Investigating aspects of immigration and attitudes towards immigration in England and Wales

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Abstract

Immigration is a contentious issue for the governments of developed countries like the UK. Despite limited evidence demonstrating any substantial detrimental impact of immigration, it is often opposed. This thesis contains three empirical works that investigate a) how immigrants view immigration and how these views compare to natives b) the role of the labour market in establishing views towards further immigration and c) the impact of immigrants on primary schools in England. Data come from the UK Citizenship Survey; the censuses, providing longitudinal data on immigration in local areas, and the Department for Education, providing panel data for primary schools. A variety of econometric techniques are employed for the data analysis: OLS, Probit, Ordered Probit, fuzzy Regression Discontinuity Design (RDD), fixed effect regressions, and Instrumental Variable (IV) are all implemented.

Results suggest that earlier immigrants are similar to natives in being opposed to further immigration, while recent immigrants are more in favour of further immigration. Financial and economic shocks are associated with stronger anti-immigration responses. However, labour market concerns do not play a large role for either group of the respondents.

The role of labour market is investigated more rigorously by studying the change in views of native males on exit from the labour market. After controlling for the potential selection and endogeneity biases using a fuzzy RDD, views of native males, essentially, remain unchanged with some evidence of reduced opposition after exit from the labour market.

Finally, this thesis investigates the impact of immigrants on educational outcomes and schools. Using past location choice of immigrants to account for the non-random selection of immigrants into areas, results suggest that increased immigration has improved educational outcomes, both in English and maths, but also placed resource pressures on primary schools, as class sizes have increased and schools had to hire additional teachers.

Dedication

To the One and Only, The Most Beneficent, The Most Merciful, Who says:

"Read! In the name of your Lord Who created – Created the human from a clot of blood. Read! And your Lord is Most Bountiful – He Who taught by (the use of) the Pen, Taught the human that which he knew not. (96:1-5)"

Acknowledgements

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Declaration

I declare that this thesis is my own original piece of research under the supervision of Prof. Dr. John Wildman and Dr. Nils Braakmann, where chapter 4 and chapter 6 is a joint work with John Wildman and Nils Braakmann.

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Chapter 1. Introduction

This chapter sheds light on the economic, political and societal importance of immigration as a research topic. It explains the research background in light of the previous immigration literature in general and in the context of immigration in the UK in particular. It provides information on the history of immigration into the UK. It explains the aims and objectives of this thesis, highlights important immigration issues and finally outlines the structure of the thesis.

1.1 Research Background

Immigration has always been an important topic of research due to its controversial nature. Irrespective of the fact that the literature often demonstrates the benefits of immigration, it is often opposed. Why is immigration opposed? An answer to this question can be very helpful in policy formation and in understanding the social fabric. This question becomes even more important if the society is ethnically, culturally and religiously diversified like the one in the UK. Issues like discrimination, racism and xenophobia can be better understood once this question is answered.

People with different ethnic, cultural or religious backgrounds perceive things differently. Every individual has his own reasons and motivations for possessing the views/attitudes that he possesses. Much of the previous economics literature, that this thesis draws upon, has referred to “attitudes” rather than views. In wider social sciences, “attitudes” are often taken to represent a deeper psychological consideration that cannot be identified from the questions normally used in the research in economics on attitudes. For purpose of this thesis the terms “attitudes/views” are used interchangeably assuming that even if they are not identical they are highly correlated.

People living in a diverse society need to interact with each other. The way one behaves towards the other is due to some certain reason or is backed up by a motive. That motive can be economic, social or based upon personal experience. This research thesis is focused on the attitudes/views towards further immigration and its consequences.

Over time, immigration has increased in developed countries and as a result different types of social and economic issues have arisen, such as: the economic impact of immigration on the host country, wage differentials, discrimination, unemployment, racism, societal integration, assimilation, xenophobia (fear of foreigners), attitudes towards immigrants and cultural aspects of immigration. All of these have remained highly debated issues during recent decades and are explained below in the light of previous literature.

1.1.1 Immigration Issues

Research has investigated the impact of immigration on the economy in the host countries. A large body of empirical literature is available that addresses the question of immigration and its impacts upon local labour markets.[1] Economic theory suggests that the decisive element of economic impact of immigration resides on the skill differences of immigrants and natives. Source country will gain more if there are greater differences in immigrant native skills. Natives having complimentary skills with immigrants gain and those having similar skills lose. Facchini and Mayda (2006) studied the redistributive welfare state effect on natives' attitudes towards immigration. They found that high earners suffer more from unskilled immigration when taxes are raised to keep the per capita share unaffected but low earners suffer more from unskilled immigration if tax rates remain same and per capita share is reduced. Its exact opposite is true in case of skilled immigration. Borjas (1992) found that skill differences exist in the second and third generation of the immigrants and part of these differences are attributable to the "ethnic externalities". These ethnic externalities affect the labour market outcomes or productivity of the children. He suggests that increasing the skill level of one generation increases the economic welfare of next generations.

Most of the research findings state that immigration does not have any considerable adverse effect on local labour markets in the US (Altonji and

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[1] For comprehensive review of the literature on the economic impact of immigration see, Borjas, G.J. (1994), Borjas, G.J. (1999), Friedberg, R.M. and Hunt, J. (1995), LaLonde, Robert, J. and Topel, R.H. (1996).

Card, 1991; Card, 1990; Card, 2001; Kuhn and Wooton, 1991; LaLonde and Topel, 1991), the UK (Dustmann et al., 2003; Dustmann et al., 2005), Germany (Haisken-De New and Zimmermann, 1994; Haisken-De New and Zimmermann, 1999; Pischke and Velling, 1997), France (Hunt, 1992), Portugal (Carrington and Lima, 1996), Austria (Winter-Ebmer and Zweimuller, 1996; Winter-Ebmer and Zweimuller, 1999) and in Western Europe as whole (Angrist and Kugler, 2003). All of these studies (except for Borjas (2003)) indicate that immigration has almost no negative effect on the wages, employability or displacement of natives in local labour markets. By contrast, Borjas (2003) detected reductions in average native wages by 3%, whereas 9% for those having minimum education on a 10% increase in immigration in the US.

Increases in net immigration mean an increase in labour supply, and theoretically, in a simple model, an increase in the labour supply decreases wages and increases unemployment in the host country. Mostly, immigration reduces the wages and increases the unemployment in immigrants (see, for example, Manacorda et al., 2012; Ottaviano and Peri, 2012). Manacorda et al. (2012) for Britain using the UK's Labour Force Survey (after 1983) and the General Household Survey (mid 1970s to mid-2000s), and similarly for the US, Ottaviano and Peri (2012) using the US Decennial Censuses 1960 – 2000 and 2006 American Community Survey. They find that wage difference between natives and immigrants is an outcome of their skill differences and that an increase in immigration decreases immigrant wages, if there is any effect of immigration on native wages, it is positive suggesting that natives and immigrants are not competitors in the labour market. These recent additions to the literature strengthen the idea of Borjas (1992) that natives and immigrants are imperfect substitutes as they possess different skills and hence are not competitors in the labour market.

A large body of literature finds a positive correlation between the earnings of immigrants and their years of stay in the host countries. As the time spent in the host country widens, the wage differentials between natives and immigrants narrow because immigrants acquire natives' skills that result in reducing the wage gap between the two groups, for instance (Bloom and Gunderson, 1991; Baker and Benjamin, 1994) for Canada, (Dustmann, 1993) for Germany, (Beggs and Chapman, 1991) for Australia, and (Chiswick, 1978; Carliner, 1980) for the US with an exception of Hammarstedt (2003) for Sweden. Hammarstedt (2003) find that even after 15 years of stay in Sweden, immigrants do not reach to natives' wage level. Bratsberg (1995) found that immigrant students after completing their education they earn more in U.S. if their home country offers them a low return to skills and earns less if home country is paying high return to skills.

Some studies attribute wage and employability differences to discrimination:[2] For instance Arai and Thoursie (2009) for Sweden use data from Patent och Registreringsverket[3] (Swedish Patent and Registration Office (PRV)) to find the foreign forfeited names from 1991 – 2000. This data is then matched with the LOUISE database (Data of entire population in Sweden) and is used to investigate the wage differences between individuals with foreign sounding names and the individuals who surrendered their foreign sounding names and adopted neutral or Swedish sounding names. Using Difference-in-Differences, they find that the change of foreign names to neutral or Swedish sounding names rewarded name changers in terms of 26% higher wages than the name keepers. Similarly, Bertrand and Mullainathan (2004) for the US find that white names receive 50% more call backs for job interviews as compared to the African American names, in their field experiment of sending fabricated CVs that differ only by name. For Sweden Hammarstedt (2003) finds wage difference in the favour of immigrants coming from Nordic countries as compared to immigrants from non-Nordic countries depicting wage differentials based on where the immigrants come from.

Apart from the labour market competition, Card et al., (2012) give another reason why people may oppose further immigration, which they term "compositional concerns". "Compositional concerns" refer to the utility derived from the non-economic social determinants like interpersonal trust, neighbourhood safety, workplace and schools. They conclude that these concerns are five to six times more crucial in the attitude formation of natives towards immigration as compared to the economic concerns like wages and

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[2] For detailed theory on discrimination read the seminal work of Becker, G.S. (1971).
[3] Name change authority in Sweden. http://www.prv.se

taxes. Additionally, a body of literature throws light on prejudices, suggesting views towards immigrants vary depending upon where those immigrants come from. Dustmann and Preston (2004) find that in the UK immigrants from European countries experience better attitudes compared to the immigrants from Asia or West Indies.

In opposition towards further immigration perceptions may be more important than the facts. Those perceptions can be caused due to various reasons and can influence the voting behavior of public and prioritization of issues (Ipsos MORI, 2014; Facchini and Mayda, 2008; Glaeser, 2005). According to the Ipsos MORI's political barometer from October 2014, 45% of the respondents consider the subject of "race relations/ immigration / immigrants" as the first most important issue, followed by 34% respondents considering "NHS / hospitals / health care" as the second most important issue and 30% respondents choose "economy / economic situation" as the third most important issue facing Britain today, (Ipsos MORI, 2014). In a recent survey conducted by the Ipsos MORI, in 14 countries including the UK, they found that mostly people are unaware of the real facts and figures behind the news in print and electronic media. In the survey, they found that people living in the UK overstate the number of immigrant population in the UK two times more as compared to the actual number of immigrant population. Additionally, people living in the UK also tend to overstate the unemployment rate by up to three times more than the actual unemployment rate. Nardelli and Arnett (2014), in their article of 29th October, 2014, report the managing director of the Ipsos MORI, Bobby Duffy, as saying that public priorities may be different if the public has correct information and a clearer view about immigration.

The following section explains immigration in the context of the UK. The UK is arguably an interesting setting for research on immigration as it has experienced a large influx of immigrants in recent years and the impact of immigration has been an area of major public concern.

1.1.2 Immigration in the UK

Immigration towards Europe increased rapidly after World War II. As far as the UK is concerned, immigration increased after the 1950s when immigration started from the New Commonwealth[4] countries as their citizens were not subject to immigration controls. Due to rapidly increasing immigration from these countries, Commonwealth citizens were brought under immigration control on 1st July, 1962 under “The Commonwealth Immigration Act 1962”. In 1967, Kenyan Asians and Ugandan Asians, started immigration into the UK due to discriminatory behaviour experienced in their home country. They started to immigrate at a rate of about 1000/month on the basis of having British citizenship after independence, meaning that they did not come under immigration control according to “The Commonwealth Immigration Act 1962”. This lead to a revision of the former immigration act to “The Commonwealth Immigration Act 1968” that ensured to bring all the entrants without a parent/grandparent born in the UK, under immigration controls. Immigration was further tightened by introduction of “The Immigration Act 1971” which was implemented in 1973 that removed the differentiation between Commonwealth and non-Commonwealth citizens to enter into the UK.

Figure 1.1 shows immigration, emigration and net migration into the UK since 1964.[5] Since 1994, net immigration has always been positive. In 2006, under “The Immigration Regulations 2006” family members of European Economic Area citizens who were not citizens of European Economic Area were granted the rights to work and live in the UK without prior permission and as a result immigration hit the highest recorded number of 596,000 immigrants into the UK.

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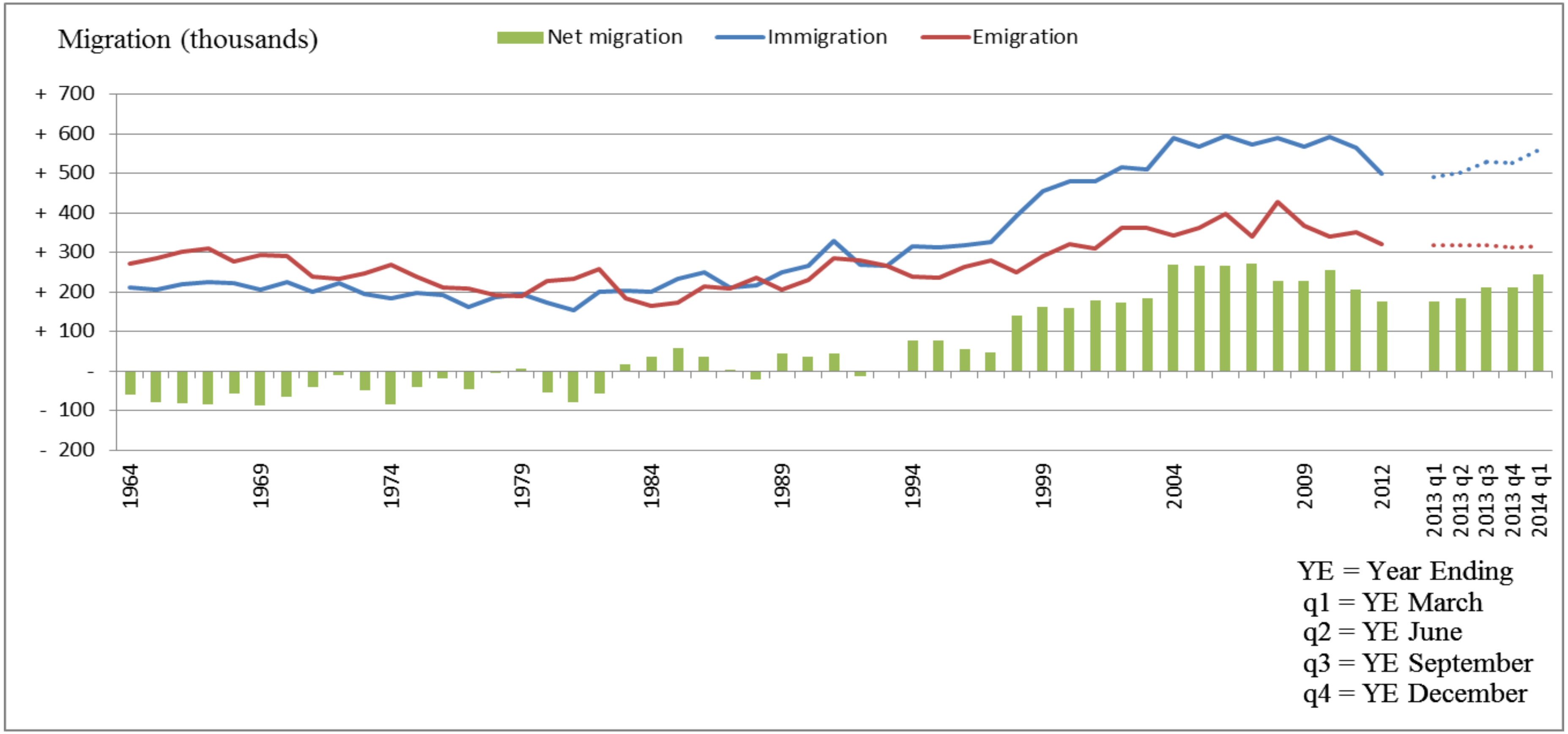
[4] In the year 1949 Modern Commonwealth began. Countries ruled by Britain who joined Commonwealth before 1945 are informally known as Old Commonwealth countries (for example, Australia, Canada, New Zealand). Countries who got independence later and joined Commonwealth are known as New Commonwealth countries (for example, Bangladesh, India, and Pakistan).

[5] Standard definitions of the terms immigration, emigration and net immigration are used. Immigration is the term used to refer to the people entering into the UK. Emigration is the term used to refer to the people leaving the UK. Net migration is the difference between immigration and emigration. If net migration is positive it means that more people entered into the UK to stay than people left it to live somewhere else.

Figure 1.1: Migration in the UK since 1964



Source: International Migration Data – ONS
Dotted lines show provisional immigration and emigration

In 2007, Bulgaria and Romania joined the European Union and gained the rights to live and work in the UK under "The Accession Immigration and Worker Authorisation" and the net migration hit the highest recorded number of 273,000 breaking the earlier highest net migration record of 268,000 migrants in 2004. In 2008, 427,000 emigrants – the highest recorded number ever – left the UK during the late 2000s UK recession. From June 2009 to June 2010, 591,000 immigrants came to the UK and the number of immigrants coming to the UK has been around this level since 2004. Net migration from 2004 to 2011 remained within minimum of 229,000 migrants in 2008 and 2009 and highest of 273,000 in 2007, followed by a decrease in net migration to 177,000 migrants in the UK in 2012. In the labour market, 690,000 National Insurance Numbers were issued to people having any nationality other than British in the year up to September 2011. This allocation of National Insurance Numbers was an increase of 11% as compared to the previous year.

According to the Office for National Statistics' quarterly report published in February 2012, immigrants from New Commonwealth countries hit the highest recorded number of 170,000 among the immigrants entering into the UK in a year from June 2010 to June 2011, (ONS, 2012). Two thirds came to the UK to study. The total number of immigrants on student visas in the year up to June 2011 was 242,000 out of which 46% were from New Commonwealth countries. India, Pakistan, Bangladesh and Sri Lanka had a 75% share in study immigrants from the New Commonwealth countries. The dotted lines in figure 1.1 show provisional numbers of immigration, emigration and net migration. According to the provisional numbers, net migration in the year ending March 2013 is standing at 175,000 immigrants into the UK. Net migration went up with an increase of 68,000 migrants to a provisional total of 243,000 migrants in the year ending March 2014.

Immigrants into the UK has been coming from several countries. So heterogeneity in immigrants is expected in the UK. Due to this heterogeneity in immigrants, different cohort of immigrants coming into the UK in different time periods or immigrants coming from different countries or immigrants with different ethnicities may behave differently and may have different attitudes towards immigration. Immigrants coming from non-English speaking Eastern European or Asian countries are generally less educated as compared to the immigrants coming from commonwealth countries. These immigrant groups coming from different countries also differ in their command over English language. Then the immigrant composition becomes heterogeneous by negative selection (generally from non-English speaking Eastern European or Asian countries) and positive selection (generally from commonwealth countries). It is possible that these two groups of immigrants have a different effect on the educational outcomes. This negative vs. positive selection may have implications on findings of chapter 6, however due to data restrictions immigrant heterogeneity could not be controlled for. We try to control for immigrant heterogeneity in this thesis wherever it is possible. Like, in chapter 4 we try to identify two immigrant groups on the basis of their stay in the UK. Although, this identification strategy is not flawless but given the data constraints it is not possible to identify immigrants in more detail and on other levels.

1.2 Aims and Objectives

The aim of this thesis is to investigate opposition towards further immigration and impact of immigration on educational outcomes and schools' resources. Despite the extensive literature trying to explain why people oppose further immigration, a large part of the question of why immigration is opposed is still unanswered. This thesis tries to explore this question from different angles. While literature exists on natives who are opposed towards immigration, little is known about the views of immigrants towards further immigration. As immigration is increasing in the UK, this makes research on the views of immigrants towards immigration even more important.

To begin with, this thesis explores the determinants of being opposed towards further immigration. Additionally, it explores the opposition of immigrants towards further immigration. Moreover, for a deeper understanding of the views of immigrants towards immigration, immigrants are further divided into earlier and recent immigrants. The former being the ones who have been in the UK for more than five years and latter being the ones who came to the UK in last five years. In the next step, this thesis then compares the views of natives towards further immigration with the views of earlier and recent immigrants. It also investigates how natives' and immigrants' views towards immigration change in the face of economic and financial shocks. Data from the UK Citizenship Survey (2007 – 2010) is used for the analysis and OLS is employed for estimation. For checking the robustness of our findings, a wide range of procedures and combination of procedures is used such as different sample restrictions, different outcome categorizations and usage of probit and ordered probit methodologies for the estimation. We find that a clear heterogeneity is present among immigrants. Immigrants who have been in the UK longer are more similar to natives in being opposed to further immigration, while recent immigrants are more in favour of further immigration. Financial and economic shocks are associated with stronger anti-immigration responses, even when holding the level of the respective variable constant. However, labour market concerns do not play a large role for either natives or either group of immigrants in determining views towards further immigration.

Even though the initial investigation shows no evidence for a role of the labour market in determining views of natives towards further immigration, this thesis explores this question more deeply in chapter 5. For this purpose, data from the UK Citizenship Survey (2009 – 2011) is employed. A Fuzzy RDD is used for estimating the change in views of native males towards further immigration upon retirement from paid work. The idea is that if the labour market plays any role in determining views of natives towards further immigration, there should be a change in views from being anti-immigration to pro/neutral views towards further immigration on exit from the labour market. As effectively, once a person is retired he is out of the labour force then the labour market competition and the labour market concerns become less of a concern. The findings once again suggest that the labour market does not play a large role in establishing anti-immigration views. OLS results do not show any significant change in views of native males towards further immigration on exit from the labour market. Even after controlling for the potential selection bias and endogeneity bias using RDD, views of native males mostly remain unchanged, however a little evidence of reduced opposition towards further immigration is found for natives males on their exit from the labour market.

As a final step, this thesis investigates the impact of immigration on the public services. There is a possibility that natives may oppose immigration due to the competition between immigrants and natives in the public services. It is likely that immigrant concentrated areas experience more pressures on resources than other areas. Although, immigrants and natives are not competitors in the labour market but they are certainly competitors in accessing the public services. This competition in public services can be the source of negative attitudes towards immigration. This thesis tries to find the impact of immigrants on educational outcomes and schools' resources using panel data on primary schools in England. The data about schools is taken from the "School League Tables" provided by the Department for Education and data about immigration at local authority level and at a low level geographical region is taken from the censuses conducted in year 2001 and 2011 by the Office for National Statistics.

This chapter uses various fixed effects regressions as well as IV, where past location choice of immigrants is used to account for the non-random selection of immigrants into areas. We find that increased immigration has improved educational outcomes, both in English and maths, but also placed resource pressures on primary schools, as class sizes have increased and schools had to hire additional teachers. The novel and innovative point is that this is the first study of its type that simultaneously studies the trade-off between expenditures and improved educational outcomes (schools' performance) on the face of increased immigration.

1.3 Structure of the Thesis

This thesis has been divided into seven chapters with additional appendices found at the end. Chapter 1 describes the research background concerning immigration in general, describing broad immigration issues, followed by a brief history of immigration into the UK.

Chapter 2 describes all the data sets used in this thesis in detail. It opens with an explanation of the UK Citizenship Survey and then moves on to describe data from the Office for National Statistics and finally ends with a description of School Performance Table data from the Department for Education. Chapter 3 is about methodologies used in this thesis. It explains OLS, why it is used, what are its advantages and what problems we face when using OLS. Subsequently, probit and ordered probit are explained, along with their advantages, disadvantages and reasons of use. Afterwards, Instrumental Variable (IV) is explained, why IV is preferred and what problems are addressed by the use of IV. It also explains the benefits of using IV when OLS fails. Eventually, Regression Discontinuity Design (RDD) is elaborated with its strengths and weaknesses. This chapter ends with an explanation of fixed effects estimates, why fixed effects are used and what type of fixed effects can be employed in different situations.

Chapter 4 is the first empirical chapter of the thesis and investigates views towards further immigration. It explores views of natives and immigrants and finds that there is a clear heterogeneity within immigrants in their views towards further immigration: Immigrants who have been in the UK more than five years are more similar to natives in their opposition to further immigration, while recent immigrants who have arrived in the UK within the last five years are more in favour of further immigration. Afterwards, determinants of natives', earlier immigrants' and recent immigrants' views are compared. Finally, this chapter explores the views of the three respondent groups towards further immigration in the face of financial difficulties and economic shocks. It suggests that financial and economic shocks are associated with stronger anti-immigration responses, whereas, labour market concerns do not play a large role for either natives or for either group of immigrants.

The role of the labour market in shaping views towards further immigration is investigated in greater detail in chapter 5. It employs a Fuzzy RDD exploiting discontinuity in labour market participation upon reaching the state retirement age. The last two waves of the UK Citizenship Survey are used for this chapter due to the non-availability of some variables in other waves. It estimates the change in views of natives towards further immigration upon exit from the labour market due to retirement from paid work and finds that views of natives remain unchanged. This chapter reinforces findings of chapter 4 that the labour market does not play a significant role in determining views towards further immigration. To further explore possible reasons for natives' opposition towards immigration, lastly, this thesis investigates whether immigrants and natives compete for public services (primary schools in this case) in chapter 6.

Chapter 6 investigates whether immigrants are a burden on public services. Primary schools as being one of the main public services are considered in this chapter. Data for schools are taken from the School League Tables provided by the Department for Education and low-level regional data on immigration are taken from the UK Censuses 2001 and 2011 provided by the Office for National Statistics. These data sets are then combined to see the impact of immigration on educational outcomes and schools' resources in England. This chapter uses various fixed effects regressions as well as IV, where past location choice of immigrants is used to account for the non-random selection of immigrants into areas. This chapter suggests that increased immigration has improved educational outcomes, both in English and maths, but also placed resource pressure on primary schools, as class sizes have increased and schools had to hire additional teachers.

Chapter 7 concludes estimations and findings of all the empirical chapters, with appendices presented in chapter 8 and references given at the end of the thesis.

Chapter 2. Data

This chapter provides detailed information about all the data sets used in this thesis. It explains the choice of data, their importance, and their advantages and limitations. Data used for this thesis are obtained from three main sources, namely, the Department for Communities and Local Government (DCLG), the Office for National Statistics (ONS), and the Department for Education.

2.1 Citizenship Survey

The Citizenship Survey formerly known as "Home Office Citizenship Survey" (HOCS) began in 2001 is a repeated cross-sectional study. Initially it was a biennial survey conducted by the Home Office in 2001, 2003, 2005 and 2007 – 2008. In May 2006, the Citizenship Survey fell under the sponsorship of the Communities and Local Government department (now known as the Department for Communities and Local Government (DCLG)). From 2007 onwards the survey has been conducted annually, with data collection taking place each quarter. The publicly available data for this period combines four quarters, giving surveys for 2007 – 08, 2008 – 09, 2009 – 10, and 2010 – 2011. In March 2008, this survey was awarded National Statistics status meaning that the data have been certified by the UK Statistics Authority in compliance with the code of practise for Official Statistics. These data are in conformance with the standard principles, procedures and practices used to carry out big projects of data collection. In the field this survey is known as "Communities Studies".

The Citizenship Survey provides a national representative sample of the adolescent and adult population of age 16 and above living in England and Wales. The method of data collection used is face-to-face interview. A multi-stage stratified random sampling method is used to obtain addresses of the houses selected for interviews. In the first stage, a systematic sample of wards is selected. There are about 8,800 wards in England and Wales each contains about 2,500 addresses. Any ward containing less than 500 addresses is grouped with a neighbouring ward. In the second stage, addresses are systematically sampled within the selected wards using a postcode address file. Each wave has approximately 15,000 respondents. Face-to-face interviews are conducted over the year in four quarters. Each wave contains a core sample of 10,000 respondents (2,500 respondents interviewed each quarter) and has an ethnic boost sample of 5,000 respondents.[6] The survey wave 2009 – 2010 contains a Muslim boost sample of around 3,000 individuals. Ethnic boost samples and Muslim boost sample are obtained by a systematic oversampling in the respective category.

Topics covered in all surveys include: feelings about the community, trust and influence, including community cohesion, trust and influence, identity and social networks, religion, volunteering, race and religious prejudice, civic engagement, perceptions of discrimination, mixing between people of different backgrounds, demographic, and values. Questions on further immigration are only included in the waves from 2007 onwards and hence data from 2007 – 2011 are used for this thesis. The questionnaire used for the Citizenship Survey includes standard established questions; demographic questions are mostly taken from the Office for National Statistics question booklets, questions about family and relationships are taken from the General Household Survey, questions on trust are taken from the World Values Survey and the British Social Attitudes Survey. Interviews are conducted by the trained professional staff of Ipsos MORI and TNS-BMRB.

The Citizenship Survey data are used for this thesis for a number of reasons. This survey has the advantage that it includes the minority ethnic boost sample of around 5,000 respondents in each wave that enables us to investigate the views of immigrants towards further immigration. However, it does not have any information about the immigrants who left the UK. As the Citizenship Survey data are not panel data, so we are unable to follow the change in individuals' attitudes over the years. A close comparison to the Citizenship Survey data is the British Social Attitudes Survey. The British Social Attitudes Survey also asks our question of interest about immigration. It is an annual survey and has been running since 1983. It has the advantage of having a large number of waves, 31st wave in 2014. However, the sample

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[6] For greater details of sampling procedure see technical report of the Citizenship Survey (DCLG and Ipsos MORI, 2007).

size of the British Social Attitudes Survey is only around 3,000 individuals in each wave. It becomes even smaller when it comes to an ethnic minority sample. The small sample size of the British Social Attitudes Survey does not allow us to investigate the views of immigrants towards further immigration. In other words, a major part of the research question this thesis is investigating is impossible to write without the use of the Citizenship Survey data.

2.2 Census Data

Every ten years, a population census is conducted in England and Wales by the Office for National Statistics (ONS). Apart from conducting a ten-yearly census, the ONS collects data in the UK on various subjects such as; economy, society at national, regional and local levels, demography, migration and crime, and publishes the official statistics. ONS is known as the national statistical institute of the UK and is the executive office of the UK Statistics Authority (ONS, 2014).

Data on immigrants, measured by people born outside the UK, is collected as part of the censuses by the ONS during the census years 2001 and 2011. We use this data at low level geographical regions to find the number of immigrants coming into the local areas. Although, some issues regarding the accuracy of this data can arise, however, this is the only available data set collected at the national level. All the residents with country of birth other than the UK are considered as immigrants. Data provided by ONS contains Middle-layer Super Output Area (MSOA) codes and Lower-layer Super Output Area (LSOA) codes with information on immigration at respective levels. LSOAs are based on post-codes, which in the UK are usually equivalent to streets, and are designed to remain stable over time. One can think of the LSOAs as being equivalent to neighbourhoods, while MSOAs are close to city quarters or smaller towns. LSOAs have a minimum population of 1,000 with a mean of 1,500, equal to approximately 650 households. LSOAs are then combined to generate an MSOA. Each MSOA contains a minimum population of 5,000 with a mean of 7,500 or around 3,000 households. At present, there are 34,753 LSOAs and 7,201 MSOAs in England and Wales. These data are then combined using a postcode joining file, with the "School

League Tables" data also known as "School Performance Tables" explained in the following section.

2.3 School Performance Tables / School League Tables

"School Performance Tables" also known as "School League Tables" are published annually by the Department for Education.[7] The underlying data is collected by LEAs (Local Education Authorities).[8] The data provide school-level information on pupils' performance and school characteristics, such as total number of pupils, pupil-teacher ratios and various performance measures. Outcomes that are measured in both years 2001 and 2011 and recorded in "School Performance Tables" are used for this thesis. We consider two sets of outcome variables; the first set of outcome variables is associated with school resources or general school characteristics, specifically the number of pupils eligible for key stage 2 assessment, the number of pupils whose first language is not English, the number of native pupils, the pupil-teacher ratio, and the number of teachers and the second set of outcome variables is educational achievement in the Key Stage 2 exams sat at the age of 11, the end of primary education.[9] These are: the percentages of pupils achieving level 4-competency or above in English or Maths respectively[10], the average point score in these exams, and the percentages of students not achieving any level of proficiency due to absence or disapplication (i.e., the percentage of pupils not sitting the respective exam) in English or Maths.

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[7] The Department for Education is the official government authority responsible for the education of children in the early years, in primary and secondary schools and in further education of young adults under the age of 19 years (DfE, 2014).

[8] In England and Wales, local government has a lower level administrative layer called as a "local council". Each local council has an education authority responsible for the education in a list of schools that comes under its control in its local area and is known as "Local Education Authority (LEA)".

[9] The English school system is structured in 4 "Key Stages". Each key stage refers to a certain age and completed educational years. Key Stage 1 starts with the reception class at the age of 4 and ends at the completion of 2 educational years at the age of 7 with an assessment in English and Maths. Key Stage 2 starts at the age of 7 and ends at the age of 11 after completion of 4 educational years with an assessment in English, Maths and Science. Primary education is completed at the end of the Key Stage 2 assessment, after which students begin their secondary education comprised on Key Stage 3 and Key Stage 4.

[10] Different levels represent the National Curriculum Test Levels, ranging from 1 to 8, with higher levels indicating higher competency. Key stage 2 exams cover levels 3 to 6, with 4 being the expected level of knowledge at this stage. The share of pupils achieving level 4 or above is thus equivalent to those performing at expected or higher levels at this stage of their education.

The “School Performance Tables” data are publically available and contains a panel of schools recorded in both years of our interest. So far, to the best of our knowledge this is the only available data that provides information about school-level pupil outcomes and schools’ resources. However, another data set National Pupil Database (NPD) is also available. It contains pupils’ test and exam results at different key stages, data about students in non-maintained schools, independent schools, and further education colleges. Essentially, we do not use this data set as we are interested in school-level outcomes as presented in “School Performance Tables” in contrast to the pupil-level outcomes presented in National Pupil Database.

Chapter 3. Methodology

This chapter explains the methodologies used in this thesis. All the empirical chapters apply with OLS as it gives the Best Linear Unbiased Estimates (BLUE) of beta coefficients given that the classical assumptions of OLS are satisfied. Problems arise when the classical assumptions are violated. To address the issues resulting from violation of assumptions, advanced methodologies are employed. This chapter explains why a particular methodology is used, what its necessary assumptions are, what problems that methodology addresses, how and why a methodology works. The formal setup, intuition behind each methodology, and a brief discussion on each methodology is also given in this chapter.

3.1 Regression Methods

Normally, OLS is used when the outcome variable is a continuous variable. Other methodologies like probit, and logit come in to the picture when the outcome is a limited dependent variable. A limited dependent variable is one that can only take a limited range of values for example, gender, education etc. OLS can also be used to model binary limited dependent variables using linear probability models (Angrist, 2001; Menard, 1995). However, one of the issues in modelling limited dependent outcome variables using linear probability models is that it may predict probabilities less than 0 or greater than 1 (unbounded probabilities). It also breaks the classical assumptions of homoscedasticity and the normal distribution of the error term. Violation of homoscedasticity and normal distribution of the error term are not a significant problem because OLS estimates still remain unbiased. Due to the fact that in large samples the Central Limit Theorem (CLT) demonstrates that as the sample size increases, sampling distribution tends to normality. The most important problem is the former one.

For tackling the issue of unbounded prediction of probabilities, methodologies like logit and probit are employed. If the error term has a logistic distribution then logit is used and if the error term has a normal distribution then probit is used. Generally, the choice of logit or probit rarely matters, as both methodologies give similar results. We use probit and ordered probit in this thesis for comparison with OLS estimates. OLS is used as a starting point for all the analysis as there are some advantages of modelling probabilities using OLS such as: a) linear probability model using OLS is simple to estimate, b) it provides consistent estimates of betas, and c) the estimated model is easy to interpret i.e. the beta coefficients gives the marginal change in probability, ceteris paribus.

Probit and likewise logit and many other estimation methods use a latent variable approach. They use an unobserved continuous latent variable Y_i^* that decides what is observed in the data. The latent variable is a linear function of the independent variables. Probit solves the unbounded probability prediction problem by using the latent variable Y_i^* that does not allow the predicted probability to fall outside 0 and 1. To illustrate the probit methodology, let us take a simple model with one observed binary outcome variable 'Y', one independent variable 'X' and 'Y^*' is a latent unobserved variable. The formal setup is as follows.

$$Y_i^* = \alpha + \beta X_i + \varepsilon_i \qquad (3.1)$$

If the latent variable $Y_i^* \leq 0$ then we observe $Y_i = 0$

If the latent variable $Y_i^* > 0$ then we observe $Y_i = 1$

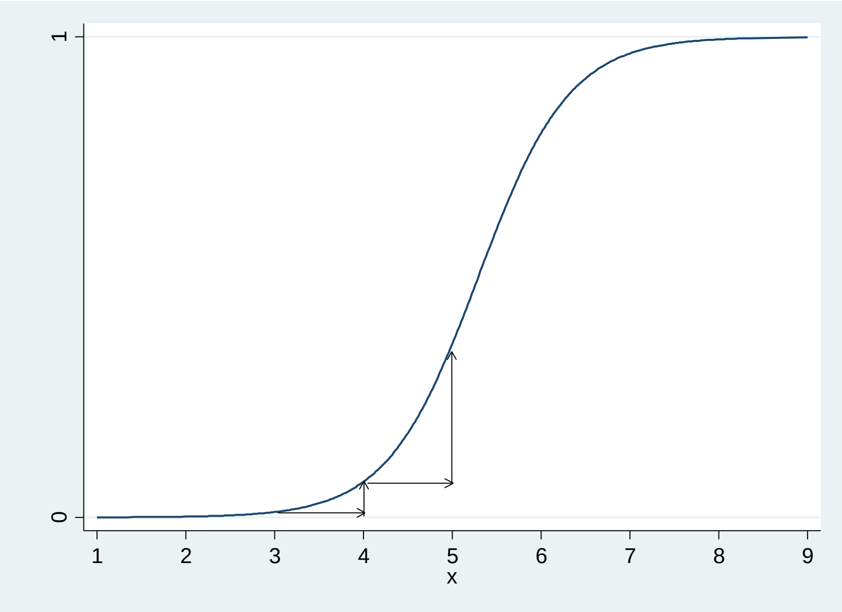
$$Y_i = 1 \text{ if } \{Y_i^* > 0\} = 1\ \{\alpha + \beta X_i + \varepsilon_i > 0\}$$

It is assumed that our latent variable Y_i^* is correlated with the independent variable 'X'. The error term ε_i is assumed to be uncorrelated with the independent variable 'X' and has a parametric distribution. In parameterising the model, if the distribution chosen for the error term is a logistic distribution, then logit is used, whereas, if the distribution chosen for the error term is standard normal distribution then probit is used.

There is a crucial point to remember in interpreting the coefficients of OLS and probit that their coefficients are neither directly comparable nor have same interpretation.[11] Coefficients of OLS are interpreted as a marginal change in Y_i, whereas, probit coefficients give the change in the latent variable Y_i^*, this is not the change in the actual binary outcome variable Y_i. Nevertheless, interpretation of the sign and significance is similar for both the latent variable Y_i^* and the original binary outcome variable Y_i.

Marginal effects provide us the change in Y_i for a one unit change in the value of *'X'*. The main disadvantage of the probit is that the change in Y_i is different for different values of *'X'*. For instance, in figure 3.1, one unit increase in '*X*' from 3 to 4 has a different effect on change in probability of '*Y*', compared to one unit increase in '*X*' from 4 to 5.

Figure 3.1: Interpretation of marginal effects in probit



Interpretation of the marginal effects becomes even more complex when the number of independent variable *'X'* is more than one. Then the change in Y_i depends upon the values of all *'X'* variables. To tackle this issue of so many marginal effects, sometimes marginal effects are calculated for an average individual after setting the values of all the *'X'* variables to their sample mean. These are called "Marginal Effects at Mean". An alternative way referred to as "Average Marginal Effects" is to calculate the marginal effect for each observation in the data and average across individuals. Occasionally, marginal

[11] Similar caution holds true for all other methodologies using latent variable approach such as logit, ordered probit, ordered logit etc.

effects are also calculated at interesting values related to the research question.

After using probit for this thesis, we also use ordered probit to investigate how much the choice of methodology affects our findings. Our outcome variable for chapter 4 and chapter 5 is originally an ordered polytomous variable that is converted into a binary variable for estimating OLS and probit regressions. Ordered probit is explained in the following section.

3.2 Ordered Probit

Ordered probit is used whenever the outcome variable is an ordered limited dependent variable, for example in a question about controlling immigration into the UK, respondents may choose from “increase a lot”, “increase a little”, “remain the same”, “reduce a little” and “reduce a lot”. In this example, there is clearly a meaningful order in terms of information respondents wanting a tighter or loose immigration policy. The benefit of using ordered probit is that we do not lose the information contained in the ordering. Just like probit, ordered probit also uses a latent variable approach. The formal setup is given below.

We have a sample of respondents. The outcome can take a value out of the given values, let us say {1, 2, ..., j} where j is some known integer. Using the latent variable approach our latent variable Y_i^* is modelled like this

$$Y_i^* = \beta X_i + \varepsilon_i \qquad (3.2)$$

We assume that ε_i has a standard normal distribution which leads us to ordered probit. In an alternative scenario if we parameterise the ε_i distribution as logistic then we get an ordered logit. To illustrate the idea, let us say that that there are 5 values (*i.e.* $j = 5$) for the outcome Y_i. The probabilities of our outcomes become as follows

$P (Y_i = 1) = P (\varepsilon_i \leq -\beta X)$
$P (Y_i = 2) = P (\varepsilon_i \leq u_1 - \beta X) - P (\varepsilon_i \leq -\beta X)$
$P (Y_i = 3) = P (\varepsilon_i \leq u_2 - \beta X) - P (\varepsilon_i \leq u_1 - \beta X)$
$P (Y_i = 4) = P (\varepsilon_i \leq u_3 - \beta X) - P (\varepsilon_i \leq u_2 - \beta X)$

$P\ (Y_i = 5) = P\ (\varepsilon_i \leq u_4 - \beta X) - P\ (\varepsilon_i \leq u_3 - \beta X)$

Here $u_1, u_2, u_3,$ *and* u_4 are the threshold parameters that determine the cut points of the probability distribution function. These threshold parameters divide the probability density function and the area bounded between the cut points gives us the respective probabilities. The observed outcome is determined by the value of the latent variable Y_i^* and the unknown threshold parameters $u_1, u_2, u_3,$ *and* u_4 determining the cut points.

