.87*
Health concern		-1.14*	-1.14*	-1.14*		-0.92*	-0.9*	-0.91*
Caring responsibilities		-0.41*	-0.4*	-0.41*		-0.3*	-0.29*	-0.29*
Age		0.55*	0.54*	0.54*		0.47*	0.47*	0.47*
Age Squared		-0.01*	-0.01*	-0.01*		-0.01*	-0.01*	-0.01*
Marital Status		0.52*	0.53*	0.53*		0.04	0.05	0.05
No. of Children		-0.67*	-0.66*	-0.66*		-0.67*	-0.66*	-0.66*
London (ref.)								
York. & Humber		-0.22	-0.23*	-0.24*		0.06	0.02	0.02
North West		-0.32*	-0.34*	-0.35*		0.11	0.08	0.08
West Midlands		-0.09	-0.11	-0.11		0.07	0.04	0.04
Rest of England		-0.12	-0.13	-0.14		0.09	0.06	0.06
Scot., Wal., N. Ire.		-0.27*	-0.27*	-0.28*		-0.07	-0.1	-0.1
Education Score		0.03*	0.03*	0.03*		0.05*	0.05*	0.05*
English proficiency		0.14	0.07	0.04		1.01*	0.88*	0.84*
Majority ties			0.18*	0.18*			0.22*	0.22*
Liberal gender values			0.07	0.08			0.55*	0.55*
Low religiosity			0.3*	0.31*			0.24*	0.24*
Interactions								
M Indian2*Education Score				0.14*				
M Pakistani2*Education Score				0.05*				
M Bangladeshi2*Education Score				0.15*				
M Black1* Health Condition				-1.89*				
M Pakistani1* Health Condition				0.82*				
M Pakistani1*Low Religiosity				-0.91*				
M Bangladeshi2*Low Religiosity				-1.13*				
M White Brit*Education Score								0.08*
M Bangladeshi1*Education Score								0.08*
M Bangladeshi1*Health Condition								-0.61*
Intercept	1.53*	-8.61*	-8.91*	-8.86*	0.81*	-10.05*	-10.65*	-10.60*
N	112764	112764	112764	112764	142376	142376	142376	142376
Pseudo r2	0.002	0.275	0.277	0.277	0.009	0.208	0.213	0.213

*p<0.05. Source: main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Limited to only economically active participants. Weighted. Logits are presented. Coefficients for dummy variables corresponding with each wave of the survey have been omitted. 1B = Basic Model, 2HC Human Capital Model, 3SC Socio-Cultural Model, 4F, Final Model.

† a simpler model without controlling for selection propensity was run. Sign and significance of results remain consistent between this model and the basic model presented here with selection controls.

‡ a simpler model without controlling for selection propensity was run. Coefficients for all groups (apart from Muslim White British) were negative and statistically significant in the model.

4.4.2.1. Avoidance of unemployment

The dependent variable used across these models include the value of 1 = those who are employed (full or part time) and 0 = unemployed but looking for work. Positive coefficients suggest higher chances of avoiding unemployment. The selection probability of participating in the labour market has been included here (and in all subsequent models) as controls. Positive coefficients suggest that the characteristics that are associated with participating in the labour market are also associated with avoiding unemployment.

Model 1B in Table 4-9 shows that controlling for selection propensity does not make a difference to the likelihood of male groups avoiding unemployment, but it does for some female groups. For example, as per the descriptive analysis, all female groups apart from Muslim White British were less likely to be employed than the majority - once controlling for participation selection propensity, being first- or second-generation Indian or first-generation Other makes no difference. Similarly to the participation models, model 2HC shows that most of the independent variables reduce chances of avoiding unemployment for both men and women. Moreover, while being married and having more education increases the chances of both genders avoiding unemployment, age and language proficiency is only significant for men. Notably, more children actually increase the chances of avoiding unemployment for women, perhaps suggesting the necessity of finding work to support family costs.

Model 3SC shows that ties to the majority and liberal gender views increases chances of avoiding unemployment for both men and women, whereas low religiosity has no effect. Negative coefficients persist for some groups suggesting that they are still disadvantaged even if they have favourable social-cultural characteristics similar to the majority. Namely, and in line with descriptive findings, there is no statistical difference between any of the Indian groups and the majority. Model 4F shows that interactions between low-religiosity and increases likelihood of employment for some groups despite not making a difference overall (as per model 3SC). For some first-generation women, more education actually has a negative effect on employment, but a positive one for second-generation Indians.

Table 4-9 Cluster robust logistic regression of avoidance of unemployment for men and women participating in the labour market.

Men					Women			
	1B †	2HC	3SC	4F	1B ‡	2HC	3SC	4F
British ancestry								
Christ. White (ref.)								
Muslim White								
British	-0.44	-0.01	0.1	-0.58	0.54	0.59	0.71	0.7
First generation								
Muslim Indian	0.11	-0.31	-0.02	-0.04	-0.25	-0.17	-0.35	2.9*
Muslim Pakistani	0.06	-0.35	-0.03	-0.04	-0.89*	-0.73*	-1.18*	1.49
Muslim								
Bangladeshi	-1.03*	-1.32*	-1.04*	-1.06*	-0.65*	-0.57	-0.91*	-0.88*
Muslim Black	-0.88*	-1.44*	-1.17*	-0.94*	-1.23*	-0.88*	-0.82*	2.45
Muslim Other	-0.47	-1.13*	-0.92	-0.94	-0.61	-0.29	-0.85	-0.84
Second generation								
Muslim Indian	0.24	0.17	0.27	0.25	-0.41	-0.39	-0.58	-4.44*
Muslim Pakistani	-0.57*	-0.78*	-0.57*	-2.06*	-0.89*	-0.71*	-0.88*	-1.07*
Muslim								
Bangladeshi	-0.36	-0.2	0.03	0.02	-0.78*	-0.39*	-0.38	-0.4*
Muslim Other	-0.97*	-1.72*	-1.54*	-1.55*	-0.85*	-0.48	-0.82*	-0.83*
Selection effect (m)	2.92*	-0.16	-0.64	-0.65				
Selection effect (f)					3.09*	3.94*	1.19*	1.26*
Health concern		-0.83*	-0.9*	-0.9*		-0.13	-0.55*	-0.55*
Caring responsibility		-0.44*	-0.47*	-0.47*		-0.1	-0.24*	-0.23*
Age		0.11*	0.14*	0.14*		-0.29*	-0.05	-0.06
Age Squared		0*	0*	0*		0*	0	0
Marital Status		1.26*	1.29*	1.29*		0.94*	0.96*	0.96*
No. of Children		-0.33*	-0.36*	-0.36*		0.29*	-0.02	-0.01
London (ref.)								
York. & Humber		-0.19	-0.21	-0.22		0.18	0.18	0.18
North West		-0.11	-0.16	-0.17		0.11	0.13	0.12
West Midlands		0.01	-0.02	-0.02		0.12	0.14	0.13
Rest of England		0.2	0.16	0.16		0.37*	0.39*	0.38*
Scot., Wal., N. Ire.		-0.05	-0.09	-0.09		0.22	0.15	0.14
Education Score		0.08*	0.08*	0.08*		0.07*	0.09*	0.09*
English proficiency		0.49*	0.38	0.37		-0.38	0.1	0.27
Majority ties			0.35*	0.35*			0.27*	0.26*
Liberal gender val.			0.36*	0.36*			0.68*	0.67*
Low religiosity			-0.06	-0.07			-0.04	-0.07
Interactions								
M White Brit*Low Religiosity.				1.28				
M Black1*Low Religiosity.				-1.47*				
M Pakistani2*Health Condition				0.83*				
M Black1*Education score								-0.07*
M Pakistani1*Education score								-0.06*
M Indian2*Education score								0.08*
M Indian1*Health Condition								-1.81*
M Pakistani2*Low Religiosity								0.78*
Intercept	-0.16	-4.08*	-4.55*	-4.52*	0.41*	1.007	-3.05*	-3.15*
N	91200	91200	91200	91200	99116	99116	99116	99116
Pseudo r2	0.051	0.141	0.144	0.145	0.063	0.144	0.148	0.149

Source, symbols and variable definitions as per Table 4.9. Logits presented. † a simpler model without controlling for selection propensity was run. Sign and significance of results remain consistent between this model and the basic model presented here with selection controls. a simpler model without controlling for selection propensity was run. Coefficients for all groups (apart from Muslim White British) were negative and statistically significant in the model.

4.4.2.1. CAMSIS

The dependent variable used across outcomes is continuous, a higher score would indicate better access to social and material resources based on your position in the social structure. Characteristics that are associated with participating in the labour market does increase the CAMSIS scores for men and women in the first two models (see table 4-10). Shown in model 2HC, men with health concerns and caring responsibilities have less CAMSIS than the majority, whereas age has a positive effect. Moreover, being married, having more education and being proficient in English increases CAMSIS for both genders. Having children makes no difference to anyone and living in any region compared to London decreases CAMSIS score across the board. Model 3SC shows that strong ties and liberal gender values increases CAMSIS whereas low religiosity decreases it for both men and women. After controlling for socio-cultural factors negative parameters remain for all first-generation Muslim men, suggesting they still experience disadvantage despite having favourable social-cultural outcomes. The same is true for only first-generation Black and Muslim Other women. These findings are in line with the descriptive statistics which suggest generational progress has been made and children of first generation are better off than their parents. Interactions in model 4F show that education score interacted with ethno-religious identity can reduce CAMSIS for some women and men across groups, whereas low religiosity can boost it for some.

Table 4-10 Cluster robust linear regression of CAMSIS for men and women participating in the labour market.

	Men				Women			
	1B †	2HC	3SC	4F	1B ‡	2HC	3SC	4F
British ancestry								
Christ. White (ref.)								
Muslim White								
British	-5.55*	-2.19	-2.38	17.79	-0.98	-2.38	-2.56	34.2*
First generation								
Muslim Indian	-1.39	-3.97*	-4.52*	-4.48*	2.29	-0.6	-1.53	-1.46
Muslim Pakistani	-3.76*	-4.52*	-4.88*	12.89*	4.84*	0.41	-0.53	33.09*
Muslim								
Bangladeshi	-4.65*	-4.94*	-5.48*	22.07*	3.36*	-2.92	-3.8*	18.05*
Muslim Black	-2.67	-8.79*	-9.46*	-9.59*	-3.34*	-4.78*	-5.61*	13.96
Muslim Other	-3.85	-8.7*	-8.59*	-8.4*	2.8	-3.94*	-4.61*	-4.54*
Second generation								
Muslim Indian	5.65*	1.11	0.06	-0.95	5.13*	1.13	0.28	0.27
Muslim Pakistani	0.76	-1.6	-2.16*	-4.07*	4.44*	0.13	-0.48	10.81
Muslim								
Bangladeshi	0.74	-1.45	-2.01	-2.1	0.82	-1.28	-2.1	24.63*
Muslim Other	8.41*	-0.88	-1.37	-1.49	9.97*	3.42	2.82	2.84
Selection effect (m)	18.69*	-3.42*	-3.11	-3.19				
Selection effect (f)					22.81*	3.34*	1.48	1.98
Health concern		-1.08*	-1.07*	-1.09*		-0.39	-0.67*	-0.61
Caring responsibility		-0.83*	-0.88*	-0.88*		-0.34	-0.47*	-0.44*
Age		0.37*	0.35*	0.35*		-0.04	0.11	0.07
Age Squared		-0.01*	0.00*	-0.01*		0.00	0.00	0.00
Marital Status		2.06*	1.95*	1.94*		2.05*	2*	1.99*
No. of Children		0.3	0.33	0.35		-0.11	-0.3	-0.25
London (ref.)								
York. & Humber		-3.71*	-3.66*	-3.65*		-3.23*	-3.24*	-3.27*
North West		-3.52*	-3.56*	-3.56*		-2.58*	-2.64*	-2.66*
West Midlands		-3.33*	-3.33*	-3.34*		-2.18*	-2.21*	-2.22*
Rest of England		-3.04*	-3.08*	-3.07*		-2.31*	-2.33*	-2.35*
Scot., Wal., N. Ire.		-4.35*	-4.42*	-4.43*		-3.43*	-3.55*	-3.56*
Education Score		1.07*	1.05*	1.06*		0.9*	0.9*	0.9*
English proficiency		8.58*	8.4*	9.81*		5.97*	6.1*	6.49*
Majority ties			1.21*	1.2*			0.73*	0.64*
Liberal gender values			1.63*	1.65*			1.69*	1.65*
Low religiosity			-2.48*	-2.63*			-1.78*	-1.77*
Interactions								
M White Brit*Education score				-0.43*				-0.72*
M Pakistani1*Education score				-0.35*				-0.41*
M Bangladeshi1*Education score				-0.59*				-0.47*
M Bangladeshi1*Low Religiosity				9.75*				10.33*
M Indian2*Low Religiosity.				6.48*				
M Pakistani2*Low Religiosity				7.44*				
M Black1*Education score								-0.41*
M Pakistani2*Education score								-0.22
M Bangladeshi2*Education score								-0.54*
M Pakistani1*Health condition								-7.15*
Intercept	32.5*	-13.47*	-12.16*	-13.75*	33.57*	1.13	-0.37	-0.56
N	83380	83380	83380	83380	90364	90364	90364	90364
r2	0.039	0.323	0.327	0.328	0.082	0.291	0.293	0.294

Source, symbols and variable definitions as per Table 4.9. Linear regression coefficients presented.

† a simpler model without controlling for selection propensity was run. Sign and significance of results remain consistent between this model and the basic model presented here with selection controls. ‡ a simpler model without controlling for selection propensity was run. Sign and significance remain for Muslim Black and second-gen Muslim Other but goes from negative to positive and non-significant to significant for first-generation Pakistani, Muslim other and second-generation Indian, Pakistani and Muslim Other.

4.4.2.2. Average Hourly Earnings

The dependent variable used in these analyses is continuous, a higher score would indicate more average hourly earnings. Table 4-11 shows similarly to other models that participation selection characteristics associated with participation does not make much of a difference for men, where as it slightly changes things for women. However, the inclusion of public sector and part-time work orientation also explains away some of the earning differentials – both increasing average earnings for men and women. Similar to the CAMSIS analysis, anyone living in any region apart from London earns less and higher age or education increases average hourly pay. For men especially, the number of children they have increases their earnings and the positive effect of English proficiency is only relevant for men. None of the social cultural controls introduced in model 3SC make a difference for men, but liberal gender values held by women does have a positive effect. After controlling for all these factors, some Muslim groups remain to earn less than the majority. These negative associations are pronounced among the first-generation, again showing while some second-generation groups still experience disadvantage, they have made progress in comparison to the generation before them. Above and beyond the additional effects, interactions between education and ethnic identity can reduce earnings for some people, but low religiosity can boost how much some women earn.

Table 4-11 Cluster robust linear regression of hourly average earnings for men and women participating in the labour market.

	Men				Women			
	1B †	2HC	3SC	4F	1B ‡	2HC	3SC	4F
Public sector	2.82*	0.43*	0.43*	0.43*	2.39*	0.49*	0.48*	0.48*
Works part time	7.34*	7.23*	7.23*	7.21*	3.95*	3.4*	3.44*	3.44*
British Ancestry								
Christ. White (ref.)								
Muslim White								
British	-2.43	-0.07	0.11	0.19	-0.41	-1.05	-0.73	10.02
First Generation								
Muslim Indian	-1.21	-3.85*	-3.39*	-3.24*	-1.41	-4.81*	-4.81*	-4.78*
Muslim								
Pakistani	-4.56*	-6.58*	-6.12*	10.05*	0.47	-4.74*	-5.03*	8.02
Muslim								
Bangladeshi	-4.54*	-7.19*	-6.79*	9.02*	2.58	-4.01*	-4.28*	-4.2*
Muslim Black	0.46	-4.04	-3.59	-3.56	3.26*	-1.56	-1.26	25.87*
Muslim Other	-1.56	-5.87*	-5.51*	-5.32*	3.76*	-2.23	-2.63	-2.61
Second Generation								
Muslim Indian	-0.19	-2.28	-1.89	12.66	0.08	-2.99*	-3.09*	-4.05*
Muslim								
Pakistani	-3.24*	-3.85*	-3.47*	4.39	-0.35	-2.78*	-2.78*	-3.89*
Muslim								
Bangladeshi	-3.68*	-3.94*	-3.54*	13.3*	-2.48*	-2.51*	-2.33*	-2.95
Muslim Other	2.41	-2.23	-1.86	-1.85	5.29*	0.05	-0.19	-0.2
Selection effect (m)	12.77*	-5.08*	-5.44*	-5.45*				
Selection effect (f)					7.47*	-12.08*	-15.55*	-15.4*
Health concern		-1.53*	-1.57*	-1.57*		-2.2*	-2.65*	-2.62*
Caring responsibility		-0.77*	-0.78*	-0.77*		-0.1	-0.24	-0.23
Age		0.82*	0.84*	0.84*		1.13*	1.4*	1.38*
Age Squared		-0.01*	-0.01*	-0.01*		-0.01*	-0.02*	-0.02*
Marital Status		3.32*	3.34*	3.33*		-1.05*	-1.02*	-1.02*
No. of Children		1.28*	1.27*	1.26*		0.78*	0.47*	0.48*
London (ref.)								
York & Humber		-4.39*	-4.43*	-4.45*		-3.77*	-3.8*	-3.81*
North West		-4.11*	-4.16*	-4.2*		-3.65*	-3.66*	-3.67*
West Midlands		-3.2*	-3.23*	-3.26*		-3.26*	-3.27*	-3.28*
Rest of England		-3.23*	-3.26*	-3.28*		-2.94*	-2.95*	-2.96*
Scot., Wal., N. Ire.		-4.73*	-4.76*	-4.79*		-3.84*	-3.93*	-3.93*
Education Score		0.54*	0.54*	0.54*		0.54*	0.56*	0.56*
English proficiency		2.66*	2.57*	3.54*		2.45	2.88*	3.68*
Majority ties			0.42*	0.42*			0.34	0.29
Liberal gender val.			0.05	0.06			1.62*	1.62*
Low religiosity			0.18	0.23			0.03	-0.01
Interactions								
M Pakistani1*Education score				-0.32*				-0.26*
M Bangladeshi1*Education score				-0.31*				
M Indian2*Education score				-0.28*				
M Pakistani2*Education score				-0.16*				
M Bangladeshi2*Education score				-0.35*				-0.19*
M White Brit*Education score								-0.21
M Black1*Education score								-0.56*
M Bangladeshi2*Health Condition								5.23*
M Indian2*Low Religiosity								3.69*
M Pakistani2*Low Religiosity								3.65*
Intercept	3.79*	-25.20*	-25.64*	-26.95*	6.62*	-26.23*	-31.14*	-31.87*
N	75942		75942		86686		86686	
r2	0.06	0.245	0.245	0.246	0.053	0.180	0.181	0.181

Source, symbols and variable definitions as per Table 4.9. Linear regression coefficients presented.

† a simpler model without controlling for selection propensity was run. Sign and significance of results remain consistent between this model and the basic model presented here with selection controls. ‡ a

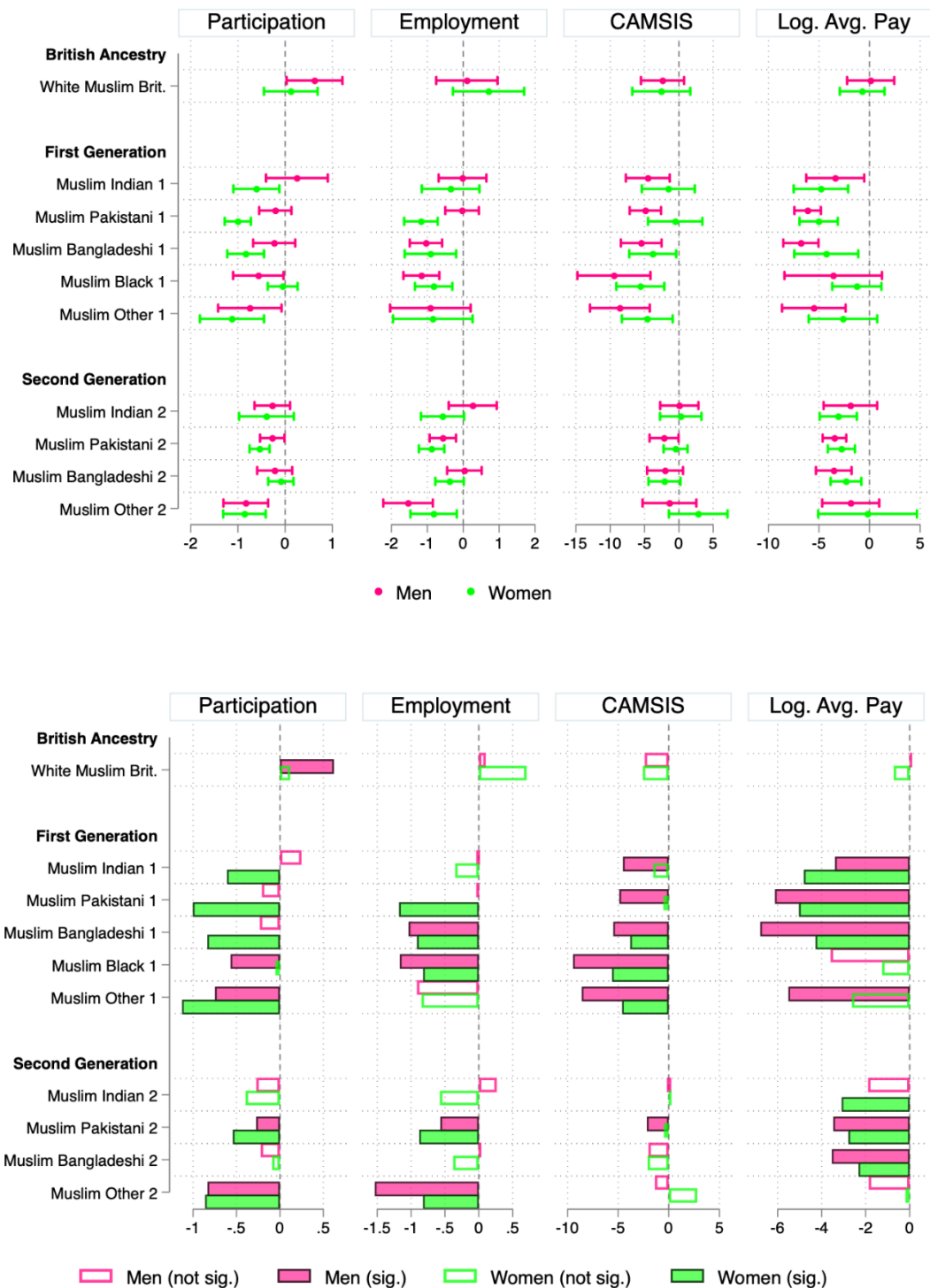


Figure 4-2 Summary coefficient plots showing regression results for the socio-cultural models for each outcome.

Note Graphs 4a and 4b provide different visualisations of the same data (UKHLS 2009-19). In (4a), point estimates with whiskers that overlap 0 are not-significant. Point estimates below 0 suggest negative outcomes, whereas the opposite is true for those over zero. In (4b), hollow bars represent non-significant results. Bars moving below 0 suggest negative outcomes, whereas the opposite is true for those moving above 0.

4.4.3. MUSLIM PENALTIES

Comparisons so far have been limited to comparing outcomes between the majority group and different generational ethnic groups within the Muslim community. While these findings show that minority ethnicity and faith identities – in addition to gender and generation – go together in shaping Muslim outcomes, they do not provide evidence for whether one may be more influential than the other. For example, recent attempts to disentangle the influence of ethnicity and religion on labour market outcomes has been made (Clark and Drinkwater, 2009). Cheung (2014), however, notes that analysis of this nature is difficult when exploring the disadvantage experienced by Muslims mostly due to the fact there is little religious variation with ethnic groups mostly associated with Islam – that is, most Pakistani and Bangladeshi are Muslim. While attempts have been made to try and tackle this ‘identification problem’²¹, sufficient data on religion and ethnicity and detailed labour market information is rare to come by (Cheung, 2014, p 142).

The pooled UKHLS provides a unique opportunity to try and explore to what extent religion may influence negative outcomes within distinct ethnic communities in the UK. The following analysis will expand the regression findings above but shift the focus from the Christian White majority as the reference category to comparing outcomes between different religious groups within minority ethnic communities. A similar sequence of models will be run with the same parameters and all the control variables included in the ‘socio-cultural’ models (model 3SC) for each outcome. Models will be limited to specific ethnic groups only (Indian, Black, and a combination of Pakistani and Bangladeshi to boost sample size) and Muslim groups are selected as reference categories. The intention here is explore whether other religious groups have better or worse outcomes in comparison to Muslims, whilst continuing to explore the influence of gender and generation and all other relevant covariates that might drive outcomes. If members of the same ethnic groups from different religious communities have favourable outcomes it may provide evidence of Muslim penalties in the labour market.

²¹ Using the APS 2005 – 2006, Heath and Martin (2013) look at how ethnicity and religion overlap in and only run analysis on groups on groups in which religion and ethnicity do not coincide. They find that ethnic penalties for Muslim groups is mostly shaped by religion over ethnicity.

Table 4-12 Better or worse outcomes compared to second-generation Muslim Indians after controlling for human capital and socio-cultural factors

	Participation		Employment		CAMSIS		Earnings	
								
First Generation								
Muslim Indian	×	×	×	×	×	×	×	×
Hindu Indian	−	×	×	+	−	×	×	×
Sikh Indian	×	×	+	×	−	−	−	+
Christian Indian	×	×	×	×	−	×	−	×
Other Indian	−	+	×	×	×	×	×	×
Second Generation								
Hindu Indian	×	×	×	×	×	×	×	×
Sikh Indian	×	×	×	×	−	×	−	×
Christian Indian	−	×	×	×	−	×	×	×
Other Indian	×	×	×	×	−	×	×	×

× = No significant difference, − = Perform worse on average + = Perform better on average.

Note: Based on multiple cluster-robust regressions (logistic and linear) modelling each outcome with a subset of Indian respondents aged between 16 and 65. All controls included in human capital and socio-cultural factors are included here but not shown in the output. Rather than comparing outcomes between all Muslim groups and Christian White British, this analysis compares other ethno-religious groups within the Indian community with Second-generation Muslim Indians. Source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. Significance threshold increased to 0.10.

Table 4-12 summarises results for Indians from regressions run for each outcome across both genders. The reference category here is second-generation Muslim Indians, chosen because previous descriptive and regression analyses suggest that this group tended to do better in comparison to others. Overall, some Indian men and women from different religious backgrounds tended to do worse than their Muslim equivalents across a range of outcomes, net of controls. For example, nearly all Indian men from other religious groups had lower scores than second-generation Muslim men. There were some examples, however, of non-Muslim Indians performing better – first-generation Sikh men and Hindu women had a higher likelihood of being employed than the Muslim reference groups. Indian women from ‘other’ religions were more likely to participate, and Sikh women earned more – possibly suggesting a Muslim penalty in this regard.

These results are somewhat surprising compared to expectations and suggest no significant first/second-generation difference for Muslims. This could indicate that the controls are important factors here, as they might be capturing key elements that

influence these outcomes. The findings highlight the complexity of the interactions between gender, religion, and generational status, and underscore the importance of considering these controls to fully understand the disparities.

It should be noted that due to the reduction in sample size, the significance threshold has shifted from 0.05 to 0.10 – this was deemed appropriate due to the exploratory nature of the analysis and is something that conventionally done in quantitative studies exploring multiple intersections (Spierings, 2023) and has been done in studies looking at inequalities experience by ethnic minorities in the UKHLS (Knies et al., 2016).

Table 4-13 shows similar results but for Black Caribbean and Black Africans with first-generation Muslim Black (mostly of African descent) as the reference category. There were a lot more positive associations here suggesting that Black people from different religious backgrounds have favourable outcomes compared to Black Muslims. Most women across both generations had a higher likelihood of employment and first-generation Caribbean Christian men tended to perform better in both employment and participation. Conversely, some Black women from other faith backgrounds earned less than their Muslim counterparts.

Summary statistics for Pakistani and Bangladeshi results are reported in Table 4-14 in which second-generation Pakistani and Bangladeshis are used as reference categories in each model. Notably, there was less religious diversity within this ethnic grouping. In particular, a moderate percentage of Pakistanis and Bangladeshis reported being Hindu, and even smaller proportion identified as Christian. While the identification problem (Cheung, 2014) mentioned above comes into focus here, it was decided to run analysis anyway to see if any differences could be found.

There were largely no statistical differences between non-Muslim Pakistani and Bangladeshi people and second-generation Muslims. However, both first- and second-generation Christian men did have more higher CAMSIS and both first-generation Hindu men and women reported less earnings, which might be illustrative of generational progress. However, with that being said, some first-generation Muslim Pakistani and Bangladeshi men had more favourable outcomes than the second generation.

Overall, this analysis has attempted to compare outcomes between people of different faiths within ethnic groups whilst controlling for other factors that can influence certain

Table 4-13 Better or worse outcomes compared to first-generation Muslim Black after controlling for human capital and socio-cultural factors

	Participation		Employment		CAMSIS		Earnings	
								
First Generation								
Christian	+	+	+	+	×	×	×	-
Caribbean								
Christian African	×	+	×	+	×	×	×	-
Caribbean Other	+	+	+	+	×	×	-	×
African Other	-	×	×	+	×	×	×	-
Second Generation								
Christian	×	+	×	+	+	×	×	×
Caribbean								
Christian African	×	×	×	+	×	×	×	×
Caribbean other	×	×	×	×	×	×	×	-
African Other	+	×	×	+	×	×	-	×

× = No significant difference, - = Perform worse on average, + = Perform better on average.

Note: Based on multiple cluster-robust regressions (logistic and linear) modelling each outcome with a subset of Black respondents aged between 16 and 65 only. All controls included in human capital and socio-cultural factors are included here but not shown in the output. Rather than comparing outcomes between all Muslim groups and Christian White British, this analysis compares other ethno-religious groups within the Black community with Second-generation Muslim Black. Source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. Due to low sample size, significance threshold increased to 0.10.

outcomes. The headline story is that most of the differences between groups and the Muslim reference categories were not significant, therefore making it hard to identify whether Muslim penalties existed or not. There are some instances where Muslims actually perform better than their non-Muslim equivalents, which suggests religion might not necessarily be the most influential factor and little evidence for Muslim penalties. On the contrary, however, it was found that most non-Muslim Black women were more likely to be employed – perhaps suggesting the unique intersections of gender, ancestry, Islamic faith and Black (most likely African) ethnic identity can result in more disadvantage than either factor alone when considering this outcome. This finding could suggest that specific attention should be paid to this group in order to help outcomes.

However, it is important to acknowledge the issue of endogenous selection.²² While this analysis shows that comparing like with like within groups does not reveal a clear penalty, if selection into control categories is linked to religion, then comparing like with like may not be entirely appropriate. Recognising these complexities highlights the need for careful interpretation of the results and suggests that further research is necessary to fully understand the interplay between religion, selection processes, and outcomes.

Table 4-14 Better or worse outcomes compared to second-generation Muslim Pakistani and Bangladeshi after controlling for human capital and socio-cultural factors.

	Participation		Employment		CAMSIS		Earnings	
								
First Generation								
Muslim P&B	+	×	×	×	×	×	+	×
Hindu P&B	×	×	×	×	×	×	-	-
Christian P&B	-	×	×	×	+	×	×	×
Second Generation								
Hindu P&B	×	×	-	×	+	×	×	×
Christian P&B	×	×	×	×	+	×	×	×

× = No significant difference, - = Perform worse on average, + = Perform better on average.

Note: Based on multiple cluster-robust regressions (logistic and linear) modelling each outcome with a subset of Pakistani and Bangladeshi respondents aged between 16 and 65 only. All controls included in human capital and socio-cultural factors are included here but not shown in the output. Rather than comparing outcomes between all Muslim groups and Christian White British, this analysis compares other ethno-religious groups within the Black community with Second-generation Muslim Black. Source: observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Weights applied. Due to low sample size, significance threshold increased to 0.10.

4.5. Discussion and conclusions

Drawing from recent developments in ethnic penalty literature, the key finding from the above analysis is that compared to the Christian White British majority, members of the Muslim community in the UK experience disadvantage across a range of labour market outcomes, even after controlling for their human capital and socio-cultural assimilation

²² Endogenous selection occurs when the factors that determine who is included in a sample are correlated with the factors that affect the outcome being studied. This correlation can lead to biased estimates because the sample is not representative of the population.

(see figure 4-2 for a summary of each socio-cultural model across all four outcomes). These outcomes are also experienced differently based on different intersecting identities that members of the community hold – including gender, ethnicity, and ancestry.

Focusing on Indian participants – which were identified in the descriptive analysis as usually outperforming or having similar outcomes to the majority - regression analysis revealed that once controlling for human capital and socio-cultural factors, some members of this group fared worse than the majority. For instance, first-generation Muslim Indian women were less likely to participate, and both Indian men and women tended to earn less – although this was not the case for second-generation Indian men. Although some groups were found to have unfavourable outcomes compared to the majority, it should be noted that second-generation seemed to fare better than first generation. An example of this is most prominent when considering that all first-generation men had less CAMSIS whereas there was no difference between their second-generation equivalents and the majority. Generational progress may be being made (Cheung, 2014) but this finding should not overshadow the fact that, in comparison to the majority, many second generational ethno-religious penalties persist. Finally, In line with the bivariate analysis (section 4.4.1), there were barely any statistical differences between British White Muslim participants and their Christian counterparts – perhaps suggesting they do not experience the same inequalities as other Muslims from ethnic minority backgrounds and providing further evidence the benefits of being White British offset the negative effects of the ethno-religious penalty associated with being Muslim (Swedia-Metwally, 2022; Modood, 2015).

This analysis contributes to existing ethnic penalty research by demonstrating that disadvantages persist even after controlling for socio-cultural factors. Using a large, pooled dataset with appropriate adjustments for clustering, the analysis provides robust insights. By integrating two common approaches to operationalising ethno-religious groups and incorporating migration status (Johnston et al., 2010; Longhi et al., 2013), it offers a more nuanced understanding of the intersection of ancestry, ethnicity and religion. Overall, it supports existing literature by showing that, compared to other ethnic and religious groups, Muslims generally face disadvantages and challenges in various labour market outcomes, with a few exceptions.

If Muslims are already in a vulnerable position, could this be worsened by the arrival of White Christian contemporary migrants who might receive more favourable treatment and have access to better opportunities that displace Muslims from the labour market? This question is assessed in Chapter 6, but before doing so, Chapter 5 confronts the challenge of conducting intersectional research in this area. Results above explore the intersection of ethnicity, ancestry, gender, and religion in detail, but there are further social categories such as age, marital status, health and education that might be accounted for. Appropriately integrating every intersectional inequality is a challenging statistical task, but recent literatures point to new opportunities which are investigated in Chapter 5.

5. ANALYSING INTERSECTIONALITY IN MUSLIM PENALTIES

5.1. Introduction

Analyses in the previous chapter sought to reflect how different dimensions of identity — gender, ethnicity, generational status, and religious affiliation — interlock to shape the labour market inequalities experienced by Muslims in comparison to the majority population. This was done by creating analytical categories that represent combinations of these identity dimensions, split by gender, and estimated using a single-level approach. These groupings are analogous to fitting main effects and interaction terms for all combinations of social identities (Evans et al., 2018). For instance, the analysis effectively captured three-way interactions between ethnicity, religion, and generational status, further stratified by gender. This approach enhanced conventional models by simplifying the interpretation of multiple interacting identities through group-level effects, rather than requiring the reader to interpret numerous complex interaction terms.

However, while the previous chapter yielded valuable insights, it also faced important limitations that restrict the scalability and inclusiveness of the analysis. The large number of models and parameters led to necessary trade-offs — most notably, focusing on comparisons between Muslims and the majority population at the expense of comparisons with other minority groups. Moreover, single-level models are often criticised for their limited scalability in intersectional research. As the number of categories and interactions grows, they struggle to capture the hierarchical, relational, and context-dependent nature of social positions like ethnicity, religion, and country of birth.

To address these challenges, this chapter explores a multilevel approach to intersectional modelling known as Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) (Evans et al., 2018; Jones et al., 2016; Merlo, 2018; Silva and Evans, 2020). MAIHDA treats individuals as nested within ‘intersectional strata’ — that is, analytically defined groups representing specific constellations of identity positions. These strata are conceptualised as structurally embedded social locations rather than

tangible environments, and multilevel models are used to estimate both group-level disadvantage and within-group heterogeneity. This approach is particularly well-suited to exploring Muslim labour market inequalities, as it overcomes several limitations of single-level models, including difficulties with sparse data, overfitting, and interpretability.

By applying MAIHDA, this chapter contributes to the broader aim of promoting methodological and applied knowledge on using quantitative intersectional methods to investigate Muslim disadvantage. Specifically, it engages with the following research questions: (4) How useful are intersectional strata for exploring Muslim labour market disadvantage? and (5) To what extent do complex interactions of gender, ethnicity, religious affiliation, and country of birth contribute to explaining inequalities in the labour market? The chapter proceeds by introducing the theoretical foundations of MAIHDA, followed by a detailed empirical application — closely following Evans et al.'s (2024a) tutorial — to evaluate Muslim labour market outcomes within an intersectional, multilevel framework.

5.1.1. INTERSECTIONALITY'S COMPATIBILITY WITH QUANTITATIVE METHODS

As outlined earlier, McCall (2005) identifies three primary approaches to operationalising intersectionality in empirical research: *anti-categorical*, *intra-categorical*, and *inter-categorical*. While anti-categorical approaches are critical of fixed social categories and intra-categorical approaches focus in-depth on single, often marginalised groups, it is the *inter-categorical* approach that has been most influential in quantitative studies — particularly within the ethnic penalty literature. This tradition involves comparing multiple analytically constructed social groups to explore how systems of advantage and disadvantage intersect across categories such as ethnicity, religion, gender, and migration background.

The ethnic penalty literature, which has grown since the late 1990s, exemplifies this inter-categorical tradition. Enabled by the increasing inclusion of detailed ethnicity variables in large-scale survey datasets, this body of work has investigated disparities in employment outcomes between ethnic minority and majority populations, often while accounting for factors like education, language proficiency, and place of birth. More recently, as discussed, this literature has evolved to consider multiple intersecting

dimensions of identity — for instance, ethnicity, religion, and generational status — as interlocking categories that shape labour market outcomes.

Building on this foundation, the preceding sections have highlighted the diverse circumstances of Muslims, which vary significantly based on ethnicity, religious affiliation, and country of birth. Insights from theoretical concepts of intersectionality are therefore likely to be beneficial in understanding how occupying different positions of advantage and disadvantage shape individual experiences across different Muslim groups. The objective here is to explore these intersectional experiences. This research draws from emerging literature on how best to use statistical techniques to do so. This literature is marked by ongoing methodological discussion, including how to operationalise variables to best represent intersectional identities (Rahouni, 2014) and which statistical frameworks are most appropriate for capturing these dynamics (McCall, 2005). Despite lingering perceptions that intersectionality is incompatible with quantitative methods, often stemming from ‘conceptual confusion’ and ‘practical barriers’ (Spierings, 2023, p. 1), there is now a growing body of work demonstrating how quantitative approaches can, when carefully applied, contribute meaningfully to intersectional analysis. This section therefore briefly summarises how quantitative methods can be used appropriately to explore intersectional experiences.

Misunderstandings about the incompatibility of intersectionality with quantitative methods have often stemmed from concerns over the use of fixed, predefined categories of analysis (Scott, 2010; Spierings, 2012), alongside practical challenges such as small sample sizes and the difficulty of modelling complex, overlapping identities. These challenges have historically led some researchers to favour qualitative methods, which allow for greater flexibility in capturing nuanced, lived experiences (Gross et al., 2016). However, this research argues that quantitative methods are not only compatible with intersectionality, but are in fact inherently linked to its core aims — particularly within fields such as ethnic penalty research.

The ethnic penalty literature exemplifies how intersectionality and quantitative methods can be productively combined. First, ethnicity is a conceptually complex and multifaceted social category that resists simplistic classification. Intersectionality offers a theoretical lens through which to unpack this complexity, by examining how ethnicity interacts with other dimensions of identity — such as religion, gender, and country of

birth — to shape differential outcomes. Second, the statistical approaches commonly used in ethnic penalty studies are themselves inherently intersectional. They often involve examining how multiple social positions combine to influence labour market outcomes, either through interaction terms or by analysing grouped identities (e.g. ethnicity × religion × migration background). Over time, as large-scale survey data resources have become more detailed and sophisticated, so too have the analytical techniques employed. Recent studies increasingly incorporate gendered analyses, generational differences among migrants, and religious variation (e.g. Connor and Koenig, 2015), reflecting a growing interest in how systems of oppression and advantage intersect.

In this context, the idea that intersectionality is incompatible with quantitative methods becomes increasingly untenable. Rather than being at odds, quantitative intersectional approaches have become essential for understanding how structural inequalities are patterned across populations. While the uptake of such methods may have been slowed by conceptual uncertainty and the limited availability of applied guidance (Spierings, 2023), recent contributions — including those by Rahouni (2014) and Spierings (2023) — have started to address these gaps. The current research draws from this emerging body of work to develop an approach that applies quantitative techniques to explore intersectional labour market disadvantage among Muslims in Britain.

