Essays on the economics of migration and labour: Empirical evidence from the UK

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"E quindi uscimmo a riveder le stelle."

Dante Alighieri, La Divina Commedia (Inferno XXXIV, 139)

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Summary

This thesis covers the analysis of current UK economic issues relating to immigration and the labour market. In particular, since the late 1990s, the UK has experienced increasing immigration inflows significantly affecting both the economy and society as a whole. In parallel, over the last two decades the country has undergone other substantial changes in the structure of the labour market, primarily due to an intrinsic rapid educational upgrading and the pervasive effect of technological change.

Chapter 1 studies immigrant assimilation by comparing the life satisfaction of immigrants across different generations against that of their native peers. The immigrant generations appear less satisfied with their lives than the native population. However, a number of individual and neighbourhood-level ethnic and socio-economic characteristics explain the observed gaps, with the exception of the 2.5 immigrant generation. Finally, assimilation is achieved with the third immigrant generation. This analysis offers interesting insights with respect to policy. In particular, the lower well-being of immigrant children appears relevantly affected by objective livelihood conditions, such as residential area or neighbourhood deprivation, and therefore can be more easily addressed by policies.

Chapter 2 develops a model to explain the channels through which heterogeneous firms may adjust their product and process innovation activities in response to local labour supply shocks. The model is empirically tested using a difference-in-difference methodology, exploiting the large low-skilled immigration inflow induced by the enlargement of the European Union in 2004. No significant

treatment effect is found on process innovation, while a negative and significant average treatment effect is detected on product innovation. This is rationalised within the theoretical framework as an incentive for firms to substitute away from a high-skill activity that is now relatively more expensive. However, a number of empirical limits in the analysis advocate for future work.

Chapter 3 estimates the causal effect of technological exposure on UK local labour markets while providing suggestive evidence on the role of changes in the composition of the labour force. The instrumental variables strategy exploits local variation in the historical specialization in routine-intensive activities. Technology appears to displace middle routine workers and push them to lower-skilled jobs. However, no significant effect of technological exposure is found on skilled non-routine cognitive employment. At the same time, a negative association is found with the start-of-the-period local relative graduate labour supply during the 1990s. This last result is reinforced by evidence of an accentuated occupational downgrading since the 1990s. The disruptive technological change and the intensifying job competition caused by educational upgrading highlight the fundamental need for policy-makers to focus on sustaining employment and promoting a more efficient allocation of skills.

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Chapter 1

Life Satisfaction Assimilation of Immigrants in the UK

Abstract

Using data from the first wave of the Understanding Society Survey (2009-2010), this paper provides first empirical evidence on the life satisfaction assimilation of immigrants in the UK. The life satisfaction of immigrants across different generations is compared against that of their native peers. First results confirm that life satisfaction appears U-shaped in the immigrant generation. A number of socio-demographic individual and neighbourhood-level characteristics help explain the life satisfaction gaps. When ethnic characteristics are taken into account, the association between first and second immigrant generations and life satisfaction halves. Conditioning on home-ownership, first generation immigrants with less than 10 years since migration seem not to differ with respect to natives. When conditioning on neighbourhood deprivation, on the one hand, being a second generation immigrant does not affect the probability of being at least somewhat satisfied or higher. On the other hand, it significantly affects the probability for second generation immigrants of being mostly satisfied or higher, but not so for those living outside the London area. The life satisfaction gap suffered by generation 2.5 remains an unsolved puzzle[1].

Key Words: Subjective well-being, Life satisfaction, Immigration, Neighbourhood

JEL Codes: I31, J15, R23

[1]Data from the Understanding Society Survey have been made available by the Institute for Social and Economic Research (ISER) through the UK Data Archive under special licence. Neither ISER nor the UK Data Archive bear any responsibility for the analysis or interpretation of the data reported here.

1.1 Introduction

In recent years increasing emphasis has been placed on the role of policy makers in the promotion of individuals' well-being. Economic outcomes, though important measures, have been widely recognized not to be able alone to capture individuals' quality of life [Graham, 2009, 2011]. As a result, governments have been developing national accounts of well being. In 2009 the European Union launched Well-being 2030, a research project for the development of policy guidelines to provide European citizens with a higher quality of life within 2030. In 2010 David Cameron announced the National Well-Being Project for the UK, with the aim of measuring national progress in a more complete way. Also, national and European longitudinal surveys have introduced relevant questions to explore individuals' well-being domains, examples are the British Household Panel Survery (BHPS), the German Socio-Economic Panel (GSOEP) and the European Social Survey (ESS).

The measurement of well-being is indeed important also with respect to immigrant communities settled in the receiving society. As a matter of fact, immigration is undertaken in pursuit of a better life. However, the settlement into a new country evolves into a long and complex process of adaptation, or so called, assimilation. Britain, along with France and other countries worldwide, has recently experienced hot public and policy debates about ethnic diversity, community cohesion, and immigration. Low levels of well-being if not addressed may ultimately lead to social breakdowns, such as the riots that spread in England in 2001 and 2011. Young [2003] highlights that these social disturbances were caused by immigrant children who expected equal economic and social opportunities with respect to the other members of the society but suffered marginalization instead.

To the best of my knowledge, this paper provides first empirical evidence on the life satisfaction assimilation across immigrant generations in the UK during the period 2009-2010. The life satisfaction of immigrants is compared against that of natives, while accounting for a wide set of socio-demographic factors. While the variables of interest are exogenous, many relationships between the dependent and the conditioning variables are simultaneous. Therefore, the model estimates will not be interpreted as causal effects but rather as associations. Furthermore, unobserved personal traits are likely to cause omitted variable bias.

Results confirm that life satisfaction is U-shaped over the immigrant generations, reaching its minimum with the second generation. Individual socio-economic characteristics partly explain the gap. When ethnic characteristics are taken into account, the association between immigrant generation and life satisfaction halves. Conditioning on home-ownership, generation 1 immigrants with less than 10 years since migration seem not to differ with respect to natives. Generation 2 and 2.5 show instead a persistent lower life satisfaction with respect to natives.

In the second part of the analysis the focus is restricted on the life satisfaction gaps suffered by the middle immigrant generations and the role of neighbourhood cultural deprivation characterstics is investigated. Final estimates suggest that conditioning on neighbourhood deprivation, being a generation 2 immigrant has a negative significant association with the probability to be mostly satisfied or higher, but not so for individuals living outside the London area. Also, ceteris paribus, being a generation 2 immigrant has no significant association with the probability to be at least somewhat satisfied or higher.

The paper proceeds as follows. The next section provides an overview of the relevant theoretical perspectives on immigrant assimilation and subjecting well-being. Section 1.3 reviews the related empirical studies. Section 1.4 presents the data sources and summary descriptive statistics. Section 1.5 describes the empirical methodology. Section 1.6 discusses the analysis results. Section 1.7 tests the robustness of estimates and section 1.8 concludes.

1.2 Theoretical Perspectives: Theories of Immigrant Assimilation and Subjective Well-being

When we think about individuals' life satisfaction, we are induced to expect that the longer the period since migration and the further the generation, the more individuals will improve their living conditions and proceed with the assimilation path. As time goes by, immigrants should report a higher level of satisfaction.

However, a number of considerations emerging from the theories on subjective well-being and assimiliation should be taken into account.

Studies on subjective well-being show that people, when developing opinions and evaluations about life circumstances, engage in internal and external social comparison [Bartram, 2010; Clark et al., 2008; Festinger, 1954]. Individuals' responses will depend on the comparison of own achievements with respect to personal aspirations (internal comparison) as well as with respect to the relevant social group (external comparison). The former is even more significant for first generation immigrants. They will in fact assign a special weight to the fulfilment of aspirations as these have importantly contributed to the decision to migrate. As regards the latter, there are two possible reference groups for immigrants: people who remain in the sending country and their native peers in the host society. First generation immigrants are in touch with two different worlds, the sending country that they left behind and the receiving country where they settle in pursuit of a better life. The general expectation is that in the early period after migration people compare themselves to the former, while as time passes, the new relevant group for comparison becomes the latter. Immigrants' children will instead be more likely to compare only to their native peers.

Bartram [2010] argues that when comparing to people left in the sending country, immigrants may experience satisfaction as they generally improve their living conditions by settling in a wealthier country. When comparing with others in the host country, immigrants are instead more likely to show dissatisfaction due to the difficulties in achieving upward mobility.

The Chicago School of Sociology in the early 20th century was the first to provide a theory of immigrant assimilation, by analysing the process of inclusion of European immigrants in the American society. This theory took the name of straight-line assimilation theory as these immigrant groups were found to become increasingly more similar in characteristics, values and behaviour to natives over time.

Since then, different ethnic groups of immigrants have established in the USA in very large numbers and the assimilation of immigrants has been subject to large debate.

Among the different reformulations, the theory of segmented assimilation of Portes and Zhou [1993] gained major popularity. By observing the "new" second generation descending from Latin-American and Asian immigrants, this theory argues that assimilation may not necessarily be the end result and opens up to a multiplicity of outcomes for second generation immigrants.

Alba and Nee [1997, 2003] reformulated assimilation theory once again. They find inconclusive many of the differences between the European immigrants and the "new" immigrants previously claimed. They argue that, although unevenly and in different ways, assimilation is taking place. Moreover, they make the important point that in many cases the children of the European immigrant groups did not fully assimilate until the third or fourth generation.

Therefore, a critical point that emerges from these theories is that assimilation may be achieved in different ways and with different timing so that it may require a number of generations to fully take place.

1.3 Literature Review

A wide economic literature is dedicated to the study of the assimilation of immigrants. One part of the research work has focused on the economic assimilation as compared to their native peers on the basis of immigrant-native wage gap [e.g. Borjas, 1995; Chiswick, 1978], immigrants' occupational mobility [e.g. Chiswick et al., 2005; Chiswick and Miller, 2009], education and economic performance [e.g. Algan et al., 2010; Chiswick and Miller, 2011; Dustmann, Frattini and Theodoropoulos, 2010], language and earnings [e.g., Dustmann and Fabbri, 2003; Leslie and Lindley, 2001; Lindley, 2002]. Another side of the literature has explored the cultural and social assimilation of immigrants, looking at fertility rates [e.g., Riphan and Mayer, 2000], religion [e.g. Bisin et al., 2008; Bisin and Verdier, 2000], residential segregation [e.g. Musterd et al., 2008] or time-use [e.g. Zaiceva and Zimmermann, 2007]. De Palo et al. [2007] focus on the social assimilation of immigrants. [Aleksynska and Algan, 2010] undertake a comprehensive analysis of immigrant assimilation along economic, cultural and civic outcomes in Europe. As the latter point out, immigrant adaptation into the settlement country is a very complex process and the empirical evidence shows that assimilation may occur along only some of its dimensions. Importantly, they also highlight that the heterogeneity among immigrants in different countries plays an important role in explaining assimilation patterns, so that more research is needed at a regional and ethnical level. A few works have analysed assimilation through subjective measures such as feelings of national identity [e.g. Dustmann, 1996; Manning and Roy, 2010].

As regards happiness and life-satisfaction measures, economists have shown a long-standing scepticism. Nevertheless, during the last decade, subjective well-being has started to gain the attention of the economic literature, with most research focusing on the relation between happiness and income.

Only a few studies, mainly in the sociology literature, have addressed the life satisfaction of immigrants in the destination country. In this respect, there are two main findings. Firstly, immigrants and their offspring typically show lower life satisfaction with respect to their native counterparts. Secondly, different immigrant groups, from different countries or ethnicity, may experience considerably different levels of well-being.

Bălţătescu [2005] uses the first wave of the European Social Survey (ESS) (2002) to provide a first attempt of comparative analysis of the well-being levels between immigrants and their native peers in thirteen European countries in terms of life satisfaction, happiness and satisfaction with societal domains. The work suggests that immigrants experience a lower well-being with respect to natives in almost all the countries in the sample. However, immigrants show on average a significantly higher satisfaction with the socio-economic environment in the settlement country with respect to natives. The author interprets these two pieces of evidence as a result of the different groups against which immigrants compare in the different domains. When judging overall life satisfaction, immigrants relate themselves to natives, and this leads to lower reported scores. Immigrants feel instead more satisfied than natives with the social environment potentially because in this domain they relate themselves to their peers in the country of origin.

Bălţătescu [2007] expands the analysis to the first and second rounds of ESS (2002, 2004) and measures the well-being of Eastern European immigrants with respect to natives in the country of settlement. This research confirms Bălţătescu [2005]'s findings and highlights a further result, i.e. Eastern European immigrants show lower well-being levels than Western immigrants.

Safi [2010] analyses the first three rounds of ESS (2002, 2004, 2006). Lower levels of life satisfaction are found for first, second and 2.5 generation immigrants in comparison to natives with no foreign born parent. In particular, the second generation shows a substantial worse-off position with respect to the first. The author focuses on understanding the determinants of the lower well-being of this generation. The significant degree of perceived discrimination experienced by second generation ethnic minorities is concluded to be a plausible explanation.

Kirmanoğlu and Başlevent [2013] analyse the fifth ESS wave and explore the life satisfaction of individuals, focusing on the effect of ethnic minority membership and its interaction with immigration, discrimination and citizenship. Results suggest that second generation immigrants present higher life satisfaction than first generation immigrants, narrowing the life satisfaction gap with respect to natives. However, a deeper analysis seems to suggest that the assimilation hypothesis applies only to second generation immigrants not identifying themselves as ethnic minority members. Citizenship seems instead less important in the context of life satisfaction.

Koczan [2012] uses longitudinal panel data from GSOEP covering the period 1984-2010 and investigates two questions: whether first generation immigrants are worse-off with respect to natives in terms of well-being and what determines the life satisfaction of immigrants. The author uses a fixed-effect estimation to remove any time-invariant unobservable characteristics such as personality traits although this leads the regression model to drop the generation dummies of interest. Lags are used to address reverse causality. Results indicate that immigrants show lower satisfaction than natives when controlling for education and employment, but this effect disappears when taking into account whether the individual works in the occupation he/she was trained for. As regards the determinants of immigrants' life satisfaction, in contrast with previous studies, feelings of belonging is not a significant predictor, and citizenship seems to have more a self-selection effect rather than a causal effect on life satisfaction. Also, residential segregation does not seem relevant when including fixed-effects.

These few studies provide some insights into the well-being of immigrants in the settlement country, although little evidence still exists on the analysis of life satisfaction of immigrant generations beyond the first.

1.4 Data and Summary Statistics

I use data from the first wave of Understanding Society (US) (2009-2010), a major household panel survey in Great Britain. The dataset covers around 30,000 UK households and contains a large variety of information on social and economic aspects of individuals' lives. Moreover, it represents an extremely valuable data source for immigration and ethnicity related research purposes. The dataset includes an ethnic minority boost sample of about 1000 individuals from each of the major ethnic groups residing in Great Britain, i.e., Indian, Pakistani, Bangladeshi, Caribbean and African, selected in areas where the estimated density of ethnic minorities exceeded 5%. The adult self-completion questionnaire contains some questions on the subjective well-being of individuals. The outcome variable of interest derives from the following question: "How are you satisfied with your life overall?" The respondents have to tick one out of seven outcomes, ranging from "completely dissatisfied, mostly dissatisfied, somewhat dissatisfied, neither satisfied nor dissatisfied, mostly satisfied and completely satisfied".

This paper investigates the effect of immigrants' own generations on their life satisfaction relative to the native population. Immigrant generations are identified through information on the country of birth of the respondent, and of his or her parents and grandparents, as well as on the respondent's age at arrival in the UK. While the classification of migrant generations is generally defined by country of birth, age at arrival is also to be considered important. The threshold used here to distinguish between first and second generations is age 5, corresponding to the age at which pupils start with primary school in the UK. Individuals born abroad but raised in the UK are expected to be more similar to UK-born individuals than to people born and raised abroad. Nevertheless, the main results do not change if generations are defined by country of birth only. According to these criteria, first generation immigrants are individuals living in the UK but who were born abroad and who arrived to the country after 5 years of age. The second immigrant generation is composed of either individuals who were born abroad but that migrated to the UK before 5 years of age or UK-born children with both parents born abroad. The 2.5 immigrant generation includes UK-born children or foreign born children with arrival age before 5 and with only one parent born outside the UK. Finally, the third immigrant generation regards UK-born children of two UK born parents, with at least one foreign-born grandparent. Natives are UK-born individuals with UK-born parents and grandparents.

The analysis restricts to those individuals aged 16 and over, therefore eligible to complete the adult self-completion questionnaire. 6301 individuals are excluded due to not enough available information to disentangle whether they belonged to a specific immigrant generation or to the native group. In total, the sample of analysis consists of about 47,000 individuals, interviewed between January 2009 and December 2010.

Figure 1.1 shows that the distribution of life satisfaction responses is skewed to the left. The mean value is 5,25 while the mode and median value is 6. Table 1.1 shows a summary of the main descriptive statistics for the different sample groups in 2009-2010. It can be observed that the immigrant generations show lower life satisfaction levels with respect to natives. The life satisfaction means of the immigrant groups increase towards that of natives the further the generation, with the exception of a drop coinciding with the second generation. This confirms the U-shape of life satisfaction over the immigrant generations found in Safi [2010].

Importantly, the first two generations distinguish themselves in a number of characteristics. Generations 2.5 and 3 are instead relatively more similar to the native population. The immigrant groups are relatively younger with respect to the native population, with the second generation being the youngest showing a mean of 34 years of age.

The first generation has the highest proportion of individuals with at least a first degree (44%) as opposite to the native group which shows the lowest percentage (30%). In more detail, 60% of first generation degree holders are immigrants with less than 10 years since migration.

First generation households present the lowest average net income (£1160), followed by native households (£1268). At the same time, first generation immigrants are the least likely to own a house or a flat at least partially (42%), while natives are the most likely (72%).

The second generation presents the highest proportion of unemployed individuals (11%), followed by the first generation (9%) while the native population shows the lowest one (5%).

The first generation registers the highest proportion of individuals employed in low skilled jobs (26%). Generation 1 and 2 show significantly higher household sizes with respect to the other groups, even though generation 2 immigrants are the least likely to be married or live as a couple.

As regards the ethnic background, the further the generation, the stronger the feeling of belonging to the "white British" ethnicity. Notably, a big jump is registered with the 2.5 generation. Only 13% of second generation immigrants define themselves as "white British", while 73% of 2.5 generation does so.

Furthermore, the first two generations show the highest proportions of individuals defining themselves as belonging to a religion. The majority of individuals lives in England, with the highest proportions in the first two generations (95% and 97% respectively), and the lowest in the native population (79%). Generation 1 and 2 individuals reside predominantly in urban areas as well as in areas with higher concentration of ethnic minorities with respect to the other groups.

1.5 Method

I analyse the life satisfaction of immigrants across different generations, compared against their native peers in the UK. The research purpose is to analyse the effect of immigrants' generations on their own life satisfaction, which is clearly unilateral. However, many relationships between the dependent and the conditioning variables will be simultaneous. Therefore, the model estimates will not be interpreted as causal effects but rather in terms of magnitude and sign of variables' associations. Although unobserved personal traits are swept into the error term and cause omitted variable bias, models such as fixed effects cannot be adopted because the variables of interest, the generation dummies, would otherwise be lost. Nevertheless, it is reasonable to expect that time-invariant personality traits, such as innate motivation, would bias the estimates of the variables of interest to the same extent. In this sense, the comparability of estimates between the generation variables would be preserved. Changes in the magnitude/significance of the estimated coefficients as a result of selected control variables will be interpreted as potential explanatory factors of the life satisfaction gaps. Given the ordinal nature of the dependent variable, an ordered regression might be seen as the most suitable choice of model. However, given the negatively skewed distribution of life satisfaction a binary choice model is the selected choice for the analysis. Moreover, an ordered regression involves one major specification issue in addition to those relevant for binary regressions, i.e. the parallel regression assumption. This means that the effect of a regressor is assumed to be invariant across any split in the data.

I estimate the probability of being in the top two categories of the life satisfaction distribution. I use a logit model where life satisfaction is reduced to a binary variable, where a value of 1 jointly indicates the categories "completely satisfied and mostly satisfied" whereas 0 comprehends all the lower categories. The consistency of the estimated associations for the generation dummies' is tested applying different specifications and regression models. Standard errors are clustered at the household level, assuming that the individuals' errors will be correlated to those of other household members.

1.6 Results

In column (1) of Table 1.2 life satisfaction is regressed on the generation dummies and basic socio-demographic individual characteristics, i.e., gender, age and its square, degree or higher qualification, long-standing illness or impairment, having a partner, belonging to a religion, unemployment, net household income. All the regressors' estimates have the expected signs and are in line with the general findings in the literature [for a detailed literature review on subjective well-being see Dolan et al., 2008].

Males appear significantly less satisfied than females. Age shows a U-shape relationship with life satisfaction, with the minimum at around 40 years of age. Holding at least a degree has a positive and significant association with life satisfaction. Long-standing illness or impairment has a strong negative coefficient. Being married or in a couple has a significant positive association, while having at least one child seems instead to have a significant negative association. Belonging to a religion has a significant positive relationship with overall life satisfaction. As expected, unemployment has instead a strong negative coefficient. Net household income is computed aggregating monthly net labour income from the (self-) employed members of the family. Net household income shows a positive but small relationship with life satisfaction.

All the generation dummies exhibit significant and negative coefficients, confirming that the immigrant generations appear relatively less satisfied than natives. Specifically, 1, 2 and 2.5 generations have a strong significant and negative association with life satisfaction. In particular, generation 2 appears to be significantly worse off with respect to all the other immigrant generation groups when compared to natives. Third generation immigrants also seem to significantly differ from natives in terms of life satisfaction but to a much lesser extent than the other generations. With respect to generation 1, I hypothesize that years since migration may play an important effect on life satisfaction. I argue that first generation immigrants will be more comparable to the other generation groups the longer the period since migration. In fact, first generation immigrants are in touch with two different worlds: the sending country that they left behind and the receiving country where they settle in pursuit of a better life. The general expectation is that in the early period after migration people compare themselves to the former, while as time passes, the new relevant group for comparison becomes the latter. Immigrants' children will instead be more likely to compare only to their native peers.

In column (2) I introduce in the specification the interaction between a dummy for whether the individual has moved to the UK since more than 10 years and the first generation dummy. Interestingly, the estimated coefficient is negative and significant.

This finding seems to suggest that the more the years since migration, the less the satisfaction of first generation immigrants. I investigate this association further. Figure 1.2 shows the frequency distribution of years since migration for first generation immigrants. I split first generation immigrants into four subcategories by years since migration (10-20, 20-30, 30-50, 50+) and include a dummy for each of them in column (3). What seems to matter is the range 10 to 20 years since migration. Migrants belonging to this cohort feel substantially less satisfied than newly arrived ones. Instead, there is no statistical difference between "new" immigrants and immigrants that have been living in the UK for more than 20 years. It is important to note that we cannot identify whether this "years since migration" effect that is observed is due to the fact that people who are not satisfied ultimately leave and therefore a composition effect or if there is a genuine non-linear relationship between years since migration and life satisfaction for first generation immigrants. Given the observed evidence I choose to use a dummy for the category 10-20 and a dummy for the category 20+ years since migration in the preferred specification as shown in column (1) of table 1.3. In the next few columns I progressively enrich the model to investigate other potential explanatory factors for the life satisfaction gaps between immigrants and natives.

In column (2) ethnic characteristics are added. Importantly, when accounting for ethnicity, the generation 1 and 2 coefficients reduce by about half of their magnitude. The chosen baseline category for ethnicity is the Indian group, which has been the largest non-white group present in Britain since census 1991 records. It can be observed that non-white groups do not significantly differ in terms of life satisfaction with respect to Indians. White British and "other white" ethnicities have instead significant and positive coefficients. Another factor which may significantly affect the life satisfaction gap of immigrant generations is home ownership. In particular, generation 1 shows a very low home ownership rate of 42%. The rate reduces to 21% if we take into account individuals with less than 10 years since migration. The other generations show a home ownership rate of 64-65% against a rate of 72% for natives.

Accordingly, in column (3) I find a substantial significant positive association for home ownership. As a result, the generation 1 coefficient reduces by 16 percentage points and turns not significant. First generation immigrants with less than 10 years since migration do not appear less satisfied than natives. The interaction dummies between years since migration and first generation are instead significantly negative. Independently of home ownership first generation immigrants with more than 10 years since migration appear unhappier than more recent immigrants. When compared with respect to natives, the omitted category, they also appear significantly less satisfied, even though the gap has decreased. No relevant change is registered for the other generation dummies.

In addition, I hypothesize that residential characteristics may be important explanatory factors of immigrant generations' life satisfaction gaps.

Column (4) accounts for whether the individual lives in a constituent country other than England, and whether the individual lives in an area (postal sector) with low density of ethnic minorities (below 5%). Both variables have positive and significant coefficients. They are positively correlated as England is the country with the highest concentration of ethnic minorities. Column (5) additionally controls for urban rather than rural residential area. The variable seems to capture the effect of low density of ethnic minority areas, which reduces in magnitude and turns not significant. These two variables are negatively correlated as urban areas are more ethnically diverse than rural areas. The generations' coefficients do not relevantly change, neither do ethnicity coefficients. Broad residential characteristics seem to explain very little about immigrants' life satisfaction gaps. Data at the neighbourhood level may shed more light on the impact of local environment on the life satisfaction of immigrant generations.

