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Aspects of Inequalities: Natives and Immigrants in the UK

by

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ABSTRACT

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This Thesis studies different aspects of inequalities between UK natives and immigrants. It investigates whether economic outcomes of immigrants are different from natives, and tries to spread some light on certain causes of differentials in economic outcomes. It also investigates whether immigrants can potentially contribute to improvement in UK economic inequality. Inequality in education is a result and a cause of inequalities, that perpetuates the income inequality of a country from generation to generation. Do immigrants, who constitute a large share of the UK population, invest more in their children's education compared with natives? Is it possible that the rising share of immigrants can make society more equal? The first chapter studies intergeneration mobility in education of natives, and second- and third-generation immigrants in the UK. It explores whether intergeneration mobility of second-generation immigrants is different from natives and whether the mobility trends persist for third-generation immigrants. It also tests the direction of mobility to investigate whether children are performing better or worse compared with their parents. The second chapter looks into two other aspects of inequality, wage gaps between natives and second-generation immigrants, and welfare dependency. We introduce an approach that estimates the impact of labour market discrimination on the welfare dependency of immigrants. State welfare policies must be designed efficiently in order to reduce economic inequality, while, at the same time, not creating disincentives. The last chapter estimates the effect of tax credit reforms in the UK on labour supply of natives and first-generation immigrants along the intensive and extensive margins.

Contents

List of Figures

List of Tables

Declaration of Authorship

I, Armine Ghazaryan, declare that the thesis entitled *Aspects of Inequalities: Natives and Immigrants in the UK* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;

Signed:...

Date:..

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Chapter 1

Introduction

1.1 Background

Income inequality remains one of the key challenges in economics. Even though government policies are directed at income redistribution to close the income gap between the rich and the poor, it is not clear how effective these policies are. Even less knowledge we have on the role of immigrants in income inequality.

Income inequality and the drivers of inequality have been studied extensively. Studies find that different periods of rising inequality in developed countries are driven by different factors (Lemieux 2008). For instance, while the increase in income inequality in English-speaking countries (US, UK, Canada) in the 1980s was predominantly explained by the increase in the relative demand for skills and was driven by skill-biased technical change generated by advancement in computer technology, in the 1990s this explanation was supplemented by the role of institutional factors (labour unions, minimum wage) in suppressing the rise in inequality in some advanced countries. Later, pre-financial crisis studies found that the growth in inequality is concentrated in the upper end of the income distribution (Lemieux 2008). Piketty (2000) discusses the theories of how intergenerational mobility is related to persistent inequalities. He highlights that even though intergenerational transmission of wealth is significantly contributing to perpetuating inequalities, income from labour is a major cause of persistent inequalities. Therefore, he stresses, intergeneration transmission of productive abilities plays an important role in addressing inequalities.

But what is the role of immigrants in income inequality in advanced countries? Does immigration increase inequality? Do they perform better or worse than natives in terms of their economic outcomes? Card (2009), looking into residual wage inequality between different skill groups in cross-city analysis in the US, finds that the effect of immigration influx on the relative wages of US natives is small. Nevertheless, since immigrants are concentrated in the tails of skill distribution and there is a higher residual inequality among immigrants than natives, therefore the effects of immigration on overall (natives and immigrants) wage inequality are large. However, immigration is responsible for a small share of the 1980-2000 increase in income inequality in the US. Dustmann et al. (2010) explore the changes in patterns of employment and wages of immigrants and natives across the business cycle for Germany and the UK. They find that low-skilled immigrants' unemployment rates are much more responsive to economic shocks than low-skilled natives, and in general low-skilled group is much more vulnerable in terms of unemployment. They find little evidence that labour income responds differently to economic shocks for immigrants versus natives. Other studies, on the other hand, find that immigrants' economic performance is worse than that of natives. For instance, Algan et al. (2010) compare economic outcomes of first- and second-generation immigrants in France, Germany, and the UK, conditional on the country of origin of immigrants. They find that labour market outcomes of first- and second-generation immigrants of most groups are on average worse than that of the natives. Zwysen & Longhi (2018), on the other hand, find little differences in the earnings of different ethnicities. However, they find significant differences in employment for ethnic minorities versus white British, and particularly for women. Barrett & Maître (2013) estimate whether immigrants are more likely to receive welfare benefits compared with natives for a number of EU countries, including the UK. Their findings indicate that there is little evidence that immigrants would receive more social benefits than natives. They, however, find higher poverty levels amongst immigrants. Dustmann & Frattini (2014) discuss the net fiscal effects of immigrants in the UK. They find that for the period 1995 to 2011, EEA immigrants have a positive contribution to the budget, whereas non-EEA immigrants, similarly to natives, have made negative contributions.

This thesis contributes to existing literature by providing a comprehensive analysis of the role of immigrants in UK inequality. Particularly, it studies the trends of immigrants versus UK natives in intergenerational educational mobility. This is, to the best of my knowledge, the first study of intergenerational mobility of UK immigrants, where the exact pairs of parents and children are used. Intergenerational mobility in education plays an important role in addressing inequalities, therefore, understanding where UK immigrants stand compared with natives will shed light on the broader dynamics of UK inequalities and the role of immigrants. The thesis also looks at labour income inequalities between natives and second-generation immigrants, and studies the effect of these inequalities on the welfare take-up of immigrants. Population on welfare dependency is concentrated in the lower tail of income distribution. If income inequality between natives and second-generation immigrants contributes towards more people moving to the lower tail of income distribution, then income inequalities between groups will contribute to increased income inequality in the country. Therefore, studying this aspect of inequality can provide important insights into potential contributors to UK inequality. Derived from that is the next study, the effect of the UK tax credit policy design on the labour market behaviour of natives and immigrants. Increase in labour force participation and hours worked improves income inequality in the country and provides opportunities for career advancement and further income growth. Understanding how the design of income tax credit in the UK affects individuals' incentive to work is important, as this can contribute to better policy-making to address income inequality.

This Introduction provides an insight into income inequality in the UK and the role of immigrants in it. This chapter aims to explore where second-generation immigrants stand in the overall picture of income inequality in the UK and how they compare with natives. It discusses inequality between skilled and unskilled individuals and also looks at the role of social benefits in reducing inequality.

We decompose inequality into inequalities within and between groups, thus creating a background for the following three papers on different aspects of inequalities. We decompose income inequality between natives and second-generation immigrants in the UK and look at the role of second-generation immigrants in income inequality. With a smaller share of second-generation immigrants in the population relative to natives, the contribution of immigrants is obviously small. However, we also look at their potential contribution had the proportion of natives and second-generation immigrants been the same. With the changing population in the UK, the role of second-generation immigrants is becoming more and more important. On the other hand, intergenerational mobility in education is a major indicator of persistence of income inequality of a country (Piketty 2000). As also shown in this section, skill composition is a major driver of income inequality. Therefore, in the first paper we study intergenerational mobility in education between natives and second-generation immigrants to understand whether the patterns of mobility are different for these groups. Higher intergenerational mobility in education, together with the growing share of second-generation immigrants, is likely to change the outlook of income inequality in the UK. Furthermore, we look at how persistent the mobility patterns are by also looking at intergenerational mobility of natives compared with third-generation immigrants. The latter provides an insight into the dynamics of income inequality across future generations.

This chapter also provides an overview of the overall income inequality between groups, as well as looking at wage inequality versus overall income inequality, which also includes income from state welfare benefits. Inequality between groups might create disincentives for the disadvantaged groups to work Brücker et al. (2002), in which case the burden of smoothing the income inequality will fall on state welfare benefits. The second paper explores these aspects of inequality: income inequality between natives and second-generation immigrants (inequality between groups), and its possible effect on welfare receipt by the groups.

This Introduction highlights the importance of state welfare benefits in smoothing the inequality. The high dependence of individuals on welfare benefits leads us to a question:

is the state welfare system in the UK not discouraging individuals to participate in the labour market? The third paper aims at answering the aforementioned question. It estimates the effect of policies aimed at providing support to low-income families on labour supply, and specifically the effect of the 2003 tax credit reform and the 2012 amendment on hours worked and labour force participation of individuals. We look at the effect on UK-born versus non-UK-born individuals to determine whether the knowledge of UK welfare system affects the behaviour of individuals.

1.2 Measuring inequality

To illustrate the levels and composition of income inequality in the UK, we use data from the UK Household Panel Survey, Understanding Society. The sample comprises of natives and second-generation immigrants, where we define natives as individuals born in the UK, whose parents and grandparents were born in the UK, and immigrants - as individuals born in the UK with parents being born outside the UK. To avoid biases in estimations associated with return-migration, we include second-generation, rather than first-generation immigrants.

By comparing the income of immigrants and natives in Table 1.1, we can see that the income of natives is lower compared with the income of natives. The largest source of this differential is income from labour, while when also adding income from benefits, the differential, though still there, becomes much smaller.

However, in order to measure inequality, we need to consider not only mean income and standard deviations, but also data of the tails of income distributions. Therefore, we construct Theil index (Theil, 1967) to discuss levels of inequality for natives versus immigrants:

$$T_t^s = \frac{1}{n} \sum_{i=1}^{n} \frac{y_{it}^s}{\overline{y}_t^s} \; ln \frac{y_{it}^s}{\overline{y}_t^s} \tag{1.1}$$

where y_{it}^s is net personal income of individual i from group s at time t, $\overline{y}_t^s$ is average net personal income of group s, and n is the size of the group sample.

Theil index is specifically used for its advantage of being a decomposable measure (Bourguignon 1979), and hence it will make it possible to estimate the contribution of each subgroup or subitem to the aggregate index. Theil index close to zero show complete equality.

As decomposition of aggregate Theil measure by groups includes the sum of weighted inequality within a group and the measure of inequality between groups, we use the

Table 1.1: Summary statistics on monthly income (GBP)

Income of natives							
	From labour		**Total, excl. benefits**[a]		**Total**		
year	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	N
2009	829.1	1196.2	1001.9	1290.3	1308.2	1214.6	24542
2010	799.2	1145.3	1031.3	1308.7	1369.1	1244.9	20628
2011	803	1098.4	1071.3	1263.7	1430.5	1209.8	18176
2012	834.6	1166.2	1121.4	1345.7	1481.9	1271.5	16649
2013	840.7	1147.3	1137.9	1304.3	1508.2	1234.5	15536
2014	892.6	1268.2	1214.5	1388.3	1586.8	1299.7	13958
Income of immigrants							
	From labour		**Total, excl. benefits**[a]		**Total**		
year	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	N
2009	1067.3	1282.8	1126.2	1335.5	1423.2	1244.7	2325
2010	962.7	1259.2	1045.8	1281.3	1368.3	1215.8	1861
2011	997.6	1125.1	1123.4	1224.5	1457.8	1146.4	1635
2012	1037.8	1265.7	1172.5	1346.1	1509.8	1264.2	1479
2013	1110.5	1313.6	1245.5	1366.4	1579	1283.9	1361
2014	1122.6	1109.9	1290.1	1302.4	1625.6	1204.2	1195
Diff	-215.3***		-192.2***		-48.24***		
	(-17.42)		(-16.88)		(-3.69)		

Notes: [a] Benefits include income from state welfare benefits.
(Diff.) is the difference in the means of natives and immigrants.
t statistics in parentheses.
* p¡0.05, ** p¡0.01, *** p¡0.001
Source: UKHLS.

following expression to calculate contributions of each group to the aggregate Theil index:

$$T^s_{contr.,t} = \frac{Y^s_t}{Y_t} T^s_t + \frac{Y^s_t}{Y_t} ln \frac{\overline{y}^s_t}{\overline{y}_t} \tag{1.2}$$

where Y^s_t is total income of group s at time t, Y^s_t - total income of the population at time t, T^s_t - Theil index of the group, calculated as in (1.1), and $\overline{y}_t$ is average income of the population.

We follow (1.2) to decompose Theil index of the sample by groups, including both weighted and unweighted decompositions.

1.3 The contribution of immigrants to income inequality.

The decomposed graphs show the contribution of each group to the overall Theil index of the sample. The weighted decomposition in Figure 1.1 reflects lower weight of immigrants, represented by the share of the total income of immigrants in the total income of the overall sample. Figure 1.2, on the other hand, ignores the weights and shows the contribution of each group to overall Theil index, had they had equal weights. Thus, unweighted shares of immigrants and natives in overall Theil index are broadly similar, with the contribution of immigrants being slightly higher than that of natives.

Figure 1.1: Decomposition of inequality: natives versus immigrants

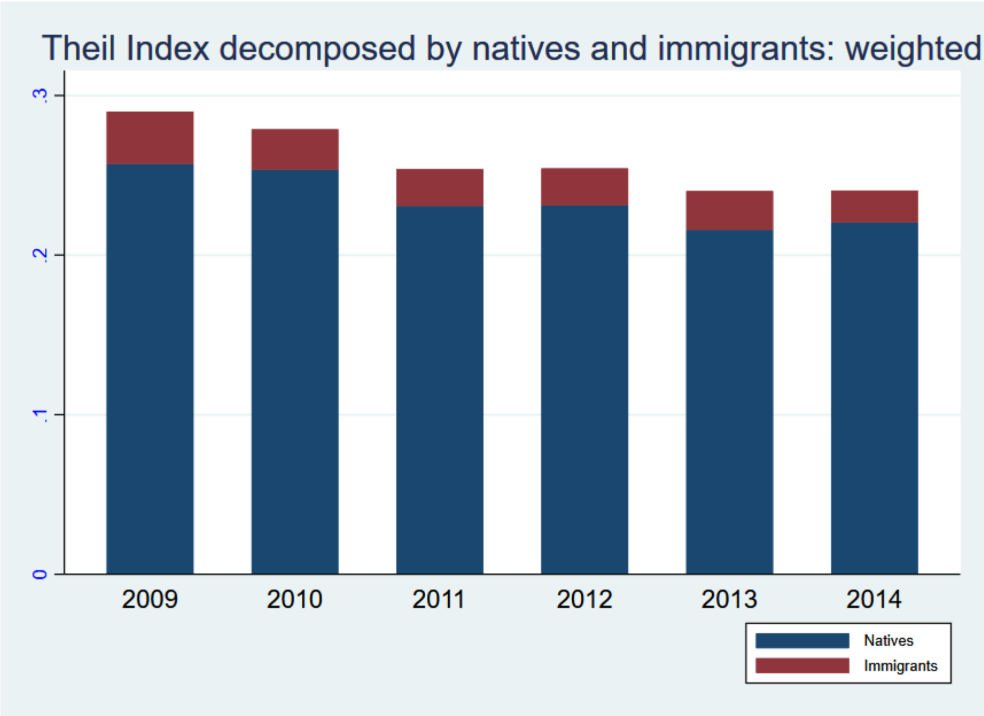
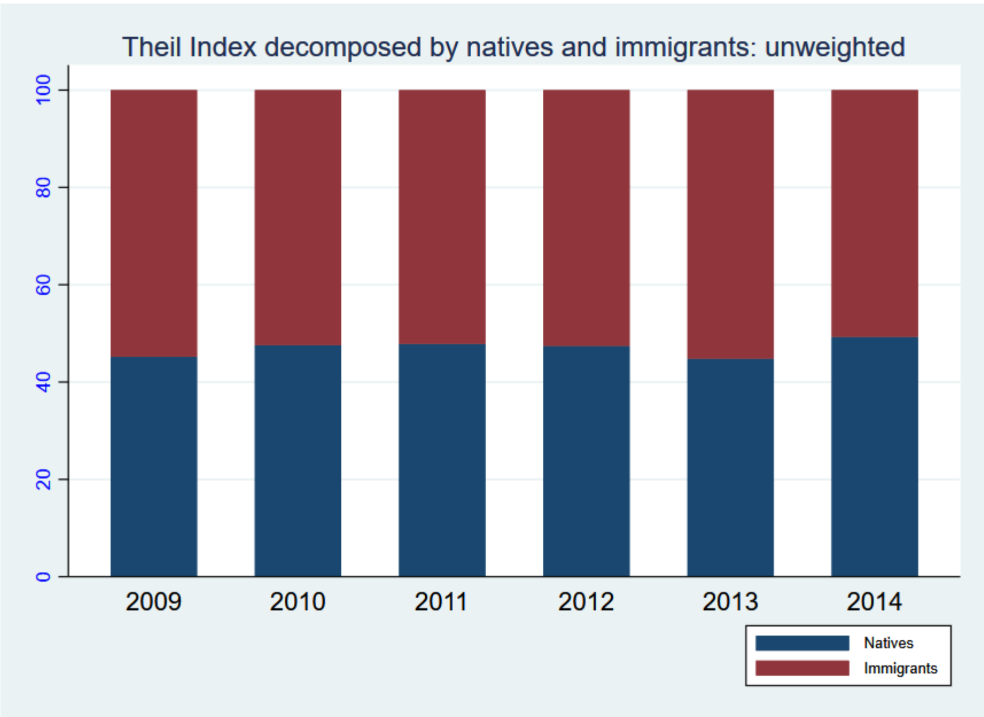


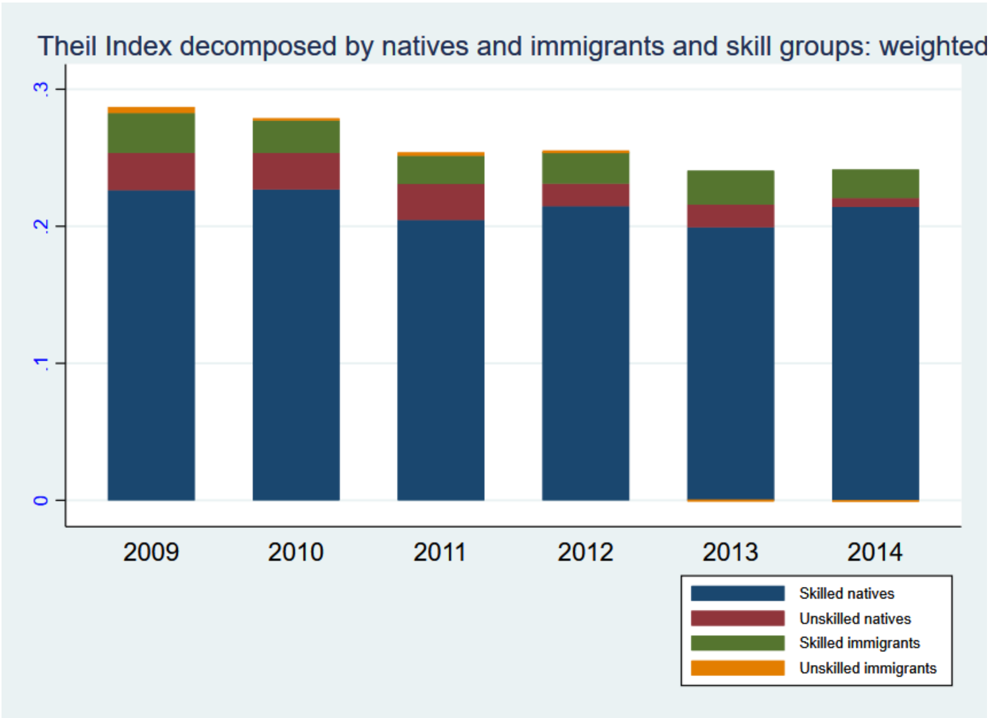
Figure 1.2: Unweighted contribution of natives and immigrants to inequality



Figures 1.3 and 1.4 show weighted and unweighted contributions of skilled and unskilled natives and immigrants. Weighted contribution of skilled natives is the highest, which

reflects both the high share of the income of natives, as well as a high level of income inequality amongst skilled natives. When looking at unweighted contributions, one can see that, overall, the Theil index is largely driven by inequality in the skilled groups of both natives and immigrants. Unskilled immigrants negatively contribute to aggregate Theil index.

Figure 1.3: Decomposition of inequality by skill groups

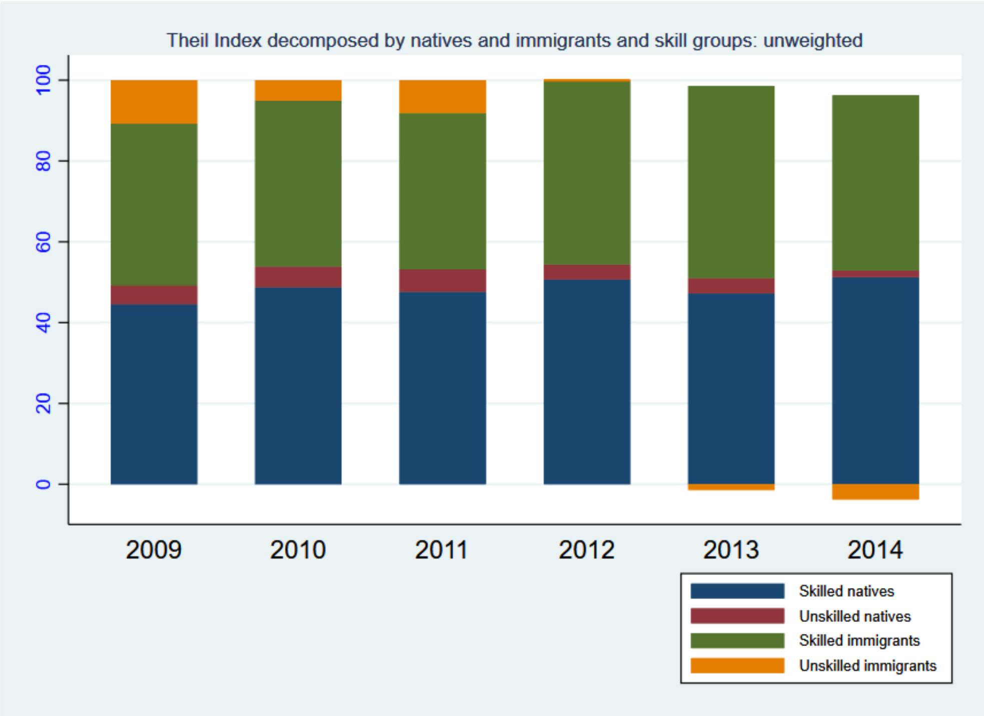


Note: Skilled individuals are individuals with education level of A-levels or higher. Unskilled individuals are individuals with education level lower than A-level.

Decomposition of Theil index following (1.2) indicates that the contribution of each subgroup is due to two factors: inequality within groups and inequality between groups. Are immigrants contributing to inequality by higher average income compared with the average income of natives (between inequality), or are they contributing by high inequality within the group of immigrants, or both? We further decompose Theil index to answer these questions.

Inequality between groups. Table 1.2 on average net personal income of natives and immigrants by skill groups indicate an anticipated difference in average income by skills. The average income of skilled immigrants is slightly exceeding the income of skilled natives, whereas the income of unskilled natives is, on average, slightly higher than that of unskilled immigrants. However, as reflected in Table 1.1, the average income of immigrants exceeds that of natives. The latter is likely to indicate lower within-inequality.

Figure 1.4: Unweighted contribution of skilled and unskilled to inequality



Note: Skilled individuals are individuals with education level of A-levels or higher. Unskilled individuals are individuals with education level lower than A-level.

Table 1.2: Average net personal income: skilled vs. unskilled (GBP)

	Natives		**Immigrants**	
Year	Skilled	Unskilled	Skilled	Unskilled
2009	1732	1081	1646	1147
2010	1791	1131	1601	1081
2011	1824	1197	1682	1175
2012	1886	1228	1774	1180
2013	1903	1255	1863	1216
2014	2006	1305	1902	1263

Note: Skilled individuals are individuals with education level of A-levels or higher. Unskilled individuals are individuals with education level lower than A-level.
Source: UKHLS.

Inequality within groups. In addition to inequality between groups, inequality within each group is another parameter that aggregates into overall inequality.

Figure 1.5 for Theil index by the aggregate groups of natives and immigrants show higher inequality level of natives when income from labour is considered. The graph also shows how social benefits and other sources of income mitigate inequality. Benefits contribute to the reduction in inequality of natives by more than 0.4 points. The contribution of benefits is smaller for immigrants. Figure 1.6 pictures Theil index for skilled and unskilled groups of natives and immigrants. Inequality of income from labour is very high for the unskilled group, and particularly for unskilled natives. It, however, decreases when social benefits are included. Wage inequality for the skilled group is considerably smaller than for the unskilled group, and it is even smaller for the group of skilled immigrants.

Figure 1.5: Inequality within groups of natives and immigrants

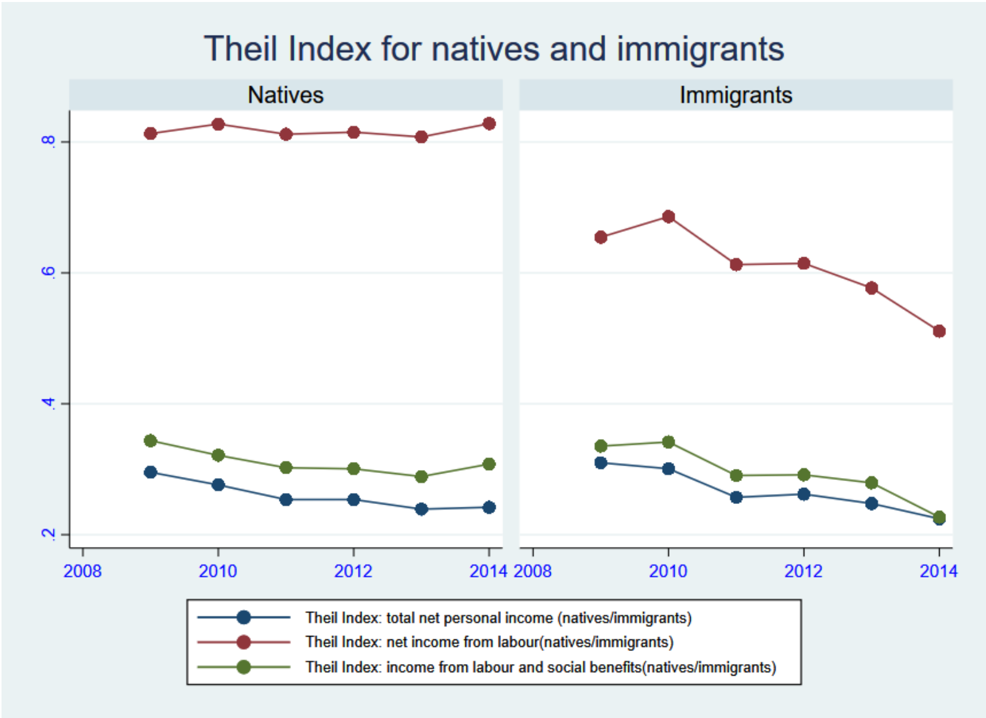
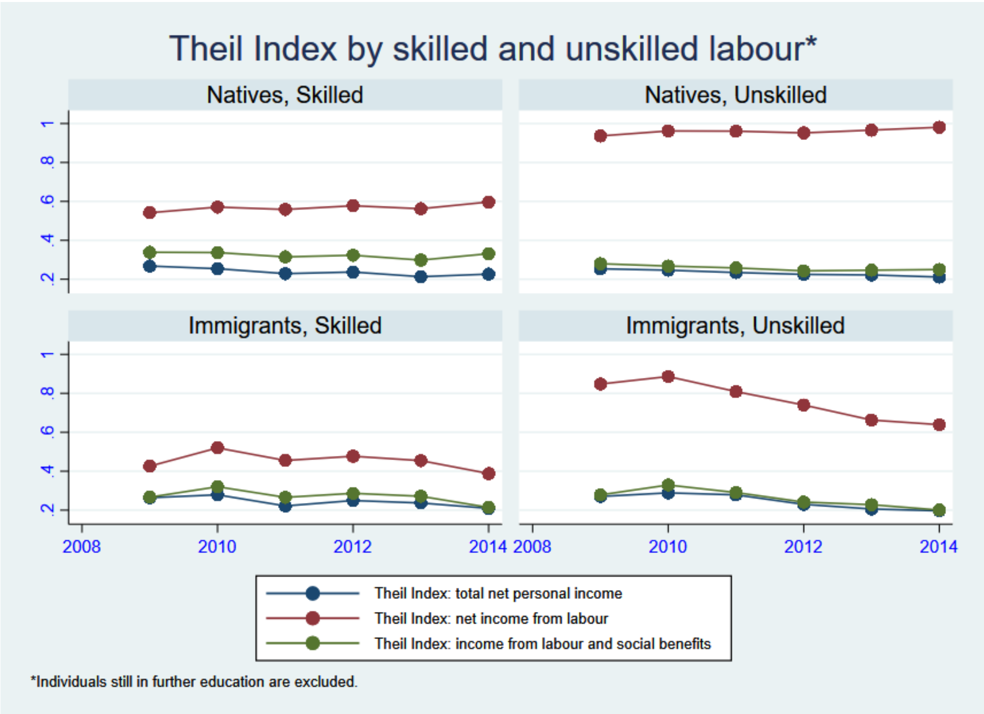


Figure 1.6: Inequality within groups of skilled and unskilled



Note: Skilled individuals are individuals with education level of A-levels or higher. Unskilled individuals are individuals with education level lower than A-level.

The impact of state welfare benefits on inequality. As we could notice in the figures on inequality within groups, inequality is much higher when measured considering income from labour. Figures 1.7-1.8 show the impact of state welfare benefits on Theil index. The negative contribution, that is, the reduction in inequality due to social benefits is around 0.5 points for natives, and it is just over 0.3 points for immigrants (Figure 1.7). The contribution is increasing for natives over the period of 2009-2014, while it has a decreasing trend for immigrants.

For the groups of skilled and unskilled individuals (Figure 1.8), the contribution is highest for the unskilled, and particularly, for unskilled natives, decreasing the Theil index of the unskilled natives by around 0.7 points, while the decrease is around 0.5 points for the unskilled immigrants. The effect of social benefits on the inequality of the skilled is smaller; it reduces inequality as measured by Theil index by just above 0.2 points for the skilled natives, and just below 0.2 points for the skilled immigrants.

Figure 1.7: Impact of social benefits on inequality: natives and immigrants

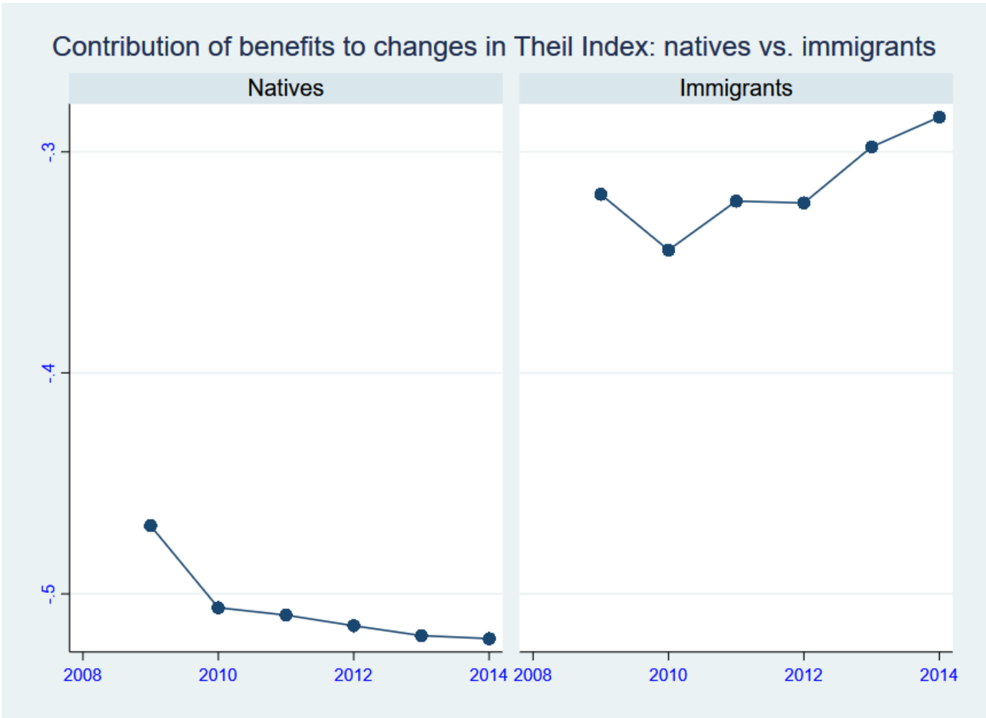
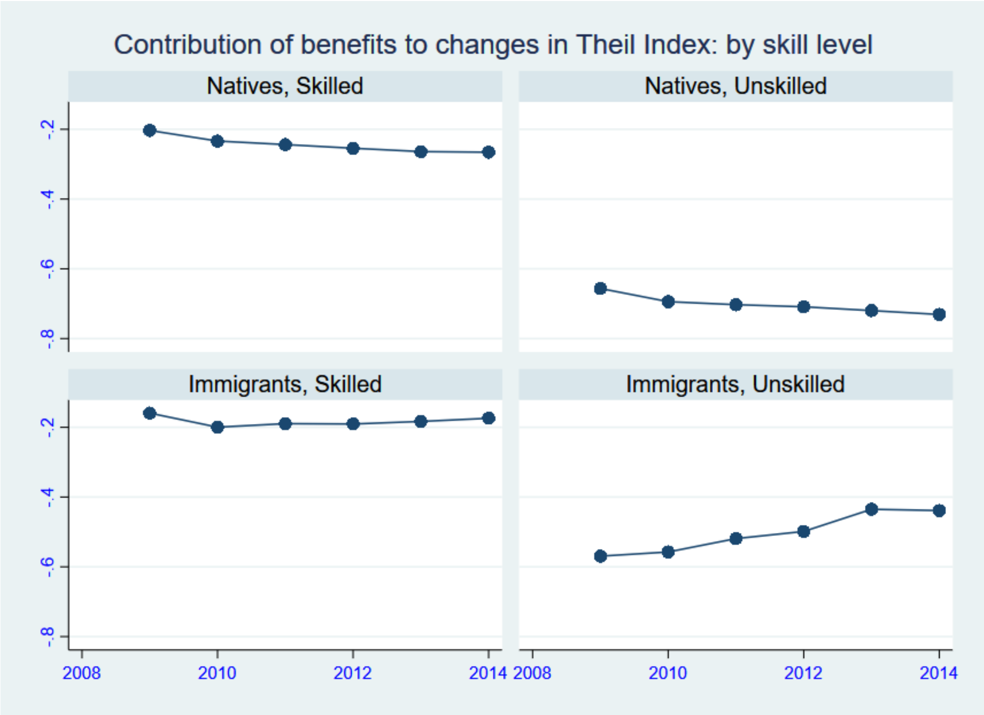


Figure 1.8: Impact of social benefits on inequality: skilled and unskilled



1.4 Summary

The discussion above highlights several important questions. Firstly, in terms of their contribution to overall income inequality, as measured by Theil index, second-generation immigrants have a lower contribution than natives due to a lower share of the population. However, if we ignore the shares, the contribution is similar to that of natives. When we decompose further by skill groups, we can see, that the major contributors to inequality are, as expected, high-skilled individuals. One question that emerges from this is whether this pattern is stable over generations. Considering the importance of intergenerational transmission of productive abilities in the persistence of inequalities, as highlighted in Piketty (2000), it is important to understand where immigrants stand in terms of their interegenerational mobility in education when compared with natives. Does the level of education improve in immigrants over generations compared with natives? Do the patterns persist across third-generation immigrants? These questions are discussed in the first paper of the thesis.

Second, we can see that income from labour of immigrants is higher than the income of natives. However, we do not consider individual characteristics of immigrants, such as age, educational qualification, and industry or region in which they work. These determinants are crucial wage differences. In the second paper, we specifically study wage differentials that are not explained by observable characteristics. Furthermore, we explore whether the wage differential affects the likelihood of individuals to rely on state welfare benefits.

And finally, we can see that the role of social welfare benefits on mitigating inequality is immense. Social benefits account for the reduction in inequality as measured by Theil index, by around 0.5 points. It is important, however, that state welfare programs are designed efficiently, so that they provide the necessary support to low-income families and vulnerable groups, while, at the same time, encouraging individuals to work. The last paper examines the effect of working tax benefit reforms on hours worked and labour force participation of natives and immigrants.

Chapter 2

Intergenerational mobility in education of immigrants in the UK

Abstract. This paper studies[1] intergenerational educational mobility of 1.5-, 2nd- and 3rd-generation immigrants in the United Kingdom compared with the native population, using rich data on child-parent pairs of immigrants by the country of origin of the parent. It finds that 1.5 and 2nd generation immigrants are, in general, more mobile than natives. Country-wise, it finds that EU migrants exhibit intergenerational mobility patterns similar to UK natives, whereas immigrants from South Asia are more mobile than natives.

Even though mobility pattern mostly disappears for 3rd-generation immigrants, for daughters it takes one more generation to catch up with the mobility patterns of sons.

The paper also estimates whether immigrants are more likely to perform better or worse compared with their parents. It finds that even though immigrants are more likely to be better educated than their parents when compared with natives, the results by countries and gender are mixed.

[1]I am very grateful to my supervisors, Jackie Wahba and Corrado Giulietti, for their continuous support and guidance. I am also grateful to Carmine Ornaghi and Emmanouil Mentzakis for their valuable comments and suggestions, as well as the participants of CEMIR Junior Economist Workshop on Migration Research, and seminars and workshops at the University of Southampton.

2.1 Introduction

According to a popular view in economics, there is a positive relationship between intergenerational immobility and economic inequality, often described as 'the Great Gatsby Curve'[2] (Erickson & Goldthorpe (1992), Björklund & Jäntti (1997), Corak (2013)). Economic immobility contradicts the notions of equal opportunities, suggesting that wealth is transferred from generation to generation with no opportunities for those left behind to catch up. The economic inequality in the UK increased drastically in the 1970s-1980s, has been broadly stable since the 2010s (*Living standards, poverty and inequality in the UK: 2018* 2018), and it currently is one of the highest amongst OECD countries. The latter stresses the importance of studying intergenerational socio-economic mobility in the UK, as well as the patterns and determinants of further development in intergenerational mobility.

On the other hand, British society is quite ethnically diverse. The latest ONS report (2015) states that of all births in England and Wales, 27.2% are to foreign-born mothers, with 27.5% to foreign-born fathers. Are the patterns in socio-economic intergenerational mobility of more than a quarter of the UK population the same as that of the native population? Do the patterns in intergenerational mobility of immigrants persist across generations?

While the Great Gatsby Curve shows the importance of studying intergenerational mobility in general, the significant share of immigrant population amplifies the importance of studying intergenerational mobility of immigrant population specifically.

The paper is aimed at shedding light on the differences in intergenerational economic mobility of immigrants compared with UK natives, as well as identifying the direction of mobility for different groups of migrants.

In terms of the link of intergenerational mobility and inequality, intergenerational mobility in education is of particular interest for us, since transmission of productive abilities from generation to generation plays an important role in the dynamics of inequalities (Piketty 2000). On the other hand, intergenerational mobility of immigrants follows different laws and is affected by different factors compared with the native population, described as differences in "ethnic capital" by Borjas (1992). Immigrants are affected by different initial conditions compared with natives, such as customs, family ties and networks, as well as other factors such as savings habits and altruism. Immigrants have different propensities of investing in human capital of their children. Countries with higher intergenerational mobility tend to have lower levels of inequality (Corak 2013), but what happens when individuals migrate to a different country - do they

[2]The Great Gatsby Curve plots the Gini coefficient of countries as a measure of inequality versus the intergenerational elasticity of income, and demonstrates positive correlation between intergenerational income elasticity and inequality. The term was first introduced by Alan Kruegman in his 2012 speech as the chairman of the Council of Economic Advisers (Krueger 2012)

merge with natives, or do their investment habits persist in the host country? One of the factors affecting intergenerational mobility patterns is governmental expenditures towards education (Mayer & Lopoo 2008). Countries with high government spending towards education are more likely to have higher intergenerational mobility, and vice versa. However, if the patterns of intergenerational mobility are determined by government spending, they will disappear for 2nd-generation immigrants once children acquire education in the host country. Therefore, we focus our study on immigrants who acquire education in the UK, that is, first-generation immigrants who moved to the country at an early age, 2nd-generation immigrants, and 3rd-generation immigrants. The latter allows us to study the effect of ethnic capital, that is, the propensity of parents to invest in human capital of their children, irrespective of country of residence.

The paper utilises the Main survey data of the UK Household Longitudinal Study. Using mainly data from Wave 1 of the Survey, we construct transition matrices of educational qualifications of two generations of migrants and derive years of schooling of parents and children and estimate intergenerational elasticities for natives and migrants. Based on the transition matrices, we estimate how different the probabilities of educational upgrade and downgrade are for different groups of immigrants, compared with the native population of the UK, while controlling for the age, respondent having siblings, years since migration of the parents, parental immigration cohort and presence of the parents while the child was growing up.

The paper has the following structure: It starts with the highlights of the background and with a review of the relevant literature on measurements and estimation of intergenerational socio-economic mobility in general, and intergenerational mobility of migrants, in particular, as well as the discussion of the issues associated with the estimation of intergenerational mobility. The theoretical review is then followed by the description of data used and methodology applied. The last part of the paper represents the discussion of the main results and robustness tests, followed by conclusions.

2.2 Background literature

Before addressing the available empirical methodology to estimate the intergenerational mobility of migrants, we briefly touch on the theoretical background of intergenerational mobility in economics. Even though the theoretical background does not directly relate to the research question of the paper, however, discussing it makes it possible to understand the intuition behind intergenerational mobility or immobility.

An early framework suggested by Becker & Tomes (1979) considers a number of factors in determining the equilibrium income of children, such as degree of inheritability of endowments from their parents (race, ability, family characteristics, family reputation and connections, and knowledge, skills and goals provided by their family environment) and parents' propensity to invest in children, in addition to child's own income and parental endowment level, as well as market and endowed luck. Hence, if the first two parameters, that is, the degree of inheritability and the propensity to invest are both less than one, then the distribution of income between generations becomes stationary. Therefore, the role of the family in determining the income of the child is important when the degree of inheritability and the propensity to invest are larger, and vice-versa.

A theoretical model suggested by Solon (2004) is based on the modification of the model by Becker and Tomes. In the framework suggested by Solon, parents maximise their utility function based on their own consumption and the child's future income, and use their after-tax income, $(1-\tau)y_{i,t-1}$, to either direct towards their own consumption, $C_{i,t-1}$, or towards investment in the child's human capital, $I_{i,t-1}$. He uses the following technology of converting parental investment into the human capital of the child:

$$h_{it} = \theta \log(I_{i,t-1} + G_{i,t-1}) + e_{it} \tag{2.1}$$

where $G_{i,t-1}$ is the investment in the human capital of the child by the government, $\theta > 0$ is a coefficient for positive (and decreasing) marginal product for investment in the human capital, and e_{it} is the endowment of human capital of the child independent of the parental or governmental investments, and which is affected by different factors of nature and/or nurture. Solon follows the previous authors assuming that the endowment is dependent on the parental endowment (heritability $\lambda \in (0;1)$) and follows first-order autoregressive process: $e_{it} = \delta + \lambda e_{i,t-1} + \nu_{it}$.

Solon also derived the child's earnings as follows:

$$\log(y_{it}) = \mu + \rho h_{it} \tag{2.2}$$

where ρ - is the return to human capital.

Parents use their after-tax income to either invest in their child's human capital or spend on their current period consumption in order to maximise their utility:

$$U_i = (1-\alpha)\log(C_{i,t-1}) + \alpha \log(Y_{it})$$

where α is an altruism parameter between 0 and 1, which shows the parent's preference towards their child's income versus their consumption. By plugging in the equations for parental income, human capital of the child and child's earnings and maximising the utility, Solon derives the parental investment in the child's human capital as follows:

$$I_{i,t-1} = [\frac{\alpha\theta\rho}{1-\alpha(1-\theta\rho)}](1-\tau)y_{i,t-1} - [\frac{1-\alpha}{1-\alpha(1-\theta\rho)}]G_{i,t-1} \quad (2.3)$$

According to these results, parental investment in the human capital of the child is higher if either the income of the parent, parental altruism or the earnings return to the human capital investment of the child are higher, while it is partly offset by the public investments in their child's human capital.

By substituting equation (2.1) into (2.2), as well as the expression for the investment in the child's education from (2.3), and considering the autoregressive form of the endowment of the human capital of the child, Solon finally derives the steady-state intergenerational income elasticity β, which depends on the level of productivity of parental investment in the human capital and the return to human capital of the child, the level of heritability of parent's endowments (described as in Becker and Tomes), as well as the degree of progressiveness of public investments in children's human capital:

$$\beta = \frac{(1-\gamma)\theta\rho + \lambda}{1 + (1-\gamma)\theta\rho\lambda} \ ,$$

where γ is progressiveness of public investment in human capital.
Hence, according to the model, the intergenerational elasticity is higher the greater the heritability (λ), the productivity of investment in human capital (θ) and the earnings return to human capital (ρ) are, and the lower the progressiveness of public investment in children (γ) is.

Given the overview of the framework above, it is obvious that immigrants have different determinants of intergenerational mobility compared with the native population, that is, different levels of heritability. Moreover, different groups of immigrants have different skills and different ethnic capital (Borjas (1992), Borjas (1993)).

Borjas defines the following CES utility function for the parent: $U = U(k_{t+1}, C_t) = [\delta_1 k_{t+1}^{\zeta} + \delta_2 C_t^{\zeta}]^{1/\zeta}$, where k_{t+1} is the human capital of the child, C_t is the parent's consumption and $\zeta < 1$. Parent has human capital k_t, which he can either sell at price R or invest in the production of the human capital of the child, thus, $C_t = R(1-s_t)k_t$. Most importantly, Borjas defines the production function of the child as:

$$k_{t+1} = \beta_0(s_t k_t)^{\beta_1}(\overline{k_t})^{\beta_2} \ ,$$

according to which the child's human capital, in addition to the human capital of the parent, is also determined by the externality of the average human capital of the ethnic

group of the parent, $\overline{k_t}$.
Borjas argues, that if $\beta_1 + \beta_2 = 1$ then the externality of human capital persists across generations, whereas if $\beta_1 + \beta_2 < 1$, then the ethnic differences in human capital will disappear in the end.

Dustmann (2008), on the other hand, adapts the framework above for migrants, in addition considering the probability of return migration, claiming that parental decision to invest in child's education depends on the further decision of return-migration. He amends the utility function of the parent to include two time periods: Period 0, when both the parent and the child live in the host country and receive utility from consumption c_0, and Period 1, when the parent either returns to the home country H with probability $1 - p$, or stays in the host (destination) country D with probability p. In Period 1 the maximisation problem includes the utility of the parent from consumption c_1, and the child's utility from his earnings y_1:

$$V = u(c_0) + p[u(c_1^D) + \gamma v(y_1^D)] + (1 - p)[u(c_1^H, b) + \gamma v(y_1^H)] \tag{2.4}$$

The child's utility is weighted by a parameter accounting for parental altruism, γ. Besides, the parent's utility when returning to their home country is also dependent on a preference parameter b. In Period 0, the parent either consumes his income Y_0, invests in the child's education I_0 or saves s_0 to consume in Period 1, therefore: $c_0 = Y_0 - I_0 - s_0$. Dustmann defines child's human capital translation technology as follows: $h_1 = \theta log(I_0) + e_0$, and he follows Solon in defining the endowed human capital e_0.

The latter, in turn, translated into child's earnings as follows: $log(y_1^i) = \mu^i + r^i h_1\ ,\ where\ i = D; H,$

μ^i - different base wages and r^i - different returns to the human capital of the child in host (D) and home (H) countries.

Thus, by substituting above mentioned equations into (2.4) and maximising with respect to investment and savings, the following expression for parental investment in the child's human capital is derived:

$$I_0 = \frac{\gamma\theta(pr^D + (1 - p)r^H)}{\gamma\theta(pr^D + (1 - p)r^H) + (1 + p + b(1 - p))} Y_0\ .$$

Thus, parental investment in the human capital of the child increases with the increase in probability of staying in the host country (permanent migration) provided the return to human capital is higher in the host country: $r^D > r^H$. On the other hand, parental investment in the human capital of the child decreases with the decrease in the probability of permanent migration (provided $b > 1$) due to higher parental utility of consuming at home and hence higher savings for the future consumption.

A significant amount of research aimed at estimating intergenerational mobility has been based on estimating ***the intergenerational elasticity of socio-economic status,*** β, or the measure of intergenerational mobility, $(1-\beta)$ (Solon (2002), Black & Devereux (2010), Björklund et al. (1999)). Alternatively, researchers use ***intergenerational correlation*** to measure intergenerational mobility. Intergenerational correlation, that is, the correlation between log-earnings of father and child, is equal to the elasticity measure if the standard deviations of log-earnings of the father and the son are the same: $correlation = (\sigma_1/\sigma_0)\beta$, where σ is the standard deviation of log-earnings.