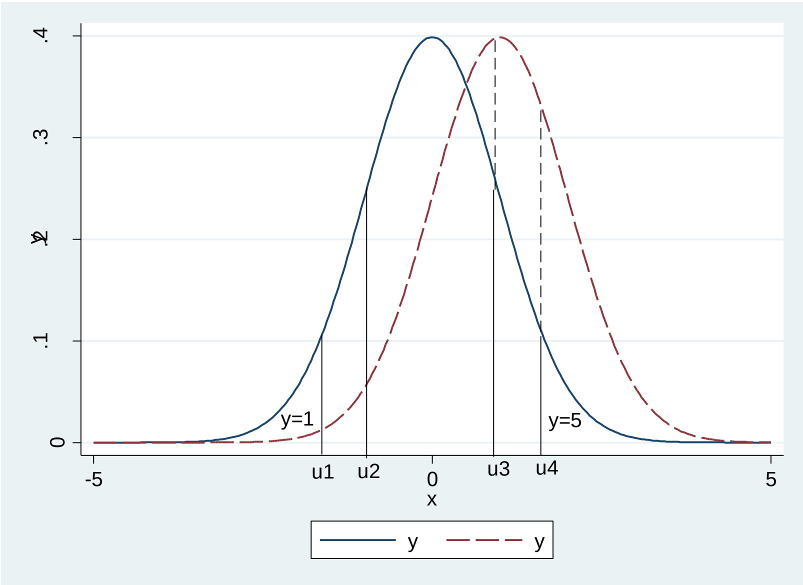
An important point to remember here is that these threshold parameters are also coefficients that need to be estimated.

If the latent variable $Y_i^* < u_1$, we observe $Y_i = 1$
If $u_1 < Y_i^* < u_2$, we observe $Y_i = 2$
If $u_2 < Y_i^* < u_3$, we observe $Y_i = 3$
If $u_3 < Y_i^* < u_4$, we observe $Y_i = 4$
If $u_4 < Y_i^*$, we observe $Y_i = 5$

Just like probit, ordered probit also calculates its coefficients and threshold parameters, using maximum likelihood method. These threshold parameters divide the probability density function into parts, and area within each part gives us the probability associated with the respective threshold parameter. If we move the cut points we change the probabilities as well, because area within each compartment changes. For interpretation of the coefficients we again need to calculate marginal effects. In ordered probit, calculating marginal effects and their interpretations becomes even more complex because a change in '*X*', changes the whole probability distribution function and ends up changing probabilities (area bounded within each cut point) in each compartment.

In calculating the marginal effects, we first need to state which probability change we are looking for, because moving the cut point changes the probabilities. For instance, as presented in figure 3.2, a one unit increase in '*X*', shifts the whole distribution to the right side, which changes the area in each compartment. After the shift, under the new distribution (shown with a dashed line), the area in the right tail increases at $P\ (Y_i = 5)$, whereas, area in the left tail at $P\ (Y_i = 1)$ decreases, while the effect on the middle choices remains unknown and requires even more calculations.

Figure 3.2: Interpretation of ordered probit coefficients



In other words, the marginal effects for $P\ (Y_i = 1)$ are different from the marginal effects of $P\ (Y_i = 5)$ and all other probability outcomes for every increase in '*X*'. Even after calculation of the marginal effects at specified probabilities, just like probit coefficients, they are not directly comparable with the OLS coefficients. OLS coefficients give us the average marginal change in outcome whereas, marginal effects calculated on the specified probability gives us the change in that probability at a specific value.

Our base methodology for this thesis is OLS. We use probit and ordered probit to check the robustness of our estimates and see whether the choice of the methodology changes the results. We find that the results look qualitatively similar, which means that in this case, the choice of OLS as the primary methodology is not a problem. When the outcome variable is a limited dependent variable and the most serious problem of unbounded probability prediction is faced in using the OLS, most common solutions to this problem are discussed above. OLS faces another serious problem called endogeneity. Endogeneity, its consequences and solution to the said problem are explained in the following section.

3.3 Instrumental Variables (IV)

The Instrumental Variables strategy is normally employed when the OLS suffers from the bias arising from endogeneity. Endogeneity refers to a situation where there is a correlation between the regressor and the error term. It can occur due to several reasons such as: a) an omitted variable which is consequently part of the error term, and affects both the dependent and one or more independent variables, b) due to measurement errors, for example, erroneous data can lead to a systematic error term in the model which can be the source of endogeneity, c) endogeneity can also result from simultaneity when the dependent and independent variables get into a loop of affecting each other, for example, in structural equation modelling. In the presence of endogeneity, coefficients from simple regressions cannot be interpreted as causal. The Instrumental Variables approach is a very powerful solution that tackles endogeneity and gives estimates that can be interpreted as causal (Angrist, 1989; Angrist and Krueger, 1991).

Let us take an example of estimating the causal effect of immigration on the UK public services. The major difficulty in estimating the impact of immigration arises from the non-random location choice of immigrants. We know from previous research that immigrants self-select into areas, possibly on the basis of the existence of successful immigrant communities or similar ethnic groups or because of current favourable conditions in an area (see, for example, Abraham and Shryock, 2000; Åslund, 2005; Bartel, 1989; Hatton and Wheatley Price, 1999; Lymperopoulou, 2013; Pacyga, 1991; Phillimore and Goodson, 2006; Phillips, 2007; Schwirian, 1983; Styan, 2003; Zorlu and Mulder, 2008). To fix this potential endogeneity of the change in immigrant numbers in an area, we use an instrumental variable strategy based on past location choices, first developed by Card and DiNardo (2000) and Card (2001) and subsequently used in the immigration literature by many, for example, Bianchi et al. (2012), Card (2009), Cortes (2008), Gonzalez and Ortega (2013), Hunt (2012), Ottaviano and Peri (2006), and Saiz (2006).

The underlying idea is that the tendency of immigrants to move to areas with many existing immigrants allows one to use historic settlement patterns of immigrants to instrument for current settlement. In principal, past-immigration patterns should influence current settlement decisions, while the historical distribution of immigrants should be unaffected by any current change in the quality of public services. More formally, to model this endogenous treatment using an instrumental variable design, consider an initial population regression of the form given below.

$$Y_i = a + \tau * D_i + \xi * M_i + \eta_i \qquad (3.3)$$

Here Y_i represents an outcome for some UK public service, D_i represents immigration into the UK and M_i is the immigration induced endogeneity that we cannot observe. So we estimate the population regression of the form presented by equation (3.4), where the endogenous variable D_i is correlated with the error term ε_i

$$Y_i = a + \tau * D_i + \varepsilon_i \qquad here,\ \varepsilon_i = \xi * M_i + \eta_i \qquad (3.4)$$

As explained above, the problem is that immigration represented by D_i is an endogenous variable correlated with the error term ε_i leading to endogeneity. The underlying idea of IV is to decompose the variation of D_i in two parts: a) part of variation in D_i that is not correlated with the error term ε_i but correlated with the endogenous variable D_i and, b) part of variation in D_i that is correlated with the error term ε_i. The part that is uncorrelated with the error term ε_i is then used to estimate τ. To do this, a new variable "*Z*" is used which affects Y_i only through its effect on D_i. Here "*Z*" is an instrument provided that it fulfils the following two conditions.

1- Relevance
   "*Z*" is correlated with the endogenous variable *D*, formally
   $Cov(D,Z) \neq 0$

2- Exogeneity
   "*Z*" is uncorrelated with the error term ε and the outcome *Y*, formally
   $Cov(Z, \varepsilon) = 0$ and $Cov(Z, Y) = 0$

Explaining the above two conditions in the context of our example. Here, "*Z*" is "historical immigration pattern". As explained earlier that immigrants follow a certain pattern in their location choices (see, for example, Abraham and Shryock, 2000; Åslund, 2005; Bartel, 1989; Hatton and Wheatley Price, 1999; Lymperopoulou, 2013; Pacyga, 1991; Phillimore and Goodson, 2006; Phillips, 2007; Schwirian, 1983; Styan, 2003; Zorlu and Mulder, 2008). Our first condition is satisfied as our instrument "historical immigration pattern" labelled as "*Z*" is correlated with our endogenous variable "*D*" that is "current immigration" into the UK. We also know that "historical immigration pattern" is not correlated with our outcome variable "*Y*" that is outcome of any public service in the UK. Similarly, our instrument "historical immigration pattern" named "*Z*" is also uncorrelated with the error term ε.

As the instrument "*Z*" satisfies the two necessary conditions, it means that the Two Stage Least Squares (2SLS) can be used for estimation. In the regression equation form, first stage reduced form looks like equation (3.5) given below

$$D_i = \pi_0 + \pi_1 * Z_i + \upsilon_i \qquad (3.5)$$

Now part of the endogenous variable (D_i) uncorrelated with the error term (ε_i) is picked up by the coefficient (π_1) and is called the "first-stage effect" of the instrument. Whereas, correlated part of D_i with the error term ε_i is now included in the last expression υ_i, and is eliminated. After getting the predicted values ($\widehat{D}_i$), the endogenous variable (D_i) in the short population regression equation (3.4) is replaced by the predicted values ($\widehat{D}_i$) and gives us the second stage which is formally written as equation (3.6) below

$$Y_i = \alpha + \tau * \widehat{D}_i + \varepsilon_i \qquad (3.6)$$

However, the IV estimates are normally not calculated using this method because it produces incorrect standard errors. For correct calculation there is another useful equation that gives the change in the outcome variable (Y_i) with a change in the instrument (Z_i) and is formally written as equation (3.7) below

$$Y_i = \alpha + \beta^* Z_i + \varepsilon_i \qquad (3.7)$$

Here β is the "reduce-form effect". When there is one endogenous variable and one instrument then the IV estimator is the ratio of the reduce-form effect to the first-stage effect and can be written as equation (3.8) below

$$\tau^{IV} = \beta / \pi_1 \qquad (3.8)$$

$$\tau^{IV} = [Cov(Y_i,Z_i)/V(Z_i)]/[Cov(D_i,Z_i)/V(Z_i)] \qquad (3.9)$$

$$\tau^{IV} = Cov(Y_i,Z_i)/Cov(D_i,Z_i) \qquad (3.10)$$

Now substituting the initial model presented by equation (3.3) in equation (3.10) we get

$$\tau^{IV} = Cov([\alpha + \tau^* D_i + \xi^* M_i + \eta_i],Z_i)/Cov(D_i,Z_i) \qquad (3.11)$$

In the above given equation,

$Cov([M_i],Z_i) = 0$ and $Cov([\eta_i],Z_i) = 0$ due to exclusion restriction

Whereas,

$Cov([D_i],Z_i) \neq 0$ due to the relevance restriction and existence of first stage.

$$\hat{\tau}^{IV} = \tau \qquad (3.12)$$

Now our τ is interpreted as a causal effect of immigration on the public services in the UK.

However, if the first stage is not considerably different from zero, we have a weak instrument problem.[12] As a consequence of using a weak instrument (low correlation between the endogenous variable and the instrument) for estimation can lead to inconsistent IV estimates. Moreover, in finite samples, if the instrument is weak it can lead to bias towards OLS estimates (see, Bound, Jaeger and Baker (1995)). To test the weak instrument problem the first stage F-Statistic is used. Stock, Wright, and Yogo (2002) and Staiger and Stock (1997) suggest that if the F-statistic is above 10, we can assume that our instrument does not suffer from the weak instrument problem. The higher the F-statistic, the better it is. It indicates that first stage exists and there is enough correlation between the endogenous regressor and the instrument that can be used for the unbiased causal estimation. Nevertheless, if there is a problem of weak instrument (weak relationship between Y_i and Z_i) then we probably need to think about using a better instrument or a different methodology.

In the context of the earlier example, our instrument works because the predicted and actual numbers of immigrants should be correlated as immigrants are likely to settle in regions with a history of immigration. At the same time, as the instrument is a purely mechanical redistribution of nationwide changes in immigration based on historical settlement patterns, it should be uncorrelated with any changes in public services and economic conditions that might affect immigrants' location choices.

So far we use classical IV, in which we assume that there is a homogenous causal effect (constant treatment effect) of the treatment on all the individuals in the estimated sample. Suppose our instrument is a binary variable which assigns 1 if the individual is selected to participate in the experiment and 0 if not selected. We get four possible groups based on the observed value and treatment value. These groups are described as follow: 1) Always-takers: individuals who always participate irrespective of the value of the instrument, 2) Never-takers: those who will not participate whether the instrument assigns them 1 or 0, 3) Defiers: individuals who participate if the

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[12] Bound, Jaeger and Baker (1995) highlighted the problems associated with the instrumental variables.

instrument assigns them 0 and do not participate if the instrument assigns them 1, and 4) Compliers: anyone who will act according to the assigned value by the instrument. Without the assumption of constant treatment effect, IV only gives us the average effect for the subsample. This subsample – out of the estimated sample – includes the individuals who changed their value driven by the instrument and are referred to as "compliers" and their average treatment effect is called Local Average Treatment Effect (LATE). In other words, LATE is defined as the Average Treatment Effect (ATE) for those observations that change their treatment status in response to a change in the instrument (for greater details, see, for example, Angrist, Imbens and Rubin, 1996; Imbens and Angrist, 1994). However, using IV to estimate ATE for the whole population is usually not possible.

Now we will explore what IV estimates if the treatment has a different effect (heterogeneous treatment effect) on the individuals in the estimated sample. It is assumed that there are no defiers in the data because presence of defiers can cancel out the effect on compliers and lead to a reduced form near to 0. Without further assumptions LATE is not informative about the sub-sample of always-takers. A necessary assumption that the LATE is equal for compliers and always-takers is required to interpret the LATE as the Average Treatment Effect of the Treated (ATT). It is important to note here that the LATE and the ATT are not same without assuming that the LATE is equal for compliers and always-takers. However, if there are no always-takers in the data, in that case LATE is equal to ATT. There are two disadvantages and one advantage of using the LATE approach. The problem with using the LATE is that, it is the effect for a non-observable population because mostly we are unable to practically identify the compliers. LATE is completely instrument dependent which means that estimates from using two different instruments are not directly comparable. However, the advantage of using the LATE is that it gives us the effect of the experiment which is very helpful in analysing the policy changes and other natural experiments.

Apart from the IV, there is another useful design called Regression Discontinuity Design (RDD) used in this thesis and is explained in the following section.

3.4 Regression Discontinuity Design (RDD)

Regression Discontinuity Design exploits a cut-off point between two groups, first introduced by Thistlethwaite and Campbell, (1960) using OLS and later developed by Imbens and Lemieux (2008) and Lee and Lemieux (2010).[13] It is a special case of selection on observables where an individual receives the treatment depending on the value of one variable referred to as a "forcing variable" and some known threshold. It is normally used in estimating the causal effect of a policy or a change in one attribute in two otherwise similar groups of people at one point in time. Epidemiologists normally use it in quasi-experimental studies. This design has high internal validity. It is easy to use and very reliable given that the conditions of using an RDD design are fulfilled, with a limitation of low external validity. RDD has two types

1- Sharp RDD
2- Fuzzy RDD

Sharp RDD is used when there are no treated individuals to the left and no untreated individuals to the right side of the threshold. In other words, Sharp RDD is used when the individuals are unable to self-select into the left or right side of the threshold. In contrast, Fuzzy RDD is used when there are treated and untreated units on both sides of the threshold.

This thesis uses a Fuzzy RDD to estimate the change in views of native males towards further immigration once they retire from paid work. It is an effort to capture the causal effect of leaving the labour market on the views towards further immigration. For the period covered by the data, the state retirement age in England and Wales was 65 and 60 for males and females respectively, and is used as a threshold that defines the cut-off point. We only focus on men because we are unable to distinguish retired females who have left the labour force and those who have retired from positions which were not part of the labour force. We use state retirement age (65) as an instrument to determine retirement (exit from the labour market) and estimate the change

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[13] For a historical insight about the development of Regression Discontinuity Design, see, Cook (2008).

in attitudes towards further immigration caused by this retirement. The starting point of a Fuzzy RDD is that there are treated and untreated individuals on both sides of the threshold. Putting it into the context, it means that there are retired and working individuals on both sides of the threshold age 65. The underlying idea is that observations on each side near to the threshold can be used as a counterfactual for the other group. The Fuzzy RDD can only be used if there is a clear visible discontinuous jump at the threshold point. In a Fuzzy RDD we also need the estimates for the likelihood of getting the treatment. We estimate for the average outcomes the likelihood of receiving the treatment on the left and right side of the threshold by trimming the sample near to the threshold on both sides and run a regression. A Fuzzy RDD is just an IV with a forced threshold value and is explained below (also see, section 6.2 in Angrist and Pischke (2009)). In this design, discontinuity becomes an instrument for the treatment.[14] The formal setup of a Fuzzy RDD is as follows.

In the first stage of a Fuzzy RDD, we plot a graph of the treatment D_i against the forcing variable S_i (see, Imbens and Lemieux (2008)). The graph should show a clear visible discontinuous jump in the data at the threshold $\bar{s}$. This can be tested by plotting the density of the forcing variable (s) for all its values. This enables the researcher to explore the distribution of the forcing variable and shows whether the discontinuity is present only at the threshold ($\bar{s}$) or, are there discontinuities elsewhere as well (see, McCrary (2008)). If suddenly there are more observations on one side of the threshold, or there are discontinuities at other points, it means individuals are trying to self-select or trying to manipulate the forcing variable according to their preference. The design is Fuzzy as individuals younger than 65 (left side of the threshold) can be retired due to any reason such as early retirement and likewise individuals aged 65 or more (right side of the threshold) can still be working in a paid job. For a Fuzzy RDD to work, we need the first stage to exist. It means that the inequality (presented below by equation (3.13)) between the probability of getting treatment before and after the threshold should hold true

[14] Trochim (1984) introduced the idea of using discontinuous jump in the likelihood of getting the treatment at threshold point as an identification strategy.

$$Pr\,(D_i = 1 \mid S_i = s^+) \neq Pr\,(D_i = 1 \mid S_i = s^-) \qquad (3.13)$$

Here D_i refers to the treatment status of an individual i (retired from paid work or still working), S_i refers to the age of the individual i and s^+ and s^- refers to the right and left sides of the threshold respectively. The above expression shows that although we have treated individuals on both sides of the threshold, there should be a clear visible discontinuous jump in the likelihood of getting treatment at the threshold. Apart from the pivotal assumption of a visible discontinuous jump at the threshold, another important assumption of the RDD is continuity of the outcome variable at the threshold in the counterfactual situation without the treatment (see, Imbens and Lemieux (2008)). This cannot be tested because we do not observe 'Y' at the threshold $\bar{s}$ in the counterfactual situation. In principle, the basic intuition is that we observe a discontinuous jump at the threshold because the treatment comes into play at that point. This becomes even more convincing if 'Y' does not show any discontinuous jumps at places other than at $\bar{s}$. This assumption implies that if there is a jump in the outcome after treatment; it is caused by the treatment alone and nothing else. In this given example, if there is a change in the views of respondents towards immigration after the retirement then it is due to exit from the labour market alone and nothing else.

For estimating effect of the treatment, we use following equation

$$\tau = E[Y_i \mid S_i{=}s^+] - E\,[Y_i \mid S_i{=}s^-] \;/\; E[D_i \mid S_i{=}s^+] - E\,[D_i \mid S_i{=}s^-] \qquad (3.14)$$

The above equation estimates an average causal effect of the treatment by calculating the ratio of the jump in the outcome (Y_i) to the jump in the probability of getting treatment (D_i) at the threshold $\bar{s}$ (age 65). Here, τ can be interpreted as the causal effect on compliers (see, section 3.3 for explanation on compliers and LATE interpretation).[15] Equation (3.14) produces a Wald

[15] Interpretation of the average causal effect in a Fuzzy RDD as a LATE was first introduced by Hahn, Todd and van der Klaauw (2001).

estimator that is equivalent to an IV estimator. Explained in greater detail below, a Fuzzy RDD is similar to IV estimation; hence, standard IV assumptions apply (see also, section 6.2 in Angrist and Pischke (2009)). Equation (3.15) presents a Fuzzy RDD model that is equivalent to an IV estimate. We run 2SLS on equation (3.15) to get τ

$$y_i = \alpha + \beta_1 * g(s_i) + \tau * D_i + \varepsilon_i \qquad \textit{where, } Z_i = 1 \textit{ when } S_i \geq \bar{s} \qquad (3.15)$$

In the above given equation, S_i is the forcing variable, $\bar{s}$ is the threshold that defines the cut-off point and in this case $\bar{s}$ is age 65 as the state retirement age in the UK is 65. $g(s_i)$ is some function of s_i that assumes a difference in slopes on both sides of the threshold. y_i is the outcome variable (opposed towards further immigration in this case). Z_i is used to instrument D_i in the first stage and assumes that no individual is able to self-select whether to get the treatment or not. When instrumenting D_i, if the age of a native male is greater or equal to 65 then Z_i = 1 and the individual gets treatment and if age is less than 65 then Z_i = 0 and the individual does not get treatment, irrespective of the fact what we actually observe for them.

Now τ is the Local Average Treatment Effect (LATE) of the treated. τ can be interpreted as the change in views of native males towards further immigration – at the threshold point (age 65) – due to retirement (exit from the labour market) alone and nothing else. This estimate of τ is considered as a causal effect of retirement (exit from the labour market) on the views of native males towards further immigration.

3.5 Fixed Effects

Estimates can also become biased when there are time constant un-observables involved in the model for example, differences in intelligence between two individuals remain fixed over time. To control for these time-invariant un-observables we use fixed effects estimation.

Fixed effects estimation is most commonly used in panel data to control for the un-observables that remain fixed over time. For demonstrating the advantage of using fixed effects estimation let us take an example in the context of this thesis. For instance, in chapter 6 we control for area fixed effects and school fixed effects. In principle, there may be some time-invariant characteristics between areas that lead towards more immigration in certain areas for example some immigrants prefer to live in areas with high concentration of their ethnicity. Similarly, schools may possess some time-invariant characteristics that remain unchanged between schools and are source of attractiveness for the immigrants. These time-invariant characteristics for areas and schools need to be controlled for so that our estimates are not biased and misleading. Let us assume that we have a population regression panel model of the form given below

$$Y_{it} = \alpha_i + \lambda_t + \beta X_{it} + \varepsilon_{it} \qquad (3.16)$$

Where Y_{it} represents the outcome Y for an individual "i" in year "t". The unobserved individual-fixed-effect is represented by α_i. Whereas, λ_t controls for year-fixed-effects. β represents the coefficients associated with the observables and ε_{it} is the error term.

There are following three ways to control for the time-invariant un-observables.

1- Least Square Dummy Variables (LSDV)
2- Within Estimator (also known as "analysis of covariance" / "deviations-from-means" / "absorbing")
3- First Differencing

In this thesis, we use the "within estimator" to control for the individual-fixed-effects. Fixed effects using a within estimator are estimated using the equations below. In the first step, individual averages are calculated across time for all the individuals in the panel to get the between estimator of the form given below.

$$\overline{Y}_i = \alpha_i + \overline{\lambda} + \beta \overline{X}_i + \overline{\varepsilon}_i \qquad (3.17)$$

Then these averages are subtracted from the original population regression panel model (3.16) that gives us this

$$Y_{it} - \overline{Y}_i = \lambda_t - \overline{\lambda} + \beta(X_{it} - \overline{X}_i) + (\varepsilon_{it} - \overline{\varepsilon}_i) \quad (3.18)$$

The above equation shows that deviations from means absorb the unobserved individual-fixed effects (a_i). This method is recommended when the sample size is large and time duration is small. Whereas, when the time duration is large and sample size is small an alternative way for estimating fixed effects known as "differencing" is recommended to use. If the data has only two time periods (as in chapter 6) then differencing is algebraically similar to within estimator. Within estimator is more efficient than differencing when the error term (ε_{it}) is homoscedastic and serially uncorrelated. Within estimator also gives smaller standard errors as compared to LSDV.

Chapter 4. Are Immigrants in Favour of Immigration?

Using the UK Citizenship Survey for the years 2007 – 2010, this chapter investigates how immigrants view immigration and how these views compare to natives. Immigrants who have been in the UK longer are similar to natives in being opposed to further immigration, while recent immigrants are more in favour of further immigration. Labour market concerns do not play a large role for natives nor does it play for either group of immigrants. However, financial and economic shocks are associated with stronger anti-immigration responses, even when holding the level of the respective variable constant.

4.1 Introduction

Most of the literature considering the support for, or opposition to, immigration has focused on natives, while the views of immigrants already in the country have gained lesser attention. Much of the previous economics literature, that this thesis draws upon, has referred to “attitudes” rather than views. In wider social sciences, “attitudes” are often taken to represent a deeper psychological consideration that cannot be identified from the questions normally used in the research in economics on attitudes. For purpose of this thesis the terms “attitudes/views” are used interchangeably assuming that even if they are not identical they are highly correlated.

According to the UK Citizenship Survey (2007 – 2010) around 71% of the respondents are opposed to further immigration. There are marked differences between natives and immigrants: 83% of all natives and 48.48% of all immigrants oppose further immigration. However immigrants are not homogeneous and we consider two groups of immigrants – those who have been in the country for 5 years or more (earlier immigrants) and those who have been in the country for less than 5 years (recent immigrants). For the former group 53% of respondents are opposed to further immigration, and for the latter group only 33% are opposed, demonstrating clear heterogeneity. In this chapter, we investigate these differences. We find that they are not simply the result of different socio-economic characteristics of the three groups (natives, earlier immigrants and recent immigrants), even though conditioning on them narrows the gap to some extent. Labour market concerns do not play a large role for either group of immigrants (or natives). However, lower income, and financial and economic shocks, are associated with stronger anti-immigration responses. Immigrants who have been in the UK for five years or more are similar to natives in being opposed to further immigration, while recent immigrants are more in favour of further immigration.

The literature investigating the views of natives towards further immigration is growing rapidly. Among others, some of the recent research papers on this topic using data from the European Social Survey include, Bridges and Mateut (2014), Malchow-Moller et al. (2009), Malchow-Moller et al. (2008), Markaki and Longhi (2013), Ortega and Polavieja (2012), and O'Connell (2011).[16] Most of the literature on natives' views finds evidence for a strong positive relation between education and support for (further) immigration.[17] Another common finding that emerges from this literature is that labour market concerns, or labour market outcomes, do not appear to be strongly associated with anti-immigration views. Furthermore, a range of studies find that welfare concerns or non-economic concerns, such as a loss of identity are more important than the labour market concerns.[18] For a comprehensive review of literature on views of natives towards further immigration, see, Hainmueller and Hopkins (2014a).

In contrast, the literature investigating attitudes of immigrants towards immigration and determinants of immigrants' attitudes is very little. Most of the research about attitudes of immigrants towards immigrants exist for the US (see, for example, Binder, Polinard and Wrinkle, 1997; Hood, Morris, and Shirkey, 1997; Miller, Polinard, and Wrinkle, 1984; Polindar, Wrinkle, and de la Garza, 1984; Sanchez and Masouka, 2010). A recent addition on this topic

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[16] For a critical review of immigration related theories and immigration related literature that used multinational survey data sets, see, Ceobanu and Escandell (2010).

[17] Card et al. (2005), Constant and Zimmermann (2013), Dustmann and Preston (2004), and Gang, Rivera-Batiz and Yun (2013) for Europe, Dustmann and Preston (2001) for England, Vervoort (2012) for Netherlands, Bauer et al. (2000), for OECD countries and Citrin et al. (1997), Espenshade and Hempstead (1996), Hainmueller and Hopkins (2014b), and Scheve and Slaughter (2001) for USA.

[18] Card et al. (2012), Hainmueller and Hiscox (2007) and Rustenbach (2010), for Europe, Dustmann and Preston (2007), for England, Fetzer (2011) for U.S. and Europe, Bakker and Dekker (2012) for Amsterdam, Facchini, Mayda, and Mendola (2013) for South Africa, Stanley et al. (2012) for Australia, Nielsen et al. (2012) for a small Italian town, and Mayda (2006) for developed and developing countries emphasize the importance of social interaction, social capital, sense of society, interpersonal trust and compositional concerns.

is by Just and Anderson, (2015) for 18 European countries. They use data from 5 rounds of the European Social Survey conducted 2002 – 2011 for 18 European countries. They explore two opposing channels of immigrants' attitudes towards immigration: a) shared experiences, unity and ties with other immigrants and b) integration into the host country. Where former channel leads to supporting attitudes and latter channel generates opposing attitudes towards further immigration.

There are three main reasons why further immigration may be opposed. Firstly, future immigration may have a detrimental effect on the labour market prospects of natives and immigrants who are already in the host country. New immigrants may be seen as a potential competition for jobs in the host labour market (see for example, Malchow-Moller et al. (2008)).[19] On this basis it may be expected that new immigrants are closer substitutes for recent immigrants, or earlier immigrants, than they are for natives. This may suggest that immigrants may be more opposed to immigration than natives. Recent research (see, for example, Ottaviano and Peri (2012) for the US, Dustmann et al. (2013) and Manacorda et al. (2012) for the UK) suggest that earlier and latter immigrants are substitutes in the labour market and as such are likely to compete for the same jobs.[20] Secondly, all three groups (natives, earlier and recent immigrants) may be opposed to further immigration if immigration places a strain on public services, such as education (see, for example, Betts and Fairlie, 2003; Geay et al., 2013; Ohinata and van Ours, 2013; or Schneeweis, 2013), public safety (for example, Bell et al., 2013), health care or welfare. Thirdly, there may be opposition to immigration because of the fear that it may be seen as a threat to the culture of the host nation. Natives and earlier immigrants may view immigration as an erosion of social cohesion (Hickman, Crowley and Mai 2008).

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[19] Although this may be a fallacy of individuals' perceptions of the fixed number of available jobs in the host labour market, whereas, new jobs are created as a natural reaction to the expansion and growth of businesses and economy on the influx of new immigrants.

[20] See the special issue of the Journal of the European Economic Association (Card, Dustmann and Preston, 2012; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012; Borjas, Grogger and Hanson, 2012; Card, 2012; Dustmann and Preston, 2012) for a comprehensive discussion of the current state of the literature.

On the other hand, natives' pro-immigration views could be because they see further immigration as beneficial for their businesses, as it can result in wage drops in job sectors in which immigrant workers are concentrated (see, for example, Ottaviano and Peri (2012) for the US, Dustmann et al. (2013) and Manacorda et al. (2012) for the UK). Natives may also favour immigration as they consider immigration is beneficial for the host country's economy (see, for example, Hainmueller and Hiscox (2007)).

Immigrants may also favour further immigration as it enables them to form links with people who share the same culture and heritage. They may also want to bring their families to the host country. Such desires stem from the want for familiarity and social cohesion – although this may lead to tensions with natives who view this as an erosion of social cohesion (see, Just and Anderson, (2015)).

The opposition to, or support for, further immigration will vary between and within the three groups identified (natives, earlier immigrants and recent immigrants). Earlier and recent immigrants may hold different views on further immigration because of a stronger assimilation of earlier immigrants into British culture. Manning and Roy (2010) provide some evidence on this assimilation process. They find that immigrants – with the exception of Irish and Italians – consider themselves more British the longer they stay in the UK and that even immigrants from a culture that is very different from the British, integrate successfully. Given this assimilation, it appears entirely possible that immigrants also adopt the natives' resistance to further immigration.

The remainder of this chapter is organised as follows. Section 4.2 describes the dataset and methodology used in this chapter, section 4.3 presents results and section 4.4 concludes.

4.2 Data and Estimation

This chapter uses the three waves (2007 – 2010) of the UK Citizenship Survey.[21] The survey is conducted in England and Wales, covers people aged

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[21] The survey has been collected since 2001. Initially it was a biennial survey conducted by the Home Office, in 2006 it fell under the auspices of the Communities and Local Government department now the Department for Communities and Local Government. From 2007 onwards the survey has been conducted annually, with data collection taking place each quarter. The publicly available data for this period combines four quarters, giving surveys for 2007-08, 2008-09, 2009-10, and 2010-11.

16 and above and consists of a core sample and a minority ethnic boost sample. Each wave of the Citizenship Survey has a sample size of around 15,000 people and consists of a core sample of around 10,000 individuals with a minority ethnic boost sample of around 5,000 further individuals.

For this chapter and chapter 5 respondents are categorized on the basis of country of birth of respondent and country of birth of their mother and father in order to differentiate between immigrants and natives. This classification gives us the six broad categories listed below. These classifications are subdivided on the basis of ethnicity and self-assessed nationality and are shown in table 4.1.

1. Respondents born in the UK with both parents born in the UK.
2. Respondents born in the UK with one parent born abroad.
3. Respondents born in the UK with both parents born abroad.
4. Respondents born abroad with both parents born in the UK.
5. Respondents born abroad with one of the parents born abroad.
6. Respondents born abroad with both parents born abroad.

Table 4.1: Respondent categorisation based on ethnicity and nationality (2007 – 2010)

Sr. No.	Categorisation (2007 – 2010)			Total 45152
1	Respondent born in the UK with both parents born in the UK			23600
	1.1	White (based on ethnicity)	22560	23592
	1.2	Non-White (based on ethnicity)	1032	
	1.3	British + Other (based on national identity)	20	
	1.4	Only British (based on national identity)	21691	23600
	1.5	Only Other (based on national identity)	1889	
2	Respondent born in the UK with one parent born abroad			1959
	2.1	White (based on ethnicity)	866	1959
	2.2	Non-White (based on ethnicity)	1093	
	2.3	British + Other (based on national identity)	32	
	2.4	Only British (based on national identity)	1754	1959
	2.5	Only Other (based on national identity)	173	
3	Respondent born in the UK with both parents born abroad			4287
	3.1	White (based on ethnicity)	298	4286
	3.2	Non-White (based on ethnicity)	3988	
	3.3	British + Other (based on national identity)	138	
	3.4	Only British (based on national identity)	3658	4287
	3.5	Only Other (based on national identity)	491	
4	Respondent born abroad and both parents born in the UK			258
	4.1	White (based on ethnicity)	244	258
	4.2	Non-White (based on ethnicity)	14	
	4.3	British + Other (based on national identity)	3	
	4.4	Only British (based on national identity)	220	258
	4.5	Only Other (based on national identity)	35	
5	Respondent born abroad with one of the parents born abroad			275
	5.1	White (based on ethnicity)	156	275
	5.2	Non-White (based on ethnicity)	119	
	5.3	British + Other (based on national identity)	14	
	5.4	Only British (based on national identity)	204	275
	5.5	Only Other (based on national identity)	57	
6	Respondent born abroad with both parents born abroad			14469
	6.1	White (based on ethnicity)	1192	14465
	6.2	Non-White (based on ethnicity)	13273	
	6.3	British + Other (based on national identity)	511	
	6.4	Only British (based on national identity)	7823	14469
	6.5	Only Other (based on national identity)	6135	

Note: There are 304 missing values in country of birth identifiers due to unknown country of birth of the respondent, his mother or his father. 13 missing in ethnicity.

We focus on groups 1 and 6 only. We refer to the first group as “natives” and group 6 as “immigrants”. While this classification may be imperfect there is no further information available for more precise classifications and we believe that they provide mechanism for distinguishing between natives and immigrants. These two categories make up 85% of the total respondents, with 55% falling into the native and 30% falling into the immigrant category. The remaining 15% of respondents fall into one of the other four groups making it difficult to assign individuals to “natives” or “immigrants”. For example, both group 2 and 5 could contain children of British servicemen who married while on duty abroad with the only difference being the place of birth of the child. Given these ambiguities, it appears unreasonable to treat one of these as a native and the other as an immigrant and we consequently omit all respondents who fall into those four categories.

Immigrants are further divided into two categories: earlier immigrants and recent immigrants. Earlier immigrants (forming 23% of the original sample), are all those immigrants who came to UK more than 5 years ago and recent immigrants (7%) are those who arrived within the last five years. The definition of 5 years is used to distinguish between earlier and recent immigrants due to data constraints, as information about when immigrants arrived is not available for all the waves for more than 5 years. There are 9,714 earlier immigrants and 2,687 recent immigrants in our sample.

The outcome variable is the answer to the question, “Do you think the number of immigrants coming to Britain nowadays should be increased, reduced or should it remain the same?” If the respondent says increased or reduced then the interviewer asks if the number should be increased or reduced by a little or a lot. For most of the analysis, “increased a lot”, “increased a little” and “remain the same” are grouped together, as all indicate that the respondent does not want immigration to be cut. People replying “increased a lot” and “increased a little” are clearly in favour of immigration, while those replying “remain the same” are also not against it. We also group the choices “reduced a lot” and “reduced a little” as both indicate a wish to see immigration reduced. Respondents selecting “cannot choose” are excluded from the analysis. This generates an indicator variable of whether an individual is opposed to further immigration (or not). We assess the robustness of these choices in two ways: We run ordered probit models on the original (5 category) outcome variable and we also run the same models without individuals who replied “remain the same”.[22] Results do not change fundamentally. Our estimating equation for all the models is

$$Y = \alpha + \beta' X + \varepsilon \qquad (4.1)$$

Where Y is the outcome variable, α is the intercept, β is the coefficient vector, X contains all the independent variables and ε represents the error term. Control variables used are: survey year, gender, age, ethnicity, religion, practicing religion, and region. Dummy variables are generated for all of these variables. Control variables for all the models are same unless mentioned. The omitted category for the variable survey year is “wave 2007 – 2008”, for gender it is “male”, and “London” for the regions.

Ethnicity variable has seven dummies namely, “White”, “Black”, “Subcontinent”, “Chinese”, “other Asian”, “mixed race” and “other ethnicities”. Where “Black” ethnicity is comprised of “Black Caribbean”, “Black African” and “other black ethnicities”. Subcontinent includes “Indian”, “Pakistani” and “Bangladeshi” ethnicities. For ethnicity variable “white” is the omitted category in the analysis. Eight dummies are created for the religion variable and are labelled as, “Budh”, “Hindu”, “Jewish”, “Muslim”, “Christian”, “Sikh”, “no religion” and “other religion”. “Christian” is the omitted dummy for religion. For the variable whether a person is “practicing religion or not”, two dummies are creating and “not practicing religion” is considered as the reference category.

These control variables have been included because most of the literature on attitudes uses these variables in their regressions (see for example, Dustmann and Preston (2007)). Although some variables that may be found in other literature on attitudes could not be included because of the

[22] In appendix B, Table B 1 presents the descriptive statistics, Table B 2 presents the conditional and unconditional comparison of the regressions, Table B 3 presents the coefficients of natives, earlier and recent immigrants and Table B 4 presents the coefficients of models for 2009 – 2010, after dropping remain the same category.

data restrictions (for example data on formal acquisition of citizenship of immigrants is not available).

Our key variable of interest is an individual's migration status. Being native serves as the reference group enabling us to explore differences between natives, earlier immigrants and recent immigrants. We are also interested in a range of variables related to economic status and economic shocks. Employment status is important for investigating the role that the labour market plays in influencing people's views towards further immigration. "Employed" is the reference group for employment status dummies. Income of the respondent is used to proxy for social status. The reference category for the income variable is "£10,000 – £15,000".

Due to data restrictions we unfortunately face a trade-off in relation to education variables as only respondents up to the age of 65 are asked about their education. Our main estimates contain all respondents at the cost of omitting information on education. However, we also estimated models with and without education on a sample restricted to individuals up to 65 and found that these changes made very little difference to native/immigrant differences in their views towards further immigration. When we included education and estimated the model on the reduced (under age 65) sample the coefficient of our key variable, migrant status, remained largely unchanged; however, we found that higher education is associated with favourable views towards immigration for natives, earlier and recent immigrants. OLS results of these estimates are presented in appendix A.

Finally, we also use the 2009/10 data that contains additional information on economic shocks, such as job loss or having to cut back on certain expenditures in last twelve months, details are provided latter in this section. These are included in separate models to consider how the onset of financial difficulties affects support for immigration.

Table 4.2 provides descriptive statistics for our sample.[23]

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[23] Table A 1, Table A 2, and Table A 3 for natives, earlier immigrants and recent immigrants in appendix A present descriptive statistics of the samples used for robustness checks by

Table 4.2: Descriptive statistics (2007 – 2010)

Variables	Natives		Earlier Immigrants		Recent Immigrants	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reduce Migration	0.823	0.382	0.530	0.499	0.334	0.472
Increase Migration	0.177	0.382	0.470	0.499	0.666	0.472
Out of Labour Force	0.313	0.464	0.323	0.468	0.218	0.413
Self Employed	0.069	0.254	0.082	0.274	0.039	0.193
Unemployed	0.150	0.357	0.162	0.368	0.181	0.385
Employed	0.468	0.499	0.434	0.496	0.563	0.496
Male	0.449	0.497	0.484	0.500	0.538	0.499
Female	0.551	0.497	0.516	0.500	0.462	0.499
Age	50.262	18.589	46.622	15.422	31.319	9.449
Income below 5K	0.189	0.392	0.257	0.437	0.344	0.475
Income 5K to 10K	0.209	0.407	0.198	0.399	0.165	0.371
Income 10K to 15K	0.156	0.363	0.158	0.365	0.163	0.369
Income 15K to 20K	0.117	0.321	0.107	0.309	0.096	0.294
Income 20K to 30K	0.158	0.365	0.149	0.356	0.125	0.331
Income 30K to 50K	0.125	0.330	0.098	0.297	0.071	0.256
Income above 50K	0.045	0.208	0.033	0.180	0.036	0.186
White	0.956	0.204	0.078	0.268	0.112	0.315
Subcontinent	0.016	0.126	0.456	0.498	0.388	0.488
Other Asian	0.001	0.027	0.057	0.232	0.078	0.268
Black	0.010	0.100	0.265	0.441	0.202	0.402
Mixed Race	0.010	0.101	0.038	0.190	0.035	0.184
Chinese	0.000	0.007	0.025	0.157	0.049	0.215
Other Ethnicities	0.006	0.079	0.080	0.272	0.136	0.343
Christian	0.776	0.417	0.341	0.474	0.368	0.482
Budh	0.002	0.045	0.016	0.127	0.037	0.189
Hindu	0.002	0.039	0.135	0.341	0.152	0.359

running all the regressions after excluding respondents over 65 and including the qualification variable.

Jewish	0.003	0.052	0.003	0.051	0.001	0.035
Muslim	0.017	0.129	0.385	0.487	0.330	0.470
Sikh	0.001	0.037	0.053	0.225	0.027	0.162
Other Religion	0.019	0.138	0.026	0.159	0.021	0.144
No Religion	0.180	0.384	0.040	0.197	0.063	0.243
Practicing Religion	0.271	0.444	0.739	0.439	0.715	0.451
Not Practicing Religion	0.729	0.444	0.261	0.439	0.285	0.451
Observations	20125		8399		2448	
Variables available only for 2009 – 2010						
Lost Job	0.059	0.236	0.055	0.228	0.088	0.284
Drop in Income	0.259	0.438	0.240	0.427	0.187	0.390
Cutbacks in Luxuries	0.390	0.488	0.307	0.461	0.213	0.410
Cutbacks in Necessities	0.332	0.471	0.334	0.472	0.228	0.420
Non listed	0.420	0.494	0.457	0.498	0.565	0.496
Observations	7068		3119		817	

Table 4.2 shows that immigrants are on average younger than natives, and recent immigrants are, on average, the youngest group. Recent immigrants are more likely to be male, employed (and unemployed) and less likely to be out of the labour force than natives. Immigrants have, on average, lower incomes than natives, with recent immigrants having over a third of respondents in the lowest income group. Natives are mostly "White" by ethnicity, "Subcontinent" is the most dominant ethnicity in earlier and recent immigrants. Natives are mostly "Christian" by faith, whereas earlier immigrants are mostly "Muslim" and recent immigrants follow "Christian" faith mostly.