5.1.2. APPLICATIONS OF METHODS FOR INTERSECTIONALITY

Comparing two well-known approaches to quantitative research and ‘fixed effects’ regression can enhance our understanding of applying these methods to intersectional analysis. To effectively explore inter-categorical experiences, it is essential to move beyond simply adding the effects of variables on an outcome. Instead, methods should be designed to account for how these variables interact with each other.

5.1.2.1. The additive approach

This approach assumes that characteristics such as age, ethnicity, religion, and sex each have independent, additive effects on outcomes. For instance, consider a young Muslim man who is Pakistani and was born in the UK. The relationship between his likelihood of employment and his social identity would be analysed by considering the separate contributions of his age, religious affiliation, sex, and ethnicity. An additive understanding of inequalities may sometimes be empirically appropriate, but it is often plausible that circumstances intersect and interact in non-additive ways, which should be allowed for in any description (Rahouni, 2014)

5.1.2.2. The multiplicative approach

This approach includes fitting two-way and three-way (or more) interaction terms of demographic categories are used to account for the conditional effects of intersecting inequalities on a social outcome (Bauer, 2014; Dubrow, 2013). This method allows researchers to explore how different combinations of social identities influence outcomes. For example, the relationship between various demographic factors and a social outcome can be expressed through multiple regression analyses, where interaction terms capture the combined effects of these intersecting categories. This approach provides a more nuanced understanding of how overlapping identities shape experiences and outcomes (Rahouni, 2014). Multiplicative analysis can also include fitting a single model with a full set of dummy variables (one representing each possible combination of social identity e.g. Bangladeshi Muslim born abroad). This is the approach originally taken by Johnston et al., (2010) and used by Longhi et al., (2013). Evans et al., (2018) note that each approach is mathematically equivalent, but researchers tend to refer to the latter in their examples (see Merlo, 2018; Alvarez et al., 2022). Both of these are considered ‘fixed effects’ approaches (Evan’s et al., 2018).

5.1.2.3. Criticisms of the conventional multiplicative approaches

While fixed effects approaches are widely employed for intercategorical analysis (Khattab and Modood, 2015) they have been criticised for their methodological limitations and for not fully meeting essential theoretical assumptions within an intersectional framework (Evans et al., 2018). For example, saturating models with interaction terms becomes cumbersome – there is a limit to how many different intersections between variables can be fit before models become unmanageable and unreadable (Evans et al., 2024a). Concerns also exist about the small sample sizes that some interactions or analytical categories that represent different groups (Johnston et al., 2010) and the uncertainty around their estimates.

On theoretical grounds, the focus of interaction terms in fixed effect approaches allows only for study of the ‘intersectionality of marginalisation’ and overlooks those who have multiple privileges and a mix of disadvantages and advantages who are treated as having no observable interaction effect. This focus could also reinforce the social dominance of privileged groups (Evans et al., 2018, Merlo, 2018). Put otherwise, interaction analysis on inequalities typically involves comparison with ‘multiply-privileged’ reference categories. For example, fitting an interaction term for Pakistani women treats White men as the default which conceptually reifies their privileged position (Alvarez and Evans, 2021). While some solutions, like changing reference categories and conducting additional analyses addresses these issues, it would be desirable to simultaneously consider all possible combinations of identities in a singular model. This approach could reveal any additional effects resulting from the interplay of these interconnected identities, beyond what would be expected from the individual effects alone (Evans et al., 2018).

5.1.2.4. Multilevel approach to modelling intersectionality.

Evans et al., (2018, 2024) offers an alternative method to conducting intersectional analysis through the use of multilevel models the: MAIHDA approach (Evans, 2018; Jones et al., 2016; Merlo, 2018, Silva and Evans, 2020). While MAIHDA has mostly

been used in epidemiology to explore health outcomes (Evans et al., 2018; Bell et al., 2024) it has been adopted in other fields as an effective approach to quantifying intersectional inequalities in a range of outcomes (see Evans et al., 2024a for commentary on MAIHDA's interdisciplinary application).

MAIHDA uses two models to analyse sociodemographic data. The first model includes a “strata” variable as random intercepts or level 2 context, while the second is a “main effects” model with fixed demographic variables. MAIHDA's advantage over single-level analysis is its ability to incorporate numerous interactions and address complexities in fixed effects approaches. It is expected, therefore, that this approach could offer a useful tool to ethnic penalty schools which are increasingly interested in accounting for the impact of different intersecting identities on an outcome.

5.1.3. APPLICATION OF MAIHDA

In summary, MAIHDA employs two models. The first model includes a “strata” variable representing various combinations of individual sociodemographic characteristics. MAIHDA's novelty lies in broadening the concept of “context” within multilevel modelling by specifying this strata variable as either random intercepts or as the level 2 context within a hierarchical framework (Wilkes and Karimi, 2024; Evans et al., 2024b). Second, a “main effects” model is estimated, adding the same demographic variables that form the strata into the fixed part of the model. These models allow researchers to assess the general importance of intersectional groupings, predict and rank mean outcomes against each other, and the overall variation between strata can be used to determine how much of the effects within these strata can be attributed to additive (fixed effects) versus intersectional (random intercepts) components (ibid, 2024).

The primary advantage of MAIHDA over single-level inter-categorical analysis lies in its ability to address the complexities associated with fixed effects approaches. Specifically, MAIHDA offers a singular, parsimonious model that allows for the incorporation of numerous interactions, including both privileged and unprivileged positions (Merlo, 2018). Moreover, the use of multilevel models means that level 2

residuals (intersectional effects) are automatically “shrunk” toward their mean which helps ensure the any reported intersectional effects are less likely to be ‘false positives’.

5.1.4. ALTERNATIVE MODELS

In addition to the single level approach discussed already, alternative models for intersectionality were considered. Sweida-Metwally (2022) followed a conventional regression-based approach to intersectional analysis by fitting terms for each ethno-religious group, effectively treating group membership as fixed effects. Although a random effects model was used, this was primarily to account for the repeated measures structure of the pooled data rather than to model group-level variation. The analysis combined 18 ethnic categories with 8 religious affiliations to construct 144 possible ethno-religious groups, with only those containing at least 100 observations retained as separate categories. The remaining smaller or unspecified groups were merged into a residual “Other” category. While this approach offered useful descriptive insight, it quickly became unwieldy due to the number of groups and was further complicated by separate models being estimated for men and women. These limitations—particularly the analytical burden of managing so many fixed terms and the difficulty in capturing the structure of intersectional disadvantage—highlighted the need for a more scalable and flexible method, ultimately supporting the adoption of MAIHDA in this study.

5.2. Sample

The following analysis uses a subset of the pooled UKHLS sample used in the previous chapter covering the time period 2009-2022 (see section 3.2 for details). As multi-level models are being used, the sample is limited to one observation per participant²³ across the 12 waves of the UKHLS as repeated observations could lead to biased estimates. To achieve this, the `tag` command in Stata was used (see [ch5a1_intersectionality_hunter24.do](#) line 29 - 32) to identify each participant’s first response, ensuring that only the initial observation for each individual was included in

the analysis. By using the first available response, potential biases that could arise from using multiple observations is minimised. This approach means that observations are being made across different waves, as not all participants entered the study in wave 1. Consequently, each participant's first available response, regardless of the wave, is used to maintain consistency.²⁴ To focus on income differentials among the working population, the data is limited to 40,149 participants aged 16-64 who are employed/self-employed with valid information across all the variables included in the analysis. A sensitivity analysis using weights revealed similar results so, it was decided to not weight the data in the following analysis.

5.2.1. DEPENDENT VARIABLE

The average hourly earnings dependent variable was derived by dividing monthly earnings by weekly job hours (employed and self-employed) as was used in Chapter 4. The influence of outliers was mitigated by limiting the variable to between the 1% and above 99% percentiles and then it was logged for a more equal distribution. While there is a range of other economic outcomes explored, this dependent variable was chosen simply as an illustrative sample for a practical application of MAIHDA on Muslim outcomes. As mentioned in Chapter 3, earnings variable has not been adjusted for inflation but extant analysis has confirmed minimal impact of this on analysis.

5.2.1.1. Intersectional strata

The following sociodemographic variables used to structure the intersectional strata were chosen as they represented the core axes of marginalisation thought to influence outcomes as illustrated by recent Muslim penalty research. In the previous chapter, it was decided to combine approaches to create multicategory identifiers which combined ethnicity, religion and generation as controls in models split by gender. Here, an alternative approach will be taken which involves grouping individuals into

²⁴ While using a three-level model with wave as the third level could provide additional insights, it would also add a layer of complexity to the analysis. This approach could be considered in future research. The main goal of this study was to explore the method and its application to understanding earnings disparities.

intersectional strata based on different combinations of core demographics: sex, ethnicity, religion, and country of birth. While it was possible to include other dimensions commonly used in MAIHDA (e.g age and education level) (see Evans et al., 2018) it was decided to omit these in the construction of the strata for two reasons.

Table 5-1 Sample size of intersectional strata defined by gender, ethnicity, religion, and country of birth.

Sample size per stratum	Number of strata	% of strata
100 or more	38	33.0%
50 or more	62	53.9%
30 or more	79	68.7%
20 or more	87	75.7%
10 or more	102	88.7%
Less than 10	13	11.3%

First, age and education are thought to significantly influence the dependent variable (average hourly earnings) and could potentially obscure the influence of demographics that are more interesting (in this instance, the intersection of ethnicity and religion are salient).²⁵ Second, including additional dimensions would mean pushing the small sample sizes of group even further, reducing statistical power. Both these variables are included as controls, however, alongside other covariates as explained below. Thus, the four strata variables are coded as follows:

Sex: 1 = Male, 2 = Female.

Ethnicity: 1 = White British, 2 = Indian, 3 = Pakistani, 4 = Bangladeshi, 5 = Black (African, Caribbean, and any other Black background), 6 = Other ethnic group (comprising Chinese, Arab, Other Asian and any other ethnic group not already listed)²⁶, and 7 = White Other.

Religion: 1 = No religion, 2 = Christian, 3 = Muslim, 4 = Hindu, and 5 = Other religion (comprising Jewish, Sikh, Buddhist and any other religion not already listed).

²⁵ Sensitivity analysis which included age and education in the construction of strata revealed that strata comprising older age categories and those with degrees consistently earned more and were thus ranked higher, whereas younger people with non-university qualifications were ranked the lowest.

²⁶ for more detailed descriptions on the operationalisation of these categories see section 3.4).

Country of birth: 1 = Born in the UK, 2 = Not born in the UK. This operationalisation improves on previous analysis as it meant third generation were not excluded.

Each stratum was given a meaningful four-digit code to allow for interpretation: sex (digit 1), ethnicity (digit 2), religion (digit 3), country of birth (digit 4). The value in each digit corresponds with the values of the variables described above. For example, stratum 2331 refers to individuals who are female, Pakistani, Muslim and born in the UK.

Table 5.1 summarises the distribution of 40,149 observations across 115 strata. Seventy-six percent of strata had 20 or more observations and 69% had 30 or more observations, suggesting the sample sizes of a majority of strata are adequate for MAIHDA analysis as outlined by Evans et al., (2024a). As minority groups and combinations across sparse categories are included in this analysis it was expected there would be strata with small n. Out of the 11% of strata with 10 or less observations, only one strata (ID= 2742) represented a single minoritised gender/ethnic/religious/generational identity (n = 1) – Female White Other Hindu Not Born in the UK.

This combination is an example of a potentially non-plausible grouping and might suggest a coding error somewhere in the survey or data management. There is likely to be a range of strata which represent intersectional combinations that do not actually exist in the real world. Despite these, it is plausible to take them at face value and leave them in the analysis, and an attraction of the conservative nature of MAIHDA is that minimal damage is done by doing so. Put otherwise, the shrinkage of MAIHDA ensures that the influence of these outliers (small unlikely strata) is minimised meaning that while they are included in the analysis, their impact on the overall results is limited, reducing the risk of skewing the findings related to bigger plausible groups.

Moreover, including all groups, even those that seem implausible avoids the introduction of bias that might occur from selectively removing data points. This approach ensures that the analysis remains comprehensive and inclusive of all intersectional combinations, which is a core strength of the method. Furthermore, the presence of these groups, albeit potentially not existing, can highlight potential areas for further investigation. For example, acknowledging these outliers can lead to improvements in data collection methods and survey design; further analysis identifying and examining these implausible groups could lead to recommendations about the survey's measurement error. This can ultimately enhance the accuracy and reliability of future rounds of data collection.

Ultimately, however, this approach can also draw attention to implausible circumstances, putting the emphasis on random data points or variations that do not have any meaningful pattern or significance. In the context of this research, emphasising white noise can be problematic because it can obscure true patterns and trends, leading to misleading conclusions, thereby reducing the overall clarity and reliability of the research outcomes. This consideration will be taken forward in the following analysis, in which these implausible/unlikely groups have been left in. Any examples of these groups will be couched with the caveat that they are probably white noise rather than anything else.

5.2.2. CONTROLS

As is done in Chapter 4, a variety of control variables that are commonly adjusted for when analysing earnings are used including age, education score, English proficiency, marital status, number of children, health condition, caring responsibilities whether the respondent works part time, works in the public sector, religiosity, social ties and liberal gender values. Individual dummies for the wave of the survey are also fit (see section 3.4 for notes on operationalisation of these variables). As the focus was on the overall method, some controls were simplified for parsimony (i.e. the control for government office region was fit including a dummy for whether they live in London or the south east of England versus the rest of the UK). As the outcome variable is calculated using number of hours a participant worked a week, a control for hours worked was not required.

5.3. Method

Three versions of a MAIHDA model intersecting gender, ethnicity, religion, and country of birth are presented: Model 1A is a null model which provides information about overall earning differentials among intersectional strata. Model 1B is the additive main effects model, and model 1C further adjusts for other controls. Model 1A predicts outcomes for different intersectional groups (strata) and assesses the variation within and between these subgroups. It specifically measures the correlation of individual outcomes within each stratum. A higher variance participation coefficient (VPC) indicates that outcome values within a stratum are similar to each other but distinct from those in other strata. Alternatively, a lower VPC could suggest strata are generally more similar to each

other and that the intersectional grouping of individuals provides less insight into individual outcomes. However, even with a low VPC, it is still possible to have an outlying stratum that behaves differently from the others. For data management and analysis command file see [ch5a1_intersectionality_hunter24.do](#).

Table 5-2 Descriptive statistics of individual observations (N = 40149) and intersectional strata (n = 384) in the UKHLS pooled sub-sample.

Strata characteristics	N	%
Sex		
Male	20289	50.5
Female	19860	49.5
Ethnic Group		
White British	31288	77.9
Indian	1775	4.4
Pakistani	1065	2.7
Bangladeshi	642	1.6
Black	1970	4.9
Other eth.	1933	4.8
White Other	1476	3.7
Religion		
No religion	21187	52.8
Christian	13988	34.8
Muslim	2349	5.9
Hindu	1142	2.8
Other religion	1483	3.7
Country of Birth		
Born in the UK	32816	81.7
Not born in the UK	7333	18.3

Controls	N	Mean	Median	SD	Min	Max
Age	40149	39.56	40	12	16	64
Lives in London	40149	0.27				
Married	40149	0.52			0	1
Education Score	40149	49.47	48.12	7.84	34.68	61.75
English proficiency	40149	0.98		0.14	0	1
Children	40149	0.28		0.66	0	3
Health condition	40149	0.23		0.42	0	1
Caring responsibility	40149	0.13		0.34	0	1
Works part-time	40149	0.21		0.41	0	1
Public sector	40149	0.30		0.46	0	1
Social ties	40149	0.55		0.50	0	1
Liberal gender attitudes	40149	0.66		0.47	0	1
Low religiosity	40149	0.81		0.40	0	1

Average Log Hourly Earnings

Individual values	40149	4.96	4.97	0.71	0.26	10.61
Observed stratum means	115	4.47	4.47	0.58	2.84	6.38
Predicted stratum means	115	4.95	4.95	0.08	4.63	5.10

Source: main adult panel (aged 16 – 64) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Limited to one observation per person, those in employment/self-employed and with valid information on all variables. The mean of 40149 individual observations of log average hourly earnings is the “sample mean.” The mean of the 115 observed stratum means is the “grand mean.” The mean of the 115 predicted stratum means from the MAIHDA model is the “precision-weighted grand mean.”

The main effects additive model (1B) includes the set of categorical variables used to construct the strata fit as explanatory variables in the fixed part of the model. Specifically, these four variables (gender, ethnicity, religion, and country of birth) are transformed into 12 dummy variables amounting to 13 beta coefficients including the intercept. Evans et al., (2024a) state that, in contrast to how these variables may usually be used in single-level analysis (as level 1 individual-specific characteristics), in this instance they function as level 2 variables (group-specific characteristics that apply to everyone in that group). This distinction is crucial because it aligns with the conceptual argument that characteristics such as gender and ethnicity are not merely individual traits but represent group memberships. These group memberships influence individuals beyond their personal attributes, particularly in relation to the characteristics of the state or their combination. Therefore, treating gender, ethnicity and similar variables as level 2 characteristics is justified as they encompass the broader social and structural contexts that impact individuals collectively within their groups. This approach acknowledges the significant role that different intersecting identities play in shaping individual experiences and outcomes. While getting further into the methodological debate around this approach is not within the current scope - see Wilkes and Karimi (2024) critique and Evans et al.'s (2024b) response for more detailed discussion. It is important to note that this model does not include 'fixed part' interaction parameters. Instead, it captures the entire interaction effect through allowing for a distribution of 'stratum random effects' (Evans et al., 2024a). The stratum random effect²⁷ reflects how much each group's average outcome deviates from what is predicted by the main effects alone. This residual, then, represents the average difference between observed outcomes for individuals within a stratum and their grand mean predicted values.

The VPC in model 1B displays how much of the overall variance between strata remains unexplained after adjustment for the additive effects of the strata variables (Silva and Evans, 2020). The addition of additive effects to the model will most likely reduce the amount of between-stratum variance estimated by model 1A, meaning the between variance and VPC will both be reduced between models. The proportional change in variance (PCV) statistic can be interpreted as the proportion of the total between-stratum

²⁷ Note that stratum random effects are not usually calculated as a direct measure. Rather, the shrunk residual is usually calculated which can be thought of as a weighted adjustment to the direct measure.

variance identified in Model 1A that can be explained by controlling for additive main effects in Model 1B. The final model (1C) simply adds other controls not included in the design of the strata which are thought to influence earnings. Likewise, the VPC here would illustrate how much between strata variance remains after additional adjustments.

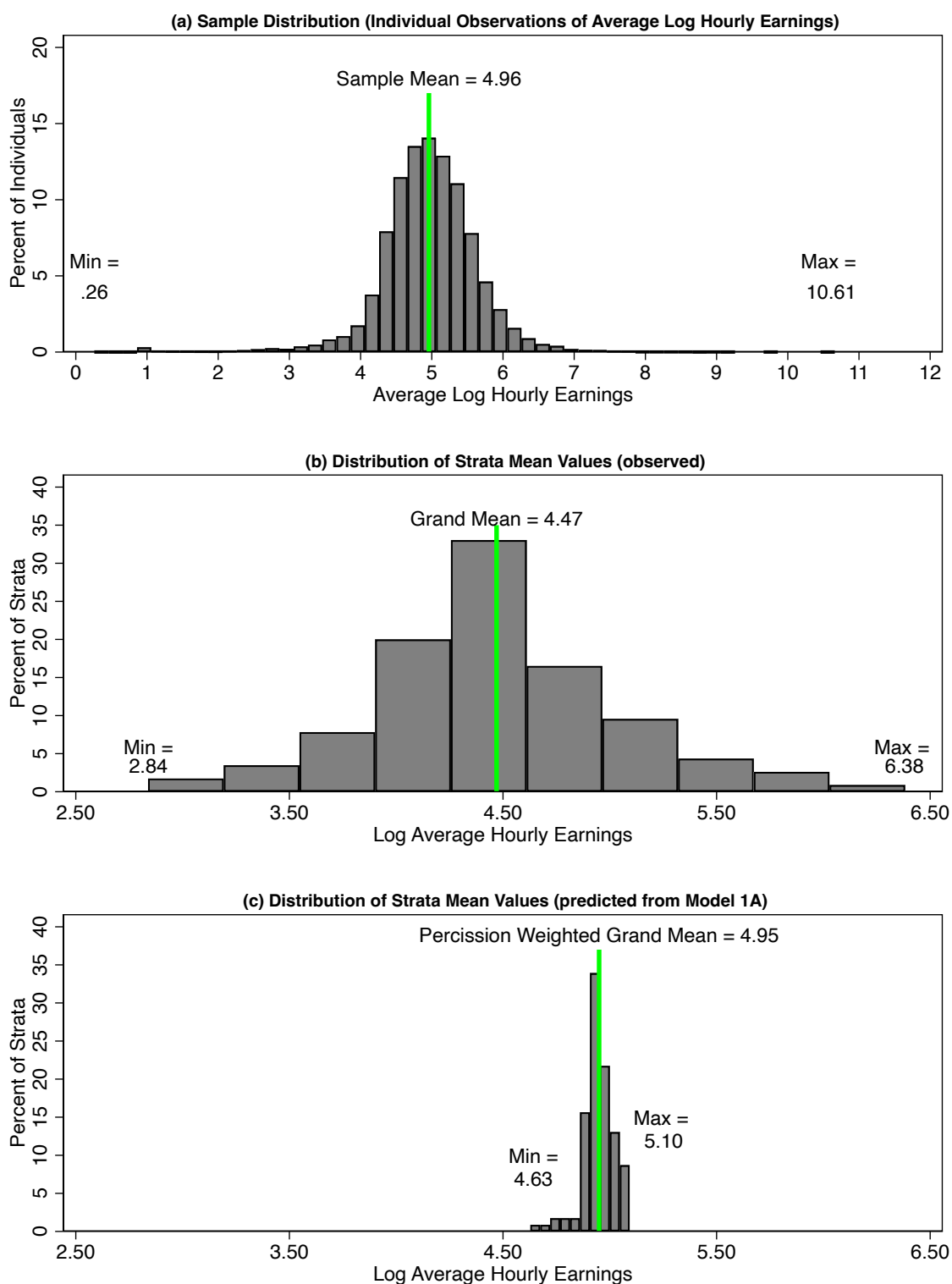


Figure 5-1 Visualising distributions - sample mean, grand mean, and precision weighted grand mean.

5.4. Findings

Table 5.2 and Figure 5.1 show the distribution of all the variables included in the construction of the strata and the extra controls, in addition to three different summary statistics of the outcome which, for brevity, will be referred to as ‘earnings’. A total of 40149 observations (individual data points) are nested within 115 strata (intersectional groupings). The sample mean of earnings across all individuals is 4.69 as shown in Panel A of figure 5-1. The large gap between the minimum and maximum values is because this is the distribution of all individuals in the data set and does not refer to strata. To get the grand mean, the mean earnings from each stratum are added and the average is taken. The grand mean represents an overall summary of earnings across all strata, which in this case is 4.47 (shown in Figure 5-1B). Notably there are some strata which have small or large mean values (min = 2.50 and max = 6.38). It is likely these extreme values may be a result of small sample sizes (groups with $n < 10$) included in some strata and thus be unreliable estimates.

Figure 1c shows the ‘precision weighted grand mean’ (PWGM) which is the equivalent to the intercept in a linear multilevel regression without explanatory variables (see Table 5.3) (Evans et al., 2024a). The PWGM is a weighted average of the observed stratum means, where the weights are based on the precision of these means. Essentially, it adjusts the stratum means to account for their reliability. This produces a “shrunk” distribution as shown in figure 5-1c, in which the values of smaller strata are reduced compared to the values of larger strata. The value of the PWGM (4.95) lies between the values of the sample and the grand mean. The minimum and maximum values are also significantly drawn inward after adjustment for the strata sample size thus providing more reliable estimates.

Table 5-3 Parameter estimates for linear models of average log hourly earnings.

	1A Null		1B Main additive effects		1C Plus controls †	
	Estimate	[95% CI]	Estimate	[95% CI]	Estimate	[95% CI]
Intercept	4.95*	[4.92,4.97]	5.00*	[4.94,5.05]	3.14*	[3.20,3.33]
Sex						
Male			-		-	
Female			0.05*	[0.01,0.09]	-0.10*	[-0.13,-0.07]
Ethnicity						
White British			-		-	
Indian			0.00	[-0.07,0.06]	-0.04	[-0.09,0.01]
Pakistani			-0.19*	[-0.28,-0.09]	-0.13*	[-0.20,-0.05]
Bangladeshi			-0.16*	[-0.26,-0.05]	-0.12*	[-0.21,-0.04]
Black			-0.01	[-0.07,0.06]	-0.08*	[-0.13,-0.02]
Other eth.			-0.04	[-0.10,0.03]	-0.07*	[-0.12,-0.02]
White						
Other			0.05	[-0.02,0.12]	0.03	[-0.09,0.01]
Religion						
No religion			-			
Christian			0.00	[-0.05,0.05]	-0.02	[-0.07,0.02]
Muslim			-0.03	[-0.09,0.04]	-0.02	[-0.08,0.03]
Hindu			0.01	[-0.06,0.08]	-0.01	[-0.07,0.05]
Oth. religion			-0.02	[-0.09,0.05]	-0.02	[-0.07,0.04]
Not born in the UK			-0.08*	[-0.12,-0.04]	-0.09*	[-0.13,-0.06]
Age					0.01*	[0.01,0.01]
Education Score					0.03*	[0.03,0.03]
London/SE.					0.14*	[0.12,0.16]
Married					0.04*	[0.03,0.06]
Works part time					0.15*	[0.13,0.16]
Works in public sector					0.15*	[0.13,0.16]
Random Effects: Variances						
Stratum						
level	-2.28*	[-2.49,-2.06]	-2.74*	[-3.03,-2.45]	-3.08*	[-3.42,-2.73]
Individual						
level	-0.35*	[-0.36,-0.35]	-0.35*	[-0.36,-0.35]	-0.44*	[-0.45,-0.44]
Summary Statistics						
Obs.	40149		40149		40149	
VPC	2.08%		0.84%		0.51%	
PCV	-		60.3%		79.9%	

* < 0.05. Notes: MLE estimation used for all models shown. 95% CIs shown in parentheses. Model 1C adjusted for the year of the survey which is omitted from the table. VPC = Variance Partition Coefficient (ICC) ; PCV = Proportional Chance in Variance

† model also adjusted for number of children, language proficiency, health condition, caring responsibility, social ties, low religiosity, liberal gender attitudes, and wave of survey (not shown) full tables here: [sup_ch5_reg_1B.log](#) & [sup_ch5_reg_1C.log](#)

Moving on to modelling, Table 5.3 shows the results from the null model (1A) the additive main effects model (1B) plus extra controls (1C) for linear models on average earnings. The intercept in the null Model 1A is the precision-weighted grand mean (also presented in table 2 and figure 1C). That is, the overall average value of earnings in the subsample. In the null model, there is a VPC of 2.08% which indicates a small amount of clustering at the stratum-level. Put otherwise, around 2% of the total variance in earnings can be attributed to differences between intersectional strata. While it is common for VPCs to be less than 5% in multilevel research (Subramanian and O'Malley, 2010 as cited in Evans et al., 2024a), it is a low VPC score, but not particularly surprising given the skewed size of the strata – much of the individual variation will be between people within the largest strata. In other words, there are more individuals in some strata compared to others. When strata sizes are skewed, the larger strata will have more individual variation simply because they contain more people. This internal variation within the larger strata contributes significantly to the overall variance in earnings. As a result, the small VPC indicates that differences between strata are relatively minor compared to the differences within the larger strata.

In model 1B, the female coefficient is positive and statistically significant, suggesting that, on average, females earn more than males. However, this model does not account for other factors that might influence earnings. When you add additional controls in Model 1C (see table note of Table 5-3 for details), once these factors are accounted for, the 'female' coefficient turns negative, indicating that, net of things thought to influence earnings, above and beyond the variables that constitute the strata, females earn less. In model 1B, the coefficients for each ethnic group are negative, indicating that on average, these groups earn less than the reference category. However, only the coefficients for Pakistani and Bangladeshi groups are statistically significant. When additional controls are added in Model 1C, the coefficients for all ethnic groups remain negative and increase in magnitude, suggesting that the earnings disparities are even larger when accounting for covariates. In this adjusted model, the coefficients for all the ethnic groups are statistically significant, except for the Pakistani group. This indicates that, (similar to chapter 4) after controlling for these additional factors, the earnings differences for most ethnic groups are more pronounced even after controlling for human capital, social capital, population characteristics and socio-cultural variables.

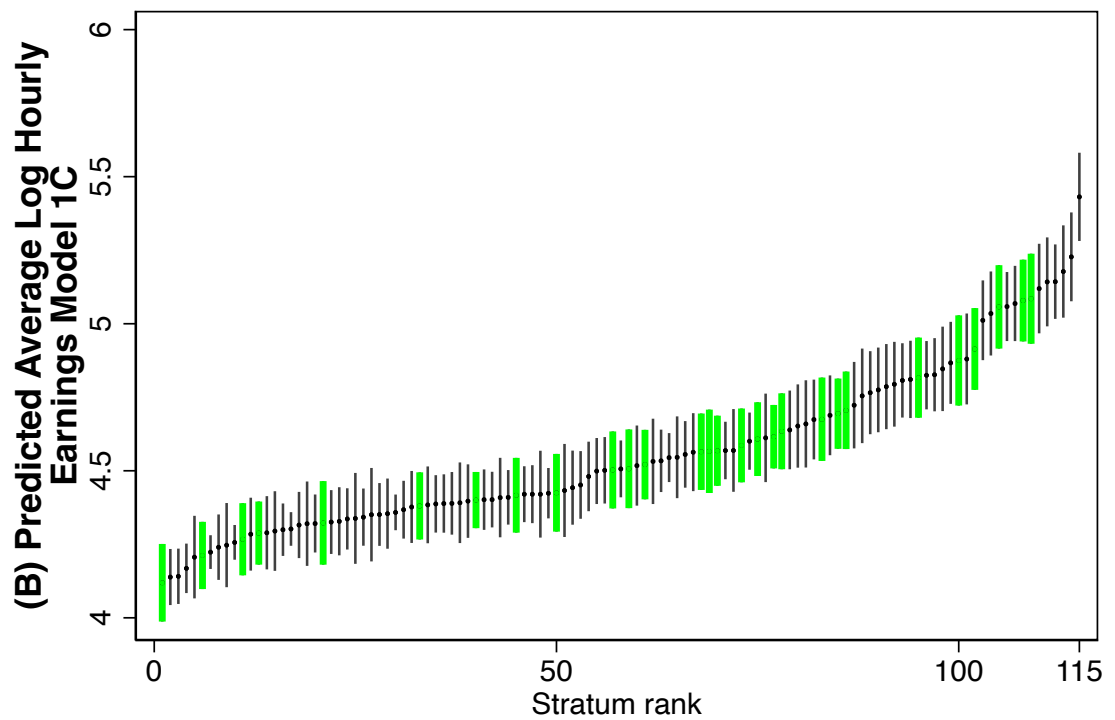
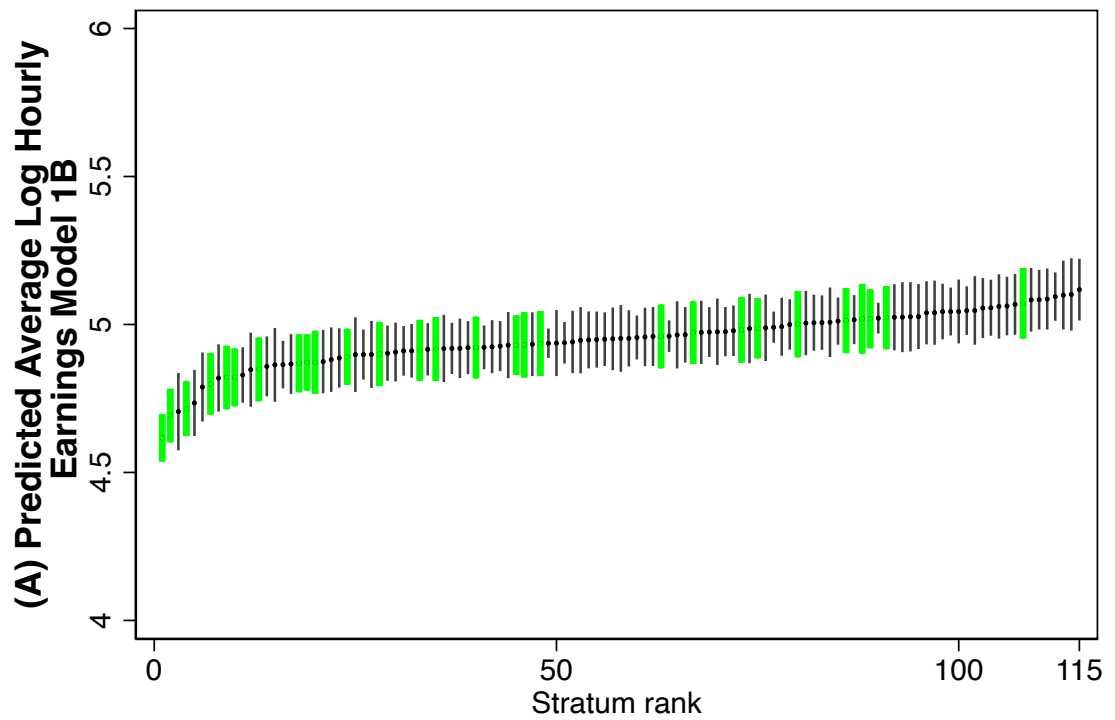


Figure 5-2 predicted values by stratum for all 115 strata, ranked low to high.

Notes: (A) includes predictions from model 1B without controls and (B) 1C with controls added. Markers indicate predicted value for each stratum. Spikes represent approximate 95% CIs. Groups with Muslim stratum represented in lime green.

Figure 5-2 shows the predicted values for all 115 strata ranked from low to high - without (Figure 5-2a) and with controls (Figure 5-2b). With no controls, there are few Muslim stratum (represented by lime green markers) at the high end of the rank scale, with most lying in the middle or bottom. The addition of controls (Figure 5-2b) changes the distribution, showing Muslim strata being more spread out across the whole range. This change underscores the importance of control variables that might contribute to the observed Muslim disadvantage. By adjusting for these controls, the analysis provides a clearer picture of the true distribution and helps to identify underlying issues that may be contributing to the disadvantage faced by Muslim strata.

One benefit of this approach is we can compare outcomes across many different combinations of social positions. Table 5-4 lists the lowest 5 and highest 5 strata based on their predicted values for Model 1B and 1C. Before looking at the results it is worth reiterating that these data are based on individuals in employment aged between 16 and 64. In general, without adjusting the models for controls, first generation (not born in the UK) Pakistani and Bangladeshi men have the lowest earnings - including both Muslims and Hindus. Pakistani Muslim men born in the UK (stratum 1331) also rank second lowest. The 5 highest ranked stratum are all female, born in the UK and mostly belong to the White Other ethnic group from secular, other religion and Christian backgrounds. Fourth from the highest rank, there is also stratum 2521 that includes Black Christian women.

While it might be surprising to see the highest 5 stratum consisting of second generation White Other women, this should be interpreted with two important caveats: (1) 'White Other' is an ambiguous category which includes a mixture of non-British people from around the world, including America, Canada, and Australia who tend to have better outcomes than their other White migrant counterparts (such as Poles or other Eastern Europeans (reference)); and (2) the sample size of two of these stratum (2751 and 2741) are noticeably small ($n = 8$ and 2 , respectively).

After introducing controls, the descriptive results from model 1C in table 5-4 show all female strata occupying the lowest 5 rankings. First-generation Bangladeshi Muslim women (2432) have the lowest predicted earnings. Interestingly, White other women born elsewhere, with no religion (2712) and of Christian faith (2722), occupy the second and third lowest ranks, respectively. Although this group has not been separated based

on different origins, they do include Eastern Europeans, which might be more evidence that they experience disadvantage in the UK (Johnston et al., 2015; Manley et al., 2019). In line with ethno-penalty literature, first generation Black Christian women (2522) are also among the lowest earners (Li and Heath, 2020). Indian Hindus usually have better outcomes than their Muslim and Sikh peers (Khattab and Modood, 2015). However, Table 4 shows an interesting interaction between Pakistani ethnicity and Hindu faith for second generation women (2341), indicating that they are also among the lowest earners. However, as mentioned above, this is not a group expected to be very common and thus observations about this group should be read with caution. On the other hand, this highlights the strength of MIAHDA in uncovering intriguing points of intersection, demonstrating how advantages in some areas can be mediated by ethnicity. This is a group that has not been extensively studied in the literature (or could just be a result of data error) and deserves further investigation.

While there is a mix of male and female strata, there are no Muslim strata among the highest earners. Each of the five highest-ranked groups are also all born in the UK, potentially providing evidence for generational progress and the success of second generations. The three highest-ranked groups represent niche combinations of the strata variables and thus have particularly small sample sizes. Caution should be taken with any of these descriptions, especially when n of strata is below 10. There are, however, Indian women with 'other religion' (2211, $n = 50$) found among the highest-ranked groups. This is noteworthy because much of the literature has focused on differences between Hindus, Sikhs, and Muslims, often overlooking the outcomes of those with 'other' religious affiliation. This finding suggests that there may be unique factors at play for this group that warrant further investigation.

Table 5-4 Inspection of five highest and lowest ranked strata for predicted average log hourly earnings with main additive effects (Model 1B) and extra controls (Model 1C)

Predicted Average Log Hourly Earnings (Model 1B)

Rank	ID	Gender	Ethnicity	Religion	UK Born	N	Predicted earnings	95% CIs	
5 Lowest									
1	1332	Male	Pakistani	Muslim	N	413	4.62	4.54	4.70
2	1331	Male	Pakistani	Muslim	Y	210	4.69	4.60	4.78
3	1442	Male	Bangladeshi	Hindu	N	23	4.71	4.57	4.84
4	1432	Male	Bangladeshi	Muslim	N	300	4.72	4.62	4.81
5	1342	Male	Pakistani	Hindu	N	55	4.73	4.62	4.85
5 Highest									
111	2711	Female	White Other	No religion	Y	40	5.09	4.98	5.19
112	2521	Female	Black	Christian	Y	268	5.09	5.01	5.18
113	2751	Female	White Other	Other religion	Y	8	5.1	4.98	5.22
114	2741	Female	White Other	Hindu	Y	2	5.1	4.98	5.22
115	2721	Female	White Other	Christian	Y	39	5.12	5.01	5.22

Predicted Average Log Hourly Earnings after adjusting for extra controls (Model 1C)

Rank	ID	Gender	Ethnicity	Religion	UK Born	N	Predicted earnings	95% CIs	
5 Lowest									
1	2432	Female	Bangladeshi	Muslim	N	75	1	4.12	3.99
2	2712	Female	White Other	No religion	N	302	2	4.14	4.04
3	2722	Female	White Other	Christian	N	334	3	4.14	4.05
4	2522	Female	Black	Christian	N	453	4	4.17	4.08
5	2341	Female	Pakistani	Hindu	Y	45	5	4.21	4.07
5 Highest									
111	1751	Male	White Other	Other religion	Y	6	111	5.14	4.99
112	2211	Female	Indian	Other religion	Y	50	112	5.14	5.02
113	2741	Female	White Other	Hindu	Y	2	113	5.18	5.02
114	1541	Male	Black	Hindu	Y	3	114	5.23	5.08
115	2751	Female	White Other	Other religion	Y	8	115	5.43	5.28

Notes: full tables with information on all 115 strata can be found here:

[sup_ch5_table_1B.log](#) & [sup_ch5_table_1C.log](#)

Figure 5-3 plots the predicted stratum random effects (residuals) for Models 1B and 1C with 95% confidence intervals around the estimates.²⁸ Most of the confidence intervals for each strata encompass 0 meaning an intersectional effect for that combination of dimensions of marginalisation is not found. However, as shown in Figure 5-3C and 5-3D there are some strata that were significantly different (higher or lower) from what the main effects alone would suggest. In the unadjusted model, Male Pakistani Muslims both born in the UK and elsewhere (stratums 1331 and 1332) had significantly lower estimates than what is predicted by the main effects in the model without controls (1B). Several other non-Muslim groups also exhibited significantly lower predicted earnings that deviated from what the model would typically expect. Among these groups, were female White British Christians born in the UK (2121) and female White British individuals with no religion, born in the UK (2111). The significance of these results is likely influenced by the large sample sizes of these groups, which can make even small deviations from the average statistically significant. This highlights the broader issue of gender disparities in earnings, where women, regardless of their religious affiliation or place of birth, may face systemic challenges that impact their economic status.

In addition, female White Others (not British) of Christian denominations who were not born in the UK (2722) had lower earnings that significantly deviated from the model's expectations. This deviation could reflect the disadvantages experienced by Eastern Europeans, who are predominantly Christian. Despite their Christian faith, White women migrants tend to earn less, highlighting the economic challenges faced by this group. Female Indians of other religions who were not born in the UK (2252) also had below average earnings than would be expected by the model, again highlighting a group for future consideration.

In the unadjusted model (1B), three groups exhibited higher earnings that significantly deviated from what the model would typically expect. Among these groups were male White British Christians born in the UK (1121), female Pakistani Muslims not born in

²⁸ Evans et al., (2024) emphasise that caution should be taken when interpreting the plotted random effects as 'a large residual interaction effect does not necessarily mean that the stratum will be more advantaged/disadvantaged in absolute terms (inclusive of additive and interaction effects), but rather it means the final predicted value of the stratum deviates meaningfully from what is predicted based on the additive effects)' (p11).

the UK (2332), and male White British Christians not born in the UK (1122). It is not unexpected that majority men, such as male strata 1121 strata (1122), earn more than what the model predicts. This aligns with broader trends where White men often have higher earnings. What is particularly interesting is the case of female Pakistani Muslims not born in the UK (2332). Initially, their earnings were higher than what the model expected. However, this effect disappears once controls are added. This suggests that factors such as education, work experience, or other socio-economic variables play a significant role in explaining any earnings advantage.