Finally, I investigate the role of occupational background. The descriptive statistics show that the employment of first generation immigrants in partly skilled or unskilled occupations is double as much as the other generations. The literature has documented that immigrants and ethnic minorities may be more likely than UK-born individuals to be overeducated with respect to the educational level common for the occupations in which they are employed [Altorjai, 2013; Lindley, 2009]. As regards individuals' occupational background, dummies were included for each Registrar General's Social Class (SC) of current job (i.e., professional, managerial and technical, skilled non-manual, skilled manual, partly skilled and unskilled). Only professional and managerial occupations appeared to have a significant positive association with life satisfaction as compared to unskilled occupations, while all the other dummies were jointly not significant. Conditioning on professional and managerial occupations in column (6) does not affect the main results.

Important key findings emerge from this analysis. All the immigrant generations show lower life satisfaction levels than their native peers. First generation immigrants with less than 10 years since migration do not longer seem less satisfied than natives once we condition on home ownership. The main result born out by the data is a substantial and negative significant effect of generations 2 and 2.5 on life satisfaction, which persists after controlling for ethnicity, home-ownership, occupational background and broad residential characteristics. The generation 3 coefficient shows the smallest magnitude, barely changing across the specifications but losing any statistical significance as the set of control variables widens. The emerging evidence is therefore that assimilation seems to be achieved by the third immigrant generation. The next step in the analysis is to focus on the life satisfaction gap of the middle immigrant generations and take into account neighbourhood-level cultural characteristics and deprivation.

1.6.1 Life Satisfaction and Neighbourhood Characteristics

Immigrant children most likely face a cultural conflict between their family background and origins against the outside world where they live, study or work. I argue that neighbourhood cultural and deprivation characteristics may explain the lower life satisfaction experienced by these generations.

Beyond ethnicity, religious differences may also play a relevant role in explaining cultural conflicts. In particular, Muslim immigrants differ substantially from non-Muslims groups. Muslims show stronger religious identity and seem to culturally integrate less and more slowly than non-Muslims groups in the UK [Bisin et al., 2008]. Unfortunately, variables registering religious affiliations contain many missing values which make such analysis insignificant. Respondents to the survey where asked about their religious affiliation, and if "none" was answered, they were further asked what was the religion they were brought up in. Therefore, such missing values most likely correspond to preferred omission of own religious beliefs. Nevertheless, a measure of religious diversity at the neighbourhood level can be retrieved from Census 2011 data.

Also, neighbourhood deprivation can be an important explanatory factor for the life satisfaction gaps. Immigrants and ethnic minorities are typically more likely to live in more deprived and more ethnically concentrated urban areas [Clark and Drinkwater, 2002; Dorsett, 1998; Petersen and Rabe, 2013].

Studies on the effect of neighbourhood characteristics on the subjective well-being of immigrants and ethnic minorities in the UK are very few and show mixed results.

Becares et al. [2009] analyses the buffering effects of ethnic density on experienced racism and health of ethnic minority people in the UK. Results show that when conditioning on area deprivation, ethnic density and mental health have a positive association.

Becares et al. [2011] investigates the association between social cohesion and ethnic residential concentration, composition and deprivation for ethnic minorities in the UK. Findings show that, once controlling for area deprivation, the positive association between own-group ethnic composition and social cohesion increases for ethnic minority people. This research suggests that it is not the neighbourhood ethnic profile but neighbourhood deprivation that undermines social cohesion for both ethnic minorities and white British people. Sturgis et al. [2013] analyse ethnic diversity, segregation and social cohesion in neighbourhoods in London. The authors find a positive association between social cohesion and ethnic diversity, once accounting for neighbourhood deprivation. Ethnic segregation is instead associated with lower perceived social cohesion. Knies et al. [2013] study the effect of neighbourhood ethnic composition on life satisfaction of ethnic minorities in the UK, while adjusting for neighbourhood type, using micro-marketing data, and for median neighbourhood income. Neighbourhood type and proportion of co-ethnics seem to have no significant benefit for the life satisfaction of ethnic minorities, with the only exception of African communities.

The findings for the 2.5 immigrant generation are instead somewhat unexpected. The presence of a native-born parent is supposed to make a difference in terms of experiences and outcomes of the offspring. The general expectation is that the 2.5 generation avoids most of the cultural conflict faced by generation 2. These unexpected results make the analysis of locality characteristics interesting for this generation as well.

In order to proceed with the analysis the dataset with Census 2011 data I define neighbourhoods in terms of Lower Layer Super Output Areas (LSOAs). LSOAs belong to the Super Output Areas (SOAs), a set of three geographical units designed from the 2001 census for the computation of indeces of deprivation and other neighbourhood statistics. LSOAs are consistent in size across the country and more stable over time as they are less likely to be subjected to frequent boundary changes unlike electoral wards. LSOAs have a minimum population of 1,000 individuals, with an overall mean of 1,500. They contain from 4 to 6 Output Areas (OAs), aggregated on the basis of similar social characteristics. OAs are the lowest neighbourhood-level statistical units of analysis, with a minimum population size of 100 and an overall mean of 300. LSOAs can be aggregated into Middle Layer Super Output Areas (MSOAs), to form higher geographical areas with a minimum population of 5,000 individuals with an overall mean of 7,200. Furthermore, I link the dataset to the 2010 Index of Multiple Deprivation (IMD) scores adjusted to align with 2011 LSOAs for England, information made recently publicly available from Public Health England. Each constituent country in the UK computes their own IMD, therefore IMD scores between constituent countries are not directly comparable. I therefore choose to restrict the sample of analysis to England.

IMDs are intended to measure deprivation in a broad sense, taking into account lack of resources in multiple life domains. The English IMD 2010 is an overall index computed combining 38 indicators, constructed across seven weighted domains of deprivation (income, employment, health and disability, education skills and training, barriers to housing and other services, crime, living environment)[1]. The higher the score, the higher the average level of deprivation in the LSOA. From 2011 census data I can construct neighbourhood-level variables regarding ethnic density, ethnic and religious diversity. Following Becares et al. (2009) I proxy ethnic density in two ways, i.e. as the share of co-ethnics (own-ethnic density) as well as the percentage of minority people (overall ethnic minority density) living in the same neighbourhood of an individual. In line with the literature, I measure ethnic and religious diversity using the so called Fractionalization Index [Alesina et al., 2003]:

$$Fr_{k,n} = 1 - \sum_{k=1}^{K} s_{k,n}^2 \tag{1.1}$$

where $s_{k,n}$ is the share of the k^{th} ethnic or religious group in neighbourhood n. This index is in fact 1 minus the Herfindal-Hirschman concentration Index (HHI).

Neighbourhood-level descriptive statistics are show in table 1.4. Generation 1 and 2 show similar patterns as opposed to the other groups. The further the generation, the lower the level of overall neighbourhood deprivation. There is a big drop (about 10 percentage points) in the IMD between generations 1 and 2 (31 to 32%) and the other groups (23 to 20%). Overall ethnic minority density is highest for generation 2 (57 %) followed by generation 1 (56%), it then halves for generation 2.5 and reduces to a quarter for natives. As regards own ethnic density, generation 1 individuals are the most likely to live in neighbourhoods with less presence of co-ethnic people, showing a rate of 16%. Own ethnic density increases to 24% for generation 2, almost triples for generation 2.5 and quadruplicates for natives. In line with overall ethnic minority density, ethnic diversity and religious diversity are highest in neighbourhoods where generation 1 and

[1] For a detailed description of the computation of the English IMD 2010 see McLennan et al. [2011].

2 individuals reside, followed by a big drop coinciding with generation 2.5. Finally, it is important to take into account the distribution of groups in and out of London [1]. About half of generation 1 and 2 individuals live in London. This proportion more than halves with generation 2.5 and further drops with generation 3. In comparison, only 6% of natives lives in the capital. I expect a negative relationship between life satisfaction and overall ethnic minority density or ethnic diversity. These two variables are highly correlated, so that I include them into separate specifications. Furthermore, I expect a positive buffering effect of own-ethnic density while a negative association with religious diversity. However, large part of these relationships could be driven by deprivation given that ethnic minorities are most likely to reside in highly deprived neighbourhoods. Also, it is important to consider that London neighbourhoods present a more distinctive ethnic and cultural composition as well as liveability conditions with respect to the rest of England.

Table 1.8 shows the first piece of regressions' results. Besides restricting the sample to England, the dummy for low ethnic minority areas is excluded as the focus is now switched on the association between life satisfaction and high density ethnic minority areas.

Column (1) shows that estimates do not alter when the sample of analysis is restricted to England.

Column (2) accounts for the overall neighbourhood ethnic minority density, which as expected, has a negative significant association with individual life satisfaction.

Column (3) further controls for own ethnic density, which has a positive but non-significant association. Its inclusion makes the association of overall ethnic minority density to drop by 6 percentage points and lose any statistical significance. The two associations appear to counterbalance. Column (4) includes neighbourhood deprivation, which appears significantly negatively associated with individual life satisfaction, although having a very low magnitude. Interestingly, the coefficient for overall ethnic minority density drops by 10 percentage points when conditioning on neighbourhood deprivation. This seems to suggest that ethnic density may be picking up a selection effect rather than a true effect.

[1] London neighbourhoods are here defined as belonging to the London county, including inner and greater London.

Religious diversity in column (5) appears to a have a large negative association although not significant. The data show that the only neighbourhood-level characteristic having a significant association with overall individual life satisfaction is deprivation. The point estimates for generations 2 and 2.5 remain robust in magnitude and significant throughout all the specifications. This finding seems to suggest that the life satisfaction gaps of the middle generations do not depend on neighbourhood specific characteristics.

Finally, in column (6) the sample excludes all neighbourhoods living in the county of London. As a result, the generation 2 coefficient drops by about 12 percentage points and turns not significant. Outside of London, generation 2 immigrants therefore do not appear less satisfied than their native peers. Table 1.6 confirms the results, where ethnic diversity replaces overall ethnic minority density in the specifications.

1.7 Robustness Checks

A number of robustness checks are performed to test the consistency of the estimates from tables 1.8 and 1.6. Firstly, tables 1.7 and 1.8 reproduce the regression specifications defining immigrant groups by using the traditional classification of immigrant generations by country of birth rather than country of birth combined with age at arrival. The estimates appear robust with respect to the definition of immigrant generation.

Secondly, regressions in tables 1.8 and 1.8 use ordered logit models in order to check whether the main findings are robust to splits in the data. The ordered logit point estimates of generation 2 in column (2) of table 1.8 drop significance, as overall ethnic minority density is controlled for, and the result persists throughout the rest of the columns. The same result is found in table 1.8, where ethnic diversity replaces overall ethnic minority density. This points towards the failure of the parallel regression assumption.

Finally, I re-estimate the logit models while changing the cut-off for the dependent variable in tables 1.8 and 1.8. The dependent variable is reduced to a dummy with value equal to 1 when the individual is at least somewhat satisfied (categories 5-7) and

0 otherwise. In column (2) of both tables, the point estimates for generation 2 lose statistical significance as overall ethnic minority density is controlled for. This confirms that estimates for generation 2 are indeed not robust to splits in the data. Once again, neighbourhood deprivation confirms to be the relevant neighbourhood-level explanatory factor. This result does not alter when the other neighbourhood-specific controls are included.

In conclusion, on the one side this analysis suggests that conditioning on neighbourhood deprivation, being a second generation immigrant does not affect the probability of being at least somewhat satisfied. On the other side, it significantly affects the probability for second generation immigrants of being mostly satisfied or higher, but not so for those living outside the London area. The significantly negative effect of generation 2.5 persists throughout all the specifications and remains an unsolved puzzle.

1.8 Conclusions

This study compares the life satisfaction of different immigrant generations as opposed to the native population in the UK. In the first part of the analysis I explore the role of a number of socio-demographic factors, i.e. ethnicity, home ownership, locality variables, occupational background. Ethnic characteristics play a substantial role in explaining the life satisfaction gaps of generation 1 and generation 2 with respect to natives. Furthermore, generation 1 immigrants with less than 10 years since migration do not appear less happy than natives, when home-ownership is taken into account. Results highlight robust evidence for significant lower life satisfaction experienced by generations 2 and 2.5 with respect to natives, which persists even after all control variables are taken into account. Assimilation seems to be achieved by the third immigrant generation. In the second part of the analysis the focus is restricted on investigating the potential role of neighbourhood characteristics as possible determinants of the lower life satisfaction of the middle immigrant generations with respect to the native population. The main dataset is matched with data from census 2011 and with the 2010 IMD scores at LSOA level for England in order to test the associations of life satisfaction with ethnic density, ethnic diversity, deprivation and religious diversity.

The analysis' results offer important insights for policy making. The assimilation of immigrants does not show a linear trend. Life satisfaction differences with respect to the native population widen with the second generation while fade away with the third generation. Ethnicity seems to play an important role in explaining well-being of immigrant groups at the individual dimension. When people's ethnic self identification is taken into account the life satisfaction gaps suffered by the first and second generations halves. Once accounting for home ownership, first generation immigrants do not longer differ in terms of well-being from their native peers. Among neighbourhood characteristics, deprivation appears as the relevant control factor. Final results show, on the one side, that conditioning on neighbourhood deprivation, being a second generation immigrant does not affect the probability of being at least somewhat satisfied. On the other side, it significantly affects the probability for second generation immigrants of being mostly satisfied or higher, but not so for those living outside the London area.
This evidence may reassure policy makers in showing potential for intervention on objective economic conditions. Neighbourhood-level overall ethnic minority density and diversity appear in fact less important when deprivation is taken into account. Also, only second generation immigrants living in London neighbourhoods register well-being gaps with respect to their native peers. The significantly negative effect of generation 2.5 persists across all the regression specifications and remains an unsolved puzzle that is left to future empirical investigation.

Tables

Table 1.1: Descriptive Statistics

Variable	Generation 1			Generation 2			Generation 2.5			Generation 3			Native		
	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.
Life satisfaction	5.10	1.48	5134	4.94	1.52	2322	5.14	1.48	2274	5.22	1.46	2938	5.33	1.43	24335
Life satisfaction (dummy)	0.50	0.50	5134	0.45	0.50	2322	0.55	0.50	2274	0.58	0.49	2938	0.62	0.49	24335
Years since migration >10	0.52	0.50	7695												
Male	0.47	0.50	7739	0.43	0.50	3043	0.43	0.49	2603	0.43	0.49	3370	0.44	0.50	27936
Age	41.82	15.68	7739	33.87	12.46	3043	42.27	17.65	2603	43.21	18.61	3370	48.74	18.29	27936
Degree or higher	0.44	0.50	7733	0.40	0.49	3043	0.36	0.48	2603	0.34	0.47	3367	0.30	0.46	27930
Longstanding illness/impairment	0.24	0.43	7712	0.22	0.41	3037	0.35	0.48	2600	0.39	0.49	3367	0.39	0.49	27902
Unemployed	0.09	0.29	7738	0.11	0.31	3042	0.08	0.26	2603	0.06	0.24	3368	0.05	0.23	27935
Household net income £	1159.84	1499.90	7739	1363.82	1573.13	3043	1413.77	1808.85	2603	1392.85	1714.05	3370	1268.45	1564.62	27936
Owned house/flat	0.42	0.49	7716	0.63	0.48	3024	0.65	0.48	2599	0.65	0.48	3360	0.72	0.45	27883
Employment															
Professional/manager	0.39	0.49	3926	0.46	0.50	1768	0.46	0.50	1541	0.46	0.50	1887	0.41	0.49	15586
Non manual	0.17	0.38	3926	0.28	0.45	1768	0.22	0.42	1541	0.22	0.42	1887	0.23	0.42	15586
Manual	0.18	0.38	3926	0.13	0.34	1768	0.16	0.36	1541	0.17	0.37	1887	0.19	0.40	15586
Partly skilled	0.21	0.41	3926	0.10	0.30	1768	0.13	0.34	1541	0.12	0.33	1887	0.13	0.34	15586
Unskilled	0.05	0.22	3926	0.02	0.13	1768	0.03	0.17	1541	0.03	0.17	1887	0.04	0.19	15586
Ethnicity															
White British	0.03	0.17	7734	0.13	0.34	3039	0.73	0.45	2602	0.91	0.29	3370	0.99	0.11	27925
Other white	0.17	0.38	7734	0.05	0.21	3039	0.05	0.22	2602	0.02	0.14	3370	0.01	0.10	27925
Indian	0.16	0.37	7734	0.19	0.39	3039	0.02	0.14	2602	0.00	0.07	3370	0.00	0.00	27925
Pakistani	0.10	0.30	7734	0.19	0.39	3039	0.03	0.16	2602	0.00	0.02	3370	0.00	0.00	27925
Bangladeshi	0.09	0.29	7734	0.12	0.33	3039	0.00	0.07	2602	0.00	0.03	3370	0.00	0.02	27925
Caribbean	0.07	0.26	7734	0.14	0.35	3039	0.03	0.16	2602	0.02	0.12	3370	0.00	0.01	27925
African	0.15	0.36	7734	0.06	0.24	3039	0.01	0.09	2602	0.00	0.04	3370	0.00	0.00	27925
Mixed	0.03	0.16	7734	0.03	0.18	3039	0.11	0.32	2602	0.04	0.19	3370	0.00	0.03	27925
Other	0.19	0.39	7734	0.09	0.29	3039	0.02	0.16	2602	0.01	0.10	3370	0.00	0.04	27925
Belong to a religion	0.83	0.38	7736	0.79	0.41	3041	0.52	0.50	2601	0.50	0.50	3368	0.49	0.50	27922
Partner	0.65	0.48	7733	0.46	0.50	3041	0.53	0.50	2601	0.57	0.50	3370	0.64	0.48	27930
Children in household	0.42	0.49	7739	0.38	0.49	3043	0.28	0.45	2603	0.28	0.45	3370	0.26	0.44	27936
Household size	3.42	1.83	7739	3.83	2.00	3043	2.87	1.48	2603	2.80	1.37	3370	2.68	1.30	27936
Residential area															
England	0.95	0.22	7739	0.97	0.17	3043	0.86	0.34	2603	0.82	0.39	3370	0.80	0.40	27936
Wales	0.01	0.12	7739	0.01	0.11	3043	0.03	0.17	2603	0.05	0.21	3370	0.06	0.24	27936
Scotland	0.02	0.14	7739	0.01	0.10	3043	0.05	0.23	2603	0.09	0.29	3370	0.09	0.28	27936
Northern Ireland	0.01	0.12	7739	0.01	0.09	3043	0.05	0.22	2603	0.04	0.20	3370	0.05	0.23	27936
Urban area	0.96	0.19	7739	0.97	0.18	3043	0.82	0.39	2603	0.80	0.40	3370	0.73	0.44	27936
Low density ethnic minority area	0.11	0.32	7739	0.08	0.27	3043	0.46	0.50	2603	0.56	0.50	3370	0.69	0.46	27936

Notes: The table shows the mean, standard deviation and number of observations for relevant variables in the analysis.

Table 1.2: Regression Analysis: Basic Socio-demographic Controls

Variables	(1)	(2)	(3)
Generation 1	-0.5059***	-0.4311***	-0.4351***
	(0.037)	(0.049)	(0.049)
Generation 1 * (ysm>10)		-0.1490**	
		(0.063)	
Generation 1 * (10<ysm≤20)			-0.2526***
			(0.083)
Generation 1 * (20<ysm≤30)			-0.0624
			(0.109)
Generation 1 * (30<ysm≤50)			-0.1016
			(0.088)
Generation 1 * (ysm>50)			-0.0239
			(0.179)
Generation 2	-0.5923***	-0.5858***	-0.5890***
	(0.049)	(0.049)	(0.049)
Generation 2.5	-0.2221***	-0.2194***	-0.2206***
	(0.049)	(0.049)	(0.049)
Generation 3	-0.1098***	-0.1077***	-0.1085***
	(0.042)	(0.042)	(0.042)
Male	-0.1529***	-0.1535***	-0.1531***
	(0.022)	(0.022)	(0.022)
Age	-0.0653***	-0.0644***	-0.0644***
	(0.004)	(0.004)	(0.004)
Age^2	0.0008***	0.0008***	0.0008***
	(0.000)	(0.000)	(0.000)
Degree or higher	0.2067***	0.2020***	0.2033***
	(0.025)	(0.025)	(0.025)
Longstanding illness\	-0.7427***	-0.7408***	-0.7415***
impairment	(0.025)	(0.025)	(0.025)
Partner	0.4892***	0.4869***	0.4871***
	(0.028)	(0.028)	(0.028)
Belong to a religion	0.0731***	0.0706***	0.0720***
	(0.024)	(0.024)	(0.024)
Child	-0.2416***	-0.2388***	-0.2361***
	(0.029)	(0.029)	(0.029)
Unemployment	-0.5199***	-0.5194***	-0.5196***
	(0.048)	(0.048)	(0.048)
Net household income	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)
Observations	36,484	36,484	36,484

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.3: Regression Analysis: All Controls

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	-0.4351***	-0.2149***	-0.0509	-0.0248	-0.0112	0.0877
	(0.049)	(0.078)	(0.079)	(0.079)	(0.079)	(0.105)
Generation 1 * (10<ysm≤20)	-0.2526***	-0.2300***	-0.3214***	-0.3162***	-0.3189***	-0.2926***
	(0.083)	(0.083)	(0.084)	(0.084)	(0.084)	(0.102)
Generation 1 * (ysm>20)	-0.0811	-0.0359	-0.1763**	-0.1684**	-0.1690**	-0.1501
	(0.074)	(0.075)	(0.076)	(0.076)	(0.076)	(0.105)
Generation 2	-0.5890***	-0.3106***	-0.3004***	-0.2690***	-0.2610***	-0.2632***
	(0.049)	(0.072)	(0.072)	(0.073)	(0.073)	(0.094)
Generation 2.5	-0.2206***	-0.1567***	-0.1497***	-0.1361***	-0.1343**	-0.1600**
	(0.049)	(0.052)	(0.052)	(0.052)	(0.052)	(0.065)
Generation 3	-0.1085***	-0.0924**	-0.0817*	-0.0747*	-0.0707*	-0.0717
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.056)
White British		0.2939***	0.3376***	0.3144***	0.3132***	0.3360***
		(0.088)	(0.089)	(0.090)	(0.090)	(0.113)
Other white		0.2720***	0.3206***	0.2934***	0.2812***	0.2543**
		(0.086)	(0.086)	(0.086)	(0.086)	(0.104)
Pakistani		-0.1303	-0.1568	-0.1518	-0.1512	0.0237
		(0.099)	(0.099)	(0.099)	(0.099)	(0.134)
Bangladeshi		-0.1546	-0.0878	-0.0841	-0.0866	-0.2453
		(0.118)	(0.118)	(0.118)	(0.118)	(0.155)
Caribbean		-0.1002	-0.0247	-0.0189	-0.0196	-0.0439
		(0.105)	(0.106)	(0.106)	(0.106)	(0.137)
African		0.0699	0.1685*	0.1690*	0.1667*	0.0481
		(0.097)	(0.098)	(0.098)	(0.098)	(0.124)
Mixed ethnicity		0.0001	0.0701	0.0728	0.0737	0.0812
		(0.115)	(0.116)	(0.116)	(0.116)	(0.147)
Other ethnicity		-0.0256	0.0111	0.0007	0.0001	-0.0913
		(0.087)	(0.087)	(0.087)	(0.087)	(0.110)
Owned house			0.3586***	0.3528***	0.3506***	0.2643***
			(0.028)	(0.028)	(0.028)	(0.037)
Rest of UK				0.0854***	0.0629*	0.1380***
				(0.033)	(0.033)	(0.044)
Low density ethnic minority area				0.0656**	0.0299	0.0063
				(0.027)	(0.028)	(0.036)
Urban area					-0.1512***	-0.0948**
					(0.032)	(0.041)
Professional/ manager						0.1970***
						(0.034)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	36,484	36,467	36,397	36,397	36,397	20,861

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.4: Descriptive Statistics: Neighbourhood Characteristics

	Generation 1			Generation 2			Generation 2.5			Generation 3			Native		
	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.
Deprivation	31.86	16.40	7348	32.46	16.81	2952	23.62	16.44	2250	21.98	15.80	2753	20.06	14.71	22331
Overall ethnic minority density	0.56	0.28	7348	0.57	0.28	2952	0.26	0.25	2250	0.19	0.21	2753	0.12	0.15	22331
Own ethnic density	0.16	0.20	7343	0.24	0.27	2948	0.61	0.38	2249	0.76	0.29	2753	0.87	0.15	22320
Ethnic diversity	0.62	0.23	7348	0.62	0.22	2952	0.36	0.27	2250	0.29	0.24	2753	0.20	0.19	22331
Religious diversity	0.63	0.10	7348	0.62	0.11	2952	0.56	0.10	2250	0.54	0.10	2753	0.51	0.08	22331
London	0.51	0.50	7348	0.47	0.50	2952	0.21	0.41	2250	0.15	0.35	2753	0.06	0.24	22331

Notes: The table shows the mean, standard deviation and number of observations for the neighbourhood-level variables.