We begin by looking first at raw differences between natives, earlier and recent immigrants. Subsequently, we include the other right hand side variables described above to check to what extent the differences between natives and immigrants can be explained by different socio-economic characteristics. We estimate these regressions by OLS, probit and ordered probit. However, results do not change much. We also estimated all models separately by gender and found no difference in the results.

We then split the sample into natives, earlier and recent immigrants to investigate to what extent the determinants of opposed views towards immigration differs between the three groups. Finally, we focus on the role of economic and financial worries using the 2009/10 data. Four types of economic worries are considered, specifically whether the respondent has lost his/her job, experienced a drop in income, had to cutback spending on necessities such as food or shelter, or had to cutback spending on non-necessities, such as entertainment expenses or charity donations in last twelve months. The reference category for this variable is “not reporting any worry”. These four additional models are estimated for the pooled sample and for natives, earlier and recent immigrants separately.

4.3 Results

Table 4.3 compares the unconditional and regression-adjusted conditional differences in immigration views between natives, earlier and recent immigrants.[24] The conditional models control for employment status, income level, age dummies, ethnicity, gender, religion, wave year and Government Office Region of residence. All models suggest that both immigrant groups are less opposed to further immigration than natives. Furthermore, earlier immigrants are always between natives and recent immigrants. Quantitatively, the unconditional models suggest that earlier immigrants are between 26 and 29 percentage points less likely to oppose immigration than natives, while the corresponding numbers for recent immigrants are between 41 and 49 percentage points. Both coefficients are economically large and highly significant. We also obtain the same pattern of results when using an ordered probit.

In the conditional models, the differences between natives and immigrants are reduced considerably. Earlier immigrants are now between

[24] Table A 4 and Table A 5 in appendix A present unconditional and conditional OLS estimates of all the regressions after excluding respondents over 65 and including the qualification variable. Whereas, Table A 9 and Table A 10 in appendix A present unconditional and conditional OLS estimates of all the regressions after excluding respondents over 65 and dropping the qualification variable.

12 and 13 percentage points less likely to oppose further immigration than natives, while recent immigrants are between 24 and 30 percentage points less likely, as presented in column (5) and (6) of table 4.3. However, the differences between the three groups remain large and statistically significant. From these results, it is clear that support for further immigration differs widely between the three groups and that earlier immigrants hold views that, on average, fall between the views of natives and recent immigrants.

Table 4.3: Comparison of unconditional and conditional models

Reduce Immigration	Unconditional Models				Conditional Models			
	OLS	Probit AME	Probit Coefficients	Ordered Probit Coefficients	OLS	Probit AME	Probit Coefficients	Ordered Probit Coefficients
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recent	-.488***	-.414***	-1.353***	-1.28***	-.299***	-.243***	-.836***	-.761***
Immigrants	(.010)	(.008)	(.028)	(.022)	(.015)	(.012)	(.041)	(.033)
Earlier	-.292***	-.260***	-.850***	-.816***	-.131***	-.120***	-.412***	-.392***
Immigrants	(.006)	(.005)	(0.017)	(.015)	(.012)	(.010)	(.035)	(.029)
Constant	.823***		.925***		.378***		.663	
	(.003)		(.010)		(.015)		(.682)	
Sample Size	30972	30972	30972	30972	30972	30969	30969	30972
R^2/ Pseudo R^2	.135		.108	.064	.181		.150	.090

Conditional models control for employment status, wave year, age dummies, ethnicity, religion, practising religion or not, income, and region. Omitted category for migrant status dummy is “natives”.
Significance levels: *10%, **5%, ***1%
Robust standard errors are given in parentheses

The separate models for natives, earlier and recent immigrants (see, table 4.4) suggest that, by and large and with the exception of earlier immigrants who are out of the labour force, none of the labour market dummies are significant.[25] It is interesting to note that the significant coefficient for "out of the labour force" suggests that these respondents are, if anything, more in favour of further immigration than employed respondents. Based on these results, it appears that labour market status is largely unrelated to anti-immigration views for any of the groups. These findings are in line with the findings of Dustmann and Preston (2007) and Card et al. (2012) who also find that labour market concerns are not important in determining natives' views towards immigration.

Among the two immigrant groups, women appear to be between 3 and 4 percentage points more opposed to further immigration than men, while there is no evidence for gender differences among natives.

Income dummies are used to analyze the impact of economic status on opposition to further immigration. It is interesting to note that for natives and earlier immigrants a clear gradient emerges: Natives and immigrants with higher income are more likely to be in support of further immigration. For recent immigrants the pattern appears to be less clear. Relative to individuals earning between £10k and £15k, individuals with lower incomes are between 8 and 1 percentage points less likely to oppose immigration, while respondent with higher income are also less opposed towards further immigration, resulting in an inverted U-shaped relationship between income and opposition to immigration. A potential explanation for this somewhat unexpected result at low incomes could be the role of non-monetary motives such as family reunification or the wish to see more of their compatriots immigrating, which should be stronger for recent immigrants than for earlier immigrants or natives.

Pooled model shows that all ethnicities except "Subcontinent" are in favour of immigration by between 5.1 – 15.8 percentage points with high

[25] Table A 6, Table A 7, and Table A 8 in appendix A present separate OLS estimates of natives, earlier and recent immigrants for the regressions after excluding respondents over 65 and including the qualification variable. Whereas, Table A 11, Table A 12 and Table A 13 in appendix A present separate OLS estimates natives, earlier and recent immigrant for the regressions after excluding respondents over 65 and dropping the qualification variable.

significance as compared to “White” ethnicity. Whereas, when the regressions are run on individual samples for natives, earlier and recent immigrants, favour towards further immigration is only shown by natives with “Black” and “mixed race” ethnicity by 27.3 and 7.3 percentage points respectively. In earlier immigrants, this favour of “Black” and “mixed race” ethnicity drop down to 9.8 and 6.1 percentage points. It is to be noted that “Black” ethnicity remains significantly in favour of further immigration with coefficient reaching 11.2 percentage points for recent immigrants. Religion dummies mostly show that respondents with any faith are generally in favour of further immigration as compared to the respondents with “Christian” faith in their sample group.

Table 4.4: Coefficients of main controls for each respondent category (2007 – 2010)

Reduce Immigration	OLS			
	Pooled	Natives	Earlier Immigrants	Recent Immigrants
Recent Immigrants	-0.299*** (0.015)			
Earlier Immigrants	-0.131*** (0.012)			
Female	0.007 (0.005)	-0.007 (0.006)	0.030*** (0.012)	0.046** (0.021)
Out of Labour Force	-0.021*** (0.008)	-0.003 (0.009)	-0.044*** (0.017)	-0.024 (0.030)
Self Employed	0.001 (0.010)	0.010 (0.011)	-0.013 (0.021)	-0.006 (0.050)
Unemployed	0.003 (0.008)	0.007 (0.009)	-0.008 (0.017)	0.016 (0.030)
Income below 5K	-0.010 (0.008)	-0.006 (0.009)	0.004 (0.018)	-0.100*** (0.032)
Income 5K to 10K	0.008 (0.008)	0.007 (0.008)	0.026 (0.018)	-0.088** (0.034)
Income 15K to 20K	-0.003 (0.009)	-0.011 (0.010)	0.015 (0.021)	-0.048 (0.041)
Income 20K to 30K	-0.038*** (0.009)	-0.046*** (0.010)	-0.022 (0.019)	-0.088** (0.037)
Income 30K to 50K	-0.086*** (0.010)	-0.092*** (0.011)	-0.066*** (0.022)	-0.150*** (0.044)
Income above 50K	-0.128*** (0.014)	-0.142*** (0.017)	-0.079** (0.034)	-0.195*** (0.055)
Subcontinent	-0.018 (0.017)	0.045 (0.051)	0.025 (0.025)	0.039 (0.043)
Other Asian	-0.073*** (0.023)	0.139 (0.127)	-0.022 (0.031)	-0.040 (0.049)
Black	-0.158***	-0.273***	-0.098***	-0.112***

	(0.015)	(0.035)	(0.022)	(0.039)
Mixed Race	-0.087***	-0.073**	-0.061*	-0.009
	(0.021)	(0.033)	(0.033)	(0.060)
Chinese	-0.094***	0.606***	0.014	-0.071
	(0.029)	(0.053)	(0.040)	(0.057)
Other Ethnicities	-0.051***	-0.015	-0.013	0.021
	(0.018)	(0.038)	(0.028)	(0.043)
Budh	-0.092***	-0.053	-0.154***	-0.002
	(0.030)	(0.067)	(0.043)	(0.057)
Hindu	-0.011	-0.258***	0.014	-0.054
	(0.018)	(0.097)	(0.022)	(0.038)
Jewish	-0.156***	-0.138**	-0.210*	0.029
	(0.054)	(0.064)	(0.107)	(0.275)
Muslim	-0.109***	-0.314***	-0.075***	-0.012
	(0.014)	(0.048)	(0.018)	(0.030)
Sikh	0.012	-0.188*	0.010	0.104
	(0.025)	(0.100)	(0.029)	(0.067)
Other Religion	0.000	-0.016	0.013	0.086
	(0.017)	(0.020)	(0.034)	(0.073)
No Religion	-0.075***	-0.081***	-0.141***	-0.032
	(0.008)	(0.008)	(0.031)	(0.049)
Practicing Religion	-0.055***	-0.050***	-0.058***	-0.023
	(0.006)	(0.006)	(0.013)	(0.025)
Constant	0.378***	1.120***	-0.088***	0.086
	(0.015)	(0.016)	(0.033)	(0.068)
Sample Size	30972	20125	8399	2448
R2	0.181	0.065	0.075	0.059

All models control for: wave year, age dummies, and region. Omitted category for migrant status, employment status and income dummies is natives, employed and income10K to 15K respectively.
Significance levels: *10%, **5%, ***1%
Robust standard errors are given in parentheses.

Finally, we look at the effect of economic shocks experienced in the previous year. Our results, shown below in table 4.5, suggest that the experience of job loss (even holding constant current labour force status), a drop in income (again holding constant current income) or having to cut back on expenses on both necessities and luxuries are associated with a stronger opposition to further immigration (see, Gang, Rivera-Batiz and Yun (2013) for similar findings).

For natives, job loss is associated with a 4 percentage points increase in opposition to further immigration, while drops in income and cutbacks in necessities are associated with a 2 percentage points fall. For earlier immigrants, drops in income and cutbacks in luxuries appear to matter most, while job loss and cutbacks in necessities appear to be less important. Finally, the point estimates for recent immigrants suggest that they react more strongly to job losses, drops in income and in particular cutbacks in necessities than the other groups. These results suggest that changes in economic status such as drops in income or job loss matter for people's views on immigration, even when holding the levels of these variables constant.

On the whole, our results suggest that earlier immigrants appear to hold views closer to those of natives than to recent immigrants.[26]

Table 4.5: Wave 2009 – 2010 models for each respondent category controlled for financial worry dummies

Reduce Immigration	OLS			
	Pooled	Natives	Earlier Immigrants	Recent Immigrants
Recent Immigrants	-0.292*** (0.023)			
Earlier Immigrants	-0.111*** (0.019)			
Lost Job	0.038** (0.017)	0.045** (0.019)	0.021 (0.041)	0.052 (0.066)
Drop in Income	0.032*** (0.010)	0.021** (0.011)	0.044** (0.022)	0.074 (0.048)
Cutbacks in Luxuries	0.027*** (0.010)	0.002 (0.011)	0.070*** (0.022)	0.017 (0.046)
Cutbacks in Necessities	0.028*** (0.010)	0.023** (0.011)	0.025 (0.021)	0.100** (0.045)
Out of Labour Force	-0.024* (0.013)	-0.010 (0.015)	-0.013 (0.026)	-0.113** (0.045)
Self Employed	-0.009 (0.017)	0.001 (0.019)	-0.013 (0.036)	-0.099 (0.085)
Unemployed	-0.005 (0.013)	0.004 (0.015)	-0.022 (0.029)	0.046 (0.050)
Female	0.000 (0.009)	-0.003 (0.010)	-0.002 (0.019)	0.036 (0.036)
Income below 5K	-0.001 (0.013)	-0.010 (0.015)	0.038 (0.028)	-0.111** (0.052)
Income 5K to 10K	0.016 (0.013)	-0.005 (0.014)	0.067** (0.029)	-0.080 (0.058)
Income 15K to 20K	0.005 (0.015)	-0.022 (0.017)	0.075** (0.035)	-0.059 (0.078)
Income 20K to 30K	-0.015 (0.014)	-0.028* (0.016)	0.025 (0.032)	-0.133** (0.066)

[26] As a robustness check, all the respondents who responded with "remain the same" to the outcome question are dropped from the data and all the models are rerun. Results from these regressions remain fairly similar. If anything, the similarities between earlier immigrants and natives increased (see, appendix B).

Income 30K to 50K	-0.069***	-0.087***	-0.032	-0.070
	(0.017)	(0.019)	(0.037)	(0.076)
Income above 50K	-0.088***	-0.112***	-0.026	-0.155
	(0.025)	(0.028)	(0.057)	(0.107)
Subcontinent	-0.024	0.017	0.029	0.161**
	(0.026)	(0.060)	(0.040)	(0.078)
Other Asian	-0.108***	0.122	-0.071	0.061
	(0.036)	(0.139)	(0.050)	(0.087)
Black	-0.189***	-0.265***	-0.123***	-0.050
	(0.023)	(0.051)	(0.038)	(0.075)
Mixed Race	-0.052	-0.013	-0.021	0.041
	(0.036)	(0.051)	(0.061)	(0.134)
Chinese	-0.128***		0.049	-0.112
	(0.048)		(0.069)	(0.087)
Other Ethnicities	-0.099***	-0.102	-0.016	0.031
	(0.031)	(0.089)	(0.047)	(0.077)
Budh	-0.039	0.023	-0.056	0.058
	(0.054)	(0.102)	(0.085)	(0.094)
Hindu	0.015	-0.190*	0.026	0.061
	(0.031)	(0.113)	(0.038)	(0.071)
Jewish	-0.206**	-0.124	-0.340*	-0.356***
	(0.096)	(0.112)	(0.187)	(0.107)
Muslim	-0.109***	-0.257***	-0.077***	0.017
	(0.021)	(0.059)	(0.027)	(0.052)
Sikh	-0.015	-0.138	-0.017	0.039
	(0.042)	(0.115)	(0.050)	(0.122)
Other Religion	0.010	-0.018	0.030	0.220
	(0.033)	(0.039)	(0.064)	(0.149)
No Religion	-0.054***	-0.058***	-0.179***	0.104
	(0.012)	(0.013)	(0.054)	(0.090)
Practicing Religion	-0.051***	-0.047***	-0.038	-0.052
	(0.010)	(0.011)	(0.023)	(0.044)
Constant	0.830***	0.951***	0.984***	-0.152
	(0.135)	(0.037)	(0.055)	(0.106)
Sample Size	11004	7068	3119	817
R2	0.195	0.089	0.100	0.140

All models control for: wave year, age dummies, and region. Omitted category for financial worry dummies is “not reporting any worry”.
Significance levels: *10%, **5%, ***1%
Robust standard errors are given in parentheses

4.4 Discussion and Conclusion

The novelty of this chapter is that it is a new addition to the sparse literature investigating how immigrants view further immigration, and how these views may vary between natives, earlier and more recent immigrants. Most of the previous literature has focused on the views of natives towards immigration. The main finding of this research is that there is heterogeneity in the attitudes of immigrants towards immigration, with recent immigrants being less opposed to immigration than earlier immigrants. The results for earlier immigrants consistently lie between those of natives and recent immigrants. This may be expected because, if there is any process of assimilation, immigrants should become closer to natives in their views.

There are essentially two explanations why earlier immigrants are more similar to natives than recent ones. The first is that as time passes immigrants integrate into British society. Alternatively, it could be the case that only those immigrants who are similar to natives stay in the country, while other immigrants, with differing views, leave. The first explanation is supported by the findings of Manning and Roy (2010) concerning cultural integration; immigrants appear to become more similar to natives the longer they have been in the country. Manning and Roy (2010) find that immigrants integrate into the British culture very easily.

The second explanation is essentially self-selection but the limited available information in the data, in particular the fact that we do not observe immigrants who have left, does not allow this to be tested. It can also be the case that people who left the UK in fact did not want to leave the UK but they had to leave because of the visa restrictions. This leads to our third explanation that may be recent immigrants want to be naturalized and that is why they are less opposed to further immigration so that the immigration policies do not change and they can obtain the UK citizenship and once they obtain the citizenship their views towards further immigration change.

However, controlling for naturalisation can be one possible solution to further explore the difference in views towards further immigration between two immigrant groups given that the data are available for all those individuals who left the UK and who stayed. Without controlling for naturalisation it is hard to observe the counterfactual that whether an individual left because he wanted to, or he left because he had to due to visa restrictions on immigrants. Just and Anderson, (2015), find some evidence of positive relationship between naturalisation and opposition towards further immigration. However, self-selection issue remains unaddressed in their paper, as they do not have the information on the immigrants who left.

This study does not find any strong consistent evidence that the anti-immigration views of natives, earlier and recent immigrants towards further immigration can be attributed to labour market outcomes. Even if the earlier immigrants and recent immigrants compete in the labour market, as suggested by the findings of Ottaviano and Peri (2012) and Dustmann et al. (2013), there is no strong evidence that the current employment status affects views towards further immigration.

Results on the income of natives and earlier immigrants suggest a clear gradient for respondents with higher income favouring further immigration, whereas there is some evidence for an inverted U-shape for recent immigrants. A potential explanation for this result is that low-income recent immigrants have concerns that family reunification may be made harder by tougher immigration laws, and these worries may overwhelm other concerns.

We further find evidence in all three groups that economic shocks such as job loss or drops in income matter, even when holding employment status and the level of income constant. This finding is in line with the previous literature (see, for example, Gang, Rivera-Batiz and Yun, 2013; and Malchow-Moller et al., 2008). This result suggests that people might be blaming immigrants for adverse shocks, regardless of whether they recover from the respective shock.

Overall, this research suggests (a) that earlier immigrants and natives share more similar views towards further immigration than earlier and recent immigrants, (b) that employment status does not play a large role in explaining anti-immigration views, (c) income matters, even though the exact effects differ at low incomes between recent immigrants and natives and earlier immigrants, and (d) that economic shocks tend to be associated with more anti-immigration views.

Chapter 5. The Role of the Labour Market in Views towards Immigration

This chapter employs a Fuzzy RDD and investigates what happens to the views of native males towards further immigration on exit from the labour market. The main conclusion of this chapter is that attitudes towards immigration largely remain unchanged after exit from the labour market, however, a little evidence of reduced opposition towards immigration is found after exit from the labour market. The OLS results do not show any significant change in views of native males towards further immigration on exit from the labour market. Even after controlling for the potential selection bias and endogeneity bias using a Fuzzy RDD, views of native males generally remain unchanged, with some evidence of reduced opposition towards further immigration after exit from the labour market.

5.1 Introduction

Immigration is often opposed, despite of the fact that there is little evidence in the literature demonstrating a detrimental impact on the natives' earnings, employment prospects or their displacement (flight of natives from immigrant concentrated areas).[27] In this chapter, we explore that how the views of natives change towards further immigration on exit from the labour market when they retire from paid work at state retirement age. Labour market competition theories (see, for example, Borjas, 1999; Scheepers et al., 2002; Scheve and Slaughter 2001; Schneider, 2007) suggest that natives oppose immigration because they compete in the labour market. Although, recent research suggests that natives and immigrants do not compete in the labour market as they have different skill sets that make them imperfect substitutes (see, for example, Dustmann et al., 2013; Manacorda et al., 2012;

[27] Contrary to Borjas (2003) most findings suggest that immigration does not have any considerable adverse effect on local labour markets, see Card (1990), Altonji and Card (1991), Kuhn and Wooton (1991), LaLonde and Topel (1991), Card (2001) for the US, Dustmann et al. (2003), Dustmann et al. (2005) for the UK, Haisken-DeNew and Zimmermann (1994), Pischke and Velling (1997), Haisken-DeNew and Zimmermann (1999) for Germany, Winter-Ebmer and Zweimuller (1996), Winter-Ebmer and Zweimuller (1999) for Austria, Hunt (1992) for France, Carrington and Lima (1996) for Portugal, and Angrist and Kugler (2003) for Western Europe as whole.

Ottaviano and Peri, 2012). Researchers have been trying to investigate the reasons for having views that are opposed to immigration by investigating the determinants of attitudes/views towards further immigration. Scheve and Slaughter (2001) using individual level data of National Election Studies (1992, 1994, and 1996) for USA find that skill level plays an important role in determining attitudes towards immigration. They find that low-skilled individuals are opposed to further immigration, whereas, high skilled individuals have more favourable views.

Facchini, Mayda, and Mendola for South Africa (2013) using individual level data from the three waves of World Values Survey (1996, 2001, and 2007) for South Africa find that labour market concerns do not play a large role in determining anti-immigration attitudes. They find that non-economic factors such as religion and culture are very important in determining attitudes towards immigration. Bauer et al. (2000), for OECD countries, find that natives are more concerned about social issues if the immigrants are refugees, however, if the immigrants are economic migrants then it leads to labour market concerns among natives. Whereas, Citrin et al. (1997) for US find that individuals' economic situation play a small role in determining views towards immigration, concerns about national economy, taxes, and general sentiments towards immigrant groups play a large role in determining attitudes towards further immigration.

See, for example, Card et al. (2005) using European Social Survey find a strong positive relationship between education and attitudes towards immigration. They find that high qualified individuals are more in favour of immigration, this finding is in line with the findings of Dustmann and Preston (2004). Similarly, Constant and Zimmermann (2013), are also of the view that education is positively related to pro-immigration views. Dustmann and Preston (2001) using 5 years of British Social Attitudes Survey (1983, 1984, 1986, 1989, 1990) investigate the attitudes of white respondents in England, and suggest that high density of ethnic minorities in local areas can result in more aggressive views towards immigration. This increased level of opposed views towards immigration due to high density of immigrants can stem from the fact that natives may feel threat to their identity or can breed fear if natives are of the view that immigrants are a reason of increased crime rate. One of the reasons of fear of natives can be explained by lack of social connections with natives. Vervoort (2012) for Netherlands finds that if the neighbourhood is concentrated with minorities then immigrants are less likely to make social connections with native Dutch.

Most of this literature has a common finding that labour market concerns are not strongly associated with opposed views towards immigration with an exception of few finding contrary evidence (in recent literature see, for example, Bridges and Mateut (2014), and Ortega and Polavieja (2012)). However, a range of studies stress that welfare concerns and non-economic concerns play a significant role in shaping views towards immigration.[28] Whereas, Mayda (2006) suggests that although non-economic concerns are more important than the economic concerns but economic concerns still play a role in determining attitudes towards immigration. Similarly, we find in chapter 4, that economic shocks play a large role in determining anti-immigration views. These confirm the findings of Gang, Rivera-Batiz and Yun (2013).

In this chapter, we are interested in estimating the effect of withdrawal from the labour market on attitudes towards immigration. This is hindered by an endogeneity problem as immigration might force people out of the labour market (for example, not obtaining any jobs). This endogeneity problem can lead towards biased estimates of OLS in the direction of increased opposition towards further immigration as respondents out of the labour force are essentially those with opposed views towards immigration. OLS estimation is also expected to suffer from selection bias that can arise because natives' decision to retire early may be a result of their fear of immigrant competition in the labour market.

To put it into the context, in our data, natives with opposing views towards immigration can be exactly those who may self-select to exit from the labour market early by choosing early-retirement due to the fear of immigrant competition in the labour market. This self-selection can result into majority

[28] Card et al. (2012) and Rustenbach (2010), for Europe, Dustmann and Preston (2007), for England, Fetzer (2011) for U.S. and Europe, Bakker and Dekker (2012) for Amsterdam, Stanley et al. (2012) for Australia, Nielsen et al. (2012) for a small Italian town, and Mayda (2006) for developed and developing countries emphasize the importance of social interaction, social capital, sense of society, interpersonal trust and compositional concerns.

of the respondents with opposing views towards immigration ending up in the data. Similarly, people out of the labour force can also be those who left the labour market as an outcome of increased immigration (endogeneity bias) and may have opposed views towards immigration. This self-selection and endogeneity can eventually cause biased OLS results in the direction of greater opposition. To sum up the above discussion, early-retired natives can be most likely natives with stronger anti-immigration views to begin with, and can eventually lead to biased results in favour of opposition to immigration. To get around this self-selection and endogeneity biases we use regression discontinuity design (explained in greater detail in section 3.4 and section 5.3).

To illustrate the idea of the research in this chapter, let us say that labour market status does affect views towards immigration. If this is the case then, in principle, a person's views towards immigration should change effectively on exit from the labour market. The rationale of this change in views on exit from the labour market is that once a person is retired, effectively he or she is out of the labour market and a retired person should care less about immigration after exit from the labour market.

The state retirement age in England and Wales for males and females is 65 and 60 respectively.[29] However, state retirement age in the UK has been phased out. State retirement age is the age at which one can claim state pension after establishing that he/she has retired from the paid work. Now, generally, anyone can carry on working without any age limit with no negative influence on their pension. Earlier, once a person established his retirement he/she could claim state pension past the retirement age, however if he/she worked after retirement they still get state pension but at a reduced rate depending upon the number of hours worked. On the other hand, if a person deferred his/her pension claim after the state retirement age, his/her pension raised at a specified rate according to a set formula. In our sample period, we expect to see respondents still working past retirement age. Respondents working past retirement age are most likely those who gain more than the loss from their pension due to working past retirement age. For greater details on

[29] It is true for the data used in this chapter.

the history of pensions and retirement in the UK read Bozio, A., Crawford, R. and Tetlow, G. (2010).

One should expect neutral views after the retirement as immigrants will no longer be a threat to the job prospects and earnings of retired people. Intuitively, we hypothesise that if there is any role of labour market involved in anti-immigration views, we should find that natives become less opposed to further immigration after exit from the labour market on retirement. The rationale of having less opposed views towards further immigration on exit from the labour market is that once a native is retired, essentially, an individual is out of the labour market and is no longer competing for jobs. So, exit from the labour market should, make him or her indifferent towards immigration.[30]

However, as explained earlier, OLS estimation of causal impact of retirement on views towards further immigration is hindered by endogeneity and self-selection issues. To deal with these issues, "retirement" (being an endogenous variable) is instrumented using state retirement age of 65 to generate a dummy instrumental variable "T_i" that assigns 1 if the respondent's age is 65 or above at the time of survey and 0 otherwise. We use a regression discontinuity design (see Imbens and Lemieux, 2008; Lee and Lemieux, 2010) for this chapter, as one would expect a clear jump in the outcome variable ("reduce immigration") when the treatment ("being retired") kicks in at the threshold point ("state retirement age of 65"). The idea of this research is that if there is a sudden jump in views towards further immigration after the retirement, principally a Fuzzy RDD suggests that the jump is due to retirement alone and nothing else. In other words, if we find any change in the views towards further immigration after the retirement, we can say that this change occurred due to exit from the labour market because of retirement.

[30] We also tried to investigate the views of native males towards further immigration on entry into the labour market at their working age. Unfortunately, due to lack of available data we do not find any clear visible discontinuity that can be used for the regression discontinuity design. This non-existence of clear discontinuity at labour market entry age does not allow us to perform the analysis for labour market entry.

This design enables us to effectively find a causal impact of retirement on views towards further immigration.[31] A Fuzzy RDD allows us to use the jump in the probability of getting treatment at the threshold point and use it as an instrument (Trochim, (1984)). The whole regression discontinuity design is explained in greater detail in section 3.4 and section 5.3.

Following section explains the data used, outcome variables, and control variables, section 5.3 explains the methodology employed in greater detail, section 5.4 presents results and section 5.5 concludes this chapter.

5.2 Data

This chapter uses the two waves (2009-2011) of the UK Citizenship Survey.[32] The survey is conducted in England and Wales, covers people aged 16 and above and consists of a core sample and a minority ethnic boost sample. Each wave of the Citizenship Survey has a sample size of around 15,000 people, consisting of a core sample of around 10,000 and a minority ethnic boost sample of around 5,000 individuals.

Native respondents are identified on the basis of country of birth of respondent and country of birth of their mother and father, explained in greater details in chapter 4, section 4.2. In this chapter, “native” refers to a respondent who is born in the UK and whose both parents are born in the UK as well. The outcome variable named “reduce immigration” is the answer to the question, “Do you think the number of immigrants coming to Britain nowadays should be increased, reduced or should it remain the same?” If the respondent says increased or reduced, then the interviewer asks if the number should be increased or reduced by a little or a lot.

To begin with, “increased a lot”, “increased a little” and “remain the same” are grouped together, as all indicate that the respondent does not want

[31] However, it is quite possible that time lag is involved in change of attitudes: firstly, as individuals may take time to realize that the problems they may or may not have faced in the labour market are no longer affecting them and secondly, change in attitudes are not likely to happen instantaneously.

[32] The survey has been collected since 2001. Initially it was a biennial survey conducted by the Home Office, in 2006 it fell under the auspices of the Communities and Local Government department (now the Department for Communities and Local Government. From 2007 onwards the survey has been conducted annually, with data collection taking place each quarter. The publicly available data for this period combines four quarters, giving surveys for 2007-08, 2008-09, 2009-10 and 2010-11.

immigration to be cut. People replying "increased a lot" and "increased a little" are clearly in favour of immigration, while those replying "remain the same" are also not against it. We group the choices "reduced a lot" and "reduced a little" as both indicate a wish to see immigration reduced. This generates an indicator variable named "reduce immigration 1" (labelled as redmig in figures) of whether an individual is opposed to further immigration (or not).

Our variable of interest for exit from the labour market is the answer to the question, "what was the main reason you did not look for work in the last 4 weeks?" An indicator variable named "retired" is generated; value is 1 if respondent replied "retired from paid work" and 0 otherwise. The reference group for "retired" is "non-retired". In principal, this reference group contains all the non-retired respondents such as students, people waiting for results of job applications, sick or injured people, long-term disabled people, people who believe no jobs are available, people who haven't started looking for jobs, people who do not need employment, and any others who are not retired. Although, this classification is not perfect as it leads to heterogeneity within the reference group. However, we have to compromise on this issue as number of observations in each type of non-retired respondents become so few and sometimes no observations at all that Fuzzy RDD cannot be employed. Despite of this heterogeneity in the reference group, we can still interpret the results as compared to the non-retired respondents. We cannot imply this interpretation as a comparison with employed or unemployed respondents. Retired respondents may or may not have different views towards immigration as compared to the employed and unemployed respondents separately, however data restrictions do not allow us to test this. Interpretation of the results as compared to the non-retired respondents still holds true.

Control variables used are: "normalized age" (age is normalized at 65 (state retirement age for males) to center it at threshold for exit from the labour market), "survey year" dummy and an interaction between "retired" and "normalized age". Interacted variable with normalized age allows us to see the difference of slope before and after the threshold. It gives the coefficient that whether age has a different or similar effect on retired and working people. Our instrument (probability of being retired) used for exit from the labour market is purely systematic that allows us to control for the potential selection bias and endogeneity bias. Instrument being purely systematic is important to make the treatment random otherwise results can be biased. Methodology, instrument, how and why methodology works is further explained in section 5.3.

We assess the robustness of our results in two ways: a) Restricting the sample near to the threshold age 54 – 74 and 61 – 69 and b) re-estimation of the models after recoding the outcome variable; once by dropping the respondents selecting "cannot choose" from the analysis (referred to as "reduce immigration 2" and labelled as redmig2 in figures) and then by assigning 1 to respondents selecting "reduce a lot" and 0 otherwise (referred to as "reduce immigration 3" and labelled as redmig3 in figures). Categorization of the outcome variable is presented in table 5.1.

Table 5.1: Outcome variable categorization

Categorization	Reduce Immigration 1	Reduce Immigration 2	Reduce Immigration 3
Increase a lot	0	0	0
Increase a little	0	0	0
Remain the same	0	Dropped	0
Reduce a little	1	1	0
Reduce a lot	1	1	1

Due to data restriction we restrict our sample to native males only, as we are unable to distinguish retired females who have left the labour force and those who have retired from positions which were not part of the labour force. However, graphical representation of treatment and the outcome for females is presented in appendix C but it is not discussed in this chapter. Descriptive statistics for the estimated sample for exit from the labour market is presented in table 5.2.

Table 5.2: Descriptive statistics for the estimated sample (Native males)

Variable	Mean	Std. Dev.	Min	Max
Retired	0.28	0.45	0	1
Age	51.12	18.50	16	95
Increased a lot	0.01	0.09	0	1
Increased a little	0.02	0.12	0	1
Remain the same	0.17	0.38	0	1
Reduce a little	0.21	0.41	0	1
Reduce a lot	0.59	0.49	0	1
Wave 2009 – 2010	0.49	0.50	0	1
Wave 2010 – 2011	0.51	0.50	0	1
Observations		7362		

Summary statistics show native males of around 51 years of age on average, with a minimum age of 16 years and maximum age of 95 and a standard deviation of over 18 years. Around 80 percent of the sample used for labour market exit analysis is opposed to further immigration, 17 percent of the sample wants the immigration to remain at the same level, and 3 percent wants an increase in immigration.

5.3 Methodology and Estimation

Initially, OLS estimation is used for the analysis but OLS results are expected to be biased as selection and endogeneity problems can arise. Natives may self-select to exit from the labour market early due to any reason by choosing early retirement. Early retirement can be the result of anything such as family responsibilities, having enough wealth, or facing difficulty in finding a job. Essentially, anyone retiring early can lead to biased results as we will not be able to compute the exact impact of retirement (exit from the labour market) alone on attitudes towards immigration. It means that the results we get will be biased as they will be the combined effect of all the heterogeneity going on in retired respondents and estimates will be unable to tell us anything about the effect of retirement (exit from the labour market) alone on attitudes towards immigration.

Whereas, if any of the reasons of early retirement sprouts from the anti-immigration sentiments or from the perceived negative impact of immigration such as non-availability of jobs, reduced wages, labour market competition then this can result in the majority of the retired respondents already having negative views towards immigration. This can again leading to biased results towards greater opposition to immigration. In other words, this means that early retirement will create heterogeneity of respondents in the retired category with higher proportion of respondents opposed to immigration that will make it impossible to calculate the correct impact of retirement alone (impact of exit from the labour market) on attitudes of retired individuals towards immigrations due to exit from the labour market.

To get around this issue of selection bias we use regression discontinuity design (see Imbens and Lemieux, 2008; Lee and Lemieux, 2010). Regression discontinuity design allows us to control for the self-selection problem by instrumenting the treatment using the discontinuity (Trochim (1984)). This technique has been used in programme evaluation, for example, in education Clark and Royer, (2010) and Thistlethwaite and Campbell, (1960).

Our RD design is Fuzzy as we observe treated and untreated observations on both sides of the threshold. We are interested in estimating the causal relationship of exit from the labour market on attitudes towards further immigration. In principle, the basic intuition is that we observe a discontinuous jump when the treatment kicks in at the threshold point (age 65). This implies that if there is a jump in the outcome after treatment (retirement); it is caused by the treatment alone and nothing else. There is a difference between the probability of getting the treatment before and after the threshold point. This difference in probability of getting the treatment or not cannot suffer from self-selection or endogeneity. It means that, if there is a change in the views of respondents towards immigration after the retirement then it is due to exit from the labour market alone and nothing else. Our relationship of interest is presented by equation (5.1) below

$$Y_i = \alpha + \rho R_i + \beta_1 A_i + \beta_2 A_i * T_i + \beta_3 W_i + \varepsilon_i \qquad (5.1)$$

where Y_i is the binary outcome variable (reduce immigration) for individual i, R_i is the indicator variable for "being retired" that shows whether the individual i has retired from paid work or not, ρ is the causal coefficient of interest, A_i is the normalized age of the individual, T_i is the dummy indicating that the respondent's age is 65 or above, W_i is the dummy for survey year and ε_i is the error term. $A_i * T_i$ allows us to see the difference in slopes for individuals before and after the threshold. It should be noted that, Y_i is a dummy variable that makes equation (5.1) a linear probability model. We run 2SLS to estimate a Fuzzy RDD.

Our first stage regression looks like as below

$$R_i = \pi_0 + \pi_1 A_i + \pi_2 T_i + \pi_3 A_i * T_i + \pi_4 W_i + \mu_i \qquad (5.2)$$

Here R_i is "being retired" and is instrumented using the instrument T_i. By substituting the first stage equation (5.2) into the causal relationship of interest equation (5.1) we get reduced form presented by equation (5.3) below

$$Y_i = \alpha + \beta_1 T_i + \beta_2 A_i + \beta_3 A_i * T_i + \beta_4 W_i + \varepsilon_i \qquad (5.3)$$

It produces a Wald estimator and is equivalent to an IV estimate

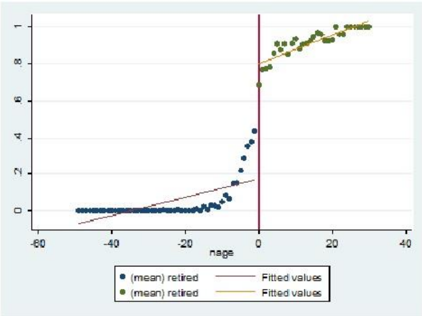
$\rho^{IV} = \beta_1/\pi_2$

Now ρ is the causal effect of being retired from paid work (exit from the labour market). The pivotal part of the RDD is discontinuity at the threshold. Not just a simple increase but one should be able to see a clear jump at the threshold when plotted against the treatment. Graphical evidence in RD designs (sharp and fuzzy) is considered a central part of the RD analysis. Graphs are the first step in any RD analysis that indicates whether employing an RD design is feasible or not, as they provide a powerful, simple and convincing way to visualize the identification strategy.

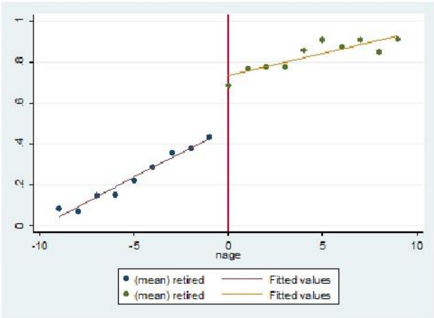
Figure 5.1 for exit from the labour market shows graphically the discontinuity and a visible jump in the treatment at the threshold point. On y-axis we have treatment status (retired or working) which is plotted against the normalized age of respondents in each age group on x-axis. All the graphs in figure 5.1 show a clear discontinuity at the threshold point. To begin with plotting the full sample, graph 5.1a) shows a discontinuity at the threshold point which remains there even when the respondents aged more than 74 and less than 54 are dropped from the analysis (graph 5.1b). Discontinuity at the threshold still appears in the graph 5.1c when the sample size is further reduced to the respondents aged 61 – 69.[33] It means that the essential condition of discontinuity in the treatment holds true, so a RD design can be employed.

[33] Figure C 1 in appendix C shows discontinuity graphs for the females.

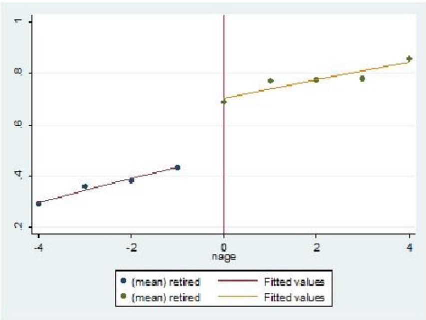
Figure 5.1: Discontinuous jump in treatment at threshold



5.1a) Discontinuous jump in treatment at threshold



5.1b) Discontinuous jump in treatment at threshold (sample trimmed at age 54 and 74)



5.1c) Discontinuous jump in treatment at threshold (sample trimmed at age 61 and 69)

Another important assumption of the RDD is continuity of the outcome variable at the threshold in the counterfactual situation without the treatment. The assumption implies that if there is a jump in the outcome after treatment it is caused by the treatment alone and nothing else, resulting in high internal validity.[34] In this scenario, if there is a change in the views of respondents towards immigration after the retirement then it is due to exit from the labour market alone and nothing else.

First stage results show that the likelihood of a person being retired at the state retirement age is significantly correlated with the actual retirement. Table 5.3 presents the first stage results for 9 different models, run by the combination of 3 different sample restrictions (age between 16 – 95, 54 – 74, and 61 – 69) and 3 different categorization of outcome variable (see, table 5.1).

[34] Internal validity means that these results hold true to a higher degree for this study at threshold point of 65. These results cannot be generalized; results may or may not change if the threshold point is changed or if estimated for a different population.

Table 5.3: First stage results (Exit from the labour market)

Outcome Variables	Reduce Immigration 1			Reduce Immigration 2			Reduce Immigration 3		
Retired	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Retirement at age 65 or above	.58*** (0.05)	.25*** (0.02)	.22*** (0.02)	.59*** (0.05)	.25*** (0.03)	.22*** (0.03)	.58*** (0.05)	.25*** (0.02)	.22*** (0.02)
Kleibergen-Paap F stat (excl. instrument)	144.45	112.26	121.16	130.20	69.88	69.10	144.45	112.26	121.16
R2	0.670	0.369	0.176	0.669	0.377	0.175	0.670	0.369	0.176
# observations	7362	2366	1239	6092	2060	1086	7362	2366	1239
Sample	Full	Trimmed	Trimmed	Full	Trimmed	Trimmed	Full	Trimmed	Trimmed
Age boundaries	16 – 95	54 – 74	61 – 69	16 – 95	54 – 74	61 – 69	16 – 95	54 – 74	61 – 69

Robust standard errors are given in parenthesis. For IV, standard errors are adjusted by clustering at age.
Significance levels: *10%, **5%, ***1%

The estimated coefficient of "retirement at age 65 or above" is between 0.58 – 0.59 with high significance for the full sample (see columns 1, 4 and 7 in table 5.3); where the outcome variable is categorized in three different ways. The results for models estimated for the sample trimmed at age 54 and 74 (see column 2, 5 and 8 in table 5.3) and for models estimated for the sample trimmed at age 61 and 69 (see column 3, 6, and 9 in table 5.3) show a decrease in the estimated coefficients. These results change across the models because trimming changes sample sizes and individuals far away from the threshold with a very low probability of getting the treatment, for example, a person of age 17 is probably not going to retire at 17, are excluded from the estimation. This also makes trimmed models more meaningful.