Another approach to estimate intergenerational mobility is based on using ***mobility matrices*** and studying the quantile of the child's earnings conditional on the parental earnings quantile (Black & Devereux (2010), Atkinson (1980), Zimmerman (1992), Dearden et al. (1997)).

The estimation of intergenerational mobility by deriving the elasticity of child's socio-economic status with respect to parents has been carried out by different methods by researchers. The intergenerational elasticity is often estimated by log-linear regressions, with the child's log-earnings being regressed on parent's log-earnings (Solon 1992):

$$y_{1i} = \beta y_{0i} + \varepsilon_i, \tag{2.5}$$

where y_{1i} and y_{0i} are correspondingly child's and parent's long-run log-earnings and β is the elasticity of the child's socio-economic status from the parent's. Nevertheless, there are a number of issues arising when estimating the equation (2.5) using child's and parental log-earnings as a measure of socio-economic status. (Solon (1992), Solon (2002), Black & Devereux (2010)).

Firstly, as a proxy for the measure of parent's long-run earnings often one-year earnings are considered. Hence, the estimations based on short-term proxies are prone to bias due to measurement error and transitory fluctuations in earnings:

$$y_{0is} = y_{0i} + v_{0is}, \tag{2.6}$$

where v_{0iS} is the bias due to measurement error and transitory fluctuations of short-term earnings measured at time s around long-term earnings of the parent.

In order to overcome the problem, many studies use multi-year measures of parent's earnings (Couch & Dunn (1997), Wiegand (1997), Corak & Heisz (1999)).

Another problem with the method often highlighted in studies is related to the measurement of the son's earnings. Several studies have shown that intergenerational mobility is higher if the child's earnings in the beginning of his career are considered, and that it gets larger further on. The proxy measures of child's earnings are therefore prone to measurement error too:

$$y_{1it} = y_{1i} + v_{1it} \tag{2.7}$$

As son's earnings can be mean-reverting, averaging the child's earnings over years might not solve the problem. On the contrary, it might increase the (downward) bias. Therefore, some researchers have used only the latest available measure of a child's earnings together with the average measure for parent's earnings.

Hence, in order to improve the results, more recent studies have focused on averaging over more years when estimating permanent earnings, as well as on the ages at which the earnings of both parents and children are measured (Black & Devereux (2010)).

As an alternative to using a multi-year average measure of parent's log-earnings to address the measurement issues of parent's long-term earnings, another approach is to use parent's such socio-economic indicators like education, occupation or social class to derive parent's log-earnings. In this case, the estimation is conducted in two stages (Zimmerman (1992), Björklund & Jäntti (1997), Dearden et al. (1997)). In the first stage of the estimation log-earnings of the parent's generation are regressed on parent's socio-economic indicators using a separate dataset. In the second stage, the child's log-earnings are regressed on the predicted log-earnings of the parent. The use of the two-stage approach is nevertheless prone to bias as well, as the parent's socio-economic indicators are not only correlated with parent's earnings but also with the child's earnings. Another set of IVs suggested by Zimmerman (1992) are instruments (i) using Duncan Index, and (ii) using Forward Quasi-Difference. As relevant instruments, these should be correlated with parent's permanent status, yet uncorrelated with the transitory component of the observed status of the parent.

Using educational attainment as a measure of intergenerational mobility is also common, although to a lesser extent (Black & Devereux 2010). Education is less susceptible to measurement error as people usually complete their education by their mid-twenties, whereas earnings can be volatile over their lifetimes.

To analyse the intergenerational mobility of different ethnic groups, Borjas (1992) includes ethnic capital effects:

$$y_{1ij} = \alpha_1 + \beta_1 y_{0ij} + \beta_2 \overline{y}_{0j} + \xi_{0ij},$$

where $\overline{y}_{0j}$ is the average log earnings of the ethnic group j of the parent's generation. In this case, the mobility coefficient is given by $\beta_1 + \beta_2$.

Dustmann (2008) generally follows Solon (1992) and Zimmerman (1992) in estimating the permanent income of fathers. He, in addition, includes probabilities of permanent migration in estimating intergenerational mobility of migrants, which he computes based on survey information on years since migration and the reported intention of permanent migration of migrant fathers:

$$\log y_{i1} = \alpha_1 + \alpha_2 P_{i0} + \textstyle\sum_{k=1}^{K} \alpha_{3k} D_{ik0} + \beta \log y_{i0} + e_{i0} \ ,$$

where P is the measure of probability of permanent migration of the parent, y_1 and y_2 are permanent earnings of the child and the parent, and D_{ik0} are dummy variables for the country of origin of the father.

Table 2.1: Overview of estimations of β for the UK

Author	**Data**	**Socio-economic indicator**	β
Atkinson et al. (1980)	Fathers in working-class neighbourhoods of York in 1950 and their sons	Log earnings	0.45
Dearden et al. (1997)	British National Child Development Survey	Log earnings	0.40-0.60 for father-son, 0.45-0.70 for father-daughter
Ermisch and Francesconi (2004)	British Household Panel Survey (BHPS)	Occupations/ Log earnings	0.45-0.75 for father-child and 0.30-0.50 for mother-child/ 0.05-0.20
Jantti et al. (2006)	National Child Development Study (NCDS)	Log earnings	0.31 for men to 0.33 for women

The studies on intergenerational socio-economic mobility in the UK have estimated β ranging from 0.4 to 0.7 (Table 2.1). For instance, one of the earlier studies of intergenerational mobility in the UK, Atkinson (1980), studies log earnings of father and reports a value of 0.45 for β[3]. A study by Jantti et al. (2006) uses data from the National Child Development Study (NCDS) on children born in a particular week in 1958 and on the income of their parents to estimate log-log regressions of parent-child income. Based on this study, the elasticity coefficient, β, for the UK ranges from 0.31 for men to 0.33 for women, which is exceeded only by the coefficient for the US in the study[4].

Another study, Dearden et al. (1997), estimates intergenerational income and educational elasticity of 0.4-0.6 for men and 0.45-0.7 for women (depending on the method

[3] The study is based on survey data on families in York.

[4] The study compares intergenerational earnings mobility across the United Kingdom, the United States, Denmark, Finland, Norway, and Sweden.

used), using longitudinal data from National Child Development Survey. A study using UKHLS predecessor BHPS Ermisch & Francesconi (2004) assesses intergenerational correlations of 0.45 to 0.75 for father-child pairs and 0.30 to 0.50 for mother-child pairs.

2.3 Data and methodology

2.3.1 Data

The paper uses Main survey data of the UK Household Longitudinal Study (UKHLS), Understanding Society, which is a successor of British Household Panel Survey (BHPS). The sample includes 14,430 observations from the first Wave of UKHLS for 1.5-, 2nd- and 3rd-generation immigrant, and native population, aged between 25 and 59.

1.5-generation of immigrants are defined as migrants born outside the UK, but moved in the UK in early childhood. When defining the 1.5-generation immigrants it is important to identify the appropriate age of arrival to the host country. The importance of it is associated with the child's ability to learn a second language, including the ability to acquire the native accent. The hypothesis of biological "critical period" for second language acquisition is suggested in neurolinguistic literature (Penfield & Roberts (2014)). The later studies (see Casey & Dustmann (2008) for the overview, Johnson & Newport (1989), Birdsong & Molis (2001), Mayberry & Lock (2003)) confirm that there is a significant relationship between age at which the child got an exposure to the second language and the subsequent proficiency in it. Overall, there a consensus in the cognitive psychology literature that second language attainment is negatively correlated with age of learning. Furthermore, in studies by Lenneberg (1967) and Penfield & Roberts (2014) it was suggested that the second language cannot be mastered fully if not acquired by puberty. Johnson & Newport (1989) discuss that English language test performances of immigrant children who arrived in the host country up to the age of seven are similar to those of natives, whereas the results tend to deteriorate for later arrivals.

Hereinafter, for the purpose of this study, we follow Johnson & Newport (1989) and define 1.5-generation immigrants as those who arrived in the UK up to and including the age of seven.

2nd-generation immigrants are defined as individuals born in the UK with at least one parent being born outside the UK.

3rd-generation immigrants are defined as individuals born in the UK with both parents being born in the UK, but at least one of the parental both grandparents being born outside the UK.

Natives are defined in our sample as the white population with both parents and all grandparents born in the UK.

UKHLS data makes it possible to study different groups of migrants by their countries of birth. In this study, countries of birth of parents of 1.5- and 2nd-generation immigrants are grouped following the current country groupings used by Office for National Statistics for International Passenger Survey [5], taking into account also sub-sample sizes of individuals from respective countries:

- UK or native;
- EU(EEA), includes the EU, Iceland, Liechtenstein, Norway, and Switzerland;
- India;
- Pakistan;
- Bangladesh;
- Other Africa, includes Sub-Saharan Africa;
- Central and South America;
- Other countries, includes all other countries.

Table 2.2 includes data on the number of pairwise combinations of individual's parents' countries of birth. Immigrants in this sample comprise 17%. The largest group of immigrants are those from the EU, which comprise around 3.5% of the sample, followed by immigrants from Central and South America, with a share of roughly 2.5%. The next largest groups of immigrants are from India (2%), Pakistan (2%), Sub-Saharan Africa (1%) and Bangladesh (1%).

Countries of birth of grandparents of 3rd-generation immigrants are grouped into three broad categories due to fewer observations, that is, UK, EU and non-EU (Table 2.3). Immigrants in this sample total to 2.3%, with the EU immigrants being around 1.1% of the sample.

[5] www.ons.gov.uk

Table 2.2: Matrix on parents' country of origin
(frequencies and relative frequencies)

	mother's birthplace			
father's birthplace	UK	EU(EEA)	Non-EU(EEA)	Total
UK	14,012 85.1	284 1.7	159 1.0	14,455 87.8
EU(EEA)	276 1.7	195 1.2	13 0.1	484 2.9
Non-EU(EEA)	281 1.7	36 0.2	1,213 7.4	1,530 9.3
Total	14,569 88.5	515 3.1	1,385 8.4	16,469 100

Table 2.3: Matrix of grandparents' country of origin
(frequencies and relative frequencies)

	maternal grandparents' birthplace			
paternal grandparents' birthplace	UK	EU	Non-EU	Total
UK	11,973 97.7	67 0.6	8 0.1	12,048 98.3
EU	90 0.7	50 0.4	8 0.1	148 1.2
Non-EU	11 0.1	12 0.1	39 0.3	62 0.5
Total	12,074 98.5	129 1.1	55 0.5	12,258 100

As discussed above, educational qualifications are used as a measure of socio-economic status of individuals and their parents due to the apparent advantage of educational qualifications against earnings. People usually get their educational qualifications by the age of 25, whereas earnings can be volatile and hence create issues described in Section 2.2.

The data on education in UKHLS is self-reported. Individuals are asked about the educational qualification achieved, as well as educational qualifications of their parents. The educational qualifications are defined differently for children and parents in the Survey. Migrant and native children are asked the following question: "Can you tell me the highest educational or school qualification you have obtained?" Moreover, children's educational qualifications are further categorised as UK and non-UK qualifications. Parents' educational qualifications are determined by the question: "which of these best describes the type of qualifications your father/mother gained?". As a result, there are nine categories of educational qualifications of children against five categories of educational qualifications of parents. In order to make educational qualifications of the two generations comparable, we match the educational qualifications of parents and children as described in Table 2.4.

Table 2.4: Matching of parental and child educational qualifications

Parents	**Children**
No school	No qualification
Left school with no qualification	Other UK qualifications
Some school qualifications	UK GCSE, etc.
Post school qualifications	UK A-levels, IB
	Other non-UK higher
	Other UK higher
University degree or higher	Non-UK degree or higher
	UK degree or higher

As a result, the matrices of matched educational qualifications of fathers and children, and mothers and children for both migrants and natives, as well as matrices for parent-son and parent-daughter pairs for migrants and natives are presented in Tables 2.5-2.6 and Tables A.1-A.4 of Appendix A.

As we can see in Table 2.5, 39% of all fathers and 44% of mothers (both immigrants and natives) in the sample left school with no qualifications, 23% of fathers and 27% of mothers have some school qualifications, while 27% of fathers and 20% of mothers have post-school qualifications. A smaller share of the sample, 9% of fathers and 6% of mothers have a university or higher degree, and around 2% of both fathers and mothers did not attend school. These results are mainly driven by natives, with slightly higher share of fathers with post-school qualifications (29%) and lower share of degree educated fathers (8%) and those who did not attend school (1%). The share of native mothers, who did not attend school, is close to 0, whereas the shares of mothers, who left school with no qualifications and with some school qualifications are slightly higher - respectively 45% and 28%.

The picture is different for immigrants. 37% of immigrant fathers and 38% of immigrant mothers left school with no qualifications, 25% of immigrants fathers and 26% of mothers attained some school qualifications. The share of individuals with post-school qualifications are lower for immigrants - 17% for fathers and 18% for mothers, whereas the share of individuals with a degree is higher - 12% for fathers and 7% for mothers. The share of immigrants who did not attend school is also higher - 9% for fathers and 12% for mothers.

Immigrant children, on the other hand, are more educated compared with native children and their parents, with 36% having a degree (as opposed to 26% natives), 31% having post-school qualification (33% native children have post-school qualifications), 21% - some school qualifications (versus 23% of natives), 5% leaving school with no qualifications (versus 9% of natives) and 7% not attending school (as opposed to 9% native children).

The evidence by gender of the child does not differ much, with sons being slightly better educated than daughters (Tables A.1-A.4).

Table 2.5: Transition matrices of educational qualifications of parent-child pairs: total

		child's educational qualifications					
father's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	29	21	62	70	48	230
	%	0.2	0.2	0.5	0.5	0.4	1.7
Left school with no qual.	N	817	612	1,300	1,600	925	5,254
	%	6.1	4.6	9.7	11.9	6.9	39.1
Some school qualifications	N	135	190	822	1,096	874	3,117
	%	1.0	1.4	6.1	8.2	6.5	23.2
Post school qualifications	N	110	212	760	1,392	1,167	3,641
	%	0.8	1.6	5.7	10.4	8.7	27.1
University degree or higher	N	5	15	118	319	723	1,180
	%	0.0	0.1	0.9	2.4	5.4	8.8
Total	N	1,096	1,050	3,062	4,477	3,737	13,422
	%	8.2	7.8	22.8	33.4	27.8	100.0

		child's educational qualifications					
mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	35	21	66	82	49	253
	%	0.3	0.2	0.6	0.7	0.4	2.1
Left school with no qual.	N	891	649	1,302	1,523	858	5,223
	%	7.5	5.5	11.0	12.9	7.3	44.2
Some school qualifications	N	128	213	869	1,147	880	3,237
	%	1.1	1.8	7.3	9.7	7.4	27.4
Post school qualifications	N	41	86	414	873	941	2,355
	%	0.3	0.7	3.5	7.4	8.0	19.9
University degree or higher	N	2	14	64	205	473	758
	%	0.0	0.1	0.5	1.7	4.0	6.4
Total	N	1,097	983	2,715	3,830	3,201	11,826
	%	9.3	8.3	23.0	32.4	27.1	100.0

Table 2.6: Transition matrices of educational qualifications of parent-child pairs: natives

father's educational qualifications		**child's educational qualifications** No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	9	9	16	16	8	58
	%	0.1	0.1	0.1	0.1	0.1	0.5
Left school with no qual.	N	738	551	1,134	1,376	733	4,532
	%	6.4	4.8	9.9	12.0	6.4	39.5
Some school qualifications	N	116	177	714	931	699	2,637
	%	1.0	1.5	6.2	8.1	6.1	23.0
Post school qualifications	N	105	198	706	1,282	1,024	3,315
	%	0.9	1.7	6.1	11.2	8.9	28.9
University degree or higher	N	4	10	92	266	573	945
	%	0.0	0.1	0.8	2.3	5.0	8.2
Total	N	972	945	2,662	3,871	3,037	11,487
	%	8.5	8.2	23.2	33.7	26.4	100.0

mother's educational qualifications		**child's educational qualifications** No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	10	8	7	12	6	43
	%	0.1	0.1	0.1	0.1	0.1	0.4
Left school with no qual.	N	816	591	1,136	1,323	689	4,555
	%	8.1	5.9	11.3	13.2	6.9	45.3
Some school qualifications	N	115	196	767	997	704	2,779
	%	1.1	1.9	7.6	9.9	7.0	27.6
Post school qualifications	N	37	79	361	781	787	2,045
	%	0.4	0.8	3.6	7.8	7.8	20.3
University degree or higher	N	2	12	58	177	386	635
	%	0.0	0.1	0.6	1.8	3.8	6.3
Total	N	980	886	2,329	3,290	2,572	10,057
	%	9.7	8.8	23.2	32.7	25.6	100.0

On the other hand, educational qualifications of fathers and sons cannot be directly compared without additional adjustment for education inflation. In order to do that, we identify the respective years in which the average parent and child were 25, that is, finished education, and then translate educational qualifications to years of schooling for a respective country. The mean age for migrants is 38 and it is 43 for natives (Table 2.8), while the average age for the migrant parents is 64, and it is 67 for native parents. Averaging the ages for all children and all parents, as in Table 2.9, and calculating the

Table 2.7: Transition matrices of educational qualifications of parent-child pairs: migrants

father's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
		child's educational qualifications					
No school	N	20	12	46	54	40	172
	%	1.0	0.6	2.4	2.8	2.1	8.9
Left school with no qual.	N	79	61	166	224	192	722
	%	4.1	3.2	8.6	11.6	9.9	37.3
Some school qualifications	N	19	13	108	165	175	480
	%	1.0	0.7	5.6	8.5	9.0	24.8
Post school qualifications	N	5	14	54	110	143	326
	%	0.3	0.7	2.8	5.7	7.4	16.8
University degree or higher	N	1	5	26	53	150	235
	%	0.1	0.3	1.3	2.7	7.8	12.1
Total	N	124	105	400	606	700	1,935
	%	6.4	5.4	20.7	31.3	36.2	100.0

mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
		child's educational qualifications					
No school	N	25	13	59	70	43	210
	%	1.4	0.7	3.3	4.0	2.4	11.9
Left school with no qual.	N	75	58	166	200	169	668
	%	4.2	3.3	9.4	11.3	9.6	37.8
Some school qualifications	N	13	17	102	150	176	458
	%	0.7	1.0	5.8	8.5	9.9	25.9
Post school qualifications	N	4	7	53	92	154	310
	%	0.2	0.4	3.0	5.2	8.7	17.5
University degree or higher	N	0	2	6	28	87	123
	%	0.0	0.1	0.3	1.6	4.9	7.0
Total	N	117	97	386	540	629	1,769
	%	6.6	5.5	21.8	30.5	35.6	100.0

respective years when average child and parent were at the age of 25 (as supposedly at the age of 25 an average person has largely acquired education[6]), we arrive at years 1970 for parents and 1995 - for children.

[6]Also confirmed by the data for children, with the age of leaving education for more than 90% being up to 25 years

Table 2.8: Average age of migrants/ natives and their living parents

Category	**Mean**	**Std. Err.**	[95% **Conf. Interval**]		**N**
Migrant sons	38.2	0.4	37.3	39.0	430
Migrant daughters	37.9	0.4	37.1	38.6	536
Native sons	43.1	0.1	42.9	43.4	6657
Native daughters	42.7	0.1	42.5	42.9	8924
Migrant fathers	65.4	0.7	64.0	66.9	176
Migrant mothers	63.5	0.5	62.5	64.5	363
Native fathers	67.6	0.2	67.3	68.0	3609
Native mothers	66.8	0.1	66.5	67.0	6290

Table 2.9: The derivation of the year when an average child and parent were of age 25

		(I) 1995		**(II)** 1969	
Average age in	2010	1997	1992	1971	1968
Migrant children	38	25			
Native children	43		25		
Migrant parents	64			25	
Native parents	67				25

Note: (2010) The actual average age of the group in 2010.
(I) and (II) the average calendar years children and parents, respectively, were of age 25.

We then use UNESCO Institute for Statistics data on theoretical years of primary and secondary education by country, to derive years of schooling of parents and children, based on the reported educational attainment, taking into account mother's and father's respective country of origin, and using UK data for children. Following the results in Table 2.9, we use data from the year 2000 for children's generation and the 1970 data for parents' generation. As a robustness test, we use theoretical years for parental country from the year 2000 for child's years of schooling. Wherever there is no specific data on the country of origin, the average of the rest of the countries is taken. Wherever the parent moved to the UK before the age of primary or secondary school, the relevant years of schooling for the UK is considered, instead of the country of birth of the parent. Since there is no data on tertiary education by countries, wherever the individual has a degree level of education, 3 years of education is added to the secondary education, regardless of the country of birth.

Tables 2.10 and 2.11 include descriptive statistics on years of schooling of children and parents by the groups of parental country of birth and grandparents' country of birth, respectively. As discussed before for 1.5- and 2nd-generation immigrants and natives, children are, on average, more educated than parents are, with average years of schooling being 10.2 years for fathers, 9.7 years-for mothers, while it is 11.1 and 10.9 years for sons with migrants father and mother, respectively, and it is 11.4 and 11.1 years for daughters with migrant father and mother, correspondingly.

UK parents are, on average, better educated than EU and non-EU parents. However, it is the opposite for children.

The situation is different though for 3rd-generation immigrants versus their 2nd-generation parents (Table 2.11). Here, there seems to be no significant difference between parents and children. UK parents, and EU/non-EU parents seem to have no significant difference in years of schooling, except for non-EU mothers, who have more years of schooling than natives. UK children, and EU/non-EU children do not have significant differences in years of schooling.

Table 2.10: Statistics on child's and parents' years of schooling by parents' country of birth

	Father-child pair									
	Son's yrs. of school		**Father's yrs. of school**			**Daughter's yrs. of school**		**Father's yrs. of school**		
Father's birthplace	Mean	St. Dev.	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	N
UK	10.9	5.7	10.6	3.7	4909	11.2	5.3	10.3	3.8	6578
EU(EEA)	11.2	6.0	7.5	3.7	87	12.1	5.2	8.3	3.3	109
Diff.	-0.3		3.1***			-0.8		2.0***		
	(-0.48)		(7.58)			(-1.62)		(5.42)		
Non-EU(EEA)	12.8	4.7	8.8	5.0	490	12.5	4.6	8.7	4.9	688
Diff.	-2.0***		1.8***			-1.3***		1.6***		
	(-7.27)		(9.82)			(-6.26)		(10.33)		
	Mother-child pair									
	Son's yrs. of school		**Mother's yrs. of school**			**Daughter's yrs. of school**		**Mother's yrs. of school**		
Mother's birthplace	Mean	St. Dev.	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	N
UK	10.7	5.8	10.1	3.7	4250	10.9	5.5	9.8	3.8	5807
EU(EEA)	10.8	6.2	7.9	3.3	89	12	5.1	8.3	3.4	120
Diff.	-0.2		2.3***			-1.1*		1.6***		
	(-0.29)		(5.68)			(-2.12)		(4.51)		
Non-EU(EEA)	12.7	4.7	7.8	5.1	440	12.3	4.8	8	5.1	671
Diff.	-2.1***		2.3***			-1.4***		1.8***		
	(-7.22)		(11.84)			(-6.17)		(11.29)		

Notes: (Diff.) is the difference in the mean years of schooling of natives and immigrants.
t statistics in parentheses.
* p¡0.05, ** p¡0.01, *** p¡0.001
Source: UKHLS.

Table 2.11: Statistics on child's and parents' years of schooling by grandparents' country of birth

	Father-child pair									
	Son's yrs. of school		**Father's yrs. of school**			**Daughter's yrs. of school**		**Father's yrs. of school**		
Patern. grandparents' birthplace	Mean	St. Dev.	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	N
UK	10.9	5.7	10.6	3.7	4907	11.2	5.3	10.3	3.8	6580
EU	11.3	6.1	10.1	4.3	48	11.4	5.3	9.7	3.9	78
Diff.	-0.4		0.5			-0.1		0.6		
	(-0.44)		(0.89)			(-0.24)		(1.36)		
Non-EU	10.7	6.5	11.6	3.7	18	10.7	6.2	11	4.7	18
Diff.	0.2		-1.0			0.5		-0.7		
	(0.13)		(-1.09)			(0.42)		(-0.79)		
	Mother-child pair									
	Son's yrs. of school		**Mother's yrs. of school**			**Daughter's yrs. of school**		**Mother's yrs. of school**		
Matern. grandparents' birthplace	Mean	St. Dev.	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	N
UK	10.7	5.8	10.1	3.7	4248	10.9	5.5	9.8	3.8	5809
EU	11.5	4.9	10.7	3.5	43	11.6	5.5	10.3	3.9	73
Diff.	-0.9		-0.6			-0.7		-0.4		
	(-0.96)		(-0.99)			(-1.07)		(-1.00)		
Non-EU	11.4	5.9	11.3	5.1	13	13	3.6	12.1	3.6	26
Diff.	-0.8		-1.2			-2.0		-2.2**		
	(-0.45)		(-1.13)			(-1.85)		(-3.00)		

Notes: (Diff.) is the difference in the mean years of schooling of natives and immigrants.
t statistics in parentheses.
* p¡0.05, ** p¡0.01, *** p¡0.001
Source: UKHLS.

2.3.2 Methodology

The paper follows the following estimation strategy:

Part I (a) Following the literature and the discussion above, estimating intergenerational coefficients β for 1.5- and 2nd-generation immigrants.

(b) In order to identify the direction of elasticity, probabilities of whether the child is more likely to upgrade or downgrade versus the parent are estimated.

Part II Estimating intergenerational coefficients and probabilities for 3rd-generation immigrants.

Following Solon (1992) and Dustmann (2008), intergenerational coefficients are estimated by the following two equations, including years of schooling of a child and a parent as an indicator of their socio-economic status:

$$Y_{i1} = \alpha_0 + \alpha_1 X_{i0} + \alpha_2 X_{i1} + \alpha_3 D_{i0} + \beta_1 Y_{i0} + \beta_2 Y_{i0} D_{i0} + \epsilon_{i1} \tag{2.8}$$

$$Y_{i1} = \alpha_0 + \alpha_1 X_{i0} + \alpha_2 X_{i1} + \sum_{j=1}^{N} \alpha_{3j} D_{ij0} + \beta_1 Y_{i0} + \sum_{j=1}^{N} \beta_{2j} Y_{i0} D_{ij0} + \epsilon_{i1} \tag{2.9}$$

Y_{i1} and Y_{i0} are years of schooling of the child and the parent, respectively; X_{i0} and X_{i1} are a set of control variables for parent and child, correspondingly; D_{i0} is a dummy variable for a migrant father; D_{ij0} is a dummy variable for a parent being from country group j.

In order to consider factors affecting parent's and child's educational qualifications, including parental investment in education of the child, the following control variables are included: age of both the child and the parent; years since migration of the parent and the birth of the child; a dummy for the parent's cohort of arrival in the UK (measured by the decade of arrival); a dummy variable for individuals who have siblings; a variable for individuals whose parent was deceased when the individual was 14 years old and a control for individuals whose parent did not live with them when the individual was 14 years old. The cohort dummy is to control for any events or migration policies associated with the year of immigration of the parent.

Number of years since migration and the birth of the child is expected to capture the probability of outmigration. As suggested by Dustmann (2008) investment in the education of children depends on the probability of return migration. On the other hand, one would expect the probability of outmigration to be decreasing in number of years since migration, and hence parents investing heavier in later years. Hence, we include number of years since migration and the birth of the child as a control variable, allowing also for negative values for 1.5-generation migrants.

Thus, we are interested in the estimate of β in the equations (2.8) and (2.9). As discussed in Section 2.2, β represents a coefficient of elasticity, and therefore, it should be explicitly noted here, β does not imply causality. If the variance of years of schooling of parent and child are equal: $\sigma^2_{Y_0} = \sigma^2_{Y_1} = \sigma^2_{Y}$, then the probability limit of β is equal to coefficient of correlation, ρ. If, on the other hand, the equality of variances does not hold, then $plim\ \beta = \rho\ \sigma_{Y_1}/\sigma_{Y_0}$[7].

It should be noted here, that the method by which we estimate years of schooling might be prone to bias. As mentioned in Section 2.3.1, whenever an individual reports educational qualification of a university degree or higher, we add 3 years to secondary schooling. Nevertheless, a degree level or higher might include years of schooling considerably exceeding 3 years if the individuals obtain a graduate degree. Furthermore, as one can observe in Table 2.5, that around 28 percent of children in the sample have university degree or higher, whereas the respective figure for fathers' is 9 percent, and it is 6.5 percent for mothers. Considering the possible measurement error, we should

[7]The F-test for equality of sample variance for our dataset rejects the hypothesis of sample variance equality of years of schooling of sons and fathers. Our interpretation of β, therefore, follows the empirical literature on intergenerational mobility discussed in Section 2.2, and is treated as intergenerational coefficient or elasticity rather than a coefficient of correlation, and $(1 - \beta)$ is interpreted as a measure of intergenerational mobility.

consider what effect it might have on the estimated β. Thus, if instead of measuring true years of schooling of the child, Y_1^*, we have the following: $Y_1 = Y_1^* + v$, and consequently: $plim\ \beta = \rho\ \sqrt{\sigma^2_{Y_1^*} + 2cov(Y_1^*, v) + \sigma^2_v}/\sigma_{Y_0}$. Since $2cov(Y_1^*, v) < 0$ as the negative error deepens with the increase of years of schooling of a child, and $Y_1 < \sqrt{\sigma^2_{Y_1^*} + 2cov(Y_1^*, v) + \sigma^2_v}$, therefore the estimated β will be overestimated, and the measure of intergenerational mobility will be underestimated.

After estimating intergenerational mobility, we move to identifying the direction in which immigrants are more mobile compared with natives. That is, in order to find out whether migrants are doing better than their parents or worse, probabilities of the child upgrading/downgrading versus the parent are estimated:

$$P(Y_i^m = 1|X_i, D_i) = \alpha_0 + \alpha_1 X_i + \alpha_2 D_i + \epsilon_i \tag{2.10}$$

$$P(Y_i^m = 1|X_i, D_{ij}) = \alpha_0 + \alpha_1 X_i + \sum_{j=1}^{N} \alpha_{2j} D_{ij} + \epsilon_i \tag{2.11}$$

where

$$Y_i^U = \begin{cases} 1 & if \quad Y_{i1} > Y_{i0} \\ 0 & if \quad Y_{i1} = Y_{i0} \end{cases}$$

and

$$Y_i^D = \begin{cases} 1 & if \quad Y_{i1} < Y_{i0} \\ 0 & if \quad Y_{i1} = Y_{i0} \end{cases}$$

X_i is a set of control variables for parent and child, including number of years since migration and the birth of the child; age of the child and the parent; parent's cohort; a dummy for siblings; a dummy for a deceased parent and a control parent not living with the child.

We estimate the equations (2.10) and (2.11) by least squares separately for $m = U$ (probability of the child upgrading his education compared with the parent) and $m = D$ (probability of the child's education downgrading compared with the parent's).

Linear probabilities estimate whether immigrants are more likely to upgrade versus their parents or downgrade. We proceed with linear probabilities as opposed to probit models due to the non-normal form of distribution of the probabilities. Furthermore, to correct heteroskedasticity associated with linear probability models, we use robust standard errors (Long (1997), p. 38-40).

2.4 Results

2.4.1 Part I: 1.5- and 2nd-generation immigrants

1.5- and 2nd-generation immigrants are defined as individuals born in the UK and those who arrive in the UK before the age of seven, respectively, with either parent being a migrant. One question that might arise with this definition is whether we must consider an individual with one of the parents being a UK-born immigrant. That is, the heterogeneous effect of immigrants (which might include the notion of ethnic capital) might not be prevailing in the case of a UK-born parent. In order to check that hypothesis, as a first step in analysing 1.5- and 2nd-generation migrants, we regress years of schooling of the parent on years of schooling of the child by including the two groups of immigrants separately in the regression. Tables 2.12 and 2.13 summarise the results of these regressions for father-child and mother-child pairs. Column I of the tables includes the variables for parent's years of schooling, dummy variables for immigrants and interaction terms of parent's years of schooling and immigrant dummy variable. Column II also includes control variables, except for variables for cohorts of arrival of the immigrant parent in the UK, while column III also includes controls for a cohort of arrival.

The mobility coefficient of natives is represented by the coefficients of father's and mother's years of schooling. The mobility coefficient of immigrants is the sum of the coefficient of parent's years of schooling and the coefficient of the interaction term of the respective immigrant group. Hence, the results indicate that in the case when mother of the child is UK-born and father is immigrant, mobility coefficient of father child parent is not statistically significant, and hence we cannot conclude that it is different from natives. The same is mostly true for mothers when the father is UK-born, except for the case of the regression with cohorts of arrival (Table 2.13).

Therefore, in the further analysis, we limit our sample of 1.5- and 2nd-generation immigrants to those whose both parents are immigrants. we concentrate on looking into father-son and father-daughter pairs while including mother-son and mother-daughter pairs as a robustness exercises.

Table 2.12: Intergenerational coefficients: both parents being immigrant versus only father being migrant

The dependent variable is child's years of schooling			
	I	**II**	**III**
Father's years of schooling	0.470***	0.395***	0.395***
	(0.013)	(0.013)	(0.013)
Both parents immigrants=1 × Father's years of schooling	–0.188***	–0.132***	–0.140***
	(0.032)	(0.031)	(0.031)
Only father immigrant=1 × Father's years of schooling	–0.045	–0.022	–0.028
	(0.055)	(0.054)	(0.055)
Both parents immigrants	3.908***	2.927***	1.726***
	(0.317)	(0.330)	(0.438)
Only father immigrant	1.193**	0.768	–0.194
	(0.589)	(0.595)	(0.653)
Years since migration of the father and birth of the child		0.009	–0.017
		(0.014)	(0.019)
father s age		0.013***	0.013***
		(0.001)	(0.001)
child's age		–0.071***	–0.072***
		(0.005)	(0.005)
Father not living with respondent when they were 14 years old		–1.860***	–1.820***
		(0.338)	(0.338)
Father deceased when the child was 14 years old		0.043	0.073
		(0.282)	(0.282)
The respondent has siblings		–0.211	–0.232*
		(0.138)	(0.138)
Controls (excluding parent's cohort)	NO	YES	YES
Controls for parent's cohort	NO	NO	YES
N	13421	13421	13421

Notes: (I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.13: Intergenerational coefficients: both parents being immigrant versus only the mother being migrant

The dependent variable is child's years of schooling			
	I	**II**	**III**
Mother's years of schooling	0.544***	0.458***	0.460***
	(0.014)	(0.014)	(0.014)
Both parents immigrants=1 × Mother's years of schooling	–0.268***	–0.201***	–0.205***
	(0.032)	(0.032)	(0.032)
Only mother immigrant=1 × Mother's years of schooling	–0.092	–0.108	–0.160**
	(0.069)	(0.068)	(0.070)
Both parents immigrants	4.715***	3.548***	1.964***
	(0.310)	(0.319)	(0.479)
Only mother immigrant	2.130***	1.759**	0.970
	(0.726)	(0.735)	(0.832)
Years since migration of the mother and birth of the child		0.037**	0.027
		(0.016)	(0.022)
mother s age		0.017***	0.017***
		(0.001)	(0.001)
child's age		–0.068***	–0.067***
		(0.005)	(0.006)
Mother not living with respondent when they were 14 years old		–2.064***	–2.034***
		(0.639)	(0.638)
Mother deceased when the child was 14 years old		–0.119	–0.074
		(0.480)	(0.480)
The respondent has siblings		–0.317**	–0.332**
		(0.148)	(0.148)
Controls (excluding parent's cohort)	NO	YES	YES
Controls for parent's cohort	NO	NO	YES
N	11826	11826	11826

Notes: (I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Intergenerational mobility patterns

Hence, we proceed by estimating intergenerational coefficients of natives and immigrants, including the groups of 1.5- and 2nd-generation immigrants separately in the regression.

Table 2.14 (and Table 2.21 in Section 2.4.3) shows the results of regressions with immigrant dummy variables for 1.5- and 2nd-generation immigrants. Based on the regression results, intergenerational mobility of father-child pairs of immigrants is higher compared with natives: β ranges between 0.35-0.53 for natives versus 0.18-0.31 for immigrants. Since intergenerational mobility is an opposite measure of intergenerational coefficient, the lower the intergenerational coefficient is the higher intergenerational mobility is.

Father-son pair of 1.5-generation immigrants appear to be more mobile than 2nd-generation immigrants, whereas the coefficients for father-daughter pairs of 1.5-generation immigrants are not statistically significant. One reason for this might be is the effect of probability of return migration for this group of immigrants, particularly if the immigrant is from a more traditional country with less value for daughters' education.

Table 2.14: Intergenerational coefficients: father-child

	Father-son pair			Father-daughter pair		
	I	II	III	I	II	III
Father's years of schooling	0.527***	0.456***	0.460***	0.432***	0.353***	0.353***
	(0.020)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)
2nd generation migrant=1 × Father's years of schooling	–0.215***	–0.156***	–0.182***	–0.153***	–0.103***	–0.108***
	(0.048)	(0.048)	(0.048)	(0.038)	(0.038)	(0.038)
1.5 generation migrant=1 × Father's years of schooling	–0.306***	–0.275**	–0.268**	–0.036	0.024	0.008
	(0.109)	(0.108)	(0.109)	(0.088)	(0.087)	(0.088)
2nd generation migrant	3.905***	3.556***	2.274***	3.253***	2.358***	0.932*
	(0.497)	(0.535)	(0.712)	(0.390)	(0.408)	(0.532)
1.5 generation migrant	5.111***	4.660***	3.029***	0.483	–0.722	–2.294**
	(1.049)	(1.046)	(1.175)	(0.896)	(0.883)	(0.951)
Years since migration of the father and birth of the child		–0.053**	–0.031		0.013	–0.030
		(0.023)	(0.033)		(0.017)	(0.024)
father s age		0.011***	0.011***		0.014***	0.013***
		(0.002)	(0.002)		(0.002)	(0.002)
child's age		–0.065***	–0.060***		–0.078***	–0.080***
		(0.008)	(0.008)		(0.006)	(0.007)
Father not living with respondent when they were 14 years old		–2.145***	–2.110***		–1.765***	–1.701***
		(0.558)	(0.557)		(0.422)	(0.422)
Father deceased when the child was 14 years old		0.215	0.232		0.027	0.042
		(0.446)	(0.446)		(0.362)	(0.362)
The respondent has siblings		–0.304	–0.324		–0.141	–0.162
		(0.220)	(0.221)		(0.177)	(0.177)
Controls (excluding parent's cohort)	NO	YES	YES	NO	YES	YES
Controls for parent's cohort	NO	NO	YES	NO	NO	YES
N	5709	5709	5709	7712	7712	7712

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results in Table 2.15 (and Table 2.22 in Section 2.4.3) identify differences in intergenerational mobility across countries of origin of the parent. These are estimated using dummy variables for countries of origin or parents and the corresponding interaction terms. The reference country in these regressions is the UK. Here, column I includes all control variables except for a cohort of arrival of the immigrant parent, while column II also includes control variables for a parental cohort of arrival in the UK.

The results by country of origin of the father are heterogeneous.

EU: The mobility coefficient of EU immigrants are not different from natives as the coefficient of the interaction term of EU dummy and father's years of schooling is not significant.

Non-EU: Amongst non-EU immigrants, father-son pairs from India and father-daughter pairs from Pakistan are more mobile than natives, so are father-son and father-daughter pairs from Bangladesh and Central and South America.

Table 2.15: Intergenerational coefficients by father's country of origin: father-child

	Father-son pair		Father-daughter pair	
	I	**II**	**I**	**II**
Father's years of schooling	0.460***	0.461***	0.352***	0.353***
	(0.021)	(0.021)	(0.016)	(0.016)
EU(EEA) × Father's years of schooling	0.001	–0.013	0.062	0.077
	(0.153)	(0.155)	(0.143)	(0.145)
India × Father's years of schooling	–0.342***	–0.354***	–0.118	–0.125
	(0.102)	(0.104)	(0.078)	(0.079)
Pakistan × Father's years of schooling	–0.125	–0.140	–0.138*	–0.138*
	(0.101)	(0.102)	(0.082)	(0.082)
Bangladesh × Father's years of schooling	–0.269**	–0.288**	–0.226*	–0.235*
	(0.131)	(0.131)	(0.135)	(0.136)
Other Africa × Father's years of schooling	–0.224	–0.214	–0.117	–0.130
	(0.170)	(0.171)	(0.114)	(0.115)
Central and South America × Father's years of schooling	–0.283**	–0.298**	–0.201**	–0.196**
	(0.139)	(0.139)	(0.090)	(0.090)
Other countries × Father's years of schooling	–0.154	–0.193	–0.144	–0.153
	(0.152)	(0.156)	(0.142)	(0.142)
Years since migration of the father and birth of the child	–0.018	0.006	0.062***	0.041
	(0.030)	(0.040)	(0.024)	(0.032)
father s age	0.012***	0.012***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
child's age	–0.059***	–0.057***	–0.080***	–0.080***
	(0.008)	(0.008)	(0.007)	(0.007)
Father not living with respondent when they were 14 years old	–2.052***	–2.053***	–1.796***	–1.787***
	(0.586)	(0.586)	(0.442)	(0.442)
Father deceased when the child was 14 years old	0.246	0.244	–0.022	–0.029
	(0.451)	(0.452)	(0.376)	(0.376)
The respondent has siblings	–0.237	–0.237	–0.145	–0.164
	(0.224)	(0.224)	(0.181)	(0.181)
Controls for parent's country	YES	YES	YES	YES
Controls for parent's cohort	NO	YES	NO	YES
N	5485	5485	7375	7375

The dependent variable is child's years of schooling.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

High mobility, however, does not indicate whether immigrants are doing better or worse compared with their parents. In order to identify the direction of mobility, we estimate linear probability models as described in Section 2.3.2.

Level of education against parents

The results of linear probability regressions are presented in Tables 2.16 and A.5 (as well as Tables 2.23 and 2.24). The linear probability regressions estimate: (U) the probability of the educational qualification of the individual (child) upgrading compared with the educational qualification of the parent; and, (D) the probability of a downgrade of the educational qualification of the individual compared with the educational qualification of the parent. Column (I) includes all controls except for cohorts of parent's arrival, and column (II) includes also cohorts.

Based on the estimation results, 2nd-generation immigrants are, overall, more likely to be better educated compared with their parents by around 10% more than natives. The evidence is particularly strong for father-son pair, which nevertheless disappears once controlled for cohort of father's arrival in the UK. Moreover, there are fewer immigrant father-child pairs downgrading, than upgrading, and the average value of the dependent binary variable for upgrading is slightly higher than for downgrading.

Table 2.16: Linear probabilities: father-child

	Father-son pair				Father-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
2nd generation migrant	0.097***	–0.024	0.048	–0.036	0.118***	0.046	0.063*	0.011
	(0.019)	(0.037)	(0.049)	(0.067)	(0.014)	(0.033)	(0.033)	(0.052)
1.5 generation migrant	0.108***	0.006	0.059	–0.038	0.046	0.013	–0.015	–0.018
	(0.034)	(0.073)	(0.056)	(0.100)	(0.038)	(0.060)	(0.050)	(0.084)
Years since migration of the father and birth of the child	–0.001	0.000	0.001	–0.002	–0.001	–0.002	–0.001	–0.001
	(0.002)	(0.003)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
father s age	0.000	–0.000	0.000	–0.000	–0.000**	–0.001***	–0.000**	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.003***	0.003***	0.003***	0.003***	0.001	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father not living with respondent when they were 14 years old	–0.006	0.082*	–0.008	0.080*	–0.017	0.074*	–0.015	0.078*
	(0.060)	(0.046)	(0.060)	(0.046)	(0.041)	(0.041)	(0.041)	(0.042)
Father deceased when the child was 14 years old	0.072**	0.086**	0.073**	0.090**	0.037	0.071**	0.036	0.069**
	(0.029)	(0.037)	(0.029)	(0.037)	(0.028)	(0.035)	(0.028)	(0.035)
The respondent has siblings	–0.018	–0.007	–0.018	–0.008	–0.010	–0.016	–0.011	–0.016
	(0.018)	(0.023)	(0.019)	(0.023)	(0.016)	(0.021)	(0.016)	(0.021)
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	3398	2840	3398	2840	4951	3529	4951	3529
ymean	0.84	0.81	0.84	0.81	0.84	0.78	0.84	0.78

Notes: The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Nevertheless, given the different educational level of parents from different country groups as discussed in Section 2.3, it is important to discuss the results for the country groups. The results by countries are mixed (Table A.5).

EU: EU immigrant-sons seem to have higher propensity to upgrade versus their parents compared with natives, even though they are not more mobile compared with natives (Table 2.15). However, when looking at the likelihood to move in either direction, that is, upgrade or downgrade (Table A.5), the likelihood of EU immigrant-sons is consistent with the mobility patterns, implying that the likelihood of upgrading/downgrading, on average results in intergenerational mobility patterns, that are not different from natives.

EU daughters, on the other hand, do not seem to exhibit different results compared with native father-daughter pair.

Non-EU: Immigrant sons from India are more likely to upgrade and downgrade versus their fathers than native sons. These results are in line with high mobility patterns of immigrant sons from India (Table 2.15). Immigrant sons from Pakistan are more likely to upgrade versus their parents than natives. Table 2.15 on intergenerational mobility, however, does not show any statistically significant results that they are more mobile than natives, even though the sign of the coefficient does, which is in line with Table A.5

for likelihood to be mobile in either direction. The latter is likely to be due to smaller sub-sample of individuals upgrading versus their parents being counterbalanced by those having similar levels of education in the overall sample of immigrant sons from Pakistan. Immigrant sons and daughters from Bangladesh are more likely to upgrade versus their fathers compared with natives, while the statistical significance disappears once we control for the cohort of arrival of the parent. The coefficient is, however, positive. The discrepancy between these results and the intergenerational coefficient for this group of immigrants in Table 2.15 is most likely driven by extreme values for years of schooling of sons, which skews the mean results for intergenerational coefficients as opposed to binary likelihood to upgrade or downgrade. And indeed, when we rerun the regression for intergenerational coefficients excluding the extreme values, the statistical significance for this group drops. Both immigrant sons and daughters from Central/South America are also more likely to upgrade versus their parents compared with natives, while daughters are also likely to downgrade at 10% significance level. These results are in line with the mobility pattern of this group of immigrants as shown in Table 2.15.

In line with intergenerational coefficients, immigrants from Sub-Saharan Africa have a lower probability to downgrade versus their fathers, while fathers in this group, on average, have higher educational qualifications than natives.

Table 2.17: Linear probabilities by father's country of origin: father-child

	Father-son pair				Father-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
EU(EEA)	0.051	–0.092	0.108*	–0.088	0.067**	–0.085	0.036	–0.082
	(0.039)	(0.096)	(0.057)	(0.127)	(0.029)	(0.085)	(0.050)	(0.105)
India	0.188***	0.247***	0.211***	0.222**	0.105***	0.003	0.057	–0.026
	(0.014)	(0.043)	(0.043)	(0.099)	(0.025)	(0.077)	(0.047)	(0.097)
Pakistan	0.112***	–0.087	0.115**	–0.137	0.059*	0.044	0.008	0.013
	(0.034)	(0.096)	(0.050)	(0.133)	(0.033)	(0.054)	(0.051)	(0.074)
Bangladesh	0.100*	0.036	0.094	–0.001	0.099**	0.089	0.049	0.037
	(0.055)	(0.101)	(0.072)	(0.147)	(0.038)	(0.098)	(0.053)	(0.122)
Other Africa	–0.025	–0.322***	–0.015	–0.382***	0.009	–0.238**	–0.045	–0.268**
	(0.058)	(0.104)	(0.064)	(0.147)	(0.044)	(0.097)	(0.060)	(0.113)
Central and South America	0.122***	0.134***	0.155***	0.109	0.135***	0.128***	0.094**	0.122*
	(0.035)	(0.042)	(0.058)	(0.105)	(0.017)	(0.045)	(0.040)	(0.069)
Other countries	0.136***	–0.068	0.159***	–0.100	0.135***	0.131	0.100*	0.084
	(0.034)	(0.172)	(0.047)	(0.192)	(0.028)	(0.102)	(0.053)	(0.123)
Years since migration of the father and birth of the child	–0.000	–0.004	0.004	–0.003	0.003**	0.002	0.003*	0.003
	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.005)
father s age	0.000	–0.000	0.000	–0.000	–0.000**	–0.001***	–0.000**	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.003***	0.003***	0.003***	0.003***	0.001	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father not living with respondent when they were 14 years old	0.006	0.101**	0.007	0.097**	–0.028	0.068	–0.029	0.070
	(0.063)	(0.047)	(0.063)	(0.047)	(0.045)	(0.043)	(0.045)	(0.043)
Father deceased when the child was 14 years old	0.077**	0.083**	0.075**	0.087**	0.031	0.071**	0.031	0.073**
	(0.030)	(0.038)	(0.030)	(0.038)	(0.031)	(0.036)	(0.031)	(0.036)
The respondent has siblings	–0.022	–0.014	–0.019	–0.014	–0.008	–0.015	–0.008	–0.015
	(0.019)	(0.024)	(0.019)	(0.024)	(0.017)	(0.022)	(0.017)	(0.022)
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	3254	2743	3254	2743	4707	3415	4707	3415
ymean	.84	.81	.84	.81	.84	.78	.84	.78

The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

2.4.2 Part II: 3rd-generation immigrants

To understand whether the patterns of intergenerational mobility of immigrants persist across generations, we look into the intergenerational mobility of 3rd-generation immigrants compared to the native population. It should be noted, however, that sub-samples of 3rd-generation immigrants by country of origin is limited, and therefore, conclusions based on these samples should be taken with caution.