Table 1.5: Regression Analysis:
Neighbourhood-level Controls (1)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1011	0.1317	0.1374	0.1335	0.1313	0.2127
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.152)
Generation 1 * (10<ysm≤20)	-0.3617***	-0.3548***	-0.3526***	-0.3520***	-0.3518***	-0.4919***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.107)	(0.151)
Generation 1 * (ysm >20)	-0.1654	-0.1517	-0.1500	-0.1583	-0.1565	-0.0463
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.153)
Generation 2	-0.2597**	-0.2240**	-0.2148**	-0.2197**	-0.2219**	-0.1030
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.126)
Generation 2.5	-0.2008***	-0.1883***	-0.1822**	-0.1827**	-0.1824**	-0.2053***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.078)
Generation 3	-0.0642	-0.0562	-0.0518	-0.0543	-0.0543	-0.0672
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.066)
White British	0.3836***	0.3241***	0.2439*	0.2557*	0.2738*	0.2756
	(0.123)	(0.125)	(0.140)	(0.140)	(0.142)	(0.191)
Other White	0.3276***	0.2737**	0.3046***	0.3066***	0.2986**	0.2212
	(0.112)	(0.114)	(0.116)	(0.116)	(0.116)	(0.152)
Pakistani	0.0803	0.1048	0.0846	0.1218	0.1085	0.0542
	(0.136)	(0.137)	(0.138)	(0.138)	(0.139)	(0.176)
Bangladeshi	-0.2019	-0.1696	-0.1982	-0.1481	-0.1541	-0.2431
	(0.157)	(0.158)	(0.159)	(0.159)	(0.160)	(0.258)
Caribbean	0.0010	0.0033	0.0202	0.0417	0.0329	-0.0348
	(0.138)	(0.138)	(0.138)	(0.138)	(0.139)	(0.208)
African	0.1211	0.1119	0.1249	0.1551	0.1469	-0.1493
	(0.126)	(0.126)	(0.126)	(0.126)	(0.127)	(0.193)
Mixed ethnicity	0.1161	0.0964	0.1327	0.1493	0.1366	0.0885
	(0.152)	(0.153)	(0.155)	(0.155)	(0.156)	(0.206)
Other ethnicity	-0.1147	-0.1445	-0.1127	-0.1029	-0.1110	-0.2954*
	(0.114)	(0.115)	(0.117)	(0.117)	(0.117)	(0.160)
House ownership	0.2731***	0.2596***	0.2570***	0.2369***	0.2335***	0.2378***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.046)
Urban area	-0.0681	-0.0416	-0.0332	-0.0119	-0.0082	-0.0074
	(0.045)	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Professional/Manager	0.2179***	0.2181***	0.2200***	0.2122***	0.2117***	0.1896***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.041)
Overall ethnic minority density		-0.2365**	-0.1761	-0.0701	-0.0214	-0.0089
		(0.096)	(0.108)	(0.112)	(0.123)	(0.164)
Own ethnic density			0.1659	0.1669	0.1223	0.0612
			(0.131)	(0.131)	(0.139)	(0.194)
Deprivation				-0.0046***	-0.0046***	-0.0057***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.2395	-0.2021
					(0.259)	(0.287)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.6: Regression Analysis:
Neighbourhood-level Controls (2)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1011	0.1251	0.1289	0.1291	0.1263	0.2102
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.152)
Generation 1 * (10<ysm≤20)	-0.3617***	-0.3549***	-0.3538***	-0.3527***	-0.3528***	-0.4907***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.151)
Generation 1 * (ysm>20)	-0.1654	-0.1523	-0.1524	-0.1603	-0.1591	-0.0459
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.153)
Generation 2	-0.2597**	-0.2293**	-0.2233**	-0.2243**	-0.2275**	-0.1058
	(0.104)	(0.104)	(0.104)	(0.103)	(0.104)	(0.126)
Generation 2.5	-0.2008***	-0.1876***	-0.1837***	-0.1837***	-0.1837***	-0.2061***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.078)
Generation 3	-0.0642	-0.0552	-0.0525	-0.0549	-0.0553	-0.0678
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.066)
White British	0.3836***	0.3416***	0.2644*	0.2587*	0.2613*	0.2591
	(0.123)	(0.124)	(0.144)	(0.144)	(0.144)	(0.196)
Other White	0.3276***	0.2973***	0.3261***	0.3193***	0.3127***	0.2350
	(0.112)	(0.113)	(0.115)	(0.115)	(0.115)	(0.152)
Pakistani	0.0803	0.0895	0.0722	0.1162	0.0950	0.0373
	(0.136)	(0.136)	(0.137)	(0.138)	(0.139)	(0.176)
Bangladeshi	-0.2019	-0.1922	-0.2162	-0.1558	-0.1661	-0.2505
	(0.157)	(0.157)	(0.158)	(0.159)	(0.159)	(0.258)
Caribbean	0.0010	0.0118	0.0247	0.0448	0.0320	-0.0330
	(0.138)	(0.138)	(0.138)	(0.138)	(0.139)	(0.208)
African	0.1211	0.1239	0.1332	0.1601	0.1470	-0.1439
	(0.126)	(0.126)	(0.126)	(0.126)	(0.127)	(0.192)
Mixed ethnicity	0.1161	0.1108	0.1436	0.1576	0.1451	0.0988
	(0.152)	(0.152)	(0.155)	(0.155)	(0.156)	(0.206)
Other ethnicity	-0.1147	-0.1266	-0.0981	-0.0936	-0.1008	-0.2838*
	(0.114)	(0.114)	(0.117)	(0.117)	(0.117)	(0.160)
House ownership	0.2731***	0.2589***	0.2585***	0.2376***	0.2342***	0.2379***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.046)
Urban area	-0.0681	-0.0371	-0.0344	-0.0131	-0.0116	-0.0096
	(0.045)	(0.047)	(0.047)	(0.048)	(0.048)	(0.048)
Professional/Manager	0.2179***	0.2193***	0.2207***	0.2122***	0.2114***	0.1894***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.041)
Ethnic diversity		-0.1950**	-0.1179	-0.0256	0.0806	0.0629
		(0.088)	(0.114)	(0.116)	(0.146)	(0.188)
Own ethnic density			0.1630	0.1819	0.1660	0.1005
			(0.150)	(0.150)	(0.151)	(0.215)
Deprivation				-0.0048***	-0.0048***	-0.0059***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.3545	-0.2620
					(0.294)	(0.323)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.7: Robustness Check: Country of Birth (1)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.0598	0.0918	0.0975	0.0924	0.0907	0.2212
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.147)
Generation 1 * (10<ysm≤20)	-0.3209***	-0.3148***	-0.3129***	-0.3112***	-0.3112***	-0.4824***
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.148)
Generation 1 * (ysm >20)	-0.1194	-0.1065	-0.1051	-0.1121	-0.1106	-0.0365
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)	(0.149)
Generation 2	-0.2538**	-0.2183**	-0.2090**	-0.2128**	-0.2152**	-0.1188
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)	(0.127)
Generation 2.5	-0.2081***	-0.1956***	-0.1899***	-0.1897***	-0.1892***	-0.2056***
	(0.072)	(0.073)	(0.073)	(0.073)	(0.073)	(0.079)
Generation 3	-0.0485	-0.0410	-0.0369	-0.0391	-0.0391	-0.0521
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.066)
White British	0.3878***	0.3267***	0.2431*	0.2545*	0.2729*	0.2889
	(0.123)	(0.125)	(0.141)	(0.141)	(0.142)	(0.191)
Other White	0.3433***	0.2879**	0.3199***	0.3223***	0.3142***	0.2157
	(0.112)	(0.114)	(0.116)	(0.116)	(0.116)	(0.152)
Pakistani	0.0603	0.0857	0.0649	0.1013	0.0880	0.0410
	(0.136)	(0.137)	(0.137)	(0.138)	(0.139)	(0.176)
Bangladeshi	-0.2316	-0.1981	-0.2276	-0.1781	-0.1842	-0.2719
	(0.157)	(0.158)	(0.159)	(0.160)	(0.160)	(0.258)
Caribbean	-0.0035	-0.0008	0.0167	0.0374	0.0286	-0.0199
	(0.138)	(0.138)	(0.138)	(0.139)	(0.139)	(0.209)
African	0.1318	0.1223	0.1357	0.1659	0.1575	-0.1476
	(0.126)	(0.126)	(0.126)	(0.126)	(0.127)	(0.192)
Mixed ethnicity	0.1187	0.0986	0.1364	0.1525	0.1396	0.0888
	(0.152)	(0.152)	(0.155)	(0.155)	(0.156)	(0.206)
Other ethnicity	-0.1072	-0.1379	-0.1048	-0.0949	-0.1031	-0.2958*
	(0.114)	(0.115)	(0.117)	(0.117)	(0.117)	(0.160)
House ownership	0.2653***	0.2516***	0.2489***	0.2290***	0.2256***	0.2359***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.046)
Urban area	-0.0674	-0.0403	-0.0315	-0.0105	-0.0068	-0.0067
	(0.045)	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Professional/Manager	0.2143***	0.2145***	0.2166***	0.2088***	0.2083***	0.1881***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.041)
Overall ethnic minority density		-0.2420**	-0.1792*	-0.0745	-0.0253	-0.0124
		(0.096)	(0.108)	(0.112)	(0.123)	(0.164)
Own ethnic density			0.1723	0.1734	0.1283	0.0608
			(0.131)	(0.131)	(0.139)	(0.194)
Deprivation				-0.0045***	-0.0046***	-0.0057***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.2421	-0.2015
					(0.259)	(0.287)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,464	17,464	17,464	17,464	17,464	14,563

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.8: Robustness Check: Country of Birth (2)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.0598	0.0854	0.0890	0.0879	0.0855	0.2185
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.147)
Generation 1 * (10<ysm≤20)	-0.3209***	-0.3150***	-0.3140***	-0.3118***	-0.3121***	-0.4811***
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.148)
Generation 1 * (ysm >20)	-0.1194	-0.1071	-0.1073	-0.1139	-0.1130	-0.0360
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)	(0.149)
Generation 2	-0.2538**	-0.2235**	-0.2175**	-0.2173**	-0.2208**	-0.1216
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)	(0.127)
Generation 2.5	-0.2081***	-0.1948***	-0.1913***	-0.1906***	-0.1906***	-0.2064***
	(0.072)	(0.073)	(0.073)	(0.073)	(0.073)	(0.079)
Generation 3	-0.0485	-0.0399	-0.0374	-0.0396	-0.0401	-0.0527
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.067)
White British	0.3878***	0.3442***	0.2644*	0.2584*	0.2612*	0.2735
	(0.123)	(0.124)	(0.144)	(0.144)	(0.144)	(0.196)
Other White	0.3433***	0.3117***	0.3414***	0.3352***	0.3284***	0.2294
	(0.112)	(0.113)	(0.115)	(0.115)	(0.115)	(0.152)
Pakistani	0.0603	0.0703	0.0525	0.0957	0.0745	0.0244
	(0.136)	(0.136)	(0.137)	(0.138)	(0.139)	(0.176)
Bangladeshi	-0.2316	-0.2210	-0.2457	-0.1861	-0.1963	-0.2793
	(0.157)	(0.157)	(0.158)	(0.159)	(0.159)	(0.257)
Caribbean	-0.0035	0.0080	0.0212	0.0405	0.0278	-0.0181
	(0.138)	(0.138)	(0.138)	(0.139)	(0.139)	(0.208)
African	0.1318	0.1345	0.1440	0.1710	0.1578	-0.1422
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.191)
Mixed ethnicity	0.1187	0.1133	0.1472	0.1606	0.1482	0.0989
	(0.152)	(0.152)	(0.155)	(0.155)	(0.156)	(0.206)
Other ethnicity	-0.1072	-0.1197	-0.0903	-0.0856	-0.0929	-0.2843*
	(0.114)	(0.114)	(0.117)	(0.117)	(0.117)	(0.160)
House ownership	0.2653***	0.2508***	0.2505***	0.2295***	0.2262***	0.2360***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.046)
Urban area	-0.0674	-0.0354	-0.0327	-0.0116	-0.0102	-0.0087
	(0.045)	(0.047)	(0.047)	(0.048)	(0.048)	(0.048)
Professional/Manager	0.2143***	0.2158***	0.2173***	0.2088***	0.2080***	0.1880***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.041)
Ethnic diversity		-0.2011**	-0.1216	-0.0304	0.0759	0.0577
		(0.088)	(0.114)	(0.116)	(0.146)	(0.188)
Own ethnic density			0.1680	0.1867	0.1708	0.0982
			(0.151)	(0.150)	(0.151)	(0.215)
Deprivation				-0.0047***	-0.0048***	-0.0058***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.3551	-0.2587
					(0.294)	(0.323)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,464	17,464	17,464	17,464	17,464	14,562

Notes: The dependent variable is LS, dummy variable for "mostly or higher" satisfaction.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.9: Robustness Check: Ordered Logit (1)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1562	0.1893*	0.1982*	0.1946*	0.1914*	0.2088
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.141)
Generation 1 * (10<ysm≤20)	-0.3678***	-0.3595***	-0.3574***	-0.3572***	-0.3574***	-0.4573***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.136)
Generation 1 * (ysm >20)	-0.1458	-0.1306	-0.1285	-0.1361	-0.1340	0.0669
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.143)
Generation 2	-0.2002**	-0.1647*	-0.1483	-0.1532	-0.1556*	-0.0267
	(0.095)	(0.095)	(0.094)	(0.094)	(0.094)	(0.116)
Generation 2.5	-0.2133***	-0.2004***	-0.1898***	-0.1906***	-0.1902***	-0.2170***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.068)
Generation 3	-0.0521	-0.0441	-0.0374	-0.0403	-0.0400	-0.0418
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.058)
White British	0.3204***	0.2632**	0.1323	0.1403	0.1696	0.3180*
	(0.116)	(0.116)	(0.132)	(0.132)	(0.134)	(0.181)
Other White	0.2783***	0.2248**	0.2734***	0.2748***	0.2627**	0.2162
	(0.100)	(0.101)	(0.102)	(0.102)	(0.102)	(0.133)
Pakistani	0.0889	0.1160	0.0804	0.1113	0.0894	0.1434
	(0.136)	(0.137)	(0.138)	(0.138)	(0.139)	(0.175)
Bangladeshi	-0.1535	-0.1152	-0.1683	-0.1305	-0.1414	-0.3026
	(0.144)	(0.146)	(0.149)	(0.149)	(0.150)	(0.287)
Caribbean	0.0208	0.0276	0.0510	0.0699	0.0557	-0.0393
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.191)
African	0.1332	0.1247	0.1450	0.1679	0.1545	0.0329
	(0.119)	(0.120)	(0.120)	(0.120)	(0.120)	(0.175)
Mixed ethnicity	0.0895	0.0741	0.1289	0.1425	0.1227	0.0500
	(0.141)	(0.141)	(0.142)	(0.142)	(0.143)	(0.189)
Other ethnicity	-0.0468	-0.0761	-0.0264	-0.0192	-0.0319	-0.1298
	(0.101)	(0.101)	(0.102)	(0.102)	(0.102)	(0.135)
House ownership	0.2502***	0.2363***	0.2321***	0.2163***	0.2104***	0.2134***
	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.043)
Urban area	-0.0624	-0.0357	-0.0220	-0.0062	-0.0003	0.0012
	(0.040)	(0.041)	(0.041)	(0.042)	(0.042)	(0.042)
Professional/Manager	0.1745***	0.1747***	0.1779***	0.1719***	0.1707***	0.1435***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.036)
Overall ethnic minority density		-0.2411***	-0.1420	-0.0578	0.0220	-0.0535
		(0.086)	(0.098)	(0.102)	(0.115)	(0.156)
Own ethnic density			0.2678**	0.2686**	0.1982	-0.0099
			(0.122)	(0.122)	(0.129)	(0.181)
Deprivation				-0.0037***	-0.0037***	-0.0049***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.3863	-0.3719
					(0.243)	(0.272)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

Notes: The life satisfaction dependent variable is an ordered variable taking values 1-7, ranging from “completely dissatisfied” to “completely satisfied”.

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.10: Robustness Check: Ordered Logit (2)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1562	0.1867*	0.1923*	0.1925*	0.1896*	0.2069
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.141)
Generation 1 * (10<ysm≤20)	-0.3678***	-0.3585***	-0.3580***	-0.3573***	-0.3583***	-0.4578***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.136)
Generation 1 * (ysm >20)	-0.1458	-0.1286	-0.1293	-0.1363	-0.1358	0.0661
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.143)
Generation 2	-0.2002**	-0.1634*	-0.1532	-0.1550*	-0.1575*	-0.0292
	(0.095)	(0.095)	(0.095)	(0.094)	(0.094)	(0.116)
Generation 2.5	-0.2133***	-0.1969***	-0.1905***	-0.1908***	-0.1908***	-0.2174***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.068)
Generation 3	-0.0521	-0.0410	-0.0374	-0.0402	-0.0407	-0.0421
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.058)
White British	0.3204***	0.2714**	0.1563	0.1513	0.1547	0.3198*
	(0.116)	(0.116)	(0.137)	(0.137)	(0.137)	(0.188)
Other White	0.2783***	0.2426**	0.2831***	0.2776***	0.2688***	0.2236*
	(0.100)	(0.100)	(0.102)	(0.102)	(0.102)	(0.133)
Pakistani	0.0889	0.1013	0.0737	0.1097	0.0809	0.1333
	(0.136)	(0.136)	(0.138)	(0.138)	(0.139)	(0.176)
Bangladeshi	-0.1535	-0.1388	-0.1791	-0.1334	-0.1488	-0.3104
	(0.144)	(0.144)	(0.148)	(0.148)	(0.149)	(0.285)
Caribbean	0.0208	0.0368	0.0526	0.0708	0.0534	-0.0387
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.191)
African	0.1332	0.1374	0.1504	0.1703	0.1523	0.0373
	(0.119)	(0.120)	(0.120)	(0.119)	(0.120)	(0.175)
Mixed ethnicity	0.0895	0.0868	0.1313	0.1429	0.1262	0.0548
	(0.141)	(0.141)	(0.142)	(0.142)	(0.142)	(0.188)
Other ethnicity	-0.0468	-0.0615	-0.0210	-0.0178	-0.0271	-0.1237
	(0.101)	(0.100)	(0.102)	(0.102)	(0.102)	(0.135)
House ownership	0.2502***	0.2326***	0.2320***	0.2158***	0.2109***	0.2132***
	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.043)
Urban area	-0.0624	-0.0246	-0.0204	-0.0049	-0.0031	0.0007
	(0.040)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)
Professional/Manager	0.1745***	0.1761***	0.1783***	0.1719***	0.1704***	0.1435***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.036)
Ethnic diversity		-0.2396***	-0.1264	-0.0549	0.0860	-0.0187
		(0.077)	(0.101)	(0.104)	(0.132)	(0.172)
Own ethnic density			0.2394*	0.2533*	0.2338*	-0.0036
			(0.140)	(0.139)	(0.140)	(0.202)
Deprivation				-0.0037***	-0.0038***	-0.0050***
				(0.001)	(0.001)	(0.001)
Religious Diversity					-0.4698*	-0.3839
					(0.274)	(0.304)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

Notes: The life satisfaction dependent variable is an ordered variable taking values 1-7, ranging from "completely dissatisfied" to "completely satisfied".

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.11: Robustness Check: Cutoff Change (1)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1456	0.1850	0.1974	0.1897	0.1852	0.2036
	(0.142)	(0.142)	(0.141)	(0.141)	(0.141)	(0.181)
Generation 1 * (10<ysm≤20)	-0.3368***	-0.3291***	-0.3237***	-0.3224***	-0.3228***	-0.4205**
	(0.122)	(0.123)	(0.122)	(0.122)	(0.122)	(0.173)
Generation 1 * (ysm >20)	-0.0727	-0.0573	-0.0529	-0.0627	-0.0585	0.2163
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.186)
Generation 2	-0.2381**	-0.1942	-0.1734	-0.1811	-0.1859	0.0259
	(0.120)	(0.121)	(0.120)	(0.120)	(0.120)	(0.151)
Generation 2.5	-0.2152***	-0.1994**	-0.1861**	-0.1861**	-0.1857**	-0.1945**
	(0.082)	(0.083)	(0.083)	(0.083)	(0.083)	(0.090)
Generation 3	-0.0253	-0.0155	-0.0059	-0.0087	-0.0086	-0.0045
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.079)
White British	0.4664***	0.3954***	0.2386	0.2500	0.2887*	0.5355**
	(0.142)	(0.145)	(0.161)	(0.161)	(0.164)	(0.230)
Other White	0.4760***	0.4106***	0.4723***	0.4751***	0.4564***	0.3481*
	(0.134)	(0.136)	(0.138)	(0.138)	(0.138)	(0.181)
Pakistani	0.0732	0.1013	0.0626	0.1062	0.0781	0.1166
	(0.147)	(0.148)	(0.149)	(0.150)	(0.150)	(0.199)
Bangladeshi	-0.0276	0.0098	-0.0454	0.0116	-0.0004	-0.4417
	(0.160)	(0.162)	(0.163)	(0.164)	(0.164)	(0.271)
Caribbean	0.2252	0.2292	0.2621*	0.2873*	0.2684*	0.0873
	(0.148)	(0.148)	(0.148)	(0.149)	(0.149)	(0.225)
African	0.2230	0.2123	0.2379*	0.2729*	0.2552*	0.3003
	(0.139)	(0.140)	(0.140)	(0.140)	(0.140)	(0.221)
Mixed ethnicity	0.1904	0.1689	0.2408	0.2619	0.2335	-0.0375
	(0.175)	(0.176)	(0.178)	(0.178)	(0.179)	(0.236)
Other ethnicity	0.2324*	0.1978	0.2606**	0.2707**	0.2525*	0.1452
	(0.128)	(0.129)	(0.130)	(0.130)	(0.130)	(0.186)
House ownership	0.2711***	0.2557***	0.2497***	0.2248***	0.2171***	0.2184***
	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)	(0.053)
Urban area	-0.0999*	-0.0677	-0.0498	-0.0215	-0.0119	-0.0082
	(0.054)	(0.056)	(0.056)	(0.057)	(0.057)	(0.058)
Professional/Manager	0.3206***	0.3207***	0.3250***	0.3153***	0.3142***	0.2963***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.050)
Overall ethnic minority density		-0.2821**	-0.1678	-0.0421	0.0604	-0.0202
		(0.110)	(0.120)	(0.125)	(0.138)	(0.188)
Own ethnic density			0.3294**	0.3325**	0.2328	-0.0739
			(0.148)	(0.148)	(0.160)	(0.232)
Deprivation				-0.0054***	-0.0055***	-0.0067***
				(0.001)	(0.001)	(0.002)
Religious Diversity					-0.5364*	-0.5367
					(0.303)	(0.343)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

Notes: The life satisfaction dependent variable is a dummy indicator for "somewhat satisfied or higher".

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 1.12: Robustness check: Cutoff Change (2)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Generation 1	0.1456	0.1854	0.1918	0.1895	0.1845	0.2036
	(0.142)	(0.142)	(0.141)	(0.141)	(0.141)	(0.181)
Generation 1 * (10<ysm≤20)	-0.3368***	-0.3270***	-0.3242***	-0.3222***	-0.3232***	-0.4209**
	(0.122)	(0.123)	(0.122)	(0.122)	(0.122)	(0.173)
Generation 1 * (ysm >20)	-0.0727	-0.0532	-0.0528	-0.0619	-0.0596	0.2161
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.186)
Generation 2	-0.2381**	-0.1897	-0.1785	-0.1811	-0.1872	0.0256
	(0.120)	(0.121)	(0.120)	(0.119)	(0.120)	(0.151)
Generation 2.5	-0.2152***	-0.1937**	-0.1865**	-0.1857**	-0.1864**	-0.1945**
	(0.082)	(0.083)	(0.083)	(0.083)	(0.083)	(0.090)
Generation 3	-0.0253	-0.0110	-0.0059	-0.0084	-0.0092	-0.0044
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.079)
White British	0.4664***	0.4020***	0.2730	0.2639	0.2683	0.5411**
	(0.142)	(0.143)	(0.167)	(0.166)	(0.167)	(0.237)
Other White	0.4760***	0.4296***	0.4789***	0.4718***	0.4602***	0.3476*
	(0.134)	(0.135)	(0.137)	(0.137)	(0.137)	(0.182)
Pakistani	0.0732	0.0865	0.0579	0.1073	0.0708	0.1172
	(0.147)	(0.147)	(0.149)	(0.150)	(0.151)	(0.201)
Bangladeshi	-0.0276	-0.0133	-0.0532	0.0126	-0.0049	-0.4422
	(0.160)	(0.160)	(0.162)	(0.163)	(0.163)	(0.270)
Caribbean	0.2252	0.2436	0.2643*	0.2874*	0.2651*	0.0874
	(0.148)	(0.148)	(0.148)	(0.149)	(0.149)	(0.225)
African	0.2230	0.2283	0.2436*	0.2736**	0.2509*	0.3009
	(0.139)	(0.139)	(0.140)	(0.140)	(0.140)	(0.220)
Mixed ethnicity	0.1904	0.1851	0.2402	0.2582	0.2362	-0.0379
	(0.175)	(0.176)	(0.178)	(0.178)	(0.179)	(0.236)
Other ethnicity	0.2324*	0.2157*	0.2638**	0.2680**	0.2553*	0.1448
	(0.128)	(0.128)	(0.130)	(0.130)	(0.130)	(0.186)
House ownership	0.2711***	0.2498***	0.2488***	0.2238***	0.2177***	0.2184***
	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)	(0.053)
Urban area	-0.0999*	-0.0509	-0.0462	-0.0189	-0.0154	-0.0078
	(0.054)	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)
Professional/Manager	0.3206***	0.3227***	0.3255***	0.3154***	0.3139***	0.2964***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.050)
Ethnic diversity		-0.3030***	-0.1708	-0.0636	0.1237	-0.0254
		(0.103)	(0.131)	(0.134)	(0.167)	(0.218)
Own ethnic density			0.2778	0.3026*	0.2747	-0.0821
			(0.174)	(0.173)	(0.175)	(0.259)
Deprivation				-0.0054***	-0.0055***	-0.0068***
				(0.001)	(0.001)	(0.002)
Religious Diversity					-0.6323*	-0.5242
					(0.343)	(0.381)
Basic socio-demographic controls	x	x	x	x	x	x
Observations	17,465	17,465	17,465	17,465	17,465	14,563

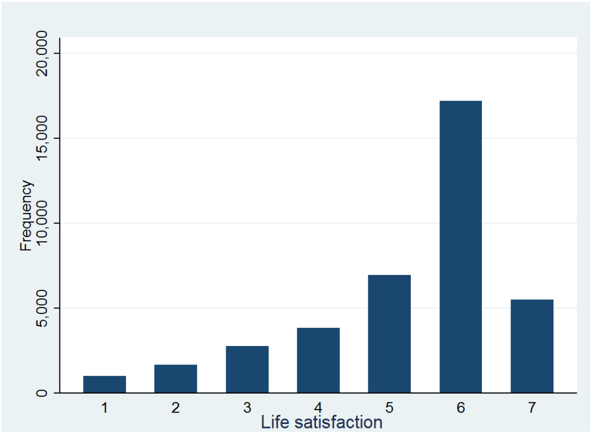
Notes: The life satisfaction dependent variable is a dummy indicator for "somewhat satisfied or higher".

ysm stands for years since migration.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

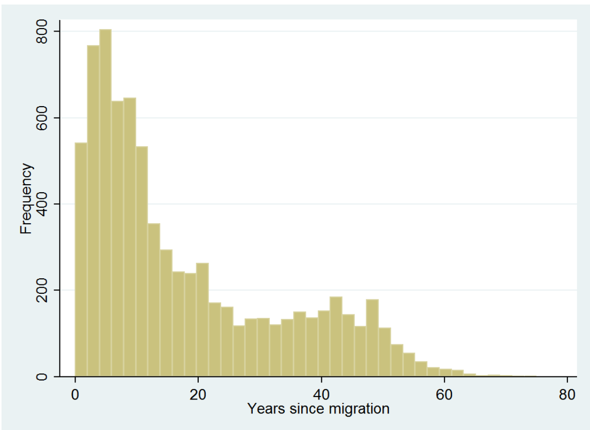
Figures

Figure 1.1: Life Satisfaction, Frequency Distribution



The figure shows the frequency distribution of responses to the question: "How are you satisfied with your life overall?" Values 1 to 7 stand for: "completely dissatisfied, mostly dissatisfied, somewhat dissatisfied, neither satisfied nor dissatisfied, mostly satisfied, completely satisfied". This question is contained in the self-completion questionnaire for which individuals aged 16 or over are eligible.