From the diagnostics there does not seem to be any weak instrument problem. The first stage F-values of all the models for the excluded instrument are between 69 and 144. Stock, Wright, and Yogo (2002) and Staiger and Stock (1997) suggest that if the F-statistic is above 10, we can imply that our instrument does not suffer from the weak instrument problem. It indicates that first stage exists for the instrument and there is enough correlation between the endogenous regressor and the instrument that can be used for the unbiased causal estimation. Estimation results are discussed in the following section.

5.4 Results

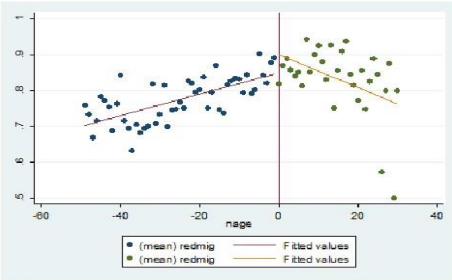
Initial OLS estimations show that on retirement views of native males towards further immigration remain the same. Panel A in table 5.4 (OLS models 1, 2, and 3) shows that OLS coefficients of being retired, for the full sample and the restricted samples age 54 – 74 and age 61 – 69 are insignificant and we are unable to reject the null of 0. It means that for a native male being retired has no significant negative or positive effect on the views towards further immigration. In other words, labour market seems to play no role in determining attitudes towards further immigration. The coefficients are insignificant and their magnitude is almost zero. However, as one would expect, OLS may over-estimate the impact of retirement on attitudes in favour of opposition towards further immigration, as respondents choosing to retire early may contain respondents opposed to further immigration that can hinder the true estimation of retirement effect on attitudes towards further immigration. This issue is discussed earlier in greater detail in section 5.1 and 5.3, we employ IV estimation to fix this problem.

Our IV estimation of model 1 also returns an insignificant coefficient. This relationship is graphically presented in figure 5.2 (graph 5.2a). The outcome variable is on y-axis and is plotted against the respondents' age on x-axis. The discontinuity or jump between the two plotted lines before and after the threshold shows that there is not a huge change in attitudes towards further immigration after the retirement. The graph in figure 5.2 (graph 5.2a) shows no discontinuity on exit from the labour market for the full sample.[35]

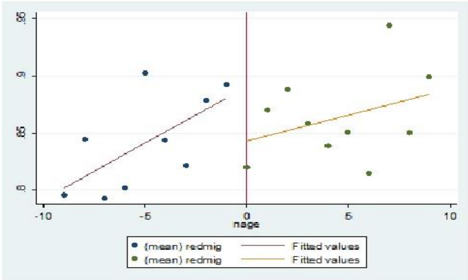
To be sure we restrict our sample near to the threshold to see a clearer picture (see, graph 5.2b and 5.2c in figure 5.2). IV estimation for the restricted models (Panel A in table 5.4 IV models 2, and 3) gives us statistically significant coefficients of retired dummy and show that a retired person has a lower probability of reporting views opposed to immigration by 0.20 p.p. and 0.30 p.p. respectively as compared to a non-retired person. These estimates show that when a respondent leaves the labour market he is less likely to oppose immigration. Looking at the graphs (see, graph 5.2b and 5.2c in figure 5.2), when samples are restricted to age 54 – 74 and 61 – 69, we can see a slight downward jump – discontinuity – at the threshold point (age 65). It means we can safely say that native males' opposition to immigration does not increase on exit from the labour market; if views change they become neutral or less opposed to immigration as there is a slight downward jump in the outcome after the retirement.

[35] Figure C 2 in appendix C presents the graphs of the outcome variable "reduce immigration 1" for female natives.

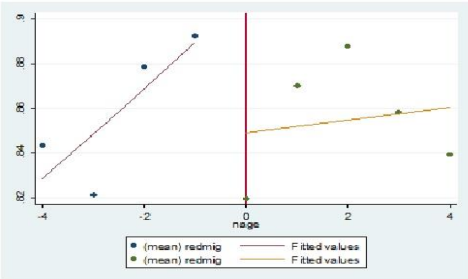
Figure 5.2: Continuity in outcome variable (Reduce Immigration 1) at threshold



5.2a) Continuity in outcome variable (reduce immigration 1) at threshold



5.2b) Slight discontinuity in outcome variable (reduce immigration 1) (sample restricted at age 54 and 74)



5.2c) Slight discontinuity in outcome variable (reduce immigration 1) (sample restricted at age 61 and 69)

Reduce Immigration 1 is labelled as redmig in figure 5.2

Table 5.4: OLS/IV estimates for all the models (Exit from the labour market)

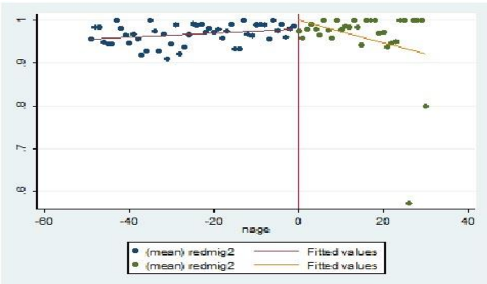
Panel A: Reduce Immigration 1 (1 for "reduce a little" & "reduce a lot" and 0 otherwise)						
Reduce Immigration 1	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
Retired	0.02	0.01	0.02	0.02	-0.20**	-0.30***
	(0.01)	(0.02)	(0.02)	(0.03)	(0.09)	(0.11)
Normalized Age	0.003***	0.01	0.00	0.003***	0.02***	0.04***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Normalized Age*above 65	-0.004***	-0.01	-0.01	-0.004***	-0.01**	-0.02**
	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)
Constant	0.85***	0.86***	0.85***	0.85***	0.99***	1.06***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.05)	(0.06)
N	7362	2366	1239	7362	2366	1239
Panel B: Reduce Immigration 2 ("remain the same" dropped from Panel A sample)						
Reduce Immigration 2	OLS (4)	OLS (5)	OLS (6)	IV (4)	IV (5)	IV (6)
Retired	0.00	0.00	-0.01	0.00	-0.03	-0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)
Normalized Age	0.001***	-0.00	-0.00	0.001**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Normalized Age*above 65	-0.001*	0.00	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Constant	0.98***	0.98***	0.98***	0.98***	0.99***	1.02***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
N	6092	2060	1086	6092	2060	1086
Panel C: Reduce Immigration 3 (1 for "reduce a lot" and 0 otherwise)						
Reduce Immigration 3	OLS (7)	OLS (8)	OLS (9)	IV (7)	IV (8)	IV (9)
Retired	0.01	0.00	0.02	0.00	-0.29**	-0.68***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.13)	(0.15)
Normalized Age	0.01***	0.01***	0.02	0.01***	0.03***	0.08***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Normalized Age*above 65	-0.01***	-0.01	-0.02	-0.01**	-0.02***	-0.04***
	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)
Constant	0.66***	0.68***	0.66***	0.66***	0.86***	1.12***
	(0.01)	(0.03)	(0.04)	(0.02)	(0.07)	(0.08)
N	7362	2366	1239	7362	2366	1239
Sample	Full	Trimmed	Trimmed	Full	Trimmed	Trimmed
Age boundaries (inclusive)	16 – 95	54 – 74	61 – 69	16 – 95	54 – 74	61 – 69

Robust standard errors are given in parenthesis. For IV, standard errors are adjusted by clustering at age.
Significance levels: *10%, **5%, ***1%

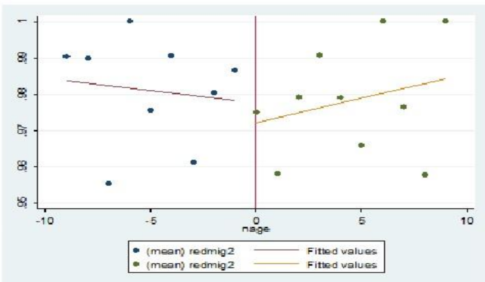
Models 1,4 and 7 are estimated using the full sample of native males, models 2,5, and 8 are estimated by trimming the sample at age 54 and 74, whereas, model 3,6 and 9 are estimated after trimming the sample at age 61 and 69.

If we look at Panel B of table 5.4, where respondents who answer "remain the same" are dropped from the analysis, OLS estimation shows that the coefficients of being retired, for full sample, restricted sample to age 54 – 74 and to age 61 – 69 (OLS models 4, 5 , and 6) are insignificant. A similar picture arises, retirement appears to play no role in views towards further immigration. Even when the native males exit from the labour market their views towards further immigration do not change. IV estimation of these models present a similar picture as well, coefficients of being retired for IV models 4, 5 and 6 are again insignificant, suggesting that treatment does not affect the outcome (see, figure 5.3). This can be clearly seen from the graphical representation in figure 5.3 that there is no visible jump in the outcome after the treatment.[36] It is important to mention that in Panel B we can see that coefficients of retired dummy fairly remain the same for all sample restrictions and estimation methods: full sample, restricted sample to age 54 – 74, and to age 61 – 69 with both OLS and IV estimations.

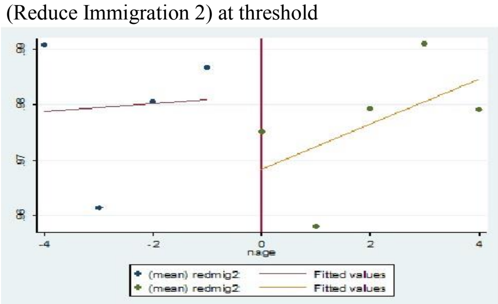
Figure 5.3: Continuity in outcome variable (Reduce Immigration 2) at threshold (Exit from the labour market)



5.3a) Continuity in outcome variable (Reduce Immigration 2) at threshold



5.3b) Continuity in outcome variable (Reduce Immigration 2) at threshold (sample restricted at 54 and 74)



5.3c) Continuity in outcome (Reduce Immigration 2) at threshold (sample restricted at 61 and 69)

Reduce Immigration 2 is labelled as redmig2 in figure 5.3.

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[36] Figure C 3 in appendix C presents the graphs of the outcome variable "reduce immigration 2" for female natives.

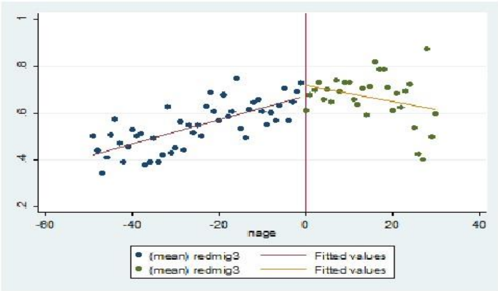
As a robustness check we use strictly categorized outcome variable (reduce immigration 3) by assigning 1 to only those respondents who are of the view to reduce immigration “a lot” and 0 otherwise. Panel C in table 5.4, shows that retired native males have no different views than native males still in the labour market. Full sample of 7,362 respondents reduce to 2,366 and 1,239 respondents on trimming the sample to 54 – 74 and 61 – 69 respectively.

Coefficients of being retired are insignificant for models 7, 8 and 9 with OLS estimation, shown in Panel C. Whereas, this coefficient is insignificant for model 7 of IV estimation but statistically significant for model 8 and 9 showing a favour of 0.29 p.p. and 0.68 p.p. of native retired males towards further immigration. It means that a retired native is likely to favour further immigration by 0.29 p.p. and 0.68 p.p. as compared to a non-retired native male, when the sample is restricted to 54 – 74 and 61 – 69 respectively. Looking at the graphs (see, figure 5.4), we see that native males' opposition to immigration do not change on exit from the labour market (see, graph 5.4a in figure 5.4); if views change they become neutral or less opposed to immigration (see, graphs 5.4b and 5.4c in figure 5.4) as there is a slight evidence of downward jump in the outcome after the retirement.[37]

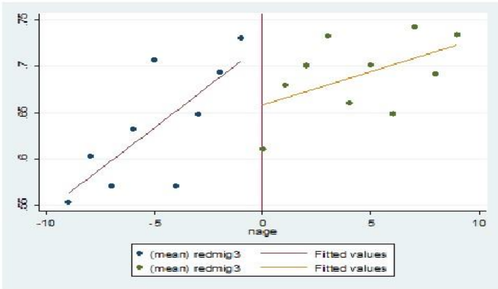
Throughout our estimation we find a consistent finding that whenever we restrict the sample near to the threshold, we find that retired native males become less likely to report opposed to further immigration as compared to those who are not retired.

[37] Figure C 4 in appendix C presents the graphs of the outcome variable “reduce immigration 3” for female natives.

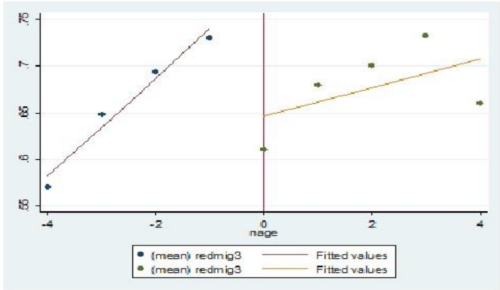
Figure 5.4: Continuity in outcome variable (Reduce Immigration 3) at threshold



5.4a) Continuity in outcome variable (Reduce Immigration 3) at threshold



5.4b) Slight discontinuity in outcome variable (Reduce Immigration 3) at threshold (sample restricted at age 54 and 74)



5.4c) Slight discontinuity in outcome (Reduce Immigration 3) (sample restricted at age 61 and 69)

Reduce Immigration 3 is labelled as redmig3 in figure 5.4.

For further robustness checks, we run all the models presented in table 5.4 after controlling for the regional dummies, ethnicity dummies, religion dummies, and practicing religion dummy as in chapter 4. We find almost similar results presented in *table c 1* in appendix C. Although, the sample size gets smaller for all the models due to missing values for some of the included control variables but results portray the same picture. This strengthen our earlier findings that labour market has a very little role in determining attitudes towards further immigration.

5.5 Conclusion

This chapter highlights that the labour market plays a slight role in determining opposition towards further immigration. Our results suggest that exit from the labour market does not largely change the attitudes towards further immigration, although a little evidence of reduced opposition is present after retirement from paid work and exit from the labour market.

It is important to note that we imply retirement from the paid work gives us the underlying effect of exit from the labour market on attitude of being opposed to further immigration. Although, retirement, especially early retirement is correlated with many other factors such as health, wealth, family responsibilities that may have resulted in retirement. But the basic argument that if labour market was playing any role in determining attitudes towards immigration then once a person is out of the labour market, labour market should become lesser of a concern for him/her. Conversely, there may be some retired individuals with some of their family members still in the labour market. These retired individuals may still be concerned about labour market issues for the success of their family members. This heterogeneity in retired natives explains the small magnitude of coefficient of being retired on attitudes towards further immigration. May be coefficients for retired individuals with family members still in the labour market and coefficients for retired individuals with no family member in the labour market have opposite signs and this ends up decreasing the overall coefficient. However, this heterogeneity cannot be controlled for due to the data limitations.

Overall, results show that a large part of anti-immigration attitudes are most likely determined through other than the labour market channels. One of the channels often found to be associated with determining attitudes towards further immigration is social channel (see, for example, Card et al., 2012; Dustmann and Preston, 2004). Evidence suggests that determinants like interpersonal trust, identity, perception, race and prejudice are often found to determine attitudes towards further immigration.

This chapter finds that attitudes of native males largely remain unchanged and slightly become pro-immigration after retirement. It means that labour market does not play a large role in determining views towards further immigration. This finding is in line with our earlier analysis in chapter 4 and the previous literature (see, for example, Card et al., 2005; Citrin et al., 1997; Dustmann and Preston, 2007; Dustmann and Preston, 2004; Dustmann and Preston, 2001; Rustenbach, 2010). If being in the labour market were influencing anti-immigration views then we would expect these views to change markedly as individuals exited from the labour market should care less about immigration as they no longer face the immigrant competition in the labour market.

Our OLS results suggest that exit from the labour market does not change the views of native males towards further immigration. Whereas, after controlling for the selection bias and endogeneity bias we see a similar picture

– for the full sample models – that the views of retired natives do no change as compared to the ones who are still in the labour market. However, we find retired native males become less opposed to immigration on exit from the labour market, compared to still working native males. We find this evidence when the sample is trimmed near to the threshold and respondents reporting "remain the same" to the outcome question of further immigration are included.[38]

The inclusion of respondents reporting "remain the same" makes the difference. They drive the coefficient of our variable of interest "retired" towards native males being less opposed to immigration on exit from the labour market – a sign of labour market competition playing a significant role in determining attitudes towards immigration. This happens because inclusion of respondents reporting "remain the same" increases the number of observations to the left side of the threshold whereas, in Panel B, on trimming the data and dropping "remain the same" we are left with small number of observations that does not allow us to see the effect with statistical significance, however sign is consistent with the other models. So careful interpretation is required, we can safely say that exit from the labour market does not completely change the attitudes towards further immigration; but some evidence of a decrease in opposition towards immigration after exit from the labour market is present. This finding of labour market playing a role in determining attitudes towards immigration is in line with Ortega and Polavieja (2012).

The main contribution of this chapter is that it explores the effect of labour market on the views towards further immigration using a Fuzzy RDD. It finds that attitudes towards immigration largely remain unchanged after exit from the labour market, however, a little evidence of reduced opposition towards immigration is found at retirement and exit from the labour market. It is safe to say that if labour market plays any role in determining views towards further immigration, the role is not that much big.

Views may change after retirement because if there is any role of labour market in determining attitudes towards immigration then once an individual

[38] See, models IV (2), IV (3) in Panel A, and IV (8) and IV (9) in Panel C in table 5.4.

is out of the labour market, he/she is more likely to care less about immigration, as he/she is not part of the labour force anymore. However, we may expect a delay in change of attitudes after retirement as attitudes are not likely to change instantaneously on retirement. We must also not forget that a large part of opposition towards immigration is determined outside the labour market. So, it is likely, that the part of opposition towards immigration coming through the labour market channel may be so little that the change in attitudes after the retirement goes without being noticed. This chapter points out a slight decrease in opposition towards further immigration after exit from the labour market. To substantiate this finding, further research is needed to investigate the magnitude of the role of labour market in determining attitudes toward further immigration. Unfortunately, due to data limitations, we are unable to do it with this data set. It is also worthwhile to investigate the change in attitudes at entry into the labour market and latter compare the two changes: a) at entry and b) at exit from the labour market, to see what exactly is the contribution of labour market in determining attitudes towards further immigration.

Chapter 6. Are Immigrants a Burden on Public Services?

Immigration might have a negative impact on public services in the host country. This chapter focuses on the impact of immigrants on educational outcomes and school resources using longitudinal data on immigration and primary schools in England. It uses various fixed effects regressions as well as IV, where past location choice of immigrants is used to account for the non-random selection of immigrants into areas. This chapter suggests that increased immigration has improved educational outcomes, both in English and maths, but also placed resource pressures on primary schools, as class sizes have increased and schools had to hire additional teachers.

6.1 Introduction

The impact of immigration on residents in the host country is a highly contentious issue. In addition to the debate on the labour market impacts of immigration,[39] a major focus in the public debate – at least in the UK – has been the impact on public services, such as healthcare or education. This chapter considers the impact of immigration to the UK on the latter. England is arguably an interesting setting for this kind of research as it has experienced a large influx of immigrants in recent years and the impact of immigration has been an area of major public concern. We use a combination of school-level data on primary schools from performance tables published by the Department for Education, combined with low-level regional data on immigration from the 2001 and 2011 censuses. This detailed data allows us, to simultaneously look at school resources and school outcomes and thus to shed some light on the trade-offs states might face when dealing with an influx of immigrants.

Ideally we would like to have considered the time period 1991 – 2011 however, this is not possible due to data limitations. Our analysis is carried out at the "Super Output Area" level and these are only available for the 2001

[39] Summarized recently in a special issue in the Journal of the European Economic Association (Card, Dustmann and Preston, 2012; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012; Borjas, Grogger and Hanson, 2012; Card, 2012; Dustmann and Preston, 2012).

and 2011 censuses. It is may be the case that our instrument may have a certain degree of correlation with the changes in school quality and economic conditions of local area that may have affected the immigrants' location decisions in 2001. It means that if the location choice of immigrants in 2001 is the outcome of changes in school quality and economic conditions at that time then validity of our instrument may have been compromised. Although, from the diagnostics in table 6.2, it shows that our analysis does not suffer from weak instrument problem. This issue can be fully addressed by using the census data from 1991, which unfortunately cannot be used due to the unavailability of data at "Super Output Area" level. However, if there is any endogeneity raising from the changes in school quality and economic conditions then after controlling for local authority and school fixed effects, the issue of endogeneity becomes less severe.

School funding in the England (and the UK more generally) is complex. Chowdry and Sibieta (2011) describe the funding models for different school types in England. While there is a formula for allocation central funds from Government to Local Authorities there are also various Local Authority formulas that allocate funding to individual schools. These formulas can take account a number of factors including, the number of pupils, school deprivation, special needs and the number of pupils with English as an additional language. So while there may be a link between the number of immigrants and school resources there is not direct funding formula.

Most of the previous literature on the impact of immigration on schools has focused on (negative) peer effects on native education outcomes caused by a higher share of immigrants in the classroom or school population. In contrast, this chapter is concerned primarily with the question whether immigration puts a strain on school resources and, simultaneously, what happens to school outcomes. To the best of our knowledge, there is a very limited set of papers that look at the link between immigration and school resources and none that looks at both school resources and education outcomes. On the resource side, Coen-Pirani (2011) uses a calibrated model to look at increased Mexican immigration into California. His results, from counterfactual simulations, suggest that spending per pupil would have been 24% higher in the year 2000 if immigration had remained on 1970-levels.

Speciale (2012) looks at 15 pre-enlargement EU countries using an identification strategy based on the inflow of immigrants following the Balkan Wars in the 1990s. His results suggest that a 1 percentage point increase in the population's immigrant share leads to a 0.1% to 0.6% decrease in education expenditure per student.

Some of the very few papers that look at immigration into geographical areas, rather than schools or classrooms, and its consequences for native outcomes are Betts (1998) and Hunt (2012) who use state-level data on immigration and native school outcomes. The former's findings from fixed effects regressions suggest a negative link between immigration and natives' high-school completion, while the latter's results suggest a small positive effect. We use data on a much smaller spatial scale – roughly on the level of city quarters rather than US states or metropolitan areas. The only other paper we are aware of that also looks at the effect of (small-scale) neighbourhood characteristics on student outcomes is Gibbons et al. (2013). They focus on characteristics such as the average grade 3 score in English (reading and writing) and mathematics, the share of students eligible for free school meals, the share of students with special education needs and the fraction of males in spatially small neighbourhoods. Their results suggest no evidence for an effect of neighbourhood composition on test scores. However, they find evidence that neighbourhood characteristics affect several behavioural outcomes.

This chapter is also complimentary to an existing literature that is concerned with the (peer) effects of having more immigrants in the classroom on the performance of native pupils. For England, Geay et al. (2013) investigated the impact of immigration, measured by being a non-native speaker, on native pupils' school outcomes. Their evidence, from a range of empirical approaches suggests that increases in the share of non-native speakers has no impact on the reading, writing or mathematics performance of natives once a limited number of controls are included. For the Netherlands, Ohinata and van Ours (2013a) investigate the impact of immigrant students on the educational performance of native Dutch pupils. They find that – while immigration leads to more incidents of bullying or stealing – there is no strong evidence of a negative impact on the educational performance of native Dutch pupils.

In another paper, Ohinata and van Ours (2013b) use quantile regression and find that native students with the best marks are adversely affected by immigration, potentially reflecting an increase in teachers attention towards low-performing students. Finally, Schneeweis (2013) considered 22 school cohorts in Austria between 1980 and 2001. She shows that an increasing share of immigrants negatively affects the attendance of immigrants in the 'high track'[40] schools, with no significant negative impacts for natives, suggesting that the negative impact of immigration is felt by immigrants themselves and not natives. Furthermore, the results demonstrate that the reallocation of immigrants to schools with a low concentration of immigrants reduces the differences in achievements between natives and immigrants, suggesting that mixed schools benefit immigrants with no discernible impact for natives.

Much of this previous literature relies on within-school differences in the number of immigrants in each class or cohort. Given our focus on school-level outcomes, such as the number of teachers, this approach is not feasible. Instead we consider how individual schools change in the face of increased immigration into the local area where they are situated. The major difficulty when estimating the impact of immigration in this way arises from the non-random assignment of immigrants to local areas. Immigrants self-select into areas, possibly on the basis of the existence of successful immigrant communities or similar ethnic groups or because of current favourable conditions in an area, all of which might also matter for our outcomes (see, for example, Abraham and Shryock, 2000; Åslund, 2005; Bartel, 1989; Hatton and Wheatley Price, 1999; Lymperopoulou, 2013; Pacyga, 1991; Phillimore and Goodson, 2006; Phillips, 2007; Schwirian, 1983; Styan, 2003; Zorlu and Mulder, 2008).

To attenuate eventual biases arising from this non-random selection into areas differing in school quality and other location characteristics, we use

[40] Austria, as well as several other countries such as Germany and Switzerland, operate a system where pupils are sorted into different school tracks based on their measured ability. High track schools get the most able students.

a variety of modelling strategies. In a first step we rely on school fixed effects that account for time-invariant differences between areas and schools that might influence immigrants' location decisions.[41] As we look at 10-year differences, these fixed effects are unlikely to fix all potential selection problems because the attractiveness of areas and schools might well change over time and it is entirely possible that immigrants react to these changes. To address this potential endogeneity of the change in immigrant numbers, we rely on an instrumental variable strategy based on past settlement patterns, first developed by Card and DiNardo (2000) and Card (2001) and subsequently used in the immigration literature by, for example, Bianchi et al. (2012), Card (2009), Cortes (2008), Gonzalez and Ortega (2013), Hunt (2012), Ottaviano and Peri (2006), and Saiz (2006). The underlying idea is that the tendency of immigrants to move to areas with many existing immigrants allows one to use historic settlement patterns of immigrants to instrument for current settlement. To illustrate the idea: the instrument effectively redistributes the nationwide change in immigrants between t_0 and t_1 according to some initial distribution of immigrants across regions. A region that was initially home to, say, 5% of all immigrants would also receive 5% of all new arrivals during the observation period. The underlying logic is that past-immigration patterns should influence current settlement decisions, while the historical distribution of immigrants should be unaffected by any current change in the quality of public schools.[42]

This approach comes with two advantages and a disadvantage relative to the use of within-school comparisons. The first advantage is that it allows us to look at our outcomes of interest, in particular school resources, which vary on the school-level but not within schools. The second advantage is that it avoids a necessary assumption of the within-school comparison approach, namely that immigrants select into schools or areas, but are then more or less randomly distributed to classes within that school. Depending on the level of student management by head teachers this assumption may or may not hold.

[41] In alternative specifications we also used low-level regional fixed effects, leading to essentially identical estimates.

[42] Note that the fixed effects would take care of any pre-existing differences between areas that would have caused these historical settlement patterns.

An example where it would be violated are cases where head teachers send immigrants into those classes that they expect to be the most able to cope with such an influx, thus mitigating any potential negative impact on other students (Vigdor and Nechyba, 2007 provide some evidence for within-school sorting in the context of peer-effects estimation).

Furthermore, within-school or within-cohort comparisons only consider spill-overs from immigrants to pupils in the same class or cohort, but not to those in other classes or cohorts in the same school. To the extent that pupils who live close to each other, but are not in the same class (or even the same school) influence each other, for example, through every-day social interactions, these comparisons might miss an important part of the picture. In the context of immigration, one could think of native pupils becoming friends with immigrant children in the same area and being influenced by each other's values or learning from each other (see, Gibbons et al., 2013, for a similar argument in relation to other neighbourhood characteristics). In contrast our approach, of looking at the local area where the school is situated, allows for such interactions outside of the school and is also agnostic about how schools sort immigrants into classes.

The advantages come at a price, however: The comparison of classes with different numbers of immigrants within the same school and cohort/year fully controls for the selection of immigrants into schools, and any difference between schools in the same year or within schools over the years, in a very simple way through the inclusion of *school*year* fixed effects. We, in contrast, have to rely on the instrumental variable strategy outlined above to attenuate concerns regarding these selection effects.

Finally, it is important to be clear that it is possible for immigration to have both positive and negative effects, both on school resources and on school performance (i.e., educational outcomes of pupils), in particular over a relatively long time such as the 10-year period considered here. Firstly, increased immigration may place pressure on schools because of larger class sizes and increasing numbers of non-native (in this case non-English) language speakers, possibly leading to a worsening of school outcomes. However, these effects can be mitigated – at least in the medium to long term – if schools in affected areas are also given more resources to hire additional teachers or to take other measures to deal with the increased population.[43] One should note, however, that the existing evidence – Coen-Pirani (2011) for California and Speciale (2012) for pre-enlargement EU-15 countries – find evidence for decreases in spending per pupil.

Secondly, native parents might start to withdraw their children from schools facing or experiencing an inflow of immigrants and relocate them to schools with a lower concentration of immigrants, either in other areas or into other types of schools, such as private schools. There is evidence of such native flight in England (Geay et al., 2013) and the US (Casio and Lewis, 2012, and for secondary schools Betts and Fairlie, 2003). Furthermore, evidence on school choice from the Netherlands suggests that native parents will choose schools with low immigrant concentration (for example, Ladd et al., 2010). To the extent that parents of more able native children are more likely to withdraw their children from schools with a high share of immigrants, school outcomes might worsen as the composition of pupils change. However, it is equally possible that a higher inflow of immigrants improves school outcomes (for example, Burgess, 2014; Cook, 2014; Cook, 2013; Greaves et al., 2014): immigrants are usually positively selected from the home country's population, which suggests that the average immigrant pupil might be of higher ability than the average native pupil.

Furthermore, some immigrant groups, in particular Asians, are well-known for placing a high value on education, which might again lead to a higher performance of their respective children (see, for example, Burgess, 2011; Fuligni, 1997; Fuligni, 2001; Fuligni and Yoshika, 2004). Similarly, Burgess et al. (2009) and Wilson et al. (2011) found that after controlling for observables, pupils from all ethnic minority backgrounds show a better

[43] Note that recent evidence (Dustmann and Frattini, 2013, and Dustmann, et al., 2010) suggest that the fiscal impact of immigrants in the UK is positive, i.e., the state appears to gain more in taxes from immigrants than is spent on them. This should in principle allow for an increase in funding for schools affected by higher immigration, however, it is not clear whether this increase actually happens. Unfortunately, information on school funding is not available for 2001, so this question cannot be investigated in the same way as our main estimates. Anecdotally, reports in the press (for example, The Economist, 2014) suggest that schools with a high immigrant concentration often get additional funds as they are also in deprived areas and benefit from extra government funding. It is important to be clear, however, that there does not appear to be any extra funding directly tied to immigrant numbers. In section 6.5, we present some suggestive evidence that immigration is associated with lower spending per pupil in a number of categories.

progress in their secondary schooling as compared to the white British pupils. They show that most of the development in their educational achievements occurs at the end of compulsory schooling in their exams when the stakes are high and this is true for all the schools wherever these ethnic minority pupils are present.

Burgess (2014) in his recent study use pupil level data of secondary schools from National Pupil Database 2012 – 2013 and stress that the better performance of London schools (initially pointed out by Cook in 2013 and referred to as 'London Effect') is caused by the ethnic composition of its schools. He states that the ethnic composition of schools has a positive effect on the GCSE results. Due to larger number of immigrant students present in London schools, white British students also perform better, most likely because of peer-effect. Burgess suggests that better results can be achieved by encouraging integrated multi-ethnic schools and by attracting immigrants in areas where there are comparatively fewer immigrants. Similarly, Greaves et al. (2014) for England using National Pupil Database from 2002 to 2012, found that disadvantaged pupils (eligible for free school meals) in inner London, Birmingham, and Manchester perform better as compared to the rest of England in Key Stage 4 exams (at the end of secondary school) is largely explained by: a) the higher number of pupils from ethnic minority backgrounds in these cities and b) prior better educational achievements at Key Stage 2 exams (at the end of primary school).

Our results suggest that immigration leads to larger schools and also changes the composition of pupils in schools by leading to lower numbers of natives and higher numbers of non-native English speakers. Furthermore, schools appear to hire more teachers to respond to the growth in student numbers, even though pupil-teacher-ratios still increase. Given this evidence, that immigration does put pressure on school resources, we also examine to what extent measures of pupil performance change in response to immigration, focusing on several key exams that pupils sit at the end of primary schooling. Our results suggest that – in spite of the resource pressure – education outcomes improve with immigration. We find increases in the performance in Maths and English exams, as well as falls in the share of pupils being absent from examination. Finally, we also provide supplementary evidence on spending per pupil – data on which, unfortunately, are only available for 2011. This evidence suggests that schools in high-immigrant neighbourhoods spend less per pupil in a number of categories than schools in neighbourhoods with fewer immigrants in the same local authority. However, the effects are comparatively small. This finding reinforces our earlier results on school resources and is consistent with sluggish adjustment of individual school budgets in the face of increased pupil numbers.

The rest of the chapter is organised as follows. Section 6.2 explains the data used, section 6.3 describes methodology, section 6.4 presents our main results, while section 6.5 presents additional results for school spending and income. Section 6.6 concludes.

6.2 Data

This chapter focuses on schools in England using data from "School Performance Tables" combined with population data from the 2001 and 2011 UK censuses. Data for primary schools are taken from "School Performance Tables" published annually by the Department for Education. The underlying data is collected by LEAs (Local Education Authorities). The data provide school-level information on pupils' performance and school characteristics, such as total number of pupils, pupil-teacher ratios and various performance measures.

In most of our analysis, we rely only on outcomes that are measured in both 2001 and 2011. Specifically, we consider two sets of outcome variables. The first set of outcome variables are associated with school resources or general school characteristics, specifically the number of pupils eligible for key stage 2 assessment, the number of pupils whose first language is not English, the number of native pupils, the pupil-teacher ratio, and the number of teachers. The second set relates to pupils' educational achievement in the Key Stage 2 exams sat at the age of 11, the end of primary education.[44] These are:

[44] The English school system is structured in 4 Key Stages. Each key stage refers to a certain age and completed educational years. Key Stage 1 starts with the reception class at the age of 4 and ends at the completion of 2 educational years at the age of 7 with an assessment in English and Maths. Key Stage 2 starts at the age of 7 and ends at the age of 11, with assessments in English, Maths and Science. Primary education is completed at the end of the Key Stage 2 assessment, after which students begin their secondary education comprised of Key Stage 3 and Key Stage 4.

the percentages of pupils achieving level 4-competency or above in English or Maths respectively, the average point score in these exams, and the percentages of students not achieving any level of proficiency due to absence or disapplication (i.e., the percentage of pupils not sitting the respective exam) in English or Maths.

Different levels represent the National Curriculum Test Levels, ranging from 1 to 8, with higher levels indicating higher competency. Key stage 2 exams cover levels 3 to 6, with 4 being the expected level of knowledge at this stage. The share of pupils achieving level 4 or above is thus equivalent to those performing at expected or higher levels at this stage of their education. Average point score of 27 is equivalent to the expected level 4 at this stage. Average point score is calculated by the following formula

$$\frac{((\text{a pupil's reading test score } + \text{ writing teacher assessment})/2 \ + \text{ maths})}{2}$$

We combine this data with information on immigrants in the local area taken from the censuses. It should be noted that the definition of immigrants has been changed as compared to the definition used in chapter 4 and chapter 5. Now, immigrants are defined as individuals being born outside of England, Wales, Scotland and Northern Ireland for the censuses data. Whereas, in the school league tables pupils whose first language is not English are considered as immigrants. While this mechanism for distinguishing between natives and immigrants may be imperfect but there is no further information available for more precise classifications.

We construct information on the number of immigrants at the level of Lower-layer Super Output Areas (LSOA) and Middle-layer Super Output Areas (MSOA). Both are spatial units used for the publication of census data. They are based on post-codes, which in the UK are usually equivalent to streets, and are designed to remain stable over time. One can think of LSOAs as being equivalent to neighbourhoods, while MSOAs are close to city quarters or smaller towns. LSOAs have a minimum population of 1,000 with a mean of 1,500, equal to approximately 650 households. LSOAs are then combined to generate an MSOA. Each MSOA contains a minimum population of 5,000 with a mean of 7,500 or around 3,000 households. At present, there are 34,753 LSOAs and 7,201 MSOAs in England and Wales.

Each school is merged to the corresponding LSOA and MSOA based on its address. The level of observation in our estimation sample is the school, i.e., not all LSOAs are present in the final dataset. As this might mean that we miss information on some immigrants who attend school in an LSOA other than the one they live in, we also use MSOA-level information in some specifications, which generally makes no difference. This latter fact is also reassuring as neither LSOAs nor MSOAs perfectly map into school catchment areas, which means that our estimates will inevitably suffer from some measurement error. The fact that changes between LSOA and MSOA-level data do not matter much for the results suggests that this potential bias will not fundamentally alter the results.

Table 6.1 presents descriptive information for our main estimation sample. It shows that, on average, schools have 77% and 80% of pupils achieving level 4 or above in Maths and English, with an average point score of around 27 in Key Stage 2 exams. Around 1% of the pupils in schools fail to achieve a level in English or Maths due to absence or disapplication. Schools have an average of around 42 pupils eligible for Key Stage 2 exams. There are around 35 pupils in every school whose first language is not English (and who are likely to be immigrants). On average, schools have around 13 teachers, 250 native pupils and a pupil-teacher ratio of 22:1.

Table 6.1: Descriptive statistics

Outcome Variables	Mean	Std. Dev.	Min	Max
Percentage of Pupils achieving level 4 or above in English	79.682	13.707	13	100
Percentage of Pupils achieving level 4 or above in Maths	77.185	14.789	7	100
Average Point Score	27.565	1.679	20.4	33.7
Percentage of Pupils failing to achieve a level in English due to absence or disapplication	1.110	2.264	0	38
Percentage of Pupils failing to achieve a level in Maths due to absence or disapplication	1.033	2.173	0	38
Number of Pupils eligible for Key Stage 2 Assessment	42.334	24.133	6	224
Pupils whose first language is not English	34.926	71.026	0	689
Pupil Teacher Ratio	22.157	3.492	6.8	135.3
Native Pupils	249.749	117.982	1	916
Total Teacher	12.672	5.919	1	99.1
Observations		19376		
Schools		9688		

6.3 Methodology

Initially, we regress the outcomes on the number of immigrants in two simple models specified below. Model (6.1) includes the number of immigrants and year dummies. Model (6.2) replaces the year dummies with local authority/year dummies. Local authorities are the basic level of local government in the UK and are equivalent to (parts of) cities or amalgamations of various towns and rural areas. This specification is more flexible than Model (6.1) in that it accounts for local authority-year-specific factors that might attract immigrants and are also related to school resources or outcomes. Examples would be changes to the local economy or city-specific changes to schools such as building programmes. It is important to be clear that Model (6.2) fully accounts for all factors that induce immigrants to select into specific cities. The variation used for the identification of the immigration effects then comes from the fact that immigrants are not uniformly distributed among school neighbourhoods in a local authority, meaning that some schools in a city are situated in areas with many immigrants and others in areas with comparatively few immigrants. Specifically, we estimate

$$Y_{slrt} = \alpha + \tau * Immigrants_{lt} + \phi_t + \varepsilon_{slrt} \qquad (6.1)$$

and

$$Y_{slrt} = \alpha + \tau * Immigrants_{lt} + \phi_{rt} + \varepsilon_{slrt} \qquad (6.2)$$

where Y_{slrt} is the outcome for school s in Lower Layer Super Output Area l in local authority r at time t. ϕ_t is a dummy for the year 2011, which is replaced by local authority-year effects ϕ_{rt} in model (6.2). The variable of interest, $Immigrants_{lt}$, is the number of immigrants (in 100s) living in LSOA l in year t. ε_{slrt} is the error term.

It is also important to be clear why we use immigrant numbers instead of the immigrant share in the population: If immigration causes a pressure on resources through population growth, using shares (i.e., dividing by population size) would take out the part of the effect of interest that operates through an increase in the population. Effectively, population size is an intermediate outcome and thus a bad control when trying to uncover the causal effect of immigration (see, for example, Angrist and Pischke, 2009, ch.

3.2.3).[45] We do not use a log-log specification for the model as almost all of our variables are already in percentages and using a log-log specification on variables in percentages makes the interpretation less convenient. However, we also estimated every model using immigrant shares as an additional robustness check. Results are qualitatively similar and can be found in the appendix D.

As there is likely to be non-random selection into schools by immigrants, and as this selection might well be due to more or less the same factors that influence settlement choice on the level of the local authorities, estimates based on model (6.2) are still likely to be biased. To attenuate these concerns, we add school fixed effects to models (6.1) and (6.2) to arrive at models (6.3) and (6.4).

$$Y_{slrt} = \alpha_s + \tau * Immigrants_{lt} + \phi_t + \varepsilon_{slrt} \qquad (6.3)$$

and

$$Y_{slrt} = \alpha_s + \tau * Immigrants_{lt} + \phi_{rt} + \varepsilon_{slrt} \qquad (6.4)$$

where α_s is the school fixed effect for school s. The inclusion of fixed effects controls for any time-invariant selection mechanism and for any time-invariant school characteristics. The variation used for identification in these models now come from the fact that some schools in a city will have experienced a greater influx of immigrants into their neighbourhood than other schools in the same city.[46]

However, even the use of fixed effects might not fully address the endogeneity problem caused by the non-random selection of immigrants into an area. Given the 10-year period covered by our data it is possible that there are time-varying factors affecting immigrant location choices that, even with the use of fixed effects, may lead to biased estimates of τ. To overcome these endogeneity problems we estimate two-stage least squares models using the residential-pattern instrument of Card and DiNardo (2000) and Card (2001).

[45] For the same reason, it would also not make sense to include population size as an additional right-hand side regressor.

[46] We also experimented with using MSOA or LSOA fixed effects instead of school fixed effects. Estimates were essentially identical.