Tables 2.18 and 2.19 (also Tables 2.25 and 2.26) include the results of estimations of intergenerational coefficients of 3rd-generation immigrants with a dummy for immigrants and by country groups, respectively.

As evidenced by the results of general regressions, intergenerational mobility of 3rd-generational immigrants disappears for father-son pair, that is, there is no evidence that immigrants are more mobile than natives. Nevertheless, father-daughter pair of 3rd-generation immigrants is significantly more mobile than natives, mainly driven by father-daughter pair from non-EU countries. If, for instance, compared with 2nd-generation immigrants, the intergenerational coefficient of father-daughter pair is much higher for 3rd-generation: around 0.10, whereas it is around 0.25 for 2nd-generation. Mobility patterns of 1.5-generation father-daughter pairs are not different from natives. Thus, one can conclude that daughters take another generation to match the mobility patterns of the sons.

Table 2.18: Intergenerational coefficients: father-child (III generation)

	Father-son pair		Father-daughter pair	
	I	**II**	**I**	**II**
Father's years of schooling	0.528***	0.464***	0.432***	0.352***
	(0.020)	(0.021)	(0.016)	(0.017)
3rd generation migrant=1 × Father's years of schooling	–0.019	–0.091	–0.261**	–0.252**
	(0.165)	(0.163)	(0.128)	(0.126)
3rd generation migrant	0.497	1.172	2.779**	2.743**
	(1.851)	(1.835)	(1.372)	(1.342)
father s age		0.013***		0.014***
		(0.002)		(0.002)
child's age		–0.052***		–0.078***
		(0.009)		(0.007)
Father not living with respondent when they were 14 years old		–1.883***		–2.408***
		(0.626)		(0.480)
Father deceased when the child was 14 years old		0.160		0.013
		(0.517)		(0.418)
The respondent has siblings		–0.287		–0.179
		(0.241)		(0.192)
N	4969	4969	6675	6675

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.19: Intergenerational coefficients by grandparents' country of origin: father-child (III generation)

	Father-son pair	Father-daughter pair
Father's years of schooling	0.463***	0.351***
	(0.021)	(0.017)
EU × Father's years of schooling	–0.185	–0.171
	(0.187)	(0.146)
Non-EU × Father's years of schooling	0.344	–0.436*
	(0.347)	(0.253)
father s age	0.013***	0.014***
	(0.002)	(0.002)
child's age	–0.052***	–0.078***
	(0.009)	(0.007)
Father not living with respondent when they were 14 years old	–1.854***	–2.396***
	(0.627)	(0.481)
Father deceased when the child was 14 years old	0.162	0.013
	(0.517)	(0.418)
The respondent has siblings	–0.291	–0.178
	(0.241)	(0.192)
Controls for paternal grandparents' country of birth	YES	YES
N	4969	6675

Notes: The dependent variable is child's years of schooling.
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.20: Linear probabilities: father-child (III generation)

	Father-son pair				Father-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
3rd generation migrant	–0.028	–0.153*			–0.075	–0.174**		
	(0.060)	(0.088)			(0.053)	(0.073)		
EU			–0.061	–0.262**			–0.084	–0.235***
			(0.070)	(0.108)			(0.057)	(0.085)
Non-EU			0.094	0.092			–0.018	0.034
			(0.098)	(0.108)			(0.127)	(0.124)
father s age	0.000	–0.000	0.000	–0.000	–0.000**	–0.001***	–0.000**	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.004***	0.003***	0.004***	0.003***	0.001	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father not living with respondent when they were 14 years old	0.037	0.100**	0.039	0.092*	–0.025	0.093**	–0.027	0.089**
	(0.067)	(0.049)	(0.067)	(0.049)	(0.058)	(0.044)	(0.058)	(0.044)
Father deceased when the child was 14 years old	0.092***	0.096***	0.092***	0.095**	0.021	0.039	0.021	0.040
	(0.034)	(0.037)	(0.034)	(0.037)	(0.039)	(0.041)	(0.039)	(0.041)
The respondent has siblings	–0.027	–0.018	–0.027	–0.016	–0.011	–0.020	–0.011	–0.020
	(0.021)	(0.024)	(0.021)	(0.024)	(0.019)	(0.022)	(0.019)	(0.022)
N	2848	2609	2848	2609	4148	3251	4148	3251
ymean	.83	.81	.83	.81	.83	.78	.83	.78

Notes: The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) With a control for a migrant grandparent (II) With controls for grandparent's country of birth
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results of linear probabilities for 3rd-generation immigrants, in line with intergenerational mobility coefficients, suggest that immigrants are significantly less likely to downgrade compared with natives: sons are 15% less likely to downgrade and daughters - 17%. The linear probabilities non-EU daughters do not reflect the mobility patterns of 3rd-generation non-EU immigrant-daughters, most likely due to a smaller sample of this group of immigrants.

2.4.3 Robustness tests

Mother-child pairs. As robustness exercises, we look into intergenerational coefficients and linear probabilities of upgrading and downgrading of mother-daughter pairs of 1.5-, 2nd- and 3rd-generation immigrants. Tables 2.21 and 2.22 include regression results for intergeneration coefficients of mother-child pairs with 1.5- and 2nd-generation immigrants, Tables 2.23 and 2.24 - linear probabilities for mother-child pairs with 1.5- and 2nd-generation immigrants, and Tables 2.25, 2.26 and 2.27 - results for mother-child pairs with 3rd-generation immigrants.

Table 2.21: Intergenerational coefficients: mother-child

	Mother-son pair			Mother-daughter pair		
	I	**II**	**III**	**I**	**II**	**III**
Mother's years of schooling	0.569***	0.486***	0.493***	0.529***	0.440***	0.440***
	(0.022)	(0.023)	(0.023)	(0.017)	(0.018)	(0.018)
2nd generation migrant=1 × Mother's years of schooling	–0.296***	–0.233***	–0.259***	–0.236***	–0.170***	–0.182***
	(0.052)	(0.052)	(0.053)	(0.041)	(0.040)	(0.041)
1.5 generation migrant=1 × Mother's years of schooling	–0.288**	–0.247**	–0.286**	–0.232***	–0.167**	–0.144*
	(0.122)	(0.121)	(0.124)	(0.086)	(0.084)	(0.085)
2nd generation migrant	5.072***	4.279***	3.278***	4.150***	3.054***	1.053*
	(0.512)	(0.539)	(0.783)	(0.402)	(0.422)	(0.610)
1.5 generation migrant	5.062***	4.486***	3.182**	2.896***	1.770**	–0.458
	(1.060)	(1.059)	(1.267)	(0.767)	(0.760)	(0.944)
Years since migration of the mother and birth of the child		–0.012	0.032		0.023	0.000
		(0.027)	(0.036)		(0.021)	(0.028)
mother s age		0.016***	0.016***		0.018***	0.017***
		(0.002)	(0.002)		(0.002)	(0.002)
child's age		–0.061***	–0.052***		–0.075***	–0.075***
		(0.008)	(0.009)		(0.007)	(0.007)
Mother not living with respondent when they were 14 years old		–1.758	–1.756		–2.245***	–2.176***
		(1.220)	(1.218)		(0.740)	(0.738)
Mother deceased when the child was 14 years old		0.197	0.346		–0.286	–0.224
		(0.819)	(0.819)		(0.588)	(0.587)
The respondent has siblings		–0.326	–0.312		–0.307	–0.335*
		(0.233)	(0.234)		(0.192)	(0.191)
Controls (excluding parent's cohort)	NO	YES	YES	NO	YES	YES
Controls for parent's cohort	NO	NO	YES	NO	NO	YES
N	4963	4963	4963	6863	6863	6863

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results for mother-child pairs are in line with the patterns of father-child pairs. Mother-child pairs of both 1.5- and 2nd-generation immigrants are (almost equally) more mobile than native mother-child pairs (Table 2.21). In general, mother-child pairs are slightly more mobile than father-child pairs, which is something one would expect, considering the lower average years of schooling of mothers from some country groups. Mobility of daughters is slightly lower than mobility of sons.

Table 2.22: Intergenerational coefficients by mother's country of origin: mother-child

	Mother-son pair		Mother-daughter pair	
	I	**II**	**I**	**II**
Mother's years of schooling	0.491***	0.494***	0.439***	0.440***
	(0.023)	(0.023)	(0.018)	(0.018)
EU(EEA) × Mother's years of schooling	0.115	0.070	0.012	−0.009
	(0.174)	(0.176)	(0.135)	(0.136)
India × Mother's years of schooling	−0.393***	−0.424***	−0.248***	−0.256***
	(0.115)	(0.116)	(0.080)	(0.081)
Pakistan × Mother's years of schooling	−0.183	−0.218*	−0.246***	−0.246***
	(0.113)	(0.116)	(0.081)	(0.081)
Bangladesh × Mother's years of schooling	−0.351**	−0.383***	−0.199	−0.161
	(0.147)	(0.148)	(0.138)	(0.138)
Other Africa × Mother's years of schooling	−0.398**	−0.405**	−0.237*	−0.268**
	(0.192)	(0.193)	(0.133)	(0.135)
Central and South America × Mother's years of schooling	−0.144	−0.185	−0.309***	−0.314***
	(0.160)	(0.161)	(0.098)	(0.098)
Other countries × Mother's years of schooling	−0.296*	−0.316*	−0.108	−0.125
	(0.175)	(0.177)	(0.158)	(0.158)
Years since migration of the mother and birth of the child	−0.037	0.001	0.077***	0.078**
	(0.035)	(0.043)	(0.027)	(0.034)
mother s age	0.017***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
child's age	−0.054***	−0.051***	−0.076***	−0.075***
	(0.009)	(0.009)	(0.007)	(0.007)
Mother not living with respondent when they were 14 years old	−1.676	−1.677	−2.394***	−2.339***
	(1.219)	(1.218)	(0.757)	(0.756)
Mother deceased when the child was 14 years old	0.554	0.607	−0.335	−0.275
	(0.862)	(0.862)	(0.601)	(0.600)
The respondent has siblings	−0.394*	−0.382	−0.274	−0.291
	(0.237)	(0.238)	(0.195)	(0.195)
Controls for parent's country	YES	YES	YES	YES
Controls for parent's cohort	NO	YES	NO	YES
N	4779	4779	6598	6598

The dependent variable is child's years of schooling.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results by countries show more similar results to fathers' for mother-daughter pair versus sons (Table 2.22).

Probabilities of upgrading of children of 1.5- and 2nd-immigrants are in line with results of father-child pairs, with higher probabilities of upgrading compared with natives for all children, except for daughters of 1.5-generation immigrants (Table 2.23).

Table 2.23: Linear probabilities: mother-child

	Mother-son pair				Mother-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
2nd generation migrant	0.099***	−0.014	0.058	−0.068	0.097***	−0.012	0.057	0.043
	(0.017)	(0.040)	(0.047)	(0.086)	(0.016)	(0.035)	(0.042)	(0.062)
1.5 generation migrant	0.109***	0.006	0.055	−0.095	0.047	−0.073	0.006	−0.012
	(0.028)	(0.083)	(0.058)	(0.140)	(0.036)	(0.074)	(0.056)	(0.097)
Years since migration of the mother and birth of the child	−0.002	−0.003	0.002	−0.004	−0.001	−0.001	0.002	−0.001
	(0.001)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.004)
mother s age	−0.000	−0.000**	0.000	−0.000**	0.000	−0.001***	0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.004***	0.004***	0.005***	0.004***	0.002***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother not living with respondent when they were 14 years old	−0.031	0.070	−0.030	0.072	−0.092	0.030	−0.090	0.029
	(0.159)	(0.073)	(0.160)	(0.074)	(0.088)	(0.069)	(0.089)	(0.070)
Mother deceased when the child was 14 years old	−0.066	−0.109	−0.055	−0.105	0.128***	0.159***	0.130***	0.160***
	(0.075)	(0.098)	(0.074)	(0.096)	(0.027)	(0.034)	(0.027)	(0.034)
The respondent has siblings	−0.025	−0.018	−0.022	−0.021	0.018	0.031	0.018	0.031
	(0.017)	(0.023)	(0.017)	(0.022)	(0.018)	(0.024)	(0.018)	(0.024)
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	2991	2358	2991	2358	4486	3049	4486	3049
ymean	.87	.84	.87	.84	.85	.78	.85	.78

Notes: The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%. Standard errors in parentheses.

Table 2.24: Linear probabilities by mother's country of birth: mother-child

	Mother-son pair				Mother-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
EU(EEA)	0.035	–0.075	0.017	–0.198	0.065**	–0.046	0.090*	0.033
	(0.041)	(0.092)	(0.065)	(0.134)	(0.032)	(0.083)	(0.049)	(0.100)
India	0.176***	0.208***	0.108**	0.019	0.110***	–0.047	0.097**	0.014
	(0.013)	(0.026)	(0.053)	(0.114)	(0.025)	(0.093)	(0.047)	(0.113)
Pakistan	0.118***	–0.141	0.041	–0.325**	0.078**	0.008	0.055	0.057
	(0.030)	(0.120)	(0.063)	(0.157)	(0.032)	(0.063)	(0.057)	(0.082)
Bangladesh	0.102**	–0.065	0.003	–0.312*	0.102**	–0.184	0.080	–0.127
	(0.048)	(0.109)	(0.075)	(0.169)	(0.043)	(0.153)	(0.062)	(0.174)
Other Africa	0.091**	–0.151	0.018	–0.325*	0.003	–0.162*	–0.016	–0.123
	(0.042)	(0.129)	(0.064)	(0.172)	(0.049)	(0.093)	(0.062)	(0.120)
Central and South America	0.088**	0.092	0.048	–0.029	0.120***	0.128***	0.119***	0.219***
	(0.041)	(0.059)	(0.076)	(0.124)	(0.017)	(0.045)	(0.040)	(0.072)
Other countries	0.138***	0.080	0.074	–0.062	0.087*	–0.112	0.097	–0.034
	(0.028)	(0.111)	(0.060)	(0.144)	(0.047)	(0.159)	(0.059)	(0.157)
Years since migration of the mother and birth of the child	–0.002	–0.007	0.000	–0.012**	0.002	–0.003	0.004*	0.001
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.006)
mother s age	0.000	–0.001**	0.000	–0.001**	0.000	–0.001***	0.000	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.004***	0.004***	0.005***	0.004***	0.002***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother not living with respondent when they were 14 years old	–0.030	0.063	–0.030	0.056	–0.048	0.052	–0.050	0.053
	(0.159)	(0.073)	(0.160)	(0.074)	(0.089)	(0.066)	(0.089)	(0.066)
Mother deceased when the child was 14 years old	–0.041	–0.097	–0.034	–0.088	0.123***	0.161***	0.124***	0.159***
	(0.077)	(0.103)	(0.076)	(0.100)	(0.029)	(0.036)	(0.029)	(0.038)
The respondent has siblings	–0.031*	–0.028	–0.028	–0.031	0.016	0.025	0.016	0.022
	(0.017)	(0.023)	(0.017)	(0.023)	(0.018)	(0.024)	(0.018)	(0.024)
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	2863	2289	2863	2289	4288	2962	4288	2962
ymean	.87	.84	.87	.84	.85	.78	.85	.78

The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Results of upgrading and downgrading by countries (Table 2.24) do not show the same mobility results due to extreme values of education levels in mobility regressions in Table 2.22.

Tables 2.25 and 2.26 show results for intergenerational coefficients for 3rd-generation immigrants. According to these results, 3rd-generation immigrants are not different from natives in terms of educational mobility, except for daughters from the EU, who are more mobile than natives.

Table 2.25: Intergenerational coefficients: mother-child (III generation)

	Mother-son pair		Mother-daughter pair	
	I	**II**	**I**	**II**
Mother's years of schooling	0.570***	0.495***	0.529***	0.439***
	(0.022)	(0.024)	(0.018)	(0.018)
3rd generation migrant=1 × Mother's years of schooling	–0.257	–0.256	–0.149	–0.181
	(0.191)	(0.189)	(0.135)	(0.132)
3rd generation migrant	3.215	3.171	2.139	2.269
	(2.206)	(2.182)	(1.552)	(1.521)
mother s age		0.018***		0.018***
		(0.002)		(0.002)
child's age		–0.048***		–0.074***
		(0.009)		(0.007)
Mother not living with respondent when they were 14 years old		–1.729		–3.079***
		(1.266)		(0.834)
Mother deceased when the child was 14 years old		0.550		0.066
		(0.989)		(0.665)
The respondent has siblings		–0.436*		–0.338
		(0.254)		(0.207)
N	4302	4302	5905	5905

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.26: Intergenerational coefficients by grandparents' country of origin: mother-child (III generation)

	Mother-son pair	Mother-daughter pair
Mother's years of schooling	0.495***	0.439***
	(0.024)	(0.018)
EU × Mother's years of schooling	–0.226	–0.258*
	(0.236)	(0.153)
Non-EU × Mother's years of schooling	–0.295	0.063
	(0.319)	(0.295)
mother s age	0.018***	0.018***
	(0.002)	(0.002)
child's age	–0.048***	–0.074***
	(0.009)	(0.007)
Mother not living with respondent when they were 14 years old	–1.730	–3.078***
	(1.266)	(0.834)
Mother deceased when the child was 14 years old	0.548	0.083
	(0.989)	(0.665)
The respondent has siblings	–0.437*	–0.336
	(0.254)	(0.207)
Controls for paternal grandparents' country of birth	YES	YES
N	4302	5905

Notes: The dependent variable is child's years of schooling.
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.27: Linear probabilities: mother-child (III generation)

	Mother-son pair				Mother-daughter pair			
	I		**II**		**I**		**II**	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
3rd generation migrant	0.047	0.011			0.033	0.023		
	(0.055)	(0.073)			(0.044)	(0.063)		
EU			0.017	–0.048			0.046	0.020
			(0.067)	(0.092)			(0.048)	(0.074)
Non-EU			0.166***	0.199***			–0.006	0.028
			(0.025)	(0.020)			(0.097)	(0.118)
mother s age	–0.000	–0.001***	–0.000	–0.001***	0.000	–0.001***	0.000	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.005***	0.004***	0.005***	0.004***	0.002***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mother not living with respondent when they were 14 years old	–0.032	0.063	–0.032	0.063	–0.116	0.052	–0.116	0.052
	(0.159)	(0.079)	(0.159)	(0.079)	(0.120)	(0.069)	(0.120)	(0.069)
Mother deceased when the child was 14 years old	–0.025	–0.057	–0.025	–0.056	0.143***	0.143***	0.143***	0.143***
	(0.096)	(0.100)	(0.096)	(0.100)	(0.034)	(0.038)	(0.034)	(0.038)
The respondent has siblings	–0.036*	–0.030	–0.036*	–0.030	0.018	0.027	0.019	0.027
	(0.019)	(0.023)	(0.019)	(0.023)	(0.020)	(0.025)	(0.020)	(0.025)
N	2469	2184	2469	2184	3715	2802	3715	2802
ymean	.86	.84	.86	.84	.84	.78	.84	.78

Notes: The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) With a control for a migrant grandparent (II) With controls for grandparent's country of birth
(U) Probability of upgrade (D) Probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results for linear probabilities mainly confirm these findings of 3rd-generation immigrants not being different from natives in terms of intergenerational mobility (Table 2.27).

Years of schooling of parental country. One of the main concerns for the estimations of intergenerational coefficients is the comparability of parental education of immigrants with the child's given they were educated in different countries. To address the issue, we conduct a robustness test using theoretical years of schooling of the parental country of birth instead of those of the UK to derive years of schooling of the child.

Table 2.28: Robustness test: dependent variable - years of schooling of the child using parent's country data

	Father-son pair			Father-daughter pair		
	I	**II**	**III**	**I**	**II**	**III**
Father's years of schooling	0.527***	0.458***	0.461***	0.433***	0.356***	0.355***
	(0.020)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)
2nd generation migrant=1 × Father's years of schooling	–0.221***	–0.164***	–0.190***	–0.146***	–0.100***	–0.104***
	(0.048)	(0.048)	(0.048)	(0.038)	(0.038)	(0.038)
1.5 generation migrant=1 × Father's years of schooling	–0.315***	–0.280***	–0.277**	–0.035	0.025	0.008
	(0.108)	(0.107)	(0.109)	(0.088)	(0.087)	(0.088)
2nd generation migrant	3.284***	2.814***	1.662**	2.454***	1.462***	0.111
	(0.494)	(0.533)	(0.709)	(0.390)	(0.409)	(0.532)
1.5 generation migrant	4.377***	3.876***	2.423**	–0.309	–1.526*	–2.999***
	(1.044)	(1.041)	(1.170)	(0.896)	(0.884)	(0.952)
Controls (excluding parent's cohort)	NO	YES	YES	NO	YES	YES
Controls for parent's cohort	NO	NO	YES	NO	NO	YES
N	5708	5708	5708	7712	7712	7712

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results in Tables 2.28 and 2.29 are largely in line with the estimates in Section 2.4.1, suggesting that heterogeneity in theoretical years of schooling across countries have no significant impact on the results.

Table 2.29: Robustness test: dependent variable - years of schooling of the child using parent's country data (by country groups)

	Father-son pair		Father-daughter pair	
	I	**II**	**I**	**II**
Father's years of schooling	0.461***	0.462***	0.352***	0.353***
	(0.021)	(0.021)	(0.016)	(0.016)
EU(EEA) × Father's years of schooling	–0.004	–0.013	0.062	0.077
	(0.154)	(0.156)	(0.143)	(0.145)
India × Father's years of schooling	–0.342***	–0.354***	–0.118	–0.125
	(0.102)	(0.103)	(0.078)	(0.079)
Pakistan × Father's years of schooling	–0.140	–0.156	–0.138*	–0.138*
	(0.101)	(0.102)	(0.082)	(0.082)
Bangladesh × Father's years of schooling	–0.282**	–0.303**	–0.226*	–0.235*
	(0.130)	(0.131)	(0.135)	(0.136)
Other Africa × Father's years of schooling	–0.242	–0.235	–0.117	–0.130
	(0.169)	(0.171)	(0.114)	(0.115)
Central and South America × Father's years of schooling	–0.286**	–0.301**	–0.201**	–0.196**
	(0.138)	(0.139)	(0.090)	(0.090)
Other countries × Father's years of schooling	–0.134	–0.183	–0.144	–0.153
	(0.151)	(0.155)	(0.142)	(0.142)
Years since migration of the father and birth of the child	–0.012	0.017	0.062***	0.041
	(0.030)	(0.040)	(0.024)	(0.032)
father s age	0.012***	0.012***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
child's age	–0.058***	–0.055***	–0.080***	–0.080***
	(0.008)	(0.008)	(0.007)	(0.007)
Father not living with respondent when they were 14 years old	–2.037***	–2.038***	–1.796***	–1.787***
	(0.584)	(0.585)	(0.442)	(0.442)
Father deceased when the child was 14 years old	0.259	0.256	–0.022	–0.029
	(0.450)	(0.451)	(0.376)	(0.376)
The respondent has siblings	–0.248	–0.246	–0.145	–0.164
	(0.223)	(0.224)	(0.181)	(0.181)
Controls (excluding parent's cohort)	YES	YES	YES	YES
Controls for parent's country	YES	YES	YES	YES
Controls for parent's cohort	NO	YES	NO	YES
N	5484	5484	7375	7375

The dependent variable is child's years of schooling.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Quality of education. As a second robustness test accounting for quality of education, we use the methodology applied by Razin & Wahba (2015). In the study, they use average test scores of international student achievement tests in maths and science (primary through to the end of secondary school) from Hanushek & Woessmann (2012) to adjust the stock of migrants and migration rates for skill quality. We follow Razin & Wahba (2015) by using the average test scores to adjust father's years of schooling for quality of education. We weight father's years of schooling by the ratio of test score of father's country of birth divided by the test score of the UK, since all children in our sample are UK-educated. Consecutively, the weight for a UK-born father is 1. In the cases where the score of a country is not available, for example, Bangladesh, we use the average test score of the respective region, which, in this case, is South Asia.

Table 2.30: Robustness test: father's years of schooling adjusted for education quality

	Father-son pair			Father-daughter pair		
	I	**II**	**III**	**I**	**II**	**III**
Adjusted father's years of schooling	0.527***	0.456***	0.460***	0.432***	0.352***	0.353***
	(0.020)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)
2nd generation migrant=1 × Adjusted father's years of schooling	–0.203***	–0.131**	–0.155***	–0.136***	–0.080*	–0.085**
	(0.054)	(0.054)	(0.054)	(0.043)	(0.042)	(0.042)
1.5 generation migrant=1 × Adjusted father's years of schooling	–0.249*	–0.229*	–0.222*	0.023	0.080	0.062
	(0.132)	(0.131)	(0.132)	(0.104)	(0.102)	(0.104)
2nd generation migrant	4.148***	3.724***	2.359***	3.440***	2.503***	1.032*
	(0.501)	(0.534)	(0.714)	(0.390)	(0.405)	(0.530)
1.5 generation migrant	5.030***	4.602***	2.940**	0.590	–0.610	–2.242**
	(1.059)	(1.053)	(1.183)	(0.898)	(0.885)	(0.954)
Controls (excluding parent's cohort)	NO	YES	YES	NO	YES	YES
Controls for parent's cohort	NO	NO	YES	NO	NO	YES
N	5709	5709	5709	7712	7712	7712

Notes: The dependent variable is child's years of schooling.
(I) No controls included (II) Controls included, except for parent's cohort (III) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.31: Robustness test: father's years of schooling adjusted for education quality (by country groups)

	Father-son pair		Father-daughter pair	
	I	**II**	**I**	**II**
Adjusted father's years of schooling	0.461***	0.462***	0.352***	0.353***
	(0.021)	(0.021)	(0.016)	(0.016)
EU(EEA) × Adjusted father's years of schooling	0.005	–0.004	0.051	0.065
	(0.156)	(0.158)	(0.143)	(0.145)
India × Adjusted father's years of schooling	–0.323***	–0.337***	–0.082	–0.090
	(0.117)	(0.119)	(0.090)	(0.091)
Pakistan × Adjusted father's years of schooling	–0.089	–0.107	–0.103	–0.104
	(0.117)	(0.118)	(0.095)	(0.095)
Bangladesh × Adjusted father's years of schooling	–0.253*	–0.277*	–0.206	–0.216
	(0.151)	(0.152)	(0.156)	(0.158)
Other Africa × Adjusted father's years of schooling	–0.194	–0.178	–0.058	–0.078
	(0.208)	(0.209)	(0.140)	(0.140)
Central and South America × Adjusted father's years of schooling	–0.235	–0.255	–0.159	–0.153
	(0.176)	(0.176)	(0.114)	(0.114)
Other countries × Adjusted father's years of schooling	–0.045	–0.103	–0.146	–0.154
	(0.180)	(0.184)	(0.155)	(0.155)
Years since migration of the father and birth of the child	–0.014	0.015	0.062***	0.041
	(0.030)	(0.040)	(0.024)	(0.032)
father s age	0.012***	0.012***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
child's age	–0.058***	–0.056***	–0.080***	–0.080***
	(0.008)	(0.008)	(0.007)	(0.007)
Father not living with respondent when they were 14 years old	–2.038***	–2.040***	–1.795***	–1.787***
	(0.584)	(0.585)	(0.442)	(0.442)
Father deceased when the child was 14 years old	0.260	0.258	–0.026	–0.033
	(0.450)	(0.451)	(0.376)	(0.376)
The respondent has siblings	–0.249	–0.247	–0.147	–0.165
	(0.223)	(0.224)	(0.181)	(0.181)
Controls (excluding parent's cohort)	YES	YES	YES	YES
Controls for parent's country	YES	YES	YES	YES
Controls for parent's cohort	NO	YES	NO	YES
N	5484	5484	7375	7375

The dependent variable is child's years of schooling.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

The results of regressions for intergenerational coefficients with quality adjusted years of schooling are presented in Tables 2.30-2.31. As a result of the quality adjustment, the magnitude of mobility of immigrants decreases slightly, particularly for separate country groups. However, that does not affect the conclusions about the patterns of intergenerational mobility of immigrants versus natives. The results by countries are mostly unaffected for sons, except for sons from Central and South America; the coefficients of interaction terms of this group become statistically not significant.

Tables 2.32-2.33 include the results for the probabilities of upgrading and downgrading with quality-adjusted years of schooling of the father. These results suggest some upwards readjustment of the probabilities of upgrading versus their parents of immigrant children compared with natives.

Table 2.32: Linear probabilities with quality-adjusted years of schooling: father-child

	Father-son pair				Father-daughter pair			
	I		II		I		II	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
2nd generation migrant	0.166***	0.048	0.150***	–0.077	0.143***	0.037	0.082**	–0.043
	(0.013)	(0.060)	(0.032)	(0.133)	(0.012)	(0.052)	(0.035)	(0.084)
1.5 generation migrant	0.170***	0.118	0.156***	0.035	0.109***	–0.018	0.032	–0.152
	(0.015)	(0.079)	(0.032)	(0.129)	(0.026)	(0.081)	(0.046)	(0.118)
Controls (excluding parent's cohort)	YES	YES	YES	YES	YES	YES	YES	YES
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	3310	2664	3310	2664	4776	3321	4776	3321
ymean	0.85	0.82	0.85	0.82	0.85	0.78	0.85	0.78

Notes: The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Adjusted probability of upgrade (D) Adjusted probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table 2.33: Adjusted linear probabilities by father's country of origin: father-child

	Father-son pair				Father-daughter pair			
	I		II		I		II	
	U	**D**	**U**	**D**	**U**	**D**	**U**	**D**
EU(EEA)	0.125***	0.124*	0.141***	0.019	0.149***	0.138***	0.106***	0.112
	(0.026)	(0.073)	(0.037)	(0.131)	(0.010)	(0.028)	(0.033)	(0.071)
India	0.194***	0.318**	0.184***	0.272	0.132***	–0.109	0.072*	–0.196
	(0.012)	(0.127)	(0.030)	(0.183)	(0.017)	(0.122)	(0.039)	(0.136)
Pakistan	0.159***	–0.083	0.136***	–0.201	0.109***	0.010	0.045	–0.086
	(0.022)	(0.129)	(0.035)	(0.165)	(0.025)	(0.068)	(0.042)	(0.092)
Bangladesh	0.146***	–0.036	0.117**	–0.159	0.114***	–0.164	0.043	–0.264
	(0.041)	(0.146)	(0.051)	(0.178)	(0.031)	(0.196)	(0.045)	(0.214)
Other Africa	0.196***	0.195***	0.172***	0.101	0.142***	–0.067	0.071*	–0.132
	(0.011)	(0.030)	(0.029)	(0.107)	(0.019)	(0.152)	(0.043)	(0.166)
Central and South America	0.164***	0.133*	0.154***	0.004	0.147***	0.059	0.100***	0.009
	(0.018)	(0.075)	(0.039)	(0.161)	(0.012)	(0.097)	(0.032)	(0.134)
Other countries	0.140***	–0.102	0.128***	–0.248	0.140***	0.077	0.080*	–0.032
	(0.033)	(0.197)	(0.039)	(0.233)	(0.026)	(0.122)	(0.046)	(0.141)
Years since migration of the father and birth of the child	–0.001	–0.006	0.002*	–0.005	0.002***	0.007***	0.003**	0.010**
	(0.001)	(0.005)	(0.001)	(0.006)	(0.001)	(0.003)	(0.001)	(0.005)
father s age	0.000	–0.000	0.000	–0.000	–0.000**	–0.001***	–0.000**	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
child's age	0.003***	0.003***	0.003***	0.003***	0.001	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father not living with respondent when they were 14 years old	0.025	0.090*	0.026	0.087*	–0.035	0.062	–0.034	0.065
	(0.056)	(0.046)	(0.056)	(0.047)	(0.044)	(0.046)	(0.044)	(0.045)
Father deceased when the child was 14 years old	0.067**	0.087**	0.065**	0.094**	0.023	0.053	0.022	0.054
	(0.027)	(0.039)	(0.027)	(0.037)	(0.029)	(0.039)	(0.029)	(0.039)
The respondent has siblings	–0.022	–0.012	–0.019	–0.014	–0.004	–0.013	–0.005	–0.013
	(0.018)	(0.024)	(0.018)	(0.024)	(0.017)	(0.022)	(0.017)	(0.022)
Controls (excluding parent's cohort)	YES	YES	YES	YES	YES	YES	YES	YES
Controls for parent's cohort	NO	NO	YES	YES	NO	NO	YES	YES
N	3310	2664	3310	2664	4776	3321	4776	3321
ymean	.85	.82	.85	.82	.85	.78	.85	.78

The dependent variable is the binary variable of child's educational qualification upgrading / downgrading versus parent's.
(I) Controls included, except for parent's cohort (II) Controls included, including parent's cohort
(U) Adjusted probability of upgrade (D) Adjusted probability of downgrade
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Other. The results are also robust when years of schooling of the parent with the highest level of education are considered.

2.5 Conclusion

This paper explores the trends of intergenerational mobility in education of 1.5-, 2nd- and 3rd-generation immigrants in the UK compared with the native population. It finds that 1.5- and 2nd-generation immigrants are more mobile than natives. Country-wise, EU immigrants do not exhibit mobility patterns different from UK natives. Non-EU immigrants, on the other hand, are more mobile than natives, particularly immigrants from South Asia. Even though the magnitude of mobility weakens slightly, when years of schooling of the father are adjusted by quality of education by countries, the mobility patterns are, overall, not altered from the adjustment.

The direction of mobility of 1.5- and 2nd-generation immigrants is mainly leaning towards outperforming their parents, although this highly depends on parents' average years of schooling.

The educational mobility pattern for 3rd-generation immigrants mainly disappears, except for daughters. It takes another generation for daughters, particularly from non-EU countries, to catch up with the mobility patterns of sons. Given the lower sample sizes by country of origin of 3rd-generation immigrants, however, these results should be taken with caution.

Higher mobility of immigrants, and particularly, higher probability of immigrants to be better educated than their parents, can potentially improve the level of equality in the UK. Knowing about the changing nature of the UK population and its effect on the economy and inequality in the country is important for long-term policy-making, as it helps to determine the scale of policy action required to address the general level of income inequality in the UK.

Chapter 3

The impact of labour market discrimination on benefit receipt of second-generation immigrants in the UK

Abstract. This paper[1] suggests and tests the hypothesis that the tendency of immigrants to claim more benefits is linked to income discrimination in the labour market. It uses panel data from the UK Household Longitudinal Survey, to look at second-generation immigrants in comparison to UK natives. By estimating labour market discrimination against immigrants using available methodology on income decomposition, the paper then uses the estimates of discrimination to study whether labour market discrimination affects the welfare dependency of immigrants. This paper shows that immigrants' likelihood to move into state welfare dependency increases when there is discrimination in the labour market. The results differ for EU versus non-EU second-generation immigrants.

3.1 Introduction

Sustaining a large number of people on state welfare benefits is costly for a country, therefore, it is important to understand the reasons behind welfare dependency. Given its importance, the issue of state welfare dependency of immigrants is a constant topic of political discussion, including in the United Kingdom.

[1] I am very grateful to my supervisors, Jackie Wahba and Corrado Giulietti, for their continuous support and guidance. I am also grateful to Jeffrey Wooldridge, Carmine Ornaghi, Michael Vlassopoulos and Thomas Gall for their valuable comments, as well as the participants of Ruhr-University Bochum 12th RGS Doctoral Conference in Economics, LISER and CPC 5th Workshop on the Economics of Migration, and workshops and seminars at the University of Southampton.

Due to the growing immigrant population of the UK, many studies concentrate on the patterns of state welfare dependency of immigrants compared with natives. And while the effect of recent immigration can be perceived as temporary and may fade over time as immigrants return to their home countries or assimilate, the effect of British-born second-generation immigrants is persistent. According to the Office for National Statistics reports[2], the share of children born in England and Wales to foreign-born parents has been increasing since the 1990s, and currently, one in three childbirths are to foreign-born parents.

Labour market outcomes of immigrants, as well as the patterns of claiming state welfare benefits by immigrants versus natives, have been vastly explored, whereas the reasons immigrants claim benefits have not been studied much. This paper explores the link between income discrimination in the labour market of the UK and state welfare dependency of second-generation immigrants.

This paper contributes to the literature in multiple ways. Firstly, it suggests a method of exploring the link between income discrimination and state welfare dependency of second-generation immigrants which, to the best of our knowledge, has not been explored.

Secondly, the estimations are strengthened by using second-generation immigrants as a subject matter, which reduces biases associated with first-generation immigrants, such as return-migration, incomparability in levels of education and the language factor, which can be a possible reason for differences in labour market outcomes for immigrants compared with natives.

And finally, the factors uncovered for second-generation immigrants can be valid for first-generation immigrants as well, as the paper explores patterns for different ethnic groups, which, if there for second-generation immigrants are most likely to be even stronger for first-generation immigrants, as discussed by Brücker et al. (2002).

There are many studies on the topic of reliance on welfare benefits by first-generation immigrants compared with natives (Borjas & Hilton 1996, Hansen & Lofstrom 2003, Barrett & McCarthy 2008, Riphahn 1998, Castronova et al. 2001, Bruckmeier & Wiemers 2017). Most studies find higher welfare dependency of immigrants when looking at raw data. Yet first-generation immigrants are subject to different initial conditions compared with the native population, thus making the comparison subject to biases, such as incomparable levels of education and work experience, or language skills of immigrants being different from natives. That is, as evidenced by Castronova et al. (2001) and Bruckmeier & Wiemers (2017), once the initial conditions are considered, there is no significant difference in the probabilities of claiming benefits by immigrants versus natives, and, in some cases, (Riphahn 1998, for instance) the probabilities of claiming are lower for immigrants.

[2] www.ons.gov.uk

The differences in the initial conditions can make immigrants less competitive in the labour market thus moving them into a higher risk of relying on welfare support. Brücker et al. (2002) discuss that several factors might place immigrants into a situation, where they are more likely to be on welfare dependency than natives. They highlight that immigrants might self-select to countries with generous welfare systems, hence their income is likely to depend not only on observable characteristics but also on some unobservables that result in welfare dependency. Immigrants are also likely to be affected by certain migration-related idiosyncrasies, such as psychological factors from moving to another country and language issues, which might increase the risk of welfare dependency, or weaken the welfare entitlement. Besides, immigrants might have limited transferability of their entitlements in their home countries, such as work experience; or immigrants might also have better or worse networks compared with natives, which will affect their labour market outcomes. Two more reasons the welfare dependency of immigrants might be different from natives outlined by Brücker et al. (2002) are discrimination and reduced wages. Discrimination in the labour market might push immigrants towards welfare dependency. Discrimination might also affect immigrants' incentives to look for a job if it results in reduced wages for immigrants.

The factors above make a comparison of natives and first-generation immigrants difficult. That is, while the probability of welfare dependency might be different for immigrants compared with natives, this might be due to these factors contributing to immigrants being different from natives, rather than being attributable to the propensity of immigrants to claim more or fewer benefits. These factors might also be different across countries.

For second-generation immigrants, on the other hand, the factors of self-selection, migration-related idiosyncrasies, non-transferability of entitlements and networks mostly disappear. The factors of discrimination, and reduced wages as a result of discrimination, however, continue to be of great importance in explaining differences in take-up of benefits between immigrants and natives.

Many studies find significant income discrimination against both first and second-generation immigrants or income gaps for certain groups of immigrants or ethnic minorities in the UK (Chiswick 1980, Blackaby et al. 2002, Bell 1997, Clark & Drinkwater 2008, Dustmann & Theodoropoulos 2010). This study uses estimates of income discrimination against second-generation immigrants to test the hypothesis that discrimination affects the probability of to claim state welfare benefits. It uses panel data from the UK Household Longitudinal Study, first to estimate wage discrimination against immigrants, which is in line with findings from previous studies. It then uses these estimates to assess the impact of discrimination on the welfare dependency of immigrants.

The paper is organised as follows: Section 3.2 provides a review of relevant literature, Section 3.3 described the data, provides data analysis and describes the estimation method, Section 3.4 discusses the results and robustness tests, and Section 3.5 concludes.

3.2 Background studies

The issue of the reliance of immigrants on the welfare system of the host country has been widely studied in economic literature. Most studies look into probabilities of claiming benefits by first-generation immigrants versus natives. Yet, there are only a few studies that discuss the reasons for immigrant dependency on welfare benefits. This paper discusses the link between income discrimination and welfare dependency of immigrants. Below is a review of the background literature on welfare dependency, followed by literature on income discrimination.

Welfare dependency of immigrants

When looking at the overall probability of immigrants claiming benefits, most studies find higher probabilities for immigrants compared with natives (Borjas & Hilton 1996, Hansen & Lofstrom 2003, Barrett & McCarthy 2008, for an overview of related literature). When controlling for individual characteristics, however, different studies find different results.

For instance, the study by Hansen & Lofstrom (2003) looking into the case of Sweden, finds that immigrants receive more welfare benefits when considering raw data, and it is not explained by their individual characteristics.

Bird et al. (1999), looking into the case of Germany, find that immigrants are both more likely to be eligible, and also, have a higher probability to take up benefits, conditional on eligibility. However, they find that, when controlling for socio-economic factors, immigrants do not tend to exhibit a higher likelihood of claiming benefits compared with natives.

On the other hand, other studies, looking into the take up of welfare benefits, conditional on eligibility, find that the immigrant take-up of benefits is not significantly different from that of natives (Riphahn 1998, Castronova et al. 2001, Bruckmeier & Wiemers 2017). Castronova et al. (2001) and Bruckmeier & Wiemers (2017) look at the differences in patterns of claiming welfare benefits by immigrants and natives in Germany, conditional on eligibility, thus capturing the differences in behaviour between immigrants and natives. Castronova et al. (2001) find that immigrants are more likely to claim benefits. However, when controlling for a number of socio-economic characteristics, immigrant take-up of benefits is no different from that of natives. Bruckmeier

& Wiemers (2017), using a microsimulation model study the probability of immigrants and natives to claim benefits, conditional on eligibility for welfare benefits. They also find no evidence that immigrants are more likely to take up benefits than natives, after controlling for eligibility, even though immigrants have a higher risk of being eligible for welfare benefits.

A more recent study by Barrett & Maître (2013) estimates whether immigrants are more likely to receive welfare benefits compared with natives for a number of EU countries, including the UK, using data from European Union Statistics on Income and Living Conditions for 2007. Their findings indicate that there is little evidence that immigrants would receive more social benefits than natives.

Drinkwater & Robinson (2013) look into welfare participation in the UK. They use data from the UK Labour Force Survey for 2004-2009 to examine welfare dependency of first-generation immigrants by types of benefits claimed and country of origin. They find different patterns of welfare dependency for different groups of immigrants and benefits claimed.

Brücker et al. (2002) study the welfare dependency of non-EU immigrants across EU countries. They derive a residual dependency, as a difference between predicted dependency, based on individual characteristics, and immigrants' actual dependency. They study welfare dependency by three types of benefits: unemployment benefits, old-age pensions and family benefits. Their findings show that the average predicted unemployment welfare dependency of immigrants is slightly higher for immigrants than natives; the average predicted old-age pension dependency is much higher for natives (almost non-existent for immigrants); and the average predicted family welfare dependency is higher for immigrants, although differs across countries. Finally, they move to comparing the predicted welfare dependency based on the certain set of characteristics with actual welfare dependency, that is, residual dependency, to understand whether immigrants are more or less likely to be dependent on welfare than natives. They find positive and significant *unemployment welfare dependency* of immigrants for Finland, Denmark, Austria, Netherlands, France and Belgium, no *old-age pension residual dependency* for immigrants, while immigrants' *family welfare dependency* is positive and significant for France and Spain, and it is negative and significant for the UK.

The authors highlight the possible reasons for residual dependency:

- **self-selection:** immigrants with low earnings will self-select to countries with generous welfare systems, and hence their earnings in host country will not only depend on observed characteristics, but also on some unobserved individual characteristics, which will result in residual welfare dependency (this phenomenon and related literature are discussed, for instance, in Borjas (1999), Giulietti & Wahba (2013), Barrett & Maître (2013), Giulietti, Guzi, Kahanec & Zimmermann (2013), Razin & Wahba (2015));

- **migration-related idiosyncratic effects:** immigrants might be affected by specific factors, such as psychological and language issues, which might increase their risk of welfare dependency; or welfare entitlement might be conditional on literacy in the language of the host country, in the case of negative residual dependency;

- **networks:** ethnic networks can make it easier for immigrants to find a job, or make them depend on welfare, if they have less developed networks than natives (this topic is explored, for instance, by Munshi (2003), Frijters et al. (2005), Battu et al. (2011), Giulietti, Schluter & Wahba (2013));

- **non-transferability of entitlements:** if immigrants cannot transfer their entitlement from home countries, then they will have negative residual dependency compared with natives with the same characteristic (particularly prominent in the case of state pensions); on the other hand immigrants might be less entitled to benefits due to non-portability of work experience;

- **discrimination:** discrimination in the labour market might push immigrants towards welfare dependency;

- **reduced wages:** factors reducing wages of immigrants could result in welfare dependency (for instance, by disincentivising looking for a job). These factors can be discrimination or reduced access to public jobs.

The discussion above highlights that studies on welfare take-up by first-generation immigrants and the comparison with natives are prone to biases, such as incomparability of labour market outputs due to immigrants having language skills different to those of natives.

When studying second-generation immigrants, the factors of self-selection, migration-related effects, non-transferability of entitlement and largely, networks, seem not to be relevant. Yet, discrimination and reduced wages as a result of discrimination continue to be of great importance in explaining differences in take-up of benefits between immigrants and natives.

There are studies on the effect of discrimination on labour market outcomes of immigrants (Giulietti et al. 2017, Jilke et al. 2018, Neumark 2016, for review of experimental research). To the best of our knowledge, however, the link between discrimination in the labour market and welfare dependency of immigrants has not been studied.

Labour market discrimination

The issue of discrimination in the labour market has been studied extensively. The first economic model on discrimination by Becker (1957) introduced "taste discrimination", according to which employers get disutility from employing minority workers. The firms, therefore, will hire minority workers only if their wage offsets the disutilty.

Later studies, Phelps (1972) and Arrow et al. (1973), discuss the notion of "statistical discrimination", according to which, when employers have limited information about productivity of an employee, they infer it from observable characteristics, for instance, gender or race, and their correlation with productivity (usually based on a group mean).

A more recent study by Bertrand et al. (2005) suggests a third concept, "implicit discrimination", when individuals are not aware of their discriminatory behaviour. In their study the discriminatory behaviour is discovered through a race Implicit Association Test.

It has been shown that persistent discrimination can be a self-fulfilling prophecy, affecting the performance and educational choices of certain groups (Glover et al. 2017, for instance).

There have been many empirical studies on ethnic discrimination and the earnings gap in the UK labour market. One of the first studies on ethnic discrimination in the UK labour market by Chiswick (1980) and McNabb & Psacharopoulos (1981) discusses earnings of the white and non-white UK population and finds that the earnings of the non-white population are lower, not attributable to education and potential experience. McNabb & Psacharopoulos (1981) argue that the disadvantage in the earnings gap is attributable to lower return to education and return to experience for the non-white population.

Blackaby et al. (1994) study wage and employment gaps between the white and black population in the UK for the periods of the 1970s and 1980s using General Household Surveys (GHS). They decompose probit equations for the probabilities of employment, and log-linear equations for the income of both groups. They find not only a significant income gap and a gap in employment prospects for the black population versus the white population, but also that the gaps tend to deteriorate in the 1980s compared with the 1970s. Blackaby et al. (1998) and Blackaby et al. (2002) update the results based on the data from the 1990s and further explore the question using the Labour Force Survey (LFS), which makes it possible for them to also look at different UK-born ethnic groups. These studies confirm disadvantaged positions in employment and income of ethnic minorities in the UK, which cannot be explained by observable characteristics, including qualifications or region.