Figure 1.2: Years since Migration, Frequency Distribution



The figure shows the frequency distribution of years since migration for first generation immigrants

Chapter 2

Within-Firm Adjustments to Labour Supply Shocks: the Role of Product and Process Innovation

Abstract

We present a model that illustrates the channels through which firms may adjust their product and process innovation activities in response to labour supply shocks. We empirically test the model with a difference-in-difference estimation strategy exploiting the large low-skill labour supply shock to local UK labour markets generated by the 2004 expansion of the European Union to Eastern European countries (EU8). On the one hand, results show a negative but not significant average effect of EU8 immigration on process innovation, challenging our model prediction. On the other hand, we find a significant and negative average effect on product innovation, but only for firms in the non-tradable sector. In line with our model, we interpret this last finding as suggesting that the dominant response of firms has been to substitute away from a now relatively more costly high-skill activity [1].

This chapter is part of a co-authored paper with Gregory Wright and Rowena Gray[2].

Key Words: Product Innovation, Process Innovation, Immigration, Labour Supply Shock

[1]Data from the Quarterly Labour Force Survey and the Community Innovation Survey have been made available by the Office for National Statistics (ONS) through the UK Data Archive under secure access. Neither the ONS nor the UK Data Archive bear any responsibility for the analysis or interpretation of the data reported here.

[2]Department of Economics, University of California, Merced.

JEL Codes: J23, J61, F22, O31, O33

2.1 Introduction

Firms adapt to local labour supply shocks in a variety of ways – for instance, there is evidence that firms alter their production methods to use the now more abundant factor more intensively [Dustmann and Glitz, 2015; Lewis, 2003, 2011, 2013].

However, this evidence either focuses narrowly on adjustments in the capital stock within firms [see, for example, Lewis [2011]] or else simply sets aside the issue of how and why firms' production changes. In this paper we explore two potential channels of firm response to labour supply shocks, namely, firm investments in process and in product innovation, both of which will affect the observed distribution of output within and across firms.

We present a model in which heterogeneous firms produce an endogenous set of branded varieties and employ both low- and high-skill workers. The firms' product and process innovation decisions are made in order to achieve their optimal product scope and their optimal production structure, respectively. In our comparative statics exercise we focus specifically on a low-skill labour supply shock, first finding that firms who employ low-skill workers relatively more intensively will engage in relatively more process innovation in response to the shock. We then show that product innovation could also, in theory, increase in all firms for two reasons: first, the increase in the local low-skill labour supply will raise the demand for firms' products, which may incentivize the development of new products; and second, the fall in the local low-skill wage due to the increase in labour supply reduces firm production costs, which raises the profitability of all products, again incentivizing the development of new products. On the other hand, to the extent that product innovation requires a high-skill workforce, a low-skill labour supply shock will reduce product innovation when high- and low-skill workers are imperfectly substitutable.

We bring the model's predictions to UK data by exploiting the expansion of the European Union (EU) in 2004 as a differential shock to the local supply of low-skill labour across UK travel-to-work areas (TTWA). On the one hand, we find an average negative treatment effect on product innovation, although only in the non-tradable sector. On the other hand, we do not detect any average significant effect on process innovation. However, we observe that larger firms respond more negatively to the low-skill labour shocks by decreasing investments in process innovation relatively more than smaller firms. This evidence challenges part of the predictions of our model.

The paper is organized as follows. Section 2.2 reviews the relevant literature. In Section 2.3 we jointly model the firm's process and product innovation choice in the face of a labour supply shock. Section 2.4 describes the data and section 2.5 introduces the empirical specifications and identification strategy. Section 2.6 shows descriptive evidence and section 2.7 discusses the regression results. Section 2.8 concludes with the main remarks.

2.2 Literature Review

The UK has experienced substantial growth in its immigrant population since the late 1990s. In particular, the European enlargement has generated a substantial shift in the composition of immigrant inflows, as the number of Eastern European immigrants increased dramatically.

A bulk of research has concentrated on analysing the cost and benefits of immigration, mainly focussing on the immigration impact on wages of native workers [Altonji and Card, 1991; Borjas, 2003; Card, 2001*a*; David and Lewis, 2007; Dustmann et al., 2005, 2013; Ottaviano and Peri, 2012].

Estimated effects are mixed although the empirical literature agrees that the impact of immigration on average wages is relatively small and centered around zero [Longhi et al., 2005, 2008]. Recent research suggests that the labour market impact of immigration on wages may be mitigated by enriching the economy and production structure of labour market models, leaving factor prices unchanged [Dustmann and Glitz, 2015; Lewis, 2003, 2011, 2013].

There are two main alternative adjustment channels that have been considered. The first adjustment is through changes in output-mix [Rybczynski, 1955]. Open economy or closed multi-sectoral models allow for skill-mix shifts to be absorbed through the so called Rybczynski effect (1955) expanding the output of those production units using the more abundant labour type more intensively.

The second adjustment is through changes in production technology [Acemoglu, 1998, 2002; Beaudry and Green, 2003; Caselli and Coleman, 2006], such that firms adopt technologies that are more intensive in the use of the now more abundant skill group. Lewis [2003] examines the effects of low-skilled inflows of Cuban immigrants to Miami and Mexican immigrants to California on the growth rate of a set of industries and shows that local skill-mix changes are largely absorbed within-industries (about 3/4 of total employment variation) without significant wage changes. Lewis [2011] uses detailed plant-level data and investigates the impact of immigration-induced labour supply's skill-mix changes on the use and adoption of automation technologies in U.S. manufacturing between 1980s and 1990s. Results show that metropolitan areas with larger numbers of high-school dropouts per high-school graduate significantly decreased the use of automation equipment per unit of output. This suggests a substitution effect between low-skilled labour and automation technologies at the plant level.

Dustmann and Glitz [2015] use administrative data covering the whole universe of firms and workers in Germany for the period 1985-1995, and exploit the large immigration labour supply shocks occurred during the decade to identify these three mechanisms. The study finds that immigration caused a decrease in the relative wages of skill groups of workers that experienced a labour supply shock in the non-tradable sector but not in the tradable and manufacturing industries. Thus, in the latter, adjustments may have occurred through output-mix and/or technology adoption. A similar decomposition to Lewis [2003] at the more detailed firm-level uncovers that within-firm technology adjustments are more important than output-mix ones, confirming Lewis [2003, 2011]'s work at industry and plant level.

While providing convincing evidence on the endogenous "choice of technique" to labour supply shocks of different skill groups, the empirical literature clearly leaves still open the question of what types of adjustments firms are making and, further, whether these adjustments differ systematically across firms in some way. The range of technology choices examined in the literature has been quite narrow, with most evidence focused on firms' adoption of either high-tech manufacturing equipment or computer purchases

[Lewis, 2003, 2011].

We contribute to the literature by taking a novel approach and consider firm investments in either process or product innovation. We argue that innovation can be seen as a within-firm adjustment to relative labour supply shocks. For instance, when the firm adjusts the relative efficiency of its inputs we can consider this to be process innovation, or when the firm endogenously chooses its optimal product scope, we can refer to it as product innovation. In particular, we consider two main channels through which low-skilled immigration may affect firms' innovation activities. On the one hand, we hypothesize a substitution effect, due to the firm's exploitation of the now more abundant low skilled labour and consequently engage less in innovation activities. On the other hand, we consider a complementary effect, via the firm's investment of immigration-induced savings in labour production costs in innovation activities. The theoretical model is tested empirically by exploiting firm-level panel data and exploring UK firms' adjustments in process and product innovation to changes in the local distribution of workers' skills due the enlargement of the European Union in 2004.

2.3 Model

2.3.1 Consumers

There are M consumers in a local labor market who maximize utility over consumption of a homogeneous good and a differentiated good. Agent m consumes some amount of the homogeneous good along with some amount of each variety $i \in \Omega_j$ associated with brand $j \in \mathfrak{J}$ of the differentiated good. Specifically, preferences of agent m are given by:

$$U^m \equiv q_0^m + \alpha Q^m - \frac{\delta}{2}\int_j \int_i (q_{ij}^m)^2 di dj - \frac{\eta}{2}\int_j (q_j^m)^2 dj - \frac{\psi}{2}(Q^m)^2$$

where q_0 represents consumption of the homogeneous good, $q_j^m \equiv \int_i q_{ij}^m di$ is the agent's consumption of brand j varieties, $Q^m \equiv \int_j q_j^m dj$ is total consumption of all varieties across all brands, and α, δ, η and ψ are constants. Consumers maximize this utility subject to their budget constraint, given by $q_0^m + \int_j \int_i p_{ij} q_{ij}^m di dj = I^m$, where I^m is agent m's income and p_{ij} is the price of variety i of brand j where $p_{00} = 1$ is the numeraire good. We further assume that $q_0^m > 0$ and that all agents are identical. Maximizing the utility function and aggregating the resulting individual demand functions across all consumers, we get the following linear inverse demand for variety i of brand j:

$$p_{ij} = \tilde{\alpha} - \frac{1}{M}\left(\delta q_{ij}^m - \eta q_j^m\right) \tag{2.1}$$

where $\tilde{\alpha} \equiv \alpha - \psi Q^m/M$ reflects demand conditions the firm takes as given. The linear demand system (2.1) is useful, in part, because it is consistent with the empirical findings of Hottman and Weinstein [2014] who show that variation in product scope can explain a substantial portion of variation in sales across U.S. firms. In addition, this demand system generates product cannibalization, a mechanism these authors find to be important in explaining firms' response to demand shocks. Finally, this demand system also provides a tractable condition to pin down the range of products produced by each firm, as we will show.

2.3.2 Firms

Each firm j is associated with a brand, and may supply multiple varieties within the brand to its local labor market. Throughout the analysis we focus narrowly on a single market, therefore setting aside considerations of geography. There is free entry in the differentiated goods industry and, after paying a fixed entry cost, f, firms can enter and produce each variety i at marginal cost c_{ij}. The firm's production function combines two labor types, high-skill and low-skill labor. An important feature of the model is that the firm can choose from an array of production methods, conditional on its given underlying production structure, and these differ in their relative efficiency of use of the inputs. When the firm adjusts the relative efficiency of its inputs we consider this to be *process innovation.*

The idea is that firms may respond to a shock to the relative labor supply not only by using labor types in different proportions, but also by altering their production methods to use the now-more-abundant factor more efficiently. Formally, the firm takes local factor prices as given and chooses from a continuous menu of production technologies. Beyond this, we assume a fixed heterogeneity in the intensity of use of labor inputs across firms. As a result, while the firm is able to adjust the relative efficiency of its inputs, it is simultaneously constrained by the unique, and fixed, production structure required to make its particular products.

Finally, apart from endogenously choosing the efficiency of its factors, the firm also endogenously chooses its optimal product (variety) scope, which we refer to as *product innovation*. As we will show, product innovation will, in part, depend on the firm's choice of process innovation, and each type of innovation will independently respond to labor supply shocks in the firm's local market.

Production. Having paid the fixed entry cost, the firm's variety-specific production technology is given by the following production function:

$$Y_{ij} = \left[\beta_{ij}(A_{ijL}L_{ij})^{\rho} + (1-\beta_{ij})(A_{ijS}S_{ij})^{\rho}\right]^{1/\rho} \tag{2.2}$$

where L and S are low-skill and high-skill labor inputs, the efficiency parameters A augment each factor (and will become choice variables later on), and the elasticity parameter $\rho \equiv \frac{\sigma-1}{\sigma}$. The terms β_{ij} and $1-\beta_{ij}$ are exogenous, variety-specific technology terms that define the fixed input proportions firms are constrained to use to produce their varieties. This feature reflects the fact that the factor content of output is to some degree determined by the nature of the product being produced, and is therefore to some extent outside of the firm's control (at least in the short run).

In order to more flexibly define the notion of process innovation later on, we do not explicitly incorporate capital in the production function. There are two primary reasons: first, many examples of process innovation combine organizational changes with investments in capital, and it is more tractable to consider these jointly as an increase in one of the efficiency variables, A. Second, process innovation may be, at times, skill-biased and, at other times, unskill-biased. An example of the former is the incorporation of computer-assisted design software for product development (which may augment the productivity of engineers), while an example of the latter is the adoptions of GPS systems for product delivery (which may augment the productivity of truck drivers). The production function, (2.2), again allows us to flexibly model these as different types of investments in factor efficiency.[1]

The production function, (2.2), indicates that the firm is constrained in its production process – reflected in the fixed β – and at the same time has a degree of flexibility in that it can choose both the relative quantities of factors employed as well as the relative efficiency of its inputs, A_{ijL}, A_{ijS}. Given the production function, (2.2), the cost minimizing choice of inputs is given by the usual first-order conditions (FOC) which equate the (exogenously determined, from the firm's point of view) wage paid to each factor with its marginal productivity. Formally, relative factor demand is given by:

$$\frac{L_{ij}}{S_{ij}} = \left[\frac{w_L}{w_S} \frac{(1-\beta_{ij})}{\beta_{ij}} \left(\frac{A_{ijS}}{A_{ijL}} \right)^{\rho} \right]^{1/(\rho-1)} \tag{2.3}$$

When relative wages change, perhaps due to an increase in the local supply of one factor, the firm responds by increasing its relative use of that factor, in order to reduce the marginal productivity of the factor and bring it back in line with its wage (conditional on the endogenous response of the efficiency terms). To be consistent in outlining the testable elements of the model, this straightforward result is summarized in our first proposition:

Proposition 1 (Factor Adjustment) *A decline in the local price of a factor will induce firms to use that factor more intensively. This effect is increasing in the firm's fixed reliance on the now-more-abundant input (β).*

Unit Costs. It is useful from this point on to work with the firm's unit cost function, which incorporates the firm's optimally chosen factor quantities, reflected in (2.3). Formally, minimizing factor costs subject to (2.2), we obtain the unit cost c_{ij} associated with production of variety i for firm (brand) j, which is given by:

$$c_{ij} = \left[(\beta_{ij})^{\sigma} \left(\frac{w_L}{A_{ijL}} \right)^{\sigma-1} + (1-\beta_{ij})^{\sigma} \left(\frac{w_S}{A_{ijS}} \right)^{\sigma-1} \right]^{\frac{1}{1-\sigma}} \tag{2.4}$$

[1] An alternative would be to combine each labor type with a capital type in a CES combination, with each combination then combined in an upper CES nest. This would give qualitatively similar results in a more complex setting.

where w_l are factor prices that the firm takes as given, with $l \in (L, S)$, and the terms A_l and β are the endogenous and exogenous technology terms, respectively.

Process Innovation. We define process innovation to be a shift toward a new, more efficient production function by the firm. Specifically, we assume that any adjustment along the frontier requires expenditure by the firm. Formally, we assume that $A_{ijl} \equiv \tilde{A}_{ijl}(1 + \kappa_{ijl})$, where $\kappa_{ijl} \in [0, \infty)$ is the variety-specific cost of increasing the efficiency of factor l and $\tilde{A}_{ijl}$ is the firm's baseline factor efficiency. The firm can increase the efficiency of one of its factors by investing in process innovation at a rate r_{ijl}, so that expenditure on process innovation is given by $r_{ijl}\kappa_{ijl}$.[1]

Product Innovation. We assume that the firm chooses its optimal product scope, h_j, producing an additional variety at a cost $r_h w_S$. The assumption is that product innovation – adding a new variety – requires payment of a variety-specific R&D cost at rate r_h, which is denominated in high-skill labor. For instance, adding a new product may require R&D expenditure on the wages of scientists and engineers, in contrast to process innovation which can perhaps be done by incurring costs that are not dependent on the skill composition of the firm's workforce.

[1] In a previous version we assumed that the firm faced a tradeoff in the extent to which it could engage in low-skill-biased process innovation versus high-skill-biased process innovation. In that case, we followed Caselli and Coleman [2006] in modeling the shift as the choice of a new (A_L,A_S) pair in the available technology space. More formally, the firm's technology frontier – i.e., the choice set of available technologies – was given by:

$$\left(A_{ijL}\right)^{\alpha} + \eta\left(A_{ijS}\right)^{\alpha} \leq B_{ij} \tag{2.5}$$

where η and α govern the tradeoff between the relative efficiency of each factor and B defines the height of the technology frontier, and is firm-specific.
However, this produces nearly identical qualitative results, but with the size of the firm response to a shock governed also by the additional parameters associated with the above technological constraint. In this version we instead pursue the simpler case in which the firm faces no tradeoff with respect to performing either type of process innovation.

Profit Maximization. Given these costs, total firm profits can be written as:

$$\Pi_j = \int_0^{h_j} \left[p_{ij} - c_{ij}(A_{ijL}(\kappa_{ijL}), A_{ijS}(\kappa_{ijS}))\right] q_{ij} di - \int_0^{h_j} \left(r_L \kappa_{ijL} - r_S \kappa_{ijS} - r_h w_S\right) di \tag{2.6}$$

where c_{ij} is given by (2.4). For tractability, we assume throughout that firms and varieties are identical except for firm-specific heterogeneity in the production technology – i.e., we assume that only β_j varies across firms and that varieties are identical within a firm. As a result, we can re-write (2.6) as:

$$\Pi_j = h_j \Big\{ \left[p_j - c_j(\kappa_{jL}, \kappa_{jS})\right] q_j - r_L \kappa_{jL} - r_S \kappa_{jS} - r_h w_S \Big\} \equiv h_j \pi_j \tag{2.7}$$

where π_j is the profit associated with each variety produced by firm j and we now simply write marginal costs as a function of the κ's. Note that since firms' costs differ – due to the heterogeneity in β – their prices, quantities, the level of investment in process innovation and the number of varieties produced by a firm will also differ, and therefore carry subscripts j.

Equilibrium. We first solve for optimal q_j. Maximizing firm profits, the FOC is $\frac{\partial \pi_j}{\partial q_j} = p_j - q_j\big(\frac{\delta}{M} + \frac{h\eta}{M}\big) - c(\kappa_{jL}, \kappa_{jS}) = 0$. Optimal firm output is therefore given by

$$q_j^* = \Big(\frac{M}{\delta + h\eta - 1}\Big)\big(c(\kappa_{jL}, \kappa_{jS}) - \tilde{\alpha}\big) \tag{2.8}$$

The optimal values of low- and high-skill process innovation are then given by the profit-maximizing expenditure on each, i.e., $\{\kappa_{jL}^*, \kappa_{jS}^*\}$. Since the FOC are symmetric, we simply solve for the FOC for low-skill process innovation. Calculating this FOC and plugging in the value for optimal q_j^*, we get the following implicit equilibrium condition for κ^*_{jL}:

$$\frac{M\beta_j^\sigma}{r_L(\delta+\eta h-1)}\left(\frac{w_L}{\tilde{A_{jL}}}\right)^{\frac{\sigma^2}{\sigma-1}}\left[c_j(\kappa^*_{jL},\kappa_{jS})^{\frac{2\sigma-1}{\sigma-1}}-\tilde{\alpha}c_j(\kappa^*_{jL},\kappa_{jS})^{\frac{\sigma}{\sigma-1}}\right]-(1-\kappa^*_{jL})^\sigma=0 \tag{2.9}$$

Next, we explore the comparative static implications of the equilibrium conditions.

2.3.3 Comparative Statics

We are primarily interested in the comparative statics with respect to an increase in the low-skill labor supply in an area, and so that is what we focus on here. The first response we are interested in is reflected in Proposition 1, whereby a local rise in the supply of the low-skill factor increases its relative use by firms, and more so for firms who are fundamentally more reliant on that factor. Next, we focus on the associated cost function, (2.4), in which the endogenous choice of technique – i.e., the choice of κ_{ijl} – operates above and beyond the firm's adjustment of its relative use of factors. In fact, the cost function explicitly incorporates the firm's optimal choice of factors and, in this sense, reflects the firm's long-run costs.

In the analysis that follows we will assume that w_L unambiguously falls when the supply of low-skill labor rises, and that the relative factor adjustment summarized in Proposition 1 only partially mitigates the fall in the low-skill wage generated by the increased local supply of low-skill labor. In making this assumption, we are able to highlight firms' innovation responses as a mechanism that may subsequently put *additional upward pressure* on the relative low-skill wage, beyond that due to the firm's adjustment of its relative use of factors.

Differentiating the implicit equilibrium condition (2.9), describing optimal low-skill-biased process innovation, with respect to the low-skill wage w_L, leads to the following result:

Proposition 2 (Process Innovation Response) *Following from (2.9),* $\frac{\partial \kappa^*_{jL}}{\partial w_L}$ <

0 iff $\sigma > 1$, where κ^*_{jL} is the firm's optimal investment in low-skill-biased process innovation. In other words, a labor supply shock which reduces the average low-skill wage leads to a rise in low-skill-biased process innovation on the part of firms.

Thus, a rise in the low-skill labor supply induces firms to increase the efficiency of their low-skill workers via process innovation. We also note that the FOC with respect to κ_{jL}, $\frac{\partial \pi_j}{\partial \kappa_{jL}} = -q\frac{\partial c_{ij}}{\partial \kappa_{jL}} - r_L = 0$, indicates that optimal process innovation is increasing in firm output. We formalize this in the following lemma:

Lemma 3 (Role of Firm Size) *Optimal process innovation is increasing in firm output.*

Furthermore, since firms are heterogeneous in their production structures, their responses to the low-skill labor supply shock are also heterogeneous. Specifically, $\frac{\partial \kappa^*_{jL}}{\partial w_L \partial \beta_j} < 0$, such that firms whose production is relatively intensive in low-skill labor increase their investments in process innovation relatively more. We summarize this result in the following lemma:

Lemma 4 (Role of Firm Heterogeneity) *The process innovation response to a local labor supply shock is increasing in the firm's intensity of use of the now more abundant factor – i.e.,* $\frac{\partial \kappa^*_{jL}}{\partial w_L \partial \beta_j} < 0$.

Optimal Product Innovation. The FOC with respect to the firm's choice of number of varieties is pinned down by the linear demand, (2.1). As shown by Dhingra [2013], the linear demand system causes new varieties to cannibalize the demand for existing varieties. As a result, the additional profit that the firm obtains due to an increase in product scope is countered by a decline in overall profits as demand for existing products falls. The balance of these forces pins down the optimal number of varieties, where the profit from the marginal variety is equal to the decline in aggregate profits due to cannibalization. This optimal product scope is given by the solution to the FOC, $\frac{\partial \Pi_j}{\partial h_j} = 0$, which is:

$$h_j^* = \frac{\pi_j^* M}{\eta (q_j^*)^2} \tag{2.10}$$

Given this, an increase in the low-skill labor supply in an area generates three primary effects on the product margin. First, plugging in for the optimal quantity – from (2.8) – and the optimal profits – obtained by substituting optimal process innovation from (2.9) and its high-skill counterpart into (2.7) – and differentiating (2.10) with respect to the low-skill wage, we find that $\frac{\partial h_j^*}{\partial w_L} < 0$. By reducing production costs, the low-skill labor supply shock makes production of all varieties more profitable, which increases the equilibrium range of profitable varieties. Second, differentiating the same condition with respect to M, the size of the local market, we find that $\frac{\partial h_j^*}{\partial M} > 0$. Since the labor supply shock will mechanically increase the size of the local market, the labor supply shock will impact firms on the demand side as well, again increasing the profitability of all products and thereby increasing firms' equilibrium optimal product scope. And third, since low-skill labor and high-skill labor are imperfect substitutes, the fall in the low-skill wage leads to an increase in the high-skill wage. Since the cost of product innovation is denominated in terms of the price of high-skill workers, this reduces the profitability of all products, and therefore reduces the optimal product scope. We summarize these findings in the following Proposition:

Proposition 5 (Product Innovation Response) *From (2.10), there are three channels through which a low-skill labor supply shock impacts optimal firm product scope:*

1. $\frac{\partial h_j^*}{\partial w_L} < 0$. *By reducing production costs, a low-skill labor supply shock increases the range of profitable varieties, thereby* ***increasing product scope****.*

2. $\frac{\partial h_j^*}{\partial M} > 0$. *By increasing the size of the local market, a low-skill labor supply shock increases the demand for varieties, thereby* ***increasing product***

scope.