To calculate the instrument we first calculate the percentage of immigrants that lived in each LSOA in 2001 as

$$\textit{Pct. Immigrants}_{l,\,2001} = \#\ \textit{immigrants}_{l,\,2001} \,/\, \textit{immigrants in England}_{2001}. \tag{6.5}$$

We then calculate the nationwide change in the number of immigrants in England as:

$$\Delta\ \textit{immig} = \#\ \textit{immigrants in England}_{2011} - \#\ \textit{immigrants in England}_{2001}. \tag{6.6}$$

From these, the shift-share predicted change in the number of immigrants in an LSOA can be calculated as:

$$R_l = \Delta\ \textit{immig} * \textit{Pct. Immigrants}_{l,2001}, \tag{6.7}$$

and the predicted number of immigrants in 2011 as:

$$\textit{Predicted \# of immigrants}_{l,\,2011} = \#\ \textit{of immigrants}_{l,2001} + R_l \tag{6.8}$$

We then use the predicted number of immigrants as an instrument for the actual number of immigrants. The logic underlying this approach is as follows: The predicted and actual numbers of immigrants should be correlated as immigrants are likely to settle in regions with a history of immigration. At the same time, as the instrument is a purely mechanical redistribution of nationwide changes in immigration based on historical settlement patterns, it should be uncorrelated with any changes in school quality and economic conditions that might affect immigrants' location choices. Ideally we would like to have considered the time period 1991 – 2011 however, this is not possible due to data limitations. However, in the worst case scenario, if the immigrants' location decisions in 2001 is already an outcome of the changes in school quality and economic conditions then our instrument constructed on historical settlement pattern may lack validity. Although, from the diagnostics in table 6.2, there is no weak instrument problem. This issue can be fully addressed by using the census data from 1991, which unfortunately cannot be used due to the unavailability of data at "Super Output Area" level.

Our instrument is constructed at the local area level and not the school level. As highlighted earlier, this allows us to estimate models for variables that vary at the school level. It also means that our estimates will incorporate neighbourhood peer effects – in cases where pupils share the same neighbourhood but not the same school – that may possibly affect school outcomes. This approach does not require the assumption that immigrants are randomly assigned to classes within schools. Table 6.2 shows the first stage results from two-stage least squares regressions.[47] The results demonstrate that the predicted number of immigrants is significantly correlated with the actual number of immigrants. The estimated coefficients are less than one, although they are very close to one for models (6.1) and (6.2). This is reflected in the very high R^2 statistics for these two models and suggests that the instrument may be indistinguishable from the actual number of immigrants. The results for models (6.3) and (6.4) are more reassuring, the estimated coefficients and the R^2 statistics are lower, reflecting the fact that once we control for school fixed effects and local authority/year dummies immigration patterns do vary, meaning that we have sufficient variation for identification. From the diagnostic statistics there does not seem to be any weak instrument problem.

Table 6.2: First stage results

	(1)	(2)	(3)	(4)
Shift-share predicted number of immigrants	0.92***	0.88***	0.72***	0.56***
	(0.01)	(0.01)	(0.02)	(0.04)
Kleibergen-Paap F stat (excl. instrument)	25979.11	7605.13	1260.91	260.094
R^2	0.90	0.92	0.57	0.67
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

[47] Table D 1 in appendix D presents the first stage results of all the specification when immigrant share is used instead of immigrant numbers. Whereas, Table E 1 in appendix E and Table F 1 in appendix F presents the first stage results of all the specifications of MSOA level data when immigrant numbers and immigrant shares are used respectively.

All models are estimated on balanced panels, as further robustness checks we also estimated all the models at the MSOA level, including the instrument generated at the MSOA level. We find that the results are essentially unchanged. Results estimated using MSOA level data with immigrant numbers are presented in appendix E and results estimated using MSOA level data with immigrant shares are presented in appendix F.

6.4 Results

We begin by looking at the results related to school resources displayed in table 6.3 The models in column (1) contain only year dummies and the variable of interest, while column (2) replaces the former with local-authority-year effects. Columns (3) and (4) are equivalent to (1) and (2) but additionally add school fixed effects.

The first thing to note is that all eight models show qualitatively identical results across all outcomes and only differ in magnitude. For an additional 100 immigrants in an LSOA, the OLS estimates suggest that schools receive on average 1 additional pupil who is eligible for assessment at Key Stage 2. The IV estimates are much larger and suggest growth by between 1 and almost 4 pupils, with larger estimates coming from our preferred specification with school fixed effects.

The estimates also suggest two somewhat different effects on the numbers of foreign and native pupils respectively. Note that these are changes to the absolute number of pupils, not just increase in the numbers of pupils eligible for Key Stage 2 assessments. As one might expect, immigration increases the number of non-native speakers considerably. The estimates range from 10 to almost 30, with our preferred models, those including school fixed effects, suggesting increases at the lower end of this range. For the number of native pupils, most estimates suggest a decrease following an increase in immigrants. These effects are also sizeable and range from -3 in the school fixed effects estimates to -18 in some other specifications. Counterintuitively, the IV results with school fixed effects actually suggest that an increase in immigration also causes an increase in the number of native pupils. These effects are also large and range from increases of 5 to 12. A potential explanation for these results is that schools expand in response to immigration, for example, by obtaining new buildings, and then subsequently accept more native and more immigrant pupils. In any case, all results point consistently towards an overall increase in the number of pupils in a given school caused by the increase in immigration.

We would expect that increases in school size have an impact on pupil-teacher ratios. However, our estimates suggest only relatively modest increases: Point estimates are usually relatively small and even the largest estimate of 0.9 is only equivalent to a roughly 0.25 standard deviation increase.

Given the previously mentioned evidence on increases in school size, the only potential explanation for this result is an increase in teacher numbers. In principle, schools can react to increases in pupil numbers by hiring additional teachers – schools with more pupils receive more resources, with a lag, through the current funding arrangements. The evidence in the final panel of table 6.3 suggests that this is what schools indeed do: All models suggest an increase in the number of teachers employed in a school with point estimates ranging from 0.2 to 1.3, with our preferred IV estimates suggesting an increase by 0.8 to 1.3 teachers.[48] These estimates suggest indeed that immigration has an impact on school resources: Schools receive more pupils and have to counter this effect by hiring additional teachers. The results on teacher-pupil-ratios suggest that they are broadly successful in this.

[48] Table D 2 in appendix D presents the results of immigration, pupil structure and resources when immigrant share is used instead of immigrant numbers. Table E 2 in appendix E and Table F 2 in appendix F presents the results of immigration, pupil structure and resources for MSOA level data when immigrant numbers and immigrant shares are used respectively.

Table 6.3: Immigration, pupil structure and resources

	(1)	(2)	(3)	(4)
Number of Pupils eligible for Key Stage 2 Assessment				
OLS				
Number of immigrants (in 100s)	1.39***	0.51***	1.08***	0.81***
	(0.11)	(0.16)	(0.10)	(0.13)
IV				
Number of immigrants (in 100s)	1.47***	0.91***	2.69***	3.88***
	(0.11)	(0.18)	(0.17)	(0.39)
Pupils whose first language is not English				
OLS				
Number of immigrants (in 100s)	24.90***	24.93***	13.39***	10.24***
	(0.51)	(0.87)	(0.52)	(0.61)
IV				
Number of immigrants (in 100s)	25.90***	29.02***	15.01***	11.50***
	(0.56)	(1.05)	(0.77)	(1.61)
Native Pupils				
OLS				
Number of immigrants (in 100s)	-6.78***	-16.69***	-3.02***	-3.95***
	(0.46)	(0.72)	(0.51)	(0.66)
IV				
Number of immigrants (in 100s)	-7.51***	-18.85***	5.73***	12.10***
	(0.49)	(0.84)	(0.84)	(2.02)
Pupil Teacher Ratio				
OLS				
Number of immigrants (in 100s)	-0.11***	-0.09***	0.11***	0.14***
	(0.01)	(0.02)	(0.04)	(0.04)
IV				
Number of immigrants (in 100s)	-0.11***	-0.07***	0.37***	0.91***
	(0.01)	(0.02)	(0.06)	(0.13)
Number of teachers				
OLS				
Number of immigrants (in 100s)	0.95***	0.45***	0.65***	0.24***
	(0.03)	(0.05)	(0.04)	(0.04)
IV				
Number of immigrants (in 100s)	0.98***	0.54***	1.26***	0.78***
	(0.04)	(0.06)	(0.07)	(0.14)
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

OLS and IV estimates for the educational outcomes of schools are presented in table 6.4.[49] For English, Mathematics and the school average point score, the OLS and IV results in columns (1) and (2) suggest that increasing immigration leads to worse school outcomes. The estimated coefficients are large and highly significant. The corresponding IV results are smaller in magnitude, but still support a detrimental effect of immigration on educational outcomes.

Once school fixed effects are included in the model (columns (3) and (4)), the results change considerably for both the OLS and the IV estimates. For mathematics, English and the average point score, increases in immigration now seem to cause increases in performance. IV estimates are again more positive, suggesting that the OLS estimates are negatively biased. The effects are not particularly large relative to the respective variable's standard deviation, but are too large to be completely negligible: The percentage of students achieving level 4 or above in the Key Stage 2 assessments increases by between 0.9 and 2 percentage points in English and by between 1.4 and 2.1 percentage points in Mathematics, while the school point average increases by between 0.07 and 0.25. These results are consistent with a recent suspicion in the popular press that immigrants who send their children to schools with poorer initial results are improving the outcomes of these schools (Cook, 2014; Cook, 2013). In any case, it is difficult to conclude from these results that immigration harms education outcomes in schools to any relevant degree.

It is possible that schools that face an inflow of immigrants maintain (or improve) performance by not submitting students for the Key Stage 2 exams. For example, a school with immigrants with low levels of English may find it worthwhile to not include them in assessment in order to maintain overall average performance. We investigate this by looking at the percentage of pupil failing to achieve a level in English and Maths due to absence or disapplication. The point estimates are usually small, often insignificant and

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[49] Table D 3 in appendix D presents the results of educational outcomes of schools when immigrant share is used instead of immigrant numbers. Table E 3 in appendix E and Table F 3 in appendix F presents the results of educational outcomes of schools for MSOA level data when immigrant numbers and immigrant shares are used respectively.

if anything negative, suggesting that immigration does not have any real impact – or a beneficial impact – on absence or disapplication. This suggests that schools have not been avoiding entering students for exams.

Table 6.4: Immigration and educational outcomes

	(1)	(2)	(3)	(4)
Percentage of Pupils achieving level 4 or above in English				
OLS				
Number of immigrants (in 100s)	-0.47***	-1.04***	1.46***	0.93***
	(0.05)	(0.09)	(0.14)	(0.17)
IV				
Number of immigrants (in 100s)	-0.28***	-0.76***	1.95***	1.79***
	(0.05)	(0.10)	(0.22)	(0.52)
Percentage of Pupils achieving level 4 or above in Maths				
OLS				
Number of immigrants (in 100s)	-0.43***	-0.94***	1.61***	1.35***
	(0.05)	(0.09)	(0.17)	(0.20)
IV				
Number of immigrants (in 100s)	-0.28***	-0.74***	1.81***	2.14***
	(0.05)	(0.10)	(0.25)	(0.58)
Average Point Score				
OLS				
Number of immigrants (in 100s)	-0.07***	-0.15***	0.14***	0.07***
	(0.01)	(0.01)	(0.02)	(0.02)
IV				
Number of immigrants (in 100s)	-0.04***	-0.11***	0.25***	0.24***
	(0.01)	(0.01)	(0.03)	(0.06)
Percentage of Pupils failing to achieve a level in English due to absence or disapplication				
OLS				
Number of immigrants (in 100s)	-0.04***	-0.01	-0.11***	-0.13***
	(0.01)	(0.01)	(0.03)	(0.03)
IV				
Number of immigrants (in 100s)	-0.04***	-0.01	-0.00	-0.03
	(0.01)	(0.01)	(0.04)	(0.10)
Percentage of Pupils failing to achieve a level in Maths due to absence or disapplication				
OLS				
Number of immigrants (in 100s)	-0.04***	-0.02	-0.08***	-0.10***
	(0.01)	(0.01)	(0.02)	(0.03)
IV				
Number of immigrants (in 100s)	-0.05***	-0.02**	0.03	-0.01
	(0.01)	(0.01)	(0.03)	(0.08)
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

6.5 Supplementary evidence on school spending and income

Arguably a more direct way to measure resource pressure on the education system would be to look into school budgets as done by, for example, Coen-Pirani (2011) and Speciale (2012). Unfortunately, data on school income and expenditures is only available from 2011 onwards. In this sub-section, we use data from the 2011 cross-section of the Department for Education's spend per pupil data, again linked to census data on the LSOA level and to teacher salary data from the Department for Education's school workforce data, to provide some additional insight whether schools in high-immigration areas face budget pressures. In the data, we have information on 13,758 primary schools. Table 6.5 presents summary statistics.

Table 6.5: Summary statistics spending sample

Variable	Mean	Std.Dev.
Total income (£ per pupil)	5293.6	5362.9
Total expenditure (£ per pupil)	5222.5	5241.6
Average annual gross salary of all full-time teachers in school	36852.4	3354.9
Spending for subgroups (£ per pupil)		
Teaching staff	2512.4	2007.6
Supply staff	169.5	195.0
Education support staff	1009.3	1702.2
Premises (incl. staff cost)	368.1	480.8
Back office (incl. staff cost)	400.6	511.4
Catering office (incl. staff cost)	90.4	181.7
Energy	74.3	86.6
Learning resources	205.6	244.3
Information and communication technology learning resources	60.2	88.7
Observations	13,758	

Given the fact that we only have a single cross-section of data available, we cannot estimate models with school fixed effects. Instead we begin by estimating simple bivariate OLS regressions with spending variables on the left hand side and the LSOA-level number of immigrants (in 100s) on the right hand side. We then subsequently add local authority fixed effects and finally instrument for the actual number of immigrants in the same way as in the previous section. These estimates are essentially identical to models (6.1) and (6.2) from the previous section. Table 6.6 presents first stage results for the IV regressions. These are very similar to the estimates for corresponding models in table 6.2.

In the context of school funding, the models with and without local authority fixed effects measure slightly different things due to the way funding is allocated in the UK: Essentially, local authorities receive grants from the central government that they then distribute across schools. The models without local authority fixed effects would include the effects of (the eventually) higher grants benefitting all schools in local authorities that have been hit by increased immigration. Obviously, these models are also more likely to suffer from biases due to the non-random selection of immigrants. The estimates with local authority fixed effects compare schools within local authorities and provide evidence whether schools in neighbourhoods with increased immigrant numbers can spend more or less per student. In other words, if the central government had allocated additional funds to a region with high immigration numbers, this effect would be included in the effect of immigration in the estimates without local authority fixed effects but would be captured by the fixed effect in models with local authority fixed effects.

Table 6.6: First stage results, spending sample

	(1)	(2)
Shift-share predicted number of immigrants	0.93***	0.86***
	(0.01)	(0.01)
Kleibergen-Paap F stat (excl. instrument)	21501.34	5810.42
R^2	0.93	0.95
# observations	13,758	13,758
Local authority effects	No	Yes

Table 6.7 presents estimation results for school spending and income.[50] For the OLS estimates in column (1), results show that total expenditure per pupil, total income per pupil, teaching staff per pupil, supply teachers per pupil, education staff per pupil and average salary of full-time teachers increase by £11.92 – £355 when there is an increase of 100 immigrants into the local area. There is an increase of £3.84 – £9.84 in the expenditure on premises, back office, catering, learning resources, and ICT learning resources when an additional 100 immigrants come into the local area. However, when local authority fixed effects are introduced into the model (column (2)) signs are reversed for almost all the coefficients. Similar story emerges when IV is used without the local authority fixed effects (column (3)), there is an increase of £4 – £410 in all the spending categories. When local authority fixed effects are introduced into the model (column (4)), results show that spending per pupil is reduced with statistical signigbetween £2 – £88 in spending categories namely, total expenditure, total income, average salary of full-time teachers, teaching staff, and energy.

Across almost all spending categories the results suggest essentially two things: First, all models without local authority fixed effects find that schools with more immigrants living nearby spend more per pupil than schools with fewer immigrants close by. Second, as soon as local authority fixed effects are included the picture is essentially reversed: While point estimates are generally smaller in absolute value and OLS estimates are often insignificant, the IV estimates indicate that per-pupil school income and spending drops the more immigrants live close by. These findings could be explained by a somewhat sluggish adjustment of individual school budgets to increases in the local population. The effects are small relative to the respective mean though, which again reaffirms our earlier findings that, while school resources seem to come under pressure, schools appear to be able to cope with these pressures.

[50] Table D 4 in appendix D presents the results for school spending and income when immigrant share is used instead of immigrant numbers.

Table 6.7: Immigration and school spending

	(1) OLS	(2) OLS	(3) IV	(4) IV
	Total expenditure (£/pupil)			
Number of immigrants (in 100s)	157.73***	-29.09	154.32***	-83.64*
	(22.34)	(38.56)	(22.41)	(49.34)
	Total income (£/pupil)			
Number of immigrants (in 100s)	162.29***	-31.30	158.74***	-88.29*
	(22.61)	(39.32)	(22.63)	(50.76)
	Average salary of full-time teacher			
Number of immigrants (in 100s)	355.31***	-82.86***	410.40***	-62.02***
	(16.31)	(20.56)	(17.58)	(23.95)
	Teaching staff (£/pupil)			
Number of immigrants (in 100s)	46.73***	-30.47*	47.68***	-46.42**
	(8.49)	(15.66)	(8.30)	(21.71)
	Supply teachers (£/pupil)			
Number of immigrants (in 100s)	11.92***	2.44*	12.41***	1.14
	(1.19)	(1.43)	(1.31)	(1.67)
	Education support staff (£/pupil)			
Number of immigrants (in 100s)	41.62***	-2.60	38.08***	-19.67
	(7.04)	(11.90)	(7.12)	(13.92)
	Premises (£/pupil)			
Number of immigrants (in 100s)	9.84***	-1.39	9.15***	-6.35
	(1.81)	(3.30)	(1.82)	(4.60)
	Back office (£/pupil)			
Number of immigrants (in 100s)	16.84***	-0.64	17.00***	-6.24
	(2.27)	(3.84)	(2.32)	(4.21)
	Catering (£/pupil)			
Number of immigrants (in 100s)	7.83***	2.96***	7.20***	0.09
	(0.48)	(0.73)	(0.51)	(0.93)
	Energy (£/pupil)			
Number of immigrants (in 100s)	-0.01	-0.47	-0.28	-1.57***
	(0.36)	(0.56)	(0.35)	(0.60)
	Learning resources (£/pupil)			
Number of immigrants (in 100s)	5.51***	1.39	4.96***	-0.50
	(1.51)	(2.08)	(1.45)	(2.16)
	ICT Learning resources (£/pupil)			
Number of immigrants (in 100s)	3.84***	0.41	3.97***	-0.54
	(0.43)	(0.72)	(0.42)	(1.01)
Local authority FEs	No	Yes	No	Yes
Observations	13758	13758	13758	13758

Coefficients, robust standard errors in parentheses.
Significance levels: *10%, **5%, ***1%

6.6 Conclusion

This chapter investigates the impact of immigration on school resources and educational outcomes. It uses panel data and IV methods that allow us to control for endogeneity and unobservable heterogeneity providing robust causal estimates of the impact of immigration. Our results demonstrate that immigration has had an impact at the school level. As immigration increases the number of pupils and the number of non-English speaker pupils increases, there is some evidence of native flight from schools but this disappears when we control for endogeneity and school fixed effects. Further, the estimates for the number of native pupils (leaving) are always smaller than for the number of non-English speaking pupils, suggesting a net increase in pupils in all estimated models. In response to these changes schools have employed more teachers, largely maintaining school pupil-teacher ratios. They also appear to be spending somewhat less on each pupil in a range of categories.

When we consider school achievements we see that increasing the number of immigrants has improved school outcomes, especially the percentages of pupils achieving level 4 or above competency in the Key Stage 2 assessments in Maths and English, as well as schools' average point scores. A potential explanation for these results is positive selection that immigrants generally have higher educational levels than natives (Dustmann and Glitz, 2011; Dustmann et al., 2011) and immigrants normally demonstrate high levels of aspiration for both themselves and their children. Both of these factors might have an effect on overall school performance and can potentially lead to positive spillovers to natives as overall standards improve. It has in fact been suggested in the popular press that the improvement in results in inner city London schools for both immigrants and non-immigrant children is partly due to highly motivated immigrant children (Cook, 2014; Cook, 2013). Similarly a recent study by Burgess (2014) found that ethnic composition of schools in inner London is the main reason for their better performance in the GCSE exams.

However, some degree of heterogeneity is expected in this positive effect of immigration on educational outcomes. This heterogeneity of immigrants could not be controlled for because of the data constraints. Generally, immigrants with higher educational levels come from the commonwealth countries whereas immigrants from non-English speaking countries are less educated. It gives rise to the issue of positive vs. negative selection of immigrants. It is possible that these two groups of immigrants have a different effect on the educational outcomes. For instance, in the worst case scenario, even if the negatively selected immigrants have a negative effect on educational outcomes of schools. Still the positive effect of positively selected immigrants is big enough that is shown by our analysis. We can expect that if the data would have allowed us to control for the heterogeneity of immigrants, this positive effect of immigrants on educational outcomes would be higher in magnitude that may have been decreased at the moment by negatively selected immigrants.

Our results for education outcomes are very similar to the findings for natives by Geay et al. (2013), even though we use a different identification strategy. While our results are robust for the data used and the time period considered some caution is required. The results suggest that increasing immigration is a good thing for school performance, and that schools have mitigation issues around more pupils, and more pupils from non-English speaking backgrounds by employing more teachers. However, with fixed budgets it would be a mistake to think that increasing immigration indefinitely would be a good thing. At some point resource constraints would become binding and it may be that immigration starts to have a detrimental impact on schools. In fact, within our sample, there may be school where immigration has caused resource and achievement difficulties, even though there seems to have been a positive effect on average. Furthermore, it is possible that in order to meet the resource demands for primary schools there have been negative impacts for secondary schools, or other parts of the education sector. Finally, Local Authorities and central Government may have diverted resources away from other public services, such as health care, personal care, or local facilities. Such wider budget issues are beyond the scope of this chapter.

Overall, we can see that over our observation period, immigration has placed schools under resource pressure, and that schools have responded to this pressure by employing more teachers. We can also see immigration has benefits for school outcomes, improving average achievement and potentially having spill-over benefits for English speaking students.

Chapter 7. Conclusion

The novel and innovative points of this thesis are: a) it is an addition to a very small existing literature that looks into the views of immigrants towards further immigration, b) an examination of the role of the labour market in determining views towards further immigration, and c) it simultaneously estimates the trade-off between increased expenditures and improved educational outcomes/school outcomes as a consequence of increased immigration in the local area. The following sections present, the brief summary of this thesis, how its findings fit into the wider literature, impact of this piece of work and policy implications of this research.

7.1 Views of Immigrants towards Immigration

We investigate how immigrants view further immigration, and how these views may change between natives, earlier and more recent immigrants. We find that there is a clear heterogeneity in the attitudes of immigrants towards further immigration. Immigrants who have been in the UK within last five years are less opposed to immigration than immigrants who have been in the UK more than five years ago. The results for earlier immigrants consistently lie between those of natives and recent immigrants.

There are essentially two explanations why earlier immigrants are more similar to natives than recent ones. The first is that as time passes immigrants integrate into British society and adopt natives' attitudes towards further immigration as well. In a recent research, Just and Anderson (2015), find that foreign-born immigrants who get citizenship in the host country become opposed to further immigration. Similarly, Manning and Roy (2010) find the cultural integration of immigrants; they appear to become more similar to natives the longer they have been in the country.

The second explanation is essentially self-selection but the limited available information in the data, in particular the fact that we do not observe immigrants who have left, does not allow this to be tested. It could be the case that only those immigrants who are similar to natives (more opposed to further immigration) stay in the country, while other immigrants, with favourable views, leave. This does not seem logical because if an immigrant wants to leave then why he would favour further immigration. However, this could be linked to family reunification motives, there is some evidence found by Just and Anderson (2015) that this pro-immigration attitude of immigrants (immigrants without citizenship of the host country) stems from kinship, solidarity and unity sentiments for their fellow immigrants. However, this explanation also suffers from selection bias as every immigrant cannot apply for citizenship due to visa restrictions and we do not know that would the immigrants who left, given a chance, had they applied for citizenship.

7.2 Financial and Economic Concerns

Results on the income of natives and earlier immigrants suggest a clear gradient for respondents with higher income favouring further immigration, whereas there is some evidence for an inverted U-shape for recent immigrants. Income matters, even though the exact effects differ at low incomes between recent immigrants and natives and earlier immigrants. A potential explanation for this result is that low-income recent immigrants have concerns that family reunification may be made harder by tougher immigration laws, and these worries may overwhelm other concerns. Just and Anderson (2015), also find that family reunification – solidarity and kinship is what they call it – is positively associated with the attitudes of immigrants towards further immigration.

We further find evidence in all three groups that economic shocks such as job loss or drops in income matter, even when holding employment status and the level of income constant. Economic shocks tend to be associated with more anti-immigration views. This result suggests that people might be blaming immigrants for adverse shocks, regardless of whether they recover from the respective shock. This is in line with the findings of Gang, Rivera-Batiz and Yun (2013) and Malchow-Moller et al., (2008).

7.3 Labour Market Concerns

For the most part, this thesis is unable to find any strong consistent evidence that the anti-immigration views of natives, earlier and recent immigrants towards further immigration are associated with the labour market outcomes. We find that employment status does not play a large role in explaining anti-immigration views. Even if the earlier immigrants and recent immigrants compete in the labour market, as suggested by the findings of Ottaviano and Peri (2012) and Dustmann et al. (2013), there is no strong evidence that the current employment status affects views towards further immigration.

Furthermore, the views of native males largely remain unchanged on retirement from the paid work and exit from the labour market. This shows that the labour market does not play any large role in determining views towards further immigration. This finding is in line with the previous literature (see, for example, Card et al., 2005; Citrin et al., 1997; Dustmann and Preston, 2007; Dustmann and Preston, 2004; Dustmann and Preston, 2001; Rustenbach, 2010). Views of native males towards immigration should essentially change on exit from the labour market. If the labour market affects views towards immigration then once a person is out of the labour market he should care less about immigration as he no longer faces the immigrant competition in the labour market. Our OLS results suggest that exit from the labour market does not change the views of native males towards further immigration.

Whereas, after controlling for the selection bias and endogeneity bias, using IV regressions, we see a similar picture – for the full sample models – that the views of retired natives do no change as compared to the ones who are still in the labour market. It means that labour market does not play an important role in determining views towards further immigration.

However, we do find some evidence of native males' reduced opposition towards further immigration after they exit from the labour market suggesting – in line with the finding of Ortega and Polavieja (2012) – that labour market concerns do play some role in determining native males' attitudes towards immigration. This finding could not be substantiated because of fewer observations available for estimation, when respondents reporting "remain the same" to immigration question are dropped from the estimated sample. So a careful interpretation is required at this stage that native males become less opposed to immigration on exit from the labour market, compared to still working native males.

7.4 Impact of Immigration on School Resources

As immigration increases in local areas, the number of pupils and the number of non-English speaker pupils increases in schools. In response to this increase in schools, there is some evidence of native flight from schools but this disappears when we control for endogeneity and school fixed effects. Further, the estimates for the number of native pupils (leaving) are always smaller than for the number of non-English speaking pupils, suggesting a net increase in pupils. In response to these changes schools have employed more teachers, largely maintaining school pupil-teacher ratios. They also appear to be spending somewhat less on each pupil in a range of categories. This finding is in line with Coen-Pirani (2011) for Mexican immigrants in California and Speciale (2012) for 15 EU-enlargement countries.

The results suggest that increasing immigration is a good thing for school performance, and that schools have mitigation issues around more pupils, and more pupils from non-English speaking backgrounds by employing more teachers. However, with fixed budgets it would be a mistake to think that increasing immigration indefinitely would be a good thing. At some point resource constraints would become binding and it may be that immigration starts to have a detrimental impact on schools. In fact, within our sample, there may be schools where immigration has caused resource and achievement difficulties, even though there seems to have been a positive effect on average.

Overall, we can see that over our observation period, immigration has placed schools under resource pressure, and that schools have responded to this pressure by employing more teachers. Furthermore, it is possible that in order to meet the resource demands for primary schools there have been negative impacts for secondary schools, or other parts of the education sector. Finally, Local Authorities and central Government may have diverted resources away from other public services, such as health care, personal care, or local facilities. Such wider budget issues are beyond the scope of this thesis.

7.5 Impact of Immigration on Educational Outcomes

We find immigration has benefits for school outcomes, improving average achievement and potentially having spill-over benefits for English speaking students. Our results for education outcomes are very similar to the recent findings for natives by Burgess (2014), and Geay et al. (2013), even though we use a different identification strategy. While our results are robust for the data used and the time period considered some caution is required. We find that increases in immigration in local areas improved the educational outcomes in English and Maths. We also find that there is a rise in school attendance on the face of increases in immigration. Panel data and IV methods allows us to control for endogeneity and unobservable heterogeneity that provide robust causal estimates of the impact of immigration.

Our results demonstrate that immigration has had an impact at the school level. We see that increasing the number of immigrants has improved school outcomes, especially the percentages of pupils achieving level 4 or above competency in the Key Stage 2 assessments in Maths and English, as well as schools' average point scores. A potential explanation for these results is that immigrants generally have higher educational levels than natives (see, for example, Dustmann and Glitz, 2011; Dustmann et al., 2011) and immigrants normally demonstrate high levels of aspiration for both themselves and their children. Both of these factors might have an effect on overall school performance and can potentially lead to positive spill-overs to natives as overall standards improve.

It has in fact been suggested in the popular press that the improvement in results in inner city London schools for both immigrants and non-immigrant children is partly due to highly motivated immigrant children (Cook, 2014; Cook, 2013). Similarly, recent study of Burgess (2014) strengthens our findings that presence of ethnic minority pupils in primary schools lead towards better primary school results.

7.6 Research Impact and Policy Implications

This research will have a larger impact and implications on the immigration policies, integration policies, education policies, public policies, and prioritization of budget allocation in the education sector. This thesis highlights the fact that immigration and attitudes towards further immigration are not straightforward and easy to understand. There is a complex interaction of variables playing their role in shaping attitudes towards further immigration. Attitudes towards immigration is not just a simple issue but a complex interplay of economic, political, social and personal factors chipping in to form the individuals' attitudes.

This thesis highlights the fact that the views of immigrants towards further immigration cannot be neglected. As the world has become a global village, and immigration is increasing into developed countries in general and into English speaking countries such as the UK in particular, this research helps in understanding the attitudes of immigrants. It calls for the attention that the governments should design immigration policies considering immigrants as a stake holder in the country. This will give them a sense of ownership and help in better integration of immigrants into the society. This research can help the policy makers to design better immigration policies and integration policies to build a well-integrated society. A well-integrated community can help promote the culture of acceptance and tolerance which in-turn will help in forming better attitudes towards a rapidly diversifying global village.

My research can help in designing better education policies; the research suggests how primary schools can be improved. Policy makers should form policies to encourage diversity in schools to strike a good balance of immigrant and native pupils in the primary schools. This can lead to better performance in primary schools as well as this will also show up in the GCSE exams as found by Greaves et al. (2014) that better primary school results are the basic reason of better performance in GCSE exams. This research will have impact on public policy design, on education policies, and can help in better budget allocations in the education sector. It has impact on public expenditure and draws attention towards prioritising the budget allocation by finding the trade-offs between expenditure on primary schools and improved school outcomes in the face of increased immigration into the local areas. However, this is just a starting point, further research is required to substantiate the amount of trade-offs.

7.7 Further Research Possibilities

This thesis is just the beginning for many new research possibilities in the area of immigration. An immediate idea for further expansion of this research would be to explore how the attitudes of natives and immigrants change on the face of increased immigration in local areas. Although, data at low level geographical areas is not available publically for the UK Citizenship Surveys but it would be worthwhile to contact data providers and request them data at low level geographical areas.

As this thesis also sheds light on the impact of immigration in local areas on primary schools and educational outcomes of pupils. Similarly, in public services, impact of immigration on NHS (National Health Service, UK) waiting times in local areas and how these waiting times change the attitudes of local population towards immigration can be investigated. Not only this, impact of immigration on general health of natives in local areas can also be investigated. Another very interesting research topic is to investigate the impact of obtaining the citizenship, do immigrants stay in the UK longer to acquire the British passport and then leave after obtaining citizenship. As, British passport brings ease of mobility around the world and is listed as one of the most powerful passports in the world with visa-free/ visa on arrival entry into several countries.

Nevertheless, data limitations may obstruct the above listed research ideas. However, data limitations can be addressed by exploring other data sources or by gathering new data.

Chapter 8. Appendices

8.1 Appendix A: OLS estimates for with and without education variables excluding respondents over 65 years of age

Table A 1: Descriptive Statistics of Natives (Excluding over 65)

Variable	Obs	Mean	Std. Dev.	Min	Max
redmig	15069	.8041675	.3968534	0	1
incmig	15069	.1958325	.3968534	0	1
outoflabfo~e	15069	.1408189	.3478462	0	1
selfemployed	15069	.0867344	.2814547	0	1
unemployed	15069	.163979	.3702688	0	1
employed	15069	.6084677	.4881092	0	1
male	15069	.447674	.497271	0	1
female	15069	.552326	.497271	0	1
w200708	15069	.3219192	.4672277	0	1
w200809	15069	.3251709	.4684542	0	1
w200910	15069	.3529099	.4778909	0	1
rage	15069	42.09483	13.39646	16	64
white	15069	.9461809	.2256679	0	1
subcont	15069	.0201075	.1403727	0	1
otherasian	15069	.0009954	.0315356	0	1
black	15069	.0131396	.1138761	0	1
mixedrace	15069	.0135377	.1155653	0	1
chinese	15069	.0000664	.0081463	0	1
otherethnic	15069	.0059725	.0770535	0	1
christ	15069	.734488	.4416201	0	1
budh	15069	.0023226	.0481395	0	1
hindu	15069	.0019908	.0445759	0	1
jew	15069	.0030526	.055168	0	1
muslim	15069	.0215011	.1450524	0	1
sikh	15069	.001659	.0406988	0	1

othreli	15069	.0189794	.1364565	0	1
noreli	15069	.2160064	.4115323	0	1
reliyes	15069	.2244343	.4172231	0	1
hdegree	15069	.0727321	.2597049	0	1
fdegree	15069	.1483177	.3554265	0	1
alevel_equiv	15069	.2611985	.4393025	0	1
otherqual	15069	.0529564	.2239539	0	1
Noqual	15069	.179773	.384011	0	1
Relino	15069	.7755657	.4172231	0	1
hdegree	15069	.0727321	.2597049	0	1
fdegree	15069	.1483177	.3554265	0	1
alevel_equiv	15069	.2611985	.4393025	0	1
olevel_equiv	15069	.2850222	.45144	0	1
otherqual	15069	.0529564	.2239539	0	1
Noqual	15069	.179773	.384011	0	1
incomebel~5k	15069	.1901254	.392413	0	1
income5k~10k	15069	.1603955	.3669846	0	1
income10~15k	15069	.1401553	.3471596	0	1
income15~20k	15069	.1233659	.3288676	0	1
income20~30k	15069	.1791758	.3835122	0	1
income30~50k	15069	.1515031	.3585505	0	1
income50kp	15069	.055279	.2285317	0	1
London	15069	.088327	.2837793	0	1
northeast	15069	.0619152	.2410094	0	1
northwest	15069	.1412834	.3483252	0	1
yorknhumber	15069	.1055146	.3072256	0	1
eastmidland	15069	.0912469	.2879695	0	1
westmidland	15069	.1053819	.3070551	0	1
eastengland	15069	.1042538	.3055996	0	1
southeast	15069	.1435397	.350634	0	1
southwest	15069	.0939677	.2917935	0	1
Wales	15069	.0645696	.2457731	0	1

Table A 2: Descriptive Statistics of Earlier Immigrants (Excluding over 65)

Variable	Obs	Mean	Std. Dev.	Min	Max
redmig	7077	.5086901	.4999598	0	1
incmig	7077	.4913099	.4999598	0	1
outoflabfo~e	7077	.2344214	.4236666	0	1
selfemployed	7077	.0934012	.2910143	0	1
unemployed	7077	.1677264	.3736496	0	1
employed	7077	.504451	.5000155	0	1
male	7077	.4679949	.4990099	0	1
female	7077	.5320051	.4990099	0	1
w200708	7077	.2920729	.4547478	0	1
w200809	7077	.3334746	.4714878	0	1
w200910	7077	.3744525	.4840154	0	1
rage	7077	41.82125	11.34203	16	64
white	7077	.0674014	.2507337	0	1
subcont	7077	.4631906	.4986785	0	1
otherasian	7077	.0611841	.2396847	0	1
black	7077	.2568885	.4369483	0	1
mixedrace	7077	.0356083	.1853246	0	1
chinese	7077	.027978	.1649213	0	1
otherethnic	7077	.087749	.2829496	0	1
christ	7077	.3146814	.4644217	0	1
budh	7077	.0173802	.1306927	0	1
hindu	7077	.134379	.3410831	0	1
jew	7077	.0019782	.0444365	0	1
muslim	7077	.4175498	.49319	0	1
sikh	7077	.0491734	.2162452	0	1
othreli	7077	.0235976	.1518024	0	1
noreli	7077	.0412604	.198906	0	1
reliyes	7077	.7354811	.4411078	0	1
hdegree	7077	.1141727	.3180433	0	1
fdegree	7077	.1427158	.3498075	0	1
alevel_equiv	7077	.1877914	.3905731	0	1
otherqual	7077	.1167161	.3211044	0	1

noqual	7077	.282323	.4501615	0	1
relino	7077	.2645189	.4411078	0	1
hdegree	7077	.1141727	.3180433	0	1
fdegree	7077	.1427158	.3498075	0	1
alevel_equiv	7077	.1877914	.3905731	0	1
olevel_equiv	7077	.1562809	.3631471	0	1
otherqual	7077	.1167161	.3211044	0	1
noqual	7077	.282323	.4501615	0	1
incomebel~5k	7077	.2590081	.438121	0	1
income5k~10k	7077	.1658895	.3720077	0	1
income10~15k	7077	.1555744	.362477	0	1
income15~20k	7077	.1121944	.3156278	0	1
income20~30k	7077	.1630634	.3694497	0	1
income30~50k	7077	.1080967	.3105244	0	1
income50kp	7077	.0361735	.1867349	0	1
london	7077	.5515049	.4973753	0	1
northeast	7077	.0077717	.08782	0	1
northwest	7077	.0750318	.2634613	0	1
yorknhumber	7077	.066271	.2487728	0	1
eastmidland	7077	.0641515	.2450399	0	1
westmidland	7077	.1000424	.3000777	0	1
eastengland	7077	.0486082	.2150627	0	1
southeast	7077	.0666949	.2495105	0	1
southwest	7077	.0128586	.1126721	0	1
wales	7077	.0070651	.0837629	0	1

Table A 3: Descriptive Statistics of Recent Immigrants (Excluding over 65)

Variable	Obs	Mean	Std. Dev.	Min	Max
redmig	2429	.3342939	.4718402	0	1
incmig	2429	.6657061	.4718402	0	1
outoflabfo~e	2429	.2136682	.4099796	0	1
selfemployed	2429	.0386991	.1929165	0	1
unemployed	2429	.1811445	.3852172	0	1
employed	2429	.5664883	.4956616	0	1
male	2429	.5372581	.4987126	0	1
female	2429	.4627419	.4987126	0	1
w200708	2429	.3120626	.4634306	0	1
w200809	2429	.3528201	.4779457	0	1
w200910	2429	.3351173	.4721287	0	1
rage	2429	31.04446	8.80788	16	63
white	2429	.1123919	.3159131	0	1
subcont	2429	.389049	.4876349	0	1
otherasian	2429	.0773981	.2672771	0	1
black	2429	.2013174	.4010672	0	1
mixedrace	2429	.0349938	.183802	0	1
chinese	2429	.0489914	.2158944	0	1
otherethnic	2429	.1358584	.3427087	0	1
christ	2429	.3692878	.4827113	0	1
budh	2429	.037464	.1899349	0	1
hindu	2429	.1515027	.358612	0	1
jew	2429	.0012351	.0351292	0	1
muslim	2429	.3285303	.4697755	0	1
sikh	2429	.0271717	.1626169	0	1
othreli	2429	.021408	.1447699	0	1
noreli	2429	.0634006	.2437322	0	1
reliyes	2429	.7134623	.4522367	0	1
hdegree	2429	.2041993	.4031983	0	1
fdegree	2429	.2009057	.4007602	0	1
alevel_equiv	2429	.1683821	.3742823	0	1
otherqual	2429	.1757925	.3807219	0	1

noqual	2429	.161795	.3683385	0	1
relino	2429	.2865377	.4522367	0	1
hdegree	2429	.2041993	.4031983	0	1
fdegree	2429	.2009057	.4007602	0	1
alevel_equiv	2429	.1683821	.3742823	0	1
olevel_equiv	2429	.0889255	.2846948	0	1
otherqual	2429	.1757925	.3807219	0	1
noqual	2429	.161795	.3683385	0	1
incomebel~5k	2429	.3441746	.4751962	0	1
income5k~10k	2429	.1634417	.3698444	0	1
income10~15k	2429	.1626184	.3690931	0	1
income15~20k	2429	.0963359	.2951122	0	1
income20~30k	2429	.1263895	.3323562	0	1
income30~50k	2429	.0712227	.2572495	0	1
income50kp	2429	.0358172	.1858724	0	1
london	2429	.4676822	.4990572	0	1
northeast	2429	.0222314	.1474656	0	1
northwest	2429	.086867	.2816981	0	1
yorknhumber	2429	.0827501	.2755609	0	1
eastmidland	2429	.0765747	.2659702	0	1
westmidland	2429	.0798683	.271145	0	1
eastengland	2429	.0551667	.2283524	0	1
southeast	2429	.0963359	.2951122	0	1
southwest	2429	.0238781	.1527009	0	1
wales	2429	.0086455	.0925976	0	1

Excluding over 65, OLS with education variables

Table A 4: Pooled sample excluding over 65 for Natives, Earlier Immigrants, and Recent Immigrants (Regression without controls)

Linear regression		Number of obs	= 24575
		F(2, 24572)	= 1765.84
		Prob > F	= 0.0000
		R-squared	= 0.1347
		Root MSE	= .43653

redmig Coef.	Robust Std. Err.	t	P>t	[95% Conf. Interval]	
recmig -.4698735	.0101036	-46.51	0.000	-.4896771	-.45007
oldmig -.2954774	.0067655	-43.67	0.000	-.3087381	-.2822167
_cons .8041675	.003233	248.74	0.000	.7978307	.8105043

Excluding over 65, OLS with education variables

Table A 5: Pooled sample excluding over 65 for Natives, Earlier Immigrants, and Recent Immigrants (Regression with controls)