Similar findings are discussed by Bell (1997), who uses GHS data of 1973-1992 to study the performance of first-generation immigrants to the UK by country of origin while accounting for their education, cohort, years since migration and foreign experience. He finds that the most disadvantaged group is black immigrants with work experience abroad. The gap remains but gets smaller as they assimilate over time. He also finds that white immigrants, in contrast, are better positioned compared with natives, but the difference disappears after a short time.

Clark & Drinkwater (2008) study labour market performance of first-generation immigrants to the UK in comparison with the UK natives, using data from LFS. They find that all immigrants perform worse compared with natives in terms of income and employment, particularly after accounting for individual characteristics, although the scale differs across groups. However, English language proficiency varies across groups and is likely to cause a disadvantage compared with UK native-born.

Dustmann & Theodoropoulos (2010) discuss the economic performance of both first and second-generation immigrants in the UK using LFS data and compare them with UK white natives. Their findings indicate that even though ethnic minorities are better educated than UK natives, they have lower employment rates. They also find that both male and female second-generation immigrants, when accounting for their observable characteristics, receive lower earnings compared with UK natives. They did not find any relationship between employment rates and self-reported perceptions of discrimination.

Algan et al. (2010) compare the economic performance of first and second-generation immigrants in Germany, France and the UK. They find that the UK has higher income and employment gaps of first-generation immigrants, but also considerable improvements for second-generation immigrants, even though the gaps persist for some groups of immigrants.

The studies discussed highlight a general pattern of an income gap between natives and immigrants. The gap is usually bigger for first-generation immigrants, which is to be expected considering the different initial conditions for immigrants versus natives, such as language skills or education. The gap, however, persists for some groups of second-generation immigrants as well, which is likely to affect immigrants' behaviour and their labour market outcomes. Therefore, this paper contributes to the literature in understanding the consequences of a persistent income gap, particularly how it is linked with welfare take-up by second-generation immigrants.

3.3 Methodology and data

3.3.1 Methodology

This study firstly uses existing methods on estimating income gap or discrimination between natives and immigrants and then uses the estimates to study the effect of the gap on the benefit take-up by immigrants. Particularly, it uses Blinder-Oaxaca decomposition (B-O) method to estimate discrimination in labour market (Blinder 1973, Oaxaca 1973, Jann et al. 2008), as the B-O method allows for direct comparison and estimation of a value of income discrimination. The latter is important as we need to estimate a measure of discrimination to use it for further analysis of welfare dependency. The comparison of decomposition methods and the details of B-O method are described in Appendix B.1.

As mentioned in Appendix B.1, there are two issues associated with estimating income inequality through B-O decomposition: sample selection bias and endogeneity from omitted variables. Selection bias arises from labour income being observed only for those individuals who are employed. Below, we discuss issues associated with selection bias and the method we apply to correct it. Blinder-Oaxaca decomposition relies on the assumption that productivity of individuals is captured through observable characteristics. The method is prone to endogeneity if the assumption is violated and variables for individual productivity are omitted. We address the potential issue of omitted variables by controlling for individual fixed effects where possible, assuming individual productivity is fixed over time. In cases where controlling for individual fixed effects is not possible, we verify the robustness of the results by using different methods, including those with fixed effects.

In order to estimate the productivity of natives and immigrants we include the following individual characteristics as an extended version of Mincer equation: potential experience = age - years of education - 6, squared potential experience, years of education, squared years of education (highest educational qualification achieved converted to years), occupations, job type: part-time/full-time, industry, UK government office region, gender, urban versus rural area, health issues.

Based on Blinder-Oaxaca decomposition, the difference in labour market outcomes for the groups of natives (N) and immigrants (M) is:

$$R = E(Y_N) - E(Y_M), \tag{3.1}$$

where $E(Y_N)$ and $E(Y_M)$ are expected value of log earnings of natives and immigrants, accordingly, the estimates of which are derived by estimating the following equation for natives and immigrants:

$$Y_k = \boldsymbol{X}'_k \boldsymbol{\beta}_k + \epsilon_k, \ \ where \ \ E(\epsilon_k) = 0, \ \ \boldsymbol{X}_k - a\ set\ of\ explanatory\ variables\ \ and\ \ k \in \{N, M\} \tag{3.2}$$

Substituting (3.2) in (3.1) and rearranging as described in Appendix B.1, we get:

$$\hat{R} = (\bar{X}_N - \bar{X}_M)' \hat{\beta}_N + \bar{X}'_N (\hat{\beta}_N - \hat{\beta}_M) \tag{3.3}$$

On the other hand, since the data under consideration is panel data, the equation (3.2) for panel data has the following form:

$$y_{it}^k = b_t^k + \boldsymbol{X}_{it}^{k\prime}\boldsymbol{\beta}^k + c_i^k + e_{it}^k, \tag{3.4}$$

where b_t^k is the time intercept, and c_i^k is the time-invariant unobserved effect.

The choice of the estimation method of (3.4) largely depends on the relationship between $\{\boldsymbol{X}_{it} : t = 1, 2, ..., T\}$ and c_i (Wooldridge 2010, 2015, Hsiao 2014). Considering that in our case y_{it} is the log income, and $\boldsymbol{X}_{it}$'s are trying to capture productivity, making an assumption that $Cov(\boldsymbol{X}_{it}, c_i) = 0$ will be too strong. That is, we need to allow correlation between $\boldsymbol{X}_{it}$ and c_i. Therefore, the estimation of (3.4) will be consistent when using Fixed Effects method (FE). However, since the Fixed Effects method removes c_i, all time-invariant variables are also removed. The latter, as pointed out by Heitmueller (2005), can potentially be an issue for Blinder-Oaxaca decomposition as it can result in an omitted variable issue when interpreting the unexplained component.

In order to tackle the above-mentioned issue, Correlated Random Effects method (CRE) is applied, in which case, rather than removing c_i, the relationship between $\boldsymbol{X}_{it}$ and c_i is modelled (Mundlak 1978, Wooldridge 2010, 2015):

$$c_i = \varrho + \bar{\boldsymbol{X}}_i\boldsymbol{\xi} + a_i, \tag{3.5}$$

where $\bar{\boldsymbol{X}}_i = T^{-}1\sum_{t=1}^{T}\boldsymbol{X}_{it}$. CRE produces exactly the same results for $\boldsymbol{\beta}$, but also allows for time-invariant variables. Thus, substituting (3.5) and allowing for time-invariant variables Q_i, (3.4) is modified into the following:

$$y_{it}^k = b_t^k + \boldsymbol{Q}_i^{k\prime}\boldsymbol{\delta}^k + \boldsymbol{X}_{it}^{k\prime}\boldsymbol{\beta}^k + \varrho^k + \bar{\boldsymbol{X}}_i^k\boldsymbol{\xi}^k + a_i^k + e_{it}^k, \tag{3.6}$$

We then estimate (3.6) using Random Effects, as $Cov(\boldsymbol{X}_{it}, a_i) = 0$ and $Cov(\boldsymbol{X}_i, a_i) = 0$.

Another major issue to consider is that the panel under consideration is unbalanced. Hence, it is important to understand whether the attrition/sample selection is uncorrelated with the idiosyncratic error, e_{it}, as well as the time-invariant unobserved effect, c_i. If we define an indicator variable, s_{it}, as follows:

$$s_{it} = \begin{cases} 1 & if\ all\ of\ (\boldsymbol{X}_{it}, y_{it})\ are\ observed \\ 0 & otherwise \end{cases},$$

then FE allows $Cov(s_{it}, c_i) \neq 0$, while for consistency it requires that $Cov(s_{it}, e_{it}) = 0$, in addition to $Cov(\boldsymbol{X}_{it}, e_{it}) = 0$. The same assumptions apply to CRE, provided one accounts for the panel being unbalanced. The paper follows Wooldridge (2010, 2015), Mundlak (1978) in applying CRE method. It uses only the observations for which the complete set of data is observed, that is, when $s_{it} = 1$. It then includes time averages of the variables for the complete set of data only:

$$\bar{\boldsymbol{X}}_i = T^{-}1 \sum_{t=1}^{T} s_{it} \boldsymbol{X}_{it}.$$

Furthermore, time averages of time effects are also included:

$$\bar{b}_i = T^{-}1 \sum_{t=1}^{T} s_{it} b_t.$$

Thus, after the adjustments for unbalanced panel for CRE, (3.6) looks like follows:

$$y^k_{it} = b^k_t \mu + \boldsymbol{Q}^{k'}_i \boldsymbol{\delta}^k + \boldsymbol{X}^{k'}_{it} \boldsymbol{\beta}^k + \varrho^k + \bar{\boldsymbol{X}}^k_i \boldsymbol{\xi}^k + \bar{b}^k_i \eta^k + a^k_i + e^k_{it}, \tag{3.7}$$

where $\bar{\boldsymbol{X}}_i = T^{-}1 \sum_{t=1}^{T} s_{it} \boldsymbol{X}_{it}$ and $\bar{b}_i = T^{-}1 \sum_{t=1}^{T} s_{it} b_t$.

However, as mentioned above, the consistency of CRE requires that $Cov(s_{it}, e_{it}) = 0$, that is the panel is unbalanced due to randomly missing data. In the data under consideration, the main reason for the panel to be unbalanced is because the dependent variable, log income from labour, is observed only if an individual is employed and receives a positive income. That is, if we denote $\boldsymbol{Z}$ the full set of independent variables regardless of whether income from labour is observed or not, we have: $s_{it} = 1[\boldsymbol{Z}_{it}\boldsymbol{\gamma} + \nu_{it} \geq 0]$, assuming that $E(\nu_{it}|\boldsymbol{Z}_{it}) = 0$ and $\nu_{it} \sim N(0, 1)$. The latter indicates that the observations are not randomly missing from the panel and creates a potential sample selection bias. As shown in Tables 3.8 and 3.9, the share of labour force participation varies across natives and different groups of immigrants, as well as for males and females. Therefore, in order to correct for the potential sample selection bias for correlated random effect models, we follow a two-step approach in Wooldridge (2005) for sample selection correction (Wooldridge 2010, 2015).

Considering that $\boldsymbol{X}_{it}$ and $\boldsymbol{Q}_i$ are sub-samples of $\boldsymbol{Z}_{it}$, the model (3.7) can be written as follows:

$$E(y_{it}|\boldsymbol{Z}_{it}, a_i, s_{it} = 1) = E(y_{it}|\boldsymbol{Z}_{it}, a_i, y_{it} \geq 0) = b_t\mu + \boldsymbol{Q}'_i\boldsymbol{\delta} + \boldsymbol{X}'_{it}\boldsymbol{\beta} + \varrho + \bar{\boldsymbol{X}}_i\boldsymbol{\xi} + \bar{b}_i\eta + a_i + E(e_{it}|\nu_{it} \geq -\boldsymbol{Z}_{it}\boldsymbol{\gamma}) \tag{3.8}$$

If we represent $E(e_{it}|\nu_{it} \geq -\boldsymbol{Z}_{it}\boldsymbol{\gamma})$ as $\rho E(e_{it}|\boldsymbol{Z}_{it}, s_{it})$, given that $s_{it} = 1[\boldsymbol{Z}_{it}\boldsymbol{\gamma} + \nu_{it} \geq 0]$ and $\nu_{it} \sim N(0,1)$, then $E(e_{it}|\boldsymbol{Z}_{it}, s_{it}) = \lambda(\boldsymbol{Z}_{it}\boldsymbol{\gamma}) = \phi(\boldsymbol{Z}_{it}\boldsymbol{\gamma})/\Phi(\boldsymbol{Z}_{it}\boldsymbol{\gamma})$, the inverse Mills ratio, when $s_{it} = 1$. Thus, the estimable version of (3.8) is the following:

$$E(y_{it}|\boldsymbol{Z}_{it}, a_i, s_{it} = 1) = b_t\mu + \boldsymbol{Q}_i^{'}\boldsymbol{\delta} + \boldsymbol{X}_{it}^{'}\boldsymbol{\beta} + \varrho + \bar{\boldsymbol{X}}_i\boldsymbol{\xi} + \bar{b}_i\eta + a_i + \rho\lambda(\boldsymbol{Z}_{it}\boldsymbol{\gamma}) \tag{3.9}$$

In the two-step approach, as a first step γ is estimated for each t from $s_{it} = 1[\boldsymbol{Z}_i\boldsymbol{\gamma}_{it} + \nu_{it} \geq 0]$ and $\nu_{it}|\boldsymbol{Z}_i \sim N(0,1)$, and $\hat{\lambda}_{it} = \lambda(\boldsymbol{Z}_{it}\hat{\gamma_{it}})$ is computed for each i and t. Since $P(s_{it} = 1|\boldsymbol{Z}_{it})$ follows a probit model, γ is estimated from the following probit model[3]:

$$P(s_{it} = 1|\boldsymbol{Z}_{it}) = \Phi(\boldsymbol{Z}_{it}\boldsymbol{\gamma}_{it}) \tag{3.10}$$

The exclusion restriction is achieved by including an additional set of variables in the first stage: number of children under 16; a binary variable if a person is married or lives with a partner, and mother's and father's educational qualifications. This set of variables satisfies two important conditions necessary to correct for sample selection bias. Firstly, these variables are observed for all individuals, regardless whether they work or not. Secondly, this set of variables, alongside $\boldsymbol{X}_{it}$ and $\boldsymbol{Q}_i$, is expected to predict labour force participation of individuals. Considering that labour force participation of individuals, particularly women, might be highly affected by the number of under-age children they have, we expect the variable of number of children under 16 to be a strong predictor of labour force participation. Similarly, individual's marital status, combined with the number of under-age children, is expected to be a strong instrument in predicting labour force participation, while mother's and father's educational qualifications are expected to capture individuals' inherited wealth level, which might affect their choice of whether to work or not.

To see how strong these variables are in predicting labour force participation, and therefore how valid they are as exclusion restrictions, we look at the results of the first stage in Appendix B.3. The variables of number of under-age children, marital status and parental educational qualifications are all statistically significant for natives, while number of children under 16 and father's educational qualifications are significant for non-EU immigrants, and only the latter for EU immigrants. Following a joint chi square-test for these variables for all groups, these variables showed joint-significance for each group. Therefore, we proceed with including these variables as an exclusion restriction in the first stage of sample selection correction.

Another question concerning the sample selection correction is to test whether there is a sample selection bias in the first place, that is, whether the sample selection is indeed non-random. We test the presence of sample selection bias in the second stage of sample

[3]For simplicity, we can also estimate: $P(s_{it} = 1|\bar{\boldsymbol{Z}}_i) = \Phi(\bar{\boldsymbol{Z}}_i\boldsymbol{\gamma}_i)$, where $\bar{\boldsymbol{Z}}_i = T^{-1}1\sum_{t=1}^{T}\boldsymbol{Z}_{it}$

selection correction. We conduct the second stage (3.9) for $\{N, M\}$, using the estimates $\hat{\lambda}_{it}$. In the case of the missing data in the unbalanced panel being random, that is, if there is no sample selection bias, then $\rho = 0$. That is, we conduct a t-test to check the presence of sample selection bias. As discussed in Section 3.4, the coefficient of the inverse Mills ratio $\rho = 0$ is statistically significant, signifying that sample selection is indeed non-random and there is a sample selection bias.

Let $\boldsymbol{\chi}_{it}^k = \{b_t^k, \boldsymbol{Q}_i^k, \boldsymbol{X}_{it}^k, \bar{\boldsymbol{X}}_i^k, \bar{b}_i^k, \hat{\lambda}_{it}^k\}$ and $\boldsymbol{B}^k = \{\mu^k, \boldsymbol{\delta}^k, \boldsymbol{\beta}^k, \varrho^k, \boldsymbol{\xi}^k, \eta^k, \rho^k\}$ with $k = \{N, M\}$, then (3.3) can be written as:

$$\hat{R} = (\bar{\boldsymbol{\chi}}_{it}^N - \bar{\boldsymbol{\chi}}_{it}^M)' \hat{\boldsymbol{B}}^N + \bar{\boldsymbol{\chi}}_{it}^{N\prime} (\hat{\boldsymbol{B}}^N - \hat{\boldsymbol{B}}^M) \tag{3.11}$$

(3.11) is the final version of B-O decomposition we estimate, where $(\bar{\boldsymbol{\chi}}_{it}^N - \bar{\boldsymbol{\chi}}_{it}^M)' \hat{\boldsymbol{B}}^N$ is the explained component, and $\bar{\boldsymbol{\chi}}_{it}^{N\prime} (\hat{\boldsymbol{B}}^N - \hat{\boldsymbol{B}}^M)$ is the unexplained difference in labour market outcomes.

After Blinder-Oaxaca decomposition, we use the results of decomposition to estimate the effect of labour market discrimination on the welfare dependency of immigrants compared with natives. The estimate of discrimination is the unexplained income differential from B-O decomposition: $D^{\tau t}$. We estimate $D^{\tau t}$ following two methods. In the first method, we make use of yearly variation in discrimination across UK regions:

$$E(y_i^{\tau tk} | \boldsymbol{Z}_i^{\tau tk}) = \boldsymbol{Q}_i^{\tau tk\prime} \boldsymbol{\delta}^{\tau tk} + \boldsymbol{X}_i^{\tau tk\prime} \boldsymbol{\beta}^{\tau tk} + \varrho^{\tau tk} + \rho^{\tau tk} \lambda(\boldsymbol{Z}_i^{\tau tk} \boldsymbol{\gamma}^{\tau tk}) \tag{3.12}$$

We decompose income following Blinder-Oaxaca decomposition and (3.12) by groups of natives and immigrants, $k = \{N, M\}$. To use variation in levels of discrimination, we apply (3.12) in B-O decomposition for each year t and each UK region τ. For each region τ and period t we estimate the unexplained income differential $discrimination^{\tau t}$. We then use lagged discrimination to estimate (3.13), that is: $D^{\tau t} = discrimination^{\tau t-1}$.

In (3.12) we correct for sample selection bias, however this method is prone to endogeneity from omitted variable bias as discussed earlier. To validate the results we use the second method; we estimate (3.9) and (3.11) for each region τ by CRE, therefore controlling for fixed effects, correcting for sample selection bias and mitigating endogeneities associated with B-O decomposition. In this case, our estimates of $D^{\tau t}$ for each region τ are for based on observations for a corresponding region from all years.

Welfare receipt is the probability of claiming benefits in period t. We expect D_t^{τ} to affect immigrants' propensity to claim benefits in period t, yet immigrants' behaviour and circumstances in period t should have no effect on income discrimination in period $(t-1)$. D_t^{τ} is the demeaned value of discrimination in region τ.

We estimate the effect of labour market discrimination on the probability of claiming benefits using panel data and a linear probability model. As in the case of B-O decomposition, the relevant method is the fixed effects method due to similar assumptions. In order to compare immigrants with natives by using a dummy variable for immigrants, we proceed with estimating the linear probabilities model by CRE to allow for time-invariant variables. Therefore, the effect of discrimination on claiming welfare benefits is estimated based on the following equation (Wooldridge 2010, 2015):

$$P(y_{it} = 1|\boldsymbol{X}_{it}, D_t^{\tau}, M_i, a_i, s_{it} = 1) = \boldsymbol{X}_{it}^{'}\boldsymbol{\alpha} + D_t^{\tau}\beta + D_t^{\tau}M_i\theta + M_i\lambda + b_t\mu + \bar{\boldsymbol{X}}_i\boldsymbol{\xi} + \bar{b}_i\eta + a_i + \epsilon_{it}, \tag{3.13}$$

assuming $E(\boldsymbol{X}_{it}^{'}\epsilon_{it}) = 0$ and $Cov(s_{it}, \epsilon_{it}) = 0$; and where M_i is a binary variable for an individual being an immigrant; $\bar{\boldsymbol{X}}_i = T^{-}1\sum_{t=1}^{T} s_{it}\boldsymbol{X}_{it}$ and $\bar{b}_i = T^{-}1\sum_{t=1}^{T} s_{it}b_t$.

In (3.13), the impact of discrimination on welfare dependency of immigrants is given by θ. (3.13) implies that we control for individual fixed effects and year effects in this part of the study, as in the first part of B-O decomposition. The only estimations carried out that do not include control for fixed are the derivations of D_t^{τ}, however, we check the robustness of these estimates by applying a second method, that controls for individual fixed effects and year effects.

3.3.2 Data

In order to test the research question, this paper uses the data from Waves 1 to 6 of the Main survey of the UK Household Longitudinal Study (UKHLS), Understanding Society, which covers years 2009-2014. We narrow down the sample to natives and second-generation immigrants. Natives are defined as white individuals born in the UK, whose parents and grandparents were born in the UK. Since we look at discrimination, we include only white individuals in the definition of natives to limit any bias from the heterogeneity of the native population. Immigrants are defined as individuals born in the UK with parents being born outside the UK.

Summary statistics

The age range of individuals in the sample is limited to native and immigrant males aged 18 to 67, and females aged 18 to 60-65, depending on the year of birth. The age 18 is chosen since individuals are eligible to claim benefits from that age. We also limit the sample to under state pension age to have only working-age individuals in the sample as the research topic concerns individuals in the labour market. State pension age in the UK for the period under consideration was 65[4]. State pension age for women was 60 before and up to 2009 (women born in December 1953) and 65 from 2010 (women born between 6 April 1950 and 5 December 1953), that is, all women born before 1950 are in the retirement age for the period under consideration.

In addition to individuals of state pension age, we exclude self-reported retirees, according to w_jbstat. We also exclude individuals in full-time education.

Since the survey data is prone to attrition, only those individuals who stay in the survey over the six waves are included in the study, so that the sample included is strongly balanced. We also exclude any observation with missing data points for any of the variables considered, thus including only complete cases, as discussed in the previous subsection.

We use positive log net monthly income from labour to measure labour market outcomes of natives and immigrants. Income from labour includes net monthly earnings from main job, net monthly income from self-employment and net monthly earnings from a second job.

Table 3.1: Summary statistics on monthly income from labour and benefits

Natives										
	Income from labour					**Benefits**				
year	**mean**	**max**	**min**	**sd**	**N**	**mean**	**max**	**min**	**sd**	**N**
2009	1506	15000	0.1	1263	6539	449	3201	1.1	435	3416
2010	1511	15000	0.1	1215	6585	479	4617	2.5	475	3595
2011	1522	15000	0.1	1142	6453	516	15000	0.1	556	3584
2012	1558	15000	0.1	1210	6353	533	4677	3.2	527	3441
2013	1568	15000	0	1181	6286	571	15000	1.1	649	3255
2014	1639	15000	0.8	1293	6144	529	4343	1.7	530	3411
Immigrants										
	Income from labour					**Benefits**				
year	**mean**	**max**	**min**	**sd**	**N**	**mean**	**max**	**min**	**sd**	**N**
2009	1543	8333	1	1023	567	567	2671	4.3	490	424
2010	1585	15000	14.1	1349	567	630	5004	13.0	617	453
2011	1564	15000	2.5	1111	572	617	3627	11.0	587	456
2012	1542	15000	5.8	1237	579	635	3458	20.0	600	435
2013	1582	15000	4.3	1209	591	659	3802	10.0	615	414
2014	1640	9944	12	1082	576	631	5246	8.3	622	423

Notes: Natives are white individuals born in the UK, whose parents and grandparents were born in the UK. Immigrants are individuals born in the UK with parents being born outside the UK. All individuals included are of working age - from 18 years old to the retirement age.
Income from labour includes monthly net positive earnings from first and second jobs and positive net self-employment income in GBP.
Benefits include total monthly state benefits in GBP, that comprise of the sum of the following: income support, job seeker's allowance (unemployment benefit); child benefits; maternity allowance; tax credits; housing benefit, council tax benefit; sickness, disability and incapacity benefits; state retirement pension; a widow's or war widow's pension; a widowed mother's allowance / widowed parent's allowance; income from any other state benefit.
Source: UKHLS

For estimating probabilities of claiming benefits, we use the data on the positive value of social benefits. Social benefits include total monthly benefits, that comprise of the sum of the following: income support, job seeker's allowance (unemployment benefit), child benefits (including lone-parent child benefit payments), maternity allowance, tax credits,

[4]https://www.nidirect.gov.uk/articles/check-your-state-pension-age

housing benefit, council tax benefit (offset against council tax); sickness, disability and incapacity benefits; state pension; a widow's or war widow's pension; a widowed mother's allowance / widowed parent's allowance; income from any other state benefit. Since the sample excludes individuals of state pension age, individuals receiving state retirement (old-age) pension are excluded from the sample. All the tables in the paper are based on the sample as defined above.

Table 3.1 shows the statistics on net personal income from labour and social benefits. Both variables are top-coded up to 15000.

The average income of natives and immigrants are similar on average, although varies over years. Average benefits, on the other hand, is higher for natives.

Table 3.2: Breakdown of shares of social benefits by source

Natives						
	2009	**2010**	**2011**	**2012**	**2013**	**2014**
Unemployment benefits	4.1	4.4	4.2	4.2	4.2	3.1
Income support	5.3	5.5	5.2	4.8	4.6	4.5
Child or family benefits	37.0	36.0	36.0	37.5	37.9	38.8
Tax credits	30.8	30.6	29.0	25.9	23.7	22.8
Sickness, disability or incapacity benefits	9.0	9.1	9.9	10.9	11.9	13.5
Housing or council tax benefits	11.3	11.9	12.8	13.4	14.4	13.0
Other benefits	2.5	2.5	3.0	3.1	3.4	4.3
Total	100.0	100.0	100.0	100.0	100.0	100.0
Immigrants						
	2009	**2010**	**2011**	**2012**	**2013**	**2014**
Unemployment benefits	5.6	6.3	6.3	6.0	5.2	4.0
Income support	5.6	6.6	5.4	5.1	5.0	4.3
Child or family benefits	37.5	35.8	35.9	37.0	36.9	38.2
Tax credits	31.2	30.4	29.2	27.4	26.9	26.8
Sickness, disability or incapacity benefits	4.8	5.3	6.5	7.8	7.8	9.5
Housing or council tax benefits	13.8	14.2	14.7	15.0	15.8	14.0
Other benefits	1.4	1.2	1.9	1.8	2.3	3.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

Note: Each row shows the percentage share of respective types of benefits in total benefits for each year. Natives are white individuals born in the UK, whose parents and grandparents were born in the UK. Immigrants are individuals born in the UK with parents being born outside the UK. All individuals included are of working age - from 18 years old to the retirement age.

In addition to the total amount of income from benefits reported, UKHLS also reports data on types of benefits claimed, without specifying the amount. Table 3.2 shows the breakdown of types of benefits claimed by natives and immigrants. Child and family benefits constitute equally the largest part of benefits for both natives and immigrants, followed by tax credits. A slightly higher share of immigrants claims unemployment benefits compared with natives, as well as slightly higher share claims housing or council tax benefits. A lower share of immigrants, compared with natives, claims sickness, disability or incapacity benefits.

Transition matrices

In order to utilise panel data and analyse the impact of discrimination on welfare dependency, we need to check whether there is any transition in and out of welfare from year to year. Table 3.3 shows the transition in and out of welfare by natives and immigrants. If an individual of working age has positive social benefits in period t, then they are considered to be on welfare (Yes), and not - otherwise (No). For instance, from 2009 to 2010, 8.3% of natives transitioned from not being on welfare to being on welfare, and 6.7% transitioned from being on welfare to not being on welfare. For the same year, more immigrants, 9.7%, transitioned into welfare, and 6.5% - out of welfare. Generally, there is a trend of decreasing welfare dependency for both natives and immigrants following the post-2008 crisis, except for 2014, when there is a slight increase in welfare dependency. Table 3.3 shows that a higher share of immigrants is on welfare benefits, compared with natives.

One factor to consider is whether the transition is different for males and females, as the higher share of immigrants on welfare dependency might be attributable to a lower share of females in the labour force and higher levels of child benefits for women. Tables 3.4-3.5 show the transition into and out of welfare by native and immigrant males and females. Indeed, a higher share of females of both natives and immigrants are on welfare benefits compared with males, with the share of immigrant women being around 12 percentage points higher than for natives. The transition in and out of welfare is higher for men - both natives and immigrants.

Another factor to consider is whether the proportions of young people are different for immigrants versus natives and whether the differences in welfare dependency of immigrants and natives are attributable to that. To look at that question, we split the sample into two age groups: 40 years and under, and 41 years and over. Tables 3.6-3.7 are on transition matrices of natives and immigrants in the two age groups. Immigrants have a higher share of younger individuals aged 40 and under - 58%, versus 41% for natives. Younger people tend to claim more benefits in the case of both immigrants and natives. However, the shares are higher for the younger group of immigrants compared with natives and the group of immigrants aged 41 and over.

Thus, when looking at raw statistics of welfare dependency, a larger share of immigrants tend to claim benefits compared with natives, which is consistent with previous studies. The next question to discuss is whether these patterns are the same when considering the observable characteristics of natives and immigrants, and most importantly, whether the patterns are dependent on income discrimination in the labour market.

Table 3.3: Year on year transition matrices on welfare dependency: immigrants vs. natives

Natives

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		4,164	676	4,840		4,201	509	4,710		4,296	463	4,759		4,427	462	4,889		4,214	787	5,001
	%		51.0	8.3	59.3		51.4	6.2	57.7		52.6	5.7	58.3		54.2	5.7	59.9		51.6	9.6	61.2
Yes	N	2009	546	2,780	3,326	2010	558	2,898	3,456	2011	593	2,814	3,407	2012	574	2,703	3,277	2013	561	2,604	3,165
	%		6.7	34.0	40.7		6.8	35.5	42.3		7.3	34.5	41.7		7.0	33.1	40.1		6.9	31.9	38.8
Total	N		4,710	3,456	8,166		4,759	3,407	8,166		4,889	3,277	8,166		5,001	3,165	8,166		4,775	3,391	8,166
	%		57.7	42.3	100.0		58.3	41.7	100.0		59.9	40.1	100.0		61.2	38.8	100.0		58.5	41.5	100.0

Immigrants

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		331	81	412		321	64	385		340	42	382		359	44	403		350	73	423
	%		39.6	9.7	49.3		38.4	7.7	46.1		40.7	5.0	45.7		43.0	5.3	48.3		41.9	8.7	50.7
Yes	N	2009	54	369	423	2010	61	389	450	2011	63	390	453	2012	64	368	432	2013	63	349	412
	%		6.5	44.2	50.7		7.3	46.6	53.9		7.5	46.7	54.3		7.7	44.1	51.7		7.5	41.8	49.3
Total	N		385	450	835		382	453	835		403	432	835		423	412	835		413	422	835
	%		46.1	53.9	100.0		45.7	54.3	100.0		48.3	51.7	100.0		50.7	49.3	100.0		49.5	50.5	100.0

Note: Natives are white individuals born in the UK, whose parents and grandparents were born in the UK. Immigrants are individuals born in the UK with parents being born outside the UK.
All individuals included are of working age - from 18 years old to the retirement age, and the sample is strictly balanced.
(No) Was not on welfare/ had zero monthly state benefits. (Yes) Was on welfare/ had positive amount of monthly state benefits.
(N) Number of individuals. (%) Share in total for the period.

Table 3.4: Year on year transition matrices on welfare dependency of natives: males vs. females

			2010				2011				2012				2013				2014		
Males																					
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N	2009	2,364	313	2,677	2010	2,389	248	2,637	2011	2,462	195	2,657	2012	2,490	221	2,711	2013	2,322	393	2,715
	%		66.4	8.8	75.2		67.1	7.0	74.1		69.2	5.5	74.7		70.0	6.2	76.2		65.2	11.0	76.3
Yes	N		273	609	882		268	654	922		249	653	902		225	623	848		219	625	844
	%		7.7	17.1	24.8		7.5	18.4	25.9		7.0	18.3	25.3		6.3	17.5	23.8		6.2	17.6	23.7
Total	N		2,637	922	3,559		2,657	902	3,559		2,711	848	3,559		2,715	844	3,559		2,541	1,018	3,559
	%		74.1	25.9	100.0		74.7	25.3	100.0		76.2	23.8	100.0		76.3	23.7	100.0		71.4	28.6	100.0
Females																					
			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N	2009	1,800	363	2,163	2010	1,812	261	2,073	2011	1,834	268	2,102	2012	1,937	241	2,178	2013	1,892	394	2,286
	%		39.1	7.9	47.0		39.3	5.7	45.0		39.8	5.8	45.6		42.0	5.2	47.3		41.1	8.6	49.6
Yes	N		273	2,171	2,444		290	2,244	2,534		344	2,161	2,505		349	2,080	2,429		342	1,979	2,321
	%		5.9	47.1	53.0		6.3	48.7	55.0		7.5	46.9	54.4		7.6	45.1	52.7		7.4	43.0	50.4
Total	N		2,073	2,534	4,607		2,102	2,505	4,607		2,178	2,429	4,607		2,286	2,321	4,607		2,234	2,373	4,607
	%		45.0	55.0	100.0		45.6	54.4	100.0		47.3	52.7	100.0		49.6	50.4	100.0		48.5	51.5	100.0

Note: Natives are white individuals born in the UK, whose parents and grandparents were born in the UK.
All individuals included are of working age - from 18 years old to the retirement age, and the sample is strictly balanced.
(No) Was not on welfare/ had zero monthly state benefits. (Yes) Was on welfare/ had positive amount of monthly state benefits.
(N) Number of individuals. (%) Share in total for the period.

Table 3.5: Year on year transition matrices on welfare dependency of immigrants: males vs. females

Males

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		199	49	248		194	27	221		205	18	223		211	27	238		198	40	238
	%		58.5	14.4	72.9		57.1	7.9	65.0		60.3	5.3	65.6		62.1	7.9	70.0		58.2	11.8	70.0
Yes	N	2009	22	70	92	2010	29	90	119	2011	33	84	117	2012	27	75	102	2013	32	70	102
	%		6.5	20.6	27.1		8.5	26.5	35.0		9.7	24.7	34.4		7.9	22.1	30.0		9.4	20.6	30.0
Total	N		221	119	340		223	117	340		238	102	340		238	102	340		230	110	340
	%		65.0	35.0	100.0		65.6	34.4	100.0		70.0	30.0	100.0		70.0	30.0	100.0		67.6	32.4	100.0

Females

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		132	32	164		127	37	164		135	24	159		148	17	165		152	33	185
	%		26.7	6.5	33.1		25.7	7.5	33.1		27.3	4.8	32.1		29.9	3.4	33.3		30.7	6.7	37.4
Yes	N	2009	32	299	331	2010	32	299	331	2011	30	306	336	2012	37	293	330	2013	31	279	310
	%		6.5	60.4	66.9		6.5	60.4	66.9		6.1	61.8	67.9		7.5	59.2	66.7		6.3	56.4	62.6
Total	N		164	331	495		159	336	495		165	330	495		185	310	495		183	312	495
	%		33.1	66.9	100.0		32.1	67.9	100.0		33.3	66.7	100.0		37.4	62.6	100.0		37.0	63.0	100.0

Note: Immigrants are individuals born in the UK with parents being born outside the UK.
All individuals included are of working age - from 18 years old to the retirement age, and the sample is strictly balanced.
(No) Was not on welfare/ had zero monthly state benefits. (Yes) Was on welfare/ had positive amount of monthly state benefits.
(N) Number of individuals. (%) Share in total for the period.

Table 3.6: Year on year transition matrices on welfare dependency of natives by age groups

Aged 40 years and under

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		1,463	283	1,746		1,459	241	1,700		1,458	233	1,691		1,505	214	1,719		1,418	358	1,776
	%		43.2	8.4	51.6		43.1	7.1	50.3		43.1	6.9	50.0		44.5	6.3	50.8		41.9	10.6	52.5
Yes	N	2009	237	1,400	1,637	2010	232	1,451	1,683	2011	261	1,431	1,692	2012	271	1,393	1,664	2013	270	1,337	1,607
	%		7.0	41.4	48.4		6.9	42.9	49.7		7.7	42.3	50.0		8.0	41.2	49.2		8.0	39.5	47.5
Total	N		1,700	1,683	3,383		1,691	1,692	3,383		1,719	1,664	3,383		1,776	1,607	3,383		1,688	1,695	3,383
	%		50.3	49.7	100.0		50.0	50.0	100.0		50.8	49.2	100.0		52.5	47.5	100.0		49.9	50.1	100.0

Aged 41 years and over

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N		2,666	283	2,949		2,733	269	3,002		2,834	222	3,056		2,918	244	3,162		2,789	431	3,220
	%		55.7	5.9	61.7		57.1	5.6	62.8		59.3	4.6	63.9		61.0	5.1	66.1		58.3	9.0	67.3
Yes	N	2009	336	1,498	1,834	2010	323	1,458	1,781	2011	328	1,399	1,727	2012	302	1,319	1,621	2013	271	1,292	1,563
	%		7.0	31.3	38.3		6.8	30.5	37.2		6.9	29.2	36.1		6.3	27.6	33.9		5.7	27.0	32.7
Total	N		3,002	1,781	4,783		3,056	1,727	4,783		3,162	1,621	4,783		3,220	1,563	4,783		3,060	1,723	4,783
	%		62.8	37.2	100.0		63.9	36.1	100.0		66.1	33.9	100.0		67.3	32.7	100.0		64.0	36.0	100.0

Note: Natives are white individuals born in the UK, whose parents and grandparents were born in the UK.
All individuals included are of working age - from 18 years old to the retirement age, and the sample is strictly balanced.
Individuals are considered "aged 40 and under" and "aged 41 and over" based on their age in year 2009.
(No) Was not on welfare/ had zero monthly state benefits. (Yes) Was on welfare/ had positive amount of monthly state benefits.
(N) Number of individuals. (%) Share in total for the period.

Table 3.7: Year on year transition matrices on welfare dependency of immigrants by age groups

Aged 40 years and under

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N	2009	187	56	243	2010	173	40	213	2011	181	34	215	2012	187	34	221	2013	177	45	222
	%		38.4	11.5	49.9		35.5	8.2	43.7		37.2	7.0	44.1		38.4	7.0	45.4		36.3	9.2	45.6
Yes	N		26	218	244		42	232	274		40	232	272		35	231	266		39	226	265
	%		5.3	44.8	50.1		8.6	47.6	56.3		8.2	47.6	55.9		7.2	47.4	54.6		8.0	46.4	54.4
Total	N		213	274	487		215	272	487		221	266	487		222	265	487		216	271	487
	%		43.7	56.3	100.0		44.1	55.9	100.0		45.4	54.6	100.0		45.6	54.4	100.0		44.4	55.6	100.0

Aged 41 years and over

			2010				2011				2012				2013				2014		
			No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total		No	Yes	Total
No	N	2009	144	25	169	2010	148	24	172	2011	159	8	167	2012	172	10	182	2013	173	28	201
	%		41.4	7.2	48.6		42.5	6.9	49.4		45.7	2.3	48.0		49.4	2.9	52.3		49.7	8.0	57.8
Yes	N		28	151	179		19	157	176		23	158	181		29	137	166		24	123	147
	%		8.0	43.4	51.4		5.5	45.1	50.6		6.6	45.4	52.0		8.3	39.4	47.7		6.9	35.3	42.2
Total	N		172	176	348		167	181	348		182	166	348		201	147	348		197	151	348
	%		49.4	50.6	100.0		48.0	52.0	100.0		52.3	47.7	100.0		57.8	42.2	100.0		56.6	43.4	100.0

Note: Immigrants are individuals born in the UK with parents being born outside the UK.
All individuals included are of working age - from 18 years old to the retirement age, and the sample is strictly balanced.
Individuals are considered "aged 40 and under" and "aged 41 and over" based on their age in year 2009.
(No) Was not on welfare/ had zero monthly state benefits. (Yes) Was on welfare/ had positive amount of monthly state benefits.
(N) Number of individuals. (%) Share in total for the period.

Heterogeneity

Table 3.8 includes summary statistics of natives as defined above and groups of immigrants by country of origin of the father. The following breakdown of the countries is due to the sample sizes of immigrants. Where the sample size is enough to have the country as a separate group, we include it separately, otherwise, we group them according to country groupings used by Office for National Statistics for International Passenger Survey[5]. "EU(EEA)" includes all European Union member-countries (excluding the UK), and Iceland, Liechtenstein, Norway and Switzerland. "Other Africa" includes Sub-Saharan African countries. "Latin America" includes Central and South American countries. "Other" includes all other countries not included in the previous categories.

Here, the variables of average monthly income from labour and benefits are averages of the entire sample, that is, total of individuals that are receiving income from labour and/or benefits, as opposed to Table 3.1, where the statistics are from sub-samples of individuals who have income from labour, and individuals who receive income from benefits.

Table 3.8: Summary statistics of immigrant versus native characteristics

	Natives	Immigrants by country of origin of father						
		EU(EEA)	India	Pakistan	Bangladesh	Other Africa	Latin America	Other
Avg. monthly labour income	1194.3	1242.7	1133.2	640.1	733.3	1366.1	1112.2	1525.3
Avg. monthly benefits	213.5	224.8	243.0	488.2	397.4	321.9	389.9	219.3
Share of labour force participation, %	80.7	81.0	79.2	60.3	69.2	80.9	81.7	84.4
Avg. age	45	49	40	35	31	36	45	42
Avg. years of school	11.1	11.9	12.7	12.1	10.9	14.1	12.1	13.6
Avg. number of children under 16	0.6	0.5	0.9	1.6	1.3	0.9	0.8	0.7
Share of females, %	55.3	56.9	57.9	55.8	60.4	66.3	63.0	52.6
N	49679	756	1062	807	364	517	1004	449

Notes: Average monthly income and benefits are computed based on the entire sample, including zero values.
"EU(EEA)" includes all European Union member-countries (excluding the UK), and Iceland, Liechtenstein, Norway and Switzerland. "Other Africa" includes countries in Sub-Saharan Africa. "Latin America" includes countries in Central and South America. "Other" includes all other countries.
Source: UKHLS

Natives and EU immigrants have, in general, similar characteristics, whereas there is a lot of heterogeneity across non-EU immigrants. EU immigrants have, on average, slightly higher income from labour than natives. Income of non-EU immigrants varies significantly depending on the country of origin of immigrants. Non-EU immigrants from *other* countries have the highest average income followed by immigrants from Other Africa. Average monthly benefits exceeds that of natives for all immigrant groups.

EU immigrants are, on average, 3 years older than natives, whereas non-EU immigrants are about 6 years younger. All immigrants have higher average years of schooling than natives do, except for immigrants for Bangladesh, for whom schooling is similar to natives. Immigrants have, on average, more children under 16 compared with natives, except for EU immigrants, who have slightly fewer. Since a higher proportion of females claim welfare benefits, the next important indicator is the share of females across groups.

[5] www.ons.gov.uk

Natives have a lower share of females compared with all groups of immigrants except for immigrants from the "other" group.

Labour force participation is similar for natives and EU immigrants, whereas it varies a lot across non-EU immigrants, with the highest being for second-generation immigrants from the "other" group. This variation might be an important issue when discussing income from labour across groups as it yields potential sample selection bias. Labour force participation here and in the rest of the paper is defined as the share of individuals with positive income or full or part-time employment, and individuals who are self-reported as unemployed.

Table 3.9: Labour force participation by groups

	Male	**Female**
Natives	84.1	77.9
EU	79.4	82.1
India	88.1	72.7
Pakistan	88.8	37.8
Bangladesh	84.0	59.5
Other Africa	90.2	76.1
Latin America	84.4	80.1
Other	89.2	80.1

Notes: The country groups of immigrants are based on father's country of birth.
Labour force participation is computed as the share of individuals who are employed/have positive earnings or are unemployed to total individuals in the group.

Table 3.9 includes a breakdown of labour force participation rates (LFP) by natives and immigrant groups and male versus female. Labour force participation varies substantially across groups, particularly for females. This creates an issue of sample selection bias, as we do not observe the income of individuals who are not in the labour force. Therefore, we need to correct for the selection before comparing the income of natives and immigrants across groups and for males and females.

UKHLS includes Ethnic Minority Boost sample, where they oversample individuals from certain ethnic minority groups, including Indian, Pakistani, Bangladeshi, Caribbean, and African. Table B.1 in Appendix B.2 includes LFP with the adjusted weights, which accounts for oversampling. LFP adjusted for sample weights are, on average, similar to the unadjusted LFP. Therefore, we proceed with the unadjusted sample.

From the discussion above we can see that the average labour income of immigrants and natives is similar. However, immigrants and natives have different characteristics. Therefore, in order to assess the differences in labour income and to understand whether there is an income gap between natives and immigrants, we should consider the differences in characteristics of immigrants and natives.

Furthermore, we can see that a higher share of immigrants tends to claim benefits compared with natives. As the next step we need to understand whether immigrants are more likely to claim benefits given eligibility, that is, when controlling for observables, and whether immigrants' probability of claiming benefits is affected by income gap in the labour market if there is one.

3.4 Results

Income discrimination

We start by decomposing income from labour for natives and immigrants by Blinder-Oaxaca decomposition following the methodology described in Section 3.3.1. As discussed, Fixed Effects method is the appropriate estimation method to decompose log wages of natives and immigrants, which is also confirmed by the Hausman test. We apply Correlated Random Effect method, as CRE results in the same coefficients for time-variant variables as Fixed Effects, but also allows for time-invariant variables, such as education, including parental education, gender, industry. Therefore, as part of CRE, time averages of all time-variant variables are included, as well as time averages of year effects, while using only complete cases of data. We also use robust standard errors to account for heteroskedasticity.

Table 3.10 shows the results of the decomposition, which includes the results of the decomposition without the adjustment for sample selection bias, and with the adjustment as in equations (3.9) and (3.11). For sample selection correction we use four exclusion restrictions, number of children aged under 16, a binary variable for being married or living with a partner, and mother's and father's educational qualifications. Since the patterns of labour force participation might differ for natives and different groups of immigrants, as well as for men and women, we conduct the 1st stage separately for different groups. The results of the first stage of sample selection correction are included in Table B.2 of Appendix B.3. The coefficients across groups indeed vary significantly. We construct the final Mills ratio for the second stage of the Wooldridge (2005) correction from these subgroups.

The difference in income of natives and immigrants is not significantly different from zero when the decomposition results are not adjusted for sample selection. When adjusted, however, natives' income exceeds that of immigrants' by 12%.

In individual regressions of B-O decomposition, the coefficients of the inverse Mills ratio, ρ from (3.9), are different from zero (negative) at 1% significance level for immigrants. Hence, since the sample selection is not random, there is a negative selection, and we will proceed with the model corrected for sample selection bias.

Table 3.10: Blinder-Oaxaca decomposition for natives and immigrants

	Correlated random effects			CRE, corrected for selection bias		
	overall	explained	unexplained	overall	explained	unexplained
group_1: natives	7.093***			7.291***		
	(0.006)			(0.026)		
group_2: migrants	7.111***			7.173***		
	(0.020)			(0.046)		
difference	–0.018			0.118**		
	(0.021)			(0.053)		
explained	–0.119***			–0.124***		
	(0.014)			(0.014)		
unexplained	0.100***			0.242***		
	(0.022)			(0.053)		
potential experience (years)		0.106**	0.548		0.092*	0.599
		(0.049)	(0.678)		(0.050)	(0.677)
squared potential experience (years)		–0.112***	0.035		–0.100***	0.019
		(0.015)	(0.122)		(0.015)	(0.126)
years of education		0.037***	–0.373*		0.037***	–0.346*
		(0.006)	(0.194)		(0.006)	(0.195)
years of education squared		–0.063***	0.283		–0.055***	0.214
		(0.007)	(0.173)		(0.007)	(0.173)
male		0.000	0.021**		0.000	0.018*
		(0.001)	(0.010)		(0.001)	(0.010)
female		0.000	–0.025**		0.000	–0.021*
		(0.001)	(0.012)		(0.001)	(0.012)
urban area		0.002	–0.064		0.002	–0.055
		(0.002)	(0.091)		(0.002)	(0.096)
rural area		0.002	0.003		0.002	0.002
		(0.002)	(0.004)		(0.002)	(0.004)
Occupational controls		X	X		X	X
Industry controls		X	X		X	X
Regional controls		X	X		X	X
Time effects		X	X		X	X
Time averages		X	X		X	X
Other controls		X	X		X	X
N	40899			40873		

Note: CRE, corrected for selection bias - correlated random effects with Heckman correction.
The dependent variable is log income from labour.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

The sample selection bias-corrected income gap of around 12% is due to unexplained income differential. Attributable to explained characteristics, immigrants' income would have been around 12.4% higher than natives'. However, that advantage for immigrants is cancelled due to an unexplained difference of around 24.2% of income of natives.

Immigrants' income, attributable to the potential experience, is lower by 9.2% (significant at 10%) compared with natives up until potential experience is higher, when the situation reverses, attributable to older native population.