3. $\frac{\partial w_S}{\partial w_L} < 0$. *Due to the imperfect substitutability of high- and low-skill labor, a low-skill labor supply shock increases the cost of product innovation, thereby* ***reducing product scope***.

Proposition 5 indicates that the direction of the product innovation response to a low-skill labor supply shock is ultimately ambiguous. This is because the relative increase in the supply of low-skill labor generates productivity gains for the firm (channel 1), but also increases the fixed costs associated with product innovation (channel 3). At the same time, the market for all products is now larger and this is a force for increasing product innovation (channel 2).

2.4 Data

We investigate firms' responses in innovation to an immigration-induced labour supply shock in their local labour market. Local labour markets are defined as UK Travel to Work Areas (TTWAs), geographical statistical units developed by the Office of National Statistics (ONS) for the purpose of bounding commuting zones.[1] In short, these labour markets are defined in order to cover both metropolitan areas as well as their commuter suburbs.[2] The variation in EU8 immigrants' labour supply across the TTWAs that we exploit in our descriptive evidence comes from the UK Quarterly Labour Force Survey (QLFS). The QLFS comprises a single-stage sample of households, implicitly stratified by geographical ordering. Furthermore, it has a quarterly frequency and a rotating panel structure such that each individual is staying in the sample for five consecutive quarters. Each quarter covers approximately 100,000 individuals, making up about 0.2%

[1] We use the 1998 ONS definition of a TTWA, according to which there are 242 TTWAs in England and Wales. Our sample covers 151 TTWAs.

[2] Formally, the ONS defines a TTWA as a collection of wards for which "of the resident economically active population, at least 75% actually work in the area, and also, that of everyone working in the area, at least 75% actually live in the area".

of the UK population. We retain individuals at their working age (16-64) and responding to their first interview. We make use of the available personal weights to make the sample representative of the UK population and to correct for non-response. A pitfall of the QLFS is that it is likely to underestimate the stock of EU8 immigrants, especially the recent ones and those living in communal establishments [Rokicka and Longhi [2012], Gilpin et al. [2006], Drinkwater et al. [2009]]. In the main empirical section we exploit cross-sectional variation in EU8 immigrant shares from the 1991 Census, which we use to predict subsequent concentrations over the 2004-2008 period, as we discuss further in Section 2.5 [1].

Firm-level panel data on innovation activities are retrieved from three waves of the Community Innovation Survey (CIS), covering the period 2002 to 2008. The CIS is the primary source of information on innovation for the UK, and asks firms a range of questions about their innovation activities as well as the extent to which they have undertaken various types of organizational change during the previous three years. The CIS consists of a stratified sample of approximately 28,000 firms with more than 10 employees. For the period we are interested in, 2002-2008, the CIS includes a panel of approximately 2,900 firms, and this is the sample we exploit in our analysis. The attrition rate is very low (4%) and the vast majority of firms operate in the same local labour market throughout the whole period (93 %). The survey questionnaire states clearly what the responding firm should consider to be a technological innovation, providing the following definition: “New or significantly improved goods or services and/or processes used to produce or supply all goods or services, that the business has introduced, regardless of their origin. These may be new to the business or to the market”. Furthermore, a set of selected examples of activities help the respondent in asse ssing what could constitute product (goods or services) or process innovation and examples of activities which instead are not

[1] The 1991 TTWA-level EU8 immigrant population distribution is retrieved from the NOMIS website, a service provided by the ONS for UK labour market statistics. The yearly immigration inflows for the period 1991-2004 is derived from ad-hoc commissioned data of the ONS Migration Statistics Unit.

technological innovations[1]. The product and process innovation outcome variables have binary nature. For instance, the question that firms are asked regarding their level of process innovation is the following: "During the three-year period ..., did your enterprise introduce any new or significantly improved processes for producing or supplying products which were new to your enterprise or industry?" The CIS is conducted every two years, such that we exploit survey responses regarding firms' innovation activities between 2002 and 2004 – the period (mostly) prior to the EU8 accession – as well as between 2004 and 2006 and 2006 and 2008. The nature of the timing of the survey requires two comments. First, there is an overlapping year in each wave, however this is inconsequential given the binary nature of our outcome variables.[2] For instance, if a firm reports product innovation for the 2002-2004 period, and then no product innovation for 2004-2006, we know that the firm engaged in product innovation in 2004 (and, of course, 2002-2003). Second, the EU enlargement occurred on May 1st 2004, whereas 2004 falls in our pre-period for firm outcomes (we do not rely on 2004 variation in immigrant inflows). As a result, any response by firms from May through December of 2004 due to the immediate inflow of immigrants from EU8 countries will be allocated to our pre-period control group, and this will work against finding an effect due to the EU8 accession – i.e., it will bias our results downward. Figure 2.1 documents the trend in EU8 inflows during the period 2002-2008. We can see that there was indeed an immediate uptick in EU8 immigration to the UK beginning in June, 2004, however the vast majority of the inflow occurred after December 2004.

As regards the geographical dimension, the CIS survey does not contain TTWA-level data but provides the anonymized postcode district of each firm. Unlike

[1]For instance, the production of carbon fibre based sport equipment, multi-function printers, IT based credit risk assessment service, online estate agency can be regarded as product innovation. The linking of computer aided design stations to parts suppliers or the digitization of pre-press in printing house are types of service innovations. Instead, the renaming and repackaging of an existing soft drink or the production of a new model of car involving minor changes with respect to previous ones cannot be considered as technology based innovations as defined in the survey.

[2]We also exploit continuous variables from the CIS in our interaction regressions, but in these cases we only use data from the pre-period survey – i.e., we do not rely on variation over time in the response.

postcodes, postcode districts do not present a one-to-one relationship with a TTWA. However, in our sample, around 90% of postcode districts fall into one TTWA. In order to establish a one-to-one link for the remaining 10% of postcode districts we use the centroid-distance method. Centroid distances are computed between any postcode district and TTWA pair, with the former assigned unilaterally to the latter with the closest centroid.

Finally, the CIS does not provide sampling weights. We construct employment weights exploiting data from the Business Structure Database Longitudinal, containing the universe of business organisations in the UK. More specifically, employment weights for each firm i are proportional to the firm's share of total employment in the industry s and band b it belongs in 2004:

$$\omega_{i,b,s} = E_{i,b,s,2004}/E_{b,s,2004} \tag{2.11}$$

We consider five employment bands (10-20, 20-50, 50-100, 100-250, 250^{+}) and 4-digit 1992 Standard Industrial Classification (SIC) codes.

2.4.1 EU8 Immigration to the UK

We bring the predictions of the model to the data by exploiting a large shock to the relative supply of low-skill labour across UK TTWAs in the form of the expansion of the EU in 2004. The expansion brought in eight Central and Eastern European countries: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia. Though citizens of these countries were immediately granted free movement across EU countries, their access to most labour markets was restricted during a seven-year phase-in period. The exceptions were Ireland, Sweden and the UK who granted immediate access, the result of which was a large inflow of immigrants into these countries.

Figure 2.2 depicts the long-run trend in immigration to the U.K., where we see that 2004 represented a significant departure from trend. In figure 2.1 we see that this discontinuity is largely driven by the EU-accession-driven inflow of EU8 imimmigrants beginning in 2004.

Most important for the purposes of our research design is the fact that the average hourly wage of EU8 immigrants over the period 2004-2008 was far below that of the native population[1]. According to Dustmann, Frattini and Halls [2010] the average hourly wage over the period 2004-2009 for men from EU8 countries was £6.81 while it was £11.91 for native-born men. This suggests that the EU8 expansion significantly changed the labour force composition in areas that received significant numbers of these immigrants. To the extent that low-skill natives and immigrants are imperfectly substitutable, this fall in the average low-skill wage would have generated a cost saving gain for firms who employed these workers, and relatively more so for firms who used low-skill labour relatively intensively, as we discussed in the model. Also important is that the magnitude of the inflow to the UK was largely unanticipated. Negotiations for the terms on which the new countries would enter the EU and enjoy its benefits, including full labour mobility, concluded only in December 2002 and the most highly publicized report at the time estimated that the net annual inflow from the new countries to the UK would be 5,000-13,000. These figures were generated by a UK government commissioned report a year before the enlargement [Dustmann and Fabbri, 2003]. At the time of publishing, it was not known with certainty whether Germany would or would not impose labour controls on the new accession countries, and so the authors' calculated an estimated extra 20,000-210,000 immigrants for Germany but emphasized that if Germany maintained labour controls then some of this expected flow might divert to the UK. The low anticipated flows for the UK were likely believable for UK firms, given the historically low inflows to the UK and the stated preference of individuals in the new accession countries to move to locations closer to home both culturally and linguistically (Germany and Austria were the top destinations of choice as listed in the Home Office Report).

[1] This was despite their higher average education level (see Dustmann, Frattini and Halls [2010]).

2.4.2 What is Process Innovation?

The notion of process innovation is typically taken to be one type of organizational change; specifically, it usually reflects the implementation of more sophisticated or appropriate production processes in order to increase efficiency. Reassuringly, this is also what respondents to the CIS have in mind. In Table 2.1 we present the correlation coefficients between the process innovation dummy and indicators regarding the importance for the firm of several organizational changes as effects of the introduced innovations[1]. In addition we consider firm's expenditure in the acquisition of machinery, equipment and software. The latter variable is included in order to determine whether process innovation is simply a proxy for capital investments which, as noted above, has been explored in the context of immigration in other papers. As we can see from the table, while process innovation is certainly correlated with capital investment, it appears to be a broader concept than that alone. The strongest correlates with process innovation are "Improvements in Production Flexibility" and "Improvements in Production Capacity".

2.5 Specifications and Identification

To bring the model to the data, we exploit the discontinuous inflow of immigrants arising from the 2004 EU8 expansion, described in Section 2.4 above. Formally, we estimate a difference-in-differences specification using OLS regression, the baseline version of which is the following:

$$INN_{iat} = c + \beta_1 EU8share_{a,2004} + \beta_2 \big[POST_t \times EU8share_{a,2004}\big] + \alpha_t + \gamma_i + \epsilon_{iat} \tag{2.12}$$

[1] The corresponding question from which these variables are drawn is formulated as following in the survey questionnaire: "How important were each of the following effects of your product (good or service) and/or process innovations introduced during the three year period ... ?" Where the respondent firm has to tick one box among "not relevant", "low", "medium", "high". Given the negative skewness of the variables' distributions, these are reduced to dummy indicators where a value of 1 indicates "medium" to "high" importance.

where INN is one of the binary innovation measures of interest, associated with firm i located in TTWA a in period t; $EU8share_{a,2004}$ is the percentage share of EU8 immigrants in TTWA a in 2004; and $POST$ is an indicator equal to 1 for post-2004 periods and 0 for the 2002-2004 period [1] [2]. Since, in this specification, the right-hand-side variable of interest varies across TTWAs in the cross-section we cluster standard errors at the TTWA level throughout. The specification includes time period dummies, to control for aggregate shocks affecting firms similarly over time, and firm dummies, to account for all time-invariant unobserved heterogeneity between firms. The regressor of interest is $POST_t \times EU8share_{a,2004}$, whose estimated coefficient gives the effect of the immigration-induced local labour market shocks due to the European enlargement on the innovation activity of firms.

The intuition behind (2.12) is that the firms most affected by the 2004 EU8 accession will be those located in the TTWAs that experienced the largest subsequent inflow of EU8 immigrants. To capture this feature of each TTWA we appeal to the "ethnic enclave" argument most commonly associated with Altonji and Card [1991] and Card [2001*b*]. The idea is that immigrant groups tend to settle in locations in which their compatriots are already settled. As a result, the pre-existing distribution of a particular immigrant group across locations will serve as a good predictor of the future pattern of immigrant settlement. In our case, the share of EU8 immigrants in an area in 2004 should then serve as a useful predictor of settlement patterns between 2004 and 2008.

In a second set of specifications we interact the intensity-of-treatment variable $EU8share_{a,2004}$ with pre-period firm-level measures in order to more fully test the

[1] Given the very small proportion of EU8 immigrants in the local population before the European enlargement, $EU8share_{a,2004}$ is rescaled in percentage terms to ease the presentation of the estimated results.

[2] $EU8share_{a,2004}$ is identified because of a small proportion of firms (7%) relocating across local labour markets during the time period of analysis.

implications of the model. We formally estimate:

$$INN_{iat} = c + \lambda_1 EU8share_{a,2004} + \lambda_2 \big[POST_t \times EU8share_{a,2004}\big] + \lambda_3 \big[POST_t \times EU8share_{a,1991} \times X_{ia,2004}\big] + \alpha_t + \gamma_i + \epsilon_{iat} \tag{2.13}$$

where $X_{ia,2004}$ includes relevant firm-level characteristics in 2002-2004[1].

A potential issue with this approach is that there may be unobserved factors that are both correlated with the EU8 share in an area in 2004 and, independently, with firm-level innovation in that area, both in 2004 and in subsequent periods. For instance, productivity shocks that drive immigrants to a particular area are also likely to increase the innovation intensity of firms in that area. To deal with this issue we estimate specifications (2.12) and (2.13) replacing the 2004 EU8 local share with a predicted share $\widehat{EU8share}_{a,2004}$ based on a lagged EU8 share variable, reflecting the share of EU8 immigrants in a TTWA in 1991. We then augment this share by the aggregate growth rate of EU8 immigrant inflows between 1991 and 2004 $(1 + g_{EU8,1991-2004})$ relative to the UK total population growth $(1 + g_{UK,1991-2004})$:

$$\widehat{EU8share}_{a,2004} = EU8share_{a,1991} \times \frac{(1 + g_{EU8,1991-2004})}{(1 + g_{UK,1991-2004})} \tag{2.14}$$

The potential endogeneity problem now only arises if, for instance, a productivity shock that drove EU8 immigrants to an area in 1991 also influences firm-level innovation in that area over the period 2004 to 2008. In other words, if the hypothetical productivity shock is serially correlated (enough) then this may be the case, and there may be lingering endogeneity. We rely on the fact that 1991 was distant enough so that the shocks driving immigrants to particular TTWAs

[1]Note that the pre-period firm-level terms are absorbed in the firm fixed effects.

in 1991 are very likely to be uncorrelated with the shocks to innovation over the recent period. At the same time, the 1991 immigrant distribution is predictive of the 2004 distribution via the persistence in immigrant networks.

Figures 2.3 and 2.4 sketch the estimation strategy. The top panel shows the OLS relationship between the 1991 working age TTWA concentrations of EU8 immigrants and their subsequent 2004 levels. $EU8share$ in 1991 has a 25^{th} percentile of 0 and a 75^{th} percentile of 0.011. Therefore, an interquartile differential in the local share of EU8 immigrants in 1991 corresponds to a 0.16 percentage points increase in the 2004 local share. The exclusion of London reduces the significance of the estimated association but does not relevantly affect its magnitude. The zero values for the $EU8share$ on the x axis are explained by the naturally lower presence of this immigrant group as far back as 1991. However, the sizeable amount of zero values for $EU8share$ on the y axis is indicative of substantial measurement error in the QLFS. This argument is confirmed in the bottom panel, where for comparison we replace on the y axis the 2004 TTWA-level of $EU8share$ with its 2001 values retrieved from the 2001 Census data[1].

Figure 2.4 depicts the OLS regression of the endogenous 2004 $EU8share$ on $\widehat{EU8share}_{a,2004}$. The estimated relationship shows a coefficient of 0.9 with a t-statistic of 10, satisfying Staiger and Stock [1997]'s rule of thumb. When London is excluded, the estimated coefficient does not relevantly change although the t-statistic value drops to 3.4.

We note that in 2.13, although the firm-level interaction terms are taken at their pre-period values, they may still be endogenous to firm innovation to some extent. As a result, the estimated relationships will be interpreted as associations. In the next paragraph we describe each of the firm-level measures considered.

[1] We retrieve EU8 immigration data for 2001 census from publicly available data on the ONS website(http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/guide-method/census/census-2001/data-and-products/data-and-product-catalogue/commissioned-output/commissioned-tables/index.html). EU8 immigrants' counts are available at district level. We apply the centroid distance method to produce TTWA-level estimates.

2.5.1 Skill Heterogeneity, Firm Size and the Role for Immigrant Demand

We first explore the role of the firm's skill distribution, captured here by the relative share of employees with a college degree in science or engineering subjects at the beginning of the period ($H/L_{ia,2004}$). Since the relevant "skill" that we are interested in is the skill required to develop and implement new product or process innovations, we believe this measure of science and engineering education is an ideal measure. Here we test the straightforward prediction reflected in Lemma 4 that initially low-skill intensive firms will have greater incentive to increase their process innovation activities in the face of the low-skill supply shock. With respect to product innovation Proposition 5 implies that the role of skill in the response is key. This is because the direction of the effect from channels (1) and (2) are unchanged in the case of a high-skill labour shock, but channel (3) switches sign. Thus, under a high-skill labour supply shock the product innovation response is unambiguously positive, whereas it is ambiguous in the case of a low-skill shock, the case captured by the Proposition. Second, we test Lemma 3 which states that the process innovation response to a low-skill labour supply shock should be increasing in firm size. Here we proxy firm size with the log of firm turnover in the initial period ($LogTurnover_{ia,2004}$).

In our final specification we explore the demand side impact of the labour supply shock by first interacting the treatment intensity variable with an indicator for whether the firm sells all of their output locally ($Local\ Sales_{ia,2004}$) – defined as within 100 miles of the firm – and, second, an indicator for whether the firm sells all of their output within the UK ($UK\ Sales_{ia,2004}$). To the extent that the population increase from the EU8 expansion generates greater demand for goods and services, and this should promote product innovation as summarized in channel (2) of Proposition 5.

2.6 Descriptive Evidence

Before discussing the econometric results we provide descriptive statistics for relevant variables during the period 2002-2008. Table 2.2 shows that the average proportion of firms investing in process innovation decreases over time, registering an overall drop of about 6 percentage points throughout the whole period. Also, the average share of firms investing in product innovation decreases by 4 percentage points. The average capital expenditure of firms decreases throughout the period by about 7 log points. The working-age population share of EU8 immigrants consistently increases over time, showing a positive change of 1.09 percentage points. At the same time, the average skill-ratio of firms decreases. This is in line with a low-skilled labour supply shock affecting the labour supply composition of firm employment by lowering the average skill-intensity. The average firm turnover, which we use as a proxy for firm size, constantly increases over time. The share of local and UK-wide sales appear to substantially decline over the period, dropping by 16 and 7 percentage points respectively.

Finally, figure 2.5 provides TTWA-level evidence by plotting OLS regressions of the mean change in the share of innovating firms on the contemporaneous change in the share of EU8 immigrants throughout the period of analysis. The plots are clearly only suggestive, but they indicate a negative correlation between the group of EU8 immigrants and the extent of process and product innovation. On the one hand, the evidence for process innovation appears in contrast with the model prediction, according to which the availability of a new set of relatively cheaper skills should induce a positive reorganization of production processes. Process innovation may be reduced by the availability of relatively cheaper labour, opposite to our expectations, or it might be the case that contemporaneous unobserved factors are, at this stage, co-founding the underlying true relationship between the two variables. On the other hand, product innovation is negatively associated with the EU8 immigrant share. This potentially indicates that the dominant response of firms to the low-skilled labour shock is to reduce investments in this high-skill activity, as it turns relatively more expensive. In the next section we apply the identification strategy to explore these relationships in more detail.

2.7 Results

2.7.1 Process Innovation Estimates

Table 2.3 shows the results from OLS regressions in which the dependent variable is a binary indicator for whether the firm engaged in process innovation during the 2004-2008 period, noting that the pre-treatment period spans 2002-2004.

Column (1) reports estimates for the baseline regression (2.12). We test whether $\beta_2 > 0$, as from Proposition 2, which states that process innovation is biased toward the now more abundant factor. This prediction is not confirmed by the data as the point estimate indicates a negative treatment effect, although not significant. Columns (2) and (3) distinguish between manufacturing and non-tradable 1-digit industry sectors[1]. The negative point estimate for the treatment effect appears somewhat larger in the manufacturing sector although it remains non-significant. In column (4) we proceed with testing Lemma 4, i.e. the low-skill bias of process innovation, by including the interaction of our treatment variable with the firm skill-intensity. The triple interaction term coefficient is negative, indicating that the treatment is mitigated by the skill content of the firm, i.e., low-skill intensive firms respond less negatively to the treatment. However, the relationship is not significant.

Next, column (5) tests Lemma 3, i.e. whether larger firms respond relatively more to the low-skill local labour supply shocks by increasing process innovation. The inclusion of the triple interaction term turns the coefficient of the treatment variable positive, albeit with a magnitude centered around 0. The triple interaction coefficient indicates a significantly negative and substantial association. The larger the pre-period size of treated firms, the less their

[1] The non-tradable sector includes: energy and water, construction, distribution , hotel, restaurants, transport and communication, finance, insurance and restaurants.

investment in process innovation after the EU enlargement. This finding contrasts with our prediction in Lemma 3 and suggests a stronger substitution away for bigger firms from process innovation activities.

As a robustness check for the negative association between EU8 immigration and process innovation we investigate in table 2.4 the treatment effect on each correlate with process innovation. The estimated effects are negative although not significant on almost all the outcomes, confirming the main findings. The only significant treatment effect is found on production flexibility, where the point estimate of -0.11 indicates an interquartile differential effect of $EU8share$ of about 0.05 percentage points.

The empirical evidence gives contradictory results with respect to our model predictions. Let us recall that the treatment effect suffers from downward bias given that any response by firms from May through December of 2004 due to the immediate inflow of immigrants from EU8 countries is allocated to the pre-period. However, we do find a negative coefficient, even if not significant.

We rationalize this finding with the hypothesis that British firms might have found the cost of process innovation larger than the benefit of cheaper low-skill labour input. Low-skill immigration might therefore be substitute to process innovation, in the same way it is to capital investments as found in the literature [Lewis, 2011]. This would imply a negative effect of EU8 immigration on process innovation.

Another important consideration is that the UK, as many other developed countries has been experiencing a process of technological change ongoing since at least the 1980s (see for example Autor and Dorn [2013] for the US; Goos and Manning [2007], Salvatori [2015] for the UK]. In particular, the "Routine Biased Technical Change" hypothesis [Autor et al., 2003] states that continuously cheaper computerization progressively replaces human labour in routine tasks leading to a polarization of the skill-employment distribution. This implies that the estimated treatment effects might suffer from endogenous bias due to unobserved technology shocks correlated with $EU8share_{a,1991}$. Montresor [2016] the Chapter 3 of this thesis investigates the job polarization of UK local labour markets during the two-decade period 1993-2013. The author provides evidence on the negative effect of technological exposure on the local employment of less-skilled workers in the UK. Local labour markets that historically specialized in routine-intensive industries registered the highest decline in the employment of non-graduate labour. Given the skill-bias of technological adoption, firms that undertook capital investment to replace less-skilled workers before the European enlargement immigration shock, would most likely not find it optimal to absorb the inflows of cheaper low-skill labour. In this sense, our theoretical model would predict at best the adjustment of firms that pre-European enlargement were labour intensive. It appears important to test the model distinguishing by capital/labour intensity of firms. Unfortunately, we currently lack the necessary data for this analysis and therefore leave it to future work.

2.7.2 Product Innovation Estimates

Table 2.5 shows the results from OLS regressions in which the dependent variable denotes whether the firm engaged in product innovation.

Column (1) reports estimates for the baseline regression (2.12). Proposition 5 states that the effect of the labour supply shock on product innovation is ambiguous, and depends on: (1) the relative strength of the cost saving gains associated with EU8 immigrants (arising from the fall in the local average low-skill wage) and, (3) the extent of substitution away from product innovation due to its high-skill intensity (due to the rise in the relative high-skill wage). We find a significant and negative average treatment effect. This suggests that the substitution effect (channel 3) is dominant in firms' response to the low skill labour supply shock. Let us recall that the Iqr for $\widehat{EU8share}$ in 2004 is 0.46. The point estimate for the treatment variable indicates that firms starting at the 75^{th} percentile of $\widehat{EU8share}$ in 2004, decrease their product innovation by 0.016 percentage points more that firms at the 25^{th} percentile. Importantly, when distinguishing between manufacturing and non-tradable sectors in columns (2) and (3), the treatment effect appears significant and negative only for the latter. Furthermore, in the manufacturing sector the point estimate for $EU8share$ is centered around 0. In the next columns we therefore focus on the non-tradable sector and we interact the treatment variable with pre-period firm characteristics. The estimated associations for the triple interaction terms are never significant.

In column (4) the coefficient of the interaction terms between our treatment variable and firm skill intensity is negative indicating that more skill-intensive treated firms in 2004 are more negatively associated with the probability of investing in product innovation after the EU enlargement.

The negative coefficient of the triple interaction with firm size in column (5) complements the previous empirical findings for process innovation, showing that bigger firms are associated with a relative higher decrease in product innovation.

Finally, columns (6) and (7) ask whether the treatment effect is increasing in the extent to which the firm sells their output locally (within 100 miles) or within the UK borders (channel). Both triple interaction coefficients indicate positive, albeit non significant associations.

In summary, on average the product innovation activity of British firms seems to have suffered from EU8 immigration, except for the manufacturing sector. We interpret the negative treatment effect as a sign of firms' reduced effort in a typically high-skill activity which becomes relatively more expensive due to the low-skill labour supply shock. No differential treatment associations are found on the basis of firm skill-intensity, firm size and firm domestic market size.