In the adjusted model (1C), which takes various controls into account, the earnings of several groups deviated from what the model would typically expect. Female White British individuals with no religion, born in the UK (2111), and female White British Christians born in the UK (2121) both had earnings below the model's expectations. This trend highlights the persistent gender disparities in earnings, where women, regardless of their socio-economic circumstances, tend to earn less. Similarly, male Pakistani Muslims not born in the UK (1332) also showed earnings below the expected levels. Like model 1B, Male White British Christians born in the UK (1121) and male White British Christians not born in the UK (1122) had earnings above the model's expectations.

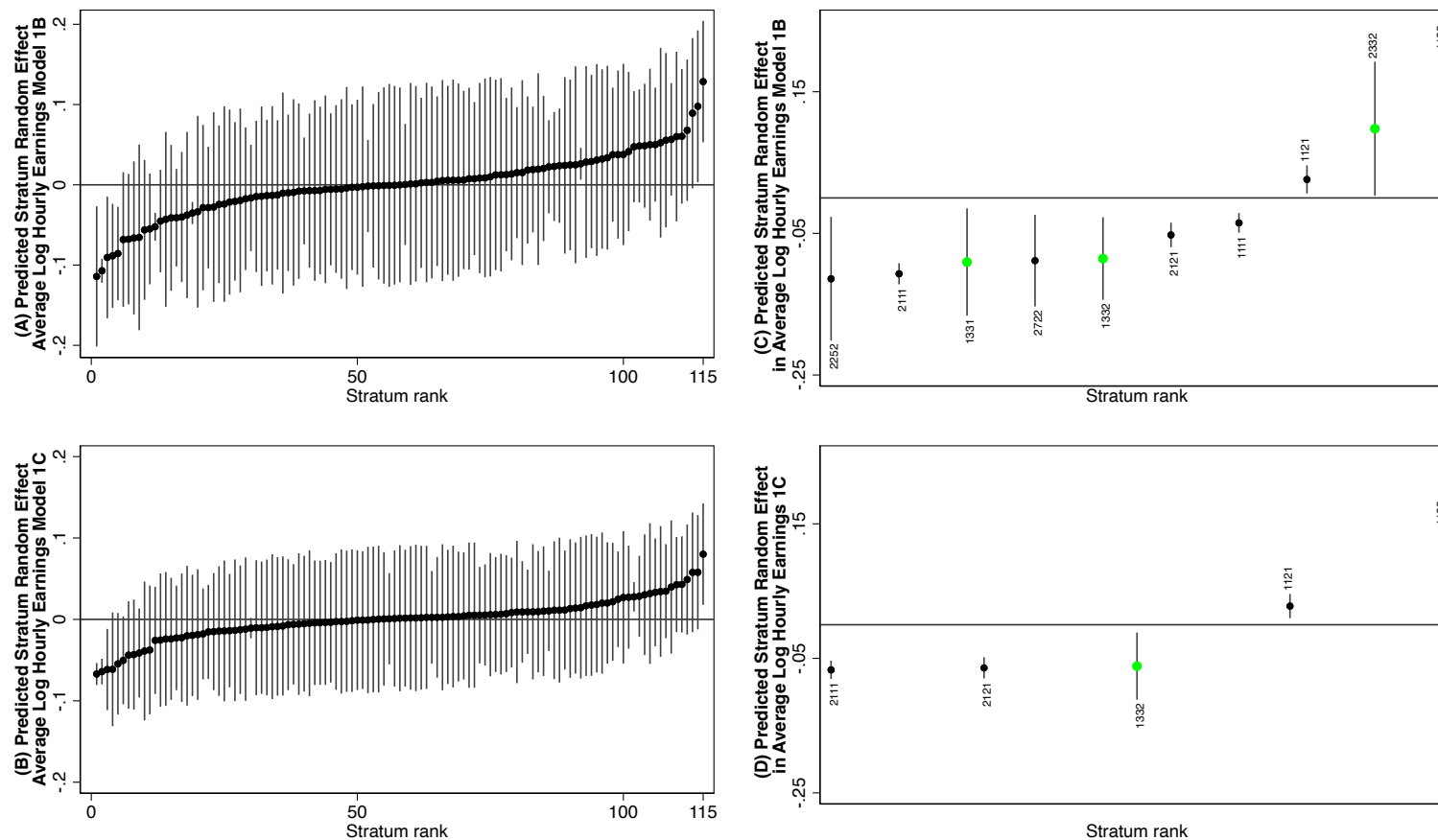


Figure 5-3 Predicted stratum interaction effects ranked low to high.

Notes: Markers indicate predicted value for each stratum. Spikes indicate approximate 95% CIs. Figure 2c and 2d lime green markers represent Muslim strata and each five-digit ID label reflect coding as follows: Digit 1 = sex [1 = Male; 2 = Female]. Digit2 = Ethnicity [1 = White British; 2 = Indian; 3 = Pakistani; 4 = Bangladeshi; 5 = Black; 6 = Other Ethnicity; 7 = White Other]. Digit3 = Religion [1 = No religion; 2 = Christian; 3 = Muslim; 4 = Hindu; 5 = Other religion]. Digit4 = COB [1 = Born in the UK ; 2 = born elsewhere

5.5. Discussion

The application of the MAIHDA model in this chapter has provided nuanced insights into the intersectional experiences of ethnic minority groups and their impact on earnings. While the analysis did not find vast earnings differentials by intersectional differences at the strata level, it did reveal important descriptive observations with significant implications for ethnic penalty scholars.

For example, before incorporating control variables, the analysis revealed that Pakistani and Bangladeshi Muslim and Hindu men occupy the lowest earnings ranks. Conversely, women, particularly those who identified as White Other (including a mix of Christian, non-religious, Hindu, and Black Christian women), tend to occupy the higher earnings ranks. This initial observation suggests that, without controlling for other covariates, these groups exhibit considerable earnings disparities. The MAIHDA model is increasingly used in health research where strata are usually designed to incorporate characteristics such as age and socio-economic circumstances, but thereafter models often deliberately include covariates beyond the main effects that define the strata. In this analysis the strata only capture gender-ethnicity combinations and ignore factors like age and socio-economic measures. This approach can be seen as a limitation because it risks overlooking important variables that significantly influence outcomes.

Including controls for human capital, population characteristics, work factors, and socio-cultural elements can substantially alter the rankings of earnings. For example, once these controls were applied, the lowest earnings ranks were predominately occupied by migrant or minority ethnic women. This included Bangladeshi women not born in the UK at the very bottom, followed by Christian White Other women and those with no religious affiliation, indicating that White migrants also face economic hardships. Additionally, the analysis highlighted some potentially understudied groups. For example, Pakistani Hindu women emerged as having unique earnings outcomes. While potentially This suggests that the MAIHDA model has the potential to uncover important observations about people with unique intersecting identities. However, it is important to approach these findings with caution. While the model can reveal significant insights, there is also

a risk that it might highlight anomalies or data errors. Therefore, further investigation and validation are necessary to ensure the robustness and accuracy of these observations.

These findings contribute to the broader discussion on ethnic penalties and intersectionality in several ways. The substantial changes in earnings rankings after applying controls underscore the importance of considering additional variables to avoid misleading conclusions. The identification of earnings disparities among non-minority groups, such as White Other women, challenges the conventional focus of ethnic penalty research, which often centres on minority versus majority comparison – although developments are being made (Manley et al., 2019). This finding supports the argument for a more nuanced approach to understanding social disadvantage (Crenshaw, 1989). Furthermore, the emergence of Pakistani Hindu women as a distinct group with unique earnings outcomes highlights the potential of the MAIHDA model to uncover hidden disparities. This aligns with intersectionality theory, which emphasises the importance of examining multiple axes of identity and their combined effects on social outcomes (McCall, 2005; Spierings, 2023).

In conclusion the MAIHDA model offers significant methodological advantages by providing a more comprehensive understanding of earnings disparities across different intersectional groups. By revealing hidden patterns and challenging traditional assumptions, this approach contributes to a deeper understanding of ethnic group outcomes and informs more effective policy interventions.

5.5.1. REFLECTIONS ABOUT THE APPLICATION OF MAIHDA

The primary goal of MAIHDA is to determine whether intersectional strata offer meaningful contexts for exploring outcomes. Alternatively, Merlo (2018) suggests it can also be used to reveal whether these strata are merely arbitrary categorisations in relation to specific outcome being explored. For instance, a low VPC (around 2%) and mostly insignificant random effects observed in the above analysis suggests not much is going on at the intersectional level and this can in turn be used to support the use of anti-categorical methods (moving beyond the use of categories in this context altogether) in future analysis on these issues .

An important consideration arising from the use of the MAIHDA method is that its inherent flexibility. Specifically, when constructing and assessing different variations of intersectional strata and evaluating them, there is a risk of unintentional data manipulation. Due to how reasonably easy MAIHDA is to apply, researchers might experiment with different combinations of identities and rework the data until they achieve a VPC that meets an acceptable threshold or findings they want to see. The possibility of tailoring the analysis to achieve desired outcomes raises broader concerns about potential data manipulation in quantitative research itself. This compromise may affect the integrity and generalisability of findings in analyses using this approach. To ensure greater transparency, it is recommended that detailed descriptions of any sensitivity analysis or the testing of different permutations of strata before main MAIHDA analysis should be made as transparent as possible. In this current practical application, for example, Sikh and Jewish respondents were grouped with ‘other religion’ after an initial analysis revealed very few respondents in these groups which impacted the overall distribution of the strata itself.

Thinking about sociological applications, perhaps the result of the empirical application above could be attributed to that fact MAIHDA is not appropriate when using observational data to explore socio-demographic outcomes. The approach is commonly used in epidemiology to predict health outcomes such as diabetes risk factors (Evans et al., 2024a), Body Mass Index (Evans et al., 2018), and biomarkers of healthy ageing (Holman et al., 2020). In light of its intersectional appeal, it was surprising when reviewing the MAIHDA literature and Evans et al.’s (2024) incredibly detailed tutorial, to see little-to-no mention of adjusting models for covariates over and beyond what is included in the strata. It is strongly recommended that controls are used in MAIHDA methods for future sociological research, given the significant differences in results that emerge after controls are applied.

Another important limitation is that the above analysis was limited to one observation per respondent over a 12-year period which most likely influenced results. It would perhaps be necessary to replicate the above analysis with a full pooled sample which incorporates measures to account for the clustering of observations within the individual (robust standard errors or equivalent) while retaining large, pooled sample sizes. In fact, one solution could be using three-level multilevel models which accounts for observations (level 1) nested in individuals (level 2) and individuals nested in strata (level

3), as demonstrated in recent literature looking to extend the use of MAIHDA for longitudinal data (Bell et al., 2024).²⁹

In summation, MAIHDA offers a valuable tool for exploratory analysis for exploring the intersections of different indemnities within the Muslim community. While there are certainly some advantages associated with the method – bringing non-minorities and those with a mix of disadvantage and privilege into focus – the method’s merits remain challenging to assess due to the limited scope of existing analysis. Applying MAIHDA alongside consideration of the inherent difficulties in ethnic penalty research (e.g. other covariates, small sample sizes, pooled data, overrepresentation, and sample weights) complicates the analysis and introduces uncertainty. The continued development of MAIHDA to overcome these challenges and its future application to assess ethnic penalties in sociological literature is well-founded. However, considering the complexities of ethnic penalty research, the remaining analysis will rely on traditional methods – such as fixed effects and conventional multilevel modelling – which offer a more established framework for analysis.

²⁹ Sensitivity analysis extending the above analysis by using pooled UKHLS repeated contacts and three-level multilevel models was attempted ([sup_ch5_3level.log](#)). The preliminary findings are that only two Muslims groups feature in the bottom ranked strata in the 3 level equivalents of model 1C (with controls): Male Other ethnicity Muslim born in the UK (1631) and Male White other Muslim not Born in the UK (1731). The only Muslim group to appear among the top ranked strata were Male White British Muslim Not born in the UK (1132). It should be noted that among the top ranked, all strata have small n. This is the case even after pooling data. This therefore furthers at the argument above that MAIHDA brings attention to the unlikely/implausible combinations of identity. It should be noted this is crude analysis in need of further investigation.

6. ASSESSING THE IMPACT OF CONTEMPORARY MIGRATIONS PATTERNS ON MUSLIM LABOUR MARKET OUTCOMES

6.1. Introduction

This chapter explores whether macro measures that are derived to indicate the amount of post-04 EU migrants in occupations and in local areas will further inform evidence about Muslim disadvantage. Using micro-data from the UKHLS and macro-data from ONS sources, the following section will build on the analysis in Chapter 4 and 5 by addressing research questions 6-7, considering whether:

- the concentration of post-04 EU accession migrants and other local area characteristics are associated with inequalities in outcomes for Muslims seeking for and securing employment, and
- whether post 0-4 EU accession migrant worker rates and other occupation factors are associated with poorer Muslim employment outcomes.

Moreover, as discussed in section 2.6.1.1, classical economic theory has been criticised for not considering variations in local labour markets. For ethnic minorities, these variations are important when assessing the labour market impacts of new migrations (Shaginyan-Shapira, 2010). Recent literature has increasingly focused on the contextual effects on ethnic penalties. Studies have considered factors such as the proportion of co-ethnics in a neighbourhood (Boeri et al., 2015; Jivraj and Alao, 2023; Patacchini and Zenou, 2012) and the level of local resources (Zwysen and Demireva, 2020; Brattbakk & Wessel, 2012; Dujardin & Goffette-Nagot, 2010; van Ham and Manley, 2010; Platt, 2019; Plum & Knies, 2019; Zucotti and Platt, 2017; Sirgy and Cornwell, 2002). These studies highlight the importance of considering neighbourhood characteristics and local resources, which should be controlled for in the analysis to better understand the circumstances of different groups.

The chapter is split into two parts. Section 6.1 examines the impact of various macro measures on labour market participation and avoiding unemployment. Inspired by Jivraj and Alao (2023) this analysis explores whether deprivation, resources, and the concentration of co-ethnics in a local area affect ethnic minorities' employment prospects. Jivraj and Also (2023) hypothesise that ethnic minorities in deprived areas may experience better employment outcomes than their non-minority counterparts due to strong informal networks and a lesser dependence on formal local institutions like job centres. This suggests that socialisation processes and negative neighbourhood effects are mitigated for Muslims in areas with higher concentrations of co-ethno-religious individuals. Additionally, prominent Islamic communities may provide safe havens, that protect Muslims from racism and support their employment efforts.

This section is inspired Jivraj and Alao's (2023) analysis by looking at the impact of neighbourhood characteristics on Muslim outcomes. It also considers how the concentration of post-04 EU migrants in deprived areas with high concentration of Muslims might increase competition for jobs and lessen the protection from negative neighbourhood processes and racism. Depending on whether post-04 EU migrants integrate into existing social networks or form separate ones, the dynamics of informal networks which originally benefited Muslim communities may change. On the other hand, the arrival of contemporary migrants in deprived areas might contribute positively to local economies by creating new jobs or bringing diverse skills, it could lead to improved employment opportunities for all, including Muslims.

This part also considers the impact of macro measures on outcomes of people who have secured employment. This analysis draws from Zwysen and Demireva's (2020) analysis of ethnic concentration in local labour markets on job quality of ethnic minorities. While local co-ethnic communities might help increase the probability of ethnic minorities finding work (Patacchini and Zenou, 2012), co-ethnic networks they rely on are likely to be lower quality and not productive in integrating workers into mainstream jobs compared to networks available to the majority. Muslims, among other ethnic minorities, might therefore only be able to find lower quality and precarious jobs through these informal networks (Zwysen and Demireva, 2020).

Moreover, ethnic minorities and migrants select into low-paid and precarious occupations compared to the majority. This occurs because migrants often find

employment in companies and occupations where other individuals from their ethnic group are already employed. Additionally, occupational segregation may also occur as migrants select into the occupations due to fear of discrimination. Studies have found that accounting for occupational segregation explains much of the ethnic and migrant pay gap (see Brynin and Guveli, 2012; Elliot and Lindley, 2008). Moreover, ethnic and migrant groups might be in occupations that are more vulnerable to increased competition from contemporary migrants as they enter the UK labour market (Boeri et al., 2015).

In section 6.2, a novel approach to exploring labour market outcomes using multilevel models is employed. In this section, similar models are run but with Standard Occupation Classification 2010 (SOC10) unit group fit at level 2. This allows models to account for the clustering of individuals in occupations at a much more granular level and can possibly lead to interesting differences between and within certain occupations. The focus of this chapter is on SOC10 unit groups with above average proportion of Muslims. This focus can help us identify any sectors in which Muslims seem to experience more or less favourable outcomes. Both these parts build on previous analysis by looking at outcomes that have not been explored this far and are not featured as frequently in the literature: financial anxiety, job related satisfaction and job quality.

6.2. Macro measures

While the UKHLS has rich micro data, it does not routinely include³⁰ macro information about different occupations or neighbourhoods nor support their derivation. For example, reliable information on the distribution of contemporary migrants from all post-04 accession countries in different occupations and geographical locations in the UK is not available in the UKHLS due to its geographically based sampling and relatively low volumes of data on Eastern European migrants. Researchers thus tend to derive these measures from elsewhere and attach them to the UKHLS data. Fortunately, the restricted version of the UKHLS that is used has detailed information about the neighbourhood

³⁰ There are a lot of existing special licence versions which already have linked macro variables across different indicators.

individuals live in and their specific occupation details. This allows for macro measures from other extant data sources to be derived and attached to individuals. The command files for these can be found in Appendix B12 and B13.

6.2.1. POPULATION STATISTICS FROM THE UK CENSUS.

Neighbourhood level data about the UK population was obtained from 2011 Census Aggregate Data (ONS, 2020) and accessed through the UK Data Service. The UK census, conducted on 27 March 2011 provides a comprehensive snapshot of the population across England, Wales, Scotland, and Northern Ireland. These census data offer detailed demographic and socio-economic information, essential for understanding national characteristics. The aggregate data includes summary counts of people, families, and households, covering themes like population, ethnicity, health, and housing, across various geographical levels, from small output areas to the entire nation (ONS, 2020).

Aggregate data is available at various levels of geography in the UK. Lower Super Output Areas (LSOAs) are small geographic areas used in the UK for statistical purposes. They are made up of groups of Output Areas (OAs), typically four or five, and each LSOA contains between 400 and 1200 households, with a usually resident population ranging from 1000 to 3000 people. While sensitivity analysis compared the impact of measures at higher geographical levels (i.e Local Authority Districts and Medium Super Output Areas), it was decided to work with data at the LSOA as they are predominately used in other studies as approximate local networks, or neighbourhoods (Zwysen and Demireva, 2020, Knies et al., 2016).

Data on the population by country of birth and religion were used to calculate the share of post-04 EU migrants and Muslims at LSOA. In addition, to measure neighbourhood resources, a composite variable (Cronbach's $\alpha > 0.8$) comprising of the respective employment rate, proportion of people in the top two NS-SEC categories and share of graduates in each LSOA is used. These aggregate indicators are divided into quintiles to ensure equal representation across the skewed distribution and then linked using LSOA codes attached to the UKHLS individuals made available through the special license version.

6.2.2. DERIVING OCCUPATION LEVEL MACRO MEASURES

Reliable information on the distribution of contemporary migrants from all post-04 accession countries in different occupations and geographical locations in the UK is not available in the UKHLS. Therefore, indicators of the potential competition faced by contemporary migration were generated by estimating the share of post-04 EU migrants in 4-digit SOC10 occupations, using the UK Quarterly Labour Force Survey (LFS).

The LFS is a large-scale and representative household survey which collects information about different economic outcomes of people in the UK. The sample design includes around 27,000 households and data is collected each quarter. Households remain in the sample for five consecutive quarters (referred to as waves), with a fifth of the sample replaced every quarter. In an attempt to mirror the same time frame of the pooled UKHLS subsample containing microdata on Muslim respondents, data from each quarter from the year 2011 to 2020 were pooled together. Data from years 2009 and 2010 were not included as this included information on SOC00 codes which could not be linked to SOC10 information.³¹ While this time frame does not exactly map onto the micro data, it was deemed appropriate as a substantial amount of data could still be pooled. When pooling LFS quarters there is a risk that the same respondents will appear on the combined dataset twice, potentially leading to biases estimates as responses are not independent of each other. Official guidance was followed to avoid the risk of individuals appearing more than once in the pooled data (ONS, 2023).³²

Once all data was pooled, information on 2,889,724 cases collected between 2011 and 2020 was used to derive macro-level variables comprising the proportion of EU10 and EU2 migrants within specific 4-digit SOC10 occupation group. Prior to 2018, information on country of birth and year of arrival to the UK was used to categorise someone as a post-04 accession migrant (comprising A8, A2 and Maltese, Cypriots and Croatians). From 2018 onwards, variables including these breakdowns were already

³² <https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=2000026#!/faqs>

available and used. Proportions were calculated by dividing the number of post-04 accession migrants by the total number of people in each 4-digit and 3-digit SOC10 codes. Following this, linkages were established between this data and the UKHLS through the use of SOC10 codes, allowing for each individual's occupation in the UKHLS to be linked with micro-data from the LFS about the average number of migrants in that particular occupation.

Figure 6-1 illustrates the correlation between the logarithmic percentage of post-04 European migrants (derived from the LFS) and the logarithmic percentage of Muslim individuals (based on data from the UKHLS) across various SOC2010 unit groups. The shading of markers shows a gradual shift from dark to light as you move from left to right on the graph. This shading pattern suggests that both groups tend to concentrate in specific occupational categories. Notably, these occupations predominately fall within major SOC10 groups at the lower end, including elementary positions, process, plant and machine operatives, as well as sales and customer service roles.

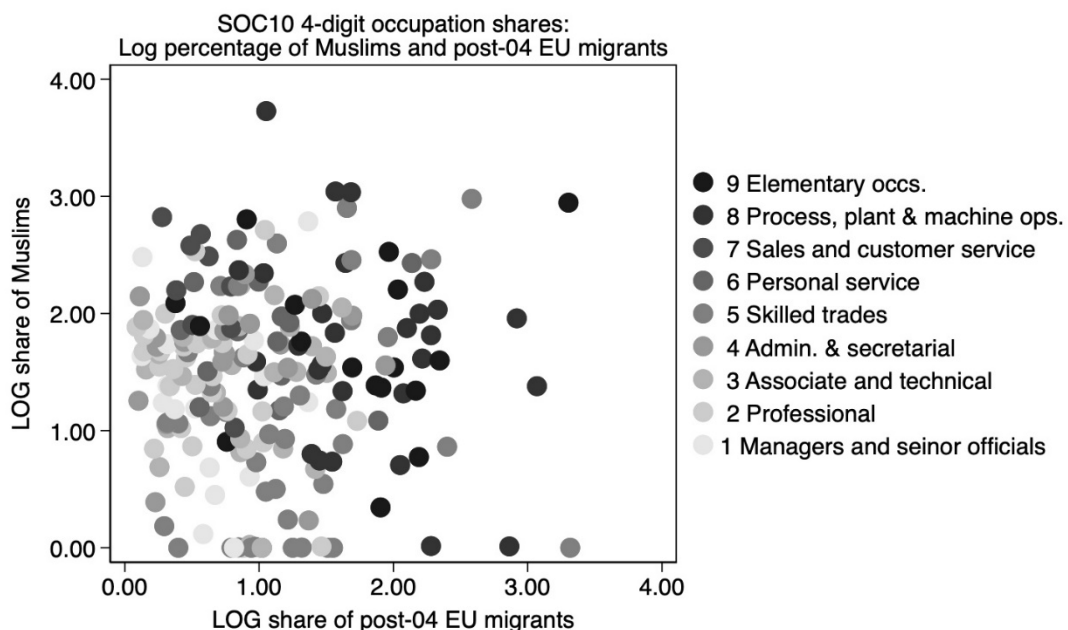


Figure 6-1 Scatterplot of share of Muslims and of EU Migrants in SOC10 unit groups

New variables were derived by dividing the four macro percentage indicators described above into five quintiles for the following analysis. This decision was driven by the skewed distribution of raw percentages across different neighbourhoods and occupations. By doing so, more balanced categories are created which helps mitigate the impact of outliers. Furthermore, using quintiles makes it easier to interact with Muslim group indicators as these discrete categories allow for straightforward comparison and visualisation. Figure 6-2 compares the raw percentages with their quintile counterparts to demonstrate how the original macro measures are grouped prior to analysis.

6.3. Part 1 – Fixed effects approach and macro measures

6.3.1. SAMPLE

This chapter uses a similar pooled sample of UKHLS micro data (see section 3.2 for an overview). It includes observations from individuals collected across the life span of the UKHLS and is limited to the working population age. Appropriate controls for each outcome that have been used thus far in the analyses are included here also. However, instead of comparing differences between first and second generations (excluding the third generation), Muslim groups will be organised based on whether they were born in the UK or not. This approach is inspired by other studies, particularly Zwysen and Demireva (2020), and provides an alternative perspective on exploring ethnic minority circumstances. In addition, UK-born Black Muslims are now combined with their foreign-born counterparts in the new group ‘Muslim Black fgn/UK born.’ Additionally, ‘Other’ Muslims have been aggregated into a single category comprising both UK and foreign-born Muslims from ‘other’ ethnic groups. Due to predominately being interested in comparing experiences between ‘visible’ migrants (e.g. racialised Muslim groups) and White migrants from European countries, the White British Muslims have also been merged with the ‘other’ Muslim category. These decisions were deemed as an appropriate compromise to enable space for additional macro characteristics that were discussed above.

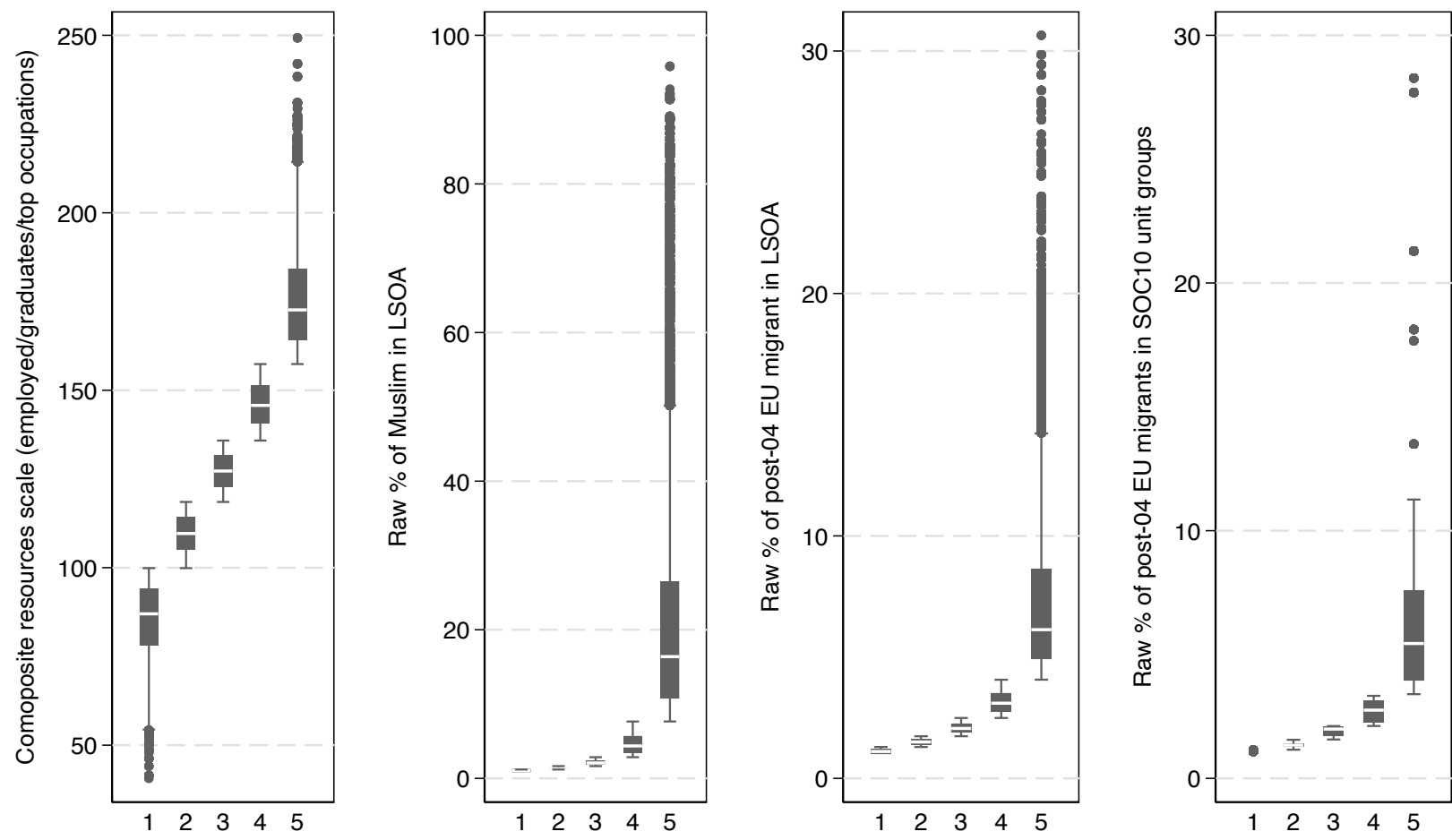


Figure 6-2 Distribution of neighbourhood and occupation measure(s) by quintiles.

6.3.2. METHOD

Preliminary analysis exploring bivariate relationships between core variables is followed by sequential logistic regression models on propensity to participate in the labour market and avoiding unemployment (including self-employment). First, gross ethnic penalties are obtained by only including dummies for each Muslim group with White British Christian as the reference category (Base Model). Second, individual level controls including age, age squared, education score, government office region, residence in an urban area and wave of survey are added (Socio-demographic model). The third model introduces neighbourhood level characteristics including continuous terms for quintile of neighbourhood resources, quintile of neighbourhood shares of Muslims, and quintile of neighbourhood shares of post-04 migrants (Neighbourhood Model). The final model includes interaction terms between Muslim group and each neighbourhood indicator to test whether there is an effect between individual group membership and local area characteristics (Interactions Model). Only estimates from the third model and selected coefficients will be presented below, with full versions available at the [online repository](#). The predictive marginal effects, based on interactions between individual group membership and neighbourhood indicators, as estimated in the final model are plotted in Figure 6-4. For corresponding analysis command files, see [ch6a1_margins_hunter24.do](#).

Next, focusing on individuals who have secured employment only - bivariate observations are followed by sequential linear regressions exploring the following outcomes: CAMSIS score, log of average hourly earnings, financial anxiety, and job-related satisfaction. A logistic regression on propensity to be in a high-quality job is also included. As is done above, a base, sociodemographic and neighbourhood level model are estimated. However, an additional model is fit including a continuous term for quintile of share of post-04 EU migrants in SOC10 4-digit occupations and additional variables such as a dummy for whether an individual works part-time, works in the public sector, and their major SOC10 group. As an approximation of potential competition from contemporary migrants, a final model is fit interacting individual Muslim group membership with the post-04 migrant indicator. Again, only results from the occupation model, selected coefficients, and predicted marginal effects based on interactions will be presented.

As was done in Chapter 4, all analyses described above are weighted for different selection properties and attrition and separate models are run by gender for only people with valid data on all the variables included in each model. Moreover, because pooled data is being used, standard errors are clustered around the individual to account for the multiple responses from the same cases, leading to more appropriate inference.

6.3.2.1. Seeking for and securing employment.

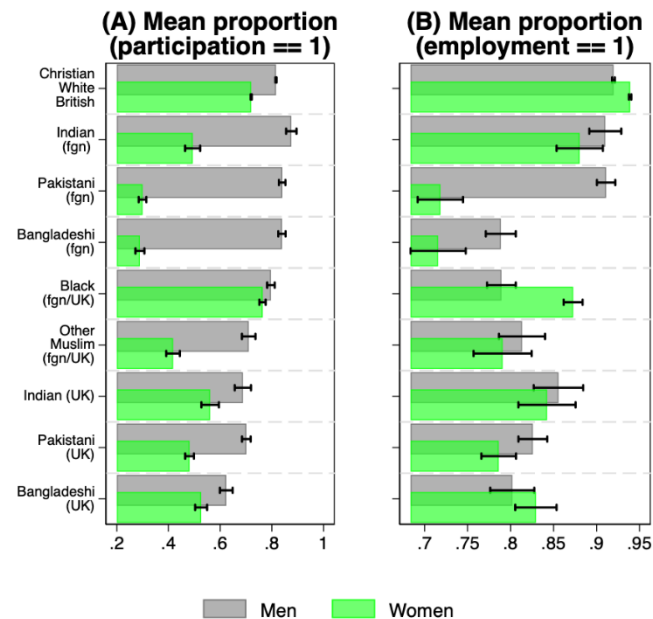


Figure 6-3 Mean proportions participating and employed by Muslim ethnic group and gender.

Figure 6-3 show that across every Muslim group, a higher proportion of men participate in the labour market compared to women. Foreign born Muslim men all have similar levels of participation to the White Christian Britons and UK born Muslims have slightly less. Foreign born Muslim women (and in particular Pakistani and Bangladeshi) have substantially lower levels of participation compared to their male and majority counterparts. It does appear that generational progress has been made, however, as participation rates for UK-born women are higher but still not as high compared to the majority or their male counterparts. Similar trends are apparent when considering employment: across all groups, more men tend to be employed apart from Black Muslims and UK born Bangladeshi in which more women are employed. Similar to participation,

first generation Pakistani and Bangladeshi women are far less likely to be in work than any other group, with generational progress being made.

Table 6-1 indicates that there is a positive correlation between residing in LSOAs with greater resources and non-Muslim male and female participation. However, correlations related to employment are minimal and not significant. A negative association is observed between participation and the number of resources at the LSOA level for Muslim men, while the correlation is marginally positive for women, although not significant. Muslim individuals living in resource-rich areas appear to have lower employment chances, potentially supporting the hypothesis put forward by Jivraj and Alao (2023) that Muslims in more deprived neighbourhoods potentially fare better. This may be related to unique socialisation processes and non-reliance on formal structures.

Table 6-1 Pearson's correlation for bivariate relationships between seeking for and securing employment outcomes and neighbourhood indicators.

	Participation		Employment	
	M	W	M	W
Non-Muslim				
LSOA: resources	0.01*	0.01*	0.00	0.00
LSOA: Exposure to Muslims	0.01*	0.01*	-0.01*	-0.02*
LSOA: Exposure to post-04 EU migrants	0.00	0.01*	0.00	-0.01*
Muslim				
LSOA: resources	-0.01	0.00	-0.02*	-0.03*
LSOA: Exposure to Muslims	-0.03*	0.00	-0.03*	-0.01
LSOA: Exposure to post-04 EU migrants	-0.01	0.00	-0.01	0.01
Data sources: micro data taken from observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020 and limited to only economically active participants. Neighbourhood characteristic variables derived from ONS 2011 Census data.				

Significant positive correlations are reported between the LSOA Muslim indicator and both male and female non-Muslim participation, indicating a slight positive correlation with labour market participation. However, the Muslim indicator is negatively associated with employment, suggesting that areas with prominent Muslim communities may have poorer employment prospects. Exposure to Muslims is negatively associated with male participation and employment among Muslims, although the correlations are not significant for Muslim women. This contrasts with the existing literature that suggests potential benefits for ethnic minorities in neighbourhoods with high co-ethnic shares,

indicating a possible detrimental correlation with Muslim concentration in neighbourhoods and perhaps increased competition within the Muslim community.

The indicator for contemporary migrants in the LSOA is marginally and positively associated with participation among non-Muslims; however, only the correlation for women is significant, suggesting they may be slightly better off in areas with more post-04 migrants when it comes to participating. A significant and negative association is observed between the contemporary migrant indicator and female employment. Evidence shows negative correlations between the LSOA indicator and male participation and employment, as well as positive correlations between the indicator and female participation and employment among Muslims. However, all these correlations are of minimal magnitude and are not statistically significant. Based on this preliminary analysis and without considering other controls, there is little evidence to suggest correlations between exposure to post-04 migrants in the neighbourhood and Muslim outcomes.

Table 6-2 Cluster robust logistic regression of labour market participation and avoidance of unemployment for Muslim men and women.

	Participation		Employment †	
	M	W	M	W
W. Brit. Christ. (ref).	0	0	0	0
Indian (foreign born)	0.65	-0.24	-0.72	-0.04
Pakistani (fgn)	0.90*	-0.75*	-0.44	-0.29
Bangladeshi (fgn)	1.39*	-1.32*	0.3	-2.06*
Indian (UK born)	0.19	-0.19	-0.02	-1.34*
Pakistani (UK)	-0.1	-0.39*	-0.95	-1.25*
Bangladeshi (UK)	-0.35	-0.79*	0.07	-0.83
Black (fgn/UK)	0.69*	1.11*	-0.24	-0.23
Other (fgn/UK)	-0.80*	-1.57*	-1.82	-1.47
LSOA: Resources	-0.01	0	0.01	0.01
LSOA: Exposure to Muslims	0.02*	0.01*	-0.05*	-0.02
LSOA: Exposure to post-04 EU migrants	-0.03*	-0.01	0.01	0
Constant	-4.29*	-5.30*	-4.68*	-5.11*
N	152112	180016	123439	125445
Pseudo R2	0.12	0.12	0.15	0.14

Data sources: micro data taken from observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020. Neighbourhood characteristic variables derived from ONS 2011 Census data. Models adjusted for age, education score, living in London/SE, marital status, children, health condition, caring responsibilities, social ties, liberal gender attitudes, religiosity, and wave of survey. Weights applied and robust standard errors clustered at the individual level. Logits presented.

* **p<0.05.**

† Limited to only economically active participants.

See [online repository](#) for full supplementary tables for each outcome.

Table 6-2 shows the main effect model results where participation and employment are predicted given Muslim group, LSOA level indicators, and a range of controls. Compared to White Christian British, first generation Pakistani and Bangladeshi, and all Black and Other Muslim men are significantly more likely to participate compared to the majority reference category. Most Muslim women are significantly less likely to participate in the labour market, net of other controls thought to influence participation. However, the coefficients are not significant for both foreign and UK born Indian Muslim women and is positive for all Black Muslim women. Among those participating in the labour market, all female groups are less likely to be employed. However, the coefficients are only significant for foreign born Bangladeshi and UK born Indian and Pakistani Muslim women. There are no significant coefficients for any of the Male Muslim groups. The main effect of LSOA resources indicate that an increase in resources at the LSOA level correlates with only marginal improvements in participation and employment, although these effects are not statistically significant. Additionally, a higher share of Muslims in an LSOA is associated with increased participation and a decrease in employment, but this association is not statistically significant in the female employment model. Moreover, increase of exposure to post-04 EU migrants in LSOAs correlates with decreased participation for men and women and increased employment for women, although only the coefficient for the male participation model is significant. Notably, a one-unit increase in exposure to post-04 migrants in LSOAs is negatively correlated with employment among men, and this correlation is significant.

Figure 6-4 shows the predictive margins of participation for different combinations of the Muslim group and neighbourhood level resources, while holding other controls constant. To test the hypothesis that Muslim groups residing in resource-scarce areas might face fewer penalties, one would expect trend lines to slope downwards from lower to higher deprivation quintiles. Overall, the patterns vary by group and country of birth but there is no consistent downward trend to provide evidence for the hypothesis that living in areas with less resources might have protective effects in terms of participation. Trend lines either appear to remain consistent as resources increase or shift marginally upwards or downwards. This is also true when looking at employment in men and women (Figure 6-4) apart from foreign born Pakistani women in which there is a notable downwards slope that might suggest a protective effect of living in more resource scarce areas as this group might benefit from unique socialisation processes and networks.