In terms of education, natives get a lower return to education until their education is about 7.5 years, from which point onwards return to education for them increases. This relation does not hold for immigrants. That is likely to be due to the native population being from an older generation, who were more likely to leave education early for work. This results in an unexplained difference in education of 34.6% in favour of immigrants.

There seems to be a small unexplained difference (significant at 10%) in favour of female immigrants and a disadvantage against male immigrants.

EU and non-EU. To understand whether the trend holds for different groups of immigrants, we look at B-O decomposition for EU and non-EU immigrants. Table 3.11 shows the results of B-O decomposition of log earnings of natives versus EU immigrants and natives versus non-EU immigrants separately for men and women.

The results are very different for EU and non-EU immigrants. The difference in log income of natives and immigrants is not statistically significant for either men or women. However, attributable to the difference explained by observable characteristics, female EU immigrants' income on average exceeds that of native females by around 17%. There seems to be no unexplained income differential for EU immigrants versus natives.

The picture is different for non-EU immigrants. Non-EU men have around 18% lower income compared with native men. Based on the individual characteristics, non-EU men would have had around 6.7% higher income than native men. However, the income of non-EU men is lower due to the unexplained difference of 24.5%.

Female non-EU immigrants' income difference, on the other hand, is not statistically significantly different from zero since the explained and unexplained difference neutralise each other. Non-EU women would have had income, explained by observable characteristics, by 18.6% higher than native women. However, this is offset by an unexplained difference of around 24% in favour of natives.

Even though the scale of income discrimination is slightly higher against non-EU men compared with women, the pattern is the same for non-EU second-generation immigrants.

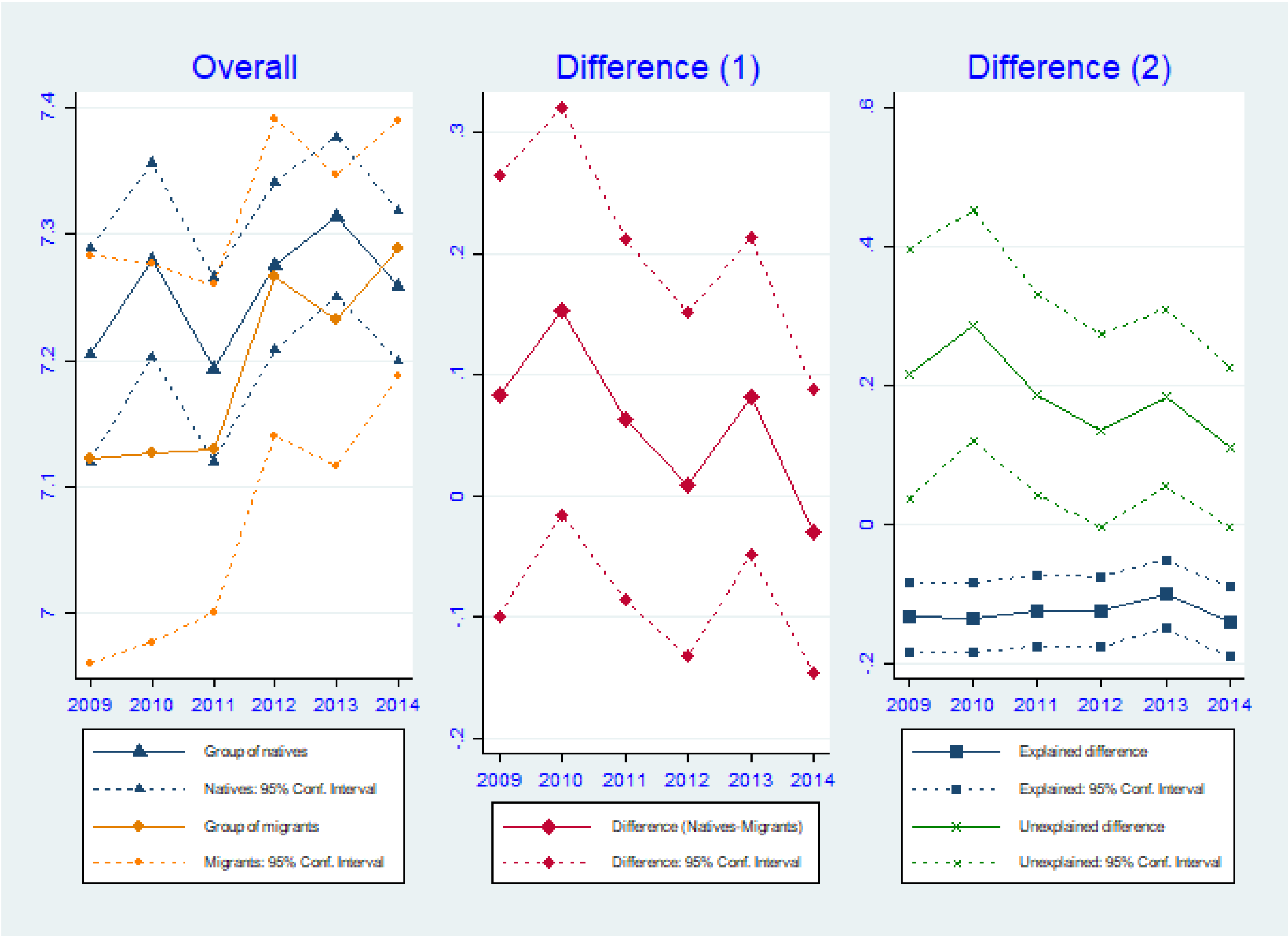
The results of B-O decomposition by individual countries are included in Table B.3 in Appendix B.4.

Table 3.11: B-O decomposition for natives versus EU / non-EU immigrants: men and women

	EU						Non-EU					
	male			female			male			female		
	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained
group_1: natives	7.476***			7.125***			7.476***			7.125***		
	(0.042)			(0.034)			(0.042)			(0.034)		
group_2: migrants	7.600***			7.179***			7.299***			7.072***		
	(0.496)			(0.270)			(0.078)			(0.070)		
difference	–0.123			–0.054			0.178**			0.053		
	(0.497)			(0.273)			(0.088)			(0.078)		
explained	–0.022			–0.173***			–0.067***			–0.186***		
	(0.029)			(0.032)			(0.021)			(0.022)		
unexplained	–0.101			0.119			0.245***			0.240***		
	(0.497)			(0.271)			(0.090)			(0.079)		
potential experience (years)		–0.064*	2.413		–0.019	0.962		0.249**	–1.131		0.024	1.721**
		(0.036)	(5.330)		(0.061)	(2.053)		(0.110)	(1.156)		(0.077)	(0.795)
squared potential experience (years)		0.043*	–0.932		0.025**	–0.567		–0.237***	0.122		–0.046**	–0.043
		(0.025)	(0.822)		(0.011)	(0.696)		(0.038)	(0.221)		(0.018)	(0.170)
years of education		0.022**	–0.564		–0.003	–0.617		0.047***	–0.803**		0.041***	–0.040
		(0.011)	(2.736)		(0.008)	(0.517)		(0.012)	(0.360)		(0.009)	(0.331)
years of education squared		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)		(.)	(.)		(.)	(.)
urban area		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)		(.)	(.)		(.)	(.)
rural area		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)		(.)	(.)		(.)	(.)
Occupational controls		X	X		X	X		X	X		X	X
Industry controls		X	X		X	X		X	X		X	X
Regional controls		X	X		X	X		X	X		X	X
Time effects		X	X		X	X		X	X		X	X
Time averages		X	X		X	X		X	X		X	X
Other controls		X	X		X	X		X	X		X	X
N	17534			20542			18598			21708		

Note: The dependent variable is log income from labour.
The estimation method is Correlated random effects, corrected for selection bias.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Figure 3.1: Dynamics of the results of Blinder-Oaxaca decomposition of log income from labour



Note: Decomposition of income of natives and immigrants by Blinder-Oaxaca method for each year.
Overall - log income of natives / immigrants.
Difference(1) - difference in long income of natives and immigrants.
Difference(2) - breakdown of Difference(1) into "explained difference" and "unexplained difference".

Figure 3.1 shows the results of B-O decomposition by years, adjusted for selection bias. The average income of natives and immigrants is volatile over the years even though the explained difference is quite stable. The major part of the volatility is due to unexplained income differential between natives and immigrants. In the next stage, we use this yearly volatility to explore the effect of income discrimination on immigrants' welfare dependency.

Welfare receipt

Figure 3.2 includes average annual results of B-O decomposition by region. Discrimination is estimated as an average unexplained difference for each region in year t and is expressed as a percent of income from labour of natives. That is, for instance, immigrants in London receive 44% less income not explained by their observable characteristics than natives, whereas immigrants in Scotland get around 37% higher income that is not explained by observables.

Studies have pointed out that there is heterogeneity in public attitudes and prejudice towards immigrants across different groups and UK regions (Dustmann & Preston 2007, 2001). That is, areas with higher shares of immigrants are likely to be more prejudiced compared to those with lower shares, also discussed by Hopkins (2010). Moreover, there is self-reported evidence of heterogeneous attitudes towards immigration and preferences for different ethnic groups (Blinder 2011).

We now turn to analysing the welfare dependency of immigrants versus natives, and the impact of discrimination on it. First, we use unexplained income difference in the UK regions in time $(t-1)$ following (3.12) to explore the impact of labour market discrimination on the probability of immigrants claiming benefits compared with natives (Table 3.12). As discussed in Section 3.3.1, we use linear CRE for estimation, (3.13). The Hausman test also confirms that the appropriate model is FE. We use linear regression for our estimations, although the results are robust to using logit regressions as well.

In this stage we introduce a new control variable, the share of individuals claiming benefits in the corresponding region, expecting the probability of claiming benefits to be positively affected by this variable. We also include the following variables as controls: number of children aged under 16, a binary variable for an individual being married or living with a partner, and parents' educational qualifications.

Table 3.12 shows the results of linear regressions on the probability of natives and immigrants to claim benefits, including results with all immigrants, EU immigrants only and non-EU immigrants only versus natives. When deriving discrimination from B-O decomposition for all these groups, we use B-O decomposition for natives versus all immigrants. The main reason for that is to have an appropriate sample size of immigrants when carrying out decomposition by individual regions.

In all three results the dummy variables for immigrants, including EU and non-EU immigrants, are not statistically significant, signifying that the likelihood of immigrants claiming benefits is overall not different from natives.

The effect labour market discrimination has on natives is given by the coefficient of the variable "discrimination in $(t-1)$", which is not statistically different from zero. That is, the propensity of natives to claim benefits is unaffected by discrimination against immigrants.

The share of individuals claiming benefits, as expected, positively affects the probability of claiming benefits. Potential experience, on the other hand, reduces the probability of claiming benefits, so does education squared. Squared potential experience positively affects welfare dependency since it is associated with older individuals who are more likely to claim some types of benefits.

The coefficient of interest, the coefficient of the interaction variable of the binary variables for immigrant groups and discrimination, is positive and significant (at 5% level) for total immigrants. Other things being equal, a 10% increase in income discrimination against immigrants results in an increase in welfare dependency by immigrants of 0.40%.

Figure 3.2: The map of average income discrimination by region, %

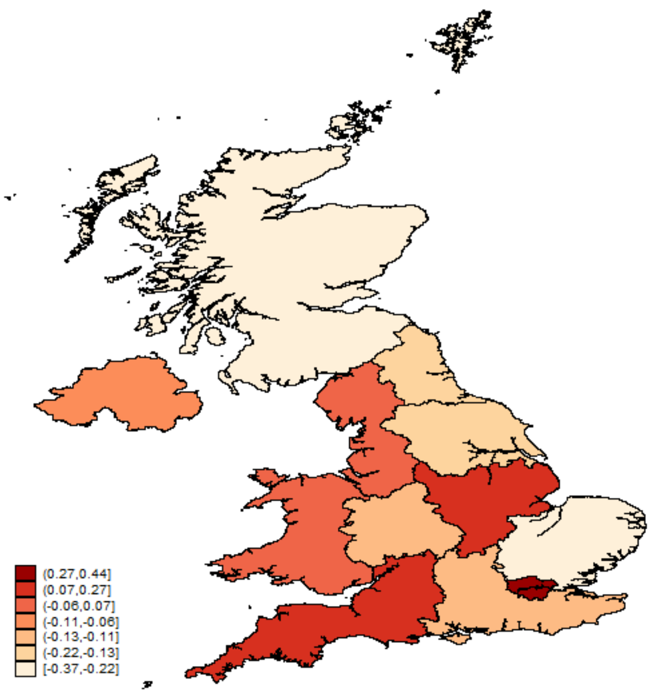


Table 3.12: The impact of discrimination on the probability of claiming benefits

	Natives / all immigrants	Natives / EU immigrants	Natives / non-EU immigrants
Discrimination in t-1	–0.005	–0.005	–0.004
	(0.005)	(0.005)	(0.005)
Immigrants × Discrimination in t-1	0.040**		
	(0.018)		
Immigrants	0.010		
	(0.013)		
EU(EEA) × Discrimination in t-1		–0.044	
		(0.044)	
EU(EEA)		0.034	
		(0.032)	
Non-EU × Discrimination in t-1			0.052***
			(0.020)
Non-EU			0.005
			(0.014)
share of individuals claiming benefits by region	0.608**	0.618**	0.580**
	(0.275)	(0.284)	(0.277)
potential experience (years)	–0.030***	–0.033***	–0.030***
	(0.008)	(0.009)	(0.008)
squared potential experience (years)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
years of education	–0.005**	–0.005**	–0.005**
	(0.002)	(0.002)	(0.002)
female	0.148***	0.144***	0.148***
	(0.008)	(0.008)	(0.008)
urban area	0.011	0.010	0.011
	(0.008)	(0.008)	(0.008)
no of children aged under 16	0.066***	0.068***	0.066***
	(0.003)	(0.003)	(0.003)
married or lives with partner	–0.074***	–0.075***	–0.075***
	(0.007)	(0.007)	(0.007)
Occupational controls	X	X	X
Industry controls	X	X	X
Regional controls	X	X	X
Time effects	X	X	X
Time averages	X	X	X
Other controls	X	X	X
N	45508	41998	44876

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

When looking at EU and non-EU immigrants separately, the welfare dependency of EU immigrants is unaffected by discrimination. This is in line with the results of Blinder-Oaxaca decomposition, since we did not observe discrimination against EU immigrants.

The effect of discrimination on welfare dependency of non-EU immigrants, on the other hand, is positive and statistically significant. That is, a 10% increase in income discrimination against immigrants results in an increase in the probability of non-EU immigrants claiming benefits by 0.52%. This is also in line with the B-O decomposition results, which exhibit income discrimination against non-EU immigrants.

If we consider the situation of no discrimination, in which case the overall probability of welfare dependency of non-EU immigrants is 54%, then the highest observed income discrimination in a single year, for instance in East Midlands, increases the probability of claiming benefits to 65% in the region in that year.

Considering the issues with the method of estimating discrimination following (3.12), we check the validity of our estimates by using the second approach to estimate discrimination discussed in Section 3.3.1. Table 3.13 shows the results of linear regressions on the probability of natives and immigrants to claim benefits, where discrimination is estimated using CRE, that is controlling for fixed effects, in addition to corrected sample selection bias. The results, although weaker, confirm the dependence of the likelihood

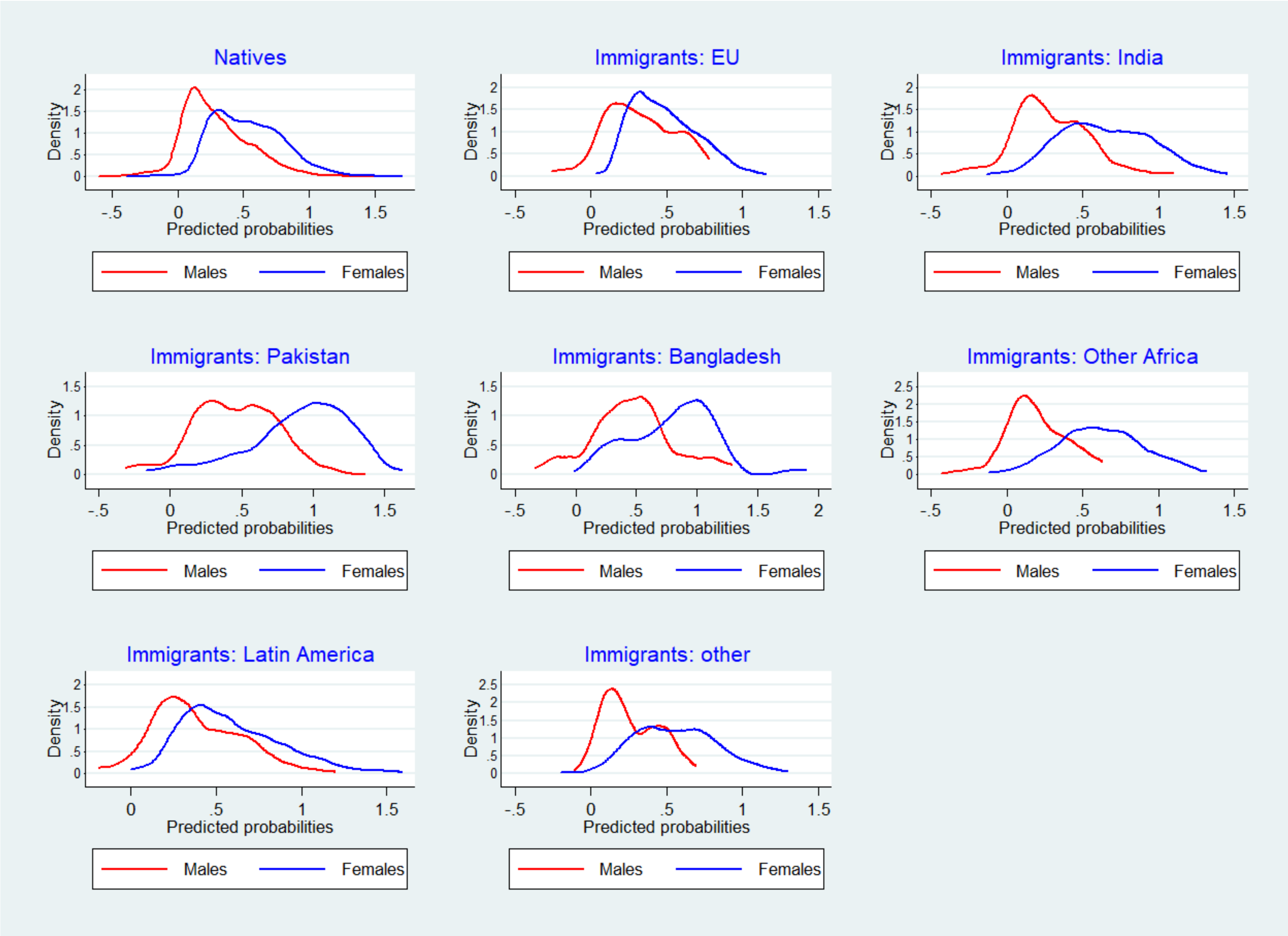
Table 3.13: The impact of discrimination on the probability of claiming benefits (approach 2)

	Natives / all immigrants	Natives / EU immigrants	Natives / non-EU immigrants
Discrimination	–0.026	–0.026	–0.025
	(0.058)	(0.059)	(0.058)
Immigrants × Discrimination	0.092		
	(0.079)		
Immigrants	0.005		
	(0.012)		
EU(EEA) × Discrimination		–0.027	
		(0.078)	
EU(EEA)		0.031	
		(0.030)	
Non-EU × Discrimination			0.180*
			(0.101)
Non-EU			0.002
			(0.012)
share of individuals claiming benefits by region	0.377**	0.410**	0.389**
	(0.178)	(0.184)	(0.179)
potential experience (years)	–0.009	–0.009	–0.008
	(0.007)	(0.008)	(0.007)
squared potential experience (years)	0.000**	0.000***	0.000**
	(0.000)	(0.000)	(0.000)
years of education	–0.007***	–0.008***	–0.007***
	(0.002)	(0.002)	(0.002)
female	0.134***	0.129***	0.134***
	(0.007)	(0.008)	(0.007)
urban area	0.012	0.012	0.012
	(0.007)	(0.007)	(0.007)
no of children aged under 16 that resp is parent of	0.071***	0.072***	0.071***
	(0.003)	(0.003)	(0.003)
married or lives with partner	–0.068***	–0.070***	–0.069***
	(0.007)	(0.007)	(0.007)
Occupational controls	X	X	X
Industry controls	X	X	X
Regional controls	X	X	X
Time effects	X	X	X
Time averages	X	X	X
Other controls	X	X	X
N	53451	49043	52725

The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

to claim benefits by non-EU immigrants on labour market discrimination. Here we do not observe immigrants to claim more benefits compared with natives either.

Figure 3.3: Distributions of predicted probabilities of claiming benefits



Note: Predictions are based on model (3.13).

Figure 3.3 shows distributions of predicted probabilities of claiming benefits by male and female natives and groups of immigrants based on model (3.13), that is, estimates in Table 3.12. The likelihood of welfare dependency is very heterogeneous across and within groups. Women, in general, are more likely to claim benefits compared with women. In terms of highest and lowest probability distributions, men from Sub-Saharan Africa have the lowest probability of welfare dependency amongst men, which, on average, is 19.7%, whereas men from Bangladesh have the highest probability of claiming benefits, with the average of 46.8%. It, however, varies a lot within the groups. EU women are the least likely to be on welfare dependency amongst women, with the average of 48.8%, whereas Pakistani women are the most likely - 90.8%.

Table 3.14: The impact of discrimination on the probability of claiming benefits by types of benefits

	I	II	III	IV	V	VI
Discrimination in t-1	–0.004**	0.001	0.001	0.002	–0.006**	–0.003
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Immigrants × Discrimination in t-1	0.027**	0.012	0.008	–0.011	0.017	–0.004
	(0.013)	(0.011)	(0.016)	(0.017)	(0.013)	(0.011)
Immigrants	0.007	–0.026***	0.029**	0.038***	–0.024**	–0.040***
	(0.006)	(0.007)	(0.012)	(0.013)	(0.011)	(0.010)
share of individuals claiming benefits by region	0.108	0.246**	0.950***	0.590**	0.338***	0.174*
	(0.093)	(0.099)	(0.264)	(0.265)	(0.126)	(0.103)
female	–0.031***	0.007*	0.201***	0.119***	–0.001	–0.004
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.005)
no of children aged under 16	0.005***	0.007***	0.046***	0.035***	0.015***	0.014***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Occupational controls	X	X	X	X	X	X
Industry controls	X	X	X	X	X	X
Regional controls	X	X	X	X	X	X
Time effects	X	X	X	X	X	X
Time averages	X	X	X	X	X	X
Other controls	X	X	X	X	X	X
N	45508	45508	45508	45508	45508	45508

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
(I) unemployment benefits, (II) income support, (III) child benefits, (IV) tax credit, (V) housing or council tax, (VI) sickness, disability or incapacity benefits.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

When looking at the probability of claiming different types of benefits in Table 3.14 (detailed Table B.4 in Appendix B.5), the effect of labour market discrimination on the probability of immigrants to claim benefits is significant in the case of unemployment benefits only. The latter is expected since, of all the benefits, unemployment benefits are most closely related to the labour market.

It should be mentioned that a similar pattern of welfare dependency by types of benefits is observed when we use the second approach to estimate labour market discrimination discussed in Section 3.3.1.

Interestingly, the probabilities of natives claiming unemployment and housing or council tax benefits are slightly lower with higher income discrimination against immigrants.

When looking at the probabilities by types of benefits, while controlling for individual characteristics, immigrants exhibit different behaviour when compared with natives. Immigrants are 2.9% more likely to claim child benefits compared with natives and 3.8% more likely to claim tax credits. However, immigrants are 2.6% less likely to claim income support benefits, 4% less likely to claim housing or council tax benefits, and 2.4% less likely to claim sickness, disability or incapacity benefits.

The probability of claiming benefits also tends to increase with a higher share of individuals claiming the corresponding type of benefits in the region.

3.4.1 Robustness tests

We check the robustness of Blinder-Oaxaca decomposition by conducting tests to check the effect of top-coding of the data on the results of B-O decomposition. By trimming the data on income from labour and assigning different values to top-coding, we conclude that the results of B-O decomposition are not sensitive to top-coding.

Table 3.15: The impact of discrimination on the probability of claiming benefits: natives versus immigrants

	Natives	EU migrants	Non-EU migrants
Discrimination in t-1	–0.004	–0.064	0.053***
	(0.005)	(0.047)	(0.019)
share of individuals claiming benefits by region	0.587**	2.343	1.271
	(0.286)	(2.386)	(1.211)
N	41366	632	3510

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The estimation method is fixed effects.
Time effects and occupational, industry, regional and other controls are included.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

As a robustness exercise for probabilistic models, we estimate probabilities of claiming benefits for separate samples of natives, EU and non-EU immigrants. The results, included in Table 3.15 (a detailed Table B.5 in Appendix B.6), confirm the estimations in Table 3.12. The likelihood of natives and EU immigrants to claim benefits is unaffected by income discrimination in the corresponding region in time $(t-1)$, whereas it increases for non-EU immigrants. Interestingly, immigrants are not responding to the share of individuals who claim benefits in the corresponding region, whereas natives are more likely to claim benefits in regions with a higher share of claimants.

We also check the robustness of the results in Table 3.12 by using the unexplained difference of regional dummy variables as a measure of discrimination in period $(t-1)$ instead of total unexplained difference of regressions for each region. The problem with

Table 3.16: The impact of discrimination on the probability of claiming benefits by men: robustness check

	All	EU	Non-EU
Discrimination in t-1	–0.084	–0.102	–0.087
	(0.229)	(0.230)	(0.230)
Immigrants × Discrimination in t-1	0.736		
	(0.518)		
Immigrants	0.021		
	(0.019)		
EU(EEA) × Discrimination in t-1		–1.477	
		(0.937)	
EU(EEA)		–0.006	
		(0.044)	
Non-EU × Discrimination in t-1			0.998*
			(0.557)
Non-EU			0.030
			(0.021)
share of individuals claiming benefits by region	0.246	0.184	0.256
	(0.397)	(0.406)	(0.401)
Occupational controls	X	X	X
Industry controls	X	X	X
Regional controls	X	X	X
Time effects	X	X	X
Time averages	X	X	X
Other controls	X	X	X
N	20059	18634	19787

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The variable for discrimination is unexplained difference of regional dummy variables.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

regional dummies is that the total difference does not get adjusted for sample selection bias. Since LFP is particularly heterogeneous in the case of women, which makes a comparison between groups difficult, we limit the sample to men only for this exercise. Table 3.16 shows the results of this robustness exercise. Here, the coefficient of the interaction term is significant (at 10% level) for non-EU men, which is in line with the results in Table 3.12. The higher values of these coefficients are due to a different scale of the variable of discrimination in this exercise compared with the original variable.

As another robustness exercise, we use a contemporaneous measure of discrimination instead of the lagged (Table 3.17). The results are robust to this exercise as well, with contemporaneous discrimination increasing likelihood of claiming benefits by immigrants, and particularly, non-EU immigrants.

We also check how sensitive the results are to removing a major region from the regression, as for instance, London. The results are robust to dropping a major region.

Table 3.17: The impact of contemporaneous discrimination on welfare dependency

	All	EU	Non-EU
Discrimination by regions	–0.009	–0.010	–0.009
	(0.008)	(0.008)	(0.008)
Immigrants × Discrimination by regions	0.064**		
	(0.030)		
Immigrants	0.008		
	(0.013)		
EU(EEA) × Discrimination by regions		0.026	
		(0.067)	
EU(EEA)		0.034	
		(0.034)	
Non-EU × Discrimination by regions			0.070**
			(0.033)
Non-EU			0.004
			(0.014)
share of individuals claiming benefits by region	0.603**	0.609**	0.578**
	(0.275)	(0.284)	(0.277)
Occupational controls	X	X	X
Industry controls	X	X	X
Regional controls	X	X	X
Time effects	X	X	X
Time averages	X	X	X
Other controls	X	X	X
N	45508	41998	44876

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

3.5 Conclusion

By using Blinder-Oaxaca decomposition to estimate labour market discrimination against second-generation immigrants in the UK, after correcting for sample selection bias, this paper shows that there is significant discrimination against non-EU second-generation immigrants, while there seems to be none against EU immigrants. These results are in line with previous studies.

We estimate discrimination in the UK regions, by decomposing income from labour by regions of the UK. We then use the estimates to analyse the impact of discrimination on the probability of welfare dependency of immigrants versus natives. The results show that discrimination does not affect welfare dependency of EU immigrants. However, it increases the probability of non-EU immigrants to claim benefits. Compared with non-EU immigrants' overall probability of claiming benefits of 54% in the situation of no discrimination, the highest observed income discrimination in a single year increases the probability of non-EU immigrants to be on welfare dependency to 65% in the region in that year.

By looking at the probability of claiming different types of benefits, while controlling for individual characteristics, we find that discrimination increases the likelihood of claiming unemployment benefits by immigrants, whereas it decreases the likelihood of claiming unemployment and housing/council tax benefits by natives. The findings also show that immigrants are more likely to claim child benefits and tax credits compared with natives, while they are less likely to claim income support, housing/council tax benefits and sickness/disability/incapacity benefits.

These results yield important potential policy implications, particularly in the areas of welfare dependency and unemployment. The link between income discrimination and dependency on welfare benefits, and above all, unemployment benefits, can be used as a tool for policy-makers, also given the opposite effect of discrimination on welfare dependency between natives and immigrants.

Chapter 4

Working (or not working) tax credit reforms in the UK

Abstract. This paper[1] studies the effects of the 2003 working tax credit reform and the 2012 amendment to the required hours of work for tax credit eligibility on the labour supply of UK-born and non-UK-born individuals. Studies show that effectively designed working tax credit policies can result in an increase in labour supply by affected individuals along intensive and extensive margins. Some studies, on the other hand, show that these policies do not result in an increase in labour force participation, while some even show a reduction in hours worked. These studies often distinguish between single parents and married couples, while some discuss the effect of tax credit reforms on individuals with different levels of education.

Using a difference-in-differences approach, this paper studies the effect of the 2003 reform on labour supply of UK-born and non-UK-born single individuals and couples without children. It examines the effect of the 2012 increase to required hours of work, from 16 to 24, for couples with children. It also discusses whether different combinations of UK-born and non-UK-born couples respond differently to the reforms.

4.1 Introduction

State welfare benefits are a costly tool for governments, yet it is an important one in addressing inequality and achieving income redistribution. The level of inequality in the UK is one of the highest among OECD countries (the 6th highest as of 2016)[2]. However, the level of inequality would have been higher without state welfare benefits.

[1]I am very grateful to my supervisors, Jackie Wahba and Corrado Giulietti, for their continuous support and guidance. I am also grateful to Carmine Ornaghi for his valuable comments.

[2]OECD (2019), Income inequality (indicator). doi: 10.1787/459aa7f1-en (Accessed on 24 January 2019)

Welfare benefits are providing income support to those in need by redistributing income from the members of the society who can afford it. On the other hand, welfare benefits should not create disincentives for individuals to work. In this context, in-work transfer schemes or working tax credit is an efficient tool to provide income support to low-income individuals and families, while simultaneously creating incentives for them to work. Working tax credits are also effective at achieving redistribution of income as they are usually means tested and because they ensure that working low-income individuals and families are receiving necessary income support. Therefore, tax credit frameworks are usually designed with the aim of creating incentives for individuals to enter into the labour force or to increase their labour market participation, while simultaneously providing support for low-income families.

Studies have shown that effectively designed working tax credit frameworks (Eissa & Liebman 1996, Francesconi & Van der Klaauw 2007, Blundell et al. 2008, 2000, Brewer et al. 2006, Leigh 2007) can result in an increase in labour force participation and hours worked by individuals. Moreover, tax credit reforms can substantially improve the general well-being of individuals and families, including the well-being of children in these families (Gregg et al. 2009). Some studies, on the other hand, show little effectiveness of these policies in terms of increase in labour force participation, while some others - decrease in hours worked (Blundell & Hoynes 2004, Blundell et al. 2000).

However, there are fewer studies of the effect of working tax credit on different groups of individuals. Most studies above distinguish between single parents and married couples. Leigh (2010) also studies the impact of tax credit reform on individuals with different levels of education. One important group of individuals that has not been studied much in this context is immigrants. Bargain et al. (2014) argue that labour supply responses to tax benefits in different countries differ attributable to their individual and social preferences. Do these preferences persist as they migrate to another country, or converge with those of natives? Therefore, understanding how policy changes in in-work benefit systems affect immigrants compared with natives can provide interesting behavioural insight and a possible tool for policy-makers.

Another factor that could affect different responses to tax benefits by natives and immigrants, is different levels of knowledge of local laws and administrative processes by immigrants versus natives.

This paper studies the impact of the UK working tax credit reform of 2003 and a particular amendment in working tax credit framework that affects a certain group of individuals. The working tax credit reform of 2003 was extended towards two new groups of people: single individuals and couples without children. The amendment in working tax credit in the UK increased the required hours of work for working couples with children effective from April 2012, thus affecting couples with children.

The initial tax credit framework in the UK, the Working Families Tax Credit, was set up in 1999 with the aim to provide support to low-income working families with children and to encourage working families to increase their participation in the labour force. It was replaced by the Working Tax Credit framework in April 2003, which was meant to simplify the Working Families Tax Credit and make it easy for families with children to anticipate the income they receive. It also provided credit support for low-income working single individuals and working couples without children provided they worked at least 30 hours a week, which could have implications on individuals' labour supply along intensive and extensive margins.

In April 2012 a new requirement came into force for Working Tax Credits[3] according to which to qualify for working tax credit (WTC) working couples must now work more hours. Before the amendments both lone parents and working families were required to work at least 16 hours a week to be eligible for working tax credit, while the amendment increased the required hours of work to 24 hours per week.

This paper studies the effect of WTC2003 and the 2012 amendment on the labour market behaviour of individuals without children and couples with children, respectively. It looks at the impact of the amendment on two groups of individuals: UK-born and non-UK-born individuals. The latter will potentially provide useful insight into how differently immigrants react in terms of labour supply to tax credit reforms compared with natives, which can be used in policy-making.

The Chapter is organised as follow: Section 4.2 provides a background of tax credit reforms, and the expected effect of these reforms on labour supply of eligible individuals, Section 4.3.2 describes the empirical methodology and data used, Section 4.4 discusses the results of estimations followed by robustness tests in Section 4.5, and Section 4.6 concludes.

4.2 Background: in-work benefits and related literature

Intensive versus extensive labour supply responses

One of the major aspects of tax credit reforms to consider is how individuals and households respond along extensive margins (labour force participation) and intensive margins (choices of hours of work)[4].

Blundell (2000), reviewing in-work benefits programs in the US, Canada and the UK in the 1980s and 1990s, concludes that in-work tax credit mechanisms have positive

[3]The Tax Credits (Miscellaneous Amendments) Regulations 2012, No. 848

[4]Heckman (1993) also highlights the importance of considering "missing wages" of those who do not work when estimating individuals' responses in terms of hours of work. He stresses that not accounting for missing wages leads to underestimating the scale of the responses/elasticities.

effect along extensive margin and slight negative effect along intensive margin, due to certain features of the programs. Since the programs are in general based on family income, he also finds some negative impact along extensive margin for married women with children.

Meyer (2002) shows that almost all labour supply response of single mothers to the EITC in 1986-2000 is along extensive margin, rather than hours of work.

Immervoll et al. (2007) use a microsimulation model to study the effect of in-work benefits systems across EU countries versus tradition welfare programs. Their findings also conclude that in-work benefit systems produce positive results along extensive margins and some negative effects along intensive margins.

Bargain et al. (2014) also look at cross-country (US and 17 European countries) labour supply own-wage elasticities to in-work tax-benefit systems using a harmonised discrete choice model approach. They find that labour supply elasticities are stronger along extensive rather than intensive margin. They find that the cross-country variation in elasticities is not due to the differences in either in-work benefit systems or the demographic composition. They conclude that the differences are attributable to individual and social preferences across the countries, including their work preferences and childcare policies.

4.2.1 The US

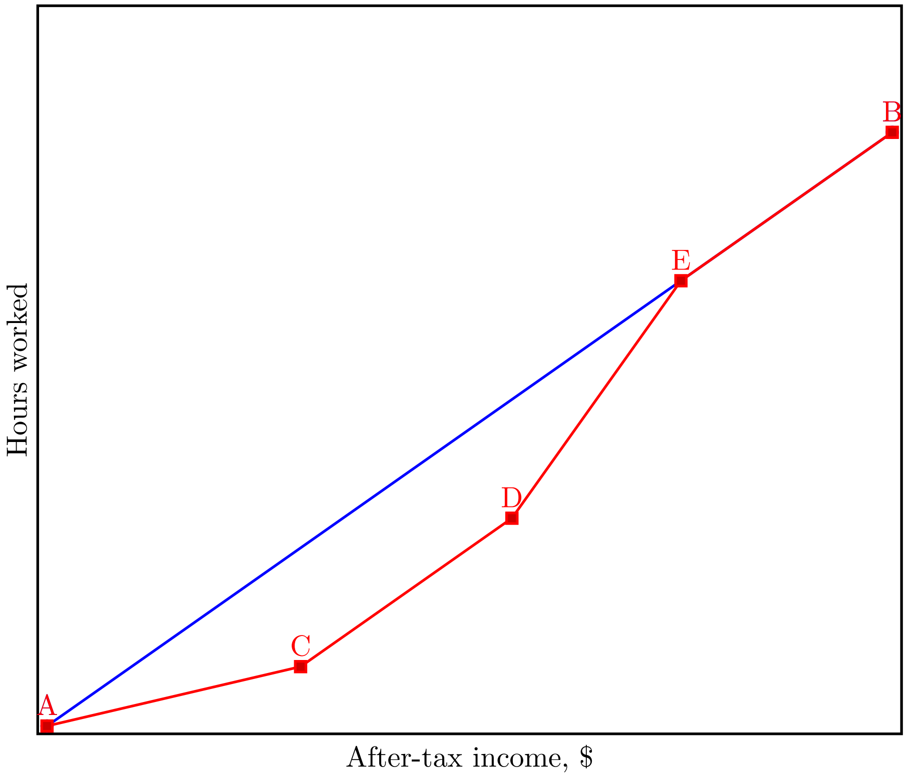
The US in-work welfare system, the Earned Income Tax Credit (EITC), was developed in the 1970s (Blundell 2000). The tax credit provided by EITC increases proportionally with the income from labour up until the maximum income level set in the system. EITC meant to create incentives to work by providing credit to low-wage workers.

Eissa & Liebman (1996) study the response of labour supply to the EITC. The introduction of the Tax Reform Act of 1986 in the US increased the income tax credit for single women with children, while presumably having no effect on single women without children.

Under the Tax Reform Act of 1986, the EITC eligibility requirement was having a qualifying child, and the amount of credit depended on earned income. Individuals in the phase-in region, that is, below earned income of \$6080, were entitled to a tax credit of 14% (up from 11%), with the maximum tax credit of \$851. Individuals earning income from \$6080-\$11000 fell in constant region, and received a tax credit of \$851. The phase-out region, where individuals, earning income over \$11000 but below \$15432, were phased out at 10%. Individuals earning over \$15432 were not eligible for a tax credit.

The introduction of the tax credit shifts the budget constraint of individuals as shown in Figure 4.1. The initial budget constraint is presented as AB, while the introduction of

Figure 4.1: The budget constraint under the Earned Income Tax Credit



Source: Eissa & Liebman (1996)
Note: AB is the budget constraint without EITC, ACDEB - is the budget constraint with EITC, showing the potential disincentive to work long hours with the introduction of EITC.
AC is the phase-in region, where individuals below earned income of $6080 receive a tax credit of 14%, with the maximum tax credit of $851. CD - constant region, where individuals earning income from $6080-$11000 receive a tax credit of $851. DE - phase-out region, where individuals with income over $11000 are phased out at 10%. EB - individuals earning over $15432 are no longer eligible for tax credit.

earned income tax credit shifts the budget constraint to the new ACDEB. The amount of the tax credit an individual is entitled to depends on the income earned and the region where it falls. With the new budget constraint for each hour worked individuals are at least as better of as with the initial one. *For individuals who do not work*, the impact of the introduction of the tax credit is the same as before. Moreover, the tax credit might create incentives for individuals to enter the labour force. *For individuals who work*, it depends on the income of the region. For individuals, whose income falls in the region AC, the phase-in region, the overall effect of the tax credit is driven by substitution and income effects. The substitution effect generates more income the more an individual works, hence incentivising individuals to work more hours. The income effect created by the tax credit, on the other hand, generates the same income for fewer hours of work, hence resulting in individuals working less. Those in the constant region CD will be driven by the income effect, resulting in working fewer hours. In the phase-out region

DE, individuals are negatively affected by both substitution and income effects, where the substitution effect comes from lower credit for each additional hour, and income effect comes from additional income from credit. In the region EB, individuals might work fewer hours in order to receive tax credit.

Eissa & Liebman (1996) use difference-in-differences approach to estimate the effect of the earned income tax credit on single women with children using data from March Current Population Surveys from 1985-1987 and 1989-1991. In addition to using all single women with children as a treatment group, they use two additional treatment groups in their estimation, single women with children and low levels of education, and single women with children, who they predict will be eligible for the tax credit. They use all single women without children as a control group for the broad treatment group, and two control groups for each of the additional treatment groups. In order to capture individuals who are in the same category as those who eligible for the tax credit, they include single women without children and low levels of education as a control group. And in order to capture women who have children in a control group, they include women who have children and have higher levels of education, who presumably earn income above the tax credit eligibility.

They find that the expansion of the tax credit in 1987 resulted in an increase in labour force participation of single women with children, particularly single women with low levels of education. When looking at hours of work, they did not find that the expansion in the tax credit resulted in decreased hours of work for individuals in the labour force.

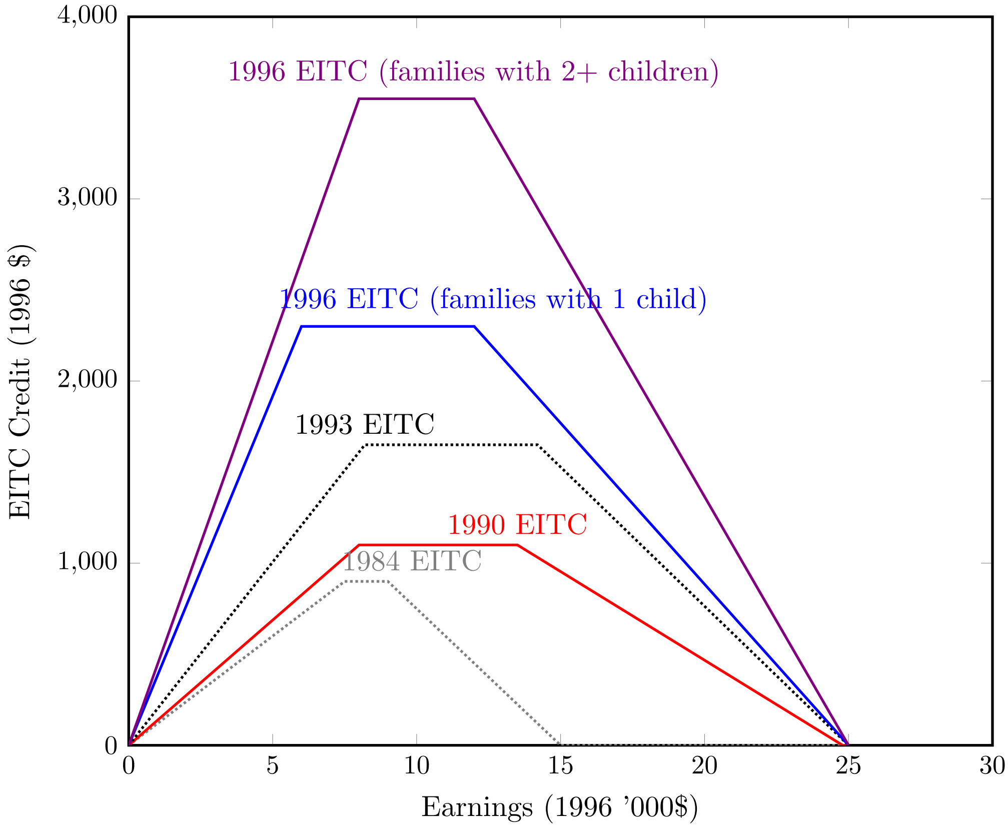
Eissa & Hoynes (2004) study further expansion to EITC up until 1996, which specifically targeted low-income families with children. They study the effect of the expansion of EITC on the labour force participation of married couples.

The expansion of EITC[5] was aimed at taxpayers who earned positive income and had children. The eligibility to EITC depended on the income level and the number of qualifying children. Figure 4.2 shows the changes in the shape of the EITC budget constraint due to the changes/expansions in EITC. The 1990 EITC had higher subsidy rate and phase-in income, which resulted in an increase in the maximum EITC from \$550 to \$953 in 1990. The 1993 IETC expansion resulted in a higher credit for families with 2+ children. The 1996 IETC expansion was the most generous. It increased both, the subsidy rate and maximum credit. For families with 2+ children, the 1996 IETC increased income eligibility.

Eissa & Hoynes (2004) use two empirical approaches to evaluate the impact of the expansion in EITC on labour market participation of families with children using 1984-1996 data from Current Population Survey. They use difference-in-differences approach,

[5] Tax Reform Act of 1986, Omnibus Reconciliation Act of 1990, and Omnibus Reconciliation Act of 1993

Figure 4.2: The dynamics of extensions in EITC: families with children



Source: Eissa & Hoynes (2004)
Note: The figure shows the changes in the shape of the EITC budget constraint due to the changes/expansions in EITC. Earnings include real family earnings for eligible taxpayers. Each area shows families tax credit increasing with raising income (phasing in) up to a point when it is constant for a certain income range, and then decreasing as the income increases further (phasing out). The 1990 EITC expansion increased maximum credit from $550 in 1986 to $953 in 1990. The 1996 EITC expansion increased the subsidy rate from 10% in 1984 to 34% for families with 1 child and to 40% for families with 2+ children in 1996. It increased the real value of the maximum credit by 185% for families with 1 child and by 370% for families with 2+ children.

comparing couples with children with couples without children. They also estimate a discrete choice model to estimate how the expansion affects labour force participation of couples with children. The model is based on a unitary household labour supply model, where a sequential, two-earner model is assumed in which the husband is the primary earner, who makes his labour supply decision independent of the wife's earning decisions. The wife, on the other hand, as the secondary earner, makes her earning decision by maximizing utility while taking into account the earnings of the primary earner, and other family income. Here, they use after-tax wage and after-tax non-labour income, which are identified from the EITC expansions. For the discrete choice estimation, they use couples with lower levels of education. Non-labour income includes net income for zero hours of work, family's capital income and transfers in case of husbands as primary earners, and husband's income from labour - for wives as secondary earners. The after-tax wage is the net wage of a worker who moves from zero hours of work to 40 hours per week, 52 weeks per year (full-time work).

Their findings from both models show that the EITC expansion negatively affected total labour supply of married couples. The reforms resulted in a drop in labour force participation of married women, which was more than the increase in labour force participation of married men, thus implying that it was effectively providing a subsidy for married mothers to stay at home.

Meyer & Rosenbaum (2001), on the other hand, studying the effect of the EITC reforms on labour response of single mothers over the same period, find that the 1984-1996 increase in labour market participation and hours of work by single mothers was largely attributable to the EITC reforms.