2.8 Conclusions

With various countries, including the UK, considering tightening their immigration policies, it is particularly relevant to measure the entire impact immigrants have on host country economies. Innovation is a key understudied area with potentially large implications for the host economy performance in the longer run. This paper focuses on within firm-adjustments to labour supply shocks. We provide a novel contribution to the literature by considering innovation as an alternative mechanism firms use to absorb skill-specific changes in local labour supply. When the firm adjusts the relative efficiency of its inputs we refer to this as process innovation, and when the firm endogenously chooses its optimal product scope, we refer to it as product innovation. Accordingly, we develop a model with heterogeneous profit-maximising firms choosing their optimal product scope and their optimal production structure, respectively. On the one hand, the model predicts that a low-skill labour supply shock has a clear positive effect on the process innovation activity of firms and operates through a greater incentive to use more intensively the now available more abundant and relatively cheaper labour production input. Furthermore, this effect is increasing in the firm's low-skill intensity and output. On the other hand, the model states that the effect of the low-skill supply shock on the product innovation activity of firms is instead ambiguous and depends on the interaction of three channels. More specifically, the supply of relatively cheaper labour supply reduces the firm's production costs, thereby increasing product scope. This positive effect is increasing in the size of the market. However, the relative increase in the supply of low-skill labour makes the high-skill product innovation activity more costly, and firms may be incentivized to substitute away from it.

We bring the model to the data and test its hypotheses by exploring the product and process innovation responses to the large influx of EU8 immigrants to the U.K. since the enlargement of the European Union in 2004. Two main findings emerge from the empirical analysis. Firstly, we detect a negative albeit not significant average effect of low-skill labour supply shocks on the process innovation of firms. Furthermore, when distinguishing across heterogeneous firms, a further contradictory result is that bigger treated firms appear associated with a relatively stronger immigration-induced decrease in their investment in process innovation with respect to smaller ones. The negative association between the local

EU8 immigration inflows and firm process innovation is confirmed in a robustness check where firm correlates with process innovation are used as outcome variables. We hypothesize that, similarly to capital investment, process innovation might be gross substitute to low-skill immigration. In line with this reasoning, British firms might have found the cost of process innovation larger than the benefit of cheaper low-skill labour input. Furthermore, we acknowledge the importance of accounting for technological shocks which are likely to generate endogeneity bias in our treatment estimates. Given the skill-bias of technological adoption, firms that undertook capital investment to replace less-skilled workers before the European enlargement immigration shock, will not find it optimal to absorb the inflows of cheaper low-skill labour. As regards product innovation, we find a significant and negative average treatment effect. According to our model predictions, this suggests that the dominant response of firms has been to substitute away from a now relatively more costly high-skill activity. However, the empirical limits of our analysis advocate for future work.

Tables

Table 2.1: Correlates with Process Innovation

Variable	ρ
Improve product quality	0.13
Improve production flexibility	0.16
Improve production capacity	0.16
Reduce per unit costs	0.10
Improve health and safety	0.08
Increase value added	0.11
Log(*capital expenditure*)	0.07

Notes: The table shows the correlation coefficients between the process innovation dummy and indicators for the firm of several organizational changes as effects of the introduced innovations as well as with capital expenditure. The corresponding question from which the organizational change variables are drawn is formulated as following in the survey questionnaire: “How important were each of the following effects of your product (good or service) and/or process innovations introduced during the three year period ... ?” Where the respondent firm has to tick one box among "not relevant", "low", "medium", "high". Given the negative skewness of the variables’ distributions, these are reduced to dummy indicators where a value of 1 indicates "medium" to "high" importance. *Capital expenditure* represents firm’s investments (,000 £) in the acquisition of machinery, equipment and software. *Log*(*capital expenditure*) is measured with the following monotonic transformation *Log*(*capital expenditure* + 1). 25% of observations have 0 value for *capital expenditure*.

Table 2.2: Decriptive Statistics

	2002-2004			2006-2008			2002-2008	
	Mean	25p	75p	Mean	25p	75p	Δ Mean	Δ Iqr
Process	0.21			0.15			-0.06	
Product	0.29			0.25			-0.04	
$Log(Capital\ expenditure)$	0.18	0.00	0.14	0.10	0	0.05	-0.07	-0.09
$EU8share$ (%)	0.3	0	0.43	1.39	0.4	2.28	1.09	1.45
$\widehat{EU8share}$ (%)	0.68	0.37	0.83					
HL	0.14	0	0.03	0.09	0	0.02	-0.05	-0.01
$LogTurnover$	1.62	0.22	2.91	1.89	0.41	3.22	0.27	0.12
Local Sales	0.29			0.13			-0.16	
UK Sales	0.22			0.16			-0.07	

Notes: The table shows mean, 25^{th} and 75^{th} percentiles values of relevant variables in every wave of the sample, as well as the respective mean and interquartile changes throughout the whole period.

Process and *Product* are dummy indicators for whether the firm engaged in either innovation type. *Capital expenditure* represents firm's investments (,000 £) in the acquisition of machinery, equipment and software. $Log(Capital\ expenditure)$ is measured with the following monotonic transformation $Log(Capital\ expenditure + 1)$. 25% of observations have 0 value for *Capital expenditure*. $EU8$ *share* is the percentage share of EU8 immigrants; $\widehat{EU8share}$ is the predicted share of EU8 immigrants computed from 1991 Census levels, augmented by the aggregate growth rate of EU8 immigrant inflows relative to the UK total population between 1991 and 2004. HL is the relative share of employees with a college degree in science and engineering subjects. *Turnover* is firm's turnover (,000 £). *Local Sales* and *UK Sales* are dummy variables indicating, respectively, whether the firm sells their output locally (within 100 miles of the enterprise) and nationally.

Table 2.3: Process Innovation

	(1)	(2)	(3)	(4)	(5)
	All	Manufacturing	Non-tradable	All	All
$\widehat{EU8share}_{a,2004}$	-0.011	0.055	-0.042	-0.015	-0.015
	(0.061)	(0.134)	(0.058)	(0.062)	(0.063)
$Post * EU8\widehat{share}_{a,2004}$	-0.024	-0.049	-0.015	-0.021	0.005
	(0.020)	(0.055)	(0.018)	(0.021)	(0.033)
$Post * EU8\widehat{share}_{a,2004} * H/L_t$				-0.021	
				(0.018)	
$Post * \widehat{EU8share}_{a,2004} * LogTurnover_t$					-0.270***
					(0.092)
N	8552	2701	5851	8319	8322
R^2	0.525	0.530	0.52	0.520	0.521

Notes: The dependent variable is *Process*, dummy indicator for whether the firm engaged in process innovation. Results are show for all, manufacturing and non-tradable (1-digit industry) firms. The non-tradable sector includes: energy and water, construction, distribution, hotel, restaurants, transport and communication, finance, insurance and restaurants. All specifications include intercept, time and firm dummies. Standard errors in parentheses are clustered by TTWA. Observations are weighted by firm's employment share in the relative band and industry sector. Recall that *EU8share* is measured in % terms.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 2.4: Process Innovation Correlates

	Improve product quality	Improve production flexibility	Improve production capacity	Reduced per unit costs	Improve health & safety	Increase value added	Log (capital expenditure)
$\widehat{EU8share}_{a,2004}$	0.046	0.104	0.086	0.055	-0.079	-0.022	0.155
	(0.057)	(0.121)	(0.115)	(0.079)	(0.104)	(0.078)	(0.197)
$Post * \widehat{EU8share}_{a,2004}$	-0.026	-0.065	-0.109*	-0.061	0.059	0.030	-0.019
	(0.060)	(0.052)	(0.049)	(0.042)	(0.068)	(0.043)	(0.069)
N	2911	2632	2528	2542	1901	2804	4938
R^2	0.693	0.712	0.724	0.729	0.869	0.714	0.662

Notes: The dependent variables are correlates with process innovatin (see table 2.1). All specifications include intercept, time and firm dummies. Observations are weighted by the pre-period firm relative share of total employment in its industry employment band. Standard errors are clustered by TTWA. Recall that $EU8share$ is measured in % terms.

$Log(Capital\ \ expenditure)$ is measured with the following monotonic transformation $Log(Capital\ expenditure + 1)$. 25% of observations have 0 value for $Capital\ expenditure$.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

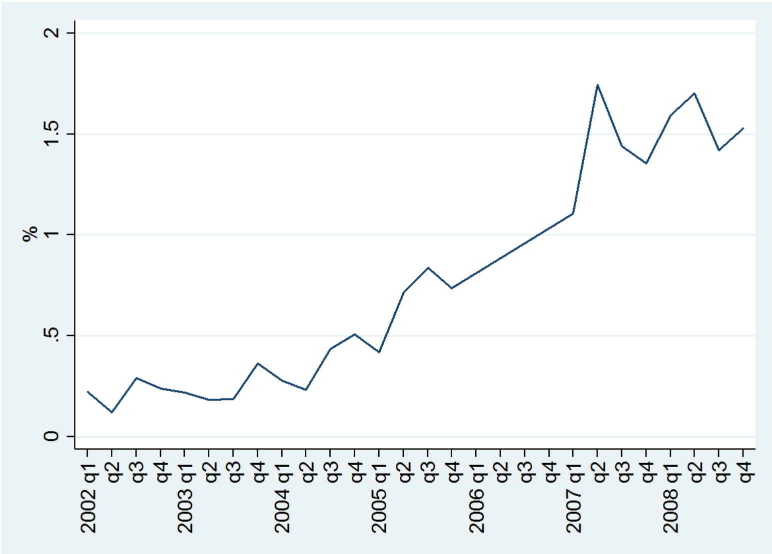
Table 2.5: Product Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Manufacturing	Non-tradable	Non-tradable	Non-tradable	Non-tradable	Non-tradable
$\widehat{EU8share}_{a,2004}$	0.126	0.006	0.149	0.147	0.146	0.147	0.145
	(0.090)	(0.076)	(0.101)	(0.101)	(0.102)	(0.102)	(0.100)
$Post * \widehat{EU8share}_{a,2004}$	-0.034*	0.038	-0.046*	-0.046*	-0.039*	-0.046*	-0.049***
	(0.013)	(0.170)	(0.016)	(0.016)	(0.020)	(0.015)	(0.016)
$Post * \widehat{EU8share}_{a,2004} * H/L_{ia,2004}$				-0.002			
				(0.022)			
$Post * \widehat{EU8share}_{a,2004} * LogTurnover_{ia,2004}$					-0.058		
					(0.055)		
$Post * \widehat{EU8share}_{a,2004} * LocalSales_{ia,2004}$						0.002	
						(0.021)	
$Post * \widehat{EU8share}_{a,2004} * UKSales_{ia,2004}$							0.013
							(0.030)
	8552	2701	5851	5691	5688	5697	5697
	0.582	0.600	0.560	0.554	0.555	0.555	0.555

Notes: The dependent variable is *Product*, dummy indicator for whether the firm engaged in process innovation. Results are show for all, manufacturing and non-tradable (1-digit industry) firms. The non-tradable sector includes: energy and water, construction, distribution, hotel, restaurants, transport and communication, finance, insurance and restaurants. All specifications include intercept, time and firm dummies. Observations are weighted by the pre-period firm relative share of total employment in its industry employment band. Standard errors are clustered by TTWA.

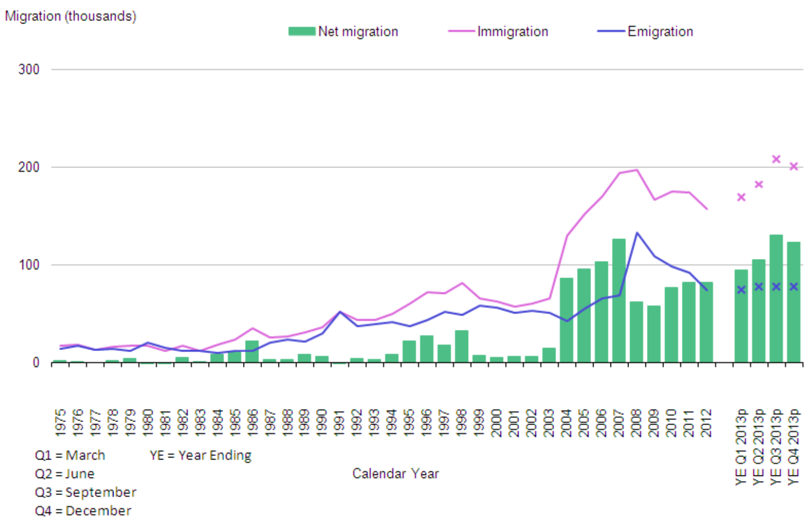
Figures

Figure 2.1: EU8 Immigrants as a Share (%) of the UK Working-age Population, 2004-2013



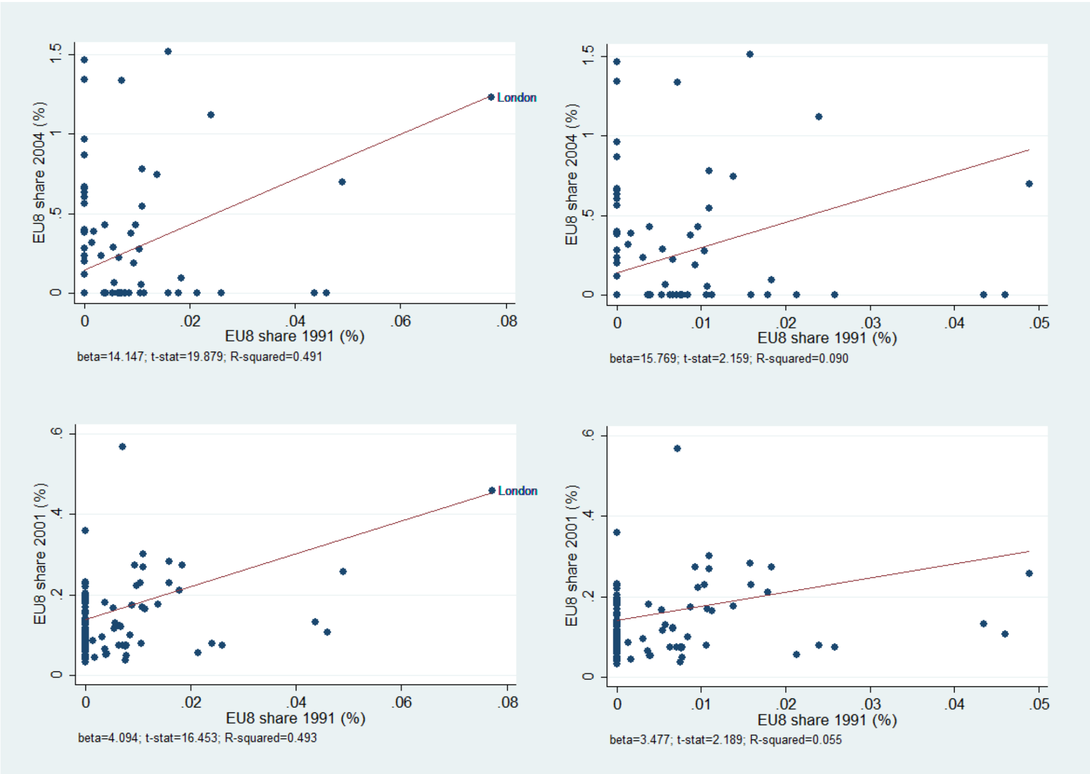
Notes: The figure plots the the percentage share of EU8 immigrants as a ratio to the working age population in the UK by quarter during 2002-2008.

Figure 2.2: Long-term International Migration of EU citizens, UK, 1975-2013



Source: Office for National Statistics [2014] (Figure 1).
Notes: The figure plots the long-term migration estimates or EU citizens. Estimates are newvisional for the year ending December 2013.

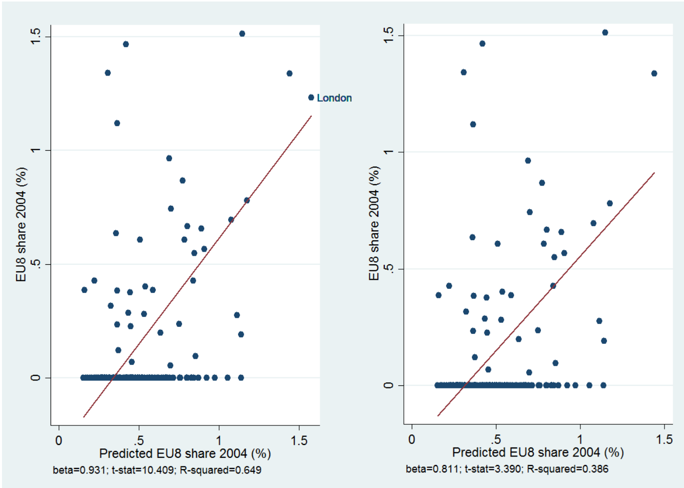
Figure 2.3: Estimation Strategy (1)



Notes: The top panels plot the fitted lines from OLS regressions of the 2004 EU8 immigrant percentage share on the respective 1991 levels, with and without London TTWA. The bottom panels plot the fitted lines from OLS regressions of the 2001 EU8 immigrant percentage share on the respective 1991 levels, with and without London TTWA. The 2004 share is computed from QLFS data, while the 2001 and 1991 shares are computed from Census data.

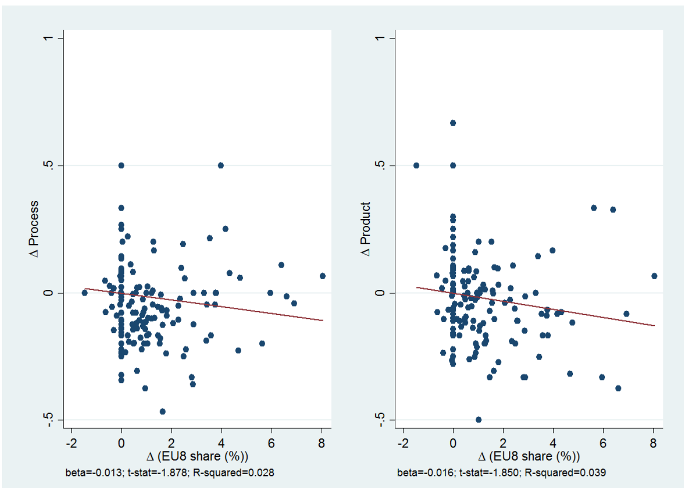
Observations are weighted by the pre-period firm relative share of total employment in its industry employment band. Standard errors are clustered by TTWA. The total number of TTWAs is 151.

Figure 2.4: Estimation Strategy (2)



Notes: The figure plots the fitted lines from OLS regression of the 2004 EU8 immigrant percentage share on the respective predicted 2004 levels, with and without London. The predicted levels are based on 1991 Census levels, augmented by the aggregate growth rate of EU8 immigrant inflows relative to the UK total population between 1991 and 2004. Observations are weighted by the pre-period firm relative share of total employment in its industry employment band. Standard errors are clustered by TTWA. The total number of TTWAs is 151.

Figure 2.5: Change in Innovation vs Change in EU8 Immigrants across TTWAs, 2004-2008



Notes: The figure plots OLS regressions of the mean changes in the share of innovating firms in process (left) and product (right) innovation on the contemporaneous change in the share of EU8 immigrants throughout the period. Observations are weighted by the pre-period firm relative share of total employment in its industry employment band. Standard errors are clustered by TTWA. The total number of TTWAs is 151.

Chapter 3

Job Polarization and Labour Supply Changes in the UK

Abstract

During the past two decades, the UK has experienced dramatic changes in the composition of its labour force, mainly due to a rapid educational upgrading and immigration surges. Over the same period, unlike the US, the UK has shown a persistent pattern of occupational polarization. This paper provides first empirical evidence on the causal effect of technological exposure on local labour markets in the UK. The analysis combines 1993-2013 QLFS data with a longitudinal Census sample spanning 1971-2011. The identification strategy exploits geographical variation across local labour markets stemming from their historical specialization in routine-intensive activities. Results confirm the leading role of technology in hollowing out middle paid jobs and pushing the reallocation of less skilled workers to the bottom of the employment distribution. However, no significant effect of technological exposure is found on skilled non-routine cognitive employment. At the same time, higher start-of-the-period local relative graduate labour supply is significantly negatively associated with top employment growth during the 1990s, in coincidence with the substantial increase in the pool of graduates. In line with this last finding, the analysis of individual occupational transitions uncovers a marked increase in the outflows of both graduates

and non-graduates from the top down the occupational ladder since 1991.

Key Words: Job Polarization, Labour Supply Changes, Local Labour Markets, Occupational Mobility

JEL Codes: J21, J23, J24, O33

3.1 Introduction

The demographic composition of the labour force in the UK in the last two decades has changed dramatically, mainly reflecting a rapid educational upgrading and surging immigrant inflows. Figure 3.1 shows the shares of graduates and of immigrants among employees between 1979 and 2012. The plot shows that both shares have started to accelerate significantly during the 1990s, more than doubling between 1990 and 2012.

Over the same period a growing number of studies have documented the polarization of employment across a number of developed countries [see for example Autor and Dorn [2013] for the US; Goos and Manning [2007], Salvatori [2015] for the UK; Goos et al. [2014], Michaels et al. [2014] for Europe].

In the seminal paper of Autor et al. [2003] (ALM henceforth) job polarization is explained through the so called routinization or routine-biased technical change (RBTC) hypothesis, stating that continuously cheaper computerization progressively replaces human labour in routine tasks, thereby leading to an increase in the relative demand for workers performing non-routine tasks.

The prevailing economic literature has so far provided empirical support to this hypothesis [Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2014; Michaels et al., 2014].

Nevertheless, while this thesis seems to fit well the US employment distribution during the 1990s, it falls short in explaining a number of recent empirical puzzles that emerged since the year 2000. Major pitfalls are the unexplained downturn in the growth of high-skilled occupations and the disappearance of wage polarization

[Autor, 2015; Beaudry et al., 2016]. In particular, as regards the deceleration of employment growth in top occupations, Autor [2015] suggests that high-skill jobs may not be growing enough to absorb the increasing supply of educated workers. A recent study from Salvatori [2015] raises doubts on the leading role of technology while highlights the contribution of changes in the structure of the labour supply in explaining the job polarization phenomenon in the UK. The author shows how the UK distinguishes itself from the US counterpart in two main features: the persistent polarized shape of the employment distribution since at least the 1980s, with growth in high skilled occupations always by far exceeding that in bottom ones, and the absence of wage polarization in any decade.

In light of the emerging literature debate, the UK offers an interesting context for testing the causal effect of exposure to technological change. On the policy side, understanding the determinants of job polarization can advice policy makers in designing policies to best promote a sustainable economic growth. This is especially salient given the wide-spreading feeling of technological anxiety [Mokyr et al., 2015]. The changing structure of the labour market raises important policy challenges in terms of job quality and occupational mobility. On the one hand, middling workers facing loss of their jobs are most likely to look towards lower-paying jobs. On the other hand, the decline in middle-pay jobs can undermine the chances of the low-paid workers of moving up the occupational ladder.

This paper provides new evidence on employment polarization in the UK. The aim is to disentangle the causal effect of technological exposure while providing suggestive evidence on the role of labour supply changes in shaping the polarized structure of employment during the last two decades (1993-2013).

The empirical strategy builds on the spatial analysis approach of Autor and Dorn [2013] and exploits geographical variation across local labour markets in their historical specialization in routine-intensive industries to identify the causal effect of technological exposure on employment changes. Employment data is derived from the Quarterly Labour Force Survey (QLFS) and local labour markets are proxied by Travel to Work Areas (TTWAs), statistical units developed by the Office for National Statistics (ONS) for the specific purpose to bound commuting zones. The construction of time-consistent local labour markets is based on the novel use of geographical weights mapping wards to TTWAs. The use of TTWAs as measures of local labour markets is validated by the unresponsive mobility of the working-age population to technological exposure observed across these areas. The endogeneity of technology exposure is addressed with an instrumental variables strategy that relies on variation obtained from the industrial and employment mix across TTWA observed in the Census for England and Wales in the year 1971, about a decade before the boom in workplace computerization [Autor et al., 1998; Bresnahan, 1999; Nordhaus, 2007]. The study is complemented by the use of longitudinal Census data spanning 1971-2011 in order to provide a finer insight into employment changes.

The econometric analysis confirms the fundamental role of technology in shaping the hollowed out structure of employment. Local labour markets that were initially specialised in routine intensive occupations exhibit larger declines in non-graduate routine employment, with its reallocation to non-routine manual occupations. However, no effect of technological exposure is found on skilled top occupational employment changes. This evidence may indicate that the growing pool of graduates may have out-weighted the demand for skills.

Because of the rapid educational catch-up, higher start-of-the-period local human capital is in fact negatively associated with employment growth in graduate non-routine cognitive occupations during the 1990s. High-skilled immigrant concentrations are instead positively associated with graduate top employment growth in both decades. At the bottom, initial local labour supply factors do not show any relevant significance. However, graduate labour supply changes appear negatively related with growth in non-routine manual occupations in both decades and the magnitude of this association grows over time. This set of results provides supportive evidence of a mere supply-side effect of the educational upgrading of the population.

Finally, the analysis of individuals' occupational transitions uncovers a marked occupational downgrading since the 1990s and quantitatively affecting non-graduates twice as much as graduates. The suggestive evidence is that there are two major forces at play: the decline in routinization explains the hollowing out of the employment distribution, while the raising supply of graduates increases job competition along the employment distribution.

The remainder of the paper is as follows. Section 3.2 reviews the relevant economic literature, section 3.3 describes the data sources, the definition of local labour markets and the routine intensity measure. Section 3.4 presents descriptive evidence on employment polarization by occupational, demographic groups and by labour market area. Section 3.5 specifies the estimation strategy and section 3.6 discusses the empirical results. Section 3.7 analyses individual occupational transitions. Section 3.8 concludes.