Linear regression		Number of obs =	24575
		F(90, 24484) =	68.54
		Prob > F =	0.0000
		R-squared =	0.1941
		Root MSE =	.42203

redmig	Coef.	Robust Std. Err.	t	P>t [95% Conf. Interval]
recmig	-.2656153	.0156685	-16.95	0.000 -.2963265 -.2349041
oldmig	-.1285076	.0137897	-9.32	0.000 -.1555364 -.1014789
female	.0129838	.0059186	2.19	0.028 .001383 .0245846
outoflabforce	-.027449	.0088573	-3.10	0.002 -.0448097 -.0100882
selfemployed	.0003738	.0100962	0.04	0.970 -.0194153 .0201629
unemployed	.0051968	.0083052	0.63	0.531 -.0110818 .0214755
w200809	-.0340343	.0066912	-5.09	0.000 -.0471494 -.0209192
w200910	-.0272757	.0066403	-4.11	0.000 -.0402911 -.0142603
subcont	-.014018	.0183236	-0.77	0.444 -.0499334 .0218973
otherasian	-.0779673	.0246782	-3.16	0.002 -.1263381 -.0295966
black	-.1808915	.0161639	-11.19	0.000 -.2125736 -.1492093
mixedrace	-.0863482	.0223274	-3.87	0.000 -.1301112 -.0425851
chinese	-.0784435	.0301875	-2.60	0.009 -.1376128 -.0192742
otherethnic	-.0588024	.0200628	-2.93	0.003 -.0981268 -.0194781
budh	-.0821899	.0310162	-2.65	0.008 -.1429835 -.0213963
hindu	.0064433	.0191237	0.34	0.736 -.0310404 .043927
jew	-.1532751	.0562089	-2.73	0.006 -.263448 -.0431023
muslim	-.1010983	.014369	-7.04	0.000 -.1292625 -.0729341
sikh	.008652	.027185	0.32	0.750 -.0446323 .0619363
othreli	-.0051093	.0203196	-0.25	0.801 -.044937 .0347184
noreli	-.0648909	.0081758	-7.94	0.000 -.080916 -.0488658
reliyes	-.0498248	.0069988	-7.12	0.000 -.0635428 -.0361068
hdegree	-.2090159	.0121043	-17.27	0.000 -.2327411 -.1852907
fdegree	-.1454938	.0097331	-14.95	0.000 -.1645713 -.1264163
alevel_equiv	-.0332974	.0075267	-4.42	0.000 -.0480502 -.0185446
otherqual	-.0396974	.0110616	-3.59	0.000 -.0613788 -.018016
noqual	-.0357149	.0080414	-4.44	0.000 -.0514765 -.0199533
incomebelow5k	-.0132618	.0097459	-1.36	0.174 -.0323644 .0058408
income5kto10k	-.0001893	.009563	-0.02	0.984 -.0189333 .0185548

income15kto20k	.0025668	.010428	0.25	0.806	-.0178727	.0230064
income20kto30k	-.012556	.0098232	-1.28	0.201	-.0318101	.0066982
income30kto50k	-.0361282	.011002	-3.28	0.001	-.0576927	-.0145636
income50kp	-.051269	.0158817	-3.23	0.001	-.0823982	-.0201399
northeast	.051951	.0145998	3.56	0.000	.0233345	.0805676
northwest	.068497	.0109621	6.25	0.000	.0470107	.0899834
yorknhumber	.0648872	.0115832	5.60	0.000	.0421835	.0875909
eastmidland	.1049043	.0115721	9.07	0.000	.0822224	.1275862
westmidland	.0970801	.0110319	8.80	0.000	.0754569	.1187032
eastengland	.0998146	.0116786	8.55	0.000	.0769238	.1227054
southeast	.0716778	.0108655	6.60	0.000	.0503808	.0929748
southwest	.0734243	.0127525	5.76	0.000	.0484286	.0984199
wales	.0803251	.0145838	5.51	0.000	.05174	.1089103
ragedumy1	0	(omitted)				
ragedumy2	.0008219	.0385507	0.02	0.983	-.0747398	.0763836
ragedumy3	.0308785	.039764	0.78	0.437	-.0470615	.1088184
ragedumy4	-.0070352	.0383554	-0.18	0.854	-.082214	.0681437
ragedumy5	.0330304	.0381659	0.87	0.387	-.0417771	.1078379
ragedumy6	.0243337	.0369169	0.66	0.510	-.0480256	.096693
ragedumy7	.0213348	.0374104	0.57	0.568	-.051992	.0946615
ragedumy8	.0329695	.036518	0.90	0.367	-.038608	.1045471
ragedumy9	.0901233	.0357297	2.52	0.012	.0200909	.1601557
ragedumy10	.0434823	.0355365	1.22	0.221	-.0261715	.113136
ragedumy11	.0607428	.0351485	1.73	0.084	-.0081504	.1296359
ragedumy12	.0363631	.0345207	1.05	0.292	-.0312996	.1040258
ragedumy13	.0319744	.0342199	0.93	0.350	-.0350987	.0990475
ragedumy14	.0514918	.0340598	1.51	0.131	-.0152675	.118251
ragedumy15	.0486673	.0341092	1.43	0.154	-.0181888	.1155235
ragedumy16	.0562778	.0346953	1.62	0.105	-.011727	.1242826
ragedumy17	.0825642	.0342034	2.41	0.016	.0155235	.1496049
ragedumy18	.0572797	.0339937	1.69	0.092	-.0093501	.1239095
ragedumy19	.0394883	.0340267	1.16	0.246	-.027206	.1061827
ragedumy20	.0833633	.0331468	2.51	0.012	.0183936	.148333
ragedumy21	.0724134	.0337713	2.14	0.032	.0062196	.1386071
ragedumy22	.099711	.0333454	2.99	0.003	.0343519	.1650701
ragedumy23	.0586328	.033348	1.76	0.079	-.0067313	.1239969
ragedumy24	.0604574	.0338583	1.79	0.074	-.0059068	.1268217
ragedumy25	.0647324	.0333811	1.94	0.052	-.0006966	.1301614
ragedumy26	.0708446	.0345309	2.05	0.040	.003162	.1385273
ragedumy27	.0992267	.0330075	3.01	0.003	.03453	.1639233
ragedumy28	.0972129	.0334954	2.90	0.004	.0315599	.162866
ragedumy29	.0973861	.0334613	2.91	0.004	.0317998	.1629723

ragedumy30	.1209461	.0334132	3.62	0.000	.0554543	.186438
ragedumy31	.1077106	.033961	3.17	0.002	.041145	.1742761
ragedumy32	.1159369	.0340227	3.41	0.001	.0492502	.1826235
ragedumy33	.1063877	.0341973	3.11	0.002	.0393589	.1734164
ragedumy34	.1201133	.0345217	3.48	0.001	.0524486	.1877779
ragedumy35	.1042066	.0343246	3.04	0.002	.0369283	.1714848
ragedumy36	.1196759	.0346762	3.45	0.001	.0517085	.1876433
ragedumy37	.1068181	.034054	3.14	0.002	.0400701	.173566
ragedumy38	.1360489	.0343998	3.95	0.000	.0686232	.2034746
ragedumy39	.1556691	.0340606	4.57	0.000	.0889083	.2224299
ragedumy40	.1406309	.0344589	4.08	0.000	.0730894	.2081724
ragedumy41	.092723	.035408	2.62	0.009	.0233211	.1621248
ragedumy42	.1327757	.0343633	3.86	0.000	.0654216	.2001298
ragedumy43	.1040966	.0343756	3.03	0.002	.0367182	.1714749
ragedumy44	.1417467	.033927	4.18	0.000	.0752476	.2082457
ragedumy45	.1430661	.0330846	4.32	0.000	.0782183	.207914
ragedumy46	.1533309	.0333127	4.60	0.000	.0880361	.2186258
ragedumy47	.1430479	.033285	4.30	0.000	.0778072	.2082885
ragedumy48	.1540223	.0333289	4.62	0.000	.0886956	.2193489
ragedumy49	.152104	.0338011	4.50	0.000	.0858518	.2183562
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				

ragedumy72	0	(omitted)					
ragedumy73	0	(omitted)					
ragedumy74	0	(omitted)					
ragedumy75	0	(omitted)					
ragedumy76	0	(omitted)					
ragedumy77	0	(omitted)					
ragedumy78	0	(omitted)					
ragedumy79	0	(omitted)					
ragedumy80	0	(omitted)					
ragedumy81	0	(omitted)					
ragedumy82	0	(omitted)					
ragedumy83	0	(omitted)					
ragedumy84	0	(omitted)					
ragedumy85	0	(omitted)					
_cons	.7577574	.0310515		24.40	0.000	.6968944	.8186203

Excluding over 65, OLS with education variables

Table A 6: Natives Sample

Linear regression	Number of obs =	15069
	F(87, 14980) =	.
	Prob > F =	.
	R-squared =	0.1083
	Root MSE =	.37585

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
female	.0052152	.006897	0.76	0.450	-.0083037	.0187341
outoflabforce	-.0097036	.0103372	-0.94	0.348	-.0299657	.0105585
selfemployed	.0101639	.0112558	0.90	0.367	-.0118988	.0322267
unemployed	.009246	.0093805	0.99	0.324	-.0091409	.0276328
w200809	-.027164	.0075556	-3.60	0.000	-.0419738	-.0123541
w200910	-.0096833	.0074972	-1.29	0.197	-.0243787	.0050122
subcont	.0520398	.053903	0.97	0.334	-.0536167	.1576963
otherasian	.1839112	.1439237	1.28	0.201	-.0981969	.4660193
black	-.2783515	.0359051	-7.75	0.000	-.3487299	-.2079731
mixedrace	-.0623254	.0327937	-1.90	0.057	-.126605	.0019542
chinese	.5418762	.0574481	9.43	0.000	.429271	.6544814
otherethnic	-.0252138	.0474651	-0.53	0.595	-.1182513	.0678236
budh	-.0020727	.0663251	-0.03	0.975	-.132078	.1279326
hindu	-.2559539	.1019495	-2.51	0.012	-.4557874	-.0561203
jew	-.1030423	.0623728	-1.65	0.099	-.2253006	.019216
muslim	-.3298466	.0511307	-6.45	0.000	-.4300691	-.2296242
sikh	-.2002452	.1002076	-2.00	0.046	-.3966644	-.0038261
othreli	-.0229475	.0237564	-0.97	0.334	-.069513	.0236179
noreli	-.0669046	.0084446	-7.92	0.000	-.083457	-.0503523
reliyes	-.0317957	.0082915	-3.83	0.000	-.0480481	-.0155434
hdegree	-.2926881	.0162801	-17.98	0.000	-.3245991	-.2607771
fdegree	-.1888776	.0115357	-16.37	0.000	-.211489	-.1662663
alevel_equiv	-.0413778	.0079866	-5.18	0.000	-.0570324	-.0257232
otherqual	.0028388	.0122749	0.23	0.817	-.0212215	.026899
noqual	.0048987	.0085374	0.57	0.566	-.0118357	.021633
incomebelow5k	-.0154924	.0112459	-1.38	0.168	-.0375357	.0065509
income5kto10k	-.0072734	.0105758	-0.69	0.492	-.0280033	.0134565
income15kto20k	-.0033655	.0115701	-0.29	0.771	-.0260443	.0193133
income20kto30k	-.0082906	.0110728	-0.75	0.454	-.0299946	.0134133

income30kto50k	-.0158124	.0124259	-1.27	0.203	-.0401687	.0085438
income50kp	-.0387042	.0182503	-2.12	0.034	-.0744771	-.0029314
northeast	.0721089	.0182075	3.96	0.000	.0364199	.1077978
northwest	.0919081	.0156643	5.87	0.000	.0612042	.1226119
yorknhumber	.1007326	.0162726	6.19	0.000	.0688363	.1326289
eastmidland	.1325176	.0163055	8.13	0.000	.1005569	.1644783
westmidland	.1376134	.0158294	8.69	0.000	.1065858	.1686411
eastengland	.1289434	.0159073	8.11	0.000	.0977631	.1601237
southeast	.100718	.0156562	6.43	0.000	.07003	.131406
southwest	.1078926	.0166268	6.49	0.000	.075302	.1404831
wales	.096468	.0180552	5.34	0.000	.0610776	.1318583
ragedumy1	0	(omitted)				
ragedumy2	.0130315	.0430494	0.30	0.762	-.0713507	.0974137
ragedumy3	.0290586	.044689	0.65	0.516	-.0585373	.1166544
ragedumy4	.0466896	.0437708	1.07	0.286	-.0391066	.1324857
ragedumy5	.0672949	.0437385	1.54	0.124	-.0184379	.1530277
ragedumy6	.0630588	.0432712	1.46	0.145	-.0217581	.1478758
ragedumy7	.0609736	.0431151	1.41	0.157	-.0235372	.1454844
ragedumy8	.0683943	.0425737	1.61	0.108	-.0150554	.151844
ragedumy9	.1293039	.0404751	3.19	0.001	.0499678	.20864
ragedumy10	.1212216	.0407075	2.98	0.003	.0414299	.2010132
ragedumy11	.1239988	.0398365	3.11	0.002	.0459144	.2020832
ragedumy12	.0940714	.0400363	2.35	0.019	.0155954	.1725474
ragedumy13	.0696974	.0400492	1.74	0.082	-.0088039	.1481987
ragedumy14	.1078193	.0390222	2.76	0.006	.031331	.1843075
ragedumy15	.0954565	.0403456	2.37	0.018	.0163742	.1745387
ragedumy16	.0816634	.0413715	1.97	0.048	.0005702	.1627567
ragedumy17	.1029682	.040045	2.57	0.010	.0244751	.1814614
ragedumy18	.0908127	.0397277	2.29	0.022	.0129415	.1686839
ragedumy19	.0931581	.0394249	2.36	0.018	.0158804	.1704357
ragedumy20	.1192954	.0378285	3.15	0.002	.0451469	.1934439
ragedumy21	.0636115	.0389537	1.63	0.102	-.0127426	.1399655
ragedumy22	.0967624	.0377281	2.56	0.010	.0228108	.170714
ragedumy23	.0808299	.0378233	2.14	0.033	.0066916	.1549683
ragedumy24	.056941	.0391716	1.45	0.146	-.0198401	.133722
ragedumy25	.0694406	.0378361	1.84	0.066	-.0047227	.1436039
ragedumy26	.0667093	.0390229	1.71	0.087	-.0097804	.143199
ragedumy27	.1200283	.036794	3.26	0.001	.0479076	.192149
ragedumy28	.0958469	.0375197	2.55	0.011	.0223037	.1693901
ragedumy29	.1039405	.0374372	2.78	0.006	.030559	.1773221
ragedumy30	.1214729	.0377018	3.22	0.001	.0475726	.1953731
ragedumy31	.1292391	.0379245	3.41	0.001	.0549025	.2035757

ragedumy32	.0968668	.0380326	2.55	0.011	.0223182	.1714154
ragedumy33	.0786994	.0382854	2.06	0.040	.0036553	.1537435
ragedumy34	.0701276	.0392934	1.78	0.074	-.0068922	.1471473
ragedumy35	.0611078	.0388434	1.57	0.116	-.01503	.1372455
ragedumy36	.1182482	.0388262	3.05	0.002	.0421441	.1943522
ragedumy37	.0841419	.0380538	2.21	0.027	.0095519	.1587319
ragedumy38	.0928207	.0383972	2.42	0.016	.0175575	.1680838
ragedumy39	.1445498	.0374804	3.86	0.000	.0710835	.218016
ragedumy40	.0879145	.0387062	2.27	0.023	.0120456	.1637834
ragedumy41	.0632011	.0394506	1.60	0.109	-.0141269	.140529
ragedumy42	.1008772	.037991	2.66	0.008	.0264102	.1753442
ragedumy43	.0719668	.0378941	1.90	0.058	-.0023102	.1462438
ragedumy44	.118819	.0373613	3.18	0.001	.0455863	.1920516
ragedumy45	.1392523	.0361696	3.85	0.000	.0683555	.2101492
ragedumy46	.1297645	.0364751	3.56	0.000	.0582688	.2012603
ragedumy47	.1281116	.0365435	3.51	0.000	.056482	.1997413
ragedumy48	.123486	.0364885	3.38	0.001	.0519642	.1950079
ragedumy49	.1378173	.0367658	3.75	0.000	.0657518	.2098828
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				

ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				
ragedumy80	0	(omitted)				
ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.7231429	.0363582	19.89	0.000	.6518765	.7944093

Excluding over 65, OLS with education variables

Table A 7: Earlier Immigrants Sample

Linear regression	Number of obs =	7077
	F(88, 6988) =	7.73
	Prob > F =	0.0000
	R-squared =	0.0778
	Root MSE =	.48313

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
female	.0354312	.0127585	2.78	0.005	.0104206	.0604418
outoflabforce	-.0476883	.0183643	-2.60	0.009	-.0836879	-.0116887
selfemployed	-.0083622	.02135	-0.39	0.695	-.0502147	.0334904
unemployed	-.0098247	.0182178	-0.54	0.590	-.0455371	.0258878
w200809	-.0479946	.0146478	-3.28	0.001	-.0767087	-.0192805
w200910	-.0349986	.0145028	-2.41	0.016	-.0634286	-.0065686
subcont	.0264204	.0279598	0.94	0.345	-.0283892	.0812301
otherasian	-.0282288	.0342675	-0.82	0.410	-.0954035	.0389459
black	-.1185312	.0258185	-4.59	0.000	-.1691434	-.067919
mixedrace	-.0694714	.0370314	-1.88	0.061	-.1420642	.0031214
chinese	.0092843	.0426136	0.22	0.828	-.0742512	.0928199
otherethnic	-.0222311	.0306387	-0.73	0.468	-.0822923	.03783
budh	-.1588691	.0456174	-3.48	0.000	-.2482929	-.0694452
hindu	.0378849	.0241199	1.57	0.116	-.0093975	.0851672
jew	-.3374081	.1192568	-2.83	0.005	-.5711876	-.1036286
muslim	-.0518649	.0190558	-2.72	0.007	-.08922	-.0145098
sikh	.0251028	.0318604	0.79	0.431	-.0373533	.0875589
othreli	.0083744	.0400123	0.21	0.834	-.0700617	.0868106
noreli	-.1176539	.0335182	-3.51	0.000	-.1833598	-.0519481
reliyes	-.0554079	.0144958	-3.82	0.000	-.083824	-.0269918
hdegree	-.1301316	.0239155	-5.44	0.000	-.1770132	-.08325
fdegree	-.0626745	.0218981	-2.86	0.004	-.1056015	-.0197476
alevel_equiv	.0041976	.0197437	0.21	0.832	-.0345062	.0429013
otherqual	-.0562566	.022566	-2.49	0.013	-.1004929	-.0120204
noqual	-.0542581	.0187828	-2.89	0.004	-.091078	-.0174382
incomebelow5k	.0129215	.0198422	0.65	0.515	-.0259752	.0518181
income5kto10k	.0236877	.0205523	1.15	0.249	-.0166011	.0639765
income15kto20k	.0216894	.0227672	0.95	0.341	-.0229413	.0663201
income20kto30k	-.0122756	.0210575	-0.58	0.560	-.0535547	.0290036

income30kto50k	-.0403306	.0245188	-1.64	0.100	-.0883949	.0077337
income50kp	-.0044809	.0364432	-0.12	0.902	-.0759206	.0669587
northeast	.0488606	.0644248	0.76	0.448	-.0774316	.1751529
northwest	.0623333	.023835	2.62	0.009	.0156094	.1090572
yorknhumber	.0224151	.0250338	0.90	0.371	-.0266588	.0714891
eastmidland	.1040161	.0243423	4.27	0.000	.0562978	.1517344
westmidland	.0786876	.0205304	3.83	0.000	.0384419	.1189334
eastengland	.0770663	.0285648	2.70	0.007	.0210707	.133062
southeast	.0755414	.0236392	3.20	0.001	.0292015	.1218813
southwest	-.0283473	.051602	-0.55	0.583	-.1295028	.0728082
wales	.1759362	.0681162	2.58	0.010	.0424079	.3094646
ragedumy1	-.061313	.11266	-0.54	0.586	-.2821607	.1595347
ragedumy2	.0175463	.1198432	0.15	0.884	-.2173828	.2524753
ragedumy3	0	(omitted)				
ragedumy4	-.0285901	.1137961	-0.25	0.802	-.2516651	.1944848
ragedumy5	.0654301	.1162986	0.56	0.574	-.1625504	.2934106
ragedumy6	.0403442	.1081547	0.37	0.709	-.1716718	.2523602
ragedumy7	.0035299	.1096933	0.03	0.974	-.2115023	.218562
ragedumy8	.0226534	.1034947	0.22	0.827	-.1802277	.2255344
ragedumy9	-.0177384	.1022587	-0.17	0.862	-.2181964	.1827196
ragedumy10	-.0527904	.100618	-0.52	0.600	-.2500322	.1444515
ragedumy11	-.0175942	.0995295	-0.18	0.860	-.2127023	.1775139
ragedumy12	.0015535	.0982401	0.02	0.987	-.191027	.194134
ragedumy13	-.0411866	.0955822	-0.43	0.667	-.2285566	.1461835
ragedumy14	-.0168242	.094928	-0.18	0.859	-.202912	.1692635
ragedumy15	.0557647	.0940697	0.59	0.553	-.1286404	.2401698
ragedumy16	.0233978	.0931737	0.25	0.802	-.1592509	.2060464
ragedumy17	.0918694	.0930633	0.99	0.324	-.0905629	.2743018
ragedumy18	.0346169	.0926744	0.37	0.709	-.147053	.2162868
ragedumy19	.0000189	.0922387	0.00	1.000	-.1807969	.1808347
ragedumy20	.0961018	.0917894	1.05	0.295	-.0838333	.2760369
ragedumy21	.11012	.0921953	1.19	0.232	-.0706106	.2908507
ragedumy22	.1546596	.0927759	1.67	0.096	-.0272093	.3365286
ragedumy23	.079202	.0923826	0.86	0.391	-.1018959	.2602999
ragedumy24	.1172905	.0924373	1.27	0.205	-.0639146	.2984955
ragedumy25	.0803902	.0920424	0.87	0.382	-.100041	.2608213
ragedumy26	.1247014	.0943879	1.32	0.186	-.0603274	.3097303
ragedumy27	.1009871	.0927845	1.09	0.276	-.0808986	.2828729
ragedumy28	.1257287	.0930249	1.35	0.177	-.0566282	.3080857
ragedumy29	.1213509	.0941881	1.29	0.198	-.0632864	.3059882
ragedumy30	.13913	.0922219	1.51	0.131	-.0416528	.3199129
ragedumy31	.0971328	.0942858	1.03	0.303	-.0876959	.2819615

ragedumy32	.1573425	.093743	1.68	0.093	-.0264221	.3411071
ragedumy33	.1989844	.0938433	2.12	0.034	.015023	.3829458
ragedumy34	.2235031	.0932195	2.40	0.017	.0407646	.4062416
ragedumy35	.2194296	.0934089	2.35	0.019	.0363199	.4025393
ragedumy36	.1543584	.0945312	1.63	0.103	-.0309515	.3396683
ragedumy37	.1924274	.0943607	2.04	0.041	.0074518	.377403
ragedumy38	.2666332	.0945889	2.82	0.005	.0812103	.4520562
ragedumy39	.2038888	.0951908	2.14	0.032	.017286	.3904916
ragedumy40	.2838923	.0944149	3.01	0.003	.0988104	.4689742
ragedumy41	.1827305	.0972216	1.88	0.060	-.0078532	.3733143
ragedumy42	.2443767	.0962751	2.54	0.011	.0556483	.4331052
ragedumy43	.1988059	.0962041	2.07	0.039	.0102166	.3873952
ragedumy44	.2458283	.0982048	2.50	0.012	.053317	.4383396
ragedumy45	.1741029	.0989633	1.76	0.079	-.0198952	.3681009
ragedumy46	.2384217	.0978854	2.44	0.015	.0465366	.4303069
ragedumy47	.1993397	.1000854	1.99	0.046	.003142	.3955375
ragedumy48	.2441391	.0983219	2.48	0.013	.0513983	.4368798
ragedumy49	.1657157	.0997408	1.66	0.097	-.0298065	.3612379
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				

ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				
ragedumy80	0	(omitted)				
ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.5128531	.0926367	5.54	0.000	.3312571	.6944491

Excluding over 65, OLS with education variables

Table A 8: Recent Immigrants Sample

Linear regression		Number of obs =	2429
		F(87, 2341) =	2.52
		Prob > F =	0.0000
		R-squared =	0.0572
		Root MSE =	.46658

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
female	.0428637	.0209799	2.04	0.041	.0017225	.0840049
outoflabforce	-.0247344	.0296194	-0.84	0.404	-.0828175	.0333486
selfemployed	-.0171611	.0498128	-0.34	0.730	-.1148429	.0805207
unemployed	.0142564	.0297029	0.48	0.631	-.0439902	.0725031
w200809	-.0121758	.0240771	-0.51	0.613	-.0593905	.0350388
w200910	-.054175	.02457	-2.20	0.028	-.1023563	-.0059937
subcont	.0456087	.0430747	1.06	0.290	-.0388599	.1300772
otherasian	-.0332237	.0496462	-0.67	0.503	-.1305788	.0641313
black	-.1099961	.0386323	-2.85	0.004	-.1857533	-.034239
mixedrace	.0013343	.0597729	0.02	0.982	-.115879	.1185475
chinese	-.0589175	.0571267	-1.03	0.302	-.1709417	.0531068
otherethnic	.0271172	.0431293	0.63	0.530	-.0574584	.1116928
budh	-.0046419	.0562426	-0.08	0.934	-.1149325	.1056486
hindu	-.050252	.0379812	-1.32	0.186	-.1247323	.0242283
jew	.020769	.2839915	0.07	0.942	-.536132	.57767
muslim	-.0075916	.0297519	-0.26	0.799	-.0659344	.0507513
sikh	.1068015	.0668235	1.60	0.110	-.024238	.2378409
othreli	.0930461	.0726283	1.28	0.200	-.0493765	.2354686
noreli	-.0299878	.0485459	-0.62	0.537	-.1251853	.0652096
reliyes	-.0239511	.0249661	-0.96	0.337	-.072909	.0250068
hdegree	-.0657163	.0434691	-1.51	0.131	-.1509582	.0195256
fdegree	-.0667682	.0427556	-1.56	0.119	-.1506109	.0170745
alevel_equiv	-.0436809	.0419177	-1.04	0.297	-.1258805	.0385187
otherqual	-.0037112	.0429518	-0.09	0.931	-.0879388	.0805163
noqual	-.0831289	.0425188	-1.96	0.051	-.1665073	.0002494
incomebelow5k	-.0969207	.0323188	-3.00	0.003	-.1602972	-.0335442
income5kto10k	-.0864178	.0344497	-2.51	0.012	-.1539729	-.0188627
income15kto20k	-.0485589	.0405924	-1.20	0.232	-.1281598	.031042
income20kto30k	-.0818198	.0375947	-2.18	0.030	-.1555421	-.0080975
income30kto50k	-.137173	.045106	-3.04	0.002	-.225625	-.0487211

income50kp	-.1766846	.0564894	-3.13	0.002	-.2874592	-.06591
northeast	.0227589	.0666179	0.34	0.733	-.1078774	.1533953
northwest	.0562605	.0369165	1.52	0.128	-.0161318	.1286529
yorknhumber	.0533148	.037753	1.41	0.158	-.020718	.1273476
eastmidland	.0593294	.0379101	1.57	0.118	-.0150115	.1336703
westmidland	.0332817	.0382141	0.87	0.384	-.0416554	.1082187
eastengland	.0517692	.0456009	1.14	0.256	-.0376531	.1411915
southeast	.020172	.0345038	0.58	0.559	-.0474891	.0878331
southwest	.0194444	.0645449	0.30	0.763	-.1071267	.1460155
wales	.0668905	.1093545	0.61	0.541	-.1475513	.2813323
ragedumy1	.413926	.1177052	3.52	0.000	.1831088	.6447433
ragedumy2	.3052188	.0959104	3.18	0.001	.1171406	.4932969
ragedumy3	.4433543	.0947149	4.68	0.000	.2576204	.6290881
ragedumy4	.1972731	.0808637	2.44	0.015	.0387011	.355845
ragedumy5	.286529	.0807695	3.55	0.000	.1281419	.4449161
ragedumy6	.283744	.0718796	3.95	0.000	.1427896	.4246983
ragedumy7	.2789014	.0751647	3.71	0.000	.1315051	.4262977
ragedumy8	.2893397	.0748668	3.86	0.000	.1425275	.4361518
ragedumy9	.3949786	.0806428	4.90	0.000	.2368399	.5531173
ragedumy10	.2902293	.0700849	4.14	0.000	.1527943	.4276643
ragedumy11	.3156521	.0708694	4.45	0.000	.1766787	.4546255
ragedumy12	.2675381	.0686538	3.90	0.000	.1329096	.4021667
ragedumy13	.3453256	.0669085	5.16	0.000	.2141196	.4765317
ragedumy14	.329197	.0712409	4.62	0.000	.1894952	.4688988
ragedumy15	.2672903	.0683079	3.91	0.000	.13334	.4012405
ragedumy16	.4037734	.0714415	5.65	0.000	.2636782	.5438686
ragedumy17	.3542726	.0722835	4.90	0.000	.2125263	.4960188
ragedumy18	.4104854	.0771523	5.32	0.000	.2591914	.5617794
ragedumy19	.3569046	.0772363	4.62	0.000	.2054459	.5083632
ragedumy20	.2911571	.0780006	3.73	0.000	.1381996	.4441145
ragedumy21	.387738	.0807237	4.80	0.000	.2294406	.5460355
ragedumy22	.3459329	.0821852	4.21	0.000	.1847696	.5070962
ragedumy23	.3417972	.0773033	4.42	0.000	.1902072	.4933873
ragedumy24	.2918898	.0842619	3.46	0.001	.126654	.4571255
ragedumy25	.4417794	.1043089	4.24	0.000	.2372319	.6463269
ragedumy26	.3455176	.10857	3.18	0.001	.1326142	.558421
ragedumy27	.3401754	.0995434	3.42	0.001	.144973	.5353777
ragedumy28	.4127557	.1219399	3.38	0.001	.1736342	.6518772
ragedumy29	.3627684	.1050738	3.45	0.001	.156721	.5688157
ragedumy30	.5377397	.1064384	5.05	0.000	.3290164	.7464629
ragedumy31	.4462922	.1068297	4.18	0.000	.2368016	.6557829
ragedumy32	.5908895	.1318687	4.48	0.000	.332298	.849481

ragedumy33	.3328009	.1442387	2.31	0.021	.049952	.6156498
ragedumy34	.4419688	.1228817	3.60	0.000	.2010005	.6829371
ragedumy35	.3241534	.1297178	2.50	0.013	.0697798	.578527
ragedumy36	.4118287	.1571161	2.62	0.009	.1037275	.7199299
ragedumy37	.2326862	.133195	1.75	0.081	-.0285063	.4938786
ragedumy38	.28563	.1522124	1.88	0.061	-.0128551	.5841151
ragedumy39	.4892568	.1904676	2.57	0.010	.1157541	.8627594
ragedumy40	.4552483	.1784875	2.55	0.011	.1052383	.8052583
ragedumy41	.4929719	.211453	2.33	0.020	.0783173	.9076265
ragedumy42	.2759938	.1926049	1.43	0.152	-.1017002	.6536878
ragedumy43	.3646597	.2428125	1.50	0.133	-.1114902	.8408096
ragedumy44	0	(omitted)				
ragedumy45	.2750261	.1656809	1.66	0.097	-.0498705	.5999228
ragedumy46	.5128401	.2590956	1.98	0.048	.0047594	1.020921
ragedumy47	.096961	.0938256	1.03	0.302	-.087029	.280951
ragedumy48	.5603473	.3202514	1.75	0.080	-.0676586	1.188353
ragedumy49	0	(omitted)				
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				
ragedumy74	0	(omitted)				

ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				
ragedumy80	0	(omitted)				
ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.1378555	.0845719	1.63	0.103	-.0279882	.3036992

Excluding over 65, OLS without education variables

Table A 9: Pooled sample excluding over 65 and qualification variable for Natives, Earlier Immigrants, and Recent Immigrants (Regression without controls)

Linear regression	
Number of obs	= 24588
F(2, 24585)	= 1768.47
Prob > F	= 0.0000
R-squared	= 0.1348
Root MSE	= .43651

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
recmig	-.4699397	.0100976	-46.54	0.000	-.4897317	-.4501477
oldmig	-.2956191	.0067632	-43.71	0.000	-.3088753	-.2823628
_cons	.8042325	.003232	248.83	0.000	.7978975	.8105674

Excluding over 65, OLS without education variables

Table A 10: Pooled sample excluding over 65 and qualification variable for Natives, Earlier Immigrants, and Recent Immigrants (Regression with controls)

Linear regression		Number of obs =	24588
		F(85, 24502) =	64.65
		Prob > F =	0.0000
		R-squared =	0.1783
		Root MSE =	.42612

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
recmig	-.3034122	.015457	-19.63	0.000	-.3337088	-.2731156
oldmig	-.1429683	.0138382	-10.33	0.000	-.1700919	-.1158446
female	.0076157	.0059547	1.28	0.201	-.0040559	.0192873
outoflabforce	-.0176277	.0087759	-2.01	0.045	-.034829	-.0004264
selfemployed	.005619	.0102689	0.55	0.584	-.0145087	.0257467
unemployed	.0051012	.0083469	0.61	0.541	-.0112592	.0214616
w200809	-.0333001	.0067573	-4.93	0.000	-.0465447	-.0200555
w200910	-.028225	.0066942	-4.22	0.000	-.0413461	-.0151039
subcont	-.0170841	.0183622	-0.93	0.352	-.0530752	.0189069
otherasian	-.0786339	.0244962	-3.21	0.001	-.1266479	-.0306199
black	-.1706452	.0161978	-10.54	0.000	-.2023938	-.1388966
mixedrace	-.0854078	.0224482	-3.80	0.000	-.1294075	-.041408
chinese	-.0963211	.0302616	-3.18	0.001	-.1556356	-.0370065
otherethnic	-.0571308	.0201316	-2.84	0.005	-.09659	-.0176716
budh	-.0877785	.0313438	-2.80	0.005	-.1492143	-.0263427
hindu	.0018028	.0191346	0.09	0.925	-.0357022	.0393079
jew	-.1862033	.0603533	-3.09	0.002	-.3044995	-.0679072
muslim	-.0914035	.0142675	-6.41	0.000	-.1193688	-.0634383
sikh	.0222725	.0271954	0.82	0.413	-.0310322	.0755772
othreli	-.0123121	.0206008	-0.60	0.550	-.0526909	.0280666
noreli	-.0726568	.0083472	-8.70	0.000	-.0890178	-.0562958
reliyes	-.0566293	.0070539	-8.03	0.000	-.0704554	-.0428032
incomebelow5k	-.0146763	.0097468	-1.51	0.132	-.0337806	.0044281
income5kto10k	.0023746	.0095906	0.25	0.804	-.0164235	.0211727
income15kto20k	-.0050811	.0104992	-0.48	0.628	-.0256602	.015498
income20kto30k	-.03804	.0097932	-3.88	0.000	-.0572354	-.0188447
income30kto50k	-.0918113	.0108078	-8.49	0.000	-.1129953	-.0706274
income50kp	-.1318936	.01565	-8.43	0.000	-.1625686	-.1012186
northeast	.060956	.0148499	4.10	0.000	.0318493	.0900626
northwest	.0753302	.0110606	6.81	0.000	.0536508	.0970096

yorknhumber	.0741036	.0116498	6.36	0.000	.0512693	.0969379
eastmidland	.1155953	.0116576	9.92	0.000	.0927456	.1384449
westmidland	.1053774	.0110919	9.50	0.000	.0836366	.1271182
eastengland	.1095605	.011819	9.27	0.000	.0863945	.1327265
southeast	.0773501	.0109772	7.05	0.000	.055834	.0988661
southwest	.0822627	.0129103	6.37	0.000	.0569577	.1075677
wales	.086923	.0147103	5.91	0.000	.0580899	.1157562
ragedumy1	0	(omitted)				
ragedumy2	.0042113	.0385237	0.11	0.913	-.0712976	.0797202
ragedumy3	.0275802	.0398708	0.69	0.489	-.0505691	.1057295
ragedumy4	-.0134046	.0382109	-0.35	0.726	-.0883003	.0614911
ragedumy5	.0302382	.038145	0.79	0.428	-.0445284	.1050047
ragedumy6	.0077685	.0368429	0.21	0.833	-.0644458	.0799828
ragedumy7	-.0076227	.0375095	-0.20	0.839	-.0811437	.0658983
ragedumy8	.0074184	.0365985	0.20	0.839	-.0643168	.0791536
ragedumy9	.0548119	.035845	1.53	0.126	-.0154466	.1250703
ragedumy10	.0019585	.0355952	0.06	0.956	-.0678103	.0717272
ragedumy11	.0225013	.0352909	0.64	0.524	-.0466711	.0916737
ragedumy12	.0039572	.0345755	0.11	0.909	-.0638128	.0717273
ragedumy13	-.0061465	.0344246	-0.18	0.858	-.0736209	.0613278
ragedumy14	.0128179	.0341889	0.37	0.708	-.0541944	.0798303
ragedumy15	.0121967	.0340372	0.36	0.720	-.0545182	.0789117
ragedumy16	.0217417	.0347361	0.63	0.531	-.0463432	.0898266
ragedumy17	.0454018	.0342211	1.33	0.185	-.0216737	.1124773
ragedumy18	.0203062	.0340638	0.60	0.551	-.0464609	.0870733
ragedumy19	.0052364	.0342577	0.15	0.879	-.0619108	.0723836
ragedumy20	.0488802	.0332355	1.47	0.141	-.0162634	.1140237
ragedumy21	.0384488	.0338936	1.13	0.257	-.0279847	.1048823
ragedumy22	.0701698	.0334476	2.10	0.036	.0046104	.1357292
ragedumy23	.0331306	.0335216	0.99	0.323	-.0325736	.0988349
ragedumy24	.0345005	.0338847	1.02	0.309	-.0319156	.1009166
ragedumy25	.0423752	.0334325	1.27	0.205	-.0231545	.1079049
ragedumy26	.0455897	.0346412	1.32	0.188	-.0223091	.1134885
ragedumy27	.0745653	.0332428	2.24	0.025	.0094075	.1397232
ragedumy28	.0735307	.0337001	2.18	0.029	.0074763	.139585
ragedumy29	.076418	.0336403	2.27	0.023	.0104811	.142355
ragedumy30	.0945587	.0334405	2.83	0.005	.0290133	.1601041
ragedumy31	.0827583	.034148	2.42	0.015	.0158261	.1496905
ragedumy32	.0942712	.034038	2.77	0.006	.0275547	.1609878
ragedumy33	.0862737	.034396	2.51	0.012	.0188555	.1536919
ragedumy34	.1017569	.0346189	2.94	0.003	.0339018	.169612
ragedumy35	.0868565	.034427	2.52	0.012	.0193776	.1543354

ragedumy36	.0955244	.0347026	2.75	0.006	.0275052	.1635436
ragedumy37	.0848852	.0341861	2.48	0.013	.0178784	.1518921
ragedumy38	.1137787	.0345453	3.29	0.001	.0460678	.1814895
ragedumy39	.1361562	.0341733	3.98	0.000	.0691745	.2031379
ragedumy40	.1210863	.0345465	3.51	0.000	.053373	.1887996
ragedumy41	.0682448	.0354799	1.92	0.054	-.0012979	.1377875
ragedumy42	.10995	.0345896	3.18	0.001	.0421522	.1777478
ragedumy43	.084117	.0345927	2.43	0.015	.0163132	.1519207
ragedumy44	.1141993	.0340644	3.35	0.001	.0474311	.1809675
ragedumy45	.1228457	.0331049	3.71	0.000	.0579581	.1877332
ragedumy46	.1287542	.0333654	3.86	0.000	.0633561	.1941523
ragedumy47	.1166791	.0333345	3.50	0.000	.0513414	.1820168
ragedumy48	.1319944	.0333683	3.96	0.000	.0665905	.1973984
ragedumy49	.1251345	.0338945	3.69	0.000	.0586993	.1915697
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				
ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				

ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				
ragedumy80	0	(omitted)				
ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.7441499	.0311917	23.86	0.000	.6830123	.8052874

Excluding over 65, OLS without education variables

Table A 11: Natives Sample

Linear regression	Number of obs =	15074	
	F(82, 14990) =	.	
	Prob > F =	.	
	R-squared =	0.0658	
	Root MSE =	.38459	