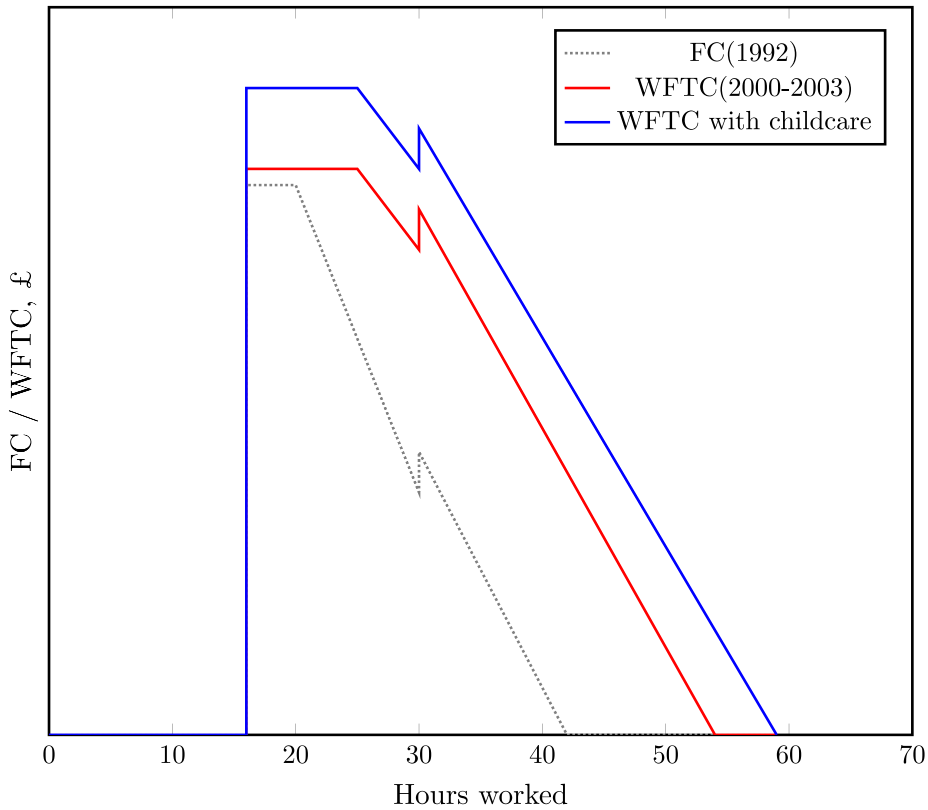
4.2.2 The UK

Blundell (2000) and Blundell et al. (2000) review and estimate the effect of the introduction of Working Families Tax Credit (WFTC) reform in the UK in 2000 (compared with similar reforms in the US and Canada) as a replacement of the UK Family Credit (FC). The Family Credit was introduced in 1988 and was meant to provide income support to low-income families with children. It was similar to EITC in the US, with one major difference being the minimum required hours of work for eligibility. The minimum requirement was set at 24 hours of work a week by one adult in the working families. In 1992, this requirement was reduced to 16 hours. In 1995, an additional credit for those working 30 hours a week was introduced, to create incentives for full-time work. In the FC framework, there was also additional credit of 12.35 added for each child under 11. In order to be eligible for FC, individuals must have income below 79 per week, while the credit was being withdrawn at 70% for each additional 1 after that threshold. FC was payable to mothers regardless of the income of which parent it was based on.

The Working Families Tax Credit reform, which was in place starting April 2000, had a similar structure to FC, but was a tax credit rather than a welfare benefit. WFTC was significantly more generous compared with FC, and it was aimed at improving incentives to move into the labour force. One of the major differences with FC was that the WFTC reform introduced a childcare component. The childcare credit covered 70% of childcare costs with the maximum credit of 100 per week for one child and 150 per week for two or more children. The credit for children under 11 increased by 2.5 to 14.85. The eligibility threshold for working families to qualify for the tax credit increased from 79 to 90 per week, while the credit withdrawal rate for income higher than the threshold was reduced from 70% to 55%. Figure 4.3 shows the difference in the credit received by families under FC, WFTC and WFTC with childcare component.

Blundell et al. (2000) use the data from the Family Resources Survey to estimate a model for labour supply of married couples and single parents. They then use the model to simulate the potential effect of WFTC reform on family labour supply. They estimate a 2.2 percentage point increase in the participation rate of single mothers and 0.57 percentage point decrease in the participation rate of married women, whose partners are employed.

Figure 4.3: The Working Families Tax Credit



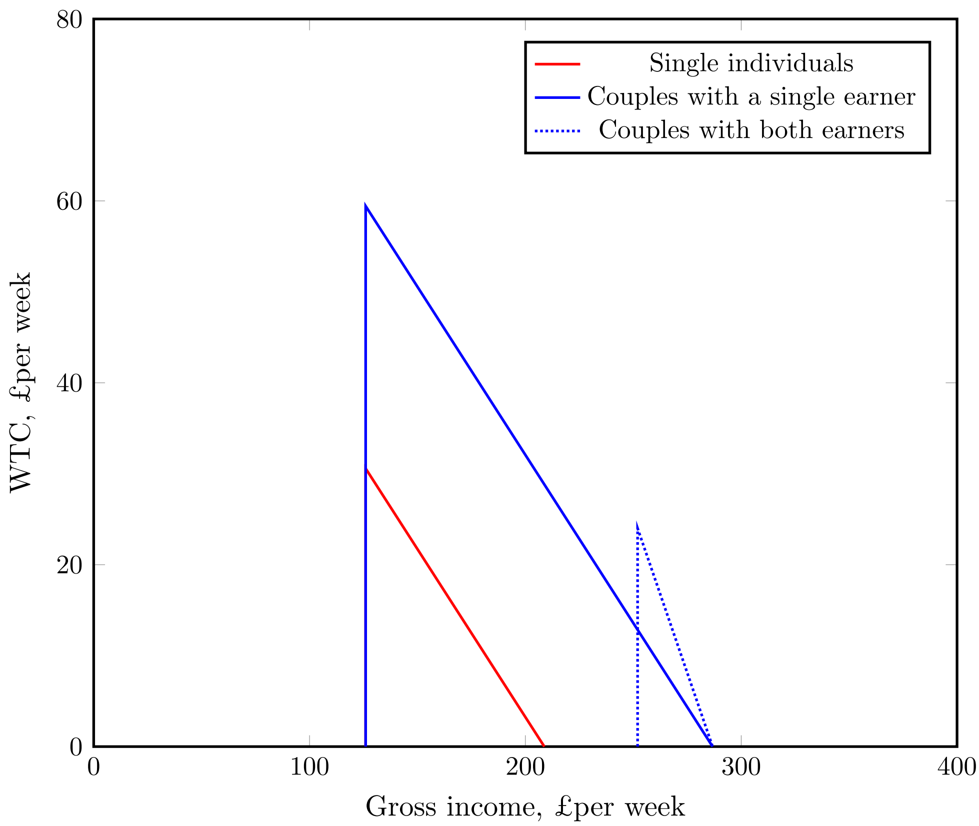
Source: Blundell (2000), Blundell et al. (2000)
Note: The figure shows the eligibility for the UK working families tax credit, working families tax credit with childcare versus family credit. The eligibility starts with families working at least 16 hours, a constant area for a range of income, and phasing out as the income rises. Families are entitled to an additional credit for working at least 30 hours a week.

Brewer et al. (2006) then use data for the period 1999-2003 to simulate the results for before and after the WFTC reform in order to evaluate the effect of the WFTC on labour supply. They find that the WFTC reform positively affected labour supply of single mothers along extensive margin, increasing the employment rate of single mothers by 5 percentage points, that is, more than estimated by Blundell et al. (2000). The effect on married women with children was, however, negative, decreasing employment by 0.57

percentage points, exactly as estimated by Blundell et al. (2000). They also find that ethnic minorities have different income and hours of work preferences compared with whites. The utility cost of participating in in-work benefits is higher for ethnic minority lone mothers and it is lower for couples compared with white couples.

The results on single mothers are confirmed by Francesconi & Van der Klaauw (2007) and Gregg et al. (2009). Both studies find that the WFTC increased the labour market participation of single mothers significantly. Gregg et al. (2009) also find a positive effect of the WFTC reform on the labour supply of single parents along the intensive margin. Leigh (2007) finds that the WFTC reform positively affected eligible single parents, and married men and women along both the intensive and extensive margins.

Figure 4.4: WTC 2003 for single individuals and couples without children



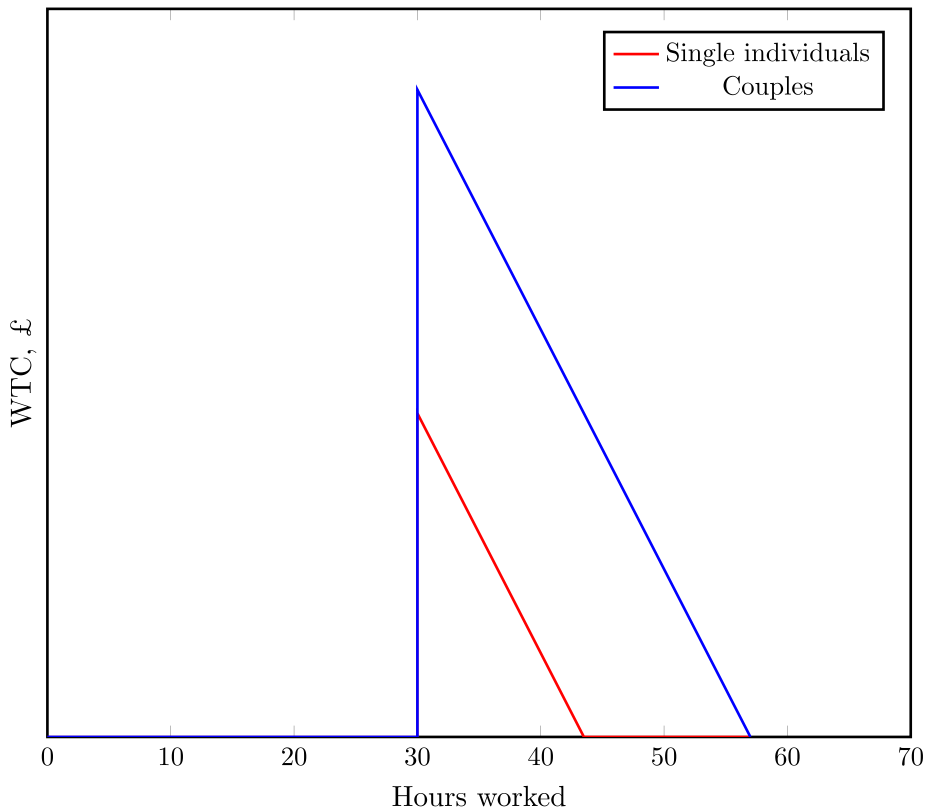
Source: Brewer (2003) and own calculations
Note: Single individuals and couples without children qualify for WTC if they work at least 30 hours per week.
The value of gross income is derived based on the minimum wage.

4.2.2.1 The 2003 Tax Credit Reform

The Working Tax Credit[6] was introduced in April 2003-2004 as a part of the tax credit reform that came to substitute the Working Families Tax Credit, which was in place from 1999 to 2003. The latter was a successor of Family Credit welfare program that was introduced in 1988 (described in Blundell & MaCurdy (1999) and Blundell et al. (2000)).

The new Tax Credit system retains the main benefits that were subsumed under WFTC for families with children and lone parents but is aimed at simplifying the system (Brewer 2003). However, for working individuals, including single individuals and families without children, the new WTC provided substantial incentives. It is supposed to benefit particularly those working full-time, and have a distributional effect in favour of poorer households.

Figure 4.5: WTC2003: the impact on working single individuals and couples without children



Note: Single individuals and couples without children qualify for WTC if they work at least 30 hours per week.

[6]Tax Credits Act 2002, 2002 c. 21

The new Tax Credit consists of Child Tax Credit and Working Tax Credit. The Child Tax Credit (CTC) is meant to replace multiple child benefits and provide income-related support to the main carer, while the Working Tax Credit (WTC) is designed to support working individuals with or without children, as well as to cover certain childcare costs. Both the Child and Working Tax Credits are based on gross annual income, which is considered jointly in case of couples. The entitlement to CTC depends on the income level. Families with incomes below 13,230 are eligible for two elements of the CTC, that is, (1) a family element of 545, which was doubled in the year a child was born, (2) an additional 1,445 for each dependent child. For families with income level above 13,230, the dependent child elements are withdrawn at 37% for each 1 over the threshold. The families are entitled to the full family element if their income was below 50,000, after which it is withdrawn at 6.7%.

The entitlement to WTC depends on the eligibility of individuals. In order to be eligible for WTC, families with children must work at least 16 hours, while those without children must work at least 30 hours a week. A qualifying child is aged under 16 or under 20 if they are enrolled in approved education or training[7]. The WTC has the following components (in 2003-2004) depending on eligibility.

- single individuals without children are entitled to a credit of 1,525 (currently 1,960) if their annual income is below 10,857;
- couples with or without children and lone parents with income below 13,230 are entitled to a credit of 3,025 (currently 3,970);
- Individuals working 30 or more hours a week are entitled to an additional credit of 620 (810 currently) if their income is below 14,911;
- Working families with children receive compensation of 70% of childcare costs below a 135 (currently 175) a week for families with one child under 16, 200 (currently 300) for those with two or more children;
- Individuals over 50, who are returning to work are entitled to additional credit;
- Also, additional credit is available for individuals with disabilities.

Individuals with or without children and couples with annual incomes of 5,060 (currently 6,420) or below are entitled to full WTC. Individuals or couples with income higher than 5,060 are withdrawn from WTC at a rate of 37% (currently 41%).

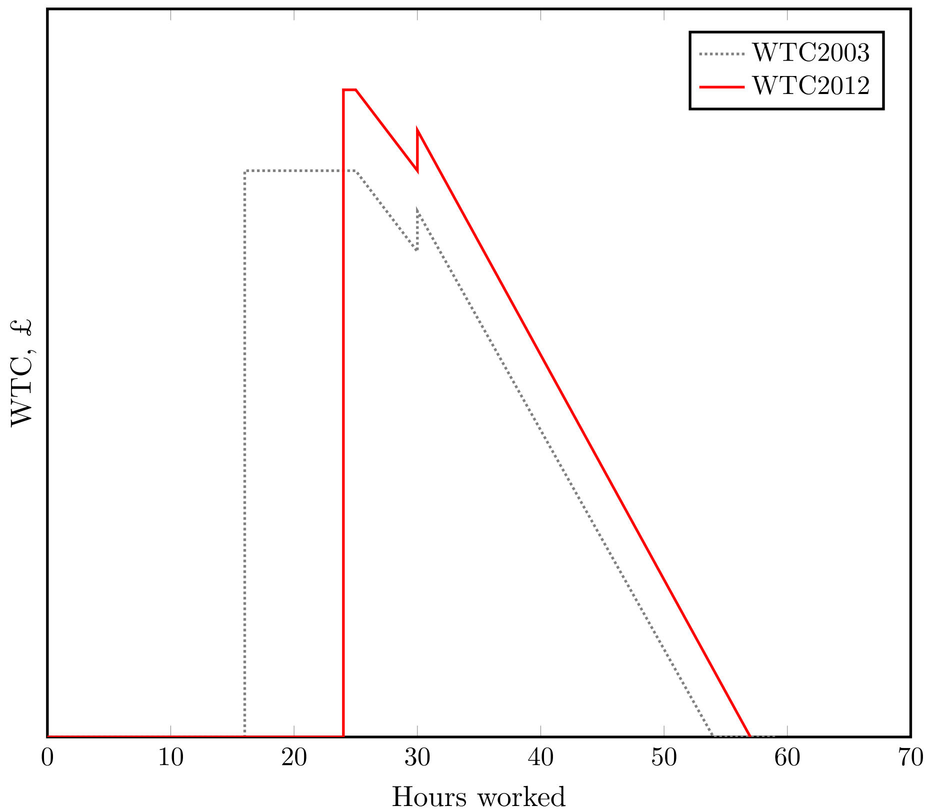
[7] Approved education includes full-time education, such as, A levels or similar, NVQs and other vocational qualifications up to level 3, home education - if started before the child turned 16 and traineeships in England. Approved training includes unpaid training, such as, Foundation Apprenticeships or Traineeships in Wales, Employability Fund programmes in Scotland, United Youth Pilot, PEACE IV Children and Young People 2.1 or Training for Success in Northern Ireland. Courses paid for by an employer or advanced degrees, as well as those that are part of a job contract are not approved. Source: https://www.gov.uk

Figure 4.4 shows the amount of WTC qualifying single individuals and couples without children are entitled to weekly, following the WTC2003 reform, while Figure 4.5 depicts WTC2003 eligibility depending on hours worked.

The 2012 changes

In April 2012 a new requirement came into force for Working Tax Credits[8] according to which in order to qualify for WTC, couples with children must work at least 24 hours a week between them, with one of them working at least 16 hours. The requirement does not apply to couples with children where one person is entitled to the WTC disability element, or is 60 years old or older.

Figure 4.6: The Working Tax Credit: the impact on working couples with children



Note: The figure shows the change in working tax credit eligibility for families with children within 2012 WTC reform versus 2003 WTC system. Within WTC 2012, families with children are eligible for WTC if they work at least 24 hours per week between them as opposed to 16 hours of WTC 2003. There is extra credit for working at least 30 hours a week.

[8]The Tax Credits (Miscellaneous Amendments) Regulations 2012, No. 848

The increase in the entitled hours of work for working families from 16 to 24 hours was aimed at making "the system fairer by reducing that disparity between couples and lone parents"[9].

Figure 4.6 shows the change in WTC2012 eligibility for working couples with children versus WTC2003 based on hours worked, depicting a shift from 16 hours for eligibility to 24 hours.

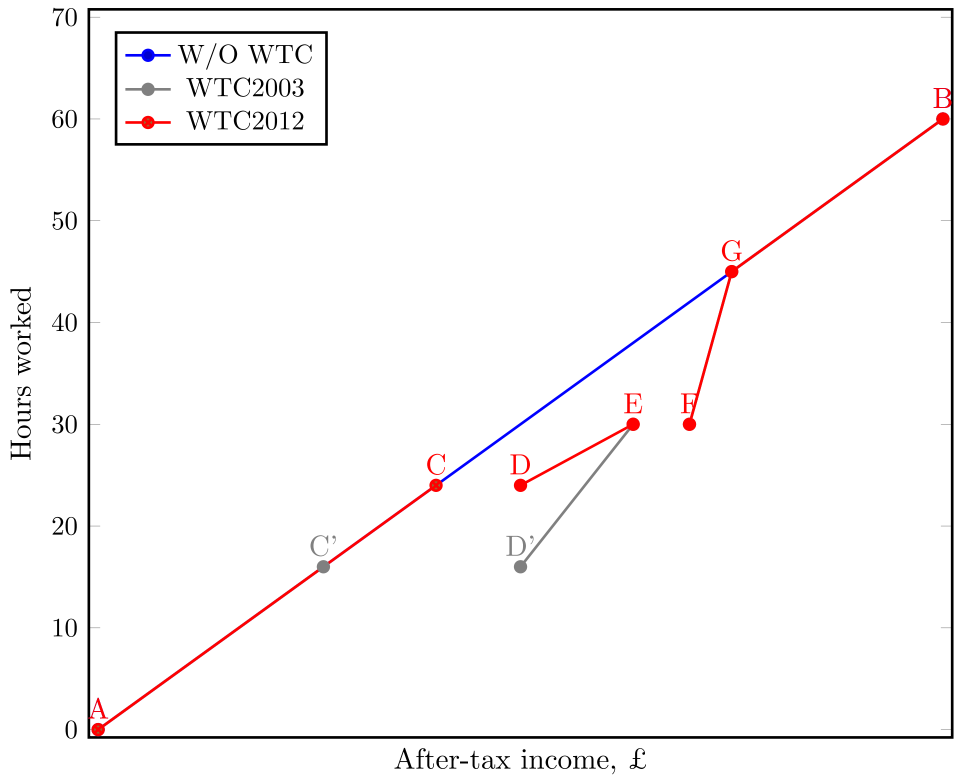
Figure 4.7 shows how WTC2003 and WTC2012 affect the budget constraint of eligible individuals with children. The budget of individuals without tax credit is presented by line AB. The introduction of WTC2003 shifts the budget constraint from AB to AC'D'EFGB. Depending on the level of income and hours worked, individuals are entitled to a different amount of tax credit. Once qualifying individuals work the required 16 hours, they are eligible for WTC2003, which results in an abrupt increase in after-tax income from C' to D', thus resulting in strong income and substitution effects. For individuals working at least 30 hours a week, there is a second jump from E to F.

For those *working less than 16 hours*, budget constraint is unaffected by WTC2003. Therefore, the substitution effect will create incentives for those working less than 16 hours to work at least 16 hours following the WTC2003 reform. For those who *work more than 16 hours but less than 30 hours*, the income effect is likely to result in them working fewer hours since their after-tax income will be the same following WTC2003 for fewer hours. On the other hand, the substitution effect will incentivise individuals to work 30 hours a week to increase their after-tax income driven by the WTC addition for 30-hours work. For individuals *who work more than 30 hours in the region FG*, there are negative substitution and income effects, resulting from lower WTC for an extra hour of work and additional income from WTC, respectively. In the region GB, individuals might reduce their hours of work in order to qualify for WTC2003.

WTC2012 shifts the budget constraint from AC'D'EFGB to ACDEFGB. The effect of WTC2012 is unchanged from that of WTC2003 for individuals *who work more than 30 hours.* With WTC2012, the first threshold of 16 hours is now shifted to 24 hours, that is, the first jump is from C to D. WTC2012 is likely to affect individuals *working between 16 and 24 hours.* The substitution effect is likely to create incentives for these group to work 24 hours to qualify for additional income WTC.

[9] Chloe Smith, The Economic Secretary to the Treasury in the Westminster Hall debate on 30 November 2011, cc319-328WH

Figure 4.7: The budget constraint under the Working Tax Credit



Note: The figure shows the change in the budget constraint depending on hours of work within 2012 WTC reform versus 2003 WTC. WTC2012 shifts the budget constraint from AC'D'EFGB to ACDEFGB. The effect of WTC2012 is unchanged from that of WTC2003 for those, who work more than 30 hours. Within WTC2012, the first threshold is now shifted to 24 hours versus the threshold of 16 hours within WTC2003.

4.3 Methodology and data

4.3.1 Methodology

We use difference-in-differences approach, following Angrist & Krueger (1999) and Angrist & Pischke (2009), to estimate the policy impact of the working tax credit reform in 2003 and the amendment of 2012 on individuals' labour supply along the intensive and extensive margins.

In order to account for any underlying economic and labour market factors affecting the treatment group, we use a control group which should be affected by the same factors as the treatment group, except for the policy treatment we intend to measure. That is, the identifying assumption under the difference-in-differences (diff-in-diff) strategy is that the control group is affected by the same time-varying factors, including economic conditions and labour market policies, as the treatment group, that is, the group we are interested in. Therefore, we use control groups that satisfy all the criteria of the treatment group, except for one.

We first study the effect of WTC2003 on two UK-born/non-UK-born groups of individuals, single individuals without children, and couples without children. Based on the discussion in section 4.2, WTC2003 could have affected single individuals and couples without children through income and substitution effects in two ways: it could have increased labour supply by incentivising individuals to work at least 30 hours a week, or it could have resulted in decreased hours of work for those working more than 30 hours a week. Therefore, as corresponding control groups for the treatment groups, we consider single individuals with children and couples with children. The control groups, therefore, satisfy the same criteria as the treatment groups, except for one condition: individuals and couples in the control groups have at least one child they are responsible for.

We then study the effect of the change in the required hours of work in order to qualify for WTC2012, on UK-born/non-UK-born couples with qualifying children. We expect WTC2012 affect couples with children in two ways. The substitution effect would have incentivised couples to increase hours of work in order to continue to be in receipt of WTC. On the other hand, increased hours of work is likely to make some couples ineligible for WTC. Furthermore, some couples might not have been able to increase hours of work. We also expect that some couples might have reduced their labour supply along the extensive margin.

Since the 2012 amendment in WTC increases the hours of work required for eligibility from 16 to 24 hours between the couple, therefore it primarily affects couples with children working 16-24 hours between them. To estimate the effect of WTC2012 amendment we consider a broad group of couples with children as a treatment group with two control groups: couples without children and single parents. Couples with children are expected to be affected by the same underlying conditions of being a couple as the treatment group, while single parents are expected to capture developments associated with children in the household. For the broad choice of control and treatment groups, we referred to Eissa & Liebman (1996).

When constructing a diff-in-diff strategy, we should note that UK citizens and non-UK citizens have different eligibility criteria. Non-EU/non-UK citizens generally can claim WTC provided they have a right to work full-time. However, their choices for other types of benefits are more limited. Therefore, in order to ensure that the treatment and control groups are comparable, when defining a control group, we use non-UK born groups for the non-UK born treatment group, and UK-born groups - for the UK-born treatment group.

Thus, we estimate the following difference-in-differences model for UK-born and non-UK-born individuals:

$$Y = \beta1 + \beta2\ T + \beta3\ Treat + \beta4\ T \times\ Treat + u, \tag{4.1}$$

where Y is hours worked per week or probability to be employed, T is a binary variable for the year of the policy change, $Treat$ - a binary variable for the treatment group. The coefficient of interest is $\beta4$.

That is, the treatment effect on the treated for each group is measured by:

$$\hat{\beta4} = (\bar{Y}_{Treat,T} - \bar{Y}_{Treat,T-1}) - (\bar{Y}_{C,T} - \bar{Y}_{C,T-1}), \tag{4.2}$$

where C is the control group.

It is important that individuals under consideration are not affected by any other policy measures apart from the WTC reforms in the required hours of work. From the 7th January 2013, child benefits become means-tested and a new income tax charge is introduced on "taxpayers, whose adjusted net income exceeds 50,000 in a tax year and who are in receipt of child benefit, and to taxpayers whose adjusted net income exceeds 50,000 and whose partner is in receipt of child benefit. If both partners have an adjusted net income that exceeds 50,000, the charge applies only to the partner with the highest income". The amount of the charge is 1% of the amount of child benefit for every 100 of income over 50,000[10]. Individuals with income over 60,000 are charged the full amount of child benefit[11]. The changes in child benefit policy are carried out through taxation rather than a reduction in benefits.

To tackle this issue, we also use more narrowly defined treatment and control groups. Since the main group affected by WTC2012 amendment is couples with children working 16-24 hours between them, we define the narrow treatment group as couples with children who worked 0-24 hours in April 2011, and we use two control groups for this treatment group: couples without children who worked 0-24 hours in April 2011 and couples with children who worked more than 24 hours April 2011. Couples working less than 24 hours are less likely to be close to the 50,000 threshold, and therefore their behaviour is less likely to be affected by the income cap. Furthermore, by including couples with children as a control group, we account for policy changes that are specific to couples with children.

Additionally, to combine the underlying developments from both control groups, we use a difference-in-difference-in-differences approach (Wooldridge 2010). If we denote

[10] For instance, for income of 50,500 the charge constitutes 5% of child benefit.

[11] Finance Act 2012, 2012 c. 14

couples who work less than 24 hours in April 2011 with a binary variable S, and define a binary variable W for couples with children, then our new estimation for UK-born and non-UK-born individuals is as follows:

$$Y = \beta 0+\beta 1\, W+\beta 2\, T+\beta 3\, S+\beta 4\, T\times S+\beta 5\, W\times S+\beta 6\, T\times W+\beta 7\, W\times S\times T+u, \quad (4.3)$$

where Y is hours worked per week or probability to be employed and T is a binary variable for the year of the policy change. The coefficient of interest here is $\beta 7$.

The treatment effect on the treated in this case is measured by:

$$\hat{\beta 7} = [(\bar{Y}_{W,S,T}-\bar{Y}_{W,S,T-1})-(\bar{Y}_{W,M,T}-\bar{Y}_{W,M,T-1})]-[(\bar{Y}_{N,S,T}-\bar{Y}_{N,S,T-1})-(\bar{Y}_{N,M,T}-\bar{Y}_{N,M,T-1})], \quad (4.4)$$

where M is couples working 24 hours or more in April 2011 the control group, and N - couples without children.

4.3.2 Data

We use the five-quarter longitudinal datasets of Labour Force Survey (LFS) to estimate the effect of WTC2003 and WTC2012 on individuals and couples. All individuals in the sample are at least 18 years of age. The discussion below will be structured within two sections, for the WTC reform of 2003 and for the WTC amendment of 2012.

As discussed in section 4.3.1 the identifying assumption under the diff-in-diff strategy is that the control group is affected by the same time-varying factors, or that the control and treatment groups follow a parallel trend in pre-treatment period. Therefore, in the subsections below we will study potential control and treatment groups for parallel trends in the pre-treatment period.

4.3.2.1 WTC2003

The two groups potentially benefiting from WTC2003 for the first time are single individuals without children and couples without children. In order to study the effect of the reform on the two groups, we need to find a relevant control group for each of them.

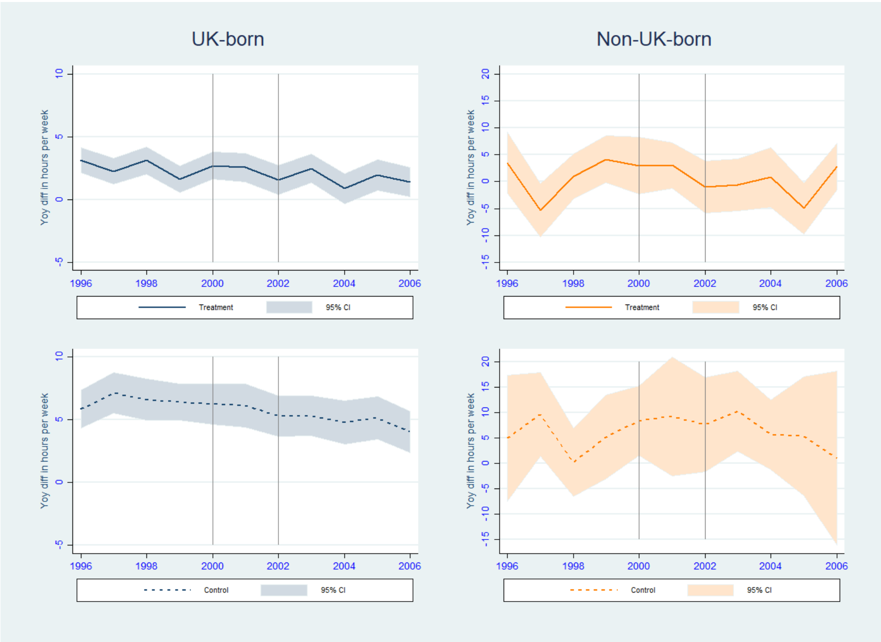
Single individuals without children When studying single parents, single individuals without children are often used as a control group (for instance, Eissa & Liebman (1996)). Therefore, when studying single individual without children, we consider single parents as a control group to account for any underlying tax/welfare and economic policy changes that could have potentially affected both groups. This group is potentially a relevant control group in the case of WTC2003 reform since the reform overall substituted all the benefits for single parents that were subsumed under WFTC, and therefore should not have affected the incentives of single parents. However, in order to consider single parents as a control group, we need to make sure that it follows a parallel trend with the treatment group.

Figure 4.8 shows mean annual changes and 95% confidence intervals of mean changes in hours worked by UK-born and non-UK-born single individuals without children (treatment groups) and single parents (control groups). The period we are interested in comparing trends for is 1999-2002. The 1999 WFTC reform significantly affected single parents, and therefore, the pre-1999 period is not relevant for comparison as the trend for single parents is likely to have changed since 1999. However, since we are taking year-on-year changes, we are particularly interested in the period 2000-2002, which excludes any developments resulting from the WFTC reform.

The trends are roughly similar also when looking at the extensive margin, average annual change in employment status (Figure 4.9). Employment status is denoted 1 when employed, and 0, when unemployed. The change in employment status is, therefore, either 0 if the status is unchanged, -1 if the individual moved from employment to unemployment, and 1, if the individual moved from unemployment to employment. The trends for UK-born and non-UK-born single individuals without and with children are characterised with a slight increase in 2001 and a subsequent decrease in 2002. The spike is more prominent for single parents.

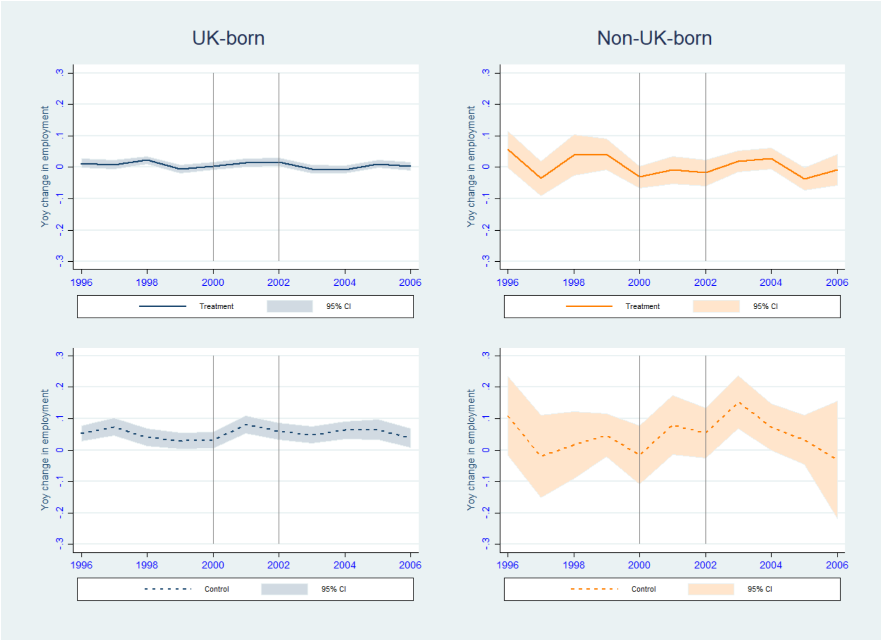
Table 4.1 shows the results of the regression to test for parallel trends between single individuals without children and single parents. The t-tests for interaction variables of the treatment group and the years 2000-2002 indicate that the treatment and control groups follow parallel trends for these years. The coefficients are significant for some groups for the year 2003, reflecting reactions to the WTC2003 reform.

Figure 4.8: Single individuals w/o children vs. single parents: intensive margin



Source: Labour Force Survey.
Note: Year-on-year changes in hours worked by the group conditional on the individuals being employed.
Control group is single parents. Treatment group is single individuals without children.

Figure 4.9: Single individuals w/o children vs. single parents: extensive margin



Source: Labour Force Survey.
Note: Year-on-year changes in employment status.
0: status unchanged, -1: moved from employment to unemployment, 1: moved from unemployment to employment.
Control group is single parents. Treatment group is single individuals without children.

Table 4.1: Parallel trend regressions: single individuals, 1999-2003

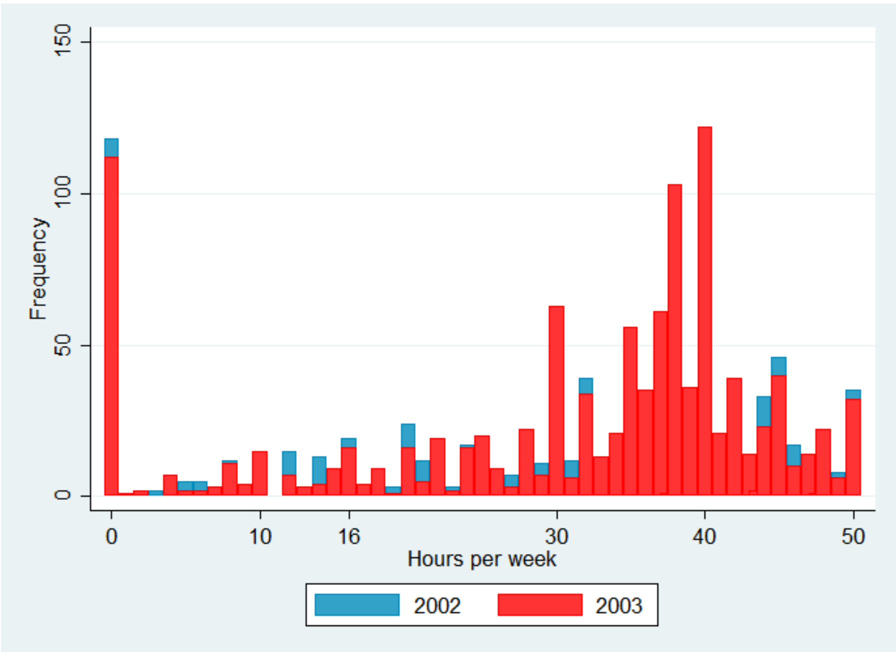
	Intensive margin			Extensive margin		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
Treat=1	–4.58***	–4.76***	–1.04	–0.03**	–0.04**	–0.00
	(0.91)	(0.92)	(4.76)	(0.01)	(0.01)	(0.04)
year=2000	0.06	–0.13	3.18	–0.00	0.00	–0.06
	(1.09)	(1.11)	(5.45)	(0.02)	(0.02)	(0.06)
year=2001	–0.11	–0.26	4.06	0.05***	0.05***	0.03
	(1.14)	(1.15)	(7.20)	(0.02)	(0.02)	(0.06)
year=2002	–0.94	–1.09	2.42	0.03*	0.03*	0.01
	(1.10)	(1.11)	(6.27)	(0.02)	(0.02)	(0.05)
year=2003	–0.69	–1.07	5.09	0.03	0.02	0.11*
	(1.10)	(1.11)	(5.80)	(0.02)	(0.02)	(0.05)
Treat=1 × year=2000	0.90	1.21	–4.37	0.01	0.01	–0.01
	(1.33)	(1.36)	(6.49)	(0.02)	(0.02)	(0.07)
Treat=1 × year=2001	0.94	1.19	–5.17	–0.03	–0.03	–0.08
	(1.38)	(1.41)	(7.85)	(0.02)	(0.02)	(0.07)
Treat=1 × year=2002	0.62	1.04	–7.58	–0.01	–0.01	–0.07
	(1.35)	(1.37)	(7.10)	(0.02)	(0.02)	(0.06)
Treat=1 × year=2003	1.22	1.92	–9.84	–0.03	–0.02	–0.13**
	(1.35)	(1.37)	(6.69)	(0.02)	(0.02)	(0.06)
N	9611	9108	503	14232	13326	906

The estimation method is linear regression.
(Intensive margin) The dependent variable is year-on-year changes in actual hours worked, conditional on being employed.
(Extensive margin) The dependent variable is year-on-year changes in employment.
The treatment group is single individuals without children. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Eissa & Liebman (1996) also use treatment group of single parents with lower education with control groups of single individuals without children with lower education (as a potentially eligible group) and single parents with higher education. We also inspect treatment groups of single individuals without children with lower education[12] and respective control groups of single parents with lower education, and single individuals without children with higher education. Figures C.1 and C.2 of Appendix C.1 show trends of annual changes in hours worked by single individuals without with lower education and without children versus the two potential control groups: single parents with lower education (Figures C.1) and single individuals with higher education and no children (Figure C.2). Neither of the potential control groups appears to have parallel trends with the treatment group.

When looking at frequencies of single individuals without children working certain hours a week in Figures 4.10 and 4.11, there seems to be an increase in the number of individuals working 30 hours per week, both in case of UK-born and non-UK-born individuals. However, we need to take into account potential changes in tax policies and economic conditions to estimate the treatment effect on the treated.

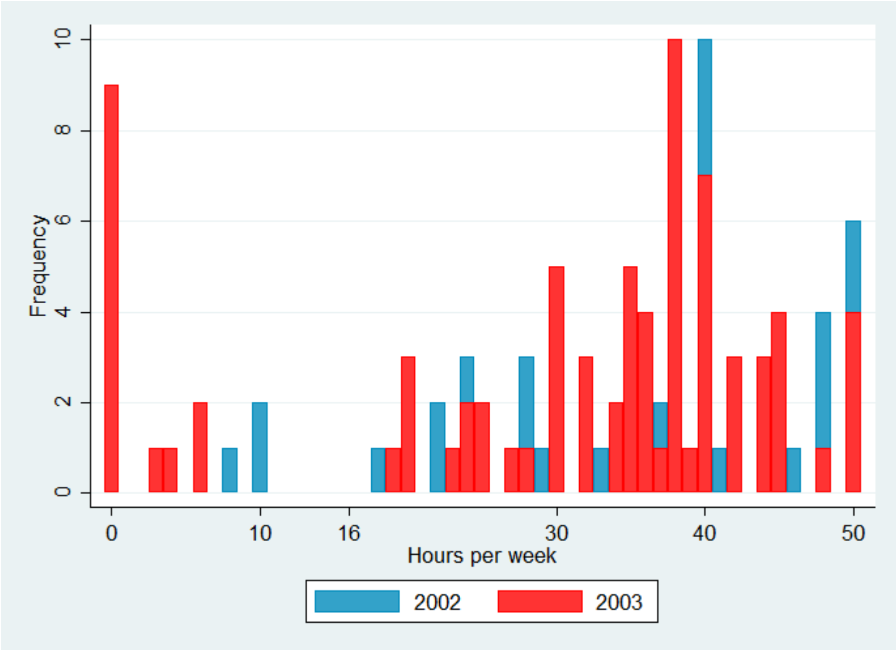
Figure 4.10: Hours worked by UK-born individuals w/o children



Source: Labour Force Survey.
Note: Hours worked - total hours worked by a single individual without children.

[12]Lower than Level 3 - "GCE, A-level or equivalent" of detailed grouping of variables hiqual, HIQUAL and HIQUL.

Figure 4.11: Hours worked by non-UK-born individuals w/o children



Source: Labour Force Survey.
Note: Hours worked - total hours worked by a single individual without children.

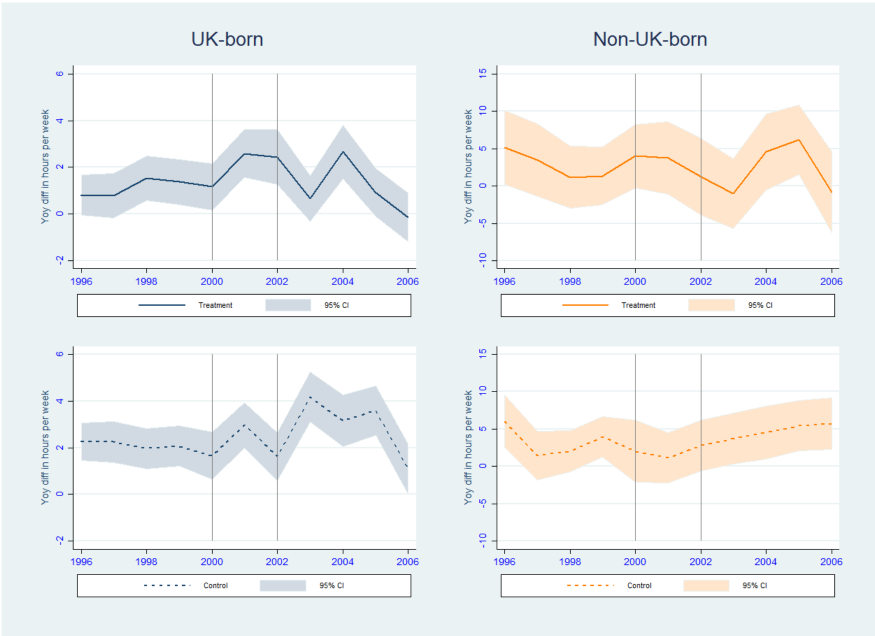
Couples without children In order to study the effect of WTC2003 on couples without children, we consider the possibility of using couples with children as a control group. Using couples with children is justified by the fact that WTC2003 did not create additional incentives for this group, therefore, this group would be unaffected by the reform. However, the two groups of couples are likely to be affected by the same socio-economic and other policy changes. Before we can use couples with children as a control group, we need to make sure they follow parallel trends. Figures 4.12 and 4.13, and Figures C.3 and C.4 in Appendix C.2, compare trends of UK-born and non-UK-born couples without children with couples with children along intensive and extensive margins.

At the intensive margin, that is, looking at annual changes in hours worked by couples with children as a potential control group with couples without children (Figure 4.12), we can observe an increasing, and then decreasing lines for UK-born couples for years 2000-2002, while the trends are moving in opposite directions for non-UK-born couples. However, when including couples, where neither is UK-born (Figure 4.13), we can observe increasing, followed by a decreasing trend, although with a more prominent peak for couples without children.

Similarly, at the extensive margin (Figure C.3 of Appendix C.2), when looking at annual changes in employment status, UK-born couples with and without children exhibit similar trends, while non-UK couples do not follow similar trends. However, when considering non-UK-couples, where both are non-UK-born (Figure C.4 of Appendix C.2), trends for non-UK-born couples with and without children are broadly similar.

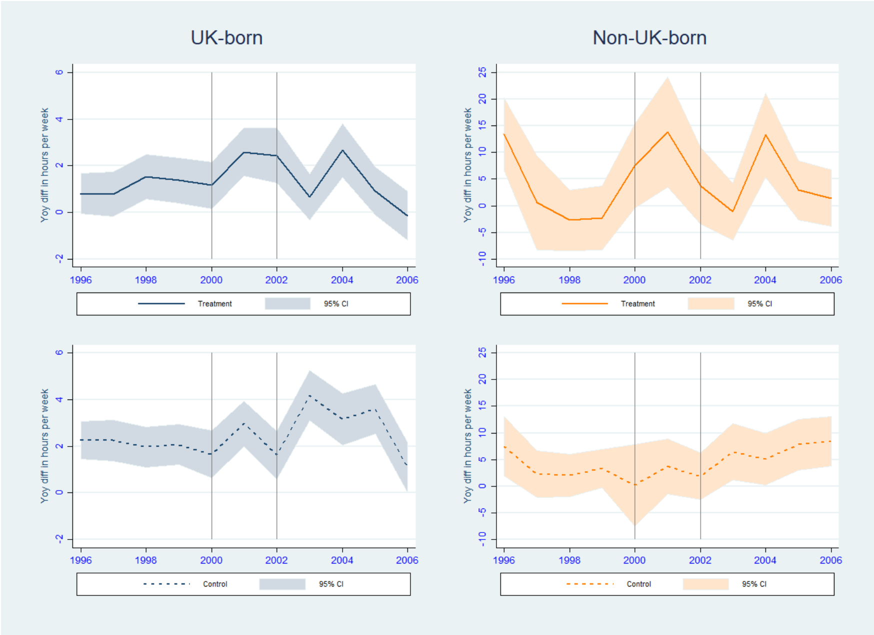
Table 4.2 shows the results of the regression for testing the parallel trends assumption between couples with and without children. The results, as in case of single individuals, indicate that the treatment and control groups follow parallel trends for years 2000-2002.

Figure 4.12: Couples w/o children vs. couples w/ children: intensive margin I



Source: Labour Force Survey.
Note: Year-on-year changes in non-zero hours worked by the group.
Control group is couples with children. Treatment group is couples without children.

Figure 4.13: Couples w/o children vs. couples w/ children: intensive margin II



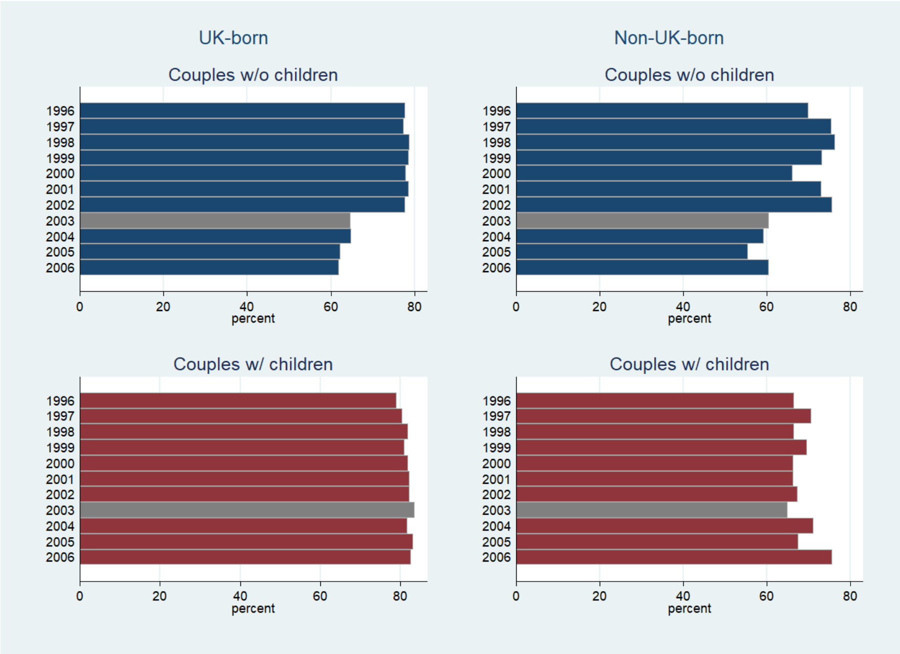
Source: Labour Force Survey.
Note: Year-on-year changes in non-zero hours worked by the group.
Non-UK-born couples include both being non-UK-born.
Control group is couples with children. Treatment group is couples without children.