3.2 Literature Review

The ALM thesis predicts that technological change is biased toward replacing human labour in routine tasks, while leading to an increase in the relative demand for workers performing non-routine tasks. Routine tasks are defined as limited and well-defined activities which can be accomplished by following a set of rules and therefore are more easily codifiable to be executed by machines. These are typical of many middle-paid cognitive and manual jobs, such as bookkeeping, clerical work, repetitive production and monitoring. At the opposite ends of the occupational-skill distribution lie non-routine abstract and manual tasks. The former are typically performed by high-skilled workers such as managers, professionals as they require activities such as intuition, creativity, problem-solving. The latter refer to activities requiring physical dexterity or interpersonal communication, that are instead typical of low-skilled occupations, such as transportation, cleaning, meal preparation, personal care.

Technology substitutes for labour in routine tasks while complements it in non-routine abstract tasks. Non-routine manual tasks are instead not directly affected by technology. However, these are subject to general equilibrium effects. Autor and Dorn [2013] explain the growth of low-skilled service occupations through the interaction of two forces: on the one hand technological progress replacing low-skilled labour in routine occupations, while on the other hand, consumer preferences favouring variety over specialization such that goods cannot substitute services. The authors use repeated cross-sectional data from the US Census and Current Population Survey (CPS) and identify the effect of technological exposure on local labour markets exploiting variation in the degree of local historical specialization in routine-intensive occupations. Results show RBTC-consistent greater decrease in routine employment and greater increase in service employment in historically routine-intensive areas. Beyond routine-intensity, Autor and Dorn [2013] have considered alternative hypotheses of job polarization, i.e. the increasing relative supply share of graduates and of low skilled immigrants, the aging of the population and the growing offshorability of job tasks. Many of these explanatory factors receive empirical support but none of them appears to play a leading role.

Cortes [2016] uses individual-level panel data from the Panel Study of Income Dynamics (PSID) for the period 1976-2007 and focuses on testing the RBTC effect by looking at the occupational transition patterns and wage changes of routine workers over 2-year windows. The study shows that since the 1990s routine workers become more likely to switch to either non-routine cognitive or manual jobs. In particular, there is strong evidence of selection on ability, with low-ability routine workers more likely to reallocate to non-routine manual jobs and high-ability routine workers more likely to move upward into non-routine cognitive jobs. This U-shape pattern is not found in non-routine occupational categories. Also, the wage premium for stayers in routine occupations has significantly fallen with respect to non-routine occupations. This evidence is interpreted as supporting the RBTC hypothesis.

In the UK, the first evidence on job polarization has been provided by Goos and Manning [2007]. The study uses repeated cross-sectional data from the Labour Force Survey (LFS) and looks at the period 1979-1999. A conterfactual exercise tests the routinization hypothesis against changes in the composition of the labour force, i.e. the increasing employment of women, of graduates, and the changing age structure in the labour market. The authors conclude that the routinization hypothesis provides the most plausible explanation for the polarized shape of the employment distribution.

Goos et al. [2014] and Akcomak et al. [2013] investigate the role of routinization and offshoring for Europe and the UK respectively. Both factors contribute in explaining employment changes, although routinization has a much more substantial effect.

More recently, Salvatori [2015] complements and extends the analysis of Goos and Manning [2007] up to 2012. The contribution of compositional changes in shaping the employment structure is assessed using a shift-share decomposition analysis where the labour force is divided into education-age-immigration-gender cells. Results indicate that the most distinctive feature of the UK labour market is the increase in the share of graduates that has accounted for the reallocation from middling to top occupations in each decade. In parallel, median wages of high-skilled workers has progressively deteriorated reaching the lowest growth across the employment distribution. Furthermore, the loss in middling occupations during this 30-year span is entirely experienced by non-graduates, who mostly appeared to reallocate to the lower tail of the distribution. Finally, also graduates have been sustaining employment growth in bottom occupations, but only during the 2000s their contribution exceeded that of non-graduates for the first time. Immigrants also started to play a more important role in the last decade and appear employed in all three categories, with larger contribution at the extremes. This study suggests that changes in the structure of the labour supply in the UK could play a much more important role than what previously considered by the literature.

The demographic composition of the labour force in the UK in the last two decades has in fact changed dramatically, mainly reflecting a rapid educational upgrading and surging immigrant inflows. As Salvatori [2015] points out, while these labour force changes might be partly endogenously driven by changes in demand, they are likely to have been largely affected by important institutional changes.

Until the mid-1980s, the UK was particularly lagging behind other OECD countries in terms of educational achievement. Since then, successive governments have pursued the objective to improve educational standards [Machin and Vignoles, 2006]. In part, this was achieved with the introduction of the General Certificate of Secondary Education (GCSE) in 1988, which switched the grading method from "norm-referencing" to "criteria referencing", thereby increasing the proportion of pupils achieving higher grades and potentially enrolling in higher education [Bolton, 2012]. Another relevant reform was the abolition of the so called binary divide between polytechnic institutions and universities in 1992, granting university status to 48 polytechnics and therefore widening the available university places. As a result, the participation rate in higher education increased sharply from 19.3% in 1990 to 33% in 2000 [Bolton, 2012; Salvatori, 2015].

In addition, the UK has started to experience large flows of immigration since late 1990s. In 1997 the incoming labour government shifted from a strict immigration policy limited to asylum and family reunion to considering immigrants as a resource and thereby favouring economic immigration. Further on 1st May 2004, the UK was one among very few countries in Europe (i.e. Ireland and Sweden) that opened the doors to new EU member states' citizens (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia). Immigration to the UK unexpectedly skyrocketed. The Worker Registration Scheme (workers from A8 countries were required to register on this scheme within a month of joining a new employer) concluded in 2011 with nearly 1,1 million applications [Home

Office, 2009, 2011].

Salvatori [2015] highlights the contribution of labour supply changes while challenging the leading role of technological exposure. Indeed, the main challenge in disentangling the effect of labour supply changes from technology is the embedded relationship between the two. This paper focuses on isolating the causal effect of technological exposure on employment, while trying to provide some suggestive evidence on the role of labour supply changes. To the best of my knowledge, this is the first study which investigates the causal effect of technological exposure on the UK local labour markets. Another important contribution is the use of longitudinal information on individuals' occupational transitions which allows to provide more disaggregated evidence on the evolution of the UK skill-employment distribution.

3.3 Data Sources and Measurement

The main data source comes from the UK Quaterly Labour Force Survey (QLFS) and covers the two-decade period 1993-2013. The QLFS represents the primary source of labour market statistics for the UK including a wide range of employment-related and demographic information. The QLFS is a household survey conducted by the Office for National Statistics (ONS). It comprises a single-stage sample of households, implicitly stratified by geographical ordering. Since 1992 it has a quarterly frequency and a rotating panel structure such that each individual is staying in the sample for five consecutive quarters. Each quarter covers approximately 100,000 individuals, making up about 0.2% of the UK population. Only individuals at their first interview in each quarter are retained. In addition, I boost the sample size by pooling together 1993-1994, 2003-2004 and 2013-2014 waves. I make use of the available personal weights to make the sample representative of the UK population and to correct for non-response.

The analysis is complemented by a random longitudinal data sample from the ONS

Longitudinal Study (LS). The LS includes a complete set of individual records linked between successive censuses during 1971-2011. The sample is composed of people born on one of four selected dates of birth, covering about 1% of the total population of England and Wales.

Occupations in the QLFS and LS were originally coded according to either the UK Classification of Occupations or Standard Occupational Classification (CO70, CO80, SOC-90, SOC-2000 and SOC-2010). I reclassify occupations according to the International Standard Classification of Occupations (ISCO-88) and use probabilistic matching to create concordance across occupational codes over time. Occupations are defined at the two-digit level. Armed forces and agriculture-related occupations are excluded from the sample (ISCO 10, 61 and 92). An extra number of occupations (ISCO 11, 23, 44, 99) are dropped in order to match the data to routine and off-shoring measures from the literature[1]. The sample of analysis is composed of employees in paid work aged between 16 and 64 in England and Wales. Employment is measured as total usual weekly hours multiplied by 52 calendar weeks. Hourly wages are measured as gross earnings over average total paid hours during the reference week.

The spatial units of analysis are local labour markets which are proxied by TTWAs. These are generated by the ONS, such that at least 75 percent of an areas' resident workforce live and work in the same area. I refer to the 2007 definition, according to which in England and Wales there is a total of 186 TTWAs. I construct time-consistent local labour market areas through the novel use of geographical weights mapping wards to TTWAs[2].

Technology exposure is measured by specialization in routine-intensive occupations with the Routine Task Intensity (RTI) index. This index was first proposed by ALM, who use the 1977 US Department of Labor's Dictionary of Occupational

[1] As discussed in more detail later, I retrieve routine-intensity and offshoring measures from Goos et al. [2014].

[2] There is a highly unique matching rate (above 96%) between wards and TTWAs. Geographical weights are created for wards overlapping with more than one TTWA. These are proportional to the area share of the ward falling in each TTWA it overlaps with.

Titles (DOT) to define the routine, abstract and manual task content of occupations. This information is merged to occupational data to provide a summary index increasing in the routine task importance and decreasing in the non-routine manual and abstract task importance. The index formula, applied to the sample base year 1993 is as follows:

$$RTI_k = ln(T^R_{k,1993}) - ln(T^M_{k,1993}) - ln(T^A_{k,1993}) \tag{3.1}$$

where $T^R_{k,t_0}, T^M_{k,t_0}, T^A_{k,t_0}$ are the routine, manual and abstract task components for occupation k in 1993.

As previously mentioned, I adopt the RTI classification from Goos et al. (2014), who use the same RTI index constructed by Autor and Dorn (2013) based on the ALM DOT task measures. The authors map the RTI index from the US census nomenclature to ISCO-88 and then standardize it across 2-digit occupational codes. Following Autor and Dorn (2013), I then measure routine-intensity within TTWAs by classifying as routine those occupations in the highest employment-weighted third share of the RTI measure in 1993. Accordingly, table 3.1 shows the 1993 employment distribution ranked from high to low RTI values and shows the occupational mix representing the set of routine-intensive occupations in the sample. Finally, the local labour market share of routine employment is computed as:

$$RSH_{jt} = (\sum_{k=1}^{k} L_{jkt} * 1[RTI_k > RTI^{66}])(\sum_{k=1}^{k} L_{jkt})^{-1} \tag{3.2}$$

Where L_{jkt} is employment in occupation k in TTWA j at time t, $1[.]$ is the indicator function taking value of one if routine intensive. The grand mean of RSH is 0.25 in 1993, and the interquartile range (Iqr, henceforth) is 7 percentage points.

3.4 Descriptive Evidence

3.4.1 Employment Polarization by Occupational Groups

Previous studies document a clear job polarization pattern for the UK, Goos and Manning [2007] for the period 1979 to 1999 and Salvatori [2015] for the period 1979 to 2009.

Figure 3.2 shows the changes in employment shares during the period 1993-2013. Occupations are grouped into employment-weighted deciles of the 1993 wage distribution. The figure shows the typical U-shaped pattern of employment polarization with greatest growth at the top of the distribution, confirming the literature's findings.

Table 3.2 shows the levels and changes in employment shares by major occupational groups (2-digit level) in England and Wales between 1993 and 2013. Occupational groups are ranked by average log hourly wages. We can observe the polarization pattern with middle-paying occupations exhibiting relative declining shares with respect to the top and the bottom. The last column shows the RTI index measure from Goos et al. (2014). The categories experiencing higher growth among top occupations are corporate managers (+2.65pp) and physical, mathematical and engineering science professionals (+1.66pp). Bottom occupational categories represent a mixture of service and sales-related jobs. We can observe that bottom employment growth (+4.59pp) is driven by personal and protective service workers (+3.82pp). The middle occupations registering the highest employment losses are machine operators and assemblers (-3.07pp); office clerks (-2.64pp); metal, machinery and related trade workers (-2.43pp).

Importantly, the polarization trend is not unique to the manufacturing industry. Table 3.12 in the Appendix shows that occupational categories losing the most are machine operators, assemblers and craft related ones in the manufacturing sector while office clerks in the non-manufacturing one. This is in line with evidence from Autor et al. (2015) for the US, and suggests the pervasive computerization across the economic sectors. The last column of table 2 reports the RTI values, which appear generally consistent with the polarization pattern. The highest positive values are associated to middle-ranked occupations. Occupations at the top are more intense in the abstract task dimension and show negative RTI values, while at the bottom the values are either negative or near zero. The occupational categories in bold are defined as routine-intensive following the criteria from Autor and Dorn (2013) as explained in section 3.3. Finally, I define the occupations in the top category as non-routine cognitive, while the remaining occupations in the bottom category as non-routine manual.

3.4.2 Employment Polarization by Demographic Groups

Figure 3.3 shows changes in employment shares in each decade between 1993 and 2013 for graduates and non-graduate workers by major occupational groups, ranked by average log hourly wages. Graduates represent workers with a degree or higher educational qualification; non-graduates are divided into GCE A level, GCSE educational qualifications, other qualifications and no qualifications. The plots show that the categories experiencing employment losses in the middle-paying jobs are non-graduates. This negative change is partly counterbalanced by an increase of non-graduate employment in low-paying occupational groups. Graduate workers have instead gained employment shares along the whole occupational distribution, but in larger magnitude at the top and bottom. It is important to point out that this classification does not capture immigrants as the UK QLFS until 2010 included foreign educational qualifications in "other qualifications". Figure 3.4 breaks down employment share changes by immigration status. Only the employment distribution of native workers appears polarized, accounting for the entire decline in middle-paying occupations. Immigrants positively contribute in all major occupational groups, with higher presence at the two extremes of the distribution. During the 2000s the contribution of immigrants to employment growth at the extremes overcomes that of natives.

For completion in figure 3.5 I replicate the same analysis distinguishing by gender. The polarization phenomenon does not seem to be gender-specific as both men and women lose employment share in middle occupations while gain at the extremes. However, the redistribution of employment between the two groups is unequal, with women disproportionately gaining shares in technical and associate professional activities at the top and in sales and service occupations at the bottom.

3.4.3 Employment Polarization by Labour Market Area

Table 3.3 shows the grandmean, standard deviation and interquartile range for TTWA's routine and manufacturing employment shares, the relative graduate and immigrant population shares. The relative supply shares are taken as ratios with respect to the non-graduate population in line with Autor and Dorn (2013).[1].

As expected, on average the employment share in routine-intensive occupations decreases over time, losing 7 percentage points in two decades. In parallel, manufacturing employment loses 11 percentage points throughout the period. On the contrary, the relative shares of graduates and immigrants increase over time. In particular, $GradSH$ increase substantially in both decades, more than doubling between 1993 and 2013 (+0.32 pp). $ImmSH$ registers an acceleration during the 2000s, due to higher inflows of both high and low skilled immigrants. Over the two decades, the relative shares of high and low skilled immigrants increase by 4 and 5 percentage points respectively.

Figure 3.6 gives a visual idea of the geographical variation of these relevant variables across TTWAs in the year 1993. Local labour markets that are more intense in routine employment seem to be most concentrated in regions with

[1] I follow the literature [Bisello, 2014; Manacorda et al., 2012] in defining as low-skilled immigrants who left education before 21 years of age or that never had education, and viceversa for high-skilled immigrants.

higher manufacturing specialization, i.e. in the Midlands, Northern England and in Wales. Graduate and immigrant relative labour supply shares are instead more spread geographically, with high presence also in the Southern-East regions which are typically more specialized towards professional, scientific and technical activities.

Finally, figure 7 provides evidence of routine employment changes across UK local labour markets in each decade. The top panels depict the start-of-the-period routine employment share on the x-axis against the next period routine employment share on the y-axis for each TTWA, while superimposing the 45 degree line. Both plots document that local routine employment shares have not fallen everywhere but it is clear that the bulk of areas with initial routine intensity above the grandmean (0.25) lie below the 45 degree line. The bottom panels depict the fitted line from an OLS regression of the change in the routine employment share throughout the period (y-axis) on the start-of-the-period routine employment share (x-axis). The estimates show a strong and negative association. Although observations are weighted by the start of the period TTWA's share of the national population, the downward slope may, at this stage, be accentuated by measurement error. This will be addressed by the instrumental variables strategy discussed in detail in the next section.

3.5 Estimation Strategy

In order to disentangle the causal effect of technology exposure on the polarization of employment I build on Autor and Dorn [2013] and adopt a spatial analysis approach exploiting variation across UK local labour markets depending on their intrinsic historical specialization in routine intensive occupations.

The RBTC hypothesis predicts the progressive substitution of technology for labour in routine tasks. On the one hand, this force will raise the relative demand for high-skill labour, who hold comparative advantage in performing non-routine cognitive tasks. On the other hand, the marginal routine worker will reallocate to non-routine manual occupations under the assumption that their relative comparative advantage is higher in low-skilled than high-skilled tasks. As a consequence, local labour markets with initially higher specialization in routine-intensive occupations should experience greater relative employment decline in routine employment (1) while experience greater relative employment growth in non-routine manual (2) and cognitive occupations (3). I test the routinization hypothesis with the following regression model:

$$\Delta Y_{jt} = \alpha + \beta_1 RSH_{jt-1} + X'_{jt-1}\beta_2 + \gamma_s + \delta_t + \epsilon_{jt} \tag{3.3}$$

Where ΔY_{jt} may represent the decadal change (1993-2003, 2003-2013) in the local employment share of either (1) routine, (2) non-routine manual or (3) non-routine cognitive occupations measured as described in section 3.3. The main regressor of interest, RSH, is the local employment share in routine occupations. The vector X includes a set of covariates controlling for potential shifts in the local supply and demand. The set includes the local relative shares of graduates and immigrants, measured as ratios to the non-graduate working-age population, and the local initial share of manufacturing employment. The latter may proxy for other labour demand shifts than technological change occurring in the manufacturing sector such as the recent acceleration in the exposure to international import competition since China's accession to the WTO. The specification includes dummies for 11 Nomenclature of Territorial Units for Statistics (NUTS1) to control for time-invariant geographical unobserved heterogeneity[1]. The stacked regression also includes dummies for each decade to account for aggregate changes over time. Regressors in the main specifications are taken at their start-of-the-period levels rather than as contemporaneous changes in order to avoid simultaneity bias. However, estimates may be biased due to the presence of time-varying local specific

[1] The NUTS1 regions are: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales and Scotland.

unobservables, which might affect both routine or non-routine employment and our regressors of interest. To address this endogeneity issue I exploit 1971 Census data and follow Autor and Dorn (2013) in using the historical local industry and employment mix in order to instrument current routine employment share levels. This generates an exogenous source of variation across TTWAs which will isolate the long-run quasi-fixed component of routine employment pre-determined by the initial differences in industry specialization, from contemporaneous technological shocks. The instrument is constructed as follows:

$$RSH_j^{IV} = \sum_i E_{i,j,1971} * R_{i,-j,1971} \tag{3.4}$$

Where $E_{i,j,1971}$ is the employment share in industry i in TTWA j in 1971, while $R_{i,-j,1971}$ is the routine occupation employment share in industry i in all regions except the one including TTWA j.

RSH_j^{IV} is based on the 1971 industrial structure, two decades before the sample of analysis and around a decade before computer technology boomed across the UK. This should lessen any endogeneity concerns arising from current economic shocks affecting routine employment. Furthermore, the use of census data for the construction of the instrument allows to address any measurement error bias in local routine employment.

3.6 Results

3.6.1 Hollowing-out of Routine Employment

The first outcome of interest is changes in routine employment. Table 4 compares OLS and 2SLS results for the stacked and single period regressions. RSH coefficients appears smaller in the 2SLS analysis where endogeneity has been controlled for by the instrument. While OLS results suggest a significant negative effect of technology exposure on both graduate and non-graduate wokers, 2SLS estimates confirm previous descriptive evidence depicting job polarization as a non-graduate phenomenon. Recall that the Iqr for RSH in 1993 is 0.07. 2SLS estimates in column 1 indicates that a TTWA with a routine employment share at the 75th percentile in 1993 decreased the non-graduate routine employment share on average by decade by around 3.3 percentage points more than a TTWA at the 25th percentile. Single decade estimates in columns (2)-(3) reveal that the magnitude of this effect decreases over time but appears significant only during the 1990s. The RSH coefficient for the second decade is in fact quite imprecisely estimated and thus not significantly different from zero.

The 2SLS estimates in columns (1)-(3) suggest a significant effect of technological exposure on total routine employment changes. However, the RSH coefficients in columns (4)-(6) lose their overall negative sign and do not appear statistically significant. The RSH coefficients in columns (7)-(9) suggest instead a sizeable technology-induced contraction in local non-graduate routine employment. In particular, the 2SLS RSH point estimate in column (4) indicates that the decadal average Iqr differential effect is of around 3 percentage points. Single decade estimates in columns (5)-(6) reveal that the magnitude of this effect seems to decrease only marginally for non-graduate employment over time but again results significant only during the 1990s.

These estimates appear somewhat larger than what found by Autor and Dorn [2013] for the US. Their OLS findings show a 1980-2005 decadal average negative association of 1.8 percentage points higher for commuting zones starting at the 80th percentile of the routine employment distribution than those at 20th percentile.

The instrumental variable strategy I exploit is appropriate as long as the historical local differences in industrial specialization have significantly persisted over time. The table reports the Kleibergen and Paap [2006] F-statistics from each of the first-stage regressions. The 1971 industrial structure is a significant predictor of recent routine employment but naturally decreasing over time. The statistics' values for 1990s and 2000s are 47 and 18, both above the Staiger and Stock [1997]'s rule of thumb threshold of 10.

In table 3.5 I further investigate the role of labour supply and demand shifters in hollowing out non-graduate employment in middling occupations. In columns (1)-(3) the specifications include the start-of-the-period relative local shares of graduates and immigrants. $GradSH$ appears only significant in the stacked regression specification. Given an Iqr of 0.09, the point estimate for $GradSH$ indicates that the average differential negative association for TTWAs with initially higher stock of human capital is of around 0.5 percentage points. Higher local initial immigrant concentrations appear instead positively associated with employment changes in non-graduate routine employment during the 1990s.

In columns (4)-(6) I condition on the initial share of manufacturing employment, which is highly correlated with the main variable of interest (ρ_{1993}=0.58 and ρ_{2003}=0.38). This makes the RSH coefficient increase in magnitude in the first decade regression even though statistically non-significant, while in the 2000s, where the effect of RSH is entirely captured by the manufacturing variable. Overall, these estimates provide a quite robust piece of evidence of technology-induced polarization, mainly happening during the 1990s.

3.6.2 Reallocation to Non-routine Manual Employment

In the ALM model, workers' supply is driven by comparative advantage. Autor and Dorn [2013] provide a framework in which the continuosly falling price of technology induces low-skilled workers to reallocate from routine to non-routine manual tasks, at the bottom of the employment distribution. Results from table 5 suggest the progressive displacement of non-graduate employment in routine intensive occupations. In this section I investigate the employment changes at the lower tail of the distribution, testing the reallocation of non-graduate workers in non-routine non-manual jobs.

Table 3.6 displays the estimates of the regression model for the employment changes in non-graduate non-routine manual employment. The first panel shows the OLS results. Columns (1)-(3) enter the start-of-the-period local routine employment share alone, while columns (4)-(6) control for the initial relative labour supply shares of graduates and low-skilled immigrants. The inclusion of the control variables decreases the magnitude of the RSH coefficient. 2SLS estimates do not substantially differ from OLS ones. Looking at the most restrictive 2SLS specifications, the Iqr differential effect for RSH on local non-routine manual employment across the two decades is about 1.5 percentage point. This estimate is again slightly higher than in Autor and Dorn [2013]'s analysis. Their 2SLS estimates suggest an average decadal effect of 0.8 percentage points for the 80-20th percentile differential of the routine employment specialization during 1980-2005. found in Autor and Dorn [2013] for the employment growth in service occupations alone in the US between 1980 and 2005.

When separating the analysis by decade, the reallocation effect appears to get stronger over time, from 1.5 percentage points in the 1990s to almost 2 percentage points in the 2000s. Although, again the RSH coefficient is poorly estimated and turns not significant in the second decade regression. The initial relative shares of graduates and of low-skilled immigrants do not appear to play any role.

In the last columns (7)-(9) the specifications include the initial local share of manufacturing. Estimates appear in line with previous findings in table 3.5. Manufacturing concentration is in fact significantly positively correlated with employment changes in non-graduate non-routine manual employment in the last decade.

Following the literature, in the next table 3.7 I explore alternative demand-based hypotheses for the reallocation of workers to non-routine manual employment, i.e., the role of offshoring and of demographic changes in the labour force.

I measure offshorability with an index developed Blinder and Krueger [2013] and mapped by Goos et al. [2014] into ISCO88 2-digit occupational code[1]. I compute the local offshorable employment share following the same procedure as for the local routine-employment share, i.e. the TTWA-level top employment third of the Offshorability Index. The variable grandmean is 0.27 and the Iqr is 0.06.

Among the demographic changes, the increasing graduate working share could boost non-routine manual employment through either a substitution effect or an income effect. Such hypotheses suggest that the employment of unskilled workers is increasingly dependent on the physical proximity to skilled ones as the latter have a high opportunity cost of time and are expected to be net buyers of time-intensive services performed by the former. Consumption spillovers of high-skilled workers substituting market for home services is proxied by changes in average annual usual hours worked by graduates. Income effects are proxied by changes in the 90^{th} percentile of weekly wages[2]. In addition, the increasing feminization of the labour market and the ageing of the population could raise the demand for in-house services [Autor and Dorn, 2013; Manning, 2004; Mazzolari and Ragusa, 2013].