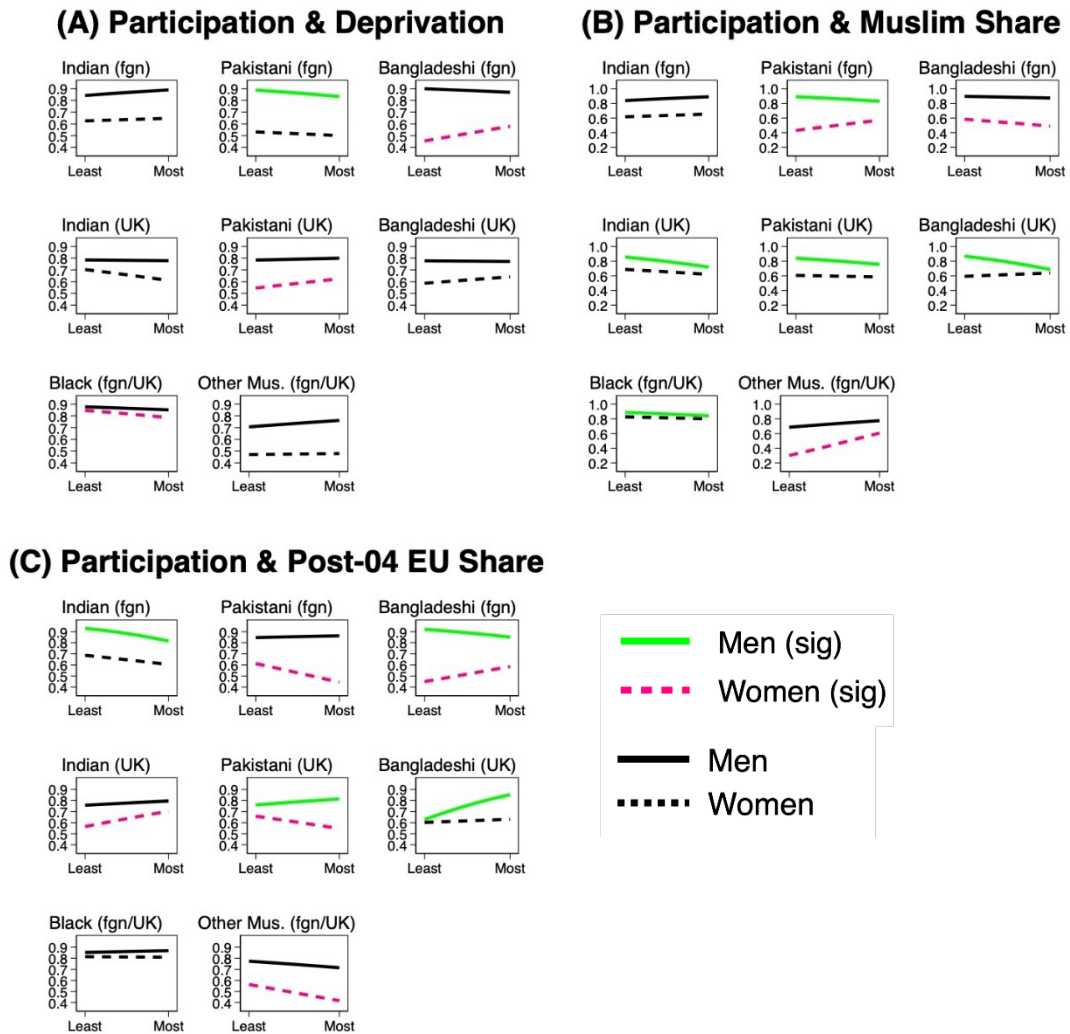


Figure 6-4 Interaction effects of Muslim group and neighbourhood characteristics on participation by gender.

Moreover, foreign born Pakistani and all UK born Indian, Pakistani, Bangladeshi and Black Muslim men have marginally lower predicted probabilities of participation in areas with a higher share of Muslims. Foreign born Pakistani and other Muslim women have large predicted probabilities as the share of Muslims increase - possibly suggesting a protective effect of living in areas with more prominent Muslim communities and thus affecting their participation probabilities.

There are also differential trends in participation of men and women by exposure of post-04 EU migrants in the neighbourhood. Overall, trend lines remain relatively constant with slight downwards or upward trends and therefore providing evidence of a muted

effect of contemporary migration on participation. With that being said, there is some evidence to suggest that Pakistani and Other Muslim women living in areas with more contemporary migrants have worse predicted probabilities. On the other hand, foreign born Bangladeshi women and UK born Indian women seem to slightly benefit from the increase of contemporary migrants at the LSOA level.



Figure 6-5 Interaction effects of Muslim group and neighbourhood characteristics on employment by gender.

Figure 6-5 illustrates the predicted probabilities of employment for various Muslim groups. In regard to the resources quintile, most trend lines remain stable, but there are notable exceptions. The predicted probabilities are lower for foreign born Bangladeshi men and Pakistani women as the resources quintile increases. This observation

challenges the notion that living in resource-scarce areas benefits these groups, as suggested by existing literature. Interestingly, there are upward trends for UK born Indian and all Other Muslim men and women. It appears people from these groups are more likely to be employed in areas with more resources.

Overall, trend lines remain relatively constant with slight downwards or upward trends and therefore providing evidence of a minimal effect of Muslim share on employment. However, as the share of Muslims in the neighbourhood increases, predicted probabilities are higher for foreign-born Indian men and women – which are the only two significant interaction terms. This potentially suggests heightened competition within these groups due to the presence of more Muslims in the area. Among foreign-born Indian men, there are lower employment rates in areas with more Eastern European migrants. Most trend lines remain stable, indicating that the European migrant indicator has minimal impact on employment among Muslims. Notably, however, foreign-born Bangladeshi men and women show a gradual increase, suggesting a positive effect of having more post-04 migrants in the neighbourhood.

In summary, the analyses challenge multiple assumptions from the ethnic penalty literature about the impact of neighbourhood resources and co-ethnic density on participation and employment. For one, there is little evidence to suggest that Muslims living in resource-scarce areas have better rates of participation and employment. In other words, being Muslim generally does not shield them from the challenges associated with living in deprived neighbourhoods, which may result from distinct socialisation processes (Jivraj and Alao, 2023). Moreover, the evidence challenges the assumption that living in areas with more post-04 EU migrants negatively impacts most Muslim groups. Contrary to expectations, increased competition does not necessarily lead to worse outcomes. The key takeaway from these analyses is that, even after accounting for individual and neighbourhood factors that influence participation and employment, most Muslim women – regardless of their country of birth or ethnic group – are still significantly less likely to be in the labour market or have a job (Table 6-2). This finding underscores the persistent challenges faced by Muslim women in accessing employment opportunities.

6.3.3. EMPLOYMENT-RELATED OUTCOMES.

As shown in Figure 6-6, economic outcomes vary significantly across ethnic group and gender. First, Muslim men and women exhibit differences in average CAMSIS scores, with women generally scoring higher than men and UK nationals scoring higher than their foreign-born counterparts. Second, all UK national men and foreign-born Indians earn on average more per hour than women within every Muslim group. Notably, both men and women in the majority Christian White British category outearn all other Muslim groups. Among UK-born individuals, Indian men and women have earnings closest to their majority peers, while Bangladeshi individuals have the lowest log hourly earnings. Third, financial anxiety levels vary across for men and women across most ethnic groups. Foreign born groups report higher anxiety than their UK national counterparts. Indian nationals' anxiety levels align more closely with Christian White Britons, while Bangladeshis experience the highest financial anxiety. Fourth, job satisfaction trends differ: foreign-born men express marginally higher satisfaction, while UK-born women report greater satisfaction. Finally, chances of securing high-quality jobs are similar between UK-born Indians and the majority, while other ethnicities face lower probabilities. These findings underscore the complex interplay of ethnicity, gender, and birthplace in shaping economic well-being and further demonstrate the need to look at ethnic and place of birth differences among the Muslim community.

In Table 6-3, the correlations indicate that non-Muslim men and women living in resource-rich areas tend to have higher CAMSIS scores, greater earnings, reduced financial anxiety, increased job satisfaction, and a higher likelihood of securing high-quality jobs. However, there are exceptions. For instance, the correlation between LSOA resources and financial anxiety is marginal and insignificant for men. Similarly, the correlations between resources and job satisfaction, as well as the likelihood of having a high-quality job, are not significant for non-Muslim women.

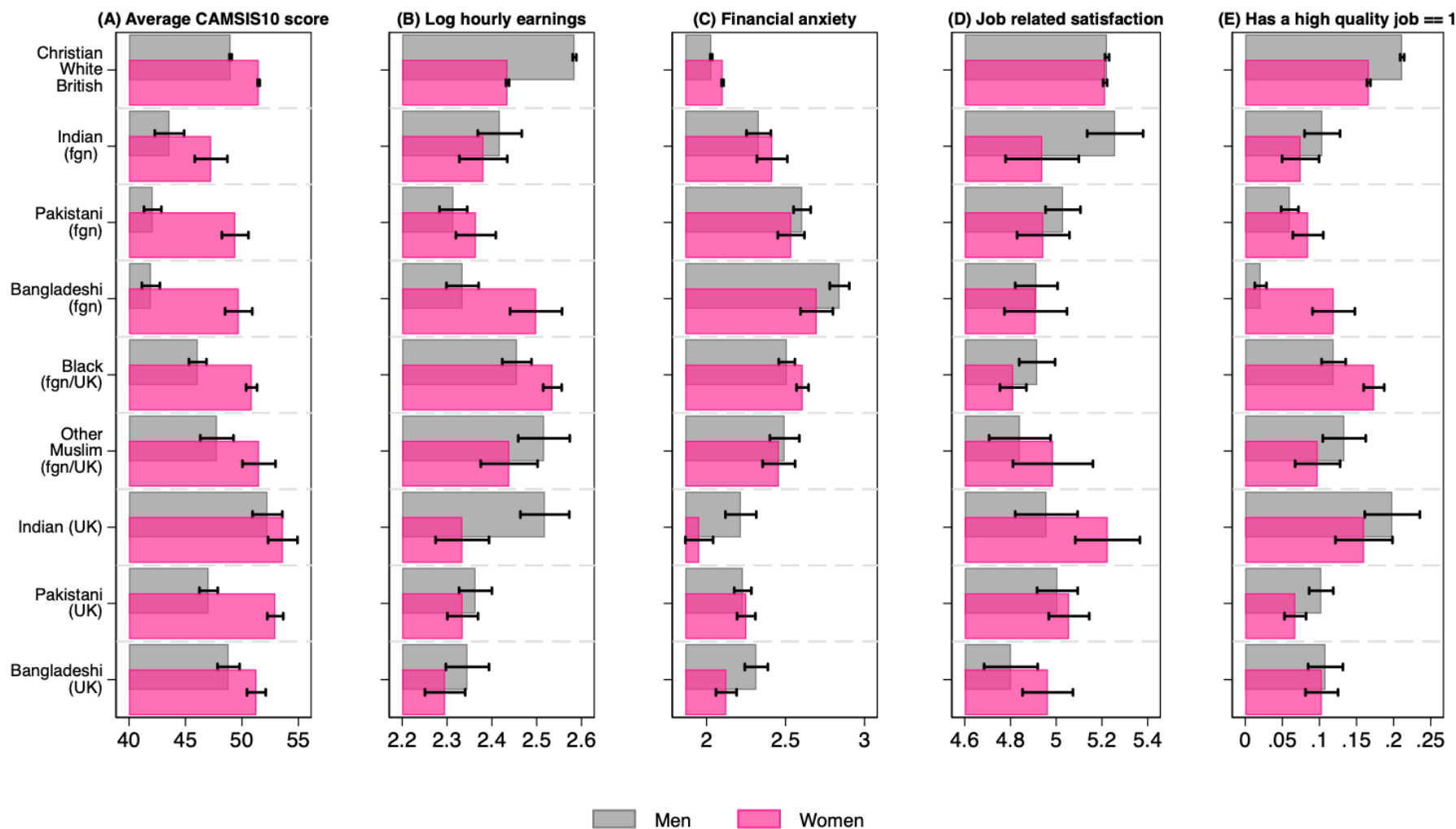


Figure 6-6 Mean proportions of employment outcome by Muslim ethnic group and gender.

Table 6-3 Pearson's correlation for bivariate relationships between employment related outcomes and neighbourhood/occupational indicators.

	CAMSIS		Average hourly earnings		Financial anxiety		Job related satisfaction		High quality job	
	M	W	M	W	M	W	M	W	M	W
Non-Muslim										
LSOA: resources	0.01*	0.01*	0.02*	0.01*	0.00	-0.01*	0.01*	-0.01	0.02*	0.00
LSOA: Exposure to Muslims	0.05*	0.02*	0.04*	0.03*	0.01*	0.02*	0.00	0.01*	0.03*	0.02*
LSOA: Exposure to post-04 EU migrants	0.05*	0.03*	0.04*	0.04*	-0.01*	0.01*	0.00	0.01*	0.02*	0.02*
SOC10 unit groups: exposure to post-04 EU migrant	-	-	-	-	-	-	-	-	-	-
	0.65*	0.62*	0.33*	0.28*	0.14*	0.13*	0.05*	0.06*	0.25*	0.19*
Muslim										
LSOA: resources	0.04*	0.05*	0.01	0.05*	0.01	0.02	-0.01	-0.02	0.01	-
LSOA: Exposure to Muslims	-0.02	0.00	0.00	0.02	0.05*	0.04*	-0.02	0.04*	0.08*	0.03*
LSOA: Exposure to post-04 EU migrants	0.00	0.02	0.03*	0.04*	0.01	0.00	-0.02	0.00	-0.02	0.07*
SOC10 unit groups: exposure to post-04 EU migrant	-	-	-	-	-	-	-	-	-	-
	0.67*	0.52*	0.29*	0.10*	0.19*	0.14*	0.04*	0.05*	0.25*	0.09*
Data sources: micro data taken from observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020 and limited to only economically active participants. Neighbourhood characteristic variables derived from ONS 2011 Census data. Occupation indicator derived from LFS 2011 – 2020.										

Comparing these correlations to those for Muslim respondents, table 6-3 shows there are generally positive associations between resources and outcomes, except for job satisfaction and the chances of high-quality employment among Muslim women. Notably, only the correlations between resources and CAMSIS are significant for both genders, while the relationship between resources and earnings or job security is significant only for women.

Overall, the macro indicator of Muslims in each LSOA suggests that areas with a higher Muslim population tend to exhibit better labour market performance. This is the case for both non-Muslims and, even more so, for Muslim individuals with stronger correlations. However, the positive correlation between the Muslim indicator and financial anxiety implies that an increase in the Muslim population could raise anxiety levels for some. Despite this, there are no significant correlations between the proportion of Muslims and CAMSIS or earnings.

Additionally, the negative correlation between the Muslim indicator and job satisfaction is significant only for women.

Turning to contemporary migration indicators, there is a marginal positive effect on labour market outcomes. The exception is the positive association between post-2004 EU migrants and financial anxiety, suggesting that the presence of these migrants might increase anxiety for some non-Muslim women. Among Muslims, positive correlations generally indicate better labour market outcomes in areas with more post-04 migrants. Table 6-4 shows the main effect model results of multiple employment related outcomes by Muslim group, neighbourhood level indicators, and by the contemporary migrant occupation measure. Compared to Christian White Britons and while there are variations among gender and place of birth, almost all Muslim men (apart from foreign born Indian) and women (apart from foreign born Bangladeshi) have a lower average CAMSIS score, lower average hourly earnings (apart from UK born Bangladeshi), higher levels of financial anxiety, lower job-related satisfaction, and poorer chances of being in a high quality job - even after adjusting the models for individual covariates and other macro indicators (see table for non-significant coefficients).

While the number of resources, the share of Muslims, and the presence of post-04 migrants in a LSOA have minimal impact on employment outcomes, there are notable gender-specific associations. For example, there is a positive association between the number of neighbourhood resources and male and female CAMSIS scores, and positive associations between the share of Muslims in an LSOA. Moreover, the share of post-04 migrants in the neighbourhood is negatively associated with male and female CAMSIS scores, average hourly earnings of both genders, and high-quality jobs. There is also a positive association between exposure to post-04 EU migrants in SOC10 occupations and financial anxiety for women, suggesting a possible detrimental impact on this group. While there is a negative correlation between the presence of European migrants in SOC10 unit groups and economic outcomes for Muslims, it is essential to consider the underlying mechanisms. Rather than directly causing worse outcomes, it is plausible that European migrants self-select into specific occupations that inherently lead to less favourable economic prospects. Therefore, caution is warranted when attributing causality solely to the number of European migrants. To try and understand this further, additional models that examine interactions between the number of post-04 migrants and each specific Muslim group were estimated. The results of this interaction models are presented below as predictive margins.

Table 6-4 Cluster robust linear regression of labour market outcomes and logistic regression of different job-related outcomes for Muslim men and women

	CAMSIS		Average hourly earnings		Financial anxiety		Job related satisfaction		High quality job †	
	M	W	M	W	M	W	M	W	M	W
W. Brit. Christ.										
Indian (fgn)	0.28	-5.77*	-0.09	0.03	0.22	0	0.06	0.27	0.65	1.25
Pakistani (fgn)	-0.19	-1.53	-0.35*	-0.21	0.42*	0.55*	-0.46	-0.15	-0.91	0.4
Bangladeshi (fgn)	-0.74	4.52*	-0.18*	0.37	0.72*	0.11	-0.42	-0.90*	-1.9	1.32
Indian (UK)	-2.50*	0.99	-0.15	-0.01	0.01	0.4	0.37*	-1.19*	-0.09	-0.81
Pakistani (UK)	-1.2	-1.78*	-0.06	-0.07	0.12	0.04	-0.22	0.07	0.2	-1.14*
Bangladeshi (UK)	-2.96*	-4.71*	0.01	0.05	0.19	0.02	-0.64*	-0.63*	0.26	-0.09
Black (fgn/UK)	-0.44	-2.73*	-0.22*	0.02	0.50*	0.41*	-0.24	-0.41*	-0.63	0.23
Other (fgn/UK)	-1.18	-6.01*	-0.11	-0.2	0.1	0.21	-0.76*	-0.16	-0.5	-2.15*
LSOA: resources	0.06*	0.04*	0.01*	0	0	-0.01	0	-0.01	0.02	0
LSOA: Exposure to Muslims	0.06*	0.05*	0	0	0.01*	0.01	0	0	0.01	0.02
LSOA: Exposure to post-04 EU migrants	0.05	-0.04	0	0	-0.01	0	0	0.01	-0.01	0.01
SOC10 unit groups: exposure to post-04 EU migrant	-5.23*	-5.20*	-0.03*	-0.02*	0.01	0.02*	-0.01	-0.03*	-0.10*	-0.08*
Constant	26.48*	31.56*	1.10*	1.39*	2.79*	2.76*	4.80*	4.73*	-5.62*	-5.54*
N	90398	100,833	80670	95095	80596	95002	79643	94312	80680	95098
R2	0.55	0.5	0.41	0.34	0.07	0.1	0.03	0.05		
Pseudo R2									0.2	0.15

Data sources: micro data taken from observations from main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020 and limited to only economically active participants. Neighbourhood characteristic variables derived from ONS 2011 Census data. Occupation indicator derived from LFS 2011 – 2020. Models adjusted for age (squared), education score, living in London/SE, marital status, children, health condition, caring responsibilities, social ties, liberal gender attitudes, and religiosity, and wave of survey. All models - apart from CAMSIS – are adjusted for sector of occupation, parttime working, major SOC10 group, and sector.. Weights applied and robust standard errors clustered at the individual level. Linear regression scores presented for first four outcomes and † logits presented for high-quality job * **p<0.05**. See [online repository](#) for full supplementary tables for each outcome.

The margin plots in Figure 6-7 indicate a consistent downward trend across all ethnic groups and both genders, suggesting that all groups are likely to have lower CAMSIS scores in occupations with a higher presence of post-2004 EU migrants. UK-born Indian and Black Muslim men, as well as Pakistani and Other Muslim women, are likely to have higher earnings in occupations with more post-2004 EU migrants. Apart from foreign-born Pakistani and Bangladeshi men, who show relatively stable trend lines, all other groups are expected to earn less in occupations with higher shares of Eastern Europeans. Foreign-born Indian and Bangladeshi women, along with all Other Muslims, are likely to experience more financial anxiety in occupations with more Eastern European migrants, whereas UK-born Indians are expected to have less anxiety in this context. The trend lines for other groups appear relatively stable, suggesting a muted effect. For the UK-born Indian group, trend lines for job-related satisfaction diverge. Men are likely to have less satisfaction in jobs with more Eastern Europeans, whereas the opposite is true for women. There are slight downward trends for both foreign-born Indian men and women, but the effects seem muted across the other groups. UK-born Indian, Pakistani, and all other Muslim women are likely to be considered to have higher quality jobs that also have higher shares of Eastern Europeans. In contrast, foreign-born Indian men and women, as well as Bangladeshi women, appear to have lower quality jobs as the number of Eastern Europeans increases, although these findings are based on non-significant results.

In summary, the impact of post-04 EU migrants in occupations on earnings and job quality varies across ethnic groups and genders. The margin plots suggest that across all ethnic groups and both genders, there is a consistent downward trend in CAMSIS scores and earnings in occupations with more post-2004 EU migrants, with variations in financial anxiety, job satisfaction, and job quality depending on the group and gender. The key takeaway from this analysis is that the main effects of the models reveal persistent gaps when comparing Muslims groups to the White majority. Even after accounting for neighbourhood controls and presence of contemporary migrants in occupations, Muslim penalties exist.

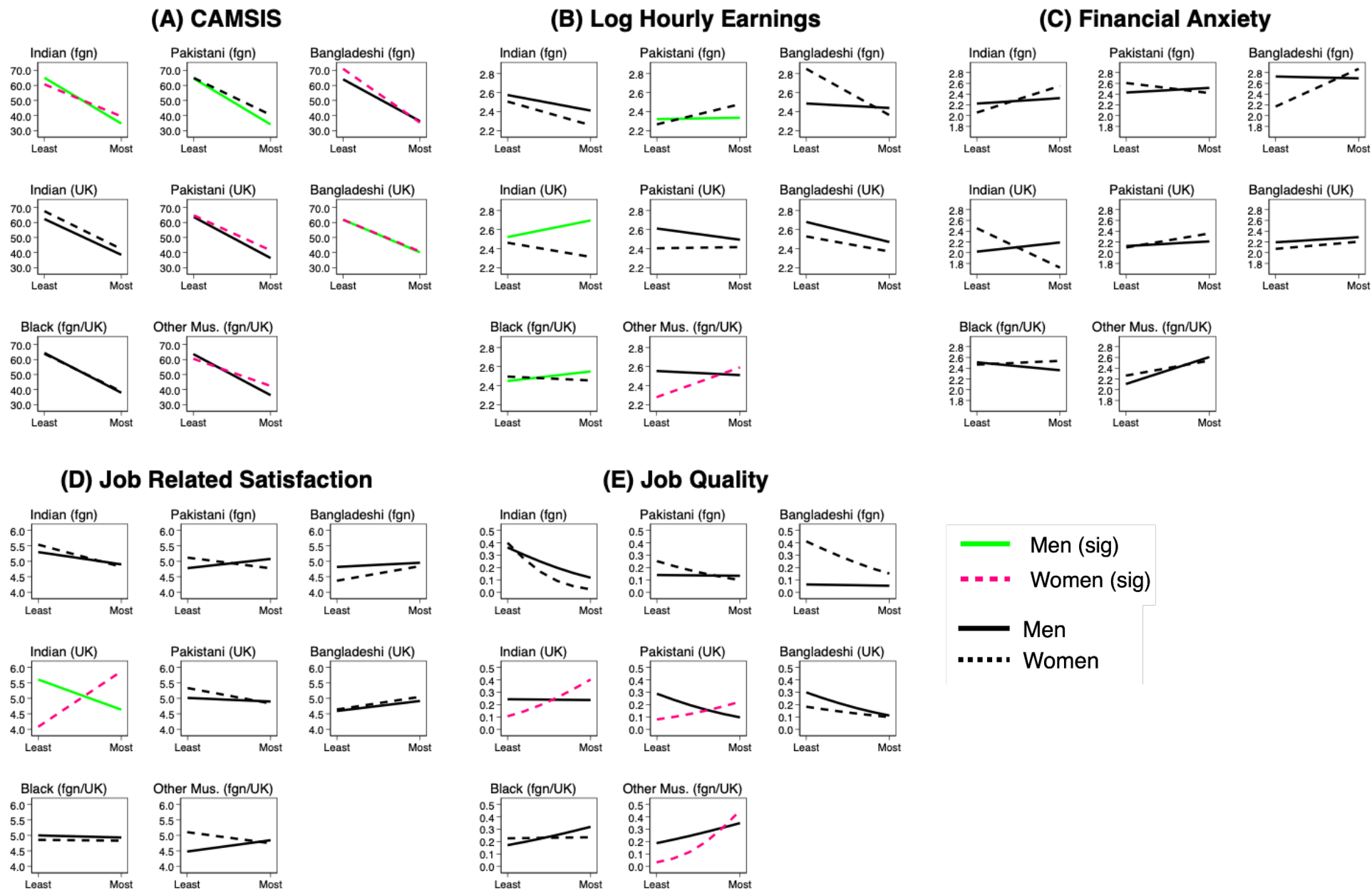


Figure 6-7 Interaction effects of post-04 EU migrants in occupations on job-related outcomes by gender.

6.4. Part 2 – Random effects and variations at the SOC10 unit group level.

Now that the broad effects of contemporary migration on various outcomes have been explored, it is worthwhile to focus on specific occupations to identify if there are certain occupation groups that experience inequalities compared to others. This detailed examination can uncover unique patterns and disparities that broad analysis might overlook. For example, in the above analysis, only controls for major SOC10 occupation were included in the models. By focusing on detailed SOC10 unit groups (available only in the restricted version of the UKHLS), it is possible to gain deeper insights into the actual occupations that are occupied by Muslims and how this interacts with other factors in shaping employment outcomes.

6.4.1. SAMPLE AND METHOD

The same sample that has been used thus far in the chapter is used again, with slight differences. Similar regressions on average hourly earnings, financial anxiety, and job-related satisfaction (as presented in Table 6-5 and 6-6) are run for both men and women, but this time incorporating a multilevel structure. The main socio-demographic controls, human capital characteristics, employment factors, socio-cultural variables, macro neighbourhood measures and share of post-04 migrants in SOC10 unit groups are fit at the individual level for each outcome and SOC10 unit group was fit at level 2. The pooled sample was condensed to include only one observation per occupation. Essentially, this process removed duplicate entries from the same individual across waves if they held the same job. Models are limited to only observations with valid data on all the variables included in the models (see table 6-5 and 6-6 for n). Null models and models with controls were estimated to provide insight into how much the variation in outcomes can be explained by individual controls and the contemporary migration measure. For corresponding syntax see [ch6a2_mixed_hunter24.do](#).

Random effects residuals based on SOC10 unit groups are also estimated. By estimating the residuals for each SOC10 unit group, we can see which are associated with better or worse outcomes and compare specific occupation effects based on other characteristics. For example,

Figure 6-8A and 6-8C shows the plotted empirical Bayes residuals for multilevel models, with 95% confidence intervals. Each circle represents the residual for a specific SOC10 unit group and the size is proportional to the number of people in that occupation. The shading of markers is darker the higher the occupation's percentage of Muslims (derived using 5 quintile version of the variable). Figure 6-8B and 6-8D shows only the significant occupation residuals. That is, the occupation residuals with confidence intervals that do not encompass 0. Lime coloured marker labels are attached to the occupations with the most Muslims in them. In Figure 6-8A and 6-8B you can generally see that darker circles are concentrated towards the bottom of the scale, suggesting occupations with more Muslims tend to have poorer outcomes than what is expected by the model.

Table 6-5 Multilevel linear and logistic regression of labour market outcomes for men with SOC10 unit group at level 2.

	Average hourly earnings		Financial anxiety		Job related satisfaction	
	Null	ME	Null	ME	Null	ME
Constant	2.44*	0.80*	2.12*	1.29*	5.23*	5.96*
Indian (fgn) †		-0.09*		0.22*		-0.32*
Pakistani (fgn)		-0.20*		0.32*		-0.34*
Bangladeshi (fgn)		-0.18*		0.46*		-0.24*
Black (fgn/UK)		-0.10*		0.34*		-0.25*
Other Muslim (fgn/UK)		-0.14*		0.42*		-0.55*
Indian (UK)		0.02		0.06		-0.41*
Pakistani (UK)		-0.04		0.11*		-0.27*
Bangladeshi (UK)		-0.05		0.20*		-0.50*
Age		0.05*		0.09*		-0.07*
Education score		0.01*		-0.01*		0
English language proficiency		0.02		-0.21*		0.08
London/SE England		0.12*		0		-0.01
Married		0.10*		-0.09*		0.25*
No. of Children		0.09*		0.03		-0.04
Health Condition		0.03*		-0.18*		0.36*
Caring Responsibilities		-0.02		0.09*		-0.09*
Majority ties		-0.01		-0.04*		0
Liberal gender val.		0.02*		-0.03*		0.03
Low religiosity		0.02*		-0.01		-0.09*
LSOA: resources		0.00*		0		0
LSOA: Exposure to Muslims		0		0.01*		-0.01
LSOA: Exposure to post-04 EU migrants		0		-0.01		0
Public sector		0.01		0		0.07*
Works part time		0.06*		0.19*		-0.07*
Professional‡		0		0		0.04
Associate and tech.		-0.13*		0.14*		-0.07*
Admin. & secretarial		-0.25*		0.22*		-0.23*
Skilled trades		-0.29*		0.28*		-0.05
Personal service		-0.40*		0.35*		-0.23*
Sales and customer.		-0.34*		0.41*		-0.32*
Process, plant & machine operatives.		-0.28*		0.33*		-0.15*
Elementary occupations.		-0.41*		0.43*		-0.20*
post-04 EU migrants in unit groups		-0.02*		0.02*		-0.02*
Random Effects: Variances						
SOC10 unit group level	0.10*	0.02*	0.06*	0.01*	0.02*	0.00*
Individual level	0.29*	0.24*	0.85*	0.80*	1.79*	0.00*
VPC (ICC)	0.26	0.08	0.06	0.01	0.01	0
PCV		79.8		80.4		80.7
N		29939		25204		26866

* p<0.05. Source: main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020.

Limited to one occupation per participant. † reference category = White British Christian ‡ reference category = Managers and senior officials. Controls for wave of the survey omitted from output. for neighbourhood characteristic variables derived from ONS 2011 Census data and an occupation indicator derived from LFS 2011 – 2020.

Table 6-6 Multilevel linear regression of labour market outcomes for women with SOC10 unit group at level 2

	Average hourly earnings		Financial anxiety		Job related satisfaction	
	Null	ME	Null	ME	Null	ME
Constant	2.38*	1.11*	2.10*	1.53*	5.26*	5.31*
Indian (fgn) †		0.03		0.15		-0.29*
Pakistani (fgn)		-0.06		0.22*		-0.38*
Bangladeshi (fgn)		-0.01		0.40*		-0.40*
Black (fgn/UK)		0.03		0.35*		-0.35*
Other Muslim (fgn/UK)		0.01		0.31*		-0.27*
Indian (UK)		0		-0.18*		-0.25
Pakistani (UK)		0.03		0.07		-0.20*
Bangladeshi (UK)		0.05*		0.08		-0.36*
Age		0.03*		0.08*		-0.06*
Education score		0.01*		-0.01*		0.01*
English language proficiency		0.02		-0.26*		0
London/SE England		0.10*		0.03		-0.03
Married		-0.12*		-0.33*		0.34*
No. of Children		0.13*		0.09*		-0.03*
Health Condition		-0.01		-0.19*		0.42*
Caring Responsibilities		0.02*		0.08*		-0.12*
Majority ties		0		-0.05*		0.04*
Liberal gender val.		0.04*		-0.04*		0
Low religiosity		0.02*		-0.01		-0.08*
LSOA: resources		0		-0.01*		-0.01
LSOA: Exposure to Muslims		0		0.01*		-0.01
LSOA: Exposure to post-04 EU migrants		0.01*		-0.02*		0
Public sector		0.04*		-0.04*		0.06*
Works part time		0.05*		0.05*		0.04*
Professional‡		0.02		-0.03		0.03
Associate and tech.		-0.11*		0.15*		-0.01
Admin. & secretarial		-0.24*		0.23*		-0.11*
Skilled trades		-0.36*		0.25*		-0.08
Personal service		-0.34*		0.33*		-0.07
Sales and customer.		-0.30*		0.36*		-0.20*
Process, plant & machine operatives.		-0.31*		0.36*		-0.11
Elementary occupations.		-0.34*		0.36*		-0.18*
post-04 EU migrants in unit groups		-0.02*		0.02*		0
Random Effects:						
Variances						
SOC10 unit group level	0.07*	0.01*	0.05*	0.01*	0.02*	0.00*
Individual level	0.23*	0.19*	0.90*	0.84*	1.90*	1.83*
VPC (ICC)	0.23	0.06	0.05	0.01	0.01	0
PCV		81.3		76.9		92.4
N		31256		29532		29884

* p<0.05. Source: main adult panel (aged 16 – 65) of the UKHLS, waves 1 – 12 covering the time period 2009 – 2020.

Limited to one occupation per participant. † Reference category = White British Christian ‡ reference category = Managers and senior officials. Controls for wave of the survey omitted from output. for neighbourhood characteristic variables derived from ONS 2011 Census data and an occupation indicator derived from LFS 2011 – 2020.

6.4.2. FINDINGS

6.4.2.1. Earnings

The main effects in Table 6-5 shows that, in comparison to the Christian White majority, all foreign Muslim men apart from UK born Indian, Pakistani, and Bangladeshis earn less on average. Put otherwise, these groups still experience earnings penalties after controlling for population characteristics, human capital, socio cultural factors, employment factors including their major SOC10 code, neighbourhood characteristics and the proportion of EU migrants in their SOC10 unit group. Resources, exposure to Muslims and post-04 EU migrants in LSOA has a marginal effect on male earnings. A one-unit increase in the amount of post-04 EU migrants in LSOA has a small negative effect. For women (see Table 6-6), there are no statistically significant differences in earnings between Muslim groups and the majority. However, the presence of post-04 EU migrants in certain occupations is associated with a substantial negative effect on women's earnings overall.

Table 6-5 also shows the random effect variances and summary statistics from the multilevel models with SOC10 unit groups fit at level 2. In the null average hourly earnings model, there is a VPC = 26% for men and 23% for women, which indicates a large amount of clustering at the SOC10 unit-group level without including controls. This means that unit group membership explains a significant portion of the variation in earnings. In the main effects models (adding controls) the VPC decreases from the null model to 0.08% for men and 0.06% for women. This reduction suggests that the inclusion of the main effects has accounted for some of the variance that was previously attributed to the unit group differences for both men and women.

Table 6-7 provides further detail on occupations with above average proportions of Muslim respondents in them. It includes a list of occupations with significantly higher or lower empirical Bayes residuals for occupations in the highest Muslim share quintile. Alongside information about the occupation, the percentage of Muslims and post-04 migrants for the occupation are included in addition to the predicted outcome and confidence intervals. These tables are based on models (above) in which various controls have been included. There are gender variations in the occupations that earn significantly more than other groups. Among men, the top five occupations include: Security guards (9241), metal working machine operatives (8125), legal professionals (2419), medical practitioners (2211), and rail travel

assistants (6215). Most of these groups have low shares of Eastern Europeans. The Metal Workers occupation, which has almost equal shares of Muslims and Eastern Europeans, and

Table 6-7 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Average Hourly Earnings

Rank	SOC10 unit group	Rank	% Muslim	% post-04 EU	Predicted Mean Outcome	[95% CI]
Men						
5 Lowest						
2	1223 Restaurant and catering establishment managers and proprietors	98	0.12	0.03	-0.4	-0.5 -0.31
4	1254 Shopkeepers and proprietors wholesale and retail	52	0.13	0	-0.36	-0.48 -0.24
9	8214 Taxi and cab drivers and chauffeurs	179	0.41	0.02	-0.25	-0.32 -0.18
12	3412 Authors, writers and translators	27	0.13	0.04	-0.22	-0.38 -0.07
14	8215 Driving instructors	16	0.14	0	-0.22	-0.4 -0.04
5 Highest						
56	9241 Security guards and related occupations	337	0.18	0.02	0.1	0.05 0.15
57	8125 Metal working machine operatives	194	0.09	0.08	0.1	0.03 0.17
75	2419 Legal professionals	27	0.13	0.01	0.16	0 0.31
84	2211 Medical practitioners	106	0.13	0.01	0.17	0.08 0.26
93	6215 Rail travel assistants	23	0.14	0.01	0.2	0.04 0.36
Women						
5 Lowest						
5	1223 Restaurant and catering establishment managers and proprietors	109	0.12	0.03	-0.24	-0.32 -0.16
6	1254 Shopkeepers and proprietors wholesale and retail	27	0.13	0	-0.24	-0.38 -0.1
15	3231 Youth and community workers	223	0.10	0	-0.14	-0.19 -0.08
16	6121 Nursery nurses and assistants	483	0.09	0.01	-0.12	-0.16 -0.08
20	6125 Teaching assistants	894	0.10	0.01	-0.11	-0.14 -0.08
Highest						
57	3412 Authors, writers and translators	52	0.13	0.04	0.14	0.03 0.24
66	2412 Barristers and judges	11	0.12	0	0.2	0.18 0.29
72	2211 Medical practitioners	150	0.13	0.01	0.25	0.18 0.32

where both groups earn more, suggests that this occupation might provide an equitable environment or opportunities that benefit both groups. This could be evidence of a labour market where diverse backgrounds do not hinder earnings potential, possibly due to the nature of the work, demand for skills, or inclusive workplace practices that support higher earnings for both Muslim and Eastern European workers.

At the other end of the scale, restaurant and catering managers (1223), shopkeepers (1254), taxi and cab drivers (8214), authors, writers and translators (3412), and driving instructors (8215) all earn less than expected. These occupations have noticeably higher shares of Muslims compared to Eastern Europeans, with a substantial 41% of taxi drivers in this sample identifying as Muslim. This earnings disparity suggests that occupations with higher shares of Muslims may face financial disadvantages. Additionally, these occupations tend to have fewer Eastern Europeans, although authors, writers and translators do have a notable 4% representation. These insights highlight the need for targeted interventions to address these disparities and promote equitable opportunities across different occupations. There are some similarities for women. Restaurant and catering managers (1223) and shopkeepers (1254) similarly occupy the lowest two earnings ranks. However, they are accompanied by youth and community workers (3231), nursery nurses and assistants (6121), and teaching assistants (6125). Interestingly, among women, authors and writers, who earn significantly less among men, are the third highest-ranked occupation for women, perhaps suggesting that women perform better in these roles. Barristers and judges are also among the top earners, although it is important to note that there are only 11 barristers and judges in this sample. As this comprises of 12% Muslim, this only amounts to one female Muslim barrister/judge. The fact that medical practitioners are among the top earners for both men and women is worth consideration. It suggests that the medical field offers equitable earning opportunities regardless of gender. This could be due to the high demand for medical professionals, the rigorous training and qualifications required, and the standardised pay scales within the healthcare sector.

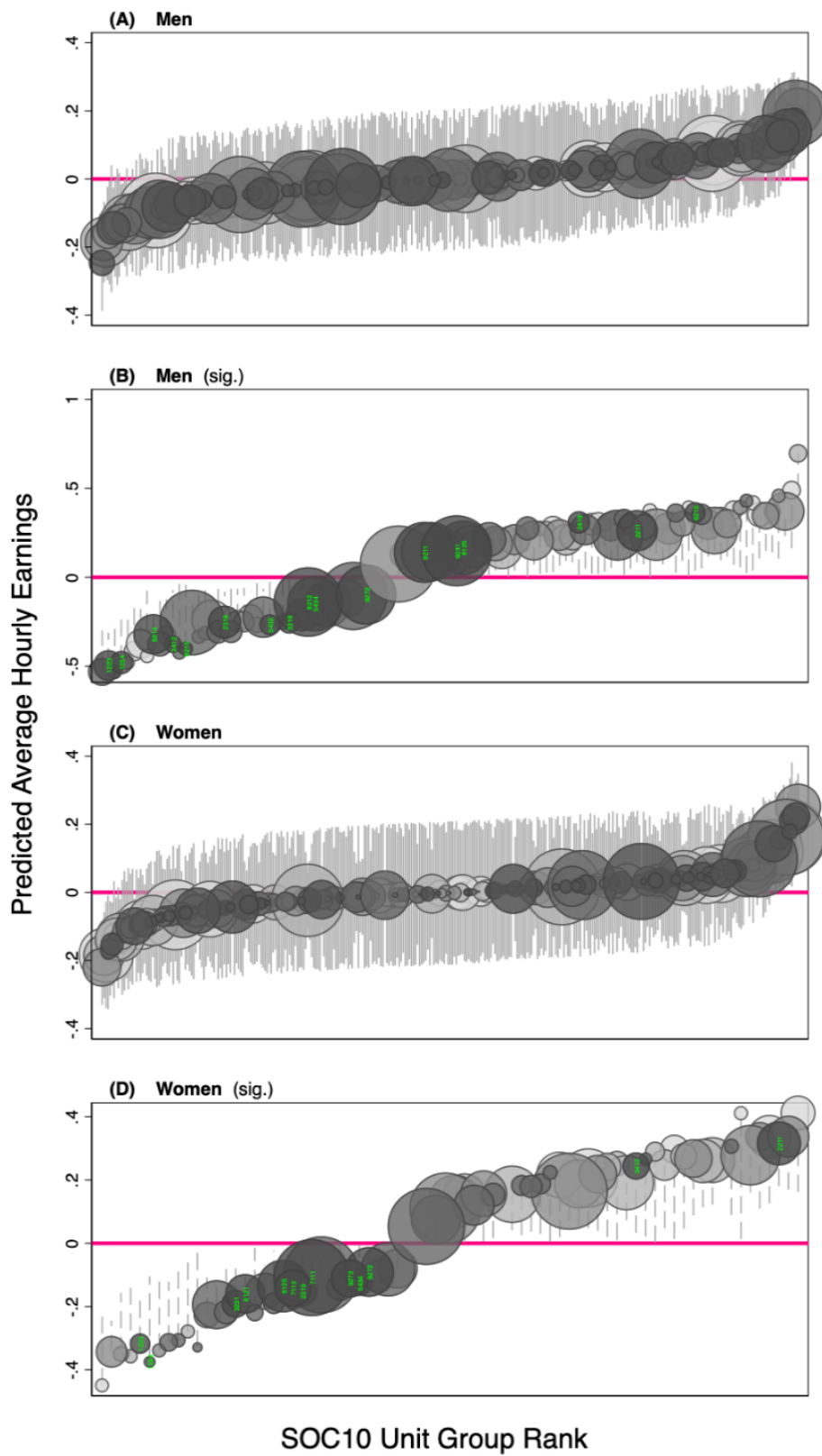


Figure 6-8 predicted occupation effects, ranked low to high.