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
female	-.0120307	.0070098	-1.72	0.086	-.0257709	.0017094
outoflabforce	.0042747	.0103462	0.41	0.679	-.0160051	.0245544
selfemployed	.0146114	.011678	1.25	0.211	-.008279	.0375018
unemployed	.0086942	.0095055	0.91	0.360	-.0099379	.0273262
w200809	-.0279953	.007743	-3.62	0.000	-.0431726	-.0128181
w200910	-.0096399	.0076541	-1.26	0.208	-.0246429	.0053631
subcont	.0697928	.0541712	1.29	0.198	-.0363892	.1759749
otherasian	.1560856	.1274081	1.23	0.221	-.0936498	.405821
black	-.262677	.0360334	-7.29	0.000	-.3333069	-.1920472
mixedrace	-.0536472	.0331457	-1.62	0.106	-.1186169	.0113225
chinese	.6235649	.0564493	11.05	0.000	.5129174	.7342124
otherethnic	-.0151364	.0485094	-0.31	0.755	-.1102208	.0799479
budh	-.0166368	.0669937	-0.25	0.804	-.1479526	.114679
hindu	-.282198	.1001143	-2.82	0.005	-.4784343	-.0859618
jew	-.1330737	.0708091	-1.88	0.060	-.2718683	.0057208
muslim	-.3199292	.0508711	-6.29	0.000	-.4196427	-.2202156
sikh	-.2313918	.1070161	-2.16	0.031	-.4411565	-.0216272
othreli	-.0323043	.0246875	-1.31	0.191	-.0806948	.0160862
noreli	-.0801785	.0086937	-9.22	0.000	-.0972193	-.0631378
reliyes	-.0542174	.0084541	-6.41	0.000	-.0707884	-.0376463
incomebelow5k	-.0121287	.0113096	-1.07	0.284	-.0342969	.0100395
income5kto10k	.0014455	.0107249	0.13	0.893	-.0195766	.0224676
income15kto20k	-.0192462	.0117948	-1.63	0.103	-.0423654	.0038731
income20kto30k	-.0484897	.0111813	-4.34	0.000	-.0704064	-.0265729
income30kto50k	-.0997291	.0123657	-8.07	0.000	-.1239673	-.0754909
income50kp	-.1565513	.0181419	-8.63	0.000	-.1921115	-.120991
northeast	.0885038	.0188438	4.70	0.000	.0515676	.12544
northwest	.1027514	.0162037	6.34	0.000	.0709902	.1345127
yorknhumber	.1128673	.0167821	6.73	0.000	.0799723	.1457623
eastmidland	.1478311	.0167698	8.82	0.000	.1149603	.1807019

westmidland	.1475607	.0162996	9.05	0.000	.1156114	.1795099
eastengland	.1470837	.0164955	8.92	0.000	.1147506	.1794168
southeast	.1099496	.0161647	6.80	0.000	.0782647	.1416344
southwest	.1199354	.0171044	7.01	0.000	.0864086	.1534622
wales	.1088714	.0184563	5.90	0.000	.0726949	.145048
ragedumy1	-.0552765	.0438873	-1.26	0.208	-.141301	.0307481
ragedumy2	-.0489115	.0422143	-1.16	0.247	-.1316566	.0338337
ragedumy3	-.0429691	.0439746	-0.98	0.329	-.1291647	.0432265
ragedumy4	-.0244318	.0425664	-0.57	0.566	-.107867	.0590035
ragedumy5	0	(omitted)				
ragedumy6	-.0185327	.0420927	-0.44	0.660	-.1010394	.0639741
ragedumy7	-.0370223	.0422458	-0.88	0.381	-.1198292	.0457846
ragedumy8	-.0182083	.0412024	-0.44	0.659	-.09897	.0625533
ragedumy9	.0337353	.0392261	0.86	0.390	-.0431527	.1106233
ragedumy10	.0173085	.039623	0.44	0.662	-.0603574	.0949745
ragedumy11	.0316422	.0392368	0.81	0.420	-.0452667	.1085511
ragedumy12	.0054116	.0386304	0.14	0.889	-.0703088	.081132
ragedumy13	-.0288955	.0392521	-0.74	0.462	-.1058344	.0480434
ragedumy14	.0077296	.0380365	0.20	0.839	-.0668266	.0822858
ragedumy15	.0012321	.0387304	0.03	0.975	-.0746842	.0771485
ragedumy16	-.0068196	.0402695	-0.17	0.866	-.0857527	.0721134
ragedumy17	.0100528	.0387963	0.26	0.796	-.0659927	.0860983
ragedumy18	-.0065373	.038504	-0.17	0.865	-.0820098	.0689351
ragedumy19	-.0047742	.0387218	-0.12	0.902	-.0806737	.0711253
ragedumy20	.0254915	.0367169	0.69	0.488	-.0464781	.0974612
ragedumy21	-.0199355	.0377102	-0.53	0.597	-.0938521	.0539811
ragedumy22	.0146376	.0365077	0.40	0.688	-.056922	.0861972
ragedumy23	.0001313	.0369042	0.00	0.997	-.0722054	.0724681
ragedumy24	-.0210266	.0378006	-0.56	0.578	-.0951204	.0530673
ragedumy25	-.0003032	.0363947	-0.01	0.993	-.0716412	.0710347
ragedumy26	-.012869	.0378306	-0.34	0.734	-.0870216	.0612836
ragedumy27	.0432537	.0358583	1.21	0.228	-.0270329	.1135403
ragedumy28	.0220176	.0364024	0.60	0.545	-.0493355	.0933707
ragedumy29	.0375995	.036302	1.04	0.300	-.033557	.1087559
ragedumy30	.0446621	.0364699	1.22	0.221	-.0268233	.1161475
ragedumy31	.055711	.0367905	1.51	0.130	-.0164029	.1278249
ragedumy32	.0324943	.0367065	0.89	0.376	-.039455	.1044436
ragedumy33	.0066609	.0372338	0.18	0.858	-.0663219	.0796438
ragedumy34	.0031412	.0381051	0.08	0.934	-.0715495	.0778318
ragedumy35	-.0030632	.037578	-0.08	0.935	-.0767208	.0705943
ragedumy36	.0421545	.0374465	1.13	0.260	-.0312451	.1155541
ragedumy37	.0156646	.0369291	0.42	0.671	-.0567211	.0880502

ragedumy38	.0200097	.0372274	0.54	0.591	-.0529607	.09298
ragedumy39	.0766136	.0361118	2.12	0.034	.00583	.1473972
ragedumy40	.0190216	.0373942	0.51	0.611	-.0542756	.0923189
ragedumy41	-.0069521	.0384803	-0.18	0.857	-.0823782	.0684739
ragedumy42	.030275	.0371075	0.82	0.415	-.0424602	.1030101
ragedumy43	.0091375	.0368996	0.25	0.804	-.0631901	.0814651
ragedumy44	.0423826	.0360597	1.18	0.240	-.0282988	.113064
ragedumy45	.0752268	.0347787	2.16	0.031	.0070563	.1433974
ragedumy46	.0615791	.0352453	1.75	0.081	-.007506	.1306641
ragedumy47	.0563165	.0352092	1.60	0.110	-.0126978	.1253308
ragedumy48	.0595778	.0352619	1.69	0.091	-.0095399	.1286955
ragedumy49	.0687774	.0355531	1.93	0.053	-.0009109	.1384658
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				
ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				

ragedumy80	0	(omitted)					
ragedumy81	0	(omitted)					
ragedumy82	0	(omitted)					
ragedumy83	0	(omitted)					
ragedumy84	0	(omitted)					
ragedumy85	0	(omitted)					
_cons	.7713556	.0348546	22.13	0.000	.7030364	.8396748	

Excluding over 65, OLS without education variables

Table A 12: Earlier Immigrants Sample

Linear regression	Number of obs =	7082	
	F(83, 6998) =	7.41	
	Prob > F =	0.0000	
	R-squared =	0.0720	
	Root MSE =	.48448	

redmig	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
female	.0388833	.0127017	3.06	0.002	.0139841	.0637825
outoflabforce	-.0519982	.017966	-2.89	0.004	-.0872171	-.0167793
selfemployed	-.0082103	.0214577	-0.38	0.702	-.0502739	.0338534
unemployed	-.0125436	.0182138	-0.69	0.491	-.0482482	.023161
w200809	-.0483367	.014672	-3.29	0.001	-.0770982	-.0195751
w200910	-.0357279	.0145364	-2.46	0.014	-.0642236	-.0072321
subcont	.0314367	.0281441	1.12	0.264	-.0237342	.0866076
otherasian	-.0256334	.0343594	-0.75	0.456	-.0929883	.0417215
black	-.1072595	.0260042	-4.12	0.000	-.1582357	-.0562833
mixedrace	-.0632907	.0375542	-1.69	0.092	-.1369083	.010327
chinese	.0102058	.042837	0.24	0.812	-.0737676	.0941793
otherethnic	-.0178615	.0308893	-0.58	0.563	-.078414	.042691
budh	-.1610008	.0457237	-3.52	0.000	-.2506331	-.0713686
hindu	.0347612	.0241435	1.44	0.150	-.0125674	.0820898
jew	-.369357	.1212322	-3.05	0.002	-.6070089	-.1317051
muslim	-.0525508	.0189458	-2.77	0.006	-.0896903	-.0154112
sikh	.0260894	.0318887	0.82	0.413	-.0364221	.0886008
othreli	.0031337	.0398369	0.08	0.937	-.0749587	.081226
noreli	-.1266549	.0338072	-3.75	0.000	-.1929273	-.0603825
reliyes	-.0565365	.0145177	-3.89	0.000	-.0849956	-.0280774
incomebelow5k	.011027	.0198386	0.56	0.578	-.0278626	.0499166
income5kto10k	.0244583	.0205278	1.19	0.234	-.0157823	.0646989
income15kto20k	.0245433	.0227728	1.08	0.281	-.0200983	.0691849
income20kto30k	-.0181723	.0207691	-0.87	0.382	-.0588861	.0225415
income30kto50k	-.06499	.0235879	-2.76	0.006	-.1112295	-.0187506
income50kp	-.047234	.0354213	-1.33	0.182	-.1166706	.0222026
northeast	.042094	.0645084	0.65	0.514	-.0843621	.1685501
northwest	.0607122	.0238556	2.54	0.011	.013948	.1074764
yorknhumber	.0207675	.024987	0.83	0.406	-.0282146	.0697497
eastmidland	.1052293	.0244142	4.31	0.000	.0573701	.1530886

westmidland	.0800901	.0205554	3.90	0.000	.0397953	.1203849
eastengland	.0793243	.0285848	2.78	0.006	.0232895	.1353591
southeast	.0773515	.0237365	3.26	0.001	.0308208	.1238821
southwest	-.0240723	.0519982	-0.46	0.643	-.1260044	.0778598
wales	.1823591	.0686051	2.66	0.008	.0478724	.3168458
ragedumy1	-.0827771	.1118539	-0.74	0.459	-.3020447	.1364905
ragedumy2	.0183921	.1192134	0.15	0.877	-.2153023	.2520865
ragedumy3	0	(omitted)				
ragedumy4	-.0313802	.1134542	-0.28	0.782	-.2537847	.1910244
ragedumy5	.0662225	.1157355	0.57	0.567	-.1606543	.2930992
ragedumy6	.0257496	.1070467	0.24	0.810	-.1840943	.2355935
ragedumy7	-.0166376	.1087141	-0.15	0.878	-.2297503	.196475
ragedumy8	-.0032507	.1030496	-0.03	0.975	-.2052592	.1987577
ragedumy9	-.0527869	.1016006	-0.52	0.603	-.251955	.1463811
ragedumy10	-.087057	.0998905	-0.87	0.383	-.2828726	.1087587
ragedumy11	-.0633805	.0982625	-0.65	0.519	-.2560047	.1292438
ragedumy12	-.0339664	.0974351	-0.35	0.727	-.2249687	.1570359
ragedumy13	-.0818649	.0948453	-0.86	0.388	-.2677904	.1040606
ragedumy14	-.0552555	.094158	-0.59	0.557	-.2398336	.1293227
ragedumy15	.0101541	.0930611	0.11	0.913	-.1722738	.1925821
ragedumy16	-.0182085	.0921632	-0.20	0.843	-.1988763	.1624593
ragedumy17	.0465481	.0921781	0.50	0.614	-.134149	.2272452
ragedumy18	-.0102626	.0916873	-0.11	0.911	-.1899975	.1694724
ragedumy19	-.0427477	.0914232	-0.47	0.640	-.2219648	.1364694
ragedumy20	.0534962	.0907533	0.59	0.556	-.1244078	.2314001
ragedumy21	.0662126	.0914122	0.72	0.469	-.112983	.2454081
ragedumy22	.1128905	.0917987	1.23	0.219	-.0670628	.2928438
ragedumy23	.0366885	.0913542	0.40	0.688	-.1423934	.2157705
ragedumy24	.0767552	.0914128	0.84	0.401	-.1024415	.255952
ragedumy25	.0391858	.0910657	0.43	0.667	-.1393306	.2177022
ragedumy26	.0845616	.0934888	0.90	0.366	-.0987049	.267828
ragedumy27	.0615828	.091919	0.67	0.503	-.1186062	.2417718
ragedumy28	.0857108	.0921659	0.93	0.352	-.0949622	.2663839
ragedumy29	.0768493	.0933256	0.82	0.410	-.1060971	.2597958
ragedumy30	.0989194	.0912833	1.08	0.279	-.0800236	.2778624
ragedumy31	.0528844	.0934119	0.57	0.571	-.1302313	.2360001
ragedumy32	.1171572	.0928557	1.26	0.207	-.0648682	.2991826
ragedumy33	.1634515	.0930197	1.76	0.079	-.0188954	.3457983
ragedumy34	.1868902	.0923499	2.02	0.043	.0058563	.3679241
ragedumy35	.1828317	.0923928	1.98	0.048	.0017138	.3639496
ragedumy36	.1211583	.0935429	1.30	0.195	-.0622141	.3045308
ragedumy37	.1529513	.0934637	1.64	0.102	-.0302658	.3361684

ragedumy38	.2269739	.0938567	2.42	0.016	.0429865	.4109614
ragedumy39	.1710012	.094451	1.81	0.070	-.0141515	.3561539
ragedumy40	.2505345	.0934946	2.68	0.007	.0672567	.4338122
ragedumy41	.1396779	.0960164	1.45	0.146	-.0485433	.3278991
ragedumy42	.2084486	.095526	2.18	0.029	.0211886	.3957085
ragedumy43	.1628391	.0954595	1.71	0.088	-.0242905	.3499687
ragedumy44	.2082873	.09762	2.13	0.033	.0169226	.3996521
ragedumy45	.1380003	.0982052	1.41	0.160	-.0545117	.3305124
ragedumy46	.195843	.0967843	2.02	0.043	.0061166	.3855695
ragedumy47	.1629595	.0994217	1.64	0.101	-.0319373	.3578562
ragedumy48	.2061563	.09724	2.12	0.034	.0155365	.3967761
ragedumy49	.1213113	.0989365	1.23	0.220	-.0726343	.3152569
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				
ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				

ragedumy80	0	(omitted)				
ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.5076805	.0913579	5.56	0.000	.3285913	.6867697

Excluding over 65, OLS without education variables

Table A 13: Recent Immigrants Sample

Linear regression		Number of obs =	2432			
		F(82, 2349) =	2.90			
		Prob > F =	0.0000			
		R-squared =	0.0537			
		Root MSE =	.46693			
		Robust				
redmig	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
female	.0465828	.0207503	2.24	0.025	.005892	.0872737
outoflabforce	-.0261296	.0295843	-0.88	0.377	-.0841437	.0318846
selfemployed	-.0057438	.0498255	-0.12	0.908	-.1034504	.0919627
unemployed	.0160136	.0297326	0.54	0.590	-.0422912	.0743183
w200809	-.0113138	.024015	-0.47	0.638	-.0584066	.0357791
w200910	-.0543936	.0245251	-2.22	0.027	-.1024867	-.0063004
subcont	.0398423	.0426203	0.93	0.350	-.043735	.1234195
otherasian	-.039614	.0493537	-0.80	0.422	-.1363953	.0571674
black	-.1129422	.038408	-2.94	0.003	-.1882593	-.0376251
mixedrace	-.0093001	.0594931	-0.16	0.876	-.1259646	.1073644
chinese	-.0707048	.0566774	-1.25	0.212	-.1818477	.040438
otherethnic	.0233311	.0431097	0.54	0.588	-.0612059	.1078681
budh	-.0024292	.0564443	-0.04	0.966	-.113115	.1082567
hindu	-.0552459	.0378709	-1.46	0.145	-.1295097	.019018
jew	.0267137	.2740851	0.10	0.922	-.5107601	.5641875
muslim	-.0118615	.0295383	-0.40	0.688	-.0697854	.0460623
sikh	.1036109	.0669508	1.55	0.122	-.0276778	.2348996
othreli	.0856415	.0731099	1.17	0.242	-.0577251	.2290081
noreli	-.032715	.0485998	-0.67	0.501	-.128018	.062588
reliyes	-.0228515	.0249474	-0.92	0.360	-.0717727	.0260697
incomebelow5k	-.1000236	.0323364	-3.09	0.002	-.1634345	-.0366127
income5kto10k	-.0892639	.0343932	-2.60	0.010	-.1567081	-.0218197
income15kto20k	-.0481293	.040608	-1.19	0.236	-.1277606	.031502
income20kto30k	-.0876041	.0373394	-2.35	0.019	-.1608257	-.0143825
income30kto50k	-.1491854	.0441692	-3.38	0.001	-.2358001	-.0625707
income50kp	-.1888573	.0553748	-3.41	0.001	-.2974458	-.0802687
northeast	.0229283	.0673246	0.34	0.733	-.1090935	.1549501
northwest	.0609337	.0366118	1.66	0.096	-.0108611	.1327284
yorknhumber	.0532822	.0372141	1.43	0.152	-.0196936	.126258
eastmidland	.0686379	.037876	1.81	0.070	-.005636	.1429119
westmidland	.0315224	.0380932	0.83	0.408	-.0431774	.1062222

eastengland	.0550139	.0456146	1.21	0.228	-.0344352	.144463
southeast	.0230915	.0344956	0.67	0.503	-.0445534	.0907365
southwest	.0238776	.0649523	0.37	0.713	-.1034921	.1512473
wales	.0574243	.1055998	0.54	0.587	-.1496542	.2645029
ragedumy1	-.0861213	.3277414	-0.26	0.793	-.7288138	.5565711
ragedumy2	-.1932819	.3214039	-0.60	0.548	-.8235467	.4369829
ragedumy3	-.0633688	.3210748	-0.20	0.844	-.6929881	.5662506
ragedumy4	-.3188869	.3167321	-1.01	0.314	-.9399904	.3022165
ragedumy5	-.2242227	.3167724	-0.71	0.479	-.8454052	.3969598
ragedumy6	-.2349177	.3152569	-0.75	0.456	-.8531283	.3832929
ragedumy7	-.2458795	.3161586	-0.78	0.437	-.8658583	.3740994
ragedumy8	-.2345713	.3155694	-0.74	0.457	-.8533949	.3842522
ragedumy9	-.1257344	.3171453	-0.40	0.692	-.7476483	.4961794
ragedumy10	-.237353	.3146955	-0.75	0.451	-.8544628	.3797569
ragedumy11	-.2128267	.3153832	-0.67	0.500	-.8312851	.4056318
ragedumy12	-.2600389	.3146468	-0.83	0.409	-.8770532	.3569753
ragedumy13	-.1788234	.3143197	-0.57	0.569	-.7951963	.4375496
ragedumy14	-.1991886	.3150308	-0.63	0.527	-.816956	.4185788
ragedumy15	-.253919	.3145104	-0.81	0.420	-.8706658	.3628277
ragedumy16	-.1214582	.315269	-0.39	0.700	-.7396927	.4967762
ragedumy17	-.1757497	.3154449	-0.56	0.577	-.7943291	.4428296
ragedumy18	-.1179997	.316496	-0.37	0.709	-.7386402	.5026408
ragedumy19	-.1618337	.316426	-0.51	0.609	-.7823369	.4586695
ragedumy20	-.2322564	.3168608	-0.73	0.464	-.8536122	.3890995
ragedumy21	-.1399077	.3175202	-0.44	0.660	-.7625567	.4827413
ragedumy22	-.1845682	.317527	-0.58	0.561	-.8072306	.4380942
ragedumy23	-.1808185	.3170546	-0.57	0.569	-.8025545	.4409175
ragedumy24	-.2396271	.3179198	-0.75	0.451	-.8630597	.3838054
ragedumy25	-.0803768	.3242246	-0.25	0.804	-.7161728	.5554193
ragedumy26	-.1812367	.3256741	-0.56	0.578	-.8198753	.457402
ragedumy27	-.1803278	.3223006	-0.56	0.576	-.812351	.4516954
ragedumy28	-.1036082	.3306312	-0.31	0.754	-.7519674	.5447511
ragedumy29	-.1619547	.3240713	-0.50	0.617	-.7974502	.4735407
ragedumy30	.0168344	.3257012	0.05	0.959	-.6218572	.655526
ragedumy31	-.0757599	.3249334	-0.23	0.816	-.7129458	.5614261
ragedumy32	.0748889	.3338233	0.22	0.823	-.5797301	.7295079
ragedumy33	-.1957421	.3389053	-0.58	0.564	-.8603267	.4688425
ragedumy34	-.0673883	.3302156	-0.20	0.838	-.7149325	.580156
ragedumy35	-.2204129	.3327652	-0.66	0.508	-.8729568	.432131
ragedumy36	-.1246149	.3444199	-0.36	0.718	-.8000135	.5507838
ragedumy37	-.2915983	.3333008	-0.87	0.382	-.9451927	.3619961
ragedumy38	-.2435988	.3422224	-0.71	0.477	-.9146882	.4274906

ragedumy39	-.0523159	.3592595	-0.15	0.884	-.7568146	.6521828
ragedumy40	-.0727314	.3563617	-0.20	0.838	-.7715475	.6260847
ragedumy41	-.0629269	.3711844	-0.17	0.865	-.79081	.6649563
ragedumy42	-.2549274	.3579257	-0.71	0.476	-.9568106	.4469558
ragedumy43	-.1787456	.3877353	-0.46	0.645	-.9390847	.5815934
ragedumy44	-.5303828	.3151687	-1.68	0.093	-1.148421	.087655
ragedumy45	-.2726801	.3493042	-0.78	0.435	-.9576567	.4122964
ragedumy46	-.0167722	.4079399	-0.04	0.967	-.8167319	.7831875
ragedumy47	-.4525349	.3200648	-1.41	0.158	-1.080174	.1751041
ragedumy48	0	(omitted)				
ragedumy49	0	(omitted)				
ragedumy50	0	(omitted)				
ragedumy51	0	(omitted)				
ragedumy52	0	(omitted)				
ragedumy53	0	(omitted)				
ragedumy54	0	(omitted)				
ragedumy55	0	(omitted)				
ragedumy56	0	(omitted)				
ragedumy57	0	(omitted)				
ragedumy58	0	(omitted)				
ragedumy59	0	(omitted)				
ragedumy60	0	(omitted)				
ragedumy61	0	(omitted)				
ragedumy62	0	(omitted)				
ragedumy63	0	(omitted)				
ragedumy64	0	(omitted)				
ragedumy65	0	(omitted)				
ragedumy66	0	(omitted)				
ragedumy67	0	(omitted)				
ragedumy68	0	(omitted)				
ragedumy69	0	(omitted)				
ragedumy70	0	(omitted)				
ragedumy71	0	(omitted)				
ragedumy72	0	(omitted)				
ragedumy73	0	(omitted)				
ragedumy74	0	(omitted)				
ragedumy75	0	(omitted)				
ragedumy76	0	(omitted)				
ragedumy77	0	(omitted)				
ragedumy78	0	(omitted)				
ragedumy79	0	(omitted)				
ragedumy80	0	(omitted)				

ragedumy81	0	(omitted)				
ragedumy82	0	(omitted)				
ragedumy83	0	(omitted)				
ragedumy84	0	(omitted)				
ragedumy85	0	(omitted)				
_cons	.6195623	.3164046	1.96	0.050	-.0008989	1.240024

8.2 Appendix B: Estimates for all models after dropping all the respondents reporting "remain the same" to the outcome question

Table B 1: Descriptive statistics (2007 – 2010)

Variables	Natives		Earlier Immigrants		Recent Immigrants	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reduce Migration	0.967	0.178	0.798	0.401	0.597	0.491
Increase Migration	0.033	0.178	0.202	0.401	0.403	0.491
Out of Labour Force	0.324	0.468	0.324	0.468	0.209	0.407
Self Employed	0.068	0.252	0.079	0.270	0.037	0.189
Unemployed	0.153	0.360	0.165	0.371	0.191	0.393
Employed	0.455	0.498	0.432	0.495	0.563	0.496
Male	0.446	0.497	0.482	0.500	0.539	0.499
Female	0.554	0.497	0.518	0.500	0.461	0.499
Age	50.969	18.589	47.878	15.352	31.596	9.298
Income below 5K	0.191	0.393	0.259	0.438	0.343	0.475
Income 5K to 10K	0.219	0.413	0.207	0.405	0.172	0.378
Income 10K to 15K	0.161	0.368	0.156	0.363	0.180	0.385
Income 15K to 20K	0.118	0.323	0.111	0.314	0.098	0.297
Income 20K to 30K	0.156	0.363	0.144	0.351	0.118	0.323
Income 30K to 50K	0.115	0.319	0.091	0.288	0.064	0.245
Income above 50K	0.040	0.195	0.032	0.176	0.024	0.153
Observations	17112		5576		1370	
Variables available only for 2009 – 2010						
Lost Job	0.062	0.241	0.056	0.231	0.102	0.303
Drop in Income	0.267	0.443	0.260	0.439	0.211	0.409
Cutbacks in Luxuries	0.396	0.489	0.326	0.469	0.226	0.419
Cutbacks in Necessities	0.339	0.473	0.352	0.478	0.269	0.444
Non listed	0.411	0.492	0.428	0.495	0.500	0.501

Observations	5911	1931	402

Table B 2: Comparison of unconditional and conditional models

Reduce Immigration	Unconditional Models				Conditional Models			
	OLS	Probit AME	Probit Coefficients	Ordered Probit Coefficients	OLS	Probit AME	Probit Coefficients	Ordered Probit Coefficients
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recent	-.37***	-.22***	-1.59***	-1.37***	-.23***	-.12***	-.90***	-.83***
Immigrants	(.013)	(.005)	(.039)	(.031)	(.016)	(.008)	(.063)	(.046)
Earlier	-.17***	-.14***	-1.01***	-.76***	-.05***	-.06***	-.44***	-.35***
Immigrants	(.005)	(.004)	(.027)	(.018)	(.011)	(.008)	(.059)	(.039)
Constant	.967***		1.84***		.93***		.97	
	(.001)		(.019)		(.012)		(.595)	
Sample Size	24058	24058	24058	24058	24058	23987	23987	24058
R2	0.13		.17	.07	.17		.22	.10

Conditional models control for employment status, wave year, age dummies, ethnicity, religion, practising religion or not, income, and region. Omitted category for migrant status dummy is "natives".
Significance levels: *10%, **5%, ***1%
Robust standard errors are given in parentheses

Table B 3: Coefficients of main controls for each respondent category (2007 – 2010)

Reduce Immigration	OLS			
	Pooled	Natives	Earlier Immigrants	Recent Immigrants
Recent Immigrants	-0.233***			
	(0.016)			
Earlier Immigrants	-0.053***			
	(0.011)			
Female	0.015***	0.001	0.043***	0.092***
	(0.004)	(0.003)	(0.012)	(0.029)
Out of Labour Force	-0.018***	-0.012**	-0.022	-0.029
	(0.006)	(0.005)	(0.017)	(0.043)
Self Employed	0.004	-0.004	0.028	0.038
	(0.007)	(0.006)	(0.021)	(0.070)
Unemployed	-0.009	-0.008*	-0.009	0.003
	(0.006)	(0.005)	(0.017)	(0.041)
Income below 5K	-0.014**	-0.002	-0.023	-0.105**
	(0.006)	(0.005)	(0.018)	(0.044)
Income 5K to 10K	-0.003	0.003	0.004	-0.118**
	(0.005)	(0.004)	(0.017)	(0.046)
Income 15K to 20K	0.000	-0.000	-0.002	0.005
	(0.006)	(0.005)	(0.021)	(0.053)
Income 20K to 30K	-0.007	-0.012**	0.002	-0.030
	(0.006)	(0.005)	(0.019)	(0.050)
Income 30K to 50K	-0.018***	-0.014***	-0.024	-0.140**
	(0.007)	(0.005)	(0.023)	(0.064)
Income above 50K	-0.029***	-0.029***	-0.052	0.038
	(0.011)	(0.010)	(0.036)	(0.088)
Constant	0.932***	1.023***	0.122***	1.080***
	(0.012)	(0.008)	(0.033)	(0.107)
Sample Size	24058	17112	5576	1370
R2	0.166	0.042	0.082	0.093

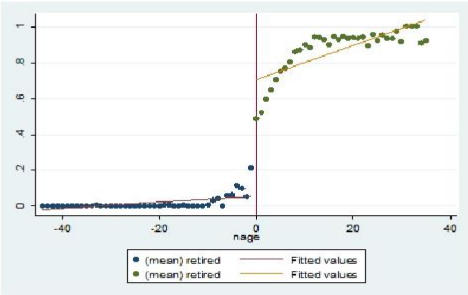
Conditional models control for employment status, wave year, age dummies, ethnicity, religion, practising religion or not, income, and region. Omitted category for migrant status dummy is “natives”.
Significance levels: *10%, **5%, ***1%
Robust standard errors are given in parentheses

Table B 4: Wave 2009 – 2010 models for each respondent category controlled for financial worry dummies

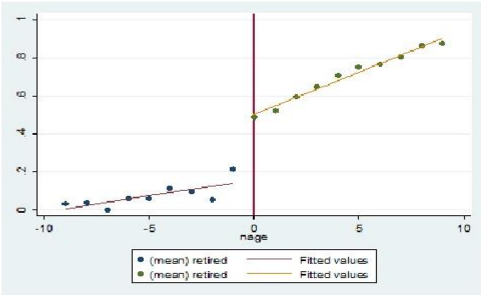
	OLS			
	Pooled	Natives	Earlier Immigrants	Recent Immigrants
Recent Immigrants	-0.219***			
	(0.028)			
Earlier Immigrants	-0.024			
	(0.017)			
Lost Job	0.025**	0.014*	0.064*	0.035
	(0.011)	(0.008)	(0.036)	(0.084)
Drop in Income	0.007	0.009*	-0.007	0.085
	(0.007)	(0.005)	(0.021)	(0.067)
Cutbacks in Luxuries	0.018***	0.001	0.061***	0.090
	(0.007)	(0.006)	(0.020)	(0.068)
Cutbacks in Necessities	0.010	0.008	-0.001	0.023
	(0.007)	(0.005)	(0.020)	(0.065)
Out of Labour Force	-0.019*	-0.008	-0.017	-0.124*
	(0.010)	(0.007)	(0.027)	(0.072)
Self Employed	-0.012	-0.026**	0.023	-0.050
	(0.012)	(0.011)	(0.033)	(0.128)
Unemployed	-0.013	-0.010	-0.032	0.091
	(0.010)	(0.008)	(0.029)	(0.074)
Female	0.013**	0.003	0.029	0.074
	(0.006)	(0.005)	(0.019)	(0.055)
Income below 5K	-0.012	-0.007	-0.004	-0.131*
	(0.010)	(0.008)	(0.029)	(0.077)
Income 5K to 10K	0.002	0.006	0.012	-0.123
	(0.009)	(0.007)	(0.028)	(0.083)
Income 15K to 20K	0.009	0.002	0.043	-0.015
	(0.010)	(0.008)	(0.034)	(0.114)
Income 20K to 30K	-0.002	-0.002	-0.005	-0.049
	(0.010)	(0.008)	(0.032)	(0.106)
Income 30K to 50K	-0.010	-0.003	-0.050	-0.088
	(0.011)	(0.009)	(0.038)	(0.126)
Income above 50K	-0.001	-0.000	-0.014	-0.102
	(0.017)	(0.014)	(0.058)	(0.192)
Constant	0.936***	0.977***	1.038***	0.853***
	(0.020)	(0.027)	(0.051)	(0.244)
Sample Size	8244	5911	1931	402
R2	0.172	0.069	0.123	0.242

8.3 Appendix C: Graphs for Females

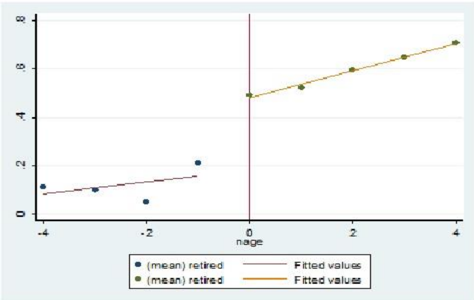
Figure C 1: Discontinuous jump in treatment at threshold (Exit from the labour market)



1a) Discontinuous jump in treatment at threshold

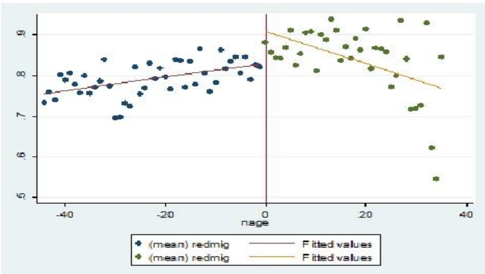


1b) Discontinuous jump in treatment at threshold (sample trimmed at age 54 and 74)

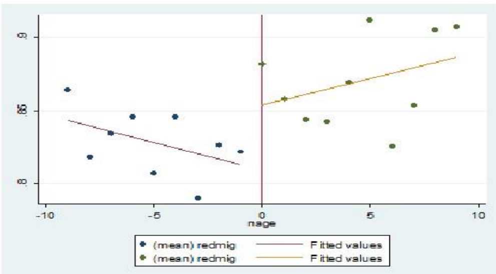


1c) Discontinuous jump in treatment at threshold (sample trimmed at age 61 and 69)

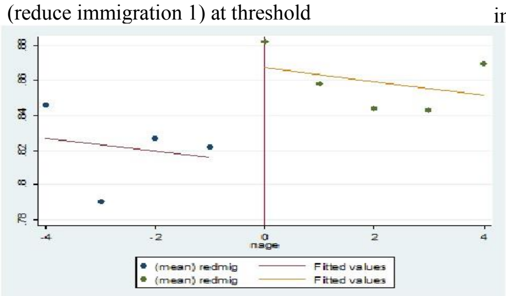
Figure C 2: Continuity in outcome variable (Reduce Immigration 1) at threshold (Exit from the labour market)



2a) Continuity in outcome variable (reduce immigration 1) at threshold

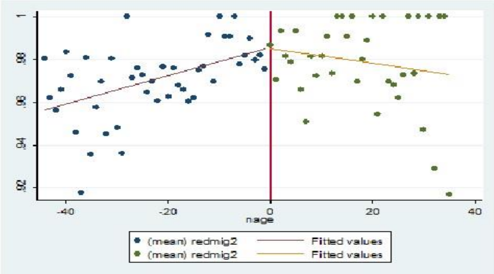


2b) No clear discontinuity in outcome variable (reduce immigration 1) (sample restricted at age 54 and 74)

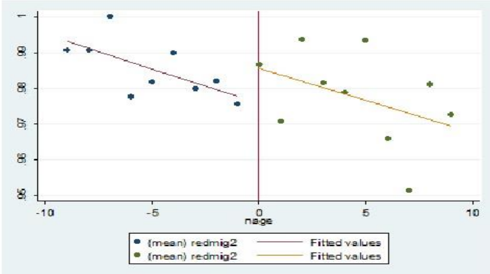


2c) No clear discontinuity in outcome variable (reduce immigration 1) (sample restricted at age 61 and 69)

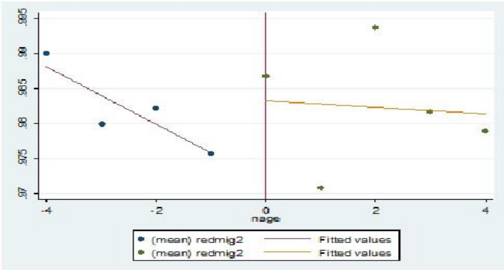
Figure C 3: Continuity/discontinuity in outcome variable (Reduce Immigration 2) at threshold



3a) Continuity in outcome variable (Reduce Immigration 2) at threshold

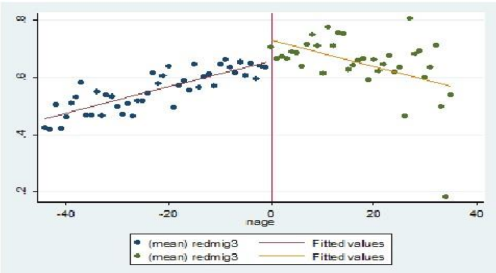


3b) Continuity in outcome variable (Reduce Immigration 2) at threshold (sample restricted at 54 and 74)

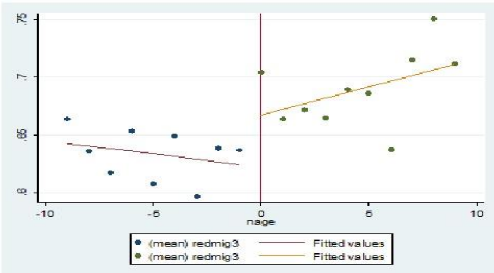


3c) Continuity in outcome (Reduce Immigration 2) at threshold (sample restricted at 61 and 69)

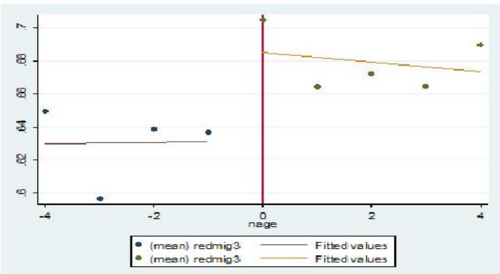
Figure C 4: Continuity in outcome variable (Reduce Immigration 3) at threshold



4a) Continuity in outcome variable (Reduce Immigration 3) at threshold



4b) Continuity in outcome variable (Reduce Immigration 3) at threshold (sample restricted at age 54 and 74)



4c) No discontinuity in outcome (Reduce Immigration 3) rather over fitting of the line (sample restricted at age 61 and 69)

Table C 1: OLS/IV estimates for all the models (Exit from the labour market models controlled for region dummies, religion dummies, ethnicity dummies, and practicing religion or not dummy)

Panel A: Reduce Immigration 1 (1 for "reduce a little" & "reduce a lot" and 0 otherwise)						
Reduce Immigration 1	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
Retired	0.03	-0.01	0.02	0.03	-0.38***	-0.21*
	(0.02)	(0.02)	(0.03)	(0.04)	(0.11)	(0.12)
Normalized Age	0.00***	0.00	-0.02*	0.00**	0.03***	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Normalized Age*above 65	-0.00*	-0.00	0.02	-0.00**	-0.01	0.02**
	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)
Constant	1.95***	1.31***	0.61	1.40***	1.52***	0.62***
	(0.06)	(0.12)	(0.39)	(0.34)	(0.17)	(0.21)
N	4465	1438	755	4465	1438	755
Panel B: Reduce Immigration 2 ("remain the same" dropped from Panel A sample)						
Reduce Immigration 2	OLS (4)	OLS (5)	OLS (6)	IV (4)	IV (5)	IV (6)
Retired	-0.00	-0.00	-0.02	-0.00	-0.06	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.08)	(0.10)
Normalized Age	0.00	-0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Normalized Age*above 65	-0.00	0.00	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Constant	1.05***	1.07***	1.11***	0.72**	1.14***	1.07***
	(0.04)	(0.30)	(0.11)	(0.34)	(0.09)	(0.10)
N	3670	1256	666	3670	1256	666
Panel C: Reduce Immigration 3 (1 for "reduce a lot" and 0 otherwise)						
Reduce Immigration 3	OLS (7)	OLS (8)	OLS (9)	IV (7)	IV (8)	IV (9)
Retired	-0.01	-0.03	-0.02	-0.02	-0.50***	-0.58***
	(0.02)	(0.03)	(0.04)	(0.05)	(0.15)	(0.21)
Normalized Age	0.00***	0.01***	0.00	0.004***	0.04***	0.05**
	(0.00)	(0.01)	(0.02)	(0.001)	(0.01)	(0.02)
Normalized Age*above 65	-0.00	-0.01	0.00	0.000	-0.02***	-0.01
	(0.00)	(0.01)	(0.03)	(0.002)	(0.01)	(0.02)
Constant	1.05***	1.57***	0.83**	0.94***	1.32***	0.61
	(0.08)	(0.15)	(0.40)	(0.33)	(0.44)	(0.43)
N	4465	1438	755	4465	1438	755
Sample	Full	Trimmed	Trimmed	Full	Trimmed	Trimmed
Age boundaries (inclusive)	16 – 95	54 – 74	61 – 69	16 – 95	54 – 74	61 – 69

Robust standard errors are given in parenthesis. For IV, standard errors are adjusted by clustering at age.
Significance levels: *10%, **5%, ***1%

Models 1,4 and 7 are estimated using the full sample of native males, models 2,5, and 8 are estimated by trimming the sample at age 54 and 74, whereas, model 3,6 and 9 are estimated after trimming the sample at age 61 and 69.