Table 4.2: Parallel trend regressions: couples, 1999-2003

	Intensive margin			Extensive margin		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
Treat=1	–0.40	–0.35	–2.43	–0.01**	–0.01**	–0.01
	(0.43)	(0.45)	(2.61)	(0.01)	(0.01)	(0.03)
year=2000	–0.02	0.07	–0.83	0.00	0.00	0.02
	(0.44)	(0.46)	(2.72)	(0.01)	(0.01)	(0.04)
year=2001	0.66	0.80*	0.44	0.01*	0.02**	–0.04
	(0.43)	(0.45)	(2.33)	(0.01)	(0.01)	(0.03)
year=2002	–0.20	–0.24	–0.51	0.00	0.00	–0.00
	(0.45)	(0.46)	(2.07)	(0.01)	(0.01)	(0.03)
year=2003	1.06**	1.13**	1.71	0.00	–0.00	0.01
	(0.45)	(0.47)	(2.12)	(0.01)	(0.01)	(0.03)
Treat=1 × year=2000	0.11	–0.01	5.59	–0.01	–0.01	–0.01
	(0.64)	(0.66)	(4.47)	(0.01)	(0.01)	(0.05)
Treat=1 × year=2001	–0.09	–0.29	7.90	–0.01	–0.01	0.00
	(0.65)	(0.67)	(4.96)	(0.01)	(0.01)	(0.07)
Treat=1 × year=2002	0.53	0.55	2.84	–0.00	–0.00	0.05
	(0.67)	(0.69)	(4.24)	(0.01)	(0.01)	(0.05)
Treat=1 × year=2003	–1.54**	–1.62**	–0.86	–0.01*	–0.01	–0.01
	(0.64)	(0.67)	(3.81)	(0.01)	(0.01)	(0.05)
N	31099	29172	848	36360	33967	1080

The estimation method is linear regression.
(Intensive margin) The dependent variable is year-on-year changes in actual hours worked, conditional on being employed.
(Extensive margin) The dependent variable is year-on-year changes in employment.
The treatment group is couples without children. The control group is couples with children.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Figure 4.14: Proportions of couples who are employed

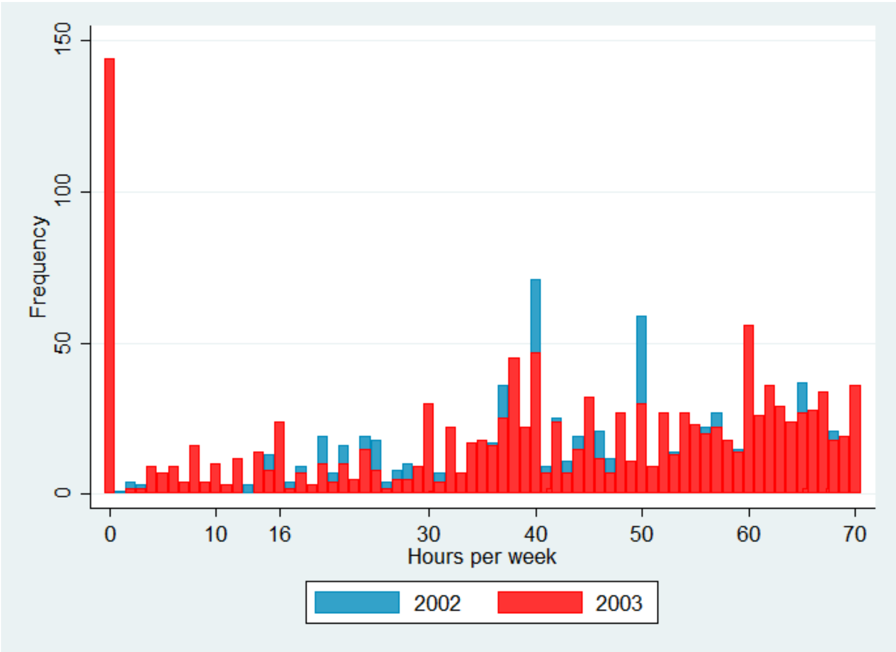


Source: Labour Force Survey.
Note: Proportions are calculated as shares of employed UK-born/non-UK-born couples without (with) children in total UK-born/non-UK-born couples without (with) children.

Figure 4.15: Proportions of couples who are employed (both non-UK-born for non-UK)

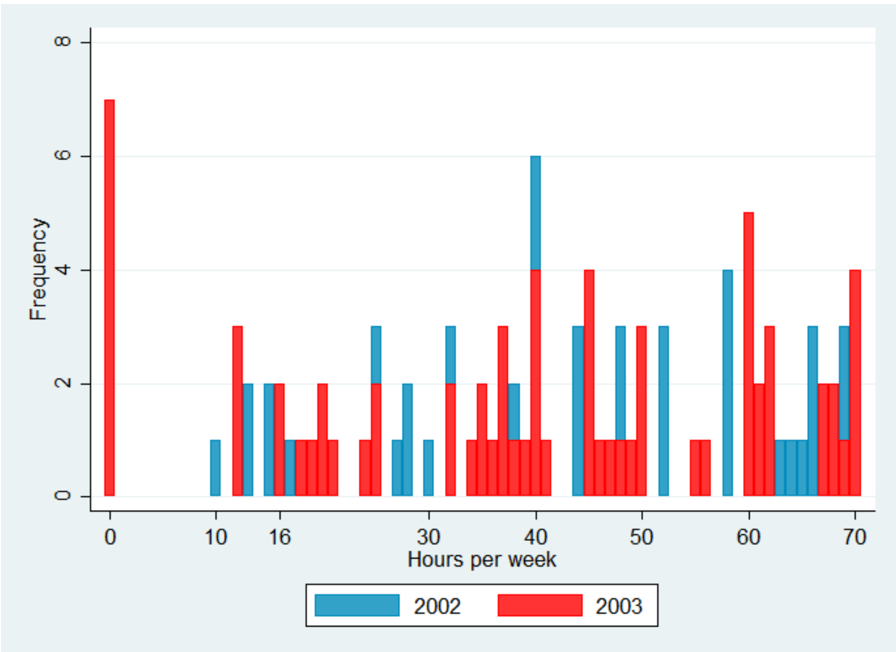
Source: Labour Force Survey.
Note: Proportions are calculated as shares of employed UK-born/non-UK-born couples without (with) children in total UK-born/non-UK-born couples without (with) children.

Figure 4.16: Hours worked by UK-born couples w/o children



Source: Labour Force Survey.
Note: Frequencies of hours worked - total hours worked by couples without children: 2003 versus 2002.

Figure 4.17: Hours worked by non-UK-born couples w/o children



Source: Labour Force Survey.
Note: Frequencies of hours worked - total hours worked by couples without children: 2003 versus 2002.

Figure 4.14 shows the proportion of couples in employment. The trends for years preceding WTC2003 are similar, particularly for the UK-born, while there is a considerable slump in 2003, with the new level persisting for the years after. When considering non-UK-born couples, where both are non-UK-born (Figure 4.14), the trends for couples with and without children become broadly parallel. For non-UK-born couples without children, the year following the treatment year is characterised by a slump, while the share of employed is stable in 2003.

Frequencies of couples without children working certain hours a week between them are shown in Figures 4.16 and 4.17. There seems to be an increase in the number of couples working 30 hours per week in the case of UK-born couples. On the other hand, the number of non-UK-born couples working 30 hours seems to have decreased. We can also see an increase in the number of UK-born and non-UK-born couples working 60 hours a week between them.

4.3.2.2 WTC2012

The 2012 amendment in WTC affected couples with children, increasing the hours of work required for eligibility from 16 to 24 hours between them. To estimate the effect of WTC2012, below we discuss the relevant control groups for the affected treatment group.

Couples with children Here, we follow similar intuition as for couples without children in Section 4.3.2.1, with the difference that couples with children are the treatment group in this section. For the 2012 WTC amendment, the period we are looking at to compare trends is 2008-2011. This period is chosen in order to exclude any potential shifts in trends arising from the economic crisis of 2007-2008[13], and to include the years preceding the WTC2012 amendment.

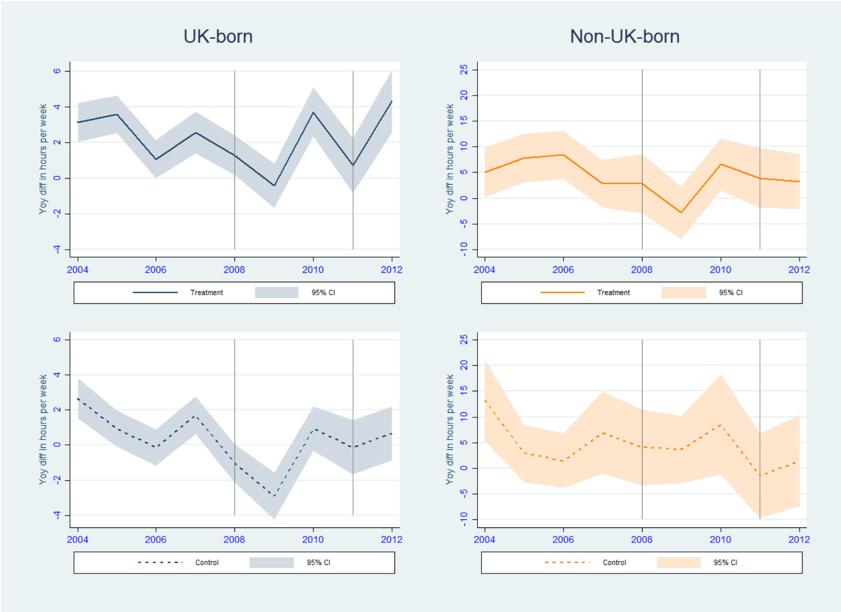
Figure C.5 in Appendix C.3 shows yearly changes in hours worked by couples with children as a treatment group and couples without children as a potential control group. The trends are similar for UK-born couples with and without children, while it is not for non-UK-born couples. When considering non-UK-born couples where both were born outside the UK in Figure 4.18, the trends become broadly similar, when looking at yearly dynamics.

In terms of changes in employment status, UK-born couples with children exhibit similar trends to couples without children (Figure C.6 of Appendix C.3), while non-UK-born couples do not seem to have parallel trends when considering either couples with at least one being from the UK (Figure C.7 in Appendix C.3) or those where both are non-UK-born (Figure C.6). Couples where both are non-UK-born, however, exhibit similar trend to UK-born couples with and without children.

The results of the test for the parallel trends assumption between hours worked and labour market participation by couples with and without children are shown in Table 4.3. The results confirm the parallel trend assumption for couples with and without children for years 2008-2011.

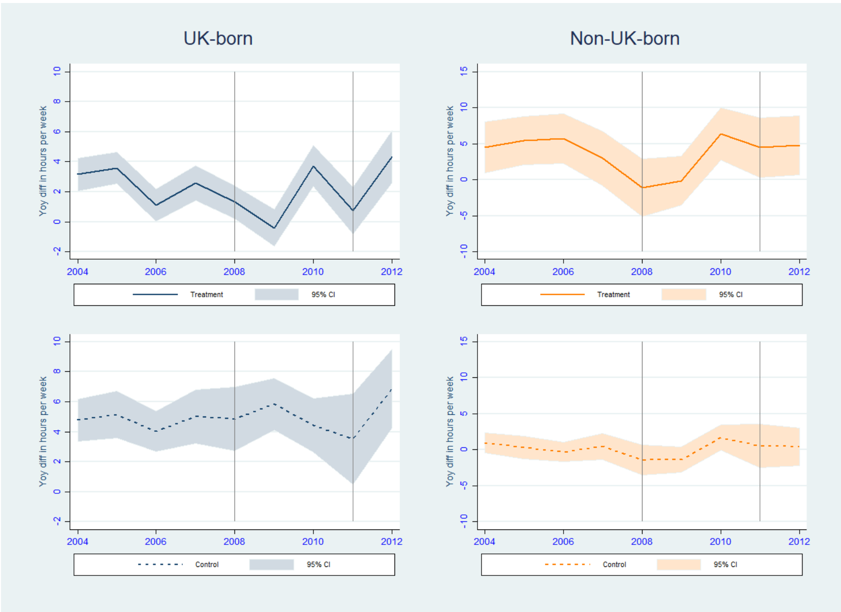
[13]A stricter approach is to consider years 2009-2011, with 2009 being the first post-crisis year.

Figure 4.18: Couples w/ children vs. couples w/o children: intensive margin I



Source: Labour Force Survey.
Note: Year-on-year changes in non-zero hours worked by the group.
Non-UK-born couples include both being non-UK-born.
Control group is couples without children. Treatment group is couples with children.

Figure 4.19: Couples w/ children vs. lone parents: intensive margin



Source: Labour Force Survey.
Note: Year-on-year changes in hours worked by the group.
Non-UK-born couples include both being non-UK-born.
Control group is lone parents, who are employed. Treatment group is couples with children working non-zero hours.

Table 4.3: Parallel trend regressions: couples, 2008-2012

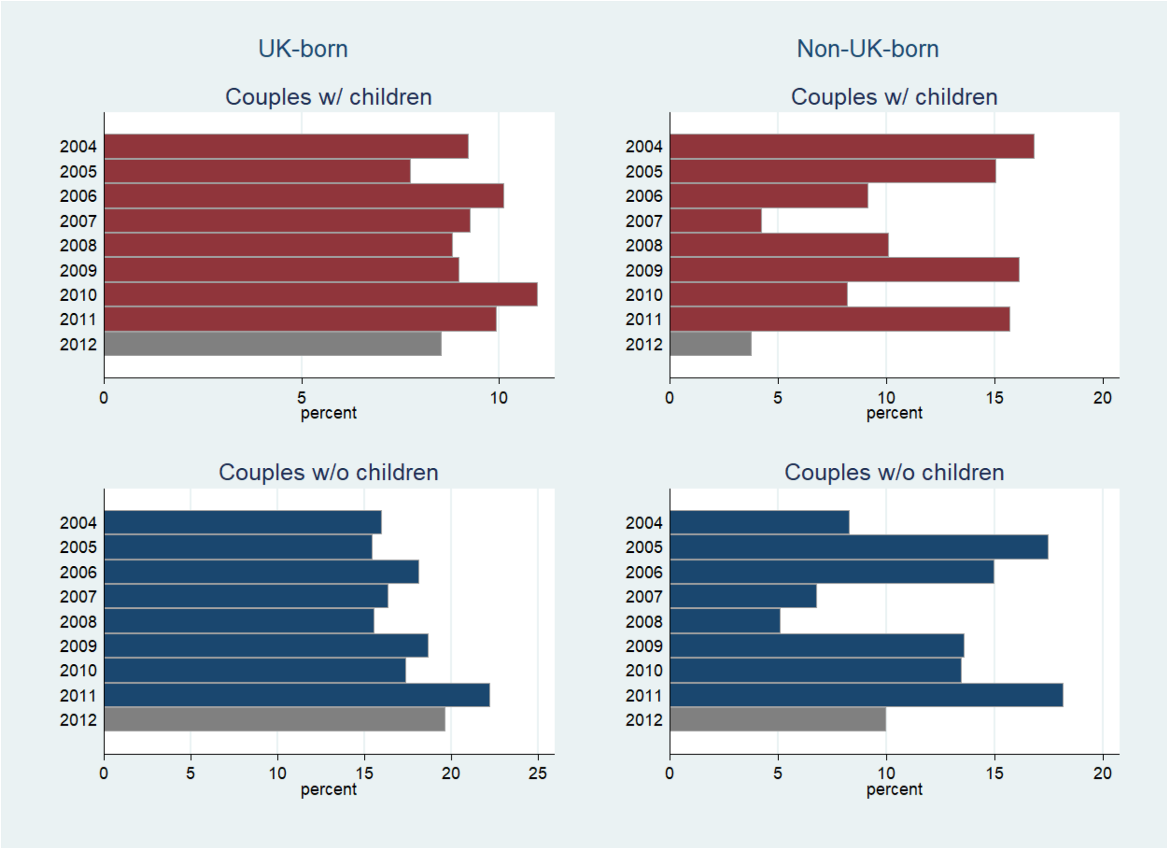
	Intensive margin			Extensive margin		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
Treat=1	1.42**	1.40**	–2.83	0.03***	0.03***	–0.04
	(0.61)	(0.64)	(3.23)	(0.01)	(0.01)	(0.05)
year=2010	2.09***	2.09***	2.75	0.02**	0.02***	–0.01
	(0.60)	(0.62)	(4.01)	(0.01)	(0.01)	(0.06)
year=2011	1.12*	1.23*	–0.88	0.02**	0.02**	0.00
	(0.67)	(0.70)	(3.76)	(0.01)	(0.01)	(0.06)
year=2012	1.44**	1.57**	–1.71	0.01	0.01	–0.04
	(0.66)	(0.68)	(4.05)	(0.01)	(0.01)	(0.06)
Treat=1 × year=2010	0.13	0.13	1.88	0.00	0.00	0.04
	(0.86)	(0.90)	(4.73)	(0.01)	(0.01)	(0.07)
Treat=1 × year=2011	–0.39	–0.58	4.19	0.01	0.01	0.02
	(0.93)	(0.98)	(4.61)	(0.01)	(0.01)	(0.07)
Treat=1 × year=2012	0.45	0.39	4.68	–0.00	–0.01	0.09
	(0.96)	(1.01)	(4.80)	(0.01)	(0.01)	(0.07)
N	11806	10761	530	15809	14544	638

The estimation method is linear regression.
(Intensive margin) The dependent variable is year-on-year changes in actual hours worked, conditional on being employed.
(Extensive margin) The dependent variable is year-on-year changes in employment.
The treatment group is couples with children. The control group is couples without children.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Another control group for couples with children used by Eissa & Liebman (1996) is lone parents. We check for a single trend for couples with children working non-zero hours and lone parents who are employed (Figure 4.19). Along intensive margin (Figure 4.19), couples with children and lone parents do not exhibit parallel trends for UK-born individuals, while the trends are broadly parallel for non-UK-born couples and lone parents. Since the parallel trend assumption do not hold for both UK-born and non-UK-born couples with children and lone parents, we do not consider lone parents as a control group.

Figure 4.20 shows the shares of couples who work less than 24 hours a week. There is significant variation in proportions across years, and no strict similarities in patterns between couples with and without children, especially for UK-born couples. Figure C.8 of Appendix C.3 shows patterns of shares of employed couples. These seem to be similar for couples with children versus couples without children, particularly following the crisis years of 2007-2008, with the exception of the spike in shares of couples without children from 2010 to 2011 for non-UK-born couples.

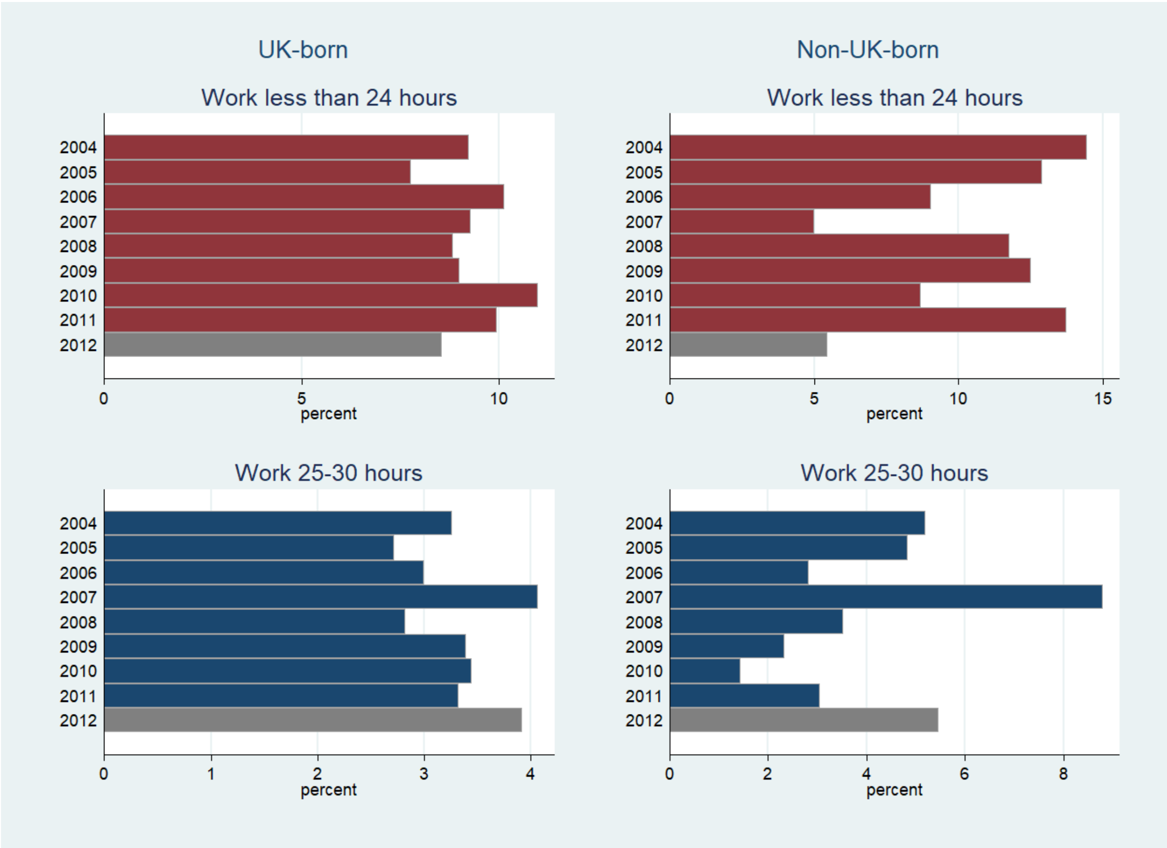
Figure 4.20: Proportions of couples who work less than 24 hours



Source: Labour Force Survey.
Note: Proportions are calculated as shares of employed UK-born/non-UK-born couples with (without) children who work less than 24 hours a week in total employed UK-born/non-UK-born couples with (without) children.
Non-UK-born couples include both being non-UK-born.

Couples without children, however, might be driven by fundamentally different socio-economic factors. This might create an argument against using couples without children as a control group for couples with children. Therefore, we consider another set of control groups for couples with children working less than 24 hours in pre-treatment year, that is, we use couples with children whose working hours are close to the treatment group, specifically, who work 25-30 hours a week. Figure 4.21 shows shares of these groups for UK-born and non-UK-born individuals. The trends of UK-born and non-UK-born couples with children working 25-30 hours are broadly similar to couples working less than 24 hours for post-2008 crisis years.

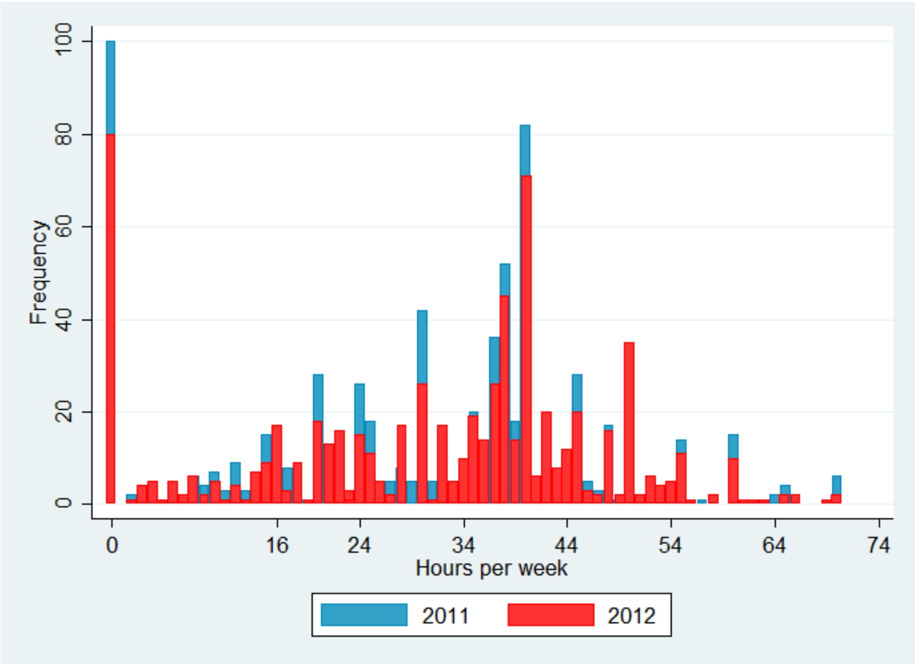
Figure 4.21: Proportions of couples with children who work less than 24 hours and 25-30 hours



Source: Labour Force Survey.
Note: Proportions are calculated as shares of employed UK-born/non-UK-born couples with children who work less than 24 hours a week (25-30 hours, included) in total employed UK-born/non-UK-born couples with children.

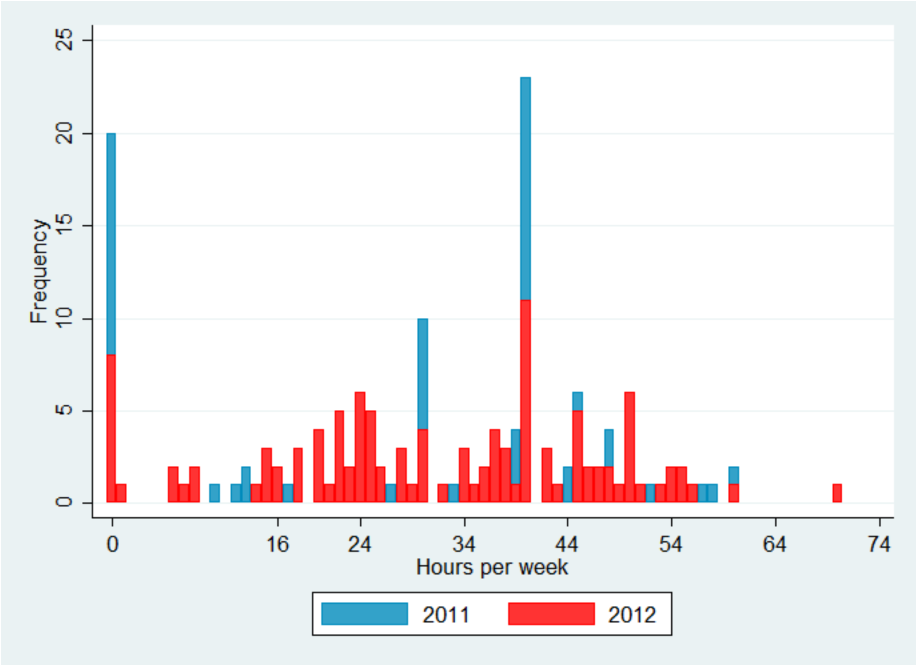
Figures 4.22 - 4.25 show the frequencies of hours worked before and after the increase in the eligibility requirement for UK-born and non-UK-born couples with at least one child under 16. There seems to be a drop in the number of UK-born individuals who work 16 hours a week with at least one partner working 16, after the policy change. However, there is a spike in the number of individuals working 24 hours for non-UK-born individuals.

Figure 4.22: Hours worked by UK-born couples with children



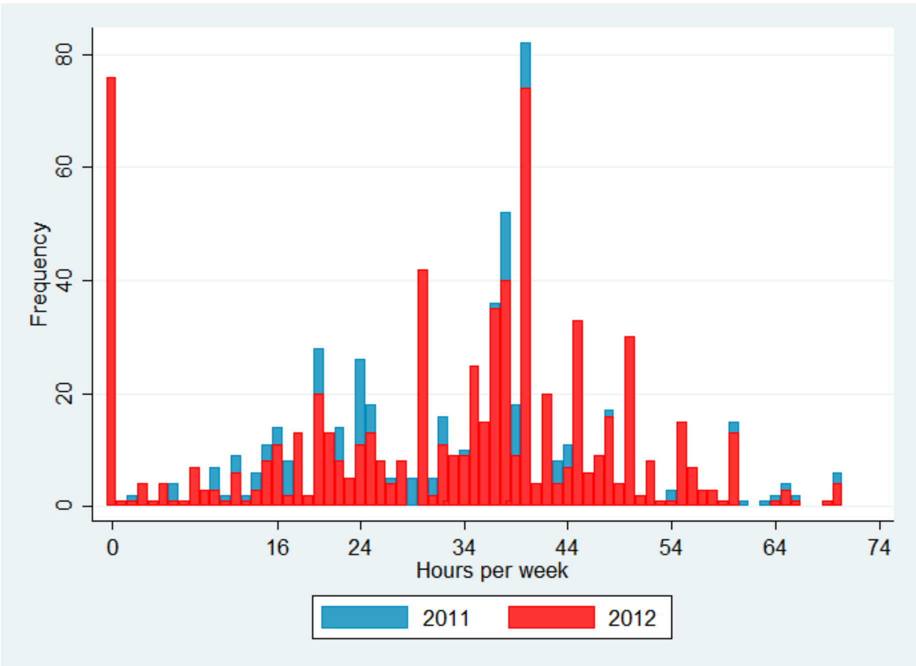
Source: Labour Force Survey.
Note: Frequencies of hours worked - total hours worked by a couple who are responsible for at least one child under 16: 2012 versus 2011.

Figure 4.23: Hours worked by non-UK-born couples with children



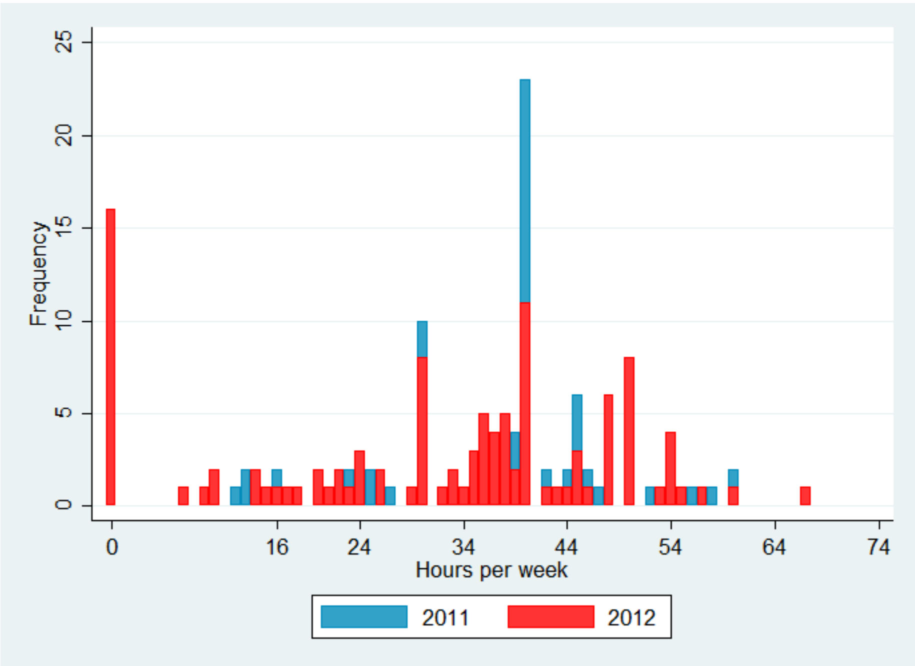
Source: Labour Force Survey.
Note: Frequencies of hours worked - total hours worked by a couple who are responsible for at least one child under 16: 2012 versus 2011.

Figure 4.24: Frequencies of hours worked by UK-born couples (at least one works 16 hours: 2012 versus 2011)



Source: Labour Force Survey.
Note: Hours worked - total hours worked by a couple who are responsible for at least one child under 16.

Figure 4.25: Hours worked by non-UK-born couples (at least one works 16 hours)



Source: Labour Force Survey.
Note: Frequencies of hours worked - total hours worked by a couple who are responsible for at least one child under 16: 2012 versus 2011.

4.4 Results

4.4.1 WTC2003

Based on the discussions in Section 4.3, we proceed with difference-in-differences approach to estimate the effect of WTC2003 on couples and single individuals without children.

Intensive margin

Following the discussion in Section 4.3.2.1, for the effect of the reform on hours worked by single individuals without children we use single individuals without children as a treatment group and single parents as a control group. Similarly, for the effect of WTC2003 on couples without children is measured by considering couples without children as a treatment group and couples with children as a control group. The results of the diff-in-diff regressions for all (UK-born and non-UK-born), UK-born and non-UK-born single individuals and couples are presented in Table 4.4.

Table 4.4: The effect of WTC2003 along intensive margin: the results of diff-in-diff regression I

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–1.30***	–1.44***	1.48	0.24	0.14	1.81
	(0.33)	(0.35)	(1.46)	(0.81)	(0.83)	(3.73)
Treat=1 × T=1	–2.07***	–1.90***	–5.63*	–2.27***	–2.03**	–6.04
	(0.42)	(0.43)	(2.92)	(0.87)	(0.89)	(4.16)
N	22620	21070	830	7955	7475	480

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is actual hours worked.
(Couples) The treatment group is couples without children who between them worked non-zero hours in April 2002. The control group is couples with children who between them worked non-zero hours in April 2002.
(Single) The treatment group is single individuals without children who were employed in April 2002. The control group is lone parents who were employed in April 2002.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

There is a general decreasing trend in hours worked for all couple, with or without children in April-2003, except for non-UK-born couples. The effect of the WTC2003 on hours worked by couples and single individuals, shown by the coefficient for the interaction term for the treatment group ($Treat$) and time variable for April-2003 (T), is negative and significant for all couples, as well as UK-born single individuals without children. The average decrease in hours of work for UK-born couples without children as a result of WTC2003 reform is 1.9 hours, while it is 5.6 hours for non-UK-born couples. The average decrease in hours worked by UK-born single individuals without children is 2.0 hours. This is something we would expect; since their tax credit is maximised when they work exactly 30 hours as shown in Figure 4.5, therefore individuals and couples working more than 30 hours are likely to reduce their hours of work to maximise the tax credit. The coefficient for non-UK-born single individuals is also negative, but statistically not significant.

Table 4.5 includes the diff-in-diff results for different sub-groups of non-UK-born couples. Couples, where at least one is non-UK-born (I) and both are non-UK born (II) exhibit similar responses to WTC2003 reform: they decrease their hours worked by 3.1 and 5.6 hours, accordingly. Couples, where only one is non-UK-born (III) exhibit different results depending on whether the wife or the husband is non-UK-born. If the non-UK-born is the husband, these couples reduce their hours of work (by 6 hours) in April-2003, while the results are positive, yet non-significant for couples a with non-UK-born wife.

Table 4.5: The effect of WTC2003 on non-UK-born couples along intensive margin

	I	II	III		
			All	UK-born husband	UK-born wife
T=1	–0.63	1.48	–1.92	–3.37*	–0.06
	(0.96)	(1.46)	(1.27)	(1.86)	(1.63)
Treat=1 × T=1	–3.06*	–5.63*	–1.57	2.22	–5.99**
	(1.57)	(2.92)	(1.88)	(2.66)	(2.57)
N	2270	830	1440	780	660

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is actual hours worked.
The treatment group is couples without children who between them worked non-zero hours in April 2002. The control group is couples with children who between them worked non-zero hours in April 2002.
(I) Includes all couples, where at least one is non-UK-born.
(II) Includes couples, where both are non-UK-born.
(III) Includes couples, where only one is non-UK-born.
(All) Includes couples, where either husband or wife is non-UK-born. (UK-born husband) Includes couples, where the husband is UK-born and the wife is non-UK-born. (UK-born wife) Includes couples, where the wife is UK-born and the husband is non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Extensive margin

In order to estimate the effect of WTC2003 on the extensive margin, we use the same control and treatment groups as for intensive margin. Table 4.6 shows the treatment effect of WTC2003 on the likelihood of couples and single individuals without children of being employed. The dependent variable in this table is a binary variable, that takes a value of one if the individual is employed and works non-zero hours, and a value of zero - otherwise. The results suggest that both UK-born and non-UK-born couples without children are less likely to work following WTC2003 by 4% and 9%, respectively. This can be expected for couples, in which case one of them might have stopped working while the other one worked the 30 hours, required for tax credit eligibility.

The results are statistically not significant in the case of UK-born single individuals without children, while it is negative and significant for non-UK-born single individuals. This puzzling for single individuals without children. One channel through which WTC2003 could affect single individuals without children is if they cohabit with couples without children and they receive a tax credit for working at least 30 hours.

Tables 4.18 and 4.19 in section 4.5 also discuss the results along extensive margin, when considering different definitions of the dependent variables.

Table 4.6: The effect of WTC2003 along extensive margin: the results of diff-in-diff regression I

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	0.02**	0.02**	0.04	0.02	0.01	0.10**
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	–0.04***	–0.04***	–0.09*	–0.02	–0.02	–0.11*
	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.06)
N	28740	26600	1220	13030	11980	1045

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable for being employed and working non-zero hours.
(Couples) The treatment group is couples without children. The control group is couples with children.
(Single) The treatment group is single individuals. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.7 includes the results along the extensive margin for different sub-groups of non-UK-born couples. The results for couples, where at least one is non-UK-born (I) are negative, but not significant. Couples, where only one is non-UK-born (III) exhibit heterogeneous results depending on whether the wife or the husband is non-UK-born. In the case, where the husband is non-UK-born, the couples reduce their employment by 11% in April-2003, while the results are the opposite for couples with a non-UK-born wife; for them, the employment increases by 10%.

Table 4.7: The effect of WTC2003 on non-UK-born couples along extensive margin

	I	II	III		
			All	UK-born husband	UK-born wife
T=1	0.01	0.04	–0.02	–0.03	–0.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Treat=1 × T=1	–0.03	–0.09*	0.01	0.10**	–0.11**
	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)
N	3060	1220	1840	1010	830

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable for being employed and working non-zero hours.
The treatment group is couples without children. The control group is couples with children.
(I) Includes all couples, where at least one is non-UK-born.
(II) Includes couples, where both are non-UK-born.
(III) Includes couples, where only one is non-UK-born.
(All) Includes couples, where either husband or wife is non-UK-born. (UK-born husband) Includes couples, where the husband is UK-born and the wife is non-UK-born. (UK-born wife) Includes couples, where the wife is UK-born and the husband is non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

4.4.2 WTC2012

To estimate the effect of the amendment in WTC in 2012 on couples with children, we use the control group of couples without children. The results for couples who work non-zero hours in the pre-amendment period are shown in Table 4.8. WTC2012 appears to have a positive impact on employment of UK-born couples with children, increasing employment by 2%, while it is not significant for non-UK-born couples, and along the intensive margin, even though the coefficients are positive. The dependent variable for the extensive margin is defined as a binary variable, that takes a value of one if the individual is employed and works non-zero hours, and zero - otherwise. Table 4.21 in section 4.5 also discusses the results along the extensive margin with different definitions of the dependent variables.

When looking at the group of couples (both treatment and control groups) who worked less than 24 hours in 2011 (Table 4.22 in section 4.5), which is the main group affected by the 2012 amendment, the effect along intensive margin appears to be positive and statistically significant for UK-born couples, while it is positive, but not significant for non-UK-born couples.

We look further into couples' responses to WTC2012 along extensive margin by checking whether only one or both of the couple increase their employment (Table 4.9). The dependent variable in (I) is a binary variable for only one of the couple being employed and working non-zero hours and in (II) - a binary variable for both being employed and working non-zero hours. The results show that, when considering all (UK-born and non-UK-born) individuals, WTC2012 decreases the likelihood of only one of the couple being employed, while it increases the likelihood of both being employed, also for UK-born. Coefficients for one being employed for UK-born and non-UK-born are also negative, and the coefficient for non-UK-born both of the couple being employed is positive, yet not significant.

Table 4.8: The effect of WTC2012: intensive and extensive margins I

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–6.44***	–6.51***	–3.96	–0.02**	–0.02**	0.02
	(0.57)	(0.59)	(2.57)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	1.17	1.11	0.79	0.04***	0.02*	0.07
	(0.73)	(0.77)	(2.97)	(0.01)	(0.01)	(0.05)
N	7035	6376	405	12490	11326	710

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked. The treatment group is couples with children who between them worked non-zero hours in April 2002. The control group is couples without children who between them worked non-zero hours in April 2002.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours. The treatment group is couples with children. The control group is couples without children.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.9: The effect of WTC2012 on being employed

	I			II		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	0.03***	0.03**	–0.00	–0.04***	–0.04***	0.03
	(0.01)	(0.01)	(0.06)	(0.01)	(0.01)	(0.06)
Treat=1 × T=1	–0.03**	–0.03	–0.03	0.05***	0.04**	0.08
	(0.02)	(0.02)	(0.07)	(0.01)	(0.02)	(0.06)
N	12490	11326	710	12490	11326	710

The estimation method is fixed effects regression. Time effects are included.
The treatment group is couples with children. The control group is couples without children.
(I) The dependent variable is a binary variable for only one of the couple being employed and working non-zero hours.
(II) The dependent variable is a binary variable for both of the couple being employed and working non-zero hours.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.10: The effect of WTC2012 on non-UK-born couples along intensive margin

	I	II	III		
			All	UK-born husband	UK-born wife
T=1	–4.02**	–3.96	–4.05*	–4.41*	–3.58
	(1.75)	(2.57)	(2.40)	(2.44)	(4.65)
Treat=1 × T=1	–0.30	0.79	–1.26	0.36	–4.00
	(1.90)	(2.97)	(2.48)	(2.70)	(4.59)
N	913	405	508	310	198

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is actual hours worked.
The treatment group is couples with children who between them worked non-zero hours in April 2011. The control group is couples without children who between them worked non-zero hours in April 2011.
(I) Includes all couples, where at least one is non-UK-born. (II) Includes couples, where both are non-UK-born. (III) Includes couples, where only one is non-UK-born.
(All) Includes couples, where either husband or wife is non-UK-born. (UK-born husband) Includes couples, where the husband is UK-born and the wife is non-UK-born. (UK-born wife) Includes couples, where the wife is UK-born and the husband is non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.11: The effect of WTC2012 on non-UK-born couples along extensive margin

	I	II	III		
			All	UK-born husband	UK-born wife
T=1	0.03	0.02	0.04	0.06	0.02
	(0.03)	(0.05)	(0.04)	(0.05)	(0.06)
Treat=1 × T=1	0.05	0.07	0.04	0.06	–0.01
	(0.03)	(0.05)	(0.05)	(0.06)	(0.07)
N	1618	710	908	550	358

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable for being employed and working non-zero hours.
The treatment group is couples with children. The control group is couples without children.
(I) Includes all couples, where at least one is non-UK-born. (II) Includes couples, where both are non-UK-born. (III) Includes couples, where only one is non-UK-born.
(All) Includes couples, where either husband or wife is non-UK-born. (UK-born husband) Includes couples, where the husband is UK-born and the wife is non-UK-born. (UK-born wife) Includes couples, where the wife is UK-born and the husband is non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Tables 4.10 and 4.11 exhibit the diff-in-diff results for different sub-groups of non-UK-born couples along intensive and extensive margins, respectively. None of the groups has a statistically significant coefficient for the effect of WTC2012. Coefficients across all sub-groups are positive for the employment effect, except for the subgroup, where only the husband is non-UK-born. The hours worked response is negative for all subgroups, except for the group where both are non-UK-born (II), and where only the wife is non-UK-born.

As discussed in section 4.3, couples with children might be subject to policy changes that are specific to only this group. Therefore, in Table 4.12 we compare couples with children, who work different hours. We use couples with children who worked less than 24 hours in 2011 as a treatment group, and couples with children who worked 25-30 hours between them, as a control group. The results show a positive effect of WTC2012 along intensive margin for UK-born individuals, and negative - for non-UK-born individuals. However, the non-UK-born sample size is too small to provide sufficient power for this estimate. The effect along the extensive margin is positive for all groups. The coefficients in these estimates are larger compared with Table 4.8, which might be an indicator of non-parallel trends of control and treatment groups in these estimations. Table 4.23 in section 4.5 uses an alternative control group with a different choice of hours, which produces very similar results.

Table 4.12: The effect of WTC2012: intensive and extensive margins II

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–0.75	–1.12	28.13***	0.01	0.01	0.07*
	(1.54)	(1.56)	(2.54)	(0.04)	(0.05)	(0.04)
Treat=1 × T=1	2.59	2.89*	–18.57***	0.17***	0.15***	0.16***
	(1.70)	(1.72)	(4.13)	(0.04)	(0.05)	(0.05)
N	1075	980	40	2480	2060	260
ymean: control	25.8	25.8	32.2	.88	.88	1.00
ymean: treat	17.5	17.4	18.1	.46	.49	.24

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours. The treatment group is couples with children. The control group is couples without children.
The treatment group is couples with children who worked less than 24 hours in April 2011. The control group is couples with children who worked 25-30 hours in April 2011.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

A better approach is to combine the trends of both couples with children and couples without children, as well as couples who work less than 24 hours. Table 4.13 shows the results of difference-in-difference-in-differences regression, as described in section 4.3.1.

Here, we are interested in the coefficient of the interaction term between couples working less than 24 hours, time variable for April-2012, and couples with children. These results confirm the previous results of the WTC2012 having a positive effect on hours worked of UK-born couples, as well as on employment.

Table 4.13: The effect of WTC2012 on couples who work less than 24 hours

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–1.25***	–1.32***	0.40	–0.07***	–0.08***	–0.03
	(0.37)	(0.38)	(2.09)	(0.02)	(0.02)	(0.07)
Couples working<24h=1 × T=1	–0.14	–0.15	0.62	0.08***	0.08***	0.10
	(0.67)	(0.69)	(3.49)	(0.02)	(0.02)	(0.09)
T=1 × Couples with children=1	0.66	0.42	0.66	0.02	0.02	0.06
	(0.59)	(0.65)	(2.25)	(0.02)	(0.02)	(0.07)
Couples working<24h=1 × T=1 × Couples with children=1	1.89	2.12*	7.69	0.06**	0.05	0.03
	(1.21)	(1.26)	(5.21)	(0.03)	(0.03)	(0.10)
N	12670	11486	720	12720	11536	720

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

4.5 Robustness tests

WTC2003

Tables 4.14 and 4.15 replicate Tables 4.4 and 4.6 with added control variables. The control variables included are the age of the person, the age of the youngest child in the household, the level of education and a binary variable for any health problems that affect the work they do. Adding of the covariates do not change the effect of the 2003 tax credit reform observed in Tables 4.4 and 4.6. The coefficients of the added control variables are in line with what we would expect; there is a negative relationship between age and intensive and extensive margins. The effects of the age of the youngest child and individual's level of education are positive along both intensive and extensive margins, while health issues affect negatively.

Table 4.14: The effect of WTC2003 along intensive margin: the results of diff-in-diff regression IA

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–1.05**	–1.05**	0.51	–3.23***	–3.21***	–2.56
	(0.47)	(0.48)	(2.34)	(1.01)	(1.03)	(5.26)
Treat=1 × T=1	–1.94***	–1.80***	–5.92**	–2.02**	–1.84**	–5.36
	(0.42)	(0.44)	(2.99)	(0.89)	(0.91)	(5.19)
AGE	–0.45	–0.57*	1.37	0.39	0.35	1.01
	(0.31)	(0.32)	(1.67)	(0.57)	(0.59)	(2.24)
CHILD AGE	0.20	0.15	–0.19	0.89***	0.90***	–0.50
	(0.16)	(0.16)	(0.13)	(0.22)	(0.22)	(3.69)
EDUCATION	0.51**	0.58***	–0.30	0.76**	0.69**	1.20
	(0.21)	(0.22)	(0.67)	(0.36)	(0.33)	(1.84)
HEALTH	–0.27	–0.21	–5.00	0.01	0.12	–1.63
	(0.77)	(0.81)	(3.66)	(1.11)	(1.12)	(5.39)
N	22620	21070	830	7225	6780	445

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is actual hours worked.
(Couples) The treatment group is couples without children who between them worked non-zero hours in April 2002. The control group is couples with children who between them worked non-zero hours in April 2002.
(Single) The treatment group is single individuals without children who were employed in April 2002. The control group is lone parents who were employed in April 2002.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.15: The effect of WTC2003 along extensive margin: the results of diff-in-diff regression IA

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	0.02**	0.03**	0.01	–0.00	–0.01	0.07
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.06)
Treat=1 × T=1	–0.03***	–0.03***	–0.09*	–0.01	–0.00	–0.10*
	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.06)
AGE	–0.01**	–0.02***	0.03	0.01	0.00	0.02
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
CHILD AGE	0.01**	0.01*	0.00	0.01**	0.02**	–0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
EDUCATION	0.02***	0.03***	–0.00	0.03***	0.02***	0.05
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
HEALTH	–0.02	–0.02	–0.05	–0.04*	–0.03	–0.09
	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.10)
N	28740	26600	1220	13030	11980	1045

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable for being employed and working non-zero hours.
(Couples) The treatment group is couples without children. The control group is couples with children.
(Single) The treatment group is single individuals. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Tables 4.16 and 4.17 show the results of WTC2003 with random effects model along intensive and extensive margin, respectively. The coefficients of the interaction of the treatment group and the binary variable for April-2003 are exactly the same as in Tables 4.4 and 4.6, respectively, indicating that individual fixed effects do not affect the results of our estimations.