6.4.2.2. Financial Anxiety

For results concerning the measures of financial anxiety, it is important to note that the interpretation of high and low ends of the scale should now be reversed: the higher end of the numerical scale implies more financial anxiety. Table 6-5 shows that all Muslim men (apart from UK born Indians) are significantly more financially anxious than the majority. There are weak effects of macro neighbourhood characteristics and EU occupation measures on the outcome. Apart from foreign born Indian and Pakistani and UK born Bangladeshi, most other women have higher levels of anxiety (Table 6-6). UK born Pakistani are the exception, with lower levels. Macro neighbourhood factors have a small effect, but once again, there is a strong effect of proportion of EU migrants in occupations on women's financial anxiety. The random effect variances show a VPC in the null model of 0.06% compared to 0.01 in the main effects model. This indicates a moderate amount of clustering at the SOC10 unit-group level without including controls which essentially disappears after their inclusion.

Figure 6-9 shows a concentration of occupations in the top Muslim quintile at the high end of the scale. Again, there are some gender variations and similarities in financial anxiety across different occupations at either end of the scale (Table 6-7). Both male and female medical practitioners have less financial anxiety than would be expected by the model. Of the male rankings, metal workers (8125) are another group expected to have less anxiety, again more evidence of an occupation with equal shares Muslim and EU respondents who also tend to have favourable outcomes on average. Male van drivers (8212), taxi and cab drivers (8214), and chefs (5434) have the highest levels of anxiety. A notable 19% of chefs identifying as Muslim and 4% as Eastern Europeans, suggests that these occupations may be particularly stressful or challenging for these groups. This could be due to various factors such as job insecurity, demanding work conditions, or potential discrimination by employers that prevent them from feeling comfortable about their financial situations.

The occupations with the highest anxiety among women include retail cashiers (7112), restaurant and catering managers (1223), telephone salespersons (7113), shopkeepers (1254), and teaching and education professionals (2319). Given that these models control for many variables, it might be the case that these groups experience considerable discrimination, which impacts their anxiety levels. These occupations also have low proportions of EU migrants, suggesting little evidence their presence could be influential. The fact that these highly anxious

occupations are only apparent among women, suggests that in these roles, women may face unique challenges and stressors related to both their gender and their ethnic or religious identity, which could exacerbate their anxiety levels.

Table 6-8 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Financial Anxiety

Rank	SOC10 unit group	Rank	% Muslim	% post-04 EU	Predicted Mean Outcome	[95% CI]
Men						
<i>Lowest</i>						
1	2211 Medical practitioners	86	0.13	0.01	-0.25	-0.39 -0.1
6	8125 Metal working machine operatives	154	0.09	0.08	-0.14	-0.26 -0.03
<i>Highest</i>						
13	8212 Van drivers	474	0.11	0.02	0.1	0.03 0.18
15	8214 Taxi and cab drivers and chauffeurs	153	0.41	0.02	0.13	0.01 0.24
17	5434 Chefs	307	0.19	0.04	0.14	0.05 0.23
Women						
<i>5 Lowest</i>						
6	2211 Medical practitioners	141	0.13	0.01	-0.15	-0.28 -0.03
9	9273 Waiters and waitresses	415	0.1	0.04	-0.1	-0.18 -0.02
<i>Highest</i>						
15	7112 Retail cashiers and check-out operators	403	0.09	0	0.14	0.06 0.23
17	1223 Restaurant and catering establishment managers and proprietors	100	0.12	0.03	0.15	0.02 0.29
22	7113 Telephone salespersons	60	0.09	0	0.18	0.02 0.33
23	1254 Shopkeepers and proprietors wholesale and retail	25	0.13	0	0.2	0.02 0.38
24	2319 Teaching and other educational professionals	239	0.09	0	0.21	0.11 0.31

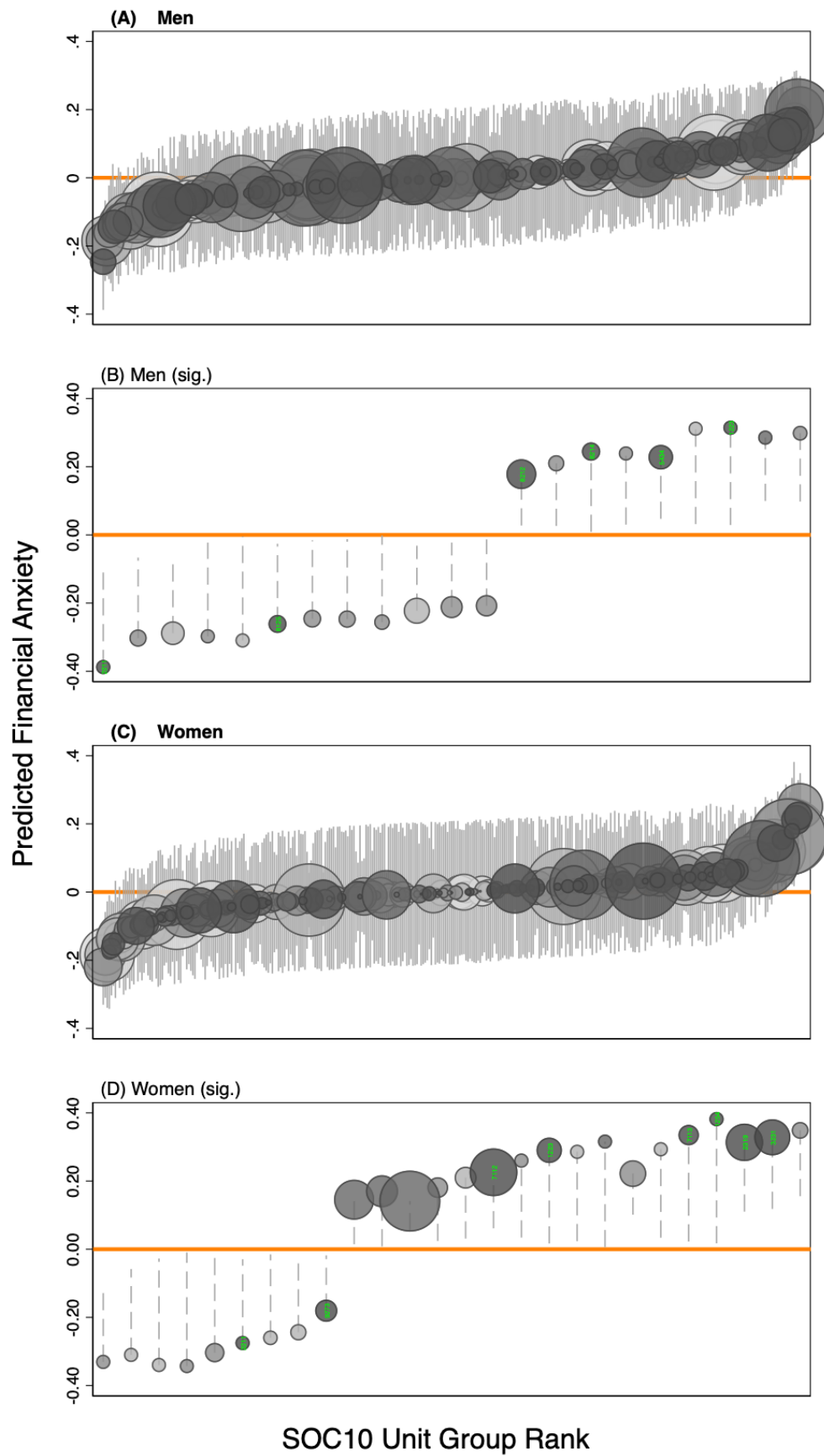


Figure 6-9 Predicted occupation effects on financial anxiety, ranked low to high.

6.4.2.3. Job related satisfaction

Table 6-5 shows that all male Muslim groups had lower job satisfaction (apart from UK born Indian women) than their majority counterparts (net of all the controls) but neighbourhood characteristics had positive significant, albeit marginal, effects. The presence of EU migrants in occupations had little influence. The null VPC is 0.01 showing very little clustering at the SOC10 unit group level for both women and men. Adjusting for controls reduces this even further.

Table 6-9 List of all SOC10 unit groups with significantly higher or lower empirical Bayes residuals – Job Related Satisfaction.

Rank	SOC10 unit group	Group Size	% Muslim	% post-04 EU	Predicted Mean Outcome	[95% CI]
Men						
Lowest						
1	9274 Bar staff	206	0.02	0.01	-0.12	-0.23 -0.02
2	1190 Managers retail and wholesale	314	0.06	0.01	-0.11	-0.21 -0.01
Women						
Lowest						
1	6145 Care workers and home carers	1673	0.07	0.02	-0.06	-0.1 -0.01

As shown in figure 6-10, occupations with high Muslim shares are concentrated at the bottom of the satisfaction scales, particularly for men. There are barely any occupations in the highest Muslim quintile that are significantly below or above, thus all occupation groups regardless of Muslim share are shown. There are considerably less occupation groups in the top Muslim percentile that are significantly different from what the models would predict in terms of job-related satisfaction. There are no groups at all, regardless of their Muslim population with significantly higher satisfaction. However, male bar staff (9274) and retail and wholesale managers (1990) appear significantly unsatisfied with their work despite all these controls. Similarly, female care workers and home carers (6145) also show high levels of dissatisfaction. The latter two occupations have high proportions of Muslims, which may indicate that these

roles are particularly challenging or stressful for Muslim workers. This could be due to a combination of factors such as workplace discrimination, lack of support, or cultural and religious barriers that impact job satisfaction. Put otherwise, the penalties associated with these specific occupations have not been explained away by population characteristics, human capital, socio-cultural variables, or neighbourhood contexts.

6.4.2.1. Summary

Due to using detailed occupational information (using the restricted version of the UKHS), this analysis represents an enhancement over the prior analysis and ethnic penalties literature by exploring the variations among detailed occupational classifications rather than broadly defined major occupational groups and other class schemes. By focusing on specific SOC10 unit groups, the analysis provides more nuanced investigation of the different economic and social dynamics influencing outcomes. This granular approach has allowed for the identification of particular occupations where disparities are most pronounced, offering a clearer picture of factors contributing to poorer outcomes experienced by the Muslim community – while also controlling for other factors such as neighbourhood and occupation indicators. One of the key improvements is the ability make fine-grained observations that were previously obscured by broader categorisations. For instance, while earlier analyses might have grouped all sales and customer service occupations together, the above approach has distinguished between shopkeepers, retail managers, and cashiers, revealing significant differences in earnings and financial anxiety within these subgroups. Such detailed insights could be useful for targeted interventions and policies that address specific needs of people in the occupations.

This analysis underscores the persistent disadvantages faced by Muslim respondents in the labour market, despite the inclusion of numerous controls to account for various factors. For example, a considerable amount of male Muslim groups still earn less compared to the majority, almost all groups regardless of gender are more financially anxious and have lower job satisfaction. This is strong evidence of the Muslim penalties experienced by these groups. A Muslim penalty which cannot be explained by population characteristics, human capital, neighbourhood characteristics, socio-cultural factors and presence of EU migrants in local areas or labour markets. The findings also reveal that certain occupations with high proportions of Muslims, such as restaurant and catering managers, shopkeepers, taxi and cab drivers,

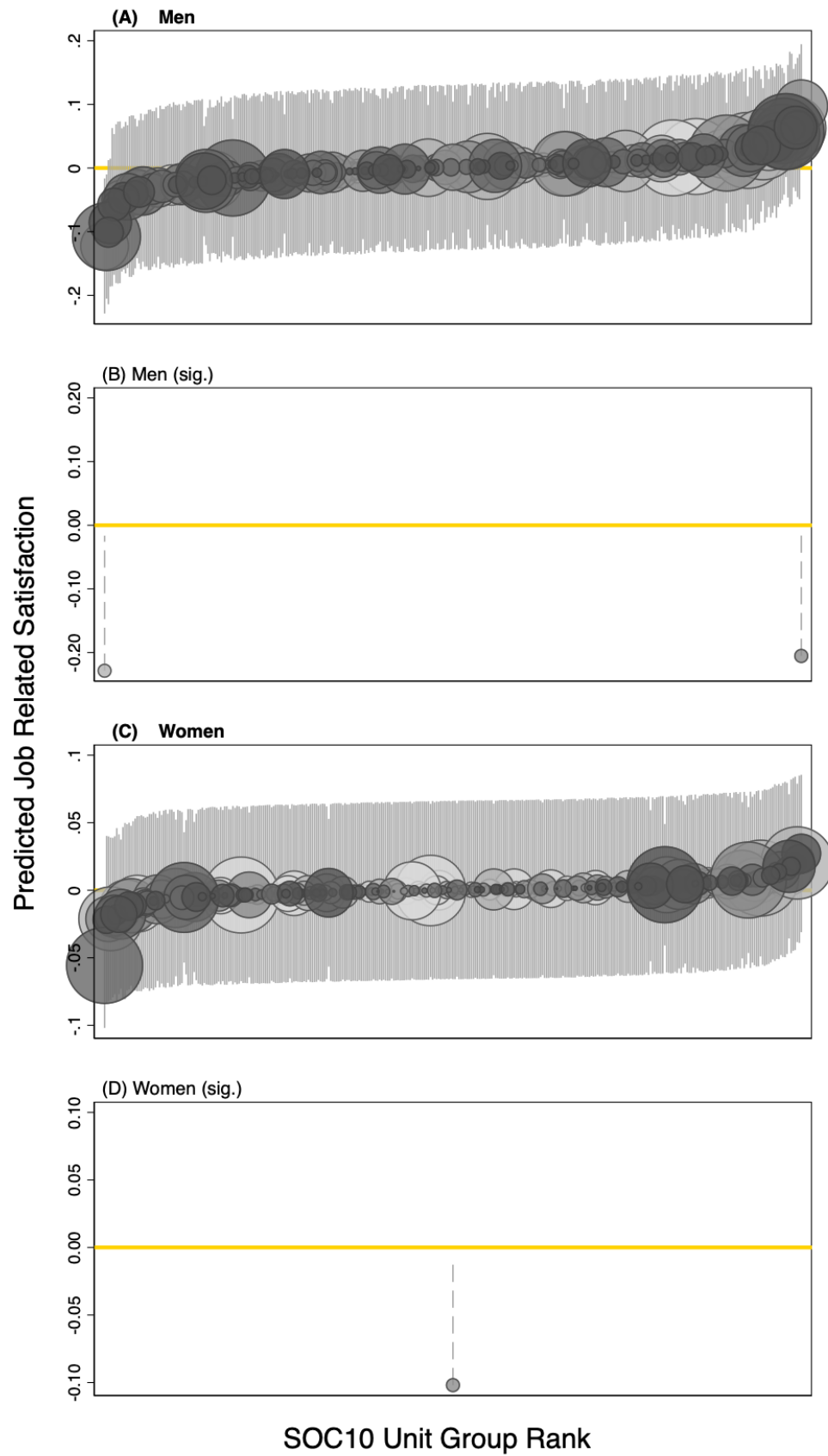


Figure 6-10 Predicted occupation effects on job related satisfaction, ranked low to high.

authors, writers, translators, and driving instructors, consistently earn less than expected. This disparity persists even though these models control for many variables. The analysis also shows that occupations with higher shares of Muslims tend to have fewer Eastern Europeans, indicating that the presence of post-2004 EU migrants is not a major influence on these outcomes.

For men, occupations like security guards, metal working machine operatives, legal professionals, medical practitioners, and rail travel assistants show better earnings and lower anxiety levels, with metal workers having almost equal shares of Muslims and Eastern Europeans. This suggests that certain sectors may provide more equitable opportunities, possibly due to the nature of the work or inclusive practices. Conversely, for women, roles such as restaurant and catering managers, shopkeepers, youth and community workers, nursery nurses, and teaching assistants are associated with lower earnings and higher anxiety, highlighting gender-specific disparities. The consistent disadvantage across various occupations, despite extensive controls, reveals remaining disadvantage which could potentially be explained by discriminatory practices. This analysis provides little evidence to support classical economic theories that suggest EU migrants might disrupt local labour markets. The findings indicate that the presence of post-2004 EU migrants does not significantly impact the earnings or employment outcomes for Muslim workers, showing very marginal associations. In fact, occupations with high shares of both Muslims and Eastern Europeans, such as metal working machine operatives, show positive outcomes, suggesting that these groups can coexist and thrive in the same sectors.

The main objective of this chapter was to examine the potential impact of contemporary migration on Muslim outcomes. While there is some evidence suggesting certain trends, nothing substantial has been found to support public narratives that Muslims would be disadvantaged by the introduction of migrants in local areas or labour markets. However, at the time the migration movements were occurring, this information was not available. Now that we have this data and the analysis has been done, these findings can contribute to the literature and help disprove the public narratives that were prevalent at the time.

7. DISCUSSION AND CONCLUSIONS

7.1. Overview

The overall objective of this thesis has been the empirical analysis of *Understanding Society* – The UK Household Longitudinal Study (UKHLS), supported by the use of extant contextual measures derived from Office of National Statistics resources. From the outset, the goal was to produce new empirical knowledge about Muslim social inequalities and the impact of new migration trends from Eastern Europe since the EU accession in 2004. This included engaging with cross-disciplinary scholarship (e.g. sociological and econometric) and building on established methodological approaches (e.g. advanced statistical modelling of pooled data resources) in order to obtain ample ethnic minority sample sizes for comprehensive analysis. A secondary objective of this research was to explore alternative operationalisations of ethnicity and methodological techniques that better respect the intersectionality of the Muslim experience.

These objectives motivated the exploration of ethno-religious social inequalities across three original analysis chapters. First, this thesis sought to provide an empirical characterisation of Muslim circumstances in modern Britain. This involved using pooled repeated contacts data and extended statistical models to compare Muslim labour market outcomes with those of the majority. This built upon recent sociological studies (Sweida-Metwally, 2022) and provided evidence of remaining disadvantage even after controlling for socio-cultural characteristics.

Second, after this characterisation was established, this analysis attempted to empirically test alternative methods, commonly used in epidemiology (Evens et al. 2018; Merlo, 2018), for examining ethnic minority social inequalities. This involved exploring multilevel statistical modelling techniques, examining the combined effects of advantage and disadvantage that arise from different social inequalities. This doctoral research revealed a useful method that could be extended to advance ethnic penalty literature in the future. The intersectional framework (Crenshaw 1991) that informs this method also provides ethnic penalty researchers with the potential to better understand and address the complex, layered nature of social inequalities. By considering multiple dimensions of inequality simultaneously, this approach

encourages researchers to think about the multidimensionality of experiences in new ways, inspiring them to explore intersections not commonly covered.

The third empirical analysis sought to define local and occupation measures of contemporary migration and assess their potential labour market impacts, as outlined in classic econometric theory. This included returning to the modelling of pooled data, as done in the first analysis, and extending this approach to incorporate contextual explanatory variables and their interaction with economic measures. Multilevel models were then used to explore detailed occupational variations. By studying the impact of immigration on the level of detailed occupations, this approach addresses a major challenge faced by studies that focus solely on local labour markets. These studies often overestimate the temporary labour supply shock while underestimating other ongoing processes in both local and national labour markets. This broader approach allows for a more accurate understanding of how these markets absorb such shocks (Borjas, 2003).

This chapter proceeds as follows. First, the key findings from the empirical chapters are discussed in an effort to address the research questions stated in Chapter 1. This is followed by a range of recommendations that have emerged through the process of undertaking this doctoral research. Finally, the ways and to what extent this thesis makes an original empirical contribution to ethnic penalty scholarship is stated, accompanied by closing remarks.

7.2. Key Findings

7.2.1. ETHNO-RELIGIOUS IDENTITY AND SOCIOCULTURAL FACTORS: PERSISTENT MUSLIM LABOUR MARKET DISADVANTAGE SUGGESTING STRUCTURAL DISCRIMINATION.

Chapter 4 directly addresses the first research aim and research questions 1-3 by offering an up-to-date empirical account of the economic circumstances of British Muslims. This is achieved through the integration of existing literature with recent data and a novel analytical approaches. Specifically, the chapter draws on pooled UKHLS data and employs a multicategorical approach inspired by Johnston et al., (2010) and Longhi et al., (2013) which disaggregates Muslim groups by gender, ethnicity, and generational status (using country of

birth as a proxy). The analysis confirms that, even after controlling for individual circumstances and human capital, members of Muslim communities in the UK experience significant disadvantages in various labour market outcomes compared to the Christian/non-religious White British majority (addressing research questions 1 and 2).

Three key findings from Chapter 4 offer substantive contributions to the literature on ethno-religious penalties and intersectionality in the British labour market. First, the analysis reveals that second-generation Pakistani Muslim men continue to face significant disadvantages in labour market participation, even after accounting for education, English language proficiency, and sociocultural integration (e.g. liberal gender attitudes and majority-group friendships). This challenges simplistic narratives of generational uplift and integration, highlighting that labour market disadvantage cannot be fully explained by human capital deficits or cultural ‘barriers’.

Second, Muslim women—particularly those of Pakistani, Bangladeshi, and “Other” ethnic backgrounds—experience persistent and substantial penalties in employment outcomes, even when compared to women of similar ethnic backgrounds but different religious affiliations. This underscores the importance of analysing religion and gender as intersecting axes of inequality, rather than treating religion as a mere proxy for ethnicity.

Third, the analysis finds that White British Muslims are not significantly disadvantaged relative to their Christian or non-religious White peers, suggesting that ethno-religious penalties are highly racialised and that “Muslimness” is differently perceived and penalised depending on the racial and ethnic identity of the respondent. Together, these findings advance existing debates by providing robust, contemporary evidence that structural and racialised discrimination plays a significant role in shaping Muslim outcomes in the UK—especially for those who, by conventional indicators, appear well integrated. They also demonstrate the analytical value of disaggregating Muslim experiences along multiple identity lines to better capture the layered dynamics of marginalisation.

Chapter 4 makes a methodological contribution to ethnic penalty literature by using a sequence of statistical models that are adjusted for a wide range of human capital and population characteristics, including measures that are not always available in data resources such as caring responsibilities.. The analysis also benefits from a larger dataset, utilising more waves of the UKHLS than other studies (12 waves covering 2009-2022), which provides contemporary insights into these issues. Moreover, while the models are quite large in scale, they remain parsimonious enough for easy interpretation. This approach is preferred over

models that are saturated with many terms interacting different identities. While it could be argued the analysis is limited by only focusing on different Muslim groups (excluding other variations of ethno-religious identities), this choice ensures that the focus on a subset does not compromise sample size and interpretation (Sweida-Metwally, 2022). Section 4.4.3 aims to address this limitation further by making religious comparisons within ethnic groups – again finding that Muslims tend to experience hardship.

This chapter enhances prior research on structural discrimination by extending Sweida-Metwally's (2022) work in two important ways. First, it introduces distinct measures of sociocultural integration, notably the presence of majority-group friendships, as indicators of bridging capital—moving beyond civic participation alone. Second, it finds that labour market gaps persist even among integrated Muslims, thereby providing further evidence against narratives that attribute Muslim marginalisation to self-exclusion or culturally rooted isolationism (Blackaby et al., 1999; Joppke, 2007). These results underscore that even well-integrated Muslims—those who are socially connected, culturally liberal, and religiously moderate—continue to face barriers rooted in structural and racialised discrimination.

7.2.2. THE VALUE OF INTERSECTIONAL ANALYSIS IN UNDERSTANDING MUSLIM LABOUR MARKET DISADVANTAGE

Chapter 5 makes a significant contribution to the literature on ethnic penalties and intersectionality by presenting several key findings that directly address research aim 2 and questions 4 and 5. The chapter applies the MAIHDA model (Evans et al., 2018; 2024) to explore the intersectional experiences of Muslim groups, particularly focusing on earnings disparities.

One important result is the compounded disadvantage faced by Muslim women, particularly those born outside the UK, due to the intersection of their religious identity and immigrant status. This finding addresses research question 4 and challenges existing narratives that typically focus on gender or ethnicity alone. It demonstrates that Muslim women encounter multiple barriers in the labour market that cannot be fully explained by either gender or ethnicity in isolation. This finding underscores the utility of intersectional strata for exploring Muslim labour market disadvantage, as it shows how overlapping identities, such as religion and immigration status, compound disadvantage in ways that single axis analyses would overlook. It adds a new layer of understanding to the study of ethnic penalties, highlighting the

importance of adopting an intersectional framework to capture the complexity of their experiences.

Another key finding is the substantial earnings disparity among White Other women, a group often overlooked in ethnic penalty research. This result speaks to research question 5, broadening the scope of labour market disadvantage beyond the more commonly studied South Asian or Black populations. By identifying earnings gaps within this group, the study underscores the need for ethnic penalty research to account for a wider array of ethnic and religious identities. It reveals that labour market disadvantages are not confined to traditionally marginalised groups but extend to a broader range of minority populations.

Finally, the analysis illustrates how overlapping sources of disadvantage—such as ethnicity, religion, and immigrant status—combine to shape labour market outcomes. This finding highlights the importance of considering multiple, interlocking forms of inequality in studies of ethnic and religious marginalisation. It emphasizes the need for nuanced policy interventions that address these complex, interrelated factors, offering valuable insights into how labour market disparities can be more effectively tackled. These findings contribute to broader debates on intersectionality and ethno-religious penalties, calling for a more comprehensive understanding of how various identities intersect to create complex patterns of disadvantage. They suggest that addressing labour market inequalities requires an intersectional approach, one that considers the combined effects of ethnicity, religion, gender, and immigration status.

MAIHDA's flexibility and focus on how different advantaged and disadvantaged positions interlock to shape outcomes is particularly fitting within the realm of ethnic penalty research, which potentially addresses the calls for a more nuanced understanding of Muslim dynamics (Khattab and Modood, 2015). This approach also offers several benefits, such as moving away from the reference category problem of always comparing minorities to the majority, which can reinforce the social prominence of these groups (Evans et al., 2018). Additionally, it allows for the simultaneous exploration of multiple interactions, yielding easily interpretable results. This synergy between this method and ethnic penalties literatures offers great potential. However, as argued in section 5.5.1, MAIHDA is not some silver bullet free of the inherent limitations of conventional ethnic penalty scholarship. It also has its own methodological considerations that are still being debated (Wilkes and Karimi, 2024; Evans et al., 2024b) and need to be considered if used further. In the application area of ethnic minority analysis, considerations such as asymmetric group sizes are likely to be most important.

7.2.3. OCCUPATION-SPECIFIC DISPARITIES AND STRUCTURAL DISCRIMINATION IN MUSLIM EMPLOYMENT OUTCOMES: LIMITED IMPACT OF CONTEMPORARY MIGRATION.

Chapter 6 addresses the third objective by deriving macro measures of contemporary migration from existing data sources and linking them to UKHLS microdata. While previous studies (Jivraj and Alao, 2023; Knies et al., 2016; Zwysen and Demireva, 2020) have explored similar themes, a novel contribution is made by focusing on local labour markets and the concentration of new migrants in fine-grained occupations. It uses special versions of the UKHLS to link these migration measures with detailed microdata about Muslims, providing fine-grained occupational information. This approach offers a more nuanced understanding of the economic and social dynamics affecting Muslim communities. Analysis in part 1 of Chapter 6 challenges assumptions about the contextual effects on ethnic penalties. It finds little evidence that Muslims in deprived areas have better employment rates, and increased competition from post-04 EU migrations does not worsen outcomes. Despite accounting for various factors, Muslim women remain significantly less likely to be employed, highlighting persistent challenges in accessing job opportunities even after contextual factors are adjusted for. For example, section 6.3 shows that predicted probabilities of employment decrease for foreign-born Bangladeshi men and Pakistani women as area-level resources increase, challenging the assumption that Muslims fare better in more deprived areas. Additionally, the presence of post-2004 Eastern European migrants show minimal negative impact on Muslim employment overall, with some groups—such as foreign-born Bangladeshi men and women—even experiencing gradual increases in employment probabilities in these contexts. This reinforces the chapter’s broader conclusion that contextual factors like deprivation and migrant concentration do not fully explain ethnic penalties. Thus, addressing research question 6, the concentration of post-2004 EU migrants and other local area characteristics are not the primary drivers of employment inequalities for Muslims. Persistent barriers related to gender, ethnicity, and discrimination remain central to their underemployment across diverse settings.

The findings in part 2 of Chapter 6 identify occupations where disparities are most pronounced, highlighting persistent disadvantage faced by Muslim respondents despite numerous controls and accounting for fine-grained occupation clustering. Certain roles, like restaurant managers and taxi drivers tend to have lower earnings over and above other factors that might influence their earning potential. This provides more granular insight into the experience of Muslims, highlighting specific areas that might be disproportionality affected by structural

discrimination than others. For example, conversely, some occupations, like security and medical professionals, offer better outcomes for Muslim men. The use of SOC10 unit groups at the 4-digit level adds extra detail which is not captured in other studies that use higher levels of occupational classification (Zwysen and Demireva, 2020). Thus, addressing research question 8, this detailed occupational information reveals unique patterns and disparities in employment outcomes for Muslims, providing a clearer understanding of how specific roles may be more or less impacted by discrimination than broader occupational categories.

7.3. Recommendations from experiential learning

Thinking reflexively about my own experience over the course of this research, it is apparent that I developed a number of positions and principles towards undertaking secondary survey research on social inequalities in the UK. In this section I outline a number of positions which impacted how I undertook the research, and which prompt my own recommendations about best practice in future research projects.

Enhancing Ethnic Penalty Research Through Interdisciplinary and Intersectional Approaches: Combining insights from sociological theory, particularly those addressing structural racism and Islamophobia, with traditional economic and demographic variables has significantly enriched the analysis of ethnic penalties. This interdisciplinary approach not only challenges outdated orientalist theories but also emphasises the role of structural factors and systemic discrimination. By incorporating variables that measure social factors alongside economic and human capital controls, the analysis has become more robust and comprehensive. Furthermore, the integration of an intersectional framework and empirical testing of these approaches has added depth to the analysis, allowing for a nuanced understanding of the multifaceted challenges faced by Muslim communities. This has also contributed to advancing econometric methods for measuring the impact of immigration. Moving forward, it is recommended that researchers continue to adopt this interdisciplinary and intersectional approach. By doing so, future studies can provide a more holistic and empathetic view of ethnic minority outcomes. This approach should be further refined and expanded to include additional social, economic, and demographic variables, ensuring that the analysis remains comprehensive and relevant in addressing the complexities of systemic discrimination and structural inequalities.

Incorporating Cultural Factors to Enhance Understanding of Labor Market Non-Participation: Much of the ethnic penalty literature reiterates known findings about disadvantage. While there are some relevant data already, it would be desirable to collect more data on cultural factors (not usually included in this type of analysis) that might be used to explain non-participation in the labour market and incorporate these into analyses. This includes gathering more detailed information about people's motivations and religious habits, such as religious dress, and exploring variations in religious denominations among Muslims themselves.

Balancing Detailed Accuracy and Simplicity in Statistical Analyses: This analysis shows the ongoing challenge of balancing detailed accuracy with simplicity in statistical analyses. It highlights specific cases where using new methods and advanced visualisations can create a detailed yet straightforward summary, which is simpler than the most complicated options (e.g. using saturating models with lots of main and interaction effects). To ensure the continued success of my research, I should strive to maintain the balance of "realistic complexity." This involves crafting analyses that are both comprehensive and comprehensible, providing valuable insights without sacrificing clarity. By doing so, I can make my research both rigorous and accessible, facilitating practical application and furthering understanding in my field.

Enhancing Research Through Advanced Programming Skills: Developing my programming skills alongside research skills has been instrumental in advancing the analysis of this doctoral research. The integration of these skills has enabled me to conduct complex analyses that would be challenging to perform otherwise. Advanced programming skills in statistical software allow researchers to efficiently manage and manipulate large datasets (Scott Long, 2009), which is particularly important in ethnic penalty research where detailed and extensive data are often required to capture the complexities of social inequalities experienced by ethnic groups. Additionally, programming enables the automation of repetitive tasks, saving time and reducing the potential for errors, while ensuring that analyses are reproducible, an important component of robust scientific research. Software tools and advanced skills in Stata programming also offer powerful visualisation capabilities, helping to create clear and informative representations of complex data. In summary, the combination of programming skills and research expertise has significantly enhanced my ability to conduct detailed and complex analyses, made possible thanks to advancements in software and computational tools that continue to push the boundaries of what is achievable in social science research.

Prioritising Transparency and Reproducibility in Research: Adopting a transparent approach to research has been invaluable throughout this doctoral project. By carefully documenting all stages of the research process – from data management to analysis and visualisation – I was able to maintain a clear and organised workflow throughout the analysis. Keeping detailed notes of the datasets used, the methodologies employed, and preliminary assumptions made during the analysis facilitated a better understanding throughout each stage of the project. Storing command files in subfolders often helped with the organisation of this doctoral research. Throughout the work of this project, preparation and analysis of data used principles of 'transparency' to support documentation and replicability of the research. The work was made transparent and replicable to myself, the researcher, by taking care to record all commands used by software in the preparation and analysis of data in coherent sequential code files (syntax files). Additional archiving of these for the benefit of transparency to others was achieved by depositing relevant code online at GitHub. These principles were attractive because it aids in critical evaluation and replication of findings, ultimately enhancing the credibility of any research (Connelly et al., 2020). Moving forward, future work building upon these findings will prioritise reproducibility and transparency from the very beginning, ensuring these principles are integral to the research process. I endeavour to continue working according to these principles and will ensure that future teaching and work in this area adhere to them.

Leveraging Large-Scale Social Survey Resources for In-Depth Analysis: The detailed statistical analysis presented in this thesis highlights the potential of large scale secondary social survey resources in social research, particularly studies of ethnic minorities and other marginalised groups. The value of the measures on ethnicity, religion, generation and detailed socio-economic variables available in the UKHLS has allowed me to conduct far more detailed analysis than other data resources would allow for. Although the UKHLS, with its complex weighting structure and numerous files, can initially seem daunting, it is worthwhile to persevere and invest in training people to effectively utilise these large social survey data in the future. The linkage facilities of these surveys, such as occupation or geographical identifiers that can be connected to extant data (as demonstrated in this research), significantly enhance the opportunities these resources offer. It is recommended that these facilities be used more frequently to add greater depth to analyses.

Opportunities for Further Development and Exploration in Ethnic Penalty Research: There is still considerable room for further development and exploration in advancing the findings of

this work. For example, the analytical outcomes are repeatedly used in other ethnic penalty research. We already know a lot about ethnic minority participation, employment, earnings differentials and occupational attainment. While the intention was to explore additional outcomes on top of these, including financial anxiety, job related satisfaction, and job quality – there is scope for future analysis on more detailed economic circumstances and heterogeneity in these circumstances. For example, one opportunity could be to incorporate more detailed measures of social class (e.g. mother and father's occupation or education) and assess its impact on social inequalities.

7.4. Closing Remarks

In summary, the purpose of this research was to produce detailed empirical analyses exploring Muslim social inequalities and the potential impact of new migrations. In addition, this thesis also aimed to demonstrate the value of methods informed by theoretical concepts of intersectionality in ethnic minority research. This doctoral research has brought together theoretical, empirical and methodological insights on social inequalities from sociology, epidemiology and econometrics. Drawing eclectically from different datasets and from analytical methods that are used in different disciplinary traditions (e.g pooling data and using multilevel models) demonstrated how combining approaches can yield richer insights. The analytical focus on Muslims in this thesis has also allowed for a detailed examination of a group that is often at the intersection of multiple forms of disadvantage, providing valuable insights into the broader impacts of new migrations on vulnerable populations.

This doctoral research makes an original contribution in the form of three distinct, yet interrelated, statistical analyses about Muslim social inequalities. It provides new empirical knowledge about the effects of new migrations on vulnerable groups, challenging econometric narratives on labour market impacts. This thesis also offers methodological insights into alternative statistical methods, showcasing a unique approach that can strengthen future research, particularly highlighting the importance of intersectionality.

Notably, this analysis underscores the importance of sociological concepts and the value of large and detailed secondary data resources, which help to add depth to the narrative established by earlier studies on ethnic penalties. These older studies often rely on large data resources that

lack key variables that are important for a comprehensive understanding of social inequalities. In contrast, the UKHLS offers a rich array of variables, such as measures of religiosity, social ties, and adherence to gender liberal attitudes. This allows for a more detailed exploration of labour market disadvantages. This doctoral research has shown that disadvantage persists even when Muslims are well integrated into British society, at least according to these measures. This persistence makes it difficult to argue that factors other than discrimination are responsible for their poorer outcomes.

REFERENCES

- Abbas, T. (2007) Muslim Minorities in Britain: Integration, Multiculturalism and Radicalism in the Post-7/7 Period, *Journal of Intercultural Studies*, 28 (3) pp.287–300. DOI: 10.1080/07256860701429717
- Abbas, T. (2010) *Islam and Muslims in the UK*. Available at: <https://www.thebritishacademy.ac.uk/documents/513/08-Abbas.pdf> (accessed 8 August 2024).
- Abdelhadi, E. (2017) Religiosity and Muslim Women’s Employment in the United States, *Socius: Sociological Research for a Dynamic World*, 3 pp.1–17. DOI: 10.1177/2378023117729969
- Akbar, M. (2019) Examining the factors that affect the employment status of racialised immigrants: a study of Bangladeshi immigrants in Toronto, Canada, *South Asian Diaspora*, 11 (1) pp.67–87. DOI: 10.1080/19438192.2018.1523092
- Alba, R. (2005) Bright vs. blurred boundaries: Second-generation assimilation and exclusion in France, Germany, and the United States, *Ethnic and Racial Studies*, 28 (1) pp.20–49. DOI: 10.1080/0141987042000280003
- Alexander, C. and Shankley, W. (2020) Ethnic inequalities in the state education system in England, In: *Ethnicity, Race and Inequality in the UK: State of the Nation*. Policy Press. Available at: <https://bristoluniversitypressdigital.com/monochap-oa/book/9781447351269/ch005.xml> (accessed 20 August 2024).
- Alotaibi, F. A. (2016) Racial Profiling as a counter- terrorism tool: To what extent has racial profiling contributed to the security of the United Kingdom since the London bombing of 7 June 2005?, *Public Policy and Administration Research*, pp.106–112.
- Alvarez, C. H. *et al.* (2022) Intersectional inequalities in industrial air toxics exposure in the United States, *Health & Place*, 77 pp.1–12. DOI: 10.1016/j.healthplace.2022.102886
- Amit, K. (2010) Determinants of Life Satisfaction Among Immigrants from Western Countries and from the FSU in Israel, *Social Indicators Research*, 96 (3) pp.515–534. DOI: 10.1007/s11205-009-9490-1
- Ansell, A. (2013) *Race and Ethnicity: The Key Concepts : Amy Ansell*. Available at: <https://www.book2look.com/book/IQlCDQ41a4> (accessed 27 September 2024).
- Anwar, M. (1979) *The Myth of Return: Pakistanis in Britain*. (s.l.): Pearson Education.
- Aradhya, S., Grotti, R. and Härkönen, J. (2023) Unemployment persistence among second-generation immigrants, *European Sociological Review*, 39 (3) pp.433–448. DOI: 10.1093/esr/jcac071
- Asaria, M. *et al.* (2024) *British Muslims Striving for Fairness: 2021 Census findings with a focus on social mobility*. Available at: <https://mcb.org.uk/wp-content/uploads/2024/01/MCB-Striving-For-Fairness-Full-Report.pdf> (accessed 13 August 2024).

- Bartkoski, T. *et al.* (2018) A Meta-Analysis of Hiring Discrimination Against Muslims and Arabs, *Personnel Assessment and Decisions*, 4 (2) pp.1–16. DOI: <https://doi.org/10.25035/pad.2018.02.001>
- Bartram, D. (2011) Economic Migration and Happiness: Comparing Immigrants' and Natives' Happiness Gains From Income, *Social Indicators Research*, 103 (1) pp.57–76. DOI: 10.1007/s11205-010-9696-2
- Bauer, G. R. (2014) Incorporating intersectionality theory into population health research methodology: challenges and the potential to advance health equity, *Social Science & Medicine* (1982), 110 pp.10–17. DOI: 10.1016/j.socscimed.2014.03.022
- Becker, G. S. (1971) *The Economics of Discrimination*. Chicago, IL: University of Chicago Press. Available at: <https://press.uchicago.edu/ucp/books/book/chicago/E/bo22415931.html> (accessed 17 August 2024).
- Becker, G. S. (1975) *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. NBER. Available at: <https://www.nber.org/books-and-chapters/human-capital-theoretical-and-empirical-analysis-special-reference-education-second-edition/front-matter-human-capital-theoretical-and-empirical-analysis-special-reference-education> (accessed 13 August 2024).
- Bell, A. *et al.* (2024) Extending intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) to study individual longitudinal trajectories, with application to mental health in the UK, *Social Science & Medicine*, 351 p.116955. DOI: 10.1016/j.socscimed.2024.116955
- Berthoud, R. (2000) Ethnic employment penalties in Britain, *Journal of Ethnic and Migration Studies*, 26 (3) pp.389–416. DOI: 10.1080/713680490
- Berthoud, R. (2002) *Poverty and prosperity among Britain's ethnic minorities*. [Institute for Social and Economic Research] pp.3–8. Available at: <https://bristoluniversitypressdigital.com/view/journals/jpsj/10/1/article-p3.xml> (accessed 5 August 2024).
- Berthoud, R. and Blekesaune, M. (2007) *Persistent employment disadvantage*. (s.l.): (s.n.).
- Blackaby, D. *et al.* (1999) Unemployment Among Britain's Ethnic Minorities, *The Manchester School*, 67 (1) pp.1–20. DOI: 10.1111/1467-9957.00130
- Blackaby, D. H. *et al.* (2002) White/Ethnic Minority Earnings and Employment Differentials in Britain: Evidence from the LFS, *Oxford Economic Papers*, 54 (2) pp.270–297.
- Blanchflower, D. G., Saleheen, J. and Shadforth, C. (2007) The Impact of the Recent Migration from Eastern Europe on the UK Economy, *SSRN Electronic Journal*, DOI: 10.2139/ssrn.969406
- Bobo, L. (2001) *America Becoming: Racial Trends and Their Consequences, Volume 1*. Washington, D.C.: National Academies Press. p.9599. Available at: <http://www.nap.edu/catalog/9599> (accessed 27 September 2024).