8.4 Appendix D: Results using immigrant shares

Table D 1: First stage of all specifications (immigrant share)

	(1)	(2)	(3)	(4)
Shift-share "predicted share"	0.90***	0.81***	0.33***	0.04*
	(0.00)	(0.01)	(0.02)	(0.02)
Kleibergen-Paap F stat (excl. instrument)	35409.20	10572.38	472.44	3.50
R^2	0.90	0.93	0.46	0.65
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table D 2: Immigration, pupil structure and resources (immigrant share)

	(1)	(2)	(3)	(4)
Number of Pupils eligible for Key Stage 2 Assessment				
OLS				
Immigrant share	0.26***	0.11***	0.14***	0.03
	(0.02)	(0.03)	(0.03)	(0.03)
IV				
Immigrant share	0.27***	0.18***	0.82***	3.03*
	(0.02)	(0.04)	(0.08)	(1.79)
Pupils whose first language is not English				
OLS				
Immigrant share	4.50***	5.18***	3.54***	2.74***
	(0.08)	(0.14)	(0.10)	(0.10)
IV				
Immigrant share	4.54***	5.63***	4.91***	6.44
	(0.09)	(0.17)	(0.32)	(4.66)
Native Pupils				
OLS				
Immigrant share	-1.18***	-3.46***	-1.50***	-1.98***
	(0.09)	(0.13)	(0.13)	(0.16)
IV				
Immigrant share	-1.25***	-3.63***	2.01***	14.92
	(0.09)	(0.15)	(0.38)	(9.27)
Pupil Teacher Ratio				
OLS				
Immigrant share	-0.02***	-0.02***	0.02**	0.01
	(0.00)	(0.00)	(0.01)	(0.01)
IV				
Immigrant share	-0.02***	-0.01***	0.14***	1.24*
	(0.00)	(0.00)	(0.03)	(0.70)
Number of teachers				
OLS				
Immigrant share	0.17***	0.09***	0.14***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
IV				
Immigrant share	0.18***	0.11***	0.44***	0.70
	(0.01)	(0.01)	(0.03)	(0.49)
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table D 3: Immigration and educational outcomes (immigrant share)

	(1)	(2)	(3)	(4)
Percentage of Pupils achieving level 4 or above in English				
OLS				
Immigrant share	-0.08***	-0.22***	0.37***	0.27***
	(0.01)	(0.02)	(0.03)	(0.04)
IV				
Immigrant share	-0.05***	-0.15***	0.58***	2.08
	(0.01)	(0.02)	(0.10)	(1.57)
Percentage of Pupils achieving level 4 or above in Maths				
OLS				
Immigrant share	-0.08***	-0.21***	0.40***	0.36***
	(0.01)	(0.02)	(0.04)	(0.05)
IV				
Immigrant share	-0.05***	-0.15***	0.43***	0.97
	(0.01)	(0.02)	(0.11)	(1.46)
Average Point Score				
OLS				
Immigrant share	-0.01***	-0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
IV				
Immigrant share	-0.01***	-0.02***	0.08***	0.31
	(0.00)	(0.00)	(0.01)	(0.21)
Percentage of Pupils failing to achieve a level in English due to absence or disapplication				
OLS				
Immigrant share	-0.01***	-0.00	-0.04***	-0.04***
	(0.00)	(0.00)	(0.01)	(0.01)
IV				
Immigrant share	-0.01***	-0.00	0.02	0.13
	(0.00)	(0.00)	(0.02)	(0.24)
Percentage of Pupils failing to achieve a level in Maths due to absence or disapplication				
OLS				
Immigrant share	-0.01***	-0.00**	-0.03***	-0.04***
	(0.00)	(0.00)	(0.01)	(0.01)
IV				
Immigrant share	-0.01***	-0.01***	0.02	-0.04
	(0.00)	(0.00)	(0.02)	(0.20)
# observations	19376	19376	19376	19376
# schools	9688	9688	9688	9688
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the LSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table D 4: Immigration and school spending (immigrant share)

	(1) OLS	(2) OLS	(3) IV	(4) IV
		Total expenditure (£/pupil)		
Immigrant share	3148.45***	-666.84	2982.37***	-177414.04*
	(426.82)	(727.68)	(418.26)	(100466.61)
		Total income (£/pupil)		
Immigrant share	3250.33***	-688.36	3074.31***	-1851.94*
	(436.29)	(744.69)	(424.22)	(1040.28)
		Average salary of full-time teacher		
Immigrant share	7164.44***	-1738.03***	7877.88***	-1287.04***
	(299.83)	(423.39)	(319.35)	(474.99)
		Teaching staff (£/pupil)		
Immigrant share	972.60***	-625.68**	916.09***	-1039.44**
	(169.38)	(297.40)	(153.91)	(442.27)
		Supply teachers (£/pupil)		
Immigrant share	228.43***	39.19	236.25***	21.90
	(22.73)	(30.09)	(24.55)	(35.39)
		Education support staff (£/pupil)		
Immigrant share	839.87***	-25.45	747.50***	-372.38
	(132.44)	(232.57)	(133.23)	(287.42)
		Premises (£/pupil)		
Immigrant share	193.43***	-39.03	177.21***	-136.25
	(36.24)	(64.57)	(34.76)	(96.47)
		Back office (£/pupil)		
Immigrant share	328.81***	-42.90	326.03***	-129.16
	(41.18)	(69.03)	(44.15)	(88.48)
		Catering (£/pupil)		
Immigrant share	149.95***	58.47***	139.76***	67.27
	(9.72)	(13.84)	(9.43)	(17.63)
		Energy (£/pupil)		
Immigrant share	-2.22	-19.56*	-5.17	-35.32***
	(6.26)	(9.98)	(6.43)	(11.25)
		Learning resources (£/pupil)		
Immigrant share	74.07***	5.06	75.82***	-12.41
	(8.22)	(13.31)	(8.01)	(21.30)
		ICT Learning resources (£/pupil)		
Immigrant share	0.04***	0.00	0.04***	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)
Local authority FEs	No	Yes	No	Yes
Observations	13758	13758	13758	13758

Coefficients, robust standard errors in parentheses.
Significance levels: *10%, **5%, ***1%

8.5 Appendix E: Results using MSOA level data with immigrant numbers

Table E 1: First stage of all specifications (immigrant numbers)

	1	2	2	4
Shift-share predicted number of immigrants	0.93***	0.92***	0.76***	0.72***
	(0.01)	(0.01)	(0.02)	(0.04)
N	19205.00	19205.00	19034.00	19034.00
r2	0.93	0.95	0.67	0.77
Kleibergen-Paap F stat (excl. instrument)	19119.39	5714.10	971.91	277.58
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table E 2: Immigration, pupil structure and resources

Pupils whose first language is not English

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	5.10***	5.27***	3.02***	2.37***
	(0.11)	(0.17)	(0.11)	(0.12)
N	19376.00	19376.00	19376.00	19376.00
r2	0.57	0.64	0.44	0.52
		IV		
Number of immigrants (in 100s)	5.21***	5.84***	3.11***	2.28***
	(0.12)	(0.20)	(0.17)	(0.30)
N	19205.00	19205.00	19034.00	19034.00
r2	0.57	0.64	0.44	0.52
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Pupil Teacher Ratio

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.02***	-0.02***	0.03***	0.04***
	(0.00)	(0.00)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.10	0.22	0.22	0.32
		IV		
Number of immigrants (in 100s)	-0.02***	-0.01**	0.07***	0.14***
	(0.00)	(0.00)	(0.01)	(0.02)
N	19205.00	19205.00	19034.00	19034.00
r2	0.09	0.22	0.22	0.31
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Number of teachers

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	0.20***	0.11***	0.15***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.13	0.32	0.15	0.26
		IV		
Number of immigrants (in 100s)	0.20***	0.12***	0.24***	0.13***
	(0.01)	(0.01)	(0.01)	(0.02)
N	19205.00	19205.00	19034.00	19034.00
r2	0.13	0.32	0.13	0.26
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Native Pupils

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-1.21***	-3.25***	-0.56***	-0.79***
	(0.11)	(0.16)	(0.13)	(0.18)
N	19376.00	19376.00	19376.00	19376.00
r2	0.03	0.22	0.21	0.27
		IV		
Number of immigrants (in 100s)	-1.33***	-3.57***	0.83***	1.35***
	(0.11)	(0.17)	(0.18)	(0.34)
N	19205.00	19205.00	19034.00	19034.00
r2	0.03	0.22	0.19	0.25
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table E 3: Immigration and educational outcomes

Percentage of Pupils achieving level 4 or above in English

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.10***	-0.23***	0.32***	0.21***
	(0.01)	(0.02)	(0.03)	(0.04)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.18	0.18	0.24
		IV		
Number of immigrants (in 100s)	-0.06***	-0.18***	0.37***	0.31***
	(0.01)	(0.02)	(0.04)	(0.09)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.18	0.18	0.24
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Percentage of Pupils achieving level 4 or above in Maths

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.10***	-0.22***	0.35***	0.30***
	(0.01)	(0.02)	(0.03)	(0.05)
N	19376.00	19376.00	19376.00	19376.00
r2	0.11	0.20	0.26	0.31
		IV		
Number of immigrants (in 100s)	-0.06***	-0.17***	0.37***	0.43***
	(0.01)	(0.02)	(0.05)	(0.10)
N	19205.00	19205.00	19034.00	19034.00
r2	0.11	0.20	0.26	0.31
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Number of Pupils eligible for Key Stage 2 Assessment

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	0.32***	0.17***	0.23***	0.17***
	(0.02)	(0.03)	(0.02)	(0.03)
N	19376.00	19376.00	19376.00	19376.00
r2	0.03	0.24	0.11	0.21
		IV		
Number of immigrants (in 100s)	0.33***	0.24***	0.50***	0.58***
	(0.03)	(0.04)	(0.04)	(0.07)
N	19205.00	19205.00	19034.00	19034.00
r2	0.03	0.24	0.10	0.20
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Percentage of Pupils failing to achieve a level in English due to absence or disapplication

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.01***	-0.00	-0.02***	-0.03***
	(0.00)	(0.00)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.11	0.11	0.16
		IV		
Number of immigrants (in 100s)	-0.01***	-0.01**	-0.00	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.11	0.11	0.16
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Percentage of Pupils failing to achieve a level in Maths due to absence or disapplication

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.01***	-0.00*	-0.01***	-0.02**
	(0.00)	(0.00)	(0.00)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.11	0.12	0.16
		IV		
Number of immigrants (in 100s)	-0.01***	-0.01***	0.01	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.11	0.12	0.16
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Average Point Score

	1	2	3	4
		OLS		
Number of immigrants (in 100s)	-0.02***	-0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
N	19376.00	19376.00	19376.00	19376.00
r2	0.02	0.15	0.03	0.10
		IV		
Number of immigrants (in 100s)	-0.01***	-0.02***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
N	19205.00	19205.00	19034.00	19034.00
r2	0.01	0.15	0.03	0.10
widstat	19119.39	5714.10	971.91	277.58

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

8.6 Appendix F: Results using MSOA level data with immigrant shares

Table F 1: First stage of all specifications (immigrant share)

	1	2	3	4
Shift-share “predicted share”	0.92***	0.88***	0.44***	0.15***
	(0.01)	(0.01)	(0.02)	(0.03)
N	19205.00	19205.00	19034.00	19034.00
r2	0.93	0.96	0.56	0.74
Kleibergen-Paap F stat (excl. instrument)	28794.88	7360.60	485.20	25.62
Year effects	Yes	No	Yes	No
Local authority*year effects	No	Yes	No	Yes
School fixed effects	No	No	Yes	Yes

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table F 2: Immigration, pupil structure and resources

Pupils whose first language is not English

	1	2	3	4
		OLS		
Immigrant share	4.54***	5.60***	4.09***	3.51***
	(0.09)	(0.15)	(0.11)	(0.13)
N	19376.00	19376.00	19376.00	19376.00
r2	0.58	0.66	0.47	0.54
		IV		
Immigrant share	4.55***	6.03***	4.99***	6.07***
	(0.10)	(0.18)	(0.27)	(1.42)
N	19205.00	19205.00	19034.00	19034.00
r2	0.58	0.66	0.46	0.50
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Pupil Teacher Ratio

	1	2	3	4
		OLS		
Immigrant share	-0.02***	-0.02***	0.03***	0.03**
	(0.00)	(0.00)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.10	0.22	0.22	0.32
		IV		
Immigrant share	-0.02***	-0.02***	0.12***	0.45***
	(0.00)	(0.00)	(0.03)	(0.13)
N	19205.00	19205.00	19034.00	19034.00
r2	0.10	0.22	0.21	0.24
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Number of teachers

	1	2	3	4
		OLS		
Immigrant share	0.18***	0.10***	0.17***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.14	0.31	0.14	0.26
		IV		
Immigrant share	0.18***	0.11***	0.40***	0.29**
	(0.01)	(0.01)	(0.03)	(0.14)
N	19205.00	19205.00	19034.00	19034.00
r2	0.13	0.32	0.05	0.21
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Native Pupils

	1	2	3	4
		OLS		
Immigrant share	-1.11***	-3.69***	-1.52***	-2.30***
	(0.10)	(0.15)	(0.15)	(0.20)
N	19376.00	19376.00	19376.00	19376.00
r2	0.03	0.23	0.21	0.28
		IV		
Immigrant share	-1.21***	-3.95***	1.27***	3.17
	(0.10)	(0.17)	(0.33)	(1.94)
N	19205.00	19205.00	19034.00	19034.00
r2	0.03	0.23	0.18	0.22
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Table F 3: Immigration and educational outcomes

Percentage of Pupils achieving level 4 or above in English

	1	2	3	4
		OLS		
Immigrant share	-0.09***	-0.25***	0.43***	0.36***
	(0.01)	(0.02)	(0.04)	(0.05)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.18	0.18	0.24

		IV		
Immigrant share	-0.05***	-0.17***	0.53***	0.97**
	(0.01)	(0.02)	(0.08)	(0.47)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.18	0.18	0.23
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

<u>Percentage of Pupils achieving level 4 or above in Maths</u>

	1	2	3	4
		OLS		
Immigrant share	-0.08***	-0.23***	0.47***	0.48***
	(0.01)	(0.02)	(0.04)	(0.06)
N	19376.00	19376.00	19376.00	19376.00
r2	0.11	0.20	0.27	0.32
		IV		
Immigrant share	-0.05***	-0.17***	0.46***	1.07*
	(0.01)	(0.02)	(0.10)	(0.55)
N	19205.00	19205.00	19034.00	19034.00
r2	0.11	0.20	0.26	0.30
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Number of Pupils eligible for Key Stage 2 Assessment

	1	2	3	4
		OLS		
Immigrant share	0.27***	0.14***	0.19***	0.06*
	(0.02)	(0.03)	(0.03)	(0.04)
N	19376.00	19376.00	19376.00	19376.00
r2	0.02	0.24	0.11	0.21
		IV		
Immigrant share	0.27***	0.20***	0.77***	1.46***
	(0.02)	(0.04)	(0.07)	(0.42)
N	19205.00	19205.00	19034.00	19034.00
r2	0.02	0.24	0.06	0.09
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Percentage of Pupils failing to achieve a level in English due to absence or disapplication

	1	2	3	4
		OLS		
Immigrant share	-0.01***	-0.00	-0.04***	-0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.11	0.12	0.16
		IV		
Immigrant share	-0.01***	-0.01**	0.01	-0.03
	(0.00)	(0.00)	(0.01)	(0.07)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.11	0.11	0.16
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Percentage of Pupils failing to achieve a level in Maths due to absence or disapplication

	1	2	3	4
		OLS		
Immigrant share	-0.01***	-0.00*	-0.03***	-0.04***
	(0.00)	(0.00)	(0.01)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.06	0.11	0.12	0.16
		IV		
Immigrant share	-0.01***	-0.01***	0.02	-0.07
	(0.00)	(0.00)	(0.01)	(0.07)
N	19205.00	19205.00	19034.00	19034.00
r2	0.06	0.11	0.11	0.16
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

Average Point Score

	1	2	3	4
		OLS		
Immigrant share	-0.01***	-0.04***	0.04***	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)
N	19376.00	19376.00	19376.00	19376.00
r2	0.01	0.15	0.03	0.10
		IV		
Immigrant share	-0.01***	-0.02***	0.08***	0.17***
	(0.00)	(0.00)	(0.01)	(0.06)
N	19205.00	19205.00	19034.00	19034.00
r2	0.01	0.15	0.02	0.03
widstat	28794.88	7360.60	485.20	25.62

Coefficients, standard errors adjusted for clustering on the MSOA level in parentheses. Significance levels: *10%, **5%, ***1%

References

Abraham, N. and Shryock, A. (2000). “Arab Detroit: From Margin to Mainstream”, Detroit: Wayne State University Press.

Altonji, J.G. and Card, D. (1991). “The effects of immigration on the labor market outcomes of less-skilled natives”, in Abowd, J.M. and R.B. Freeman (eds.) *Immigration, Trade and Labor*. University of Chicago Press, pp. 201 – 234.

Angrist, J. (1989). “Lifetime earnings and the Vietnam era draft lottery: Evidence from social security administrative records”, *American Economic Review*, vol. 80, pp. 313 – 335.

Angrist, J. and Krueger, A. (1991). “Does compulsory school attendance affect schooling and earnings?”, *Quarterly Journal of Economics*, vol. 106, pp. 979 – 1014.

Angrist, J.D. and Kugler, A.D. (2003). “Protective or counter-productive? Labour market institutions and the effect of immigration on EU natives”, *Economic Journal*, vol. 113(488), pp. F302 – F331.

Angrist, Joshua D. (2001). “Estimation of limited-dependent variable models with dummy endogenous regressors: Simple strategies for empirical practice”, Journal of Business and Economic Statistics, vol. 19(1), pp. 2 – 28.

Angrist, Joshua D. and Pischke, Joern-Steffen (2009). “Mostly harmless econometrics: An empiricist’s companion”. Princeton: Princeton University Press.

Angrist, Joshua D., Imbens, G. W. and Rubin, D. B. (1996). “Identification of causal effects using instrumental variables”, *Journal of the American Statistical Association*, vol. 91(434), pp. 444 – 455.

Arai, M. and Thoursie, P.S. (2009). “Renouncing personal names: An empirical examination of surname change and earnings”, *Journal of Labor Economics*, 27(1), pp. 127 – 147.

Åslund, O. (2005). “Now and forever? Initial and subsequent location choices of immigrants”, *Regional Science and Urban Economics,* vol. 35, pp. 141–165.

Baker, M. and Benjamin, D. (1994). “The performance of immigrants in the Canadian labor market”, *Journal of Labor Economics*, vol. 12(3), pp. 369 – 405.

Bakker, L. and Dekker, K. (2012). “Social trust in urban neighbourhoods: The effect of relative ethnic group position”, *Urban Studies*, vol. 49(10), pp. 2031 – 2047.

Bartel, A. (1989). “Where do the new US immigrants live?”, *Journal of Labor Economics,* vol. 7, pp. 371–391.

Bauer, T.K., Lofstrom, M. and Zimmermann, K.F. (2000). “Immigration policy, assimilation of immigrants and natives' sentiments towards immigrants: Evidence from 12 OECD-Countries”, *Swedish Economic Policy Review*, vol. 7(2), pp. 11 – 53.

Becker, G.S. (1971). “The economics of discrimination”, 2nd edn., Chicago, University of Chicago Press.

Beggs, J.J. and Chapman, B.J. (1991). “Male immigrant wage and unemployment experience in Australia”, in Abowd, J.M. and Freeman, R.B. (eds.) *Immigration, trade and the labor market*. Chicago, IL: University of Chicago Press, pp. 369 – 384.

Bell, B., Fasani, F. and Machin, S. (2013). “Crime and immigration: Evidence from large immigrant waves in the UK”, *Review of Economics and Statistics,* vol. 95(4), pp. 1278-1290.

Bertrand, M. and Mullainathan, S. (2004). “Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination”, *American Economic Review*, vol. 94(4), pp. 991 – 1013.

Betts, J.R. (1998). “Educational crowding out: Do immigrants affect the educational attainment of American minorities?”, in Hamermesh, D.S. and Bean, F.D. (eds.) *Help or hindrance? The economic implications of immigration for African-Americans.* New York: Russell Sage Foundation, pp. 253 – 281.

Betts, J.R. and Fairlie, R.W. (2003). “Does immigration induce ‘native flight’ from public schools into private schools?”, *Journal of Public Economics*, vol. 87(5–6), pp. 987 – 1012.

Bianchi, M., Buonanno, P. and Pinotti, P. (2012). “Do immigrants cause crime?”, *Journal of the European Economic Association*, vol. 10(6), pp. 1318 – 1347.

Binder, N., Polinard, J.L., Wrinkle, R. (1997). “Mexican American and Anglo attitudes toward immigration reform: A view from the border”, *Social Science Quarterly*, vol. 78(2), pp. 324 – 337.

Bloom, D.E. and Gunderson, M. (1991). “An analysis of the earnings of Canadian immigrants”, in Abowd, J.M. and Freeman, R.B. (eds.) *Immigration, trade and the labor market.* Chicago, IL: University of Chicago Press, pp. 321 – 342.

Borjas, G.J. (1992). “Ethnic capital and intergenerational mobility”, *The Quarterly Journal of Economics*, vol. 107(1), pp. 123 – 150.

Borjas, G.J. (1994). “The economics of immigration”, *Journal of Economic Literature*, vol. 32(4), pp. 1667 – 1717.

Borjas, G.J. (1999). “The economic analysis of immigration”, in Ashenfelter, O. and Card, D. (eds.) *Handbook of Labor Economics, edition 1, volume 3, chapter 28*. Elsevier, pp. 1697 – 1760.

Borjas, G.J. (2003). “The labor demand curve is downward sloping: Re-examining the impact of immigration on the labor market”, *Quarterly Journal of Economics*, vol. 118(4), pp. 1335 – 1374.

Borjas, G.J., Grogger, J. and Hanson, G.H. (2012). "Comment: On estimating elasticities of substituition", *Journal of the European Economic Association*, vol. 10(1), pp. 198 – 223.

Bound, J., Jaeger, D. A. and Baker, R. M. (1995). "Problems with instrumental variables estimation when the correlation between the instruments and the endogeneous explanatory variable is weak", *Journal of the American Statistical Association*, vol. 90(430), pp. 443 – 450.

Bozio, A., Crawford, R. and Tetlow, G. (2010). "The history of state pensions in the UK: 1948 to 2010", Institute for Fiscal Studies, IFS Briefing Note BN105.

Bratsberg, B. (1995). "The incidence of non-return among foreign students in United States", *Economics of Education Review*, vol. 14(4), pp. 373 – 384.

Bridges, S. and Mateut, S. (2014) "Should they stay or should they go? Attitudes towards immigration in Europe", *Scottish Journal of Political Economy*, vol. 61 (4), pp. 397 – 429.

Burgess, S. (2011). "Who is aiming high?", Available at: https://cmpo.wordpress.com/2011/04/20/who-is-aiming-high/. (accessed on: 25th November, 2014)

Burgess, S. (2014). "Understanding the success of London's schools", Centre for Market and Pulic Organization, Bristol Institute of Pulic Affairs, University of Bristol, CMPO DP no. 14/333.

Burgess, S., Wilson, D., and Worth, J. (2009). "Passing through school: The evolution of attainment of England's ethnic minorities", Report for the National Equality Panel, Centre for Market and Pulic Organization, Bristol Institute of Pulic Affairs, University of Bristol.

Card, D. (1990). "The impact of the Mariel boatlift on the Miami labor market", *Industrial and Labor Relations Review*, vol. 43(2), pp. 245 – 257.

Card, D. (2001). "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration", *Journal of Labor Economics*, vol. 19(1), pp. 22 – 63.

Card, D. (2009). "Immigration and Inequality", *American Economic Review*, vol. 99(2), pp. 1 – 21.

Card, D. (2012). "Comment: The elusive search for negative wage impacts of immigration", *Journal of the European Economic Association*, vol. 10(1), pp. 211 – 215.

Card, D. and DiNardo, J. (2000). "Do immigrant inflows lead to native outflows?", *The American Economic Review*, vol. 90(2), pp. 360 – 367.

Card, D., Dustmann, C. and Preston, I. (2005). "Understanding attitudes to immigration: The migration and minority module of the first European Social Survey", CReAM UCL, DP no. 03/05.

Card, D., Dustmann, C. and Preston, I. (2012). "Immigration, Wages, and Compositional Amenties", *Journal of the European Economic Association*, vol. 10(1), pp. 78 – 119.

Carliner, G. (1980). "Wages, earnings and hours of first, second and third generation American males", *Economic Inquiry*, vol. 18(1), pp. 87-102.

Carrington, W.J. and Lima, P.d. (1996). "The impact of 1970s repatriates from Africa on the Portuguese labor market", *Industrial and Labor Relations Review*, vol. 49(2), pp. 330 – 347.

Casio, E.U. and Lewis, E.G. (2012). "Cracks in the melting pot: immigration, school choice and seggregation", *American Economic Journal: Economic Policy*, vol. 4(3), pp. 91 – 117.

Ceobanu, A.M. and Escandell, X. (2010) "Comparative analysis of public attitudes toward immigrants and immigration using multinational survey data: A review of theories and research", Annual Review of Sociology, vol. 36, pp. 309 – 328.

Chiswick, B.R. (1978). "The effect of Americanization on the earnings of foreign-born men", *Journal of Political Economy*, vol. 86(5), pp. 897 – 921.

Chowdry, H. and Sibieta, L. (2011). “School funding reform: An empirical analysis of options for a national funding formula”, Institute for Fiscal Studies, IFS Briefing Note BN123.

Citrin, J., Green, D.P., Muste, C. and Wong, C. (1997). “Public Opinion Toward Immigration Reform: The Role of Economic Motivations”, *The Journal of Politics*, vol. 59(3), pp. 858 – 881.

Coen-Pirani, D. (2011). “Immigration and spending on public education: California, 1970 – 2000”, *Journal of Public Economics*, vol. 95, pp. 1386 – 1396.

Constant, A.F. and Zimmermann, K.F. (2013). “Migration, ethnicity and economic integration”, in Jovanovic, M.N. (ed.) *International handbook on the economics of migration*. Cheltenham, UK, and Northampton, USA: Edward Elgar Publishing, pp. 13 – 36.

Cook, C. (2013). “London school children perform the best”, *Financial Times*, 13 January 2013.

Cook, C. (2014). “A happy whodunit in London schools”, *BBC News*, 20 June 2014. Available at: http://www.bbc.co.uk/news/education-27979096 (accessed on: 25th November, 2014).

Cook, T. D. (2008). “Waiting for life to arrive: A history of the regression-discontinuity design in psychology, statistics and economics”, *Journal of Econometrics,* vol. 1422, pp. 636 – 54.

Cortes, P. (2008). “The effect of low-skilled immigration on US prices: Evidence from cpi data”, *Journal of Political Economy*, vol. 116 (3), pp. 381 – 422.

Department for Communities and Local Government and Ipsos MORI (2007-2010). “Citizenship Survey, 2007-2010”. Colchester, Essex: UK Data Archive.

Department for Communities and Local Government and Ipsos MORI (2009-2010). “Citizenship Survey 2007-08: Technical Repoprt”. Available at: http://webarchive.nationalarchives.gov.uk/20120919132719/http://www.communities.gov.uk/documents/statistics/pdf/1395313.pdf. (accessed on: 13th October, 2014).

Department for Communities and Local Government and Ipsos MORI (2009-2010). “Citizenship Survey, 2009-2010”. Colchester, Essex: UK Data Archive. Available at: http://dx.doi.org/10.5255/UKDA-SN-6733-1. (accessed on: 13th October, 2014).

Department for Education (2014). Available at: https://www.gov.uk/government/organisations/department-for-education/about. (accessed on: 13th October, 2014)

Dustmann, C. (1993). “Earnings adjustment of temporary immigrants”, *Journal of Population Economics*, vol. 6(2), pp. 153 – 168.

Dustmann, C. and Frattini, T. (2013). “The fiscal effects of immigration to the UK”, Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London, DP no. 22/13.

Dustmann, C. and Glitz, A. (2011). “Migration and education”, in Hanushek, E., Machin, S. and Woessmann, L. (eds.) *Handbook of the Economics of Education*. Amsterdam: Elsevier, pp. 327 – 441.

Dustmann, C. and Preston, I. (2001). “Attitudes to ethnic minorities, ethnic context and location decisions”, *The Economic Journal*, vol. 111(470), pp. 353 – 373.

Dustmann, C. and Preston, I. (2004). “Is immigration good or bad for the Economy? Analysis of attitudnal responses.”, *Research in Labor Economics*, vol. 24, pp. 3 – 34.

Dustmann, C. and Preston, I. (2007). “Racial and economics factors in attitudes to immigration”, *The B.E. Journal of Economics Analysis & Policy*, vol. 7(1 (Advances)), article no. 62.

Dustmann, C. and Preston, I. (2012). “Comment: Estimating the effect of immigration on wages”, *Journal of the European Economic Association*, vol. 10(1), pp. 216 – 223.

Dustmann, C., Fabbri, F. and Preston, I. (2003). “The local labour market effects of immigration in the UK”, *Royal Economic Society Annual Conference*

2003, no. 70. Royal Economic Society, Available at: http://ideas.repec.org/p/ecj/ac2003/70.html. (accessed on: 13th October, 2014).

Dustmann, C., Fabbri, F. and Preston, I. (2005). "The impact of immigration on the British labour market", *The Economic Journal*, vol. 115(507), pp. F324 – F341.

Dustmann, C., Frattini, T. and Halls, C. (2010). "Assessing the fiscal costs and benefits of A8 migration to the UK", *Fiscal Studies*, vol. 31(1), pp. 1 – 41.

Dustmann, C., Frattini, T. and Preston, I. (2013). "The effect of immigration along the distribution of wages", *The Review of Economic Studies*, vol. 80(1), pp. 145 – 173.

Dustmann, C., Frattini, T. and Theodorpoulos, N. (2011). "Ethnicity and second generation immigrants", in Gregg, P. and Wadsworth, J. (eds.) *The labour market in winter: The state of working Britain.* Oxford: Oxford University Press, pp. 220 – 239.

Espenshade, T.J., Hempstead, K. (1996). "Contemprary American attitudes toward U.S. immigration", *International Migration Review*, vol. 30(2), pp. 535 – 570.

Facchini, G. and Mayda, A.M. (2008). "From individual attitudes towards migrants to migration policy outcomes: Theory and evidence", *Economic Policy*, CEPR, CES, MSH, vol. 23, pp. 651 – 713.

Facchini, G. and Mayda, A. M. (2006). "Individual attitudes towards immigrants: Welfare-state determinants across countries", Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London, DP no. 0604.

Facchini, G., Mayda, A.M. and Mendola, M. (2013). "What drives individual attitudes towards immigration in South Africa?", *Review of International Economics*, vol. 21 (2), pp. 326 – 341.

Fetzer, J.S. (2011). “The evolution of public attitudes toward immigration in Europe and the United States, 2000-2010”, San Domenico di Fiesole (FI): European University Institute: Robert Schuman Centre for Advanced Studies, EU-US Immigration Systems No. 2011/10.

Friedberg, R.M. and Hunt, J. (1995). “The impact of immigrants on host country wages, employment and growth”, *The Journal of Economic Perspectives*, vol. 9(2), pp. 23 – 44.

Fuligni, A. J. (2001). “Family obilgation and the academic motivation of adolescents from Asian, Latin American, and European backgrounds”, *New directions for child and adolescent development*, vol. 94, pp. 61 – 75.

Fuligni, A.J. (1997). “The academic achievement of adolescents from immigrant families: The roles of family background, attitudes, and behavior”, *Child Development*, vol. 68(2), pp. 351 – 363.

Fuligni, A.J. and Yoshika, H. (2004). “Parental investments in children in immigrant families”, in Khalil, A. and DeLeire, T. (eds.) *Parent investments in children: Resources and behaviors that promote success*, Mahwah, NJ: Lawrence Erlbaum, pp. 139 – 161.

Gang, I.N., Rivera-Batiz, F.L. and Yun, M. (2013). “Economic strain, education and attitudes towards foreigners in the European Union”, *Review of International Economics*, vol. 21 (2), pp. 177 – 190.

Geay, C., McNally, S. and Telhaj, S. (2013). “Non-native speakers of English in the classroom: What are the effects on pupil performance?”, *The Economic Journal*, vol. 123(570), pp. F281 – F307.

Gibbons, S., Silva, O. and Weinhardt, F. (2013). “Everybody needs good neighbours? Evidence from students’ outcomes in England”, *The Economic Journal*, vol. 123(571), pp. 831 – 874.

Glaeser, E.L. (2005). “The political economy of hatred”, *The Quarterly Journal of Economics*, vol. 120(1), pp. 45 – 86.

Gonzalez, Libertad and Francesc Ortega (2013). “Immigration and housing booms: Evidence from Spain”, *Journal of Regional Science*, vol. 53(1), pp. 37 – 59.

Greaves, E., Macmillan, L. and Sibieta, L. (2014). “Lessons from London schools for attainment gaps and social mobility”, Institute for Fiscal Studies and Institute of Education, Social Mobility and Child Poverty Commission, SMCP Research Report SMCP-RR363.

Hahn, J., Todd, P., and van der Klaauw, W. (2001). “Identification and estimation of treatment effects with a Regression Discontinuity Design”, *Econometrica*, vol. 69, pp. 315 – 331.

Hainmueller, J. and Hiscox, M.J. (2007). “Educated preferences: Explaining attitudes toward immigration in Europe”, *International Organization*, vol. 61(2), pp. 399 – 442.

Hainmueller, J. and Hopkins, D.J. (2014a). “Public attitudes toward immigration”, *Annual Review of Political Science*, vol. 17, pp. 225 – 249.

Hainmueller, J. and Hopkins, D.J. (2014b). “The hidden American immigration consensus: A conjoint analysis of attitudes toward immigrants”, *American Journal of Political Science*, pp. 1 – 20. Advance online publication, Available at: http://web.stanford.edu/~jhain/Paper/comparative.pdf (accessed on: 15th October, 2015)

Haisken-DeNew, J.P. and Zimmermann, K.F. (1994). “Native wage impacts of foreign labor: A random effects panel analysis”, *Journal of Population Economics*, vol. 7(2), pp. 177 – 192.

Haisken-DeNew, J.P. and Zimmermann, K.F. (1999). “Wage and mobility effects of trade and migration”, in Dewatripont, M. and Sapir, A. (eds.) *International Trade and Employment: The European Experience*. Oxford University Press, pp. 139 – 160.

Hammarstedt, M. (2003). “Income from work among immigrants in Sweden”, *Review of Income and Wealth*, vol. 49(2), pp. 185 – 203.

Hatton, T. J., Wheatley, Price. S. (1999). "Migration, migrants and policy in the United Kingdom", Institute for the Study of Labor (IZA), IZA DP no. 81.

Hickman, M., Crowley, H. and Mai, N. (2008). "Immigration and social cohesion in the UK: The rhythms and realities of everyday life", Joseph Rowntree Foundation, The Homestead, York.

Hood, M.V., Morris, I., and Shirkey, K. (1997). "Quedate o Vente!: Uncovering the determinants of Hispanic public opinion toward immigration", *Political Research Quarterly*, vol. 50(3), pp. 627 – 647.

Hunt, J. (1992). "The impact of the 1962 repatriates from Algeria on the French labor market", *Industrial and Labor Relations Review*, vol. 45(3), pp. 556 – 572.

Hunt, J. (2012). "The impact of immigration on the educational attainment of natives", Institute for the Study of Labor (IZA), IZA DP no. 6904.

Imbens, Guido W. and Angrist, J. D. (1994). "Identification and estimation of local average treatment effects", *Econometrica*, vol. 62(2), pp. 467 – 475.

Imbens, Guido W. and Lemieux, T. (2008). "Regression discontinuity designs: A guide to practice", *Journal of Econometrics*, Elsevier, vol. 142(2), pp. 615 – 635.

Ipsos MORI (2014). "Perceptions are not reality: Things the world gets wrong", Available at: https://www.ipsos-mori.com/researchpublications/researcharchive/2905/Issues-Index-2012-onwards.aspx?view=wide (accessed on: 27th November, 2014).

Ipsos MORI (2014). Available at: https://www.ipsos-mori.com/researchpublications/researcharchive/3466/Perceptions-are-not-reality-10-things-the-world-gets-wrong.aspx (accessed on: 27th November, 2014).

Just, A., and Anderson, C.J. (2015). "Dual allegiances? Immigrants' attitudes toward immigration", *The Journal of Politics*, vol. 77 (1), pp. 188 – 201.

Kuhn, P. and Wooton, I. (1991). "Immigration, international trade and the wages of native workers", in Abowd, J.M. and Freeman, R.B. (eds.) *Immigration, Trade and Labor.* University of Chicago Press, pp. 285 – 304.

Ladd, H.F., Fiske, E.B. and Ruijs, N. (2010). "Parental choice in the Netherlands: growing concerns about segregation", Stanford School of Public Policy, Working Paper Series Duke University, SAN10-02.

LaLonde, R.J. and Topel, R.H. (1991). "Labor market adjustments to increased immigration", in Abowd, J.M. and Freeman, R.B. (eds.) *Immigration, Trade and Labor.* University of Chicago Press, pp. 167 – 199.

LaLonde, R.J. and Topel, R.H. (1996). "Economic impact of international migration and the economic performance of immigrants", in Rosenzweig, M.R. and Stark, O. (eds.) *Handbook of population and family economics (North Holland, Amsterdam)*, pp. 799 – 849.

Lee, David S. and Lemieux, T. (2010). "Regression discontinuity designs in Economics", *Journal of Economic Literature*, American Economic Association, vol. 48(2), pp. 281 – 355.

Lymperopoulou, K. (2013). "The area determinants of the location choices of new immigrants in England", *Environment and Planning A*, vol. 45(3), pp. 575 – 592.

Malchow-Moller, N., Munch, J.R., Schroll, S. and Skaksen, J.R. (2008). "Attitudes towards immigration – perceived consequences and economic self-interest", *Economics Letters*, vol. 100, pp. 254 – 257.

Malchow-Moller, N., Munch, J.R., Schroll, S. and Skaksen, J.R. (2009). "Explaining cross-country differences in attitudes towards immigration in the EU-15*", Social Indicators Research*, vol. 91, pp. 371 – 390.

Manacorda, M., Manning, A. and Wadsworth, J. (2012). "The impact of immigration on the structure of wages: Theory and evidence from Britain", *Journal of the European Economic Association*, vol. 10(1), pp. 120 – 151.

Manning, A. and Roy, S. (2010). "Culture clash or culture Club? National identity in Britain", *The Economic Journal,* vol. 120(542), pp. F72-F100.

Markaki, Y. and Longhi, S. (2013). "What determines attitudes to immigration in European countries? An analysis at the regional level", *Migration Studies*, vol. 1(3), pp. 311 – 337.

Mayda, A.M. (2006). "Who is against immigration? A cross-country investigation of individual attitudes toward immigrants", *Review of Economics and Statistics*, vol. 88(3), pp. 510 – 530.

McCrary, J. (2008). "Manipulation of the running variable in the regression discontinuity design: A density test", *Journal of Econometrics*, vol. 142(2), pp. 698 – 714.

Menard S. (1995). "Applied logistic regression analysis", Sage University, Paper series on quantitative applications in the social sciences, Series no. 07 – 106, Thousand Oaks (CA), Sage pp. 98.

Nardelli, A., Arnett, G. (2014). "Today's key fact: You are probably wrong about almost everything", *The Guardian*, 29 October 2014. Available at: http://www.theguardian.com/news/datablog/2014/oct/29/todays-key-fact-you-are-probably-wrong-about-almost-everything?CMP=fb_gu (accessed on: 27th November, 2014).

Nielsen, I., Paritski, O. and Smyth, R. (2012). "A minority-status perspective on intergroup relations: A study of an ethnic Chinese population in a small Italian town", *Urban Studies*, vol. 49(2), pp. 307 – 318.

O'Connell, M. (2011). "How do high-skilled natives view high-skilled immigrants? A test of trade theory predictions", *European Journal of Political Economy*, vol. 27, pp. 230 – 240.

Ohinata, A. and Ours, J.v. (2013b). "Spillover effects of studying with immigrant students in the same classroom: Evidence from Quantile regression analysis", European Association of Labour Economists 25th Annual Conference. Turin.

Ohinata, A. and van Ours, J.v. (2013a). “How immigrant children affect the academic achievement of native Dutch children”, *The Economic Journal*, vol. 123(570), pp. F308 – F331.

ONS (2012). Migration Statistics Quarterly.

ONS (2014). http://www.ons.gov.uk/ons/about-ons/index.html (accessed on: 13th October, 2014)

ONS (2014). International Migration Data.

Ortega, F. and Polavieja J.G. (2012) “Labor-market exposure as a determinant of attitudes toward immigration”, *Labour Economics*, vol. 19, pp. 298 – 311.

Ottaviano, G.I.P. and Peri, G. (2006). “The economic value of cultural diversity: evidence from US cities”, *Journal of Economic Geography*, vol. 6 (1), pp. 9 – 44.

Ottaviano, G.I.P. and Peri, G. (2012). “Rethinking the effect of immigration on wages”, *Journal of the European Economic Association*, vol. 10(1), pp. 152 – 197.

Pacyga, Dominic A. (1991). “Polish Immigrants and Industrial Chicago: Workers on the South Side 1880 – 1922”, Chicago: University of Chicago Press.

Phillimore, J., Goodson, L. (2006). “Problem or opportunity? Asylum seekers, refugees, employment and social exclusion in deprived urban areas”, *Urban Studies*, vol. 43, pp. 1 – 22.

Phillips, D. (2007). “Ethnic and racial segregation: a critical perspective”, *Geography Compass*, vol. 15, pp. 1138 – 1159.

Pischke, J. and Velling, J. (1997). “Employment effects of immigration to Germany: An analysis based on local labor markets”, *The Review of Economics and Statistics*, MIT Press, vol. 79(4), pp. 594 – 604.

Polinard, J., Wrinkle, R., and de la Garza, R. (1984). “Attitudes of Mexican Americans toward irregular Mexican immigrants”, *International Migration Review*, vol. 18(3), pp. 782 – 899.

Rustenbach, E. (2010). “Sources of negative attitudes toward immigrants in Europe: A multi-level Analysis”, *International Migration Review*, vol. 44(1), pp. 53 – 77.

Saiz, Albert (2006). “Immigration and housing rents in American cities”, *Journal of Urban Economics*, vol. 61(2), pp. 345 – 371.

Sanchez, G.R. and Masouka, N. (2010). “Brown-Utility Heuristic? The presence and contributing factors of Latino linked fate”, *Hispanic Jounral of Behavioural Sciences*, vol. 32(4), pp. 519 – 531.

Scheepers, P., Gijsberts, M. and Coenders, M. (2002). “Ethnic exclusionism in European countries. Public opposition to civil rights”, *European Sociological Review*, vol. 18(1), pp. 1 – 17.

Scheve, K.F. and Slaughter, M.J. (2001). “Labor market competition and individual preferences over immigration policy”, *The Review of Economic and Statistics*, vol. 83(1), pp. 133 – 145.

Schneeweis, N. (2013). “Immigrant concentration in schools: Consequences for native and migrant students”. The Austrian Center for Labor Economics and the Analysis of the Welfare State, Johannes Kepler University Linz, Austria, Institute for the Study of Labor, IZA DP No. 7230.

Schneider, S.L. (2007). “Anti-immigrant attitudes in Europe: Outgroup size and perceived ethnic threat”, *European Sociological Review,* vol. 24(1), pp. 53 – 67.

Schwirian, K. P. (1983). “Models of neighborhood change”, *Annual Review of Sociology,* vol. 9, pp. 83 – 102.

Speciale, B. (2012). “Does immigration affect public education expenditures? Quasi-experimental evidence”, *Journal of Public Economics*, vol. 96, pp. 773 – 783.

Staiger, D., and Stock, J. H. (1997). “Instrumental variables regression with weak instruments”, *Econometrica*, vol. 65, pp. 557 – 586.

Stanley, J., Stanley, J. and Hensher, D. (2012). “Mobility, social capital and sense of community: What value?”, *Urban Studies*, vol. 49(16), pp. 3595 – 3609.

Stock, J.H., Wright, J.H. and Yogo, M. (2002). "A survey of weak instruments and weak identification in generalized method of moments", American Statistical Association, *Journal of Business and Economic Statistics*, vol. 20(4), pp. 518 – 529.

Styan, D. (2003). “Lanouvelle vague? Recent francophone African settlement in London”, in K Koser (ed.) *New African diasporas,* London: Routledge Press, pp. 17–36.

The Economist (2014). “Island mentality: Schools outside cities”, avilable at: http://www.economist.com/news/britain/21594986-bad-schools-and-low-aspirations-used-be-inner-city-problems-not-any-more-island-mentality (accessed on: 25th January, 2014).

Thistlethwaite, Donald L., and Donald T. Campbell. (1960). “Regression-Discontinuity Analysis: An Alternative to the Ex Post Facto Experiment”, *Journal of Educational Psychology*, vol. 51(6), pp. 309 – 17.

Trochim, W. (1984). “Research Design for Program Evaluation: the Regression-Discontinuity Approach”, Beverly Hills, Sage Publications.

Vervoort, M. (2012). “'Ethnic concentration in the neighbourhood and ethnic minorities’ social integration: Weak and strong social ties examined”, *Urban Studies*, vol. 49(4), pp. 897 – 915.

Vigdor, J.L. and Nechyba, T.S. (2007). “Peer effects in North Carolina public schools”, in Woessmann, L. and Peterson, P.E. (eds.) *Schools and the equal oppurtunity problem,* Cambridge: MA: MIT Press, pp. 73 – 101.

Wilson, D., Burgess, S. and Briggs, A. (2011). “The dynamics of school attainment of England’s ethnic minorities”, *Journal of Population Economics*, vol. 24(2), pp. 681 – 700.

Winter-Ebmer, R. and Zweimuller, J. (1996). “Immigration and the earnings of young native workers”, *Oxford Economics Papers*, vol. 48(3), pp. 473 – 491.

Winter-Ebmer, R. and Zweimuller, J. (1999). “Do immigrants displace young native workers: The Austrian experience”, *Journal of Population Economics*, vol. 12(2), pp. 327 – 340.

Zorlu, A., Mulder, C. H. (2008). “Initial and subsequent location choices of immigrants to the Netherlands”, *Regional Studies*, vol. 422, pp. 245–264.