Table 4.16: Robustness: The effect of WTC2003 along intensive margin

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
Treat=1	–2.34***	–2.63***	2.56	6.32***	6.43***	4.72
	(0.51)	(0.52)	(3.61)	(0.74)	(0.77)	(3.02)
T=1	–1.30***	–1.44***	1.48	0.24	0.14	1.81
	(0.33)	(0.35)	(1.46)	(0.81)	(0.83)	(3.73)
Treat=1 × T=1	–2.07***	–1.90***	–5.63*	–2.27***	–2.03**	–6.04
	(0.42)	(0.43)	(2.92)	(0.87)	(0.89)	(4.17)
N	22620	21070	830	7955	7475	480

The estimation method is random effects regression. Time effects are included.
The dependent variable is actual hours worked.
(Couples) The treatment group is couples without children who between them worked non-zero hours in April 2002. The control group is couples with children who between them worked non-zero hours in April 2002.
(Single) The treatment group is single individuals without children who were employed in April 2002. The control group is lone parents who were employed in April 2002.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.17: Robustness: The effect of WTC2003 along extensive margin

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
Treat=1	–0.19***	–0.20***	–0.03	0.02	0.01	0.09
	(0.01)	(0.01)	(0.06)	(0.02)	(0.02)	(0.07)
T=1	0.02**	0.02**	0.04	0.02	0.01	0.10**
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	–0.04***	–0.04***	–0.09*	–0.02	–0.02	–0.11*
	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.06)
N	28740	26600	1220	13030	11980	1045

The estimation method is random effects regression. Time effects are included.
The dependent variable is a binary variable for being employed and working non-zero hours.
(Couples) The treatment group is couples without children. The control group is couples with children.
(Single) The treatment group is single individuals without children. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.18: The effect of WTC2003 along extensive margin: the results of diff-in-diff regression II

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	0.02**	0.02**	0.05*	0.02	0.01	0.10**
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	–0.04***	–0.04***	–0.09**	–0.02	–0.02	–0.11*
	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.06)
N	28690	26554	1216	13027	11977	1045

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable, that take a value of one if the individual is employed and works non-zero hours, and zero - if the individual is unemployed and looking for a job.
(Couples) The treatment group is couples without children. The control group is couples with children.
(Single) The treatment group is single individuals. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Tables 4.18 and 4.19 show the results of diff-in-diff regressions along the extensive margin, when considering different definitions of the dependent variables to the one in Table 4.6. The dependent variable in Table 4.18 is defined as a binary variable that takes a value of one if the individual is employed and works non-zero hours, and a value of zero - if the individual is unemployed and looking for a job, that is, the individual is in the labour market. These results are identical to those in Table 4.6, and the number of observations indicates that the number of individuals out of labour force is quite small. The dependent variable in Table 4.19 is defined as a binary variable that takes a value of one if the individual is employed and works non-zero hours, or is unemployed and looking for a job, and a value of zero - otherwise. This variable, therefore, is a binary variable for labour force participation (LFP). The results for single individuals without children are negative, but insignificant, indicating that WTC2003 did not affect LFP of single individuals. It is, however negative and significant for both UK-born and non-UK born couples without children.

Table 4.19: The effect of WTC2003 along extensive margin: the results of diff-in-diff regression III

	Couples			Single		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	0.01**	0.02**	0.01	0.01	0.00	0.04
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	–0.04***	–0.04***	–0.08*	–0.01	–0.01	–0.06
	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.05)
N	28740	26600	1220	13030	11980	1045

The estimation method is fixed effects regression. Time effects are included.
The dependent variable is a binary variable for labour force participation, that takes a value of one if an individual is employed (and works non-zero hours) or looking for a job, and zero - otherwise.
(Couples) The treatment group is couples without children. The control group is couples with children.
(Single) The treatment group is single individuals. The control group is lone parents.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

WTC2012

Table 4.20 replicates Table 4.8 with added control variables. The added control variables do not change the conclusions about the effects of the 2012 tax credit reform drawn from Table 4.8. The effects of the added control variables are similar to those observed during 2003 reform, with statistically non-significant effect of individual's level of education along intensive and extensive margins, positive effect of the age of the youngest child, while negative effects of the age and the binary variable for health issues.

Table 4.20: The effect of WTC2012: intensive and extensive margins IA

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–5.56***	–5.47***	–6.22*	–0.01	–0.01	0.03
	(0.78)	(0.81)	(3.39)	(0.01)	(0.01)	(0.06)
Treat=1 × T=1	1.07	1.05	–0.66	0.03***	0.02	0.05
	(0.73)	(0.77)	(3.08)	(0.01)	(0.01)	(0.05)
AGE	–1.01*	–1.16**	1.87	–0.02*	–0.02**	–0.00
	(0.52)	(0.55)	(2.46)	(0.01)	(0.01)	(0.04)
CHILD AGE	0.27*	0.18	3.01**	0.00	0.00	0.02*
	(0.14)	(0.13)	(1.35)	(0.00)	(0.00)	(0.01)
EDUCATION	0.25	0.33	–0.08	0.00	0.00	0.01
	(0.44)	(0.49)	(1.31)	(0.00)	(0.00)	(0.01)
HEALTH	–0.31	–0.30	–2.58	–0.05***	–0.06***	–0.12
	(1.14)	(1.17)	(5.67)	(0.02)	(0.02)	(0.07)
N	7035	6376	405	12490	11326	710

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked. The treatment group is couples with children who between them worked non-zero hours in April 2002. The control group is couples without children who between them worked non-zero hours in April 2002.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours. The treatment group is couples with children. The control group is couples without children.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.21 discusses the results of WTC2012 along the extensive margin with different definitions of the dependent variables to the one in Table 4.8. The dependent variable in (I) is defined as a binary variable that takes a value of one for individuals, who are employed and work non-zero hours, and zero - if they are unemployed and looking for a job. The dependent variable in (II) is a binary variable for labour force participation. Both these results are similar to the results in Table 4.8, indicating that the increased participation is driven by increased employment.

Table 4.21: Robustness: The effect of WTC2012 along extensive margin

	I			II		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–0.02**	–0.02***	0.02	–0.03***	–0.03***	0.03
	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.05)
Treat=1 × T=1	0.04***	0.02*	0.07	0.04***	0.03**	0.05
	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.05)
N	12474	11310	710	12490	11326	710

The estimation method is fixed effects regression. Time effects are included.
(I) The dependent variable is a binary variable, that takes a value of one if the individual is employed and works non-zero hours, and zero - if the individual is unemployed and looking for a job.
(II) The dependent variable is a binary variable for labour force participation, that takes a value of one if an individual is employed (and works non-zero hours) or looking for a job, and zero - otherwise.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.22 shows the results for couples (both treatment and control groups) who worked less than 24 hours in April-2011. This is the main group affected by the 2012 amendment, as discussed in section 4.3. The effect along the intensive and extensive margins appear to be positive and significant for UK-born couples, while it is positive, yet not significant for non-UK-born couples.

Table 4.22: Robustness test: the effect of WTC2012 along intensive and extensive margins

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–1.09	–1.13	1.01	0.07***	0.07***	0.14**
	(0.78)	(0.81)	(3.44)	(0.01)	(0.01)	(0.07)
Treat=1 × T=1	2.73**	2.73**	8.35	0.08***	0.07***	0.07
	(1.08)	(1.11)	(5.05)	(0.02)	(0.02)	(0.08)
N	1625	1505	65	7080	6455	370

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours.
The treatment group is couples with children who worked less than 24 hours in April 2011. The control group is couples without children who worked less than hours in April 2011.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.23: The effect of WTC2012: intensive and extensive margins III

	Intensive			Extensive		
	All	UK-Born	Non-UK-Born	All	UK-Born	Non-UK-Born
T=1	–0.00	–0.51	28.13***	0.05	0.04	0.07*
	(1.43)	(1.42)	(2.54)	(0.04)	(0.04)	(0.04)
Treat=1 × T=1	1.87	2.25	–18.57***	0.13***	0.11***	0.16***
	(1.59)	(1.58)	(4.13)	(0.04)	(0.04)	(0.05)
N	1110	1025	40	2515	2105	260
ymean: control	28.1	28.4	27.2	.89	.88	.96
ymean: treat	17.5	17.4	18.1	.46	.49	.24

The estimation method is fixed effects regression. Time effects are included.
(Intensive) The dependent variable is actual hours worked.
(Extensive) The dependent variable is a binary variable for being employed and working non-zero hours.
The treatment group is couples with children who worked less than 24 hours in April 2011. The control group is couples with children who worked 26-32 hours in April 2011.
(All) includes UK-born and non-UK-born individuals. (UK-Born) includes only UK-born sub-sample. (Non-UK-Born) includes only non-UK-born sub-sample, where both are non-UK-born.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table 4.23 uses an alternative control group to the one in Table 4.12. Here, the control group is couples with children, who work 26-32 hours between them. These results are very similar to those in Table 4.12. The large coefficients in both tables might be an indicator of the trends of control and treatment groups not being parallel.

4.6 Conclusion

This paper studies the implications of the tax credit reform of 2003 and the 2012 changes in working tax credit eligibility for working families on the labour market behaviour of these families. It uses difference-in-differences approach to estimate the impact of the WTC2003 reform and WTC2012 amendments for UK-born and non-UK-born single individuals/ couples without children and couples with children, respectively, along the intensive and extensive margins.

WTC2003 has a negative effect for couples and single individuals without children along both the intensive and extensive margins. Non-UK-born individuals decrease their hours of work more than UK-born individuals as a response to the 2003 WTC reform. Non-UK-born couples have a larger decrease (by 5 percentage points) in the likelihood of being employed than UK-born couples.

The 2012 amendment to working tax credit, where the required hours of work was increased from 16 to 24 for couples with children has a positive effect on hours worked by couples with children, and positive and significant effect on the likelihood of being employed by UK-born couples. The coefficient for non-UK-born couples is positive, yet statistically not significant.

When considering different combinations of UK-born and non-UK-born couples without children, the effects of WTC2003 are more negative along the intensive and extensive margins for couples, where both are non-UK-born, as well as couples, where only the husband is non-UK-born. On the contrary, in the case of couples where only the wife is non-UK-born, the effect is positive along the intensive margin (even though not significant) and the extensive margin (the likelihood of being employed increases by 10%). WTC2012 does not produce any significant results in terms of labour supply responses by different combinations of non-UK-born couples with children.

This study highlights how the design of a tax credit framework affects labour market responses of eligible individuals, where WTC2003, in general, has negative implications on labour supply, while WTC2012 - positive. Non-UK-born individuals have stronger responses to WTC2003 compared with those born in the UK, however, they did not respond to WTC2012, primarily as they work more hours than the group most affected by the amendment - those working 16-24 hours. The non-significant results for non-UK-born individuals' response to WTC2012, however, should be taken with caution, since the sample size for the non-UK-born is small and therefore might be insufficient for power of these estimates.

This paper also provides an insight into labour market behaviour of different combinations of UK-born and non-UK-born couples. It can potentially have important policy implications by highlighting the behaviour of low-income groups and assist in policy-making and policy design.

Chapter 5

Conclusions

This Thesis studies different aspects of inequalities in the UK and the role of natives and immigrants. It contributes to the economic literature by providing a comprehensive analysis of the role of immigrants in different aspects of UK inequality.

In the first part of the Thesis, we decompose income inequality as measured by Theil index into inequalities between and within groups. We learn that overall income inequality is dependent on income inequalities between the rich and the poor, as well as the average income between groups, specifically, the average income of UK native population and second-generation immigrants.

In the second part of the Thesis, we study the prospects of income inequality between top- and bottom-earner natives and second-generation immigrants by looking at intergenerational mobility in education. Intergenerational mobility in education plays an important role in addressing inequalities. By using data from the UK Household Longitudinal Survey, which enables us to identify exact pairs of parents and children, we estimate intergenerational coefficients in education for 1.5-, 2nd- and 3rd generation immigrants versus natives. The study enhances the relevant literature by providing a comprehensive comparison between UK natives and immigrants by countries of birth of their parents and grandparents. We find that 1.5- and 2nd-generation immigrants are, in general, more mobile than natives. The mobility pattern, however, is not persistent across the next generation, as it mostly disappears for 3rd-generation immigrants. Intergenerational mobility is different across the groups of country of origin. While mobility patterns of EU immigrants are not dissimilar from those of UK natives, non-EU immigrants are more mobile. The mobility patterns are different for daughters whose parents are non-EU immigrants; it takes another generation for daughters to catch up. In terms of the performance of 1.5- and 2nd-generation immigrants versus their parents, overall, they tend to outperform the educational levels of their parents. In the context of the general discussion in Chapter 1, the positive direction of intergenerational mobility might have a positive contribution towards mitigating inequality. However, if the patterns of intergenerational mobility of the current second-generation immigrants behave like those of current third-generation immigrants, the effect of intergenerational mobility in productive ability might not have any positive effect on the persistence of inequality. Due to smaller sample sizes for third-generation immigrants, the results for third-generation immigrants should be taken with caution.

The study of intergenerational mobility in education of UK natives versus second-generation immigrants, considering that a significant share of the UK population is currently born to at least one foreign parent, is insightful for policy-makers in terms of future policy actions directed towards mitigating income inequalities. It is important, however, to monitor whether the trend is persistent over years as more data becomes available.

Given the importance of inequalities between groups for overall income inequality of the country as shown from the decomposition of Theil index, in the third part of the Thesis we concentrate on inequalities between groups, and specifically, on UK native population and second-generation immigrants. Inequalities between groups, particularly if not justified by individual characteristics, in addition to contributing to overall inequality, also impedes certain groups from being employed and creates disincentives to look for employment, thus worsening inequalities.

Therefore, in the third part, we study income discrimination between groups by decomposing between inequality due to observed individual characteristics, and unexplained inequality. We use the unexplained inequality or difference between groups as a measure of discrimination to study the effect on welfare receipt by second-generation immigrants versus UK natives. To address the criticism of the method of income decomposition, we correct for sample selection bias, and control for individual fixed effects, where possible, and check for the validity of the results by using different methods, where individual fixed effects are not controlled for.

This paper provides a substantial contribution to the literature by introducing a method that links labour market discrimination and welfare dependency. We find significant labour market discrimination, particularly against non-EU immigrants. The labour market discrimination increases the likelihood of certain immigrant groups to claim welfare benefits. While EU immigrants are not affected by discrimination in the labour market, it increases the probability of non-EU second-generation immigrants to claim benefits. We also find that income discrimination increases the likelihood of immigrants to claim unemployment benefits, while it reduces the probability of natives to claim unemployment and housing/council tax benefits. Even though it studies the discrimination and welfare dependency of second-generation immigrants, the results could apply to first-generation immigrants as well, since the patterns uncovered for different ethnic groups are likely to be even stronger for first-generation immigrants, because the discrimination is due to their ethnicity.

In terms of the bigger picture of inequality, this paper uncovers an important finding: wage equality does not necessarily imply equality between groups, once we account for individual characteristics. The findings on income inequality between natives and second-generation immigrants contributing towards more people claiming welfare benefits is another important finding for overall income inequality of the country. Population on welfare dependency is concentrated in the lower tail of income distribution. Therefore more people claiming welfare benefits due to income inequalities between groups contributes to increased income inequality in the country.

Furthermore, inequalities might be worsened by income discrimination, creating a fiscal burden to mitigate the inequalities. Hence, tackling discrimination, in addition to improving inequalities between natives and immigrants, also contributes to improved overall inequality in the country and reduces fiscal burden for the country.

The fourth chapter of the thesis studies the efficiency of certain government policies in reducing inequalities by encouraging individuals to work. Specifically, it studies the effects of the UK tax credit reforms on hours worked and labour market participation of UK-born and non-UK-born working individuals. Increase in participation in labour market and in hours worked smooths income inequality and provides opportunities for career advancement and further growth in income. This paper studies the effect of working tax credit reform of 2003 on individuals and couples without children, as well as the 2012 amendment to required hours of work for working tax credit eligibility of couples with children. This paper has two major contributions: it is the first study that looks at the 2003 working tax credit reform in the UK and the 2012 amendment (which increased the required hours of work from 16 to 24 for couples with children), and it differentiates between the effect of the reforms on natives and immigrants. We find that the working tax credit reform of 2003 had a negative effect on hours worked and labour market participation of couples and single individuals without children. We find a larger negative effect from the 2003 reform in hours of work of non-UK-born single individuals compared with UK-born individuals, as well as a larger decrease in the likelihood of being employed by non-UK-born couples compared with UK-born couples. On the other hand, the 2012 amendment to the working tax credit had a positive effect, particularly on labour supply along the extensive margin of couples with children. The effects are more significant for UK-born couples with children than non-UK-born couples, although the results of the 2012 reform on non-UK-born individuals should be interpreted with caution due to small sample size.

This paper highlights the implications of the design of a state welfare policy for shaping labour market behaviour of vulnerable individuals, and the importance of designing a policy that protects low-income and vulnerable groups without disincentivising them.

As part of my future research, I plan to continue studies on UK inequalities. In my further research, I will concentrate on studying the link between immigrants and immigration, and inequalities and well-being of UK natives.

Appendix A

Appendix to Chapter 2

Table A.1: Transition matrices of educational qualifications of father-child pairs: migrants

father's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
		son's educational qualifications					
No school	N	9	3	16	21	25	74
	%	1.1	0.4	2.0	2.6	3.1	9.2
Left school with no qual.	N	37	32	58	87	88	302
	%	4.6	4.0	7.2	10.9	11.0	37.7
Some school qualifications	N	10	7	38	61	81	197
	%	1.2	0.9	4.7	7.6	10.1	24.6
Post school qualifications	N	3	5	21	41	50	120
	%	0.4	0.6	2.6	5.1	6.2	15.0
University degree or higher	N	1	2	10	27	68	108
	%	0.1	0.2	1.2	3.4	8.5	13.5
Total	N	60	49	143	237	312	801
	%	7.5	6.1	17.9	29.6	39.0	100.0
		daughter's educational qualifications					
father's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	11	9	30	33	15	98
	%	1.0	0.8	2.6	2.9	1.3	8.6
Left school with no qual.	N	42	29	108	137	104	420
	%	3.7	2.6	9.5	12.1	9.2	37.0
Some school qualifications	N	9	6	70	104	94	283
	%	0.8	0.5	6.2	9.2	8.3	25.0
Post school qualifications	N	2	9	33	69	93	206
	%	0.2	0.8	2.9	6.1	8.2	18.2
University degree or higher	N	0	3	16	26	82	127
	%	0.0	0.3	1.4	2.3	7.2	11.2
Total	N	64	56	257	369	388	1,134
	%	5.6	4.9	22.7	32.5	34.2	100.0

Table A.2: Transition matrices of educational qualifications of mother-child pairs: migrants

		son's educational qualifications					
mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	12	3	22	28	22	87
	%	1.7	0.4	3.1	3.9	3.1	12.2
Left school with no qual.	N	30	30	61	67	78	266
	%	4.2	4.2	8.6	9.4	10.9	37.3
Some school qualifications	N	3	6	37	58	85	189
	%	0.4	0.8	5.2	8.1	11.9	26.5
Post school qualifications	N	1	4	21	36	64	126
	%	0.1	0.6	2.9	5.0	9.0	17.7
University degree or higher	N	0	0	2	14	29	45
	%	0.0	0.0	0.3	2.0	4.1	6.3
Total	N	46	43	143	203	278	713
	%	6.5	6.0	20.1	28.5	39.0	100.0

		daughter's educational qualifications					
mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	13	10	37	42	21	123
	%	1.2	0.9	3.5	4.0	2.0	11.6
Left school with no qual.	N	45	28	105	133	91	402
	%	4.3	2.7	9.9	12.6	8.6	38.1
Some school qualifications	N	10	11	65	92	91	269
	%	0.9	1.0	6.2	8.7	8.6	25.5
Post school qualifications	N	3	3	32	56	90	184
	%	0.3	0.3	3.0	5.3	8.5	17.4
University degree or higher	N	0	2	4	14	58	78
	%	0.0	0.2	0.4	1.3	5.5	7.4
Total	N	71	54	243	337	351	1,056
	%	6.7	5.1	23.0	31.9	33.2	100.0

Table A.3: Transition matrices of educational qualifications of father-child pairs: natives

father's educational qualifications		son's educational qualifications: No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	2	3	9	3	5	22
	%	0.0	0.1	0.2	0.1	0.1	0.4
Left school with no qual.	N	315	264	398	553	304	1,834
	%	6.4	5.4	8.1	11.3	6.2	37.4
Some school qualifications	N	57	88	301	429	328	1,203
	%	1.2	1.8	6.1	8.7	6.7	24.5
Post school qualifications	N	45	96	264	579	438	1,422
	%	0.9	2.0	5.4	11.8	8.9	29.0
University degree or higher	N	1	3	37	118	269	428
	%	0.0	0.1	0.8	2.4	5.5	8.7
Total	N	420	454	1,009	1,682	1,344	4,909
	%	8.6	9.2	20.6	34.3	27.4	100.0
father's educational qualifications		**daughter's educational qualifications:** No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	7	6	7	13	3	36
	%	0.1	0.1	0.1	0.2	0.0	0.5
Left school with no qual.	N	423	287	736	823	429	2,698
	%	6.4	4.4	11.2	12.5	6.5	41.0
Some school qualifications	N	59	89	413	502	371	1,434
	%	0.9	1.4	6.3	7.6	5.6	21.8
Post school qualifications	N	60	102	442	703	586	1,893
	%	0.9	1.6	6.7	10.7	8.9	28.8
University degree or higher	N	3	7	55	148	304	517
	%	0.0	0.1	0.8	2.2	4.6	7.9
Total	N	552	491	1,653	2,189	1,693	6,578
	%	8.4	7.5	25.1	33.3	25.7	100.0

Table A.4: Transition matrices of educational qualifications of mother-child pairs: natives

		son's educational qualifications					
mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	1	6	2	4	6	19
	%	0.0	0.1	0.0	0.1	0.1	0.4
Left school with no qual.	N	338	276	365	545	296	1,820
	%	8.0	6.5	8.6	12.8	7.0	42.8
Some school qualifications	N	60	94	330	480	357	1,321
	%	1.4	2.2	7.8	11.3	8.4	31.1
Post school qualifications	N	16	36	142	305	328	827
	%	0.4	0.8	3.3	7.2	7.7	19.5
University degree or higher	N	1	5	24	81	152	263
	%	0.0	0.1	0.6	1.9	3.6	6.2
Total	N	416	417	863	1,415	1,139	4,250
	%	9.8	9.8	20.3	33.3	26.8	100.0
		daughter's educational qualifications					
mother's educational qualifications		No school	Left school with no qualifications	Some school qualifications	Post school qualifications	University degree or higher	Total
No school	N	9	2	5	8	0	24
	%	0.2	0.0	0.1	0.1	0.0	0.4
Left school with no qual.	N	478	315	771	778	393	2,735
	%	8.2	5.4	13.3	13.4	6.8	47.1
Some school qualifications	N	55	102	437	517	347	1,458
	%	0.9	1.8	7.5	8.9	6.0	25.1
Post school qualifications	N	21	43	219	476	459	1,218
	%	0.4	0.7	3.8	8.2	7.9	21.0
University degree or higher	N	1	7	34	96	234	372
	%	0.0	0.1	0.6	1.7	4.0	6.4
Total	N	564	469	1,466	1,875	1,433	5,807
	%	9.7	8.1	25.2	32.3	24.7	100.0

Table A.5: Linear probabilities of mobility: 2nd generation

	Father-son pair	Father-daughter pair
EU(EEA)	0.036	0.009
	(0.042)	(0.035)
India	0.121***	0.024
	(0.031)	(0.034)
Pakistan	0.041	0.001
	(0.037)	(0.034)
Bangladesh	0.039	0.024
	(0.054)	(0.039)
Other Africa	–0.070	–0.062
	(0.052)	(0.048)
Central and South America	0.087**	0.056**
	(0.037)	(0.028)
Other countries	0.076**	0.058
	(0.038)	(0.039)
Years since migration of the father and birth of the child	0.002	0.002
	(0.002)	(0.001)
father s age	–0.000	–0.000***
	(0.000)	(0.000)
child's age	0.002***	0.001
	(0.000)	(0.000)
Father not living with respondent when they were 14 years old	0.029	0.008
	(0.030)	(0.026)
Father deceased when the child was 14 years old	0.046***	0.025
	(0.018)	(0.018)
The respondent has siblings	–0.010	–0.006
	(0.012)	(0.011)
		(0.061)
N	5486.00	7375.00
ymean	0.91	0.90

The dependent variable is the binary variable of child's educational qualification upgrading or downgrading versus parent's.
Controls included, including parent's cohort.
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Table A.6: Linear probabilities of mobility: 3rd generation

	Father-son pair	Father-daughter pair
EU	–0.086	–0.088**
	(0.056)	(0.045)
Non-EU	0.056	–0.001
	(0.055)	(0.074)
father s age	–0.000	–0.000***
	(0.000)	(0.000)
child's age	0.002***	0.001
	(0.000)	(0.000)
Father not living with respondent when they were 14 years old	0.042	0.018
	(0.031)	(0.029)
Father deceased when the child was 14 years old	0.053***	0.017
	(0.019)	(0.023)
The respondent has siblings	–0.013	–0.009
	(0.013)	(0.012)
N	4973.00	6676.00
ymean	0.90	0.89

The dependent variable is the binary variable of child's educational qualification upgrading or downgrading versus parent's.
Controls included.
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

Appendix B

Appendix to Chapter 3

B.1 Methods of measuring income discrimination. Blinder-Oaxaca decomposition

The main notion behind measuring labour income discrimination is that individuals with similar levels of productivity should be paid similarly. The task of measuring income discrimination, therefore, is reduced to measuring productivity. And here, one would expect that the observable characteristics of individuals will capture productivity. Thus, individuals with the same observable characteristics are expected to be paid similarly.

There are two major approaches to measuring income discrimination. One approach, suggested by Neal & Johnson (1996), is to estimate the income gap between majority and minority groups by estimating wage equations that include individual characteristics and adding a dummy variable for minority groups:

$$lny_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + g_i\alpha + e_{it},$$

where y_{it} is income, $\boldsymbol{x}_{it}$ is a vector of individual characteristics, and g_i is a dummy variable for a minority group i.

The second approach, suggested by Blinder (1973) and Oaxaca (1973) is based on estimating wage equations separately and then comparing the results of the estimates. For two groups, minority group (A) and majority group (B), the following two equations are estimated:

$$Y_k = \boldsymbol{X}_k^{'}\boldsymbol{\beta}_k + \epsilon_k, \;\; where \;\; E(\epsilon_k) = 0, \;\; \boldsymbol{X}_k - a \; set \; of \; explanatory \; variables \;\; and \;\; k \in \{A, B\} \tag{B.1}$$

The differences in labour market outcomes for the two groups are derived as follows:

$$R = E(Y_A) - E(Y_B), \tag{B.2}$$

where R is the difference between labour market outcomes of the minority and majority groups, $E(Y_A)$ and $E(Y_B)$ are the expected values of an outcome variable of natives and immigrants, accordingly.

Substituting (B.1) in (B.2), we get:

$$R = E(X_B)^{'}\beta_B - E(X_A)^{'}\beta_A, \tag{B.3}$$

After estimating the equations as in (B.1), substituting the estimates into (B.3) and rearranging, the authors derive the following expression:

$$\hat{R} = (\bar{X}_B - \bar{X}_A)^{'}\hat{\beta}_B + \bar{X}_B^{'}(\hat{\beta}_B - \hat{\beta}_A) \tag{B.4}$$

In (B.4), $(\bar{X}_B - \bar{X}_A)^{'}\hat{\beta}_B$ is the explained difference in labour market outcomes, and $\bar{X}_B^{'}(\hat{\beta}_B - \hat{\beta}_A)$ is the unexplained component.

There are two issues associated with estimating income inequality through wage equations. Firstly, income equations are prone to sample selection bias as income from labour is observed only for those individuals who are employed. Secondly, the productivity of individuals might depend on characteristics that might not necessarily be observed.

B.2 Labour force participation: adjusted

Table B.1: Labour force participation by groups: adjusted for sample weights

	Male	**Female**
Natives	84.5	77.9
EU	78.2	79.9
India	90.0	75.5
Pakistan	85.4	46.8
Bangladesh	83.3	74.1
Other Africa	86.1	77.6
Latin America	81.0	80.5
Other	90.6	81.0

Notes: The country groups of immigrants are based on father's country of birth.
Labour force participation is computed as share of individuals who are employed/have positive earnings or are unemployed to total individuals in the group, after adjusting the sample for longitudinal weights.

B.3 Sample selection bias correction - 1st stage

Table B.2: The 1st stage of sample selection correction

	Natives	EU immigrants	Non-EU immigrants
no of children aged under 16	–0.033***	–0.191	–0.188***
	(0.010)	(0.198)	(0.023)
married or lives with partner	0.083***	0.289	0.076
	(0.019)	(0.268)	(0.060)
father's educational qualifications	–0.020***	–0.274*	–0.062***
	(0.007)	(0.143)	(0.020)
mother's educational qualifications	–0.035***	0.005	0.016
	(0.006)	(0.121)	(0.021)
Regional controls	X	X	X
Other controls	X	X	X
chi2	18448	281	1837
N	47850	566	4264

The estimation method is Probit regression.
The dependent variable is labour force participation.
Significance levels: *:10% **:5% ***:1%
Standard errors in parentheses.

B.4 Blinder-Oaxaca decomposition by country of origin of immigrants

Table B.3: B-O decomposition for natives and immigrants: by country of origin

	EU	India	Pakistan	Bangladesh	Other Africa	Latin America	Other
group_1: natives	7.116***	7.116***	7.116***	7.116***	7.116***	7.116***	7.116***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
group_2: migrants	7.241***	7.173***	6.941***	7.046***	7.138***	7.175***	7.263***
	(0.076)	(0.053)	(0.061)	(0.049)	(0.082)	(0.051)	(0.062)
difference	–0.125	–0.057	0.175***	0.070	–0.022	–0.060	–0.147**
	(0.076)	(0.054)	(0.061)	(0.051)	(0.082)	(0.052)	(0.063)
explained	–0.122***	–0.119***	0.102***	–0.006	–0.259***	–0.227***	–0.232***
	(0.019)	(0.017)	(0.020)	(0.028)	(0.026)	(0.019)	(0.022)
unexplained	–0.003	0.062	0.073	0.077	0.237***	0.167***	0.085
	(0.074)	(0.053)	(0.059)	(0.048)	(0.081)	(0.052)	(0.059)

Note: Dependent variable is log income from labour.
The estimation method is correlated random effects, corrected for sample selection bias.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Table B.3 shows the result of income decomposition by country of origin of immigrants. The breakdown is limited by the sample sizes of immigrants, based on which, the following groups of immigrants are identified: EU, India, Pakistan Bangladesh, Other Africa (excluding North Africa), Latin America (Central and South America), Other (any other country not included in the previous groups). Based on individual country group decomposition, there are two countries with a statistically significant unexplained difference - Other Africa and Latin America, with unexplained difference against immigrants of 23.7% and 16.7% of income of natives, respectively.

B.5 Probabilities by types of benefits: detailed

Table B.4: The impact of discrimination on the probability of claiming benefits by types of benefits

	I	II	III	IV	V	VI
Discrimination in t-1	–0.004**	0.001	0.001	0.002	–0.006**	–0.003
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Immigrants × Discrimination in t-1	0.027**	0.012	0.008	–0.011	0.017	–0.004
	(0.013)	(0.011)	(0.016)	(0.017)	(0.013)	(0.011)
Immigrants	0.007	–0.026***	0.029**	0.038***	–0.024**	–0.040***
	(0.006)	(0.007)	(0.012)	(0.013)	(0.011)	(0.010)
share of individuals claiming benefits by region	0.108	0.246**	0.950***	0.590**	0.338***	0.174*
	(0.093)	(0.099)	(0.264)	(0.265)	(0.126)	(0.103)
potential experience (years)	0.001	0.004	0.003	–0.006	–0.002	0.003
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.004)
squared potential experience (years)	–0.000**	–0.000***	–0.000***	0.000	–0.000	–0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of education	–0.006***	–0.008***	–0.008***	–0.001	–0.011***	–0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
years of education squared	0.000*	0.000	–0.000*	–0.001***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female	–0.031***	0.007*	0.201***	0.119***	–0.001	–0.004
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.005)
urban area	0.001	0.007*	0.004	0.002	0.018***	0.010*
	(0.003)	(0.004)	(0.007)	(0.007)	(0.006)	(0.005)
no of children aged under 16	0.005***	0.007***	0.046***	0.035***	0.015***	0.014***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
married or lives with partner	–0.030***	–0.064***	–0.000	–0.055***	–0.128***	–0.032***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.006)	(0.005)
Occupational controls	X	X	X	X	X	X
Industry controls	X	X	X	X	X	X
Regional controls	X	X	X	X	X	X
Time effects	X	X	X	X	X	X
Time averages	X	X	X	X	X	X
Other controls	X	X	X	X	X	X
N	45508	45508	45508	45508	45508	45508

Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
(I) unemployment benefits, (II) income support, (III) child benefits, (IV) tax credit, (V) housing or council tax, (VI) sickness, disability or incapacity benefits.
The estimation method is correlated random effects.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

B.6 Robustness: probabilities regressions by groups

Table B.5: The impact of discrimination on the probability of claiming benefits: natives versus immigrants

	Natives	EU migrants	Non-EU migrants
Discrimination in t-1	–0.004	–0.064	0.053***
	(0.005)	(0.047)	(0.019)
share of individuals claiming benefits by region	0.587**	2.343	1.271
	(0.286)	(2.386)	(1.211)
potential experience (years)	–0.032***	–0.120	–0.015
	(0.009)	(0.074)	(0.024)
squared potential experience (years)	0.000***	0.001	–0.000
	(0.000)	(0.001)	(0.000)
no of children aged under 16 that resp is parent of	0.068***	0.087***	0.049***
	(0.003)	(0.029)	(0.008)
N	41366	632	3510

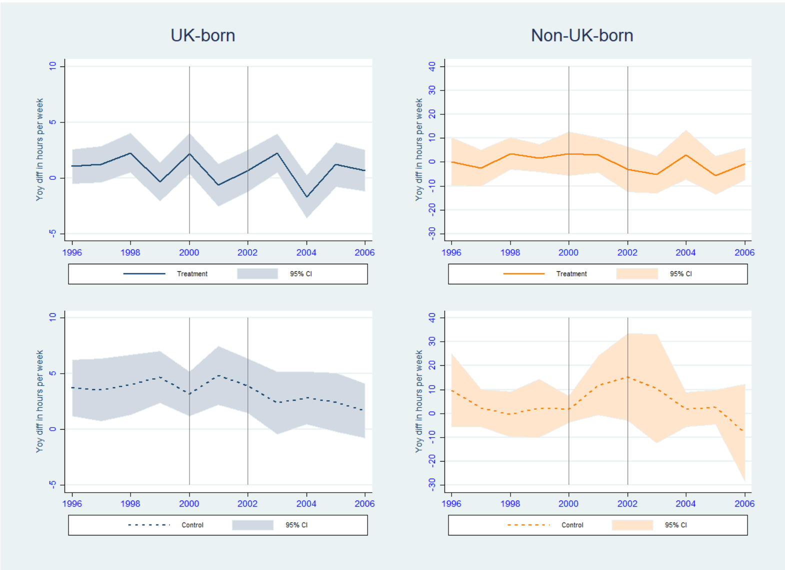
Note: The dependent variable is a binary variable, equal to 1 if an individual claims benefits.
The estimation method is fixed effects.
Time effects and occupational, industry, regional and other controls are included.
Significance levels: *:10% **:5% ***:1%
Robust standard errors in parentheses.

Appendix C

Appendix to Chapter 4

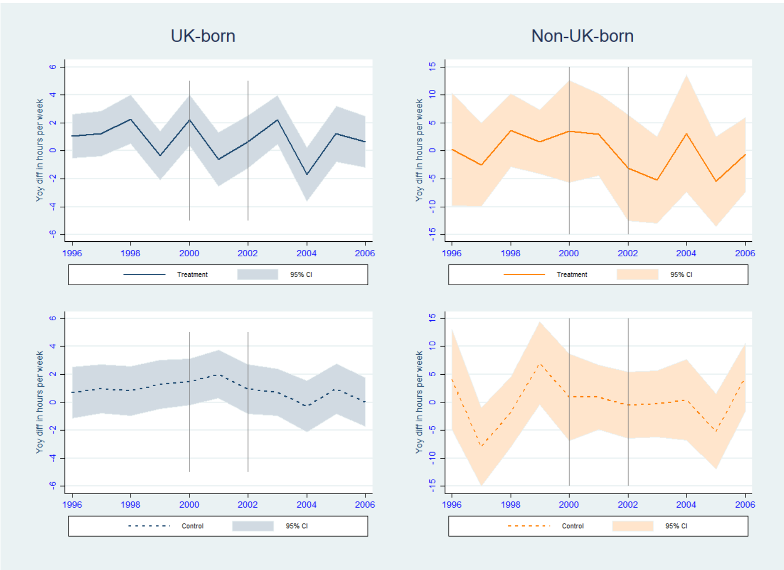
C.1 Single individuals without children: treatment and control

Figure C.1: Single individuals w/o children vs. single parents (lower education)



Source: Labour Force Survey.
Note: Average hours worked by the group conditional on the individuals being employed, age 25 or over, and having lower education. Control group is single parents. Treatment group is single individuals without children.

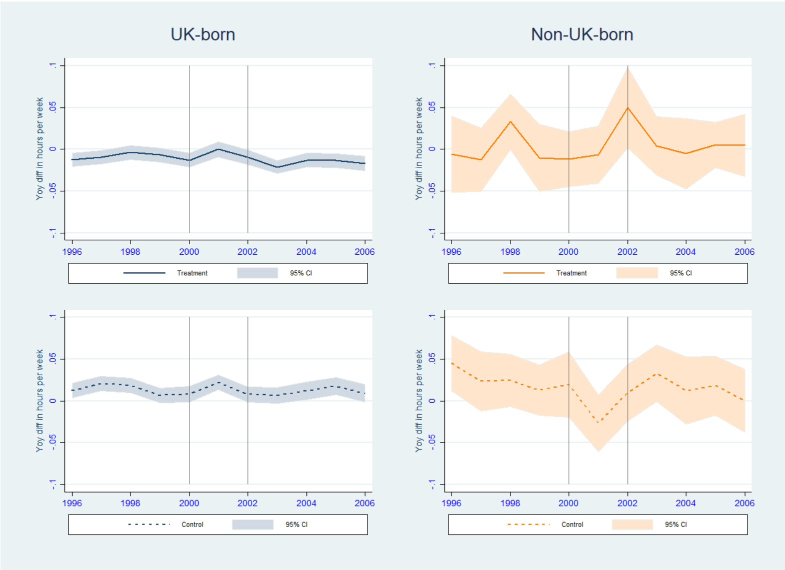
Figure C.2: Single individuals w/o children with lower vs. higher education



Source: Labour Force Survey.
Note: Average hours worked by the group, conditional on individuals being employed and age 25 or over.
Control group is single individuals without children with higher education. Treatment group is single individuals without children with lower education.

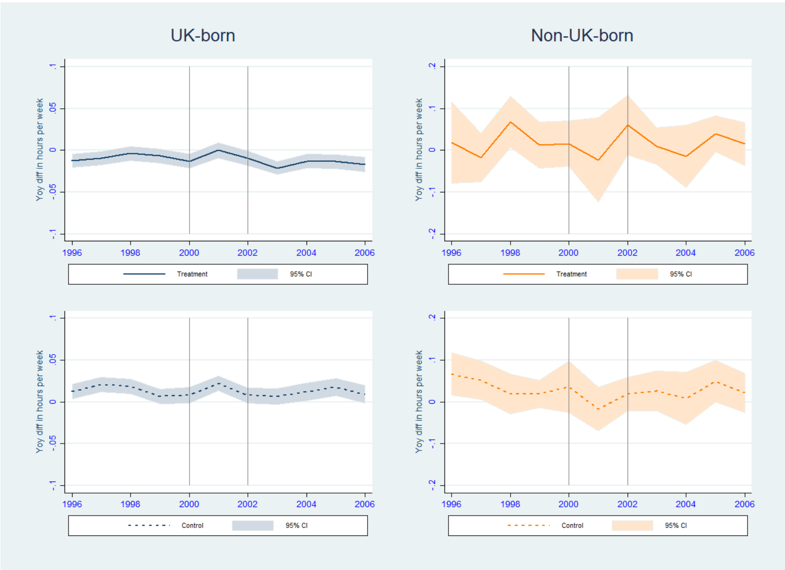
C.2 Couples without children: treatment and control

Figure C.3: Couples w/o children vs. couples w/children: extensive margin I



Source: Labour Force Survey.
Note: Year-on-year changes in employment status.
0: status unchanged, -1: moved from employment to unemployment, 1: moved from unemployment to employment.
Control group is couples with children. Treatment group is couples without children.

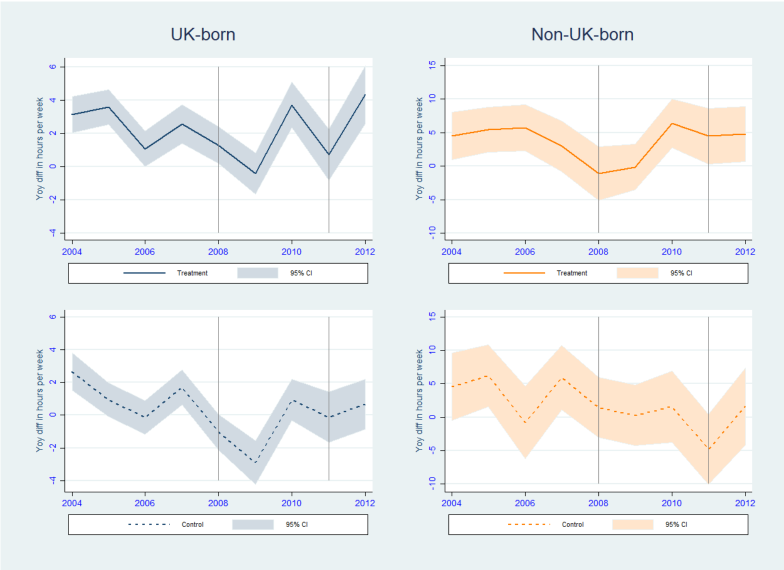
Figure C.4: Couples w/o children vs. couples w/children: extensive margin II



Source: Labour Force Survey.
Note: Year-on-year changes in employment status.
0: status unchanged, -1: moved from employment to unemployment, 1: moved from unemployment to employment.
Non-UK-born couples include both being non-UK-born. Control group is couples with children. Treatment group is couples without children.

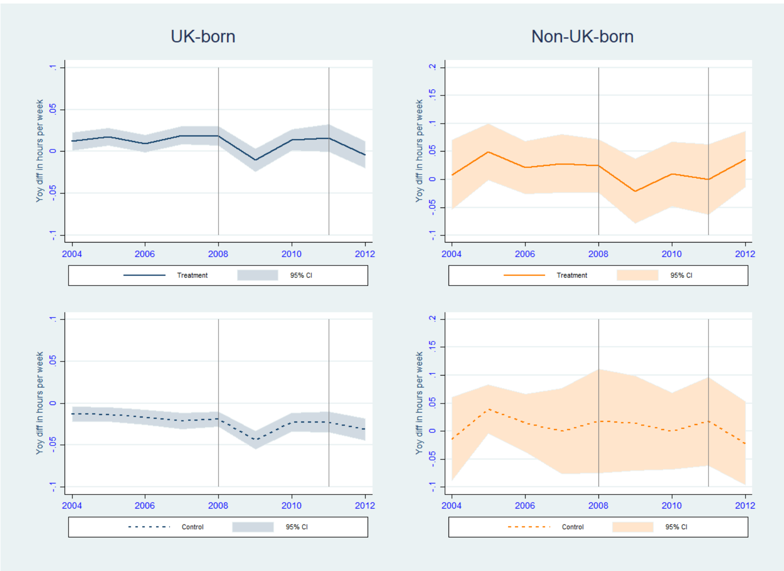
C.3 Couples with children: treatment and control

Figure C.5: Couples w/ children versus couples w/o children: intensive margin II



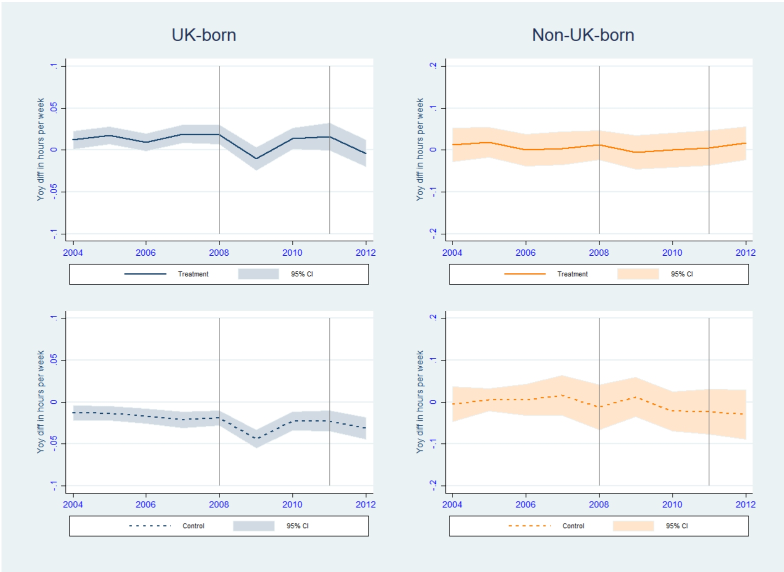
Source: Labour Force Survey.
Note: Year-on-year changes in non-zero hours worked by the group. Control group is couples without children. Treatment group is couples with children.

Figure C.6: Couples w/ children vs. couples w/o children: extensive margin I



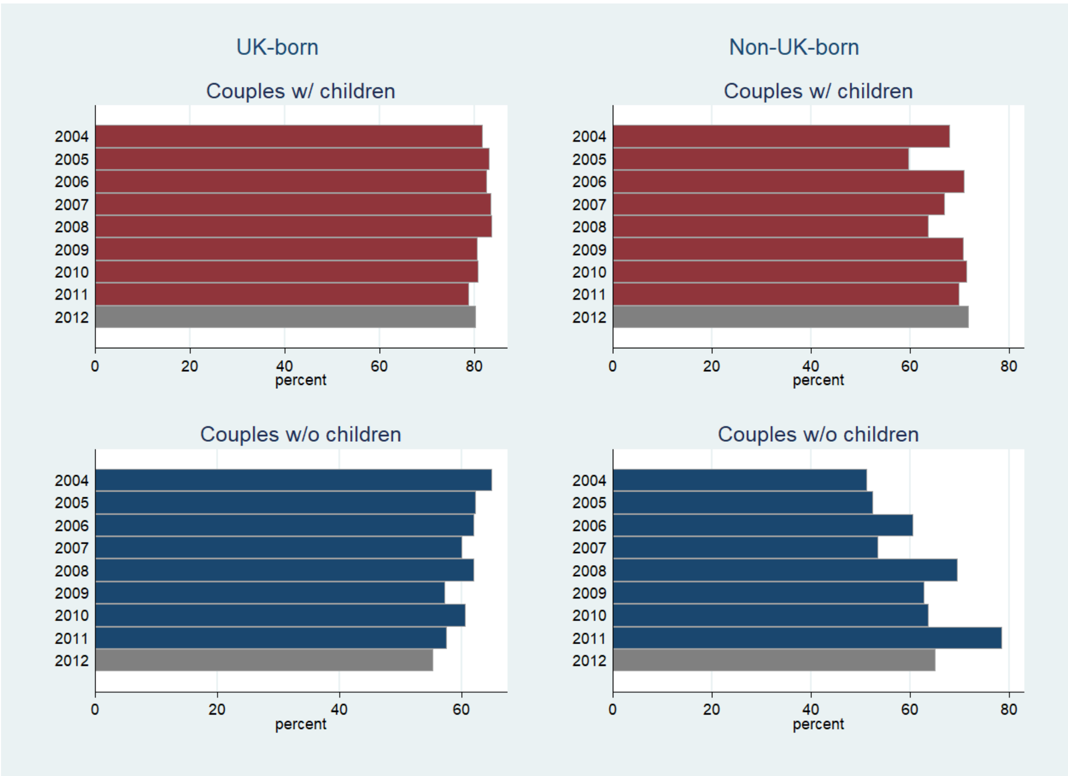
Source: Labour Force Survey.
Note: Year-on-year changes in employment status.
0: status unchanged, -1: moved from employment to unemployment, 1: moved from unemployment to employment.
Non-UK-born couples include both being non-UK-born.
Control group is couples without children. Treatment group is couples with children.

Figure C.7: Couples w/ children vs. couples w/o children: extensive margin II



Source: Labour Force Survey.
Note: Year-on-year changes in employment status.
0: status unchanged, -1: moved from employment to unemployment, 1: moved from unemployment to employment.
Control group is couples without children. Treatment group is couples with children.

Figure C.8: Proportions of couples who are employed



Source: Labour Force Survey.
Note: Proportions are calculated as shares of employed UK-born/non-UK-born couples with (without) children in total UK-born/non-UK-born couples with (without) children.

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