Boeri, T. *et al.* (2015) Immigration, Housing Discrimination and Employment, *The Economic Journal*, 125 (586) pp.82–114. DOI: 10.1111/ecoj.12232

Bonino, S. (2013) Prevent-ing Muslimness in Britain: The Normalisation of Exceptional Measures to Combat Terrorism, *Journal of Muslim Minority Affairs*, 33 (3) pp.385–400. DOI: 10.1080/13602004.2013.853977

Borjas, G. J. (1995) The Economic Benefits from Immigration, *Journal of Economic Perspectives*, 9 (2) pp.3–22. DOI: 10.1257/jep.9.2.3

Borjas, G. J. (2003) The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market, *The Quarterly Journal of Economics*, 118 (4) pp.1335–1374. DOI: 10.1162/003355303322552810

Brattbakk, I. and Wessel, T. (2012) Long-term Neighbourhood Effects on Education, Income and Employment among Adolescents in Oslo, *Urban Studies*, 50 (2) pp.391–406.

Breach, A. and Li, Y. (2017) Gender Pay Gap by Ethnicity in Britain – Briefing,

Brown, M. S. (2000) Religion and economic activity in the South Asian population, *Ethnic and Racial Studies*, 23 (6) pp.1035–1061. DOI: 10.1080/014198700750018405

Brynin, M. and Güveli, A. (2012) Understanding the ethnic pay gap in Britain, *Work, Employment and Society*, 26 (4) pp.574–587. DOI: 10.1177/0950017012445095

Brynin, M. and Longhi, S. (2015) *The effect of occupation on poverty among ethnic minority groups*. [Joseph Rowntree Foundation] Available at: <https://www.jrf.org.uk/race-and-ethnicity/the-effect-of-occupation-on-poverty-among-ethnic-minority-groups#:~:text=Ethnic%20minority%20workers%20were%20more%20likely%20to%20receive%20less%20than,men%20relative%20to%20White%20men>.

Bunglawala, Z. (2008) *Valuing-Family-Valuing-Work-British-Muslim-Women-and-the-Labour-Market-October-2008.pdf*. [The London Development Agency] Available at: <https://youngfoundation.org/wp-content/uploads/2013/01/Valuing-Family-Valuing-Work-British-Muslim-Women-and-the-Labour-Market-October-2008.pdf> (accessed 21 August 2024).

Byrne, B. *et al.* (2020) *Ethnicity, Race and Inequality in the UK: State of the Nation*. Available at: <https://bristoluniversitypressdigital.com/monochap-ooa/book/9781447351269/ch006.xml> (accessed 20 August 2024).

Carlsson, M. (2010) Experimental Evidence of Discrimination in the Hiring of First- and Second-generation Immigrants, *LABOUR*, 24 (3) pp.263–278. DOI: 10.1111/j.1467-9914.2010.00482.x

Chen, W., Petitti, D. B. and Enger, S. (2004) Limitations and potential uses of census-based data on ethnicity in a diverse community, *Annals of Epidemiology*, 14 (5) pp.339–345. DOI: 10.1016/j.annepidem.2003.07.002

Cheung, S. L. and Heath, A. (2016) *HeathCheung2016DWPreport (1).pdf*. (s.l.): (s.n.).

Cheung, S. Y. (2014) Ethno-religious minorities and labour market integration: generational advancement or decline?, *Ethnic and Racial Studies*, 37 (1) pp.140–160. DOI: 10.1080/01419870.2013.808757

Cheung, S. Y. and Heath, A. (2007) Nice Work if You can Get it: Ethnic Penalties in Great Britain, In: Heath, A.F. and Cheung, S.Y. (eds.) *Unequal Chances: Ethnic Minorities in Western Labour Markets*. British Academy. p.0. Available at: <https://doi.org/10.5871/bacad/9780197263860.003.0012> (accessed 21 August 2024).

Chiswick, B. R. (2001) The Effect of Americanization on the Earnings of Foreign-born Men, In: *The New Immigrant in the American Economy*. (s.l.): Routledge.

Chiswick, B. R. and Miller, P. W. (2003) The complementarity of language and other human capital: immigrant earnings in Canada, *Economics of Education Review*, 22 (5) pp.469–480. DOI: 10.1016/S0272-7757(03)00037-2

Chouhan, K. and Nazroo, J. (2020) Health inequalities, In: *Ethnicity, Race and Inequality in the UK: State of the Nation*. Policy Press. Available at: <https://bristoluniversitypressdigital.com/display/book/9781447351269/ch004.xml> (accessed 20 August 2024).

Ciupijus, Z. (2011) Mobile central eastern Europeans in Britain: successful European Union citizens and disadvantaged labour migrants?, *Work, Employment and Society*, 25 (3) pp.540–550. DOI: 10.1177/0950017011407962

Clark, K. and Drinkwater, S. (2009) The Labour Market Impact of Recent Immigration on Ethnic Groups in The UK, *Nordic Journal of Political Economy*, 35

Clark, K. and Shankley, W. (2020) Ethnic minorities in the labour market in Britain, In: *Ethnicity, Race and Inequality in the UK: State of the Nation*. Policy Press. Available at: <https://bristoluniversitypressdigital.com/monochap-oa/book/9781447351269/ch006.xml> (accessed 20 August 2024).

Clark, T. N. (2003) Rising Tide: Gender Equality and Cultural Change around the World by Ronald Inglehart and Pippa Norris, *American Journal of Sociology*, 111 (3) pp.952–954. DOI: 10.1086/500778

Coleman, D. A. and Dubuc, S. (2010) The fertility of ethnic minorities in the UK, 1960s–2006, *Population Studies*, 64 (1) pp.19–41. DOI: 10.1080/00324720903391201

Commission for Racial Equality (1996) *Commission for Racial Equality Annual Report 1996*. Commission for Racial Equality. Available at: <https://jstor.org/stable/community.28327755> (accessed 8 August 2024).

Connelly, R., Gayle, V. and Lambert, P. S. (2016) A review of educational attainment measures for social survey research, *Methodological Innovations*, 9 p.205979911663800. DOI: 10.1177/2059799116638001

Connelly, R., Gayle, V. and Playford, C. (2020) Transparent and reproducible data analysis, In: *SAGE Research Methods Foundations*. SAGE Publications. Available at: <https://www.research.ed.ac.uk/en/publications/transparent-and-reproducible-data-analysis> (accessed 27 September 2024).

- Connor, P. and Koenig, M. (2015) Explaining the Muslim employment gap in Western Europe: Individual-level effects and ethno-religious penalties, *Social Science Research*, 49 pp.191–201. DOI: 10.1016/j.ssresearch.2014.08.001
- Constant, A. and Massey, D. S. (2003) Self-selection, earnings, and out-migration: A longitudinal study of immigrants to Germany, *Journal of Population Economics*, 16 (4) pp.631–653. DOI: 10.1007/s00148-003-0168-8
- Crenshaw, K. (1991) Mapping the Margins: Intersectionality, Identity Politics, and Violence against Women of Color, *Stanford Law Review*, 43 (6) pp.1241–1299. DOI: 10.2307/1229039
- Crompton, R. and Lyonette, C. (2005) The new gender essentialism – domestic and family ‘choices’ and their relation to attitudes, *The British Journal of Sociology*, 56 (4) pp.601–620. DOI: 10.1111/j.1468-4446.2005.00085.x
- van Damme, M., Kalmijn, M. and Uunk, W. (2008) The Employment of Separated Women in Europe: Individual and Institutional Determinants, *European Sociological Review*, 25 (2) pp.183–197. DOI: 10.1093/esr/jcn042
- Daoud, Y. and Khattab, N. (2022) Women, labour market outcomes and religion: evidence from the British labour market, *Review of Social Economy*, 80 (3) pp.283–313. DOI: 10.1080/00346764.2020.1739321
- Di Stasio, V. *et al.* (2021) Muslim by default or religious discrimination? Results from a cross-national field experiment on hiring discrimination, *Journal of Ethnic and Migration Studies*, 47 (6) pp.1305–1326. DOI: 10.1080/1369183X.2019.1622826
- Dobson, J. R. (2009) Labour mobility and migration within the EU following the 2004 Central and East European enlargement, *Employee Relations*, 31 (2) pp.121–138. DOI: 10.1108/01425450910925283
- Drinkwater, S., Eade, J. and Garapich, M. (2006) Poles Apart? EU Enlargement and the Labour Market Outcomes of Immigrants in the UK, *SSRN Electronic Journal*, pp.1–29. DOI: 10.2139/ssrn.944475
- Du Bois, W. E. B. (2007) *The Souls of Black Folk*. (s.l.): OUP Oxford.
- Dubrow, J. (2013) Why Should We Account for Intersectionality in Quantitative Analysis of Survey Data?, In: Kallenberg, V., Meyer, J. and Müller, J.M. (eds.) *Intersectionality und Kritik: Neue Perspektiven für alte Fragen*. Wiesbaden: Springer Fachmedien. pp.161–177. Available at: https://doi.org/10.1007/978-3-531-93168-5_8 (accessed 21 August 2024).
- Dujardin, C. and Goffette-Nagot, F. (2010) Neighborhood effects on unemployment?: A test à la Altonji, *Regional Science and Urban Economics*, 40 (6) pp.380–396.
- Durkheim, E. (1961) *Moral Education*. (s.l.): Free Press.
- Dustmann, C. and Fabbri, F. (2003) Language proficiency and labour market performance of immigrants in the UK, *The Economic Journal*, 113 pp.695–717. DOI: <https://doi.org/10.1111/1468-0297.t01-1-00151>

- Dustmann, C., Fabbri, F. and Preston, I. (2005) The Impact of Immigration on the British Labour Market, *The Economic Journal*, 115 (507) pp.324–341. DOI: 10.1111/j.1468-0297.2005.01038.x
- Dustmann, C., Frattini, T. and Halls, C. (2010) Assessing the Fiscal Costs and Benefits of A8 Migration to the UK, *Fiscal Studies*, 31 (1) pp.1–41. DOI: 10.1111/j.1475-5890.2010.00106.x
- 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
- Elliott, R. and Lindley, J. (2008) Immigrant wage differentials, ethnicity and occupational segregation, *Journal of the Royal Statistical Society Series A*, 171 (3) pp.645–671.
- England, P. (2010) The Gender Revolution: Uneven and Stalled, *Gender and Society*, 24 (2) pp.149–166. DOI: <https://doi.org/10.1177/0891243210361475>
- Evans, C. R. *et al.* (2018) A multilevel approach to modeling health inequalities at the intersection of multiple social identities, *Social Science & Medicine*, 203 pp.64–73. DOI: 10.1016/j.socscimed.2017.11.011
- Evans, C. R. *et al.* (2024a) A tutorial for conducting intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA), *SSM - Population Health*, 26 p.101664. DOI: 10.1016/j.ssmph.2024.101664
- Evans, C. R. *et al.* (2024b) Clarifications on the intersectional MAIHDA approach: A conceptual guide and response to Wilkes and Karimi (2024), *Social Science & Medicine*, 350 p.116898. DOI: 10.1016/j.socscimed.2024.116898
- Favell, A. (2008) The New Face of East–West Migration in Europe, *Journal of Ethnic and Migration Studies*, 34 (5) pp.701–716. DOI: 10.1080/13691830802105947
- Fenton, S. (2010) *Ethnicity*. (s.l.): Polity.
- Fernandex-Reino, M. and Rienzo, C. (2021) Migrants in the UK Labourmarket: An Overview., *University of Oxford.*, (Migration Observatory Briefing, COMPAS)
- Finney, N. *et al.* (2023) *Racism and Ethnic Inequality in a Time of Crisis: Findings from the Evidence for Equality National Survey*. Bristol: Bristol University Press.
- Foner, N. and Alba, R. (2008) Immigrant Religion in the U.S. and Western Europe: Bridge or Barrier to Inclusion?, *International Migration Review*, 42 (2) pp.360–392. DOI: 10.1111/j.1747-7379.2008.00128.x
- Fox, J. E. (2013) The uses of racism: whitewashing new Europeans in the UK, *Ethnic and Racial Studies*, 36 (11) pp.1871–1889. DOI: 10.1080/01419870.2012.692802
- Fox, J. E., Moroşanu, L. and Szilassy, E. (2012) The Racialization of the New European Migration to the UK, *Sociology*, 46 (4) pp.680–695. DOI: 10.1177/0038038511425558

- Frank, K., Hou, F. and Schellenberg, G. (2016) Life Satisfaction Among Recent Immigrants in Canada: Comparisons to Source-Country and Host-Country Populations, *Journal of Happiness Studies*, 17 (4) pp.1659–1680. DOI: 10.1007/s10902-015-9664-2
- Franks, M. (2000) Crossing the borders of whiteness? White Muslim women who wear the hijab in Britain today, *Ethnic and Racial Studies*, 23 (5) pp.917–929. DOI: 10.1080/01419870050110977
- Frattoni, T. (2017) Evaluating the Labour Market Integration of New Immigrants in the UK, *Social Policy and Society*, 16 (4) pp.645–658. DOI: 10.1017/S1474746417000239
- Friedman, S. and Laurison, D. (2020) *The Class Ceiling*. Bristol: Policy Press. Available at: <https://policy.bristoluniversitypress.co.uk/trade/the-class-ceiling> (accessed 21 August 2024).
- Gayle, V. and Connelly, R. (2022) The Stark realities of reproducible statistically orientated sociological research: Some newer rules of the sociological method, *Methodological Innovations*, 15 (3) pp.207–221. DOI: 10.1177/20597991221111681
- Gayle, V. and Lambert, P. (2018) *What Is Quantitative Longitudinal Data Analysis?*. 1st edn. London: Bloomsbury Publishing Plc.
- Geddes, A. (2014) The EU, UKIP and the Politics of Immigration in Britain, *The Political Quarterly*, 85 (3) pp.289–295. DOI: 10.1111/1467-923X.12095
- Gilks, M. (2020) The security-prejudice nexus: “Islamist” terrorism and the structural logics of Islamophobia in the UK, *Critical Studies on Terrorism*, 13 (1) pp.24–46. DOI: 10.1080/17539153.2019.1650874
- Gilpin, N. et al. (2006) *The impact of free movement of workers from Central and Eastern Europe on the UK labour market*. (s.l.): (s.n.).
- Glauber, R. (2008) Race and Gender in Families and at Work: The Fatherhood Wage Premium, *Gender and Society*, 22 (1) pp.8–30.
- Glock, C. Y. (1962) *To Comfort and to Challenge*. (s.l.): University of California Press.
- Granovetter, M. (1983) The Strength of Weak Ties: A Network Theory Revisited, *Sociological Theory*, 1 pp.201–233. DOI: 10.2307/202051
- Gregory, M. and Connolly, S. (2008) Feature: The Price of Reconciliation: Part-Time Work, Families and Women’s Satisfaction, *The Economic Journal*, 118 (526) pp.1–7. DOI: 10.1111/j.1468-0297.2007.02113.x
- Gross, C., Gottburgsen, A. and Phoenix, A. (2016) Education systems and intersectionality, (s.l.): (s.n.). pp.51–72. DOI: 10.51952/9781447326113.ch003
- Guest, M. et al. (2020) *Islam and Muslims on UK University Campuses: perceptions and challenges*. Available at: 10.13140/RG.2.2.32005.78560
- Guveli, A. and Platt, L. (2023) Religiosity of Migrants and Natives in Western Europe 2002–2018: Convergence and Divergence, *European Journal of Population*, 39 (9) pp.1–27. DOI: 10.1007/s10680-023-09660-9

- Hakim, C. (2017) *Models of the Family in Modern Societies: Ideals and Realities*. London: Routledge. DOI: 10.4324/9781315197937
- van Ham, M. and Manley, D. (2010) The effect of neighbourhood housing tenure mix on labour market outcomes: a longitudinal investigation of neighbourhood effects, *Journal of Economic Geography*, 10 (2) pp.257–282. DOI: 10.1093/jeg/lbp017
- Hancock, A.-M. (2007) When Multiplication Doesn't Equal Quick Addition: Examining Intersectionality as a Research Paradigm, *Perspectives on Politics*, 5 (1) pp.63–79. DOI: 10.1017/S1537592707070065
- 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
- Heath, A. and Cheung, S. L. (2006) *Ethnic Penalties in the Labour Market: Employers and Discrimination*. [Department for Work and Pensions] Available at: https://www.researchgate.net/publication/265248323_Ethnic_Penalties_in_the_Labour_Market_Employers_and_Discrimination (accessed 21 August 2024).
- Heath, A. and Cheung, S. Y. (2007) The Comparative Study of Ethnic Minority Disadvantage, In: Heath, A.F. and Cheung, S.Y. (eds.) *Unequal Chances: Ethnic Minorities in Western Labour Markets*. British Academy. p.0. Available at: <https://doi.org/10.5871/bacad/9780197263860.003.0001> (accessed 21 August 2024).
- Heath, A. and Martin, J. (2013) Can religious affiliation explain 'ethnic' inequalities in the labour market?, *Ethnic and Racial Studies*, 36 (6) pp.1005–1027. DOI: 10.1080/01419870.2012.657660
- Heath, A., McMahon, D. and Roberts, J. (2000) Ethnic Differences in the Labour Market: A Comparison of the Samples of Anonymized Records and Labour Force Survey, *Journal of the Royal Statistical Society Series A: Statistics in Society*, 163 (3) pp.303–339. DOI: 10.1111/1467-985X.00172
- Holman, D., Salway, S. and Bell, A. (2020) Mapping intersectional inequalities in biomarkers of healthy ageing and chronic disease in older English adults, *Scientific Reports*, 10 (1) p.13522. DOI: 10.1038/s41598-020-69934-8
- House of Commons (2017) *Employment opportunities for Muslims in the UK*. (s.l.): (s.n.).
- Inglehart, R. and Norris, P. (2003) *Rising Tide: Gender Equality and Cultural Change Around the World*. Cambridge: Cambridge University Press. Available at: <https://www.cambridge.org/core/books/rising-tide/E28A6E8662971242917902E0A7E0FFEE> (accessed 21 August 2024).
- Jenkins, S. P. and Siedler, T. (2007) Using Household Panel Data to Understand the Intergenerational Transmission of Poverty, *SSRN Electronic Journal*, DOI: 10.2139/ssrn.1752996
- Jivraj, S. and Alao, C. (2023) Are ethnic employment penalties mitigated in deprived neighbourhoods and in ethnically dense neighbourhoods?, *Population, Space and Place*, 29 (3) p.e2646. DOI: 10.1002/psp.2646

- Johnston, R. *et al.* (2010) Ethno-Religious Categories and Measuring Occupational Attainment in Relation to Education in England and Wales: A Multilevel Analysis, *Environment and Planning A: Economy and Space*, 42 (3) pp.578–591. DOI: 10.1068/a42180
- Johnston, R., Khattab, N. and Manley, D. (2015) East versus West? Over-qualification and Earnings among the UK's European Migrants, *Journal of Ethnic and Migration Studies*, 41 (2) pp.196–218. DOI: 10.1080/1369183X.2014.935308
- Jones, K., Johnston, R. and Manley, D. (2016) Uncovering interactions in multivariate contingency tables: a multi-level modelling exploratory approach, *Methodological Innovations*, 9 p.2059799116672874. DOI: 10.1177/2059799116672874
- Joppke, C. (2009) Limits of Integration Policy: Britain and Her Muslims, *Journal of Ethnic and Migration Studies*, 35 (3) pp.453–472. DOI: 10.1080/13691830802704616
- Kaminska, O. and Lynn, P. (2019) *Weighting and Sample Representation: Frequently Asked Questions*. (s.l.): University of Essex.
- Kanitsar, G. (2025) The same social elevator? Intergenerational class mobility of second-generation immigrants across Europe, *European Sociological Review*, 41 (1) pp.1–16. DOI: 10.1093/esr/jcae007
- Karlsen, S., Nazroo, J. Y. and Smith, N. R. (2020) Ethnic, Religious and Gender Differences in Intragenerational Economic Mobility in England and Wales, *Sociology*, 54 (5) pp.883–903. DOI: 10.1177/0038038520929562
- Kaushal, N., Kaestner, R. and Reimers, C. (2007) Labor Market Effects of September 11th on Arab and Muslim Residents of the United States, *Journal of Human Resources*, XLII (2) pp.275–308. DOI: 10.3368/jhr.XLII.2.275
- Kenway, P. and Palmer, G. (2007) *Poverty among ethnic groups*. (s.l.): (s.n.).
- Khattab, N. (2009) Ethno-religious Background as a Determinant of Educational and Occupational Attainment in Britain, *Sociology*, 43 (2) pp.304–322. DOI: 10.1177/0038038508101167
- Khattab, N. (2016) The Ethno-Religious Wage Gap within the British Salaried Class: How Severe is the Penalty?, *Sociology*, 50 (4) pp.813–824. DOI: 10.1177/0038038515575865
- Khattab, N. *et al.* (2020) Human Capital and Labour Market Performance of Muslim Women in Australia, *Journal of Muslim Minority Affairs*, 40 (3) pp.410–428. DOI: 10.1080/13602004.2020.1813989
- Khattab, N. and Hussein, S. (2018) Can Religious Affiliation Explain the Disadvantage of Muslim Women in the British Labour Market?, *Work, Employment & Society*, 32 (6) pp.1011–1028. DOI: org/10.1177/0950017017711099
- Khattab, N. and Johnston, R. (2013) Ethnic and Religious Penalties in a Changing British Labour Market from 2002 to 2010: The Case of Unemployment, *Environment and Planning A: Economy and Space*, 45 (6) pp.1358–1371. DOI: 10.1068/a45454

- Khatab, N., Miaari, S. and Mohamed-Ali, M. (2020) Visible minorities in the Canadian Labour Market: Disentangling the effect of religion and ethnicity, *Ethnicities*, 20 (6) pp.1218–1245. DOI: 10.1177/1468796819847750
- Khatab, N. and Modood, T. (2015) Both Ethnic and Religious: Explaining Employment Penalties Across 14 Ethno-Religious Groups in the United Kingdom, *Journal for the Scientific Study of Religion*, 54 (3) pp.501–522.
- van Klingeren, M. and Spierings, N. (2020) Acculturation, decoupling, or both? Migration's impact on the linkage between religiosity and gender equality attitudes, *Journal of Ethnic and Migration Studies*, 46 (15) pp.3079–3100. DOI: 10.1080/1369183X.2020.1733947
- Knies, G., Nandi, A. and Platt, L. (2016) *Life Satisfaction, Ethnicity and Neighbourhoods: Is There an Effect of Neighbourhood Ethnic Composition on Life Satisfaction?*. (s.l.): (s.n.).
- Koopmans, R. (2016) Does assimilation work? Sociocultural determinants of labour market participation of European Muslims, *Journal of Ethnic and Migration Studies*, 42 (2) pp.197–216. DOI: 10.1080/1369183X.2015.1082903
- Lambert, P. and Griffiths, D. (2018) *Social Inequalities and Occupational Stratification*. London: Palgrave Macmillan UK. Available at: <http://link.springer.com/10.1057/978-1-137-02253-0> (accessed 28 September 2024).
- Larsen, E. N. and Di Stasio, V. (2021) Pakistani in the UK and Norway: different contexts, similar disadvantage. Results from a comparative field experiment on hiring discrimination, *Journal of Ethnic and Migration Studies*, 47 (6) pp.1201–1221. DOI: 10.1080/1369183X.2019.1622777
- Lemos, S. and Portes, J. (2008) New Labour? The Impact of Migration from Central and Eastern European Countries on the UK Labour Market, *SSRN Electronic Journal*, DOI: 10.2139/ssrn.1286694
- Li, D. *et al.* (2021) Does ethnic diversity affect well-being and allostatic load among people across neighbourhoods in England?, *Health & Place*, 68 p.102518. DOI: 10.1016/j.healthplace.2021.102518
- Li, Y. and Heath, A. (2008) Minority ethnic men in British labour market (1972-2005), *International Journal of Sociology and Social Policy*, 28 (5/6) pp.231–244. DOI: 10.1108/01443330810881277
- Li, Y. and Heath, A. (2016) Class Matters: A Study of Minority and Majority Social Mobility in Britain, 1982–2011, *American Journal of Sociology*, 122 (1) pp.162–200. DOI: 10.1086/686696
- Li, Y. and Heath, A. (2020) 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
- Lieberson, S. (1980) *A Piece of the Pie: Blacks and White Immigrants Since 1880*. California: University of California Press.

- Lindley, J. (2002) Race or religion? The impact of religion on the employment and earnings of Britain's ethnic communities, *Journal of Ethnic and Migration Studies*, 28 (3) pp.427–442. DOI: 10.1080/13691830220146536
- Lippens, L. *et al.* (2022) Is labour market discrimination against ethnic minorities better explained by taste or statistics? A systematic review of the empirical evidence, *Journal of Ethnic and Migration Studies*, 48 (17) pp.4243–4276. DOI: 10.1080/1369183X.2022.2050191
- Longhi, S. (2020) A longitudinal analysis of ethnic unemployment differentials in the UK, *Journal of Ethnic and Migration Studies*, 46 (5) pp.879–892. DOI: 10.1080/1369183X.2018.1539254
- Longhi, S., Nicoletti, C. and Platt, L. (2013) Explained and unexplained wage gaps across the main ethno-religious groups in Great Britain, *Oxford Economic Papers*, 65 (2) pp.471–493. DOI: 10.1093/oep/gps025
- Manley, D., Khattab, N. and Johnston, R. (2019) Whiteness, Migration and Integration into the British Labour Market, *Journal of International Migration and Integration*, 21 (3) pp.925–947. DOI: 10.1007/s12134-019-00681-0
- Maskileyson, D. and Semyonov, M. (2017) On race, ethnicity and on the economic cost of immigration, *Research in Social Stratification and Mobility*, 50 pp.19–28. DOI: 10.1016/j.rssm.2017.06.003
- McCall, L. (2005) The Complexity of Intersectionality, *Signs: Journal of Women in Culture and Society*, 30 (3) pp.1771–1800. DOI: 10.1086/426800
- McPherson, M., Smith-Lovin, L. and Cook, J. M. (2001) Birds of a Feather: Homophily in Social Networks, *Annual Review of Sociology*, 27 (Volume 27, 2001) pp.415–444. DOI: 10.1146/annurev.soc.27.1.415
- Meer, N. (2013) Racialization and religion: race, culture and difference in the study of antisemitism and Islamophobia, *Ethnic and Racial Studies*, 36 (3) pp.385–398. DOI: 10.1080/01419870.2013.734392
- Meer, N. and Modood, T. (2009) The Multicultural State We're In: Muslims, 'Multiculture' and the 'Civic Re-balancing' of British Multiculturalism, *Political Studies*, 57 (3) pp.473–497. DOI: 10.1111/j.1467-9248.2008.00745.x
- Meer, N. and Modood, T. (2014) Cosmopolitanism and integrationism: is British multiculturalism a 'Zombie category'?, *Identities*, 21 (6) pp.658–674. DOI: 10.1080/1070289X.2013.875028
- Merlo, J. (2018) Multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) within an intersectional framework, *Social Science & Medicine*, 203 pp.74–80. DOI: 10.1016/j.socscimed.2017.12.026
- Miaari, S., Khattab, N. and Johnston, R. (2019) Religion and ethnicity at work: a study of British Muslim women's labour market performance, *Quality & Quantity*, 53 (1) pp.19–47. DOI: 10.1007/s11135-018-0721-x

- Mincer, J. A. (1974) *Schooling, Experience, and Earnings*.
- Model, S. (1991) Caribbean Immigrants: A Black Success Story?1, *International Migration Review*, 25 (2) pp.248–276. DOI: 10.1177/019791839102500201
- Model, S. and Lin, L. (2002) The Cost of Not Being Christian: Hindus, Sikhs and Muslims in Britain and Canada, *International Migration Review*, 36 (4) pp.1061–1092. DOI: 10.1111/j.1747-7379.2002.tb00118.x
- Modood, T. *et al.* (1997) *Ethnic Minorities in Britain: Diversity and Disadvantage*. London: Policy Studies Institute. Available at: http://www.psi.org.uk/site/publication_detail/694 (accessed 9 August 2024).
- Moosavi, L. (2015) The Racialization of Muslim Converts in Britain and Their Experiences of Islamophobia, *Critical Sociology*, 41 (1) pp.41–56. DOI: 10.1177/0896920513504601
- Muñoz de Bustillo, R. *et al.* (2011) *Measuring More than Money*. [Books] Edward Elgar Publishing. Available at: <https://econpapers.repec.org/bookchap/elgeebook/14072.htm> (accessed 21 August 2024).
- Mustafa, A. (2016) Young British Muslims: Between Rhetoric and Realities, In: *Young British Muslims Between Rhetoric and Realities*. Routledge & CRC Press. Available at: <https://www.routledge.com/Young-British-Muslims-Between-Rhetoric-and-Realities/Hamid/p/book/9781138385702> (accessed 21 August 2024).
- Neumark, D. (2018) Experimental Research on Labor Market Discrimination, *Journal of Economic Literature*, 56 (3) pp.799–866. DOI: 10.1257/jel.20161309
- Neves, H. D. (2024) Young, Muslim and poor: The persistent impacts of the pandemic on mental health in the UK, *Social Science*, 353 DOI: <https://doi.org/10.1016/j.socscimed.2024.117032>
- Oaxaca, R. (2001) Discrimination, Economics of, In: Smelser, N.J. and Baltes, P.B. (eds.) *International Encyclopedia of the Social & Behavioral Sciences*. Oxford: Pergamon. pp.3756–3762. Available at: <https://www.sciencedirect.com/science/article/pii/B0080430767022920> (accessed 19 August 2024).
- Office For National Statistics (2023) *Labour Force Survey*. Available at: <https://beta.ukdataservice.ac.uk/datacatalogue/series/doi/?id=2000026> (accessed 21 April 2023).
- Office of National Statistics (2020a) *Census: Aggregate Data*. Available at: <https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=7427>
- Office of National Statistics (2020b) *Religion, education and work in England and Wales*. (s.l.): (s.n.).
- Panayi, P. (2010) *An immigration history of Britain : multicultural racism since 1800*. Harlow, England ; N.Y. : Pearson Longman. Available at: <http://archive.org/details/immigrationhisto0000pana> (accessed 9 August 2024).

- Paradies, Y. *et al.* (2015) Racism as a Determinant of Health: A Systematic Review and Meta-Analysis, *PLoS ONE*, 10 (9) p.e0138511. DOI: 10.1371/journal.pone.0138511
- Parekh, B. (2008) *A New Politics of Identity: Political Principles for an Interdependent World*. Basingstoke: Red Globe Press.
- Patacchini, E. and Zenou, Y. (2012) Ethnic networks and employment outcomes, *Regional Science and Urban Economics*, 42 (6) pp.938–949.
- Pędziwiatr, K. (2017) Conversions to Islam and Identity Reconfigurations among Poles in Great Britain, *Studia Religiológica*, 50 (3) DOI: 10.4467/20844077SR.17.014.7747
- Pettit, B., Hook, J. and FERBER, M. (2010) Gendered Tradeoffs: Family, Social Policy, and Economic Inequality in Twenty-One Countries, *Perspectives on Work*, 14 pp.53–54. DOI: 10.2307/41810193
- Platt, L. (2007) *Poverty and ethnicity in the UK*. Bristol, UK: Published for the Joseph Rowntree Foundation by the Policy Press.
- Platt, L. (2019) *Understanding Inequalities: Stratification and Difference*. (s.l.): John Wiley & Sons.
- Platt, L. and Nandi, A. (2020) Ethnic diversity in the UK: new opportunities and changing constraints, *Journal of Ethnic and Migration Studies*, 46 (5) pp.839–856. DOI: 10.1080/1369183X.2018.1539229
- Plum, A. and Knies, G. (2019) Local unemployment changes the springboard effect of low pay: Evidence from England, *PloS One*, 14 (11) p.e0224290. DOI: 10.1371/journal.pone.0224290
- Portes, J. (2019) *Immigration: what do we know and what should we do*. London: Sage Publishing.
- Portes, J. and French, S. (2005) The impact of free movement of workers from central and eastern Europe on the UK labour market: early evidence, *Department for Work and Pensions Working Paper*, 18
- Prandy, K. and Lambert, P. (2003) Marriage, Social Distance and the Social Space:: An Alternative Derivation and Validation of the Cambridge Scale, *Sociology*, 37 (3) pp.397–411. DOI: 10.1177/00380385030373001
- Putnam, R. (2001) *Bowling Alone: The Collapse and Revival of American Community*. New edition London: Simon & Schuster Ltd.
- Putnam, R. D. (2007) E Pluribus Unum: Diversity and Community in the Twenty-first Century The 2006 Johan Skytte Prize Lecture, *Scandinavian Political Studies*, 30 (2) pp.137–174. DOI: 10.1111/j.1467-9477.2007.00176.x
- Reynolds, L. and Birdwell, J. (2015) *476_1509_RisingtotheTop_web.pdf*. [Demos] Available at: https://demos.co.uk/wp-content/uploads/2015/10/476_1509_RisingtotheTop_web.pdf (accessed 21 August 2024).

- Ribar, D. C. (2004) What Do Social Scientists Know About the Benefits of Marriage? A Review of Quantitative Methodologies, *SSRN Electronic Journal*, DOI: 10.2139/ssrn.500887
- Robins, G., Elliott, P. and Pattison, P. (2001) Network models for social selection processes, *Social Networks*, 23 (1) pp.1–30. DOI: 10.1016/S0378-8733(01)00029-6
- Röder, A. (2014) Explaining religious differences in immigrants' gender role attitudes: the changing impact of origin country and individual religiosity, *Ethnic and Racial Studies*, 37 (14) pp.2615–2635. DOI: 10.1080/01419870.2013.854919
- Rouhani, S. (2014) *Intersectionality-informed Quantitative Research: A Primer*. Available at: <https://www.semanticscholar.org/paper/1-Intersectionality-informed-Quantitative-Research-Rouhani/d56a9eba2da23ab70bfadd9ca2e076af4a3a62cc>
- Ryan, L. (2022) The Direct and Indirect Role of Migrants' Networks in Accessing Diverse Labour Market Sectors: An Analysis of the Weak/Strong Ties Continuum, In: Keskiner, E., Eve, M. and Ryan, L. (eds.) *Revisiting Migrant Networks: Migrants and their Descendants in Labour Markets*. Cham: Springer International Publishing. pp.23–40. Available at: https://doi.org/10.1007/978-3-030-94972-3_2 (accessed 21 August 2024).
- Safi, M. (2010) Immigrants' Life Satisfaction in Europe: Between Assimilation and Discrimination, *European Sociological Review*, 26 (2) pp.159–176. DOI: 10.1093/esr/jcp013
- Salt, J. and Millar, J. (2006) *Foreign labour in the United Kingdom: current patterns and trends*.
- Scarpetta, S., Sonnet, A. and Manfredi, T. (2010) *Rising Youth Unemployment During The Crisis: How to Prevent Negative Long-term Consequences on a Generation?*. (Vol. 106). [OECD Social, Employment and Migration Working Papers] Available at: https://www.oecd-ilibrary.org/social-issues-migration-health/rising-youth-unemployment-during-the-crisis_5kmh79zb2mmv-en (accessed 13 August 2024).
- Schmid, L. (2023) The Impact of Host Language Proficiency on Migrants' Employment Outcomes, *American Economic Review: Insights*, 5 (4) pp.477–93. DOI: 10.1257/aeri.20220386
- Scotland, J. (2012) Exploring the Philosophical Underpinnings of Research: Relating Ontology and Epistemology to the Methodology and Methods of the Scientific, Interpretive, and Critical Research Paradigms, *English Language Teaching*, 5 (9) p.9. DOI: 10.5539/elt.v5n9p9
- Scott, J. (2010) Quantitative methods and gender inequalities, *International Journal of Social Research Methodology*, 13 (3) pp.223–236. DOI: 10.1080/13645579.2010.482258
- Scott Long, J. (2008) *The Workflow of Data Analysis Using Stata*. 1st edition (s.l.): Stata Press.
- Selod, S. and Embrick, D. G. (2013) Racialization and Muslims: Situating the Muslim Experience in Race Scholarship, *Sociology Compass*, 7 (8) pp.644–655. DOI: 10.1111/soc4.12057

Shaginyan-Shapira, M. (2010) Understanding the Impact of Immigration on the Labour Market Outcomes of British Workers, In: Stillwell, J. and van Ham, M. (eds.) *Ethnicity and Integration: Understanding Population Trends and Processes: volume 3*. Dordrecht: Springer Netherlands. pp.153–178. Available at: https://doi.org/10.1007/978-90-481-9103-1_8 (accessed 20 August 2024).

Shahid, H. J., Khan, A. and Hall, J. (2023) Gendered health inequalities and British Muslim women: an intersectional approach and analysis, In: Dogra, S. (ed.) *British Muslims, Ethnicity and Health Inequalities*. Edinburgh University Press. pp.47–73. Available at: <https://www.degruyter.com/document/doi/10.1515/9781399502672-006/html> (accessed 14 August 2024).

Shams, T. (2020) Successful yet Precarious: South Asian Muslim Americans, Islamophobia, and the Model Minority Myth, *Sociological Perspectives*, 63 (4) pp.653–669. DOI: 10.1177/0731121419895006

Shankley, W. and Byrne, B. (2020) Citizen rights and immigration, In: Shankley, W. *et al.* (eds.) *Ethnicity and Race in the UK*. 1st edn. Bristol University Press. pp.35–50. Available at: <https://www.jstor.org/stable/j.ctv14t47tm.8> (accessed 27 September 2024).

Shankley, W., Hannemann, T. and Simpson, L. (2020) The demography of ethnic minorities in Britain, In: *Ethnicity, Race and Inequality in the UK: State of the Nation*. Policy Press. Available at: <https://bristoluniversitypressdigital.com/display/book/9781447351269/ch001.xml> (accessed 20 August 2024).

Shankley, W. and Williams, P. (2020) Minority ethnic groups, policing and the criminal justice system in Britain, In: *Ethnicity, Race and Inequality in the UK: State of the Nation*. Policy Press. Available at: <https://bristoluniversitypressdigital.com/display/book/9781447351269/ch003.xml> (accessed 20 August 2024).

Sian, K., Law, I. and Sayyid, S. (2012) *The Media and Muslims in the UK*. (s.l.): (s.n.).

Silva, T. and Evans, C. R. (2020) Sexual Identification in the United States at the Intersections of Gender, Race/Ethnicity, Immigration, and Education, *Sex Roles*, 83 (11–12) pp.722–738. DOI: 10.1007/s11199-020-01145-x

Sirgy, M. J. and Cornwell, T. (2002) How Neighborhood Features Affect Quality of Life, *Social Indicators Research*, 59 (1) pp.79–114. DOI: 10.1023/A:1016021108513

Small, M. L. and Pager, D. (2020) Sociological Perspectives on Racial Discrimination, *Journal of Economic Perspectives*, 34 (2) pp.49–67. DOI: 10.1257/jep.34.2.49

Spierings, N. (2012) The inclusion of quantitative techniques and diversity in the mainstream of feminist research, *European Journal of Women's Studies*, 19 (3) pp.331–347. DOI: 10.1177/1350506812443621

Spierings, N. (2014) How Islam Influences Women's Paid Non-farm Employment: Evidence from 26 Indonesian and 37 Nigerian Provinces, *Review of Religious Research*, 56 (3) pp.399–431. DOI: 10.1007/s13644-014-0159-0

Spierings, N. (2023) Quantitative intersectional research: approaches, practices, and needs, In: *The Routledge International Handbook of Intersectionality Studies*. Routledge. Available at: https://www.routledge.com/The-Routledge-International-Handbook-of-Intersectionality-Studies/Davis-Lutz/p/book/9780367545048?srsId=AfmBOopoXQcfm7LPtTy1Aedm6hXICPqjLyBha_0_e7_kTc-tdXUPKlx

Spierings, N., Smits, J. and Verloo, M. (2010) Micro- and Macrolevel Determinants of Women's Employment in Six Arab Countries, *Journal of Marriage and Family*, 72 (5) pp.1391–1407. DOI: 10.1111/j.1741-3737.2010.00772.x

Stasio, V. D. *et al.* (2021) Muslim by default or religious discrimination? Results from a cross-national field experiment on hiring discrimination, *EconStor Open Access Articles and Book Chapters*, 47 (6) pp.1305–1326.

Stillwell, J. and Van Ham, M. (eds.) (2010) *Ethnicity and Integration*. Dordrecht: Springer Netherlands. Available at: <http://link.springer.com/10.1007/978-90-481-9103-1> (accessed 19 August 2024).

Stopforth, S., Gayle, V. and Boeren, E. (2021) Parental social class and school GCSE outcomes: two decades of evidence from UK household panel surveys, *Contemporary Social Science*,

Sweida-Metwally, S. (2022) Does the Muslim penalty in the British labour market dissipate after accounting for so-called “socio, *Ethnic and Racial Studies*, 45 (16) pp.359–388. DOI: <https://doi.org/10.1080/01419870.2022.2097887>

The Economist (2006) Shutting the door, *The Economist*, Available at: <https://www.economist.com/britain/2006/10/26/shutting-the-door> (accessed 27 September 2024).

The Telegraph (2004) Eastern European migration ‘far exceeds estimate’, *The Telegraph*, 11 November, Available at: <https://www.telegraph.co.uk/education/3347009/Eastern-European-migration-far-exceeds-estimate.html> (accessed 27 September 2024).

University of Essex and Institute for Social and Economic Research (2022a) *Understanding Society: Waves 1-13, 2009-2022 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access*. Available at: <https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=6931> (accessed 21 August 2024).

University of Essex and Institute for Social and Economic Research (2022b) *Understanding Society: Waves 1-13, 2009-2022: Special Licence Access, Census 2011 Lower Layer Super Output Areas*. Available at: <https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=7248> (accessed 21 August 2024).

Vargas-Silva, C. (2014) *What do we know about EU migration to the UK?*.

Voas, D., Beckford, J. and Demerath, N. J. (2007) Surveys of behaviour, beliefs and affiliation, In: *Handbook of the Sociology of Religion*. Sage Publications Ltd. pp.128–150.

Available at: <https://research.manchester.ac.uk/en/publications/surveys-of-behaviour-beliefs-and-affiliation> (accessed 27 September 2024).

Wallace, S., Nazroo, J. and Bécaries, L. (2016) Cumulative Effect of Racial Discrimination on the Mental Health of Ethnic Minorities in the United Kingdom, *American Journal of Public Health*, 106 (7) pp.1294–1300. DOI: 10.2105/AJPH.2016.303121

Weber, M. (1930) *The Protestant Ethic and the Spirit of Capitalism*. (s.l.): (s.n.).

Wilkes, R. and Karimi, A. (2024) What does the MAIHDA method explain?, *Social Science & Medicine*, 345 p.116495. DOI: 10.1016/j.socscimed.2023.116495

Winant, H. (1997) Behind Blue Eyes: Whiteness and Contemporary US Racial Politics, *New Left Review*, (1/225) pp.73–88.

Yemane, R. (2020) Cumulative disadvantage? The role of race compared to ethnicity, religion, and non-white phenotype in explaining hiring discrimination in the U.S. labour market, *Research in Social Stratification and Mobility*, 69 p.100552. DOI: 10.1016/j.rssm.2020.100552

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. (2017) 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) p.e2041. DOI: 10.1002/psp.2041

Zwysen, W. and Demireva, N. (2020) Ethnic and migrant penalties in job quality in the UK: the role of residential concentration and occupational clustering, *Journal of Ethnic and Migration Studies*, 46 (1) pp.200–221. DOI: 10.1080/1369183X.2018.1498777

Zwysen, W., Di Stasio, V. and Heath, A. (2021) Ethnic Penalties and Hiring Discrimination: Comparing Results from Observational Studies with Field Experiments in the UK, *Sociology*, 55 (2) pp.263–282. DOI: 10.1177/0038038520966947

APPENDICES

APPENDIX A: **Assigned education score based on average CAMSIS for that age group and qualification combination – sorted by education score from low to high.**

Decade born in	Highest qualification held	Assigned Score
00s	5. Other qual	34.7
60s	6. No Quals	35.8
70s	6. No Quals	36.1
00s	4. GCSE etc	36.8
80s	6. No Quals	37.3
50s	6. No Quals	37.8
90s	6. No Quals	38.0
90s	5. Other qual	38.1
40s	6. No Quals	38.8
90s	4. GCSE etc	39.0
80s	5. Other qual	39.1
00s	3. A level etc	39.2
00s	6. No Quals	39.6
00s	2. Other higher	40.2
70s	5. Other qual	40.5
60s	5. Other qual	40.8
50s	5. Other qual	41.1
80s	4. GCSE etc	41.8
00s	1. Degree	41.9
40s	5. Other qual	42.0
90s	3. A level etc	42.1
70s	4. GCSE etc	43.8
60s	4. GCSE etc	44.0
90s	2. Other higher	44.6
50s	4. GCSE etc	44.9
40s	4. GCSE etc	45.2
80s	3. A level etc	46.9
50s	3. A level etc	46.9

40s	3. A level etc	47.0
70s	3. A level etc	48.1
60s	3. A level etc	48.4
80s	2. Other higher	49.1
70s	2. Other higher	51.7
40s	2. Other higher	51.8
60s	2. Other higher	51.9
50s	2. Other higher	53.9
90s	1. Degree	54.8
80s	1. Degree	58.4
50s	1. Degree	60.8
60s	1. Degree	60.9
70s	1. Degree	60.9
40s	1. Degree	61.8

APPENDIX B: Selected syntax for operationalisation of measures and data management.

B1 Programme for rendering weights across different UKHLS wave files.

```
*      a_indinus_xw (for wave a)
*      *_indinub_xw (for wave b - e)
*      *_indinui_xw (for wave f - l).
capture program drop ren_wts
program define ren_wts
    capture rename indinus_xw nwei
    capture rename indinub_xw nwei
    capture rename indinui_xw nwei
end

*** In summary, this code defines a program that renames specific variables to nwei, handling
different waves of data. The capture command ensures that any errors during the renaming
process are ignored.
```

B2 Data file prep, loading in variables from the UKHLS and merging files together.

```
* cross wave file
use pidp psu strata plbornc paedqf maedqf ethn_dv plbornc_all macob_all pacob_all      ///
doby_dv bornuk_dv yr2uk4 scend scend_dv generation masoc* pasoc* yr2uk4 plbornc plbornc_al
///
using $pprotect/xwavedat_protect.dta, clear
sort pidp
save $ptemp/xwavetemp.dta, replace

* hhresp
foreach wav in $allwaves {
    use `wav'*hidp `wav'*tenure_dv `wav'*agechy_dv `wav'*hrpno `wav'*hrpid ///
    `wav'*fihhmngs_dv `wav'*hhsize `wav'*hhtype_dv `wav'*nkids_dv ///
    `wav'*n wage_dv `wav'*nemp_dv `wav'*fihhmnlabgrs_dv `wav'*psu///
    `wav'*gor* `wav'*nch02_dv `wav'*nch34_dv ///
    using $pprotect/`wav'_hhresp_protect.dta, clear
    rename `wav'_gor_dv `wav'_gor_dv_hh
    sav $ptemp/`wav'_hh_crossfile.dta, replace
}

* indresp (responses for every wave a - l)
foreach wav in $allwaves {
    use pidp ///
    `wav'*psu `wav'*strata `wav'*gor_dv `wav'*age_dv `wav'*opr1g `wav'*jbstat      ///
    `wav'*nirel `wav'_sex `wav'*sex_dv `wav'*racel ///
    `wav'*opr1g1 `wav'*ethn_dv `wav'*yr2uk4 `wav'*marstat ///
    `wav'*nchild_dv `wav'*country `wav'*marstat `wav'_fimngs_dv      ///
    `wav'*yr2uk4 `wav'*_birthy `wav'*jbnsec*_dv `wav'*qfhigh      ///
    `wav'_jul4wk `wav'*jbhas `wav'*jbboff `wav'*jbsemp      ///
    `wav'*jbstat `wav'*jbterm1 `wav'*jbiindb_dv `wav'*jbsemp      ///
    `wav'*jbsoc00 `wav'*jbsoc10 `wav'*jbsoc00_cc `wav'*gor_dv      ///
    `wav'*jbsoc10_cc `wav'*labgrs* `wav'*jbhrs `wav'*racel_dv      ///
    `wav'*pacob `wav'*macob `wav'*jbhad `wav'*jbseg_dv      ///
    `wav'*fimngs_dv `wav'*jbft_dv `wav'*jbterm* `wav'*jbhrs      ///
```

```

`wav'*payu `wav'*_employ `wav'_scghq*_dv `wav'_j2has ///
`wav'*jbotpd `wav'*jshrs `wav'*pasoc* `wav'*masoc* ///
`wav'*hhstype_dv `wav'*jbrgsc* `wav'*nchild_dv `wav'*_hiqual_dv ///
`wav'*pasoc10 `wav'*masoc10 `wav'*hidp `wav'_indi* ///
`wav'*plbornc `wav'*jbft_dv `wav'*jbsect `wav'*nchl4resp ///
`wav'*health `wav'*plbornc_all `wav'*plbornc `wav'*intdaty_dv ///
`wav'*jshrs `wav'*aidhh `wav'*aidhrs `wa'*aideft `wav'*aidxhh ///
`wav'*scghq1_dv `wav'*sclfsat1 `wav'*sclfsato `wav'*sclfsat2 `wav'*sclfsat7 ///
`wav'*finfut `wav'*finnow using $pprotect/`wav'_indresp_protect.dta, clear
sort pidp
gen `wav'_indrespmarker = 1
sav $ptemp/`wav'_crossfile.dta, replace

}

* indall
foreach wav in $allwaves {
use pidp ///
`wav'_hidp `wav'_nchild_dv `wav'_urban_dv ///
`wav'_dvage `wav'_age_dv `wav'_ethn_dv `wav'_gor_dv///
`wav'_employ `wav'_sex `wav'_sex_dv `wav'_country `wav'*psnenu* `wav'_marstat_dv
`wav'_hhsz `wav'_imd*///
using $pprotect/`wav'_indall_protect.dta, clear

foreach var in ///
`wav'_nchild_dv `wav'_urban_dv ///
`wav'_dvage `wav'_ethn_dv `wav'_gor_dv///
`wav'_employ `wav'_sex `wav'_country `wav'*psnenu* `wav'_marstat_dv `wav'_hhsz
///
{
rename `var' `var'_ind

}

sort pidp
sav $ptemp/`wav'_indall_crossfile.dta, replace
}

* lsoa file
foreach wav in $allwaves {
use `wav'*_hidp `wav'*_lsoallusing $plsoa/`wav'_lsoall_protect.dta, clear
sort `wav'*_hidp
// foreach var in `wav'_lsoall {
// encode `var' , gen(`wav'_lsoa_cd)
// capture drop `var'
// }
sav $ptemp/`wav'_lsoa_crossfile.dta, replace
}

* matching in spouse data
foreach wav in $allwaves {
use pidp `wav'_ethn_dv `wav'_sppid `wav'_pno ///

```

```

        `wav'_ppno `wav'_hidp `wav'_sex_dv `wav'_age_dv ///
        using $pprotect/`wav'_indall_protect.dta, clear
    keep if `wav'_ppno > 0
    rename `wav'_* `wav'_sp_*
    rename `wav'_sp_ppno `wav'_pno
    rename `wav'_sp_hidp `wav'_hidp
    drop `wav'_sp_pno
    save $petemp/`wav'_data1.dta, replace
}

foreach wav in $allwaves {
    use pidp `wav'_sppid `wav'_pno `wav'_ppno `wav'_hidp `wav'_sex_dv `wav'_age_dv using
    $pprotect/`wav'_indall_protect.dta, clear
    keep if `wav'_ppno>0
    merge 1:1 `wav'_hidp `wav'_pno using $petemp/`wav'_data1.dta
    keep if _merge == 3
    drop _merge
    renpfix `wav'_
    rename age_dv age_dv_ind
    rename sex_dv sex_dv_ind
    rename hidp `wav'_hidp
    sav $petemp/`wav'_ukhls_spouses.dta, replace
}

** 1.3 matching in co-residents parents data

local tm "mother"
local tf "father"
local file indall_protect.dta
foreach w in $allwaves {
    local i=strpos("abcdefghijklmnopqrstuvwxyz","`w'")
    local idvar nspid
    local vars `w'_age_dv `w'_employ `w'_ethn_dv
    foreach k in m f {
        use $testy/`w'_indall_protect.dta, clear
        drop if `w'_'`k'`idvar'<0
        keep `w'_'`k'`idvar' pidp
        rename pidp kpidp
        rename `w'_'`k'`idvar' pidp
        merge m:1 pidp using $testy/`w'_'_file', nogen keep(3) ///
        keepus(`vars')
        foreach var of local vars {
            rename `var' `var'_'`k'
            local l`var': var label `var'
            lab var `var' "`t`k': `l`var'"
        }
        drop pidp
        rename kpidp pidp
        merge 1:1 pidp using $testy/`w'_'_file', nogen
    }
}

```

```

keep pidp *_`k' `w'_`k'`idvar'
    // check1
    isid pidp
    save `k', replace
}
use m, clear
merge 1:1 pidp using f
// check
assert _merge==3
drop _merge
order pidp, first
order *_m *_f, last
// check2
foreach k in m f {
    foreach var of local vlist {
        assert (`w'_`var'_m==. & `w'_m`idvar'==8) | ///
            (`w'_`var'_m<. & `w'_m`idvar'>8)
    }
}
renpfix `w'_
save $testy/new/`w'_parentsfile, replace
su
d
}

* fathers and mothers education and job from indresp
foreach k in fn mn {
    foreach wav in $allwaves {
        use pidp `wav'*oprlg* `wav'_hiqual_dv `wav'_jbsoc10 `wav'_jbsoc00 ///
        using $pprotect/`wav'_indresp_protect.dta, clear
        foreach var in `wav'*oprlg* `wav'_hiqual_dv `wav'_jbsoc10 `wav'_jbsoc00 {
            rename `var' `var'_`k'
        }

        rename pidp `k'pid
        sort `k'pid
        lab var `k'pid "`k''s cross-wave person identifier"
        renpfix `wav'_
        rename `k'pid `wav'_`k'pid
        sav $petemp/`wav'_`k'_indresp.dta, replace
    }

    foreach wav in $allwaves {
        use pidp `wav'_`k'pid ///
        using $pprotect/`wav'_indresp_protect.dta, clear
        sort `wav'_`k'pid
        merge m:1 `wav'_`k'pid using $petemp/`wav'_`k'_indresp.dta
        keep if _merge==1 | _merge==3
        drop _merge
        renpfix `wav'_
        drop if hiqual_dv_`k' == .
        drop if jbsoc10_`k' == .
        sav $petemp/`wav'_`k'_collected.dta, replace
    }
}

```

```

}

** 1.4 Merge together the individual inderesp files with xwave,
    * indall, lsoa, and xwave files.
foreach wav in $allwaves {
    use $ptemp/`wav'_hh_crossfile.dta, clear
    merge 1:m `wav'_hidp using $ptemp/`wav'_indall_crossfile.dta
    keep if _merge == 1 | _merge == 3
    drop _merge
    drop if (pidp == .)
    merge 1:m `wav'_hidp pidp using $ptemp/`wav'_ukhls_spouses.dta
    keep if _merge == 1 | _merge==3
    drop _merge
    merge 1:1 pidp using $ptemp/`wav'_crossfile.dta
    keep if _merge == 1 | _merge == 3
    drop _merge
    merge m:1 `wav'_hidp using $ptemp/`wav'_lsoa_crossfile.dta
    keep if _merge == 3
    drop _merge
    renpfix `wav'_
    merge 1:1 pidp using $ptemp/xwavetemp.dta
    keep if _merge == 3
    drop _merge
    merge 1:1 pidp using $testy/new/`wav'_parentsfile.dta
    keep if _merge == 3
    drop _merge
    foreach k in fn mn {
        merge 1:1 pidp using $ptemp/`wav'_`k'_collected.dta
        keep if _merge == 1 | _merge == 3
        drop _merge
    }
    gen waveno="`wav'"
    ren_wts
    sav $ptemp/`wav'_temps.dta, replace
}

* append together.
use $ptemp/a_temps.dta, clear
foreach wav in b c d e f g h i j k l {
    append using $ptemp/`wav'_temps.dta
    order pidp waveno, first
}

```

B3 Generate different age groups based on decades and make an education score variable based on average Camsis for each qualification group adjusted by age group.

```

capture drop decades
recode birthy (2000/2005 = 1 "00s") (1990/1999 = 2 "90s") ///
    (1980/1989 = 3 "80s") (1970/1997 = 4 "70s") (1960/1969 = 5 "60s") ///
    (1950/1959 = 6 "50s") (1940/1949 = 7 "40s") (1930/1939 = 8 "30s") ///
    (1920/1929 = 9 "20s") (1910/1919= 10 "10s") (*=.), gen(decades)

lab          var          decades          "Decade          born          in"

```

```
egen educscore = mean(mcaml0) if (decades == 1 | decades == 2 | decades == 3 | decades ==
4|decades == 5 | decades == 6 | decades == 7) & (hiqua1_dv >= 1 & hiqua1_dv <= 9) & (mcaml0
> 0) , by(hiqua1_dv decades)
```

B4 Generating religious affiliation variable taking information from Northern Ireland and replacing missing data forwards or backwards from waves.

```
tab oprlg // whether belong to a religion (everyone)
tab oprlg1 // religious affiliation E/S/W
tab nirel // religious affiliation Northern Ireland

* Loop through variables
foreach var in oprlg1 nirel {
* replace oprlg1 and nirel values with 0 where oprlg == 2 (no religion)
replace `var' = 0 if oprlg==2
* drop the variable max1_ if it exists.
capture drop max1_`var'
* create new var that contains the max value of oprlg1/nirel across rows.
egen max1_`var'=rowmax(`var')
* freq.
tab max1_`var'
}

*rename for ease.
rename max1_oprgl1 max1_rel

* define religious affiliation labels (long version)
label define max1_rel 0 "no religion" ///
2 "Church of england/anglican" 3 "Roman catholic" ///
4 "Church of Scotland" 5 "Free church or free presbyterian church" ///
6 "episcopalian" 7 "Methodist" 8 "Baptist" ///
9 "congregational/united reform/urc" 10 "Other Christian" ///
11 "Christian no DOM" 12 "Muslim" 13 "Hindu" 14 "Jewish" ///
15 "Sikh" 16 "Buddhist" 17 "Church of Wales" 97 "Other"

* attach labels to variable.
label values max1_rel max1_rel

* create condensed version of var called 'ff_religion'
gen ff_religion=max1_rel

* define condensed labels
recode ff_religion 2 3 4 5 6 7 8 9 10 11 17 = 2
replace ff_religion = 2 if max1_nirel == 2 /* Christian */
replace ff_religion = 12 if max1_nirel == 5 /* Muslim */
replace ff_religion = 16 if max1_nirel == 3 /* Buddhist */
replace ff_religion = 13 if max1_nirel == 4 /* Hindu */
replace ff_religion = 97 if max1_nirel == 6 /* Other. */
label define l_religion 0 "No religion" 2 "Christian" 12 "Muslim" ///
13 "Hindu" 14 "Jewish" 15 "Sikh" 16 "Buddhist" 97 "Other"

* attach labels to variable.
label values ff_religion l_religion
```

```

* assign missing data.
recode ff_religion -9 / -1 =.

* parents religion
sum *oprlg*
tabl ff_oprlgl_fn ff_oprlgl_mn // father (fn) and mother (mn)
foreach var in oprlg1_fn oprlg1_mn ff_oprlgl_fn ff_oprlgl_mn {
    recode `var' -100/-1 =. 2 3 4 5 6 7 8 9 10 11 17 = 2
    tabl `var'
}
tab ff_religion

*Recoding missing data
foreach var in ///
sex sex_dv age_dv marstat ethn_dv ff_religion generation scghql_dv ///
marstat hiqual_dv sppid sp_sex_dv sp_age_dv sp_ethn_dv sp_sppid ///
jspayu mnspid fnspid birthy {
    recode `var' (-10 / -1 = .)
    summ `var'
}

* Taking responses from the next available observation when missing.
foreach myvar in jbstat marstat hiqual_dv ff_religion oprlg1_fn oprlg1_mn ff_oprlgl_fn
ff_oprlgl_mn {
    * Loop through each variable in the list
    by pidp (waveno), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
    * For each variable, replace missing values with the value from the previous observation
    within the same pidp, sorted by waveno
}

foreach num of numlist 1/11 {
    di "`num'"
    * Display the current number in the loop (1 to 11)

    foreach myvar in marstat hiqual_dv ff_religion oprlg1_fn oprlg1_mn ff_oprlgl_fn
ff_oprlgl_mn {
        * Loop through each variable in the list again
        by pidp (waveno), sort: replace `myvar' = `myvar'[_n+1] if `myvar' == .
        * Replace missing values with the value from the next observation within the same
        pidp, sorted by waveno

        by pidp (waveno), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
        * Replace missing values with the value from the previous observation within the
        same pidp, sorted by waveno

        sum `myvar' if missing(`myvar')
    }
}

```

<pre> * Summarize the variable to check for remaining missing values } } </pre>
B5 replacing missing religious affiliation data with parent's religious affiliation. <pre> * replacing 'no' or 'missing' with parents religion if both share it. foreach k in fn mn { tab ethn_cc religion_`k' if ff_religion == .     replace ff_religion = 0 if ff_religion == 0 & religion_`k' == 0 replace ff_religion = 2 if ff_religion == . & religion_`k' == 2     replace ff_religion = 2 if ff_religion == 0 & religion_`k' == 2 replace ff_religion = 12 if ff_religion == . & religion_`k' == 12     replace ff_religion = 12 if ff_religion == 0 & religion_`k' == 12 replace ff_religion = 13 if ff_religion == . & religion_`k' == 13     replace ff_religion = 13 if ff_religion == 0 & religion_`k' == 13 replace ff_religion = 14 if ff_religion == . & religion_`k' == 14     replace ff_religion = 14 if ff_religion == 0 & religion_`k' == 14 replace ff_religion = 15 if ff_religion == . & religion_`k' == 15     replace ff_religion = 15 if ff_religion == 0 & religion_`k' == 15 replace ff_religion = 16 if ff_religion == . & religion_`k' == 16     replace ff_religion = 16 if ff_religion == 0 & religion_`k' == 16 replace ff_religion = 97 if ff_religion == . & religion_`k' == 97     replace ff_religion = 97 if ff_religion == 0 & religion_`k' == 97 tab ethn_cc religion_`k' if ff_religion == . } replace ff_religion = 12 if ff_religion == . & ethn_cc == 6 replace ff_religion = 12 if ff_religion == 0 & ethn_cc == 6 replace ff_religion = 12 if ff_religion == . & ethn_cc == 7 replace ff_religion = 12 if ff_religion == 0 & ethn_cc == 7 </pre>
B6 Using information on parents country of birth to replace missing ethnicity information. <pre> use \$petemp/splitfile.dta, clear capture drop *owhite *asianother *blackother foreach k in ma pa { foreach var in `k'cob_all {         recode `k'cob_all (1/4 223 = 1 "UK") /// (6/12 108 110 123 124 132 140 147 173 176 177 179 192 198 205 209 223 225 252 248 259 263 278 296 312 318 320 327 332 333 346 353 365 367 376 385 347 = 2 "Europe") /// (13/14 = 3 "Aus/NZ") (15/16 = 4 "USA/CA") (5 = 5 "Ireland") (26 = 6 "South Africa") (*.=), gen(`k'cob_owhite)          replace ethn_cc = 1 if ethn_cc == 3 & `k'cob_owhite == 1 /* uk*/ replace ethn_cc = 2 if ethn_cc == 3 & `k'cob_owhite == 5 /* ire.*/          replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite == 2 /*europe */ replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite == 3 /*Aus/NZ */          replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite == 4 /*USA/CA*/ replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite == 6 /*south // africa*/ </pre>

```

        replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite != 2
/* replace everyone who doesn't have both a mum or dad from */
        replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite != 1
        replace ethn_cc = 3 if ethn_cc == 3 & `k'cob_owhite != 5
        replace ethn_cc = 3 if ethn_cc==15
***
recode `k'cob_all (18=1 "India") (19=2 "Pakistan") (20 = 3 "Bangladesh") ///
(* = 4 "Other"), gen(`k'cob_asianother)
        replace ethn_cc = 5 if ethn_cc == 8 & `k'cob_asianother == 1 &
ethn_dv != 12 /* replace 'other asians' with two parents from india as indians*/
        replace ethn_cc = 6 if ethn_cc == 8 & `k'cob_asianother == 2 /*
pakistan*/
        replace ethn_cc = 7 if ethn_cc == 8 & `k'cob_asianother == 3
/*bangladesh*/
        *sorting out 'other black background' (ethn_cc == 11)
***
recode `k'cob_all (1/12 108 312 = 1 "Europe") ///
        (13/16 197 = 2 "North America & Oceania") (17/21 101 = 3 "Asia")
///
        (22/26 112 152 178 235 256 265 273 283 321 328 330 335 343 386
387 = 4 "Africa") ///
        (27 114 129 182 211 282 337 339 341 388 = 5 "Caribbean") ///
        (230 231 348 359 = 6 "Middle east") ///
        (142 165 217 309 = 7 "South America") (997 = . ), gen
(`k'cob_blackother)
}
}
replace ethn_cc = 9 if ethn_cc == 11 & macob_blackother ==5 & pacob_blackother == 5
/*caribbean*/
replace ethn_cc = 10 if ethn_cc == 11 & macob_blackother ==4 & pacob_blackother == 4
/*africa*/
replace ethn_cc = 11 if ethn_cc == 11 & macob_blackother !=5 & pacob_blackother != 4
replace ethn_cc = 4 if ethn_cc == 11 & macob_blackother ==5 & pacob_blackother == 4
list pidp year ethn_cc macob_blackother pacob_blackother if ethn_cc == 11

```

B7 Generating ethno-religious permutations variables (various versions of the variable indicative of sensitivity analysis trying different operationalisations of the variable).

```

recode ethn_dv ///
(1 = 1 "white British") (2 3 = 2 "white Irish") (4 = 3 "Other white") ///
(5 = 4 "white and Black Caribbean") (6 = 5 "white and Black African") ///
(7 = 6 "Asian and white") (8 = 7 "Other Mixed") (9 = 8 "Indian") ///
(10 = 9 "Pakistani") (11 = 10 "Bangladeshi") (12 = 11 "Chinese") ///
(13 = 12 "Other Asian Background") (14 = 13 "Caribbean") ///
(15 = 14 "African") (16 = 15 "Other Black Background") ///
(17 = 16 "Arab") (97 = 17 "Other Ethnic Group") (56 -9 . = .m) , gen(mc_ethn)
label var mc_ethn "Ethnic group (many categories)"
capture drop ethn_cc
recode ethn_dv ///
(1 = 1 "w. Brit.") (2 3 = 2 "w. Irish") (4 = 3 "w. Other") ///
(5 6 7 8 = 4 "Mixed." ) (9 = 5 "Indian") (10 = 6 "Pakistani") ///
(11 = 7 "Bangladeshi") (12 13 = 8 "Other Asian") ///
(14 = 9 "Caribbean") (15 = 10 "African") ///

```

```

(16 = 11 "Oth. Black backg.") (17 = 12 "Arab") (97 = 13 "Other Ethn."), gen(ethn_cc)
label          var          ethn_cc          "(Ethnic          group          (condensed)"

* creating ethno-religious permutations
capture drop cwhiteb
gen cwhiteb = .
replace cwhiteb = 1 if ethn_cc == 1 & ff_religion == 0
replace cwhiteb = 1 if ethn_cc == 1 & ff_religion == 2
replace cwhiteb = 1 if ethn_cc == 1 & ff_religion == .
lab var cwhiteb "Christ. / Ag. w. Brit. "
capture drop cwhitei
gen cwhitei = .
replace cwhitei = 1 if ethn_cc == 2 & ff_religion == 0
replace cwhitei = 1 if ethn_cc == 2 & ff_religion == 2
replace cwhitei = 1 if ethn_cc == 2 & ff_religion == .
lab var cwhitei "Christ. / Ag. w. Irish."
capture drop cwhiteoth
gen cwhiteoth = .
replace cwhiteoth = 1 if ethn_cc == 3 & ff_religion == 2
lab var cwhiteoth "Christ. w. other."
*2702 'no religion' observations from black caribbean people, inclined to treat
* these as 'christian / agnostic as done above for whites.
capture drop cblackc
gen cblackc = .
replace cblackc = 1 if ethn_cc == 9 & ff_religion == 0
replace cblackc = 1 if ethn_cc == 9 & ff_religion == 2
lab var cblackc "Christ. / Ag. Black Caribbean."
capture drop cblacka
gen cblacka = .
replace cblacka = 1 if ethn_cc == 10 & ff_religion == 2
lab var cblacka "Christ. Black African."
capture drop owhiteb
gen owhiteb = .
replace owhiteb = 1 if ethn_cc == 1 & ff_religion == 13
replace owhiteb = 1 if ethn_cc == 1 & ff_religion == 15
replace owhiteb = 1 if ethn_cc == 1 & ff_religion == 16
replace owhiteb = 1 if ethn_cc == 1 & ff_religion == 97
lab var owhiteb "Other rel. w. Brit. (Hindu, Sikh, Budd., & 'other')."
capture drop mindian
gen mindian = .
replace mindian = 1 if ethn_cc == 5 & ff_religion == 12
lab var mindian "Muslim Indian."
capture drop mpakistani
gen mpakistani = .
replace mpakistani = 1 if ethn_cc == 6 & ff_religion == 12
replace mpakistani = 1 if ethn_cc == 7 & ff_religion == .
lab var mpakistani "Muslim Pakistani"
capture drop mbangladeshi
gen mbangladeshi = .

```

```

replace mbangladeshi = 1 if ethn_cc == 7 & ff_religion == 12
replace mbangladeshi = 1 if ethn_cc == 7 & ff_religion == .
lab var mbangladeshi "Muslim Bangladeshi."
capture drop mwhiteb
gen mwhiteb = .
replace mwhiteb = 1 if ethn_cc == 1 & ff_religion == 12
lab var mwhiteb "Muslim w. Brit."
* only 175 muslim black caribbean - so mergeing together with african and other black.
capture drop mblack
gen mblack = .
replace mblack = 1 if ethn_cc == 9 & ff_religion == 12
replace mblack = 1 if ethn_cc == 10 & ff_religion == 12
replace mblack = 1 if ethn_cc == 11 & ff_religion == 12
lab var mblack "Muslim Black (African, Caribbean, & Black oth.)"
capture drop jwhiteb
gen jwhiteb = .
replace jwhiteb = 1 if ethn_cc == 1 & ff_religion == 14
lab var jwhiteb "Jewish w. Brit."
capture drop hindian
gen hindian = .
replace hindian = 1 if ethn_cc == 5 & ff_religion == 13
lab var hindian "Hindu Indian."
capture drop sindian
gen sindian = .
replace sindian = 1 if ethn_cc == 5 & ff_religion == 15
lab var sindian "Sikh Indian."
capture drop marab
gen marab = .
replace marab = 1 if ethn_cc == 12 & ff_religion == 12
lab var marab "Muslim Arab."
capture drop therest
gen therest = .
*white irish
global v1 "12 13 14 15 16 97"
foreach val in $v1 {
    replace therest = 1 if ethn_cc == 2 & ff_religion == `val'
}

capture drop ercats
gen ercats = 0
replace ercats = 1 if cwhiteb == 1
replace ercats = 2 if cwhitei == 1
replace ercats = 3 if cwhiteoth == 1
replace ercats = 4 if cblackc == 1
replace ercats = 5 if cblacka == 1
replace ercats = 6 if owhiteb == 1
replace ercats = 7 if mindian == 1
replace ercats = 8 if mpakistani == 1
replace ercats = 9 if mbangladeshi == 1
replace ercats = 10 if mblack == 1

```

```

replace ercats = 11 if mwhiteb == 1
replace ercats = 12 if jwhiteb == 1
replace ercats = 13 if hindian == 1
replace ercats = 14 if sindian == 1
replace ercats = 15 if marab == 1
replace ercats = 16 if therest == 1
recode ercats 0 = 16
label values ercats erlabs
label var ercats "Ethno-religious categories"
// capture drop ethn_ind_cc
// recode ethn_dv_ind ///
// (1 = 1 "w. Brit.") (2 3 = 2 "w. Irish") (4 = 3 "w. Other") ///
// (5 6 7 8 = 4 "Mixed." ) (9 = 5 "Indian") (10 = 6 "Pakistani") ///
// (11 = 7 "Bangladeshi") (12 13 = 8 "Other Asian") ///
// (14 = 9 "Caribbean") (15 = 10 "African") ///
// (16 = 11 "Oth. Black backg.") (17 = 12 "Arab") (97 = 13 "Other Ethn.")(-9 = .),
gen(ethn_ind_cc)
// label var ethn_ind_cc "(Ethnic group (condensed) indall"

recode generation 5 6 = 4

*first gen & second gen
foreach var in cwhitei cwhiteoth cblackc cblacka owhiteb mindian mpakistani mbangladeshi
mblack mwhiteb jwhiteb hindian sindian marab therest {
    foreach num in 1 2 {
        capture drop `var'`num'
        gen `var'`num' = `var' if generation == `num'
        tab1 `var'`num'
    }
}

foreach num in 1 2 {
    capture drop ercatsgen`num'
    gen ercatsgen`num' = 0
    replace ercatsgen`num' = 1 if cwhiteb == 1
    replace ercatsgen`num' = 4 if cwhitei`num' == 1
    replace ercatsgen`num' = 5 if cwhiteoth`num' == 1
    replace ercatsgen`num' = 6 if cblackc`num' == 1
    replace ercatsgen`num' = 7 if cblacka`num' == 1
    replace ercatsgen`num' = 8 if owhiteb`num' == 1
    replace ercatsgen`num' = 9 if mindian`num' == 1
    replace ercatsgen`num' = 10 if mpakistani`num' == 1
    replace ercatsgen`num' = 11 if mbangladeshi`num' == 1
    replace ercatsgen`num' = 12 if mblack`num' == 1
    replace ercatsgen`num' = 13 if mwhiteb`num' == 1
    replace ercatsgen`num' = 14 if jwhiteb`num' == 1
    replace ercatsgen`num' = 15 if hindian`num' == 1
    replace ercatsgen`num' = 16 if sindian`num' == 1

```

```

replace ercatsgen`num' = 17 if marab`num' == 1
replace ercatsgen`num' = 18 if therest`num' == 1
}

recode ercatsgen1 0 = 18
recode ercatsgen2 0 = 18

label values ercatsgen1 erlabs2
label values ercatsgen2 erlabs2
tab1 ercatsgen*, m

capture drop ercatsgen
gen ercatsgen = 0
replace ercatsgen = 0 if cwhiteb
replace ercatsgen = 1 if mwhiteb == 1
replace ercatsgen = 2 if owhiteb == 1 & generation == 4
replace ercatsgen = 3 if jwhiteb == 1 & generation == 4
replace ercatsgen = 4 if cwhitei1 == 1
replace ercatsgen = 5 if cwhiteoth1 == 1
replace ercatsgen = 6 if cblackc1 == 1
replace ercatsgen = 7 if cblacka1 == 1
replace ercatsgen = 8 if owhiteb1 == 1
replace ercatsgen = 9 if mindian1 == 1
replace ercatsgen = 10 if mpakistani1 == 1
replace ercatsgen = 11 if mbangladeshi1 == 1
replace ercatsgen = 12 if mblack1 == 1
// replace ercatsgen = 13 if mwhiteb1 == 1
replace ercatsgen = 14 if jwhiteb1 == 1
replace ercatsgen = 15 if hindian1 == 1
replace ercatsgen = 16 if sindian1 == 1
replace ercatsgen = 17 if marab1 == 1
replace ercatsgen = 18 if therest1 == 1
replace ercatsgen = 24 if cwhitei2 == 1
replace ercatsgen = 25 if cwhiteoth2 == 1
replace ercatsgen = 26 if cblackc2 == 1
replace ercatsgen = 27 if cblacka2 == 1
replace ercatsgen = 28 if owhiteb2 == 1
replace ercatsgen = 29 if mindian2 == 1
replace ercatsgen = 210 if mpakistani2 == 1
replace ercatsgen = 211 if mbangladeshi2 == 1
replace ercatsgen = 212 if mblack2 == 1
// replace ercatsgen = 213 if mwhiteb2 == 1
replace ercatsgen = 214 if jwhiteb2 == 1
replace ercatsgen = 215 if hindian2 == 1
replace ercatsgen = 216 if sindian2 == 1
replace ercatsgen = 217 if marab2 == 1
replace ercatsgen = 218 if therest2 == 1
recode ercatsgen 0 = -8 if ethn_cc != 1

```

```

sort pidp
list pidp ethn_cc ff_religion generation ercatsgen if ercatsgen == -8 in 1/1000

label define labsxx 4 "cwhitei" 5 "cwhiteoth" 6 "cblackc" 7 "cblacka" 8 "owhiteb" 9 "mindian"
10 "mpakistani" 11 "mbangladeshi" 12 "mblack" 13 "mwhiteb" 14 "jwhiteb" 15 "hindian" 16
"sindian" 17 "marab" 18 "therest" ///
24 "cwhitei2" 25 "cwhiteoth2" 26 "cblackc2" 27 "cblacka2" 28 "owhiteb2" 29 "mindian2" 210
"mpakistani2" 211 "mbangladeshi2" 212 "mblack2" 213 "mwhiteb2" 214 "jwhiteb2" 215 "hindian2"
216 "sindian2" 217 "marab2" 218 "therest2" 1 "mwhiteb0" 2 "owhiteb0" 3 "jwhiteb0"
capture label drop ercatsgen
label values ercats erlabs
label values ercatsgen labsxx
// regress educscore i.ercatsgen
// regress gb_csm i.ercatsgen

// replace ercatsgen = . if cwhiteb == 1 & generation == 1
// replace ercatsgen = . if cwhiteb == 1 & generation == 2
// foreach var in $serverlist2 {
//     replace ercatsgen = . if `var' == 1 & generation == 1
//     replace ercatsgen = . if `var' == 1 & generation == 2
// }

capture drop freshcats
gen freshcats = ercatsgen
recode freshcats 3 8 14 17 25 28 212 214 217 = 218 6 7 = 6 26 27 = 26

capture label drop flabs
label define flabs 4 "cwhitei" 5 "cwhiteoth" 6 "cblackc&a" 8 "owhiteb" 9 "mindian" 10
"mpakistani" 11 "mbangladeshi" 12 "mblack" 13 "mwhiteb" 14 "jwhiteb" 15 "hindian" 16
"sindian" 17 "marab" 18 "therest" 24 "cwhitei2" 25 "cwhiteoth2" 26 "cblackc&a2" 28
"owhiteb2" 29 "mindian2" 210 "mpakistani2" 211 "mbangladeshi2" 212 "mblack2" 213 "mwhiteb2"
214 "jwhiteb2" 215 "hindian2" 216 "sindian2" 217 "marab2" 218 "therest2" 1 "mwhiteb0" 2
"owhiteb0" 3 "jwhiteb0"
label          values          freshcats          flabs

capture drop muslim
gen muslim = ff_religion == 12
capture drop redcats
gen redcats = .
replace redcats = 0 if freshcats == 0
replace redcats = 1 if freshcats == 1
replace redcats = 9 if freshcats == 9
replace redcats = 10 if freshcats == 10
replace redcats = 11 if freshcats == 11
replace redcats = 12 if freshcats == 12

```

```

replace redcats = 20 if freshcats == 18 & muslim == 1
replace redcats = 29 if freshcats == 29
replace redcats = 210 if freshcats == 210
replace redcats = 211 if freshcats == 211
replace redcats = 220 if freshcats == 218 & muslim == 1
tab freshcats redcats
label define fc 0 "Christian w. Brit." 1 "White Muslim Brit." ///
9 "Muslim Indian 1" 10 "Muslim Pakistani 1" 11 "Muslim Bangladeshi 1" 12 "Muslim Black 1"
20 "Muslim Other 1" 29 "Muslim Indian 2" 210 "Muslim Pakistani 2" 211 "Muslim Bangladeshi
2" 220 "Muslim Other 2" , modify

```

B8 Generate interactions between dummies for each ethno-religious generation group and education score, health, and religiosity.

```

capture drop mwhiteb0
gen mwhiteb0 = freshcats == 1 if freshcats != .
capture drop mindian1
gen mindian1 = freshcats == 9 if freshcats != .
capture drop mpakistani1
gen mpakistani1 = freshcats == 10 if freshcats != .
capture drop mbangladeshi1
gen mbangladeshi1 = freshcats == 11 if freshcats != .
capture drop mblack1
gen mblack1 = freshcats == 12 if freshcats != .
capture drop mindian2
gen mindian2 = freshcats == 29 if freshcats != .
capture drop mpakistani2
gen mpakistani2 = freshcats == 210 if freshcats != .
capture drop mbangladeshi2
gen mbangladeshi2 = freshcats == 211 if freshcats != .
capture drop major
gen major = regions
recode major 1 2 3 4 = 1 * = 0
recode hiqual_dv 9 = 6
capture drop quals
gen quals = 7 - hiqual_dv
foreach x in mwhiteb0 mblack1 mindian1 mpakistani1 mbangladeshi1 mindian2 mpakistani2
mbangladeshi2 {
    foreach y in educscore health religiosity {
        capture drop `x'`y'
        gen `x'`y' = `x'*`y'
    }
}

```

B9 Data preparation and generating missing data variables for analysis in Chapter 3.

```

tab gor_dv_ind gor_dv, m
capture drop regions
gen regions = gor_dv
recode regions 7 = 1 3 = 2 2 = 3 5 = 4 1 4 6 8 9 = 5 10 11 12 = 6
label define regglabs 1 "London" 2 "Yorkshire & The Humber" 3 "North West" ///
4 "West Midlands" 5 "Rest of England" 6 "Scot., Wales. & N.Ire."
label values regions regglabs

```

```

*recoding smaller groups
recode ercatsgen 13 14 = 18 213 217 212 = 218

*recoding other white british categories - they don't really fit into
* first and second gen groups.
recode ercatsgen 8 28 = 2 214 = 3
* creating dummies.

*demographics
capture drop fem
gen fem=(sex_dv == 2) if (sex_dv > 0 & sex_dv < 10)
gen mar=(marital == 2) if (marital > 0 & marital < 10)

*caring resp.
capture drop caringhh
gen caringhh = aidhh
recode caringhh -100/-1 = . 1 =1 2 = 0
replace caringhh = 0 if caringhh == .
tab freshcats caringhh
capture drop caringoh
gen caringoh = aidxhh
recode caringoh -100/-1 = . 1 =1 2 = 0
replace caringoh = 0 if caringoh == .
tab freshcats caringoh, row

* so we have people who care for those in the household and outside the household
* we have 2296 who care for both inside and outside the household. New var?
capture drop caringall
gen caringall = .
replace caringall = 1 if caringhh == 1
replace caringall = 2 if caringoh == 1
replace caringall = 3 if caringhh == 1 & caringoh == 1
recode caringall . = 0
tab caringall
label define cal 0 "no caring resp." 1 "caring for person(s) inside hh" ///
2 "caring for person(s) outside hh" ///
3 "caring for person(s) both in and outside hh"
label values caringall cal
gen cardum = caringall
recode cardum 1 2 3 = 1 0 = 0
tab cardum
recode jbstat (1=1 "Self Employed") (2 3 5 6 12 13 9 = 2 "Active") (4 7 8 10 97 11 = 3
"Outisde the labour market"), gen(participation3cat)

* sorting out cont. vars.
su fimngrs_dv, detail
capture drop earnings
gen earnings = fimngrs_dv
recode earnings -60000/-1 8566.67/1000000 = .
capture drop earnings2
gen earnings2 = fimngrs_dv
recode earnings2 8566.67/1000000 = .
summ earnings, detail
gen logearn = log(earnings)

```

```

su jbhrrs, detail
capture drop nssec
gen nssec = jbnsssec8_dv

* add variable labels
lab var nchild_dv_ind "no. kids in hh"
lab var hiqual_dv "highest qual."
lab var ercatsgen "social origin cats"
lab var english "whet. inter. cond. english"
lab var tradl "traditional gender views"
lab var ties "close ties with majority"
lab var re_cum "relgiosity scale"
lab var fem "female"
lab var mar "married"
lab var employment "employed"
lab var participation "active in labour market"
lab var earnings "earnings"
lab var nssec "NS-SEC 8 categories"
lab var generation "Original generation var."
lab var wave "Wave of survey "
lab var tie1 "First best friend = majority"
lab var tie2 "Second best friend = majority"
lab var tie3 "Third best friend = majority"
lab var re1 "freq. of prayer"
lab var re2 "freq. of attendance at relg. service"
lab var re3 "importance of religion to life"
lab var re_cum "religiosity scale"
lab var logearn "log earnings"
capture drop educscore
egen educscore = mean(mcaml0) if (decades == 1 | decades == 2 | decades == 3 | decades ==
4|decades == 5 | decades == 6 | decades == 7) & (hiqual_dv >= 1 & hiqual_dv <= 9) & (mcaml0
> 0) , by(hiqual_dv decades)
sav $pnew/readyforanalysis.dta, replace

** Analysis 1 - Participation.
global parvars "pidp wave nwei participation freshcats fem health dvage mar child caringall
regions hiqual_dv educscore engprof liberal religiosity ties"
sort pidp wave
list $parvars in 1/50
capture drop par_miss
egen par_miss=rmiss($parvars)
codebook $parvars if par_miss == 0 & dvage > 16 & dvage < 66, compact

** Analysis 2 - Employment.
global empvars "pidp wave nwei participation employment freshcats fem health dvage mar child
caringall regions hiqual_dv educscore engprof liberal religiosity ties"
sort pidp wave
list $empvars in 1/50

```

```

capture drop emp_miss
egen emp_miss=rmiss($empvars)
codebook $empvars if emp_miss == 0 & dvage > 16 & dvage < 66, compact

** Analysis 3 - CAMSIS.
** lets do some checks re: CAMSIS and soc in general tbh.
su pidp wave occ10_cc occ10 occ00_cc occ00 mcam10 *mod* lfs_soc3_p04 lfs_soc4_p04 if
participation == 1 & employment == 1
sort pidp wave
list pidp wave jbstat employment participation *mod* *lfs* if participation == 1 &
employment == 1 in 1/150
browse pidp wave jbstat employment participation *mod* *lfs* if participation == 1 &
employment == 1

* so now what i want, is to only carry across soc codes for people who are
* active (active == 1 ) and are employed (employed != 0 )

foreach myvar in occ10_cc_mod occ10_mod lfs_soc3_p04 lfs_soc4_p04 mcam10 {
  by pidp (waveno), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
}
list pidp waveno participation employment jbsoc00_cc jbsoc10_cc mcam10 if employment in
300/350
foreach num of numlist 1/11 {
  di "`num'"
  foreach myvar in occ10_cc_mod occ10_mod lfs_soc3_p04 lfs_soc4_p04 mcam10 {
    by pidp (waveno), sort: replace `myvar' = `myvar'[_n+1] if `myvar' == .
    by pidp (waveno), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
    sum `myvar' if missing(`myvar')
  }
}
list pidp waveno participation employment occ10_cc_mod occ10_mod lfs_soc3_p04 lfs_soc4_p04
mcam10 in 785/795
list pidp waveno participation employment occ10_cc_mod occ10_mod lfs_soc3_p04 lfs_soc4_p04
mcam10 in 683/694
*this has carried over soc codes even for unemployed or not active people.

foreach var in occ10_cc_mod occ10_mod lfs_soc3_p04 lfs_soc4_p04 mcam10 {
  replace `var' = . if participation == 0
  replace `var' = . if employment == 0
  replace `var' = . if participation == .
  replace `var' = . if employment == .
}

global camvars "pidp wave nwei mcam10 participation freshcats fem health dvage mar child
caringall regions hiqua1_dv educscore engprof liberal religiosity ties"
sort pidp wave
codebook $camvars, compact

```

```

capture drop cam_miss
egen cam_miss=rmiss($camvars)
codebook $camvars if cam_miss == 0 & dvage > 16 & dvage < 66, compact

// ** Analysis 4 -
capture drop parttime
gen parttime=(jbft_dv == 2)
capture drop pubsector
gen pubsector=(jbsect==2)
capture drop earningmiss
egen earningmiss=rmiss(earningsxhours parttime pubsector pidp wave nwei participation
freshcats fem health dvage mar child caringall regions hiqual_dv educscore engprof liberal
religiosity ties)
codebook earningsxhours parttime pubsector pidp wave nwei participation freshcats fem health
dvage mar child caringall regions hiqual_dv educscore engprof liberal religiosity ties if
earningmiss == 0 & dvage > 16 & dvage < 66, compact
sav $pnew/readyforanalysis2.dta, replace

```

B10 Attaching information on liberal gender attitudes, religiosity and English language proficiency to main UKHLS sample.

```

*****
* Liberal Gender Attitudes *
*****

foreach wav in b d j {
    use pidp `wav'*scopf* using $pprotect/`wav'_indresp_protect.dta, clear
    sort pidp
    renpfix `wav'
    gen waveno=`wav'"
    renpfix _
    sav $ptemp/`wav'_scopf.dta, replace
}

use $ptemp/b_scopf.dta, clear
foreach wav in d j {
    append using $ptemp/`wav'_scopf.dta
}

merge m:m pidp waveno using $ptemp/file6merge0.dta
tab _merge
keep if _merge == 2 | _merge == 3
drop _merge
save $ptemp/file6merge1.dta, replace

*****
* Inter Ethnic Ties *
*****

foreach wav in c f {
    use pidp `wav'*netet_* using $pprotect/`wav'_indresp_protect.dta, clear
    sort pidp

```

```

        renpfix `wav'
        gen waveno="`wav'"
        renpfix _
        sav $ptemp/`wav'_netet, replace
    }
    use $ptemp/c_netet, clear
    append using $ptemp/f_netet.dta
    merge m:m pidp waveno using $ptemp/file6merge1.dta
    tab _merge
    keep if _merge == 2 | _merge == 3
    drop _merge
    save $ptemp/file6merge2.dta, replace

*****
* Religiosity *
*****

foreach wav in d h l {
    use pidp `wav'*prayfreq using $pprotect/`wav'_indresp_protect.dta, clear
    sort pidp
    renpfix `wav'
    gen waveno="`wav'"
    renpfix _
    sav $ptemp/`wav'_pray.dta, replace
}

use $ptemp/d_pray.dta, clear
foreach wav in h l {
    append using $ptemp/`wav'_pray.dta
}

merge m:m pidp waveno using $ptemp/file6merge2.dta
tab _merge
keep if _merge == 2 | _merge == 3
drop _merge
save $ptemp/file6merge3.dta, replace

foreach wav in a d h l {
    use pidp `wav'*opr1g2 `wav'*opr1g3 using $pprotect/`wav'_indresp_protect.dta, clear
    sort pidp
    renpfix `wav'
    gen waveno="`wav'"
    renpfix _
    sav $ptemp/`wav'_relgi.dta, replace
}

```

```

use $ptemp/a_relgi.dta, clear
foreach wav in d h l {
    append using $ptemp/`wav'_relgi.dta
}

merge m:m pidp waveno using $ptemp/file6merge3.dta
tab _merge
keep if _merge == 2 | _merge == 3
drop _merge
save $ptemp/file6merge4.dta, replace

*****
* Language Prof. *
*****

foreach wav in f g h i j k l {
use pidp `wav'_hglieng using $pprotect/`wav'_indall_protect.dta, clear
sort pidp
    renpfix `wav'
    gen waveno="`wav'"
    renpfix _
sav $ptemp/`wav'_lang.dta, replace
}
use $ptemp/f_lang.dta, clear
foreach wav in g h i j k l {
append using $ptemp/`wav'_lang.dta
}
merge m:m pidp waveno using $ptemp/file6merge4.dta
tab _merge
keep if _merge == 2 | _merge == 3
drop _merge
save $ptemp/file6merge5.dta, replace

*****
* Filling in Missing Data *
*****
foreach var in hglieng oprlg2 oprlg3 prayfreq netet_1 netet_2 netet_3 scopfama scopfamb
scopfamd scopfamf scopfamh {
    recode `var' -100/-1 = .
}
recode prayfreq 8 = .
sort pidp wave

foreach myvar in hglieng oprlg2 oprlg3 prayfreq netet_1 netet_2 netet_3 scopfama scopfamb
scopfamd scopfamf scopfamh {
    by pidp (wave), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
}

```

```

* this code took from the next available observation -
foreach num of numlist 1/11 {
  di "`num'"
  foreach myvar in  hglieng oprlg2 oprlg3 prayfreq netet_1 netet_2 netet_3 scopfama scopfamb
  scopfamd scopfamf scopfamh {
    by pidp (wave), sort: replace `myvar' = `myvar'[_n+1] if `myvar' == .
    by pidp (wave), sort: replace `myvar' = `myvar'[_n-1] if `myvar' == .
    *sum `myvar' if missing(`myvar')
  }
}

codebook hglieng oprlg2 oprlg3 prayfreq netet_1 netet_2 netet_3 scopfama scopfamb scopfamd
scopfamf scopfamh, compact
save $ptemp/file6merge5.dta, replace
use $ptemp/file6merge5.dta, clear
*****
* English prof.r *
*****
tab hglieng
gen english = hglieng
recode english 1=1 2=0
tab english
gen notenglish = hglieng
recode notenglish 2=1 1=0
table ercatsgen, stat(m english notenglish)
*****
* Making liberal attitudes var *
*****
d scopfama scopfamb scopfamd scopfamf scopfamh
// alpha scopfama scopfamb scopfamd scopfamf scopfamh, item
capture drop trad*
gen trad1=(scopfamf==1 | scopfamf==2) if (scopfamf >= 1 & scopfamf <= 5)
// gen trad2=(scopfama==1 | scopfama==2) if (scopfama >= 1 & scopfama <= 5)
// gen trad3=(scopfamb==1 | scopfamb==2) if (scopfamb >= 1 & scopfamb <= 5)
// gen trad4=(scopfamd==1 | scopfamd==2) if (scopfamd >= 1 & scopfamd <= 5)
// gen trad5=(scopfamh==1 | scopfamh==2) if (scopfamh >= 1 & scopfamh <= 5)
table ercatsgen, stat(m trad1)
*****
* Making network var *
*****
tab1 net*
capture drop tie1
gen tie1=(netet_1 == 1) if (netet_1 >= 1 & netet_1 <=97)
gen tie2=(netet_2 == 1) if (netet_2 >= 1 & netet_2 <=97)
gen tie3=(netet_3 == 1) if (netet_3 >= 1 & netet_3 <=97)
capture drop ties
gen ties = 0
replace ties = 1 if (tie1 == 1 | tie2 == 1 | tie3 == 1)
table ercatsgen, stat(m tie1 tie2 tie3 ties) stat(n ties)
*****

```

```

* Making religiosity scale *
*****
numlabel _all, add
tab1 oprlg2 oprlg3 prayfreq
capture drop re1 re2 re3
gen re1=(oprlg2== 1) if (oprlg2 >= 1 & oprlg2 <=5)
gen re2=(oprlg3== 1 ) if (oprlg2 >= 1 & oprlg2 <=4)
gen re3=(prayfreq==1 | prayfreq == 2 | prayfreq ==3) if (prayfreq >= 1 & prayfreq <=7)

capture drop re_cum
gen re_cum = 0
replace re_cum = 1 if (re1 == 1 | re2 == 1 | re3 == 1)
table ercatsgen, stat(m re1 re2 re3 re_cum)

codebook english notenglish trad1 tie1 tie2 tie3 ties re1 re2 re3 re_cum, compact

capture drop liberal
gen liberal=trad1
recode liberal 0 = 1 1 = 0
capture drop religiosity
gen religiosity=re_cum
recode religiosity 0 = 1 1 = 0

```

B11 Earnings variable

```

Remove outliers
su fimngrs_dv, detail
capture drop earnings
gen earnings = fimngrs_dv
recode earnings -60000/-1 8566.67/1000000 = .
capture drop earnings2
gen earnings2 = fimngrs_dv
recode earnings2 8566.67/1000000 = .
summ earnings, detail
gen                                logearn                                =                                log(earnings)

su jshrs, detail
recode jshrs -100/7 = .
su jshrs if jbstat == 1
/* we have all the jshrs dat available for all self employed. */
sort pidp wave
list pidp wave jbstat occ10_cc jbhrs jshrs if jbstat == 1 in 1/10000
capture drop allhours
gen allhours = jbhrs
replace allhours = jshrs if allhours == .
list pidp wave jbstat freshcats occ10_cc jbhrs jshrs allhours if jbstat == 1 in 1/10000

```

```

* monthly earnings
sum earnings if participation == 1, detail
* weekly work hours
sum allhours if participation == 1, detail
capture drop allwhours
gen allwhours = allhours if participation == 1
recode allwhours 0/6 = . 60/10000 = .
* let's make weekly earnings
capture drop allwearnings
gen allwearnings = earnings / 4 if participation == 1
capture drop earningsxhours
gen earningsxhours = allwearnings / allwhours if participation == 1
capture drop logearningsxhours
gen logearningsxhours = log(earningsxhours)

```

B12 LFS macro measures data operationalisation.

```

**** **** **** **** **** **** **** **** **** **** **** **** **** **** **** **** ****
** Explore main LFS quarters

** has all variables needed (3 and 4 Digit SOCS & Detailed country of birth)

** General advice is not to combine quarters of the LFS together.

** 2009 & 2010

use $plfs/lfsp_aj09.dta, clear

// WAVFND = wave
// ETHCEN15 = ethnicity (2 = white other)
// SC2KMMN = 3 digit SOC
// SOC2KM = 4 digit SOC
// CRYOX7 = country of birth

// post 2004 migrants 203 971 Czech Republic, 233 Estonia, 348 Hungary, 428 Latvia, 440
Lithuania, 616 Poland, 705 Slovenia, 703 Slovakia. 100 Bulgaria and 642 Romania joined in
2007, followed by 191 Croatia in 2013
tab CRYOX7 if ETHCEN15 == 2
capture drop woth
gen woth = CRYOX7 if ETHCEN15 == 2
recode woth 203 971 233 348 428 449 616 705 703 100 642 191 = 1 * = 0
tab CRYOX7 woth

// woth = 'white other' respondents born in the countries above.

```

```

global ntvars "SEX WAVFND AGE ILODEFR SC2KMMN SOC2KM ETHCEN15 CRYOX7"
foreach n in 09 10 {
    foreach w in jm aj js od {
        use $ntvars using $plfs/lfsp_`w`n'.dta, clear
        keep if WAVFND == 1 | WAVFND == 5
        keep if ILODEFR == 1
        capture drop woth
        gen int file = `n'
        gen `w`n'_woth = CRYOX7 if ETHCEN15 == 2
        recode `w`n'_woth 203 971 233 348 428 449 616 705 703 100 642 = 1 * = 0
        foreach var in $ntvars {
            recode `var' -100/-1 = .
        }
        renpfix `w`n'_
        rename SC2KMMN lfs_soc3
        rename SOC2KM lfs_soc4
        sav $plfstemp/`n'e_`w'.dta, replace
    }

    use $plfstemp/`n'e_jm.dta, clear
        foreach w in aj js od {
            append using $plfstemp/`n'e_`w'.dta
        }

        sav $plfstemp/`n'm.dta, replace
    }
}

** 2011

// SC10MMN = 3 DIGIT
// SOC10M = 4 DIGIT
// ETHGBEUL = ethnicity at GB level (3 = other white)
// CRYOX7 = country of birth
// something up with 2011 quarters
// *og* file included as i i'm going to overwrite it.
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M ETH* using $plfs/lfsp_jm11_og.dta, clear
// okay so jm11 does have 'ETHBEUL'. Instead it has ETHCEN15, ETHCEN6, ETHUK14 and ETHUK8.
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M ETH* using $plfs/lfsp_aj11.dta, clear
// From aj onwards, ETHEWEUL and ETHGBEUL appear. So, need to go into the jm file and change
out the ETH variable, rename?
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M ETH* CRY* using $plfs/lfsp_jm11_og.dta, clear
// there are no 'other white' values in these ethnicity variables, there is country of birth
though.
capture drop woth_exm
gen woth_exm = CRYOX7 if ETHUK8 == 1 /* just white this time */
recode woth_exm 203 971 233 348 428 449 616 705 703 100 642 = 1 * = 0
capture drop ETHBEUL
gen ETHGBEUL = .
replace ETHGBEUL = 3 if woth_exm == 1
save $plfs/lfsp_jm11.dta, replace
// okay thats sorted the issue, now all of the below runs.

```

```

// something funky on going on with 2017.

use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRYOX7 ETHGBEUL using $plfs/lfsp_jm17.dta, clear
su // has CRYOX7
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRYOX7 ETHGBEUL using $plfs/lfsp_aj17.dta, clear
su // has CRYOX7
// use WAVFND AGE SC10MMN SOC10M CRYOX7 ETHGBEUL using $plfs/lfsp_js17.dta, clear
su // DOESN'T have CRYOX7
// use WAVFND AGE SC10MMN SOC10M CRY* ETHGBEUL using $plfs/lfsp_js17.dta, clear
* It looks like CRYOX7 has been replaced by CRY12 CRYOX7_EUL_Sub CRYOX7_EUL_Main.
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRY* ETHGBEUL using $plfs/lfsp_od17_og.dta, clear
*same for the od file.

* This means that jm and aj are not consistent with js and od. We need a way
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRYOX7 ETHGBEUL using $plfs/lfsp_jm17.dta, clear
// i think this best way to do it, would be to make CRYOX7 variables for js and od.
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRY* CRYOX7_EUL_Sub ETHGBEUL using
$plfs/lfsp_js17_og.dta, clear
// okay that isn't going to work, because detailed information on country of birth is gone,
we do still have POLAND in the CRY12 measure though. So Let's just do Polish people.
// Just noticed that coding is the same, Poland is 616 is both measures. so we can just
rename CRY12 to CRYOX7.
rename CRY12 CRYOX7
save $plfs/lfsp_js17.dta, replace
use SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRY* CRYOX7_EUL_Sub ETHGBEUL using
$plfs/lfsp_od17_og.dta, clear
rename CRY12 CRYOX7
save $plfs/lfsp_od17.dta, replace

global evars "SEX WAVFND AGE ILODEFR SC10MMN SOC10M CRYOX7 ETHGBEUL"
foreach n in 11 12 13 14 15 16 17 {
    foreach w in jm aj js od {
        use $evars using $plfs/lfsp_`w'`n'.dta, clear
        keep if WAVFND == 1 | WAVFND == 5
        capture drop woth
        gen `w'`n'_woth = CRYOX7 if ETHGBEUL == 3
        gen int file = `n'
        recode `w'`n'_woth 203 971 233 348 428 449 616 705 703 100 642 = 1 * = 0
        foreach var in $evars {
            recode `var' -100/-1 = .
        }
        renpfix `w'`n'_
        rename SC10MMN lfs_soc3
    }
}

```

```

        rename SOC10M lfs_soc4
        sav $plfstemp/`n'e_`w'.dta, replace
    }

    use $plfstemp/`n'e_aj.dta, clear
        foreach w in js od {
            append using $plfstemp/`n'e_`w'.dta
        }

        sav $plfstemp/`n'm.dta, replace
    }

*** I am a god amongst men.

* information from user guide file:///Users/scothunter/Downloads/volume41.pdf
* p 92
*EU 8 = 203 (CZ), 233 (ESTONIA), 348 (hungary) , 428 (LATVIA), 440 (LITUAINA), 616 (POLAND),
703 (SLOVAKIA), 705 (SLOVENIA), 971 (CZ OTHER)
*EU 2 = 100 (BULGARIA), 642 (ROMANIA)
* OTHER EU = 191 (CROITA) , 470 (MALTA) , 901 (CYPRUS eu), 902 cyprus non eu, 903 (not
otherwise specified. )
* okay so based on this, just combined EU8 and EU2 together.
* remove CROITA and MALTA from above (191 and 470 - done.
***** NOTE REMEMBER TO DO THIS IN THE UKHLS CATEGORISATION.

**** POST 2004 MIGRANTS = EU8 & EU 2.
**** 10 in total.
*** Czech, Estonia, Hungary, Latvia, Lituania, Poland, Bulgaria, Romania, Croita and Romania.


global nevars "SEX WAVFND AGE ILODEFR SC10MMN SOC10M ETHGBEUL CRYOX7_EUL_Sub"
foreach n in 18 19 20 {
    foreach w in jm aj js od {
        use $nevars using $plfs/lfsp_`w`n'.dta, clear
        keep if WAVFND == 1 | WAVFND == 5
        gen int file = `n'
        capture drop woth
        gen `w`n'_woth = CRYOX7_EUL_Sub == 3 | CRYOX7_EUL_Sub == 4 & ETHGBEUL == 3
        foreach var in $nevars {
            recode `var' -100/-1 = .
        }
        renpfix `w`n'_
        rename SC10MMN lfs_soc3
        rename SOC10M lfs_soc4
        sav $plfstemp/`n'e_`w'.dta, replace
    }

    use $plfstemp/`n'e_jm.dta, clear
        foreach w in aj js od {
            append using $plfstemp/`n'e_`w'.dta
        }

        sav $plfstemp/`n'm.dta, replace
    }
}

```

```

**** pooled LFS survey ****

// foreach n in 10 11 12 13 14 15 16 17 18 19 20 {
//   use $plfstemp/09m.dta, clear
//   append using $plfstemp/`n'm.dta
//
// use $plfstemp/09m.dta, clear /* 196,591 */
// append using $plfstemp/10m.dta /* 188,422 */
// append using $plfstemp/11m.dta /* 290,973 */
// append using $plfstemp/12m.dta /* 290,973 */
// append using $plfstemp/13m.dta /* 282,504 */
// append using $plfstemp/14m.dta /* 279,098 */
// append using $plfstemp/15m.dta /* 269,658 */
// append using $plfstemp/16m.dta /* 256,895 */
// append using $plfstemp/17m.dta /* 256,734 */
// append using $plfstemp/18m.dta /* 342,925 */
// append using $plfstemp/19m.dta /* 333,661 */
// append using $plfstemp/20m.dta /* 288,169 */
//

foreach n in 11 12 13 14 15 16 17 18 19 20 {
    use $plfstemp/`n'm.dta, clear
    keep if ILODEFR == 1 /*participating only */
    keep if AGE > 15 & AGE < 66
    gen poland = (CRYOX7 == 616)
    egen regmiss=rmiss(lfs_soc3 lfs_soc4 woth)
    drop if regmiss == 2
    drop regmiss
    capture drop soc3props
    egen soc3props`n' = mean(woth), by(lfs_soc3)
    egen soc3sd`n' = sd(woth), by(lfs_soc3)
    egen soc3cu`n' = count(woth), by(lfs_soc3)
    capture drop upper`n'
    gen upper`n' = soc3props`n' + 1.96*(soc3sd`n' / sqrt(soc3cu`n'))
    gen lower`n' = soc3props`n' - 1.96*(soc3sd`n' / sqrt(soc3cu`n'))
    capture drop soc4props`n'
    egen soc4props`n' = mean(woth), by(lfs_soc4)
    egen soc4sd`n' = sd(woth), by(lfs_soc3)
    egen soc4cu`n' = count(woth), by(lfs_soc3)
    gen upper4`n' = soc4props`n' + 1.96*(soc4sd`n' / sqrt(soc4cu`n'))
    gen lower4`n' = soc4props`n' - 1.96*(soc4sd`n' / sqrt(soc4cu`n'))
    rename *`n' *
    save $plfstemp/`n'mv2.dta, replace
}

```

```

use $plfstemp/11mv2.dta, clear /* 290,973 */
append using $plfstemp/12mv2.dta /* 290,973 */
append using $plfstemp/13mv2.dta /* 282,504 */
append using $plfstemp/14mv2.dta /* 279,098 */
append using $plfstemp/15mv2.dta /* 269,658 */
append using $plfstemp/16mv2.dta /* 256,895 */
append using $plfstemp/17mv2.dta /* 256,734 */
append using $plfstemp/18mv2.dta /* 342,925 */
append using $plfstemp/19mv2.dta /* 333,661 */
append using $plfstemp/20mv2.dta /* 288,169 */

capture drop fem
gen fem =(SEX==2)
capture drop eumen
gen eumen =(woth == 1 & fem == 0)
capture drop mfem
gen eufem =(woth == 1 & fem == 1)
foreach var in eumen eufem {
    capture drop lfs_soc3_`var'
    capture drop lfs_soc4_`var'
    egen lfs_soc3_`var' = mean(`var') , by(lfs_soc3)
    egen lfs_soc4_`var' = mean(`var') , by(lfs_soc4)
}

rename soc3props lfs_soc3_p04
rename soc4props lfs_soc4_p04
egen one_soc3 = tag(lfs_soc3)
egen one_soc4 = tag(lfs_soc4)
rename one_soc4 lfs_one_soc4
rename one_soc3 lfs_one_soc3
keep if lfs_one_soc4
keep lfs_soc3* lfs_soc4* lfs_soc3_p04 *soc* upper* lower* lfs_soc4_p04
save $plfsnew/appended1120.dta, replace

```

B13 Management of ONS data

```

global          geo          "/Users/scothunter/Library/CloudStorage/OneDrive-
UniversityofStirling/thesis/directory/data/geounits"

*information on age of people in LSOA for entire UK
import delimited $geo/age.csv, clear
* limit to just 16 - 65 year old population
gen age = ageage16to17unitpersons + ageage18to19unitpersons + ageage20to24unitpersons +
ageage25to29unitpersons      + ageage30to44unitpersons  + ageage45to59unitpersons  +
ageage60to64unitpersons
keep geo_code age

```

```

rename age lsoa_total_n
sav $geo/master.dta, replace

import delimited $geo/postcodes_data.csv, clear
rename lsoa_dz_code lsoallcd
egen lsoatag = tag(lsoallcd)
keep if lsoatag == 1
rename eimd_2015_decile eimd_qt
xtile wimd_qt = wimd_2014_rank, nq(10)
xtile simd_qt = simd_2016_rank, nq(10)
xtile nimd_qt = nimdm_2017_rank, nq(10)
keep lsoallcd eimd_qt wimd_qt simd_qt nimd_qt
sort lsoallcd
rename lsoallcd geo_code
sav $geo/depriv.dta, replace

// import delimited $geo/depriv.csv, clear
// rename quintile tds_qt
// keep geo_code tds tds_qt
// sav $geo/depriv.dta, replace

import delimited $geo/cob.csv, clear
capture drop lsoa_eu
gen lsoa_eu = v19 + v18 + v20
keep lsoa_eu geo_code
sav $geo/cob.dta, replace

*not including northern ireland.
import delimited $geo/relig_gb.csv, clear
rename religioneswmuslimunitpersons lsoa_muslim
rename religioneswtotalreligionunitpers lsoa_rttotal_n
keep geo_code lsoa_rttotal_n lsoa_muslim
sav $geo/relig_gb.dta, replace

import delimited $geo/ethn.csv, clear
rename ethnicgroupukharmonisedtotaletn lsoa_etotal_n
rename ethnicgroupukharmonisedasianasia lsoa_indian
rename v9 lsoa_pakistani
rename v10 lsoa_bangladeshi
gen lsoa_other_asian = v11 + v12
rename ethnicgroupukharmonisedblackafri lsoa_black
keep geo_code lsoa*
sav $geo/ethn.dta, replace

*information on employment and % in occupations.
import delimited $geo/occ_emp_ons11.csv, clear

```

```

keep geo_code geo_label ageage16to74economicactivityinem v6 v21 v42 v63 v72 v90 v100 v108
v118
rename ageage16to74economicactivityinem lsoa_employed
rename v6 lsoa_managers
rename v21 lsoa_pro_occs
gen lsoa_top2 = lsoa_managers + lsoa_pro_occs
keep lsoa_employed lsoa_top2 geo_code
sav $geo/occ_emp_ons11.dta, replace

*information on highest qualification held
import delimited $geo/educ.csv, clear
* limited to those with level 4 quals and above.
keep geo_code v18
rename v18 lsoa_educ16plus4
sav $geo/educ.dta, replace

*** 1 : GEO-UNIT CROSS WALK FOR ENGLAND, SCOTLAND AND WALES.
/* This file doesn't have any observations, it's just a cross walk for geo units.*/
import excel $pgeo/lsoa_full.xls, firstrow clear
drop TT* CTY* *NMW LAD20*
rename LSOA11CD lsoa11cd
rename LSOA11NM lsoa11nm
rename MSOA11CD msoa11cd
rename MSOA11NM msoa11nm
rename LAD11CD lad11cd
rename LAD11NM lad11nm
rename CTRYCD ctrycd
rename CTRYNM ctrynm
clonevar geo_code = lsoa11cd
sav $pgeo/crosswalk_2.dta, replace

import delimited $pgeo/output_areas.csv, clear
keep lsoa11cd rgn11nm
rename lsoa11cd geo_code
egen geo_code_tag = tag(geo_code)
keep if geo_code_tag
drop geo_code_tag
sav $geo/crosswalk_3.dta, replace

* link together using geo_code.
use $geo/master.dta, clear
merge 1:1 geo_code using $geo/depriv.dta
drop _merge
merge 1:1 geo_code using $geo/occ_emp_ons11.dta
drop _merge
merge 1:1 geo_code using $geo/educ.dta
drop _merge

```

```

merge 1:1 geo_code using $geo/crosswalk_2.dta
drop _merge
merge 1:1 geo_code using $geo/crosswalk_3.dta
drop _merge
encode rgn11nm, gen(rgn)
replace rgn = 12 if rgn == .
label define rgn 12 "Norther Ireland", modify
drop rgn11nm
merge 1:1 geo_code using $geo/cob.dta
drop _merge
merge 1:1 geo_code using $geo/relig_gb.dta
keep if _merge == 1 | _merge == 3
drop _merge
merge 1:1 geo_code using $geo/ethn.dta
drop _merge
gen lsoa_ni_muslim = lsoa_pakistani + lsoa_bangladeshi if ctrycd == "N92000002"
format lsoa_ni_muslim %9.0f
replace lsoa_muslim = lsoa_ni_muslim if lsoa_muslim == . & ctrycd == "N92000002"
drop lsoa_ni_muslim
sav $geo/master.dta, replace

use $geo/master.dta, clear
collapse (sum) lsoa_total_n, by(msoa11cd)
rename lsoa_total_n msoa_total_n
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_employed, by(msoa11cd)
rename lsoa_employed msoa_employed
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_2.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_educ16plus4, by(msoa11cd)
rename lsoa_educ16plus4 msoa_educ16plus4
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_3.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_top2, by(msoa11cd)
rename lsoa_top2 msoa_top2
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_4.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_eu, by(msoa11cd)
rename lsoa_eu msoa_eu
encode msoa11cd, gen(_msoa11cd)

```

```

sort _msoa11cd
sav $geo/msoa_sum_5.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_etotal_n, by(msoa11cd)
rename lsoa_etotal_n msoa_etotal_n
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_6.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_indian, by(msoa11cd)
rename lsoa_indian msoa_indian
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_7.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_pakistani, by(msoa11cd)
rename lsoa_pakistani msoa_pakistani
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_8.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_bangladeshi, by(msoa11cd)
rename lsoa_bangladeshi msoa_bangladeshi
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_9.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_black, by(msoa11cd)
rename lsoa_black msoa_black
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_10.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_other_asian, by(msoa11cd)
rename lsoa_other_asian msoa_other_asian
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_11.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_rttotal_n, by(msoa11cd)
rename lsoa_rttotal_n msoa_rttotal_n
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_12.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_muslim, by(msoa11cd)
rename lsoa_muslim msoa_muslim
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
sav $geo/msoa_sum_13.dta, replace
use $geo/master.dta, clear

```

```

encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
use $geo/master.dta, clear
encode msoa11cd, gen(_msoa11cd)
sort _msoa11cd
foreach n in 2 3 4 5 6 7 8 9 10 11 12 13 {
    merge m:1 _msoa11cd using $geo/msoa_sum.dta
    drop _merge
    merge m:1 _msoa11cd using $geo/msoa_sum_`n'.dta
    drop _merge
}
sav $geo/master2.dta, replace

*reverting to original master file just to carry forward information from
* lsoa level to lad for most variables.
use $geo/master.dta, clear
collapse (sum) lsoa_total_n, by(lad11cd)
rename lsoa_total_n lad_total_n
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_employed, by(lad11cd)
rename lsoa_employed lad_employed
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_2.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_educ16plus4, by(lad11cd)
rename lsoa_educ16plus4 lad_educ16plus4
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_3.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_top2, by(lad11cd)
rename lsoa_top2 lad_top2
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_4.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_eu, by(lad11cd)
rename lsoa_eu lad_eu
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_5.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_etotal_n, by(lad11cd)
rename lsoa_etotal_n lad_etotal_n
encode lad11cd, gen(_lad11cd)
sort _lad11cd

```

```

sav $geo/lad_sum_6.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_indian, by(lad11cd)
rename lsoa_indian lad_indian
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_7.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_pakistani, by(lad11cd)
rename lsoa_pakistani lad_pakistani
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_8.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_bangladeshi, by(lad11cd)
rename lsoa_bangladeshi lad_bangladeshi
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_9.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_black, by(lad11cd)
rename lsoa_black lad_black
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_10.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_other_asian, by(lad11cd)
rename lsoa_other_asian lad_other_asian
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_11.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_rttotal_n, by(lad11cd)
rename lsoa_rttotal_n lad_rttotal_n
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_12.dta, replace
use $geo/master.dta, clear
collapse (sum) lsoa_muslim, by(lad11cd)
rename lsoa_muslim lad_muslim
encode lad11cd, gen(_lad11cd)
sort _lad11cd
sav $geo/lad_sum_13.dta, replace
use $geo/master2.dta, clear
encode lad11cd, gen(_lad11cd)
sort _lad11cd
foreach n in 2 3 4 5 6 7 8 9 10 11 12 13 {
    merge m:1 _lad11cd using $geo/lad_sum.dta
    drop _merge
    merge m:1 _lad11cd using $geo/lad_sum_`n'.dta
    drop _merge

```

```

}
foreach var in lsoa msoa lad {
    capture drop `var'_empratecc
    gen `var'_empratecc = `var'_employed / `var'_total_n
    capture drop `var'_top2cc
    gen `var'_top2cc = `var'_top2 / `var'_total_n
    capture drop `var'_educ16plus4cc
    gen `var'_educ16plus4cc = `var'_educ16plus4 / `var'_total_n
    capture drop `var'_eucc
    gen `var'_eucc = `var'_eu / `var'_total_n
    // capture drop `var'_indiancc
    // gen `var'_indiancc = `var'_indian / `var'_etotal_n
    // capture drop `var'_pakistanicc
    // gen `var'_pakistanicc = `var'_pakistani / `var'_etotal_n
    // capture drop `var'_bangladeshicc
    // gen `var'_bangladeshicc = `var'_bangladeshi / `var'_etotal_n
    // capture drop `var'_blackcc
    // gen `var'_blackcc = `var'_black / `var'_etotal_n
    // capture drop `var'_other_asiancc
    // gen `var'_other_asiancc = `var'_other_asian / `var'_etotal_n
    capture drop `var'_muslimcc
    gen `var'_muslimcc = `var'_muslim / `var'_etotal_n
    mean `var'_*cc
}

encode lsoallcd, gen(_lsoallcd)
encode lsoallnm, gen(lsoalab)
encode msoallnm, gen(msoalab)
encode ladllnm, gen(ladlab)
encode ctrycd, gen(_ctrycd)
encode ctrynm, gen(nm)
drop lsoallcd lsoallnm msoallcd ladllcd msoallnm ladllnm ctrycd ctrynm
**** log variables
foreach var in lad lsoa msoa {
    foreach w in top2 emprate educ16plus4 eu /* indian pakistani bangladeshi black
other_asian */ muslim {
        capture drop raw_`var'_`w'
        capture drop log_`var'_`w'
        gen raw_`var'_`w' = `var'_`w'cc * 100 + 1
        gen log_`var'_`w' = log(raw_`var'_`w')
        lab var raw_`var'_`w' "raw % of `w' in `var'"
        format raw_`var'_`w' %8.2g
        lab var log_`var'_`w' "log % of `w' in `var'"
        format log_`var'_`w' %8.2g
        mean log_*
    }
}

table rgn , stat(m raw_lsoa_muslim) stat(m raw_lsoa_eu) nformat(%8.2g)

** regional variables

```

```

order _ctrycd nm _lsoal1cd lsoalab *lsoa* _msoal1cd msoalab *msoa* _ladl1cd ladlab *lad* ,
first
renpfix _
keep lsoa_total_n   ctrycd nm rgn lsoal1cd lsoalab raw_lsoa* log_lsoa* msoal1cd msoalab
raw_msoa* log_msoa* ladl1cd ladlab raw_lad* log_lad* *imd*
capture drop imd_qt
gen imd_qt = .
replace imd_qt = eimd_qt
replace imd_qt = wimd_qt if imd_qt == . & rgn == 9
replace imd_qt = simd_qt if imd_qt == . & rgn == 6
replace imd_qt = nimd_qt if imd_qt == . & rgn == 12
drop eimd_qt wimd_qt simd_qt nimd_qt
save $geo/macro_master.dta, replace

gsort -raw_lsoa_muslim
list lsoalab raw_lsoa_muslim log_lsoa_muslim msoalab raw_msoa_muslim log_msoa_muslim ladlab
raw_lad_muslim log_lad_muslim in 1/100

* local area charactersitics
    * share of muslims and eu migrants (%)
    mean raw*_muslim log*_muslim raw*_eu log*_eu
    * employment rate in areas (%)
    mean raw*_emprate log*_emprate
    * share of people in top 2 professions (%)
    mean raw*_top2 log*_top2
    * share of people with degrees or higher (%)
    mean raw*_educ16plus4 log*_educ16plus4

save $geo/macro_master.dta, replace

```

APPENDIX C Summary of micro and macro data sources used

Type	Name	Reason	Source
Micro	Understanding Society (UKHLS): Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. (SN - 6931).	Gives access to more detailed occupation codes (such as 4-digit codes for SOC2000, SOC2010 and ISCO-88/ISCO).	University of Essex (2022), accessed through UK Data Service. https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=6931
	Understanding Society (UKHLS): Waves 1-12, 2009-2021: Special Licence Access, Census 2011 Lower Layer Super Output Areas. (SN - 7248).	Gives access to lower levels of geography for individuals than what is available in the general access version.	University of Essex (2021), accessed through UK Data Service. https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=7248
Macro			
	Quarterly Labour Force Survey January - March 2018.	Gives access to proportion of white migrants from different EU countries in occupations (SOC00 and SOC10 codes). Linked to individual data in UKHLS.	Office for National Statistics. (2023b). <i>Labour Force Survey</i> . [data series]. 7th Release. UK Data Service. SN: 2000026, DOI: http://doi.org/10.5255/UKDA-Series-2000026 . FAQs accessed: https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=2000026#!/faqs
	2011 Area Classification for Super Output Areas.	Gives access to derived cluster information such as proportion of EU migrant groups (contemporary migrants) in each LSOA. Linked to individual data in UKHLS.	Office for National Statistics. (2020). <i>2011 Census: Aggregate Data</i> . [data collection]. UK Data Service. SN: 7427, DOI: http://doi.org/10.5257/census/aggregate-2011-2