Table 3.7 shows 2SLS estimates. The direction of the estimated associations appear in line with Autor and Dorn [2013]. Columns (1)-(3) control the start-of-the-period share of local offshorable employment. The $Offsh$ coefficients suggest quantitatively very small effects and do not appear significant. The RSH point estimates barely change while turning not significant, possibly because of the very high correlation between the two measures (ρ_{1993}=0.86 and ρ_{2003}=0.84). The negative point estimate for changes, $GradHRS$, shows evidence against consumption spillovers while pointing towards a mere supply-side substitution effect. $GradHRS$ is significantly associated with non-routine manual employment

[1]Goos et al. [2014] adopt Blinder and Krueger [2013] preferred offshorability measure. This measure is based on professional coders' offoshorability assessment of workers' description of their job tasks in the Princeton Data Improvement Initiative (PDII) survey. The questions in the survey to evaluate self-reported offshorability regard the requirement of face-to-face or physical presence at the job and whether the task could be performed at a remote location without substantial quality deterioration.

[2]Results do not change if the 75th percentile is used instead.

changes in both decades and increases in magnitude over time. Furthermore, there is no evidence for income effects. Finally, neither the change in the population share of senior citizens (aged 65+) nor the change in the share of working women show relevant contributions. The results confirm the driving role of technological exposure in fuelling employment growth at the bottom of the occupational skill distribution.

3.6.3 Changes in Non-routine Cognitive Employment

The analysis has so far provided empirical evidence for non-graduate routine-task work displacement and its subsequent reallocation to the bottom of the employment distribution. A further emerging relevant factor is that changes in graduate employment are significantly negatively related to employment growth in non-graduate bottom occupations and the association is growing over time.

I complete the picture by switching the focus to the upper tail of the occupational distribution and investigate employment changes in non-routine cognitive employment. The RBTC hypothesis predicts increases in the relative demand for non-routine cognitive tasks, through a direct complementarity between high-skilled workers and computer technologies. In this section I test whether historically routine intensive areas have registered any employment growth in high-skill (high-wage) occupations such as professional and managerial ones.

Table 3.8 focuses therefore on graduate employment outcomes[1]. While the OLS point estimates for RSH suggest significant employment gains, this association is wiped away when using the instrumental variables estimation. Furthermore, the 2SLS RSH point estimates decrease substantially when labour supply controls are plugged-in. The absence of a technology-induced effect may indicate that the increase in the supply of high-skilled workers might have out-weighted the demand for skills. This hypothesis is reinforced by the negative point estimate for

[1]The estimated results for non-graduate employment are non-significant, confirming the essential reallocation of the marginal non-graduate routine worker to lower-skilled occupations.

the start-of-the-period local relative graduate labour supply share.

$GradSH$ is significantly negatively associated with top employment changes during the 1990s, in coincidence with the rapid educational upgrading of the labour force. The coefficient for $GradSH$ indicates that the Iqr differential for initially more human capital-intensive areas is of about -2 percentage points.

Higher initial local high-skilled immigrants' relative labour supply is instead strongly positively related to graduate employment changes at the top of the distribution during each decade. The average decadal Iqr differential association for $HighImmSH$ is of about 4 percentage points. Single decade regressions show that this effect is higher during the 1990s. This is consistent with the outlined policy context of the UK. Between the late 1990s and the enlargement of the European Union, the government specifically supported high-skilled economic immigration.

Finally, in the last three columns (7)-(9) I plug in the initial share of manufacturing employment. This does not alter the main results. However, the initial share of manufacturing employment appears significantly negatively correlated with changes in graduate non-routine cognitive employment during the 2000s. The variable may capture the impact of exposure to international trade. The negative association of $ManufSH$ appears broadly in line with Bilici [2016]'s findings of a detrimental effect of China's import exposure on graduate employment during the period 1998-2013.

3.6.4 Effects on the Working-age Population and Robustness Checks

The empirical evidence from the spatial analysis described above is valid as long as the mobility responses to technological shocks of the local population are weak. If technological change induces local workers to move in or out of localities, the employment effect of technology would disperse through the national economy. This would undermine the ability to identify the direct effect of technology within local labour markets. The dependent variable in table 3.9 denotes the change in the log of the overall, graduate and non-graduate local working-age population. 2SLS estimates show that local initial routine intensity does not lead to any significant substantial change in the working age population. This confirms the adequacy of the empirical strategy.

In table 3.10 I check the sensitivity of technology exposure effect when controlling for contemporaneous labour supply changes. The table reports the OLS and 2SLS RSH coefficients for the routine, non-routine manual and non-routine cognitive main specifications. The plug-in of contemporaneous labour supply changes does not significantly alter the interpretation of the main results.

Finally, as a robustness check with respect to the definition of routine intensity, table 3.11 reports the estimated RSH coefficients where the set of routine-intensive occupations is extended to the top employment-weighted 40% of the RTI index. The results do not relevantly differ from the main analysis, although show a more substantial relevance of labour supply changes in the polarization of the employment distribution. Furthermore, the negative RSH coefficient in panel C confirms that technological change does not appear to have contributed to growth in non-routine cognitive employment.

3.7 Occupational Transitions

In this last section I complement the main analysis with the use of a 1% random longitudinal census sample covering the period 1971-2011. This sample links individuals' census records over their lifespan. The tracking of individuals' job transitions allows to perform a finer-level analysis on employment changes. Furthermore, transitions are analysed decade by decade in a longer time span and separately for graduates and non-graduates. This is specifically done with the purpose to assess the contribution of the recent labour supply changes in shaping the current employment structure. The mobility process can be depicted using a transition matrix, such that:

$$Occ_t = P * Occ_{t-1} \tag{3.5}$$

Where Occ_{t-1} and Occ_t represent the vectors of the marginal occupational distributions in periods $t-1$ and t respectively. P is the m x m probability matrix characterising the transition process by determining the probability that an individual in occupation i at time $t-1$ remains in the same job or transits to another occupation $j \neq i$ in next period.

Occupational concordance has been created following the same probabilistic matching procedure used for the main sample of analysis as discussed in section 3.3. Such method assigns each individual A with a conditional probability $w_{i,j}$ at each point in time for each occupational pair (i,j). With the simplifying assumption of independence between occupational distributions over time, I compute the transition probability entries of matrix P as following:

$$p_{i,j} = P_{i,j}/p_{i,0} = \sum_{A=i}^{n}(w^A_{i,j,t-1} * w^A_{i,j,t}) / \sum_{A=i}^{n} w^A_{i,t-1} \tag{3.6}$$

where, for each individual A, the first component gives an estimate of the joint probability to belong to the occupational transition pair (i,j) during the period $t-1$ to t and the second component gives an estimate of the marginal probability of being employed in occupation i at time $t-1$.

Figure 3.8 compares the exit probabilities for each skill category of workers, routine, non-routine manual and non-routine cognitive across each decade. The whole matrices are available in the Appendix, table 3.13.

A number of changes in the occupational trends are registered since the 1990s, in coincidence with the great expansion in the pool of graduates. Panel A plots the exit probabilities for routine workers. Notably, during the 1990s graduates see a substantial decrease in the probability to switch to the top (-13 percentage points). At the same time they become gradually more likely to switch to the bottom, registering an overall change of +4 percentage points throughout the whole period 1971-2011. Over time non-graduate workers become more likely to move out of middle-paid jobs, both towards the top and the bottom. However, while the former appears as a gradual phenomenon, the latter emerges since the 1990s. The probability to move to the bottom increases from a stable 12% during 1971-1991 to 17% in the 1990s and 21% in the 2000s.

Panel B shows the exit probabilities for top-paid workers. During the 1990s both skill categories of workers become substantially more likely to move down the occupational ladder towards either middle or bottom ranked jobs. Focusing on the exit patterns from top to middle, the switching probability for graduate workers increases by 7 percentage points in the 1990s, while stabilizes thereafter. The same switching probability for non-graduate workers increases by 9 percentage points during the 1990s and by further 4 percentage points during the 2000s. Therefore a generalized occupational downgrading pattern appears, although quantitatively affecting non-graduates twice as much as graduates.

Finally, panel C shows the exit probabilities for non-routine manual workers. The left hand side plot clearly shows a progressive decline in upward mobility for graduate workers, which accentuates during the 1990s (-23 percentage points). The general picture does not alter when the whole set of middle-ranked occupations is considered instead of routine-intensive occupational groups only. Results only partly comply with the literature findings for the US. Cortes (2016) observes that, since 1990s, the probability of switching out of routine jobs to both types of non-routine occupations increases, although more towards non-routine cognitive ones. The empirical evidence emerging for the UK shows that non-graduate workers become markedly more likely to move to bottom ranked jobs after 1991, which is in line with the RBTC hypothesis. However, this is clearly only part of the story, as the increase in the outflows from any occupational group has increasingly concentrated towards the bottom of the distribution, showing a generalized downgrading pattern. An important observation is that Cortes [2016] looks at two-year windows, while this analysis focuses on decadal transitions. This makes the results of this paper quite robust. Longer time-windows allow for stronger learning effect which in general would work against finding occupational downgrading patterns.

3.8 Conclusions

This paper advances the literature on employment polarization in the UK. The main contribution is the identification of the effect of technological exposure on the occupational structure. The empirical strategy builds on the spatial analysis approach of Autor and Dorn [2013] and exploits geographical variation across local labour markets stemming from their historical specialization in routine-intensive activities to identify the causal effect of technological exposure during the period 1993-2013. The study is complemented with longitudinal census data spanning 1971-2011 in order to provide a further test for the routinization phenomenon and look at the evolution of the employment-skill distribution.

The econometric analysis shows that technological change has merely substituted routine labour and caused a downward shift of the marginal less-skilled middle workers. However, no effect is found at the top of the employment distribution. Additionally, there is some suggestive evidence on the long-run effect of demographic factors on employment changes. Areas starting with higher human capital are significantly associated with lower growth in graduate non-routine cognitive employment during the 1990s. Initial local high-skilled immigrants' concentrations are instead strongly positively associated with graduate non-routine cognitive employment changes during each decade. At the bottom, the initial local skill-mix does not show any relevant association. Contemporaneous changes in the relative graduate labour supply shares are instead significantly negatively related to non-routine manual occupations and the magnitude of this association is growing over time.

While the polarization phenomenon has been detected in the literature since at least the 1980s, the occupational transition analysis shows that the reallocation of non-graduates to the bottom of the distribution accentuates during the 1990s, in coincidence with the important changes in graduate labour supply. However, the 1990s more strikingly mark a pronounced occupational downgrading of graduate workers. This unveils the role of the educational upgrading as a distinctive force of polarization. The disruptive technological change and the intensifying job competition along the occupational ladder caused by educational upgrading highlight the fundamental need for policy-makers to focus on sustaining employment and promoting a more efficient allocation of skills.

Tables

Table 3.1: RTI classification using the 1993 employment distribution (%)

Occupations	Code	RTI	Level	Cumulative	Top 33%
Office clerks	41	2.24	15.08	15.08	x
Precision, handicraft, printing and related trades workers	73	1.59	1.25	16.33	x
Customer service clerks	42	1.41	3.37	19.70	x
Other craft and related trades workers	74	1.24	1.87	21.57	x
Machine operators and assemblers	82	0.49	5.49	27.06	x
Metal, machinery and related trades workers	72	0.46	7.489	34.55	
Labourers in mining, construction, manufacturing and transport	93	0.45	2.84	37.39	
Stationary plant and related operators	81	0.32	1.02	38.41	
Models, salespersons and demonstrators	52	0.05	3.74	42.15	
Sales and services elementary occupations	91	0.03	4.08	46.23	
Extraction and building trade workers	71	-0.19	2.82	49.05	
Life science and health associate professionals	32	-0.33	1.36	50.41	
Physical, mathematical and engineering science associate professionals	31	-0.4	2.48	52.89	
Other associate professionals	34	-0.44	5.07	57.96	
Personal and protective service workers	51	-0.6	8.19	66.15	
Other professionals	24	-0.73	3.84	69.99	
Corporate managers	12	-0.75	8.97	78.96	
Physical, mathematical and engineering science professionals	21	-0.82	4.71	83.67	
Life science and health professionals	22	-1	3.34	87.01	
Drivers and mobile plant operators	83	-1.5	4.77	91.78	
General Managers	13	-1.52	8.23	100.01	

Notes: The table contains the full list of 2-digit ISCO-88 occupations in the sample, ranked from high to low values of the RTI index. The RTI index is the same used by Goos et al. [2014]. The levels and cumulative employment shares of each occupation are shown for the year 1993. Following Autor and Dorn [2013], the routine-intensive occupations are defined as those belonging to the top employment-weighted 33% of the RTI index.

Table 3.2: Levels and changes in employment shares (%), 1993-2013

			Level			Delta	
Occupations	Code	Log wage	1993	2003	2013	1993-2013	RTI
Top							
PMES professionals[1]	21	2.78	4.71	5.44	6.37	1.66	-0.82
Corporate managers	12	2.76	8.97	9.73	11.62	2.65	-0.75
Other professionals	24	2.68	3.84	4.26	4.91	1.07	-0.73
Life, science and health professionals	22	2.66	3.34	3.84	4.7	1.36	-1
PMES associate professionals[2]	31	2.54	2.48	2.04	2.23	-0.25	-0.4
Other associate professionals	34	2.51	5.07	5.6	6.17	1.1	-0.44
General managers	13	2.48	8.23	8.16	8.6	0.37	-1.52
Middle							
Metal, machinery and related trades workers	72	2.38	7.48	6.17	5.05	-2.43	0.46
Stationary plant and related operators	81	2.34	1.02	0.55	0.36	-0.66	0.32
Extraction and building trade workers	71	2.31	2.82	3.49	2.73	-0.09	-0.19
Life science and health professionals	32	2.31	1.36	1.5	2.24	0.87	-0.33
Precision, handicraft, printing and related trades workers	73	2.27	1.25	0.81	0.55	-0.69	1.59
Office clerks	41	2.21	15.08	14.74	12.44	-2.64	2.24
Drivers and mobile plant operators	83	2.15	4.77	5.08	4.07	-0.7	-1.5
Machine operators and assemblers	82	2.11	5.49	3.43	2.42	-3.07	0.49
Labourers in mining, construction, manufacturing and transport	93	2.02	2.84	2.5	2.16	-0.68	0.45
Customer service clerks	42	2.01	3.37	2.8	2.45	-0.92	1.41
Bottom							
Personal and protective service workers	51	1.96	8.2	10.05	12.02	3.82	-0.6
Other craft and related trades workers	74	1.95	1.87	1	0.67	-1.2	1.24
Sales and services elementary occupations	91	1.88	4.08	4	3.75	-0.34	0.03
Models, salespersons and demonstrators	52	1.84	3.74	4.8	4.51	0.77	0.05

Notes: The table reports the levels and changes in the employment shares as well as the RTI index values by 2-digit ISCO-88 occupation. Occupations are ranked by median log hourly wages. Routine-intensive occupations appear bold font. Average log hourly wages are computed across all the years in the period 1993-2013 and then adjusted using the 2015 Consumer Price Index (CPI). The wage distribution for the period 1993-1996 is taken from respondents at the fith interview (instead of first) because of data limitation.

[1−2] PMES stands for Physical, Mathematical and Engineering Science.

Table 3.3: Summary Statistics of Relevant Variables

	1993			2003			2013		
	Mean	S. D.	Iqr	Mean	S. D.	Iqr	Mean	S. D.	Iqr
RSH	0.246	0.573	0.071	0.207	0.053	0.057	0.174	0.056	0.06
$ManufSH$	0.275	0.091	0.12	0.213	0.083	0.103	0.163	0.078	0.091
$GradSH$	0.237	0.075	0.093	0.35	0.115	0.143	0.563	0.339	0.267
$ImmSH$	0.042	0.031	0.037	0.055	0.04	0.042	0.096	0.06	0.069
$HighImmSH$	0.013	0.014	0.014	0.026	0.026	0.025	0.058	0.057	0.051
$LowImmSH$	0.039	0.029	0.036	0.045	0.035	0.042	0.081	0.057	0.069

Notes: The table shows the mean, standard deviation and interquartile range values of relevant variables in the analysis for each year in the sample. RSH is the TTWA employment share in routine-intensive; $ManufSH$ is the TTWA employment share in the manufacturing sector; $GradSH$ is the TTWA relative share of graduates as a ratio with respect to the non-graduate population; $ImmSH$, $HighImmSH$ and $LowImmSH$ are respectively the TTWA relative share of immigrants, high-skilled immigrants and low-skilled immigrants, as ratios with respect to the non-graduate population. High-skilled immigrants are defined as having left education at least at 21 years of age. Viceversa, low-skilled immigrants are considered as those who left education before 21 years of age or that never had education.

Table 3.4: Changes in Routine Employment

	All			Graduate			Non-graduate		
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
$RSH_{j,t-1}$	-0.820***	-0.749***	-0.923***	-0.086**	-0.063**	-0.111***	-0.731***	-0.681***	-0.816***
	(0.051)	(0.052)	(0.083)	(0.020)	(0.020)	(0.040)	(0.044)	(0.051)	(0.070)
R^2	0.474	0.559	0.417	0.139	0.097	0.309	0.446	0.526	0.406
2SLS									
$RSH_{j,t-1}$	-0.465***	-0.519***	-0.347	0.021	-0.018	0.098	-0.488**	-0.499**	-0.454
	(0.106)	(0.108)	(0.296)	(0.041)	(0.042)	(0.118)	(0.108)	(0.106)	(0.278)
1Stage									
K-P F-stat	48.906	46.989	17.751	48.906	46.989	17.751	48.906	46.989	17.751
N	372	186	186	372	186	186	372	186	186

Notes: The dependent variables are changes in the routine employment share for all, graduate and non-graduate workers. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 3.5: Changes in Routine Employment

	Non-graduate					
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
OLS						
$RSH_{j,t-1}$	-0.785***	-0.720***	-0.926***	-0.825***	-0.778***	-0.961***
	(0.046)	(0.051)	(0.067)	(0.054)	(0.061)	(0.072)
$GradSH_{j,t-1}$	-0.103***	-0.073*	-0.151***	-0.095***	-0.069*	-0.145***
	(0.024)	(0.039)	(0.029)	(0.024)	(0.039)	(0.028)
$ImmSH_{j,t-1}$	0.037	0.180**	0.089	0.030	0.179**	0.096*
	(0.054)	(0.072)	(0.060)	(0.058)	(0.071)	(0.058)
$ManufSH_{j,t-1}$				0.057***	0.066*	0.057
				(0.028)	(0.035)	(0.038)
R^2	0.482	0.541	0.501	0.488	0.548	0.506
2SLS						
$RSH_{j,t-1}$	-0.443**	-0.569**	-0.242	-0.381**	-0.575**	-0.004
	(0.105)	(0.108)	(0.388)	(0.153)	(0.186)	(0.680)
$GradSH_{j,t-1}$	-0.060**	-0.037	-0.075	-0.062**	-0.038	-0.067
	(0.024)	(0.044)	(0.049)	(0.023)	(0.045)	(0.061)
$ImmSH_{j,t-1}$	-0.012	0.132*	-0.067	-0.011	0.132*	-0.120
	(0.042)	(0.072)	(0.112)	(0.039)	(0.076)	(0.170)
$ManufSH_{j,t-1}$				-0.046	0.004	-0.104
				(0.045)	(0.066)	(0.125)
1Stage						
P-K test	54.135	60.437	10.859	26.335	25.872	4.783
N	372	186	186	372	186	186

Notes: The dependent variable is changes in the routine employment share of non-graduate workers. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 3.6: Changes in Non-routine Manual Employment

	Non-graduate								
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RSH_{j,t-1}$	0.210***	0.224***	0.258***	0.205***	0.235***	0.248**	0.156***	0.263***	0.152
	(0.046)	(0.063)	(0.097)	(0.049)	(0.066)	(0.101)	(0.052)	(0.077)	(0.093)
$GradSH_{j,t-1}$				0.003	0.029	-0.003	0.011	0.028	0.017
				(0.021)	(0.043)	(0.029)	(0.021)	(0.044)	(0.031)
$ImmSH_{j,t-1}$				0.071	0.035	0.044	0.066	0.036	0.062
				(0.056)	(0.102)	(0.091)	(0.055)	(0.103)	(0.095)
$ManufSH_{j,t-1}$							0.070**	-0.032	0.165***
							(0.028)	(0.042)	(0.057)
R^2	0.209	0.185	0.123	0.212	0.189	0.124	0.220	0.191	0.167
2SLS									
$RSH_{j,t-1}$	0.270***	0.242**	0.332	0.210**	0.211**	0.282	0.081	0.254	-0.194
	(0.081)	(0.118)	(0.287)	(0.087)	(0.106)	(0.397)	(0.134)	(0.178)	(0.586)
$GradSH_{j,t-1}$				0.003	0.025	-0.000	0.005	0.027	-0.003
				(0.023)	(0.043)	(0.046)	(0.023)	(0.043)	(0.047)
$ImmSH_{j,t-1}$				0.070	0.043	0.034	0.081	0.038	0.161
				(0.059)	(0.096)	(0.145)	(0.060)	(0.099)	(0.194)
$ManufSH_{j,t-1}$							0.087*	-0.029	0.222**
							(0.045)	(0.068)	(0.111)
1Stage									
P-K F-test	48.91	46.99	17.75	49.608	60.234	11.093	24.942	26.506	5.28
N	372	186	186	372	186	186	372	186	186

Notes: The dependent variable is changes in the non-routine manual employment share of non-graduate workers. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 3.7: Changes in Non-routine Manual Employment, 2SLS

	Non-graduate											
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$RSH_{j,t-1}$	0.279	0.331	0.299	0.289***	0.254**	0.384	0.254***	0.171	0.328	0.276***	0.252**	0.365
	(0.564)	(0.584)	(4.384)	(0.079)	(0.114)	(0.296)	(0.098)	(0.144)	(0.287)	(0.081)	(0.117)	(0.302)
$Offsh_{j,t}$	-0.008	-0.088	0.026									
	(0.457)	(0.482)	(3.230)									
Δ $GradHRS_{j,t}$				-0.138***	-0.127**	-0.221***						
				(0.048)	(0.056)	(0.055)						
Δ $Wage(p90)_{j,t}$							-0.033**	-0.027*	-0.045**			
							(0.013)	(0.015)	(0.021)			
Δ $OldSH_{j,t}$										-0.010	-0.211	-0.012
										(0.086)	(0.188)	(0.086)
Δ $FemaleSHR_{j,t}$										0.065	0.053	0.095
										(0.047)	(0.062)	(0.066)
N	372	186	186	372	186	186	340	154	186	372	186	186
P-K F-test	2.931	4.594	0.145	48.77	47.761	17.51	35.066	26.694	17.991	45.916	46.801	15.499

Notes: The dependent variable is changes in the non-routine manual employment share of non-graduate workers. The conditioning variables are: $Offsh$, the share of offshorable employment; Δ $GradHRS$, changes in the average annual usual worked hours by graduates; Δ $Wage(p90)$, changes in the 90^{th} percentile of weekly wages; Δ $OldSH$, changes in the share of the 65^{+} population; Δ $FemaleSHR_{j,t}$, changes in the employment share of women.

All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 3.8: Changes in Non-routine Cognitive Employment

	Graduate								
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
$RSH_{j,t-1}$	0.175**	0.239***	0.124	0.175**	0.185***	0.110	0.225**	0.151*	0.249
	(0.072)	(0.071)	(0.151)	(0.072)	(0.070)	(0.158)	(0.088)	(0.091)	(0.166)
$GradSH_{j,t-1}$				-0.042	-0.193***	0.019	-0.052	-0.190***	0.004
				(0.036)	(0.065)	(0.061)	(0.036)	(0.065)	(0.060)
$HighImmSH_{j,t-1}$				0.725***	1.389***	0.591*	0.747***	1.384***	0.474
				(0.105)	(0.415)	(0.313)	(0.110)	(0.412)	(0.304)
$ManufSH_{j,t-1}$							-0.070	0.039	-0.225***
							(0.045)	(0.058)	(0.066)
R^2	0.288	0.127	0.262	0.352	0.191	0.306	0.356	0.193	0.341
2SLS									
$RSH_{j,t-1}$	0.194	0.089	0.416	0.056	0.030	0.091	0.115	-0.160	0.625
	(0.152)	(0.172)	(0.392)	(0.141)	(0.156)	(0.424)	(0.204)	(0.250)	(0.616)
$GradSH_{j,t-1}$				-0.054	-0.226***	0.017	-0.058*	-0.233***	0.044
				(0.035)	(0.078)	(0.068)	(0.034)	(0.079)	(0.076)
$HighImmSH_{j,t-1}$				0.742***	1.475***	0.602*	0.752***	1.497***	0.250
				(0.100)	(0.429)	(0.353)	(0.103)	(0.422)	(0.440)
$ManufSH_{j,t-1}$							-0.044	0.136	-0.291**
							(0.062)	(0.089)	(0.129)
1Stage									
K-P F-test	48.906	49.989	17.751	62.915	67.458	16.341	32.516	28.45	8.825
N	372	186	186	372	186	186	372	186	186

Notes: The dependent variable is changes in the non-routine cognitive employment share of graduate workers. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population. *** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 3.9: Effects on the Working-age Population, 2SLS

	All			Graduate			Non-graduate		
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RSH_{j,t-1}$	0.183**	-0.019	0.597**	0.030	-0.408	0.891	0.080	-0.076	0.411
	(0.081)	(0.068)	(0.291)	(0.531)	(0.741)	(1.096)	(0.227)	(0.202)	(0.591)
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RSH_{j,t-1}$	0.102	-0.016	-0.016	-0.707	-0.491	0.387	0.789**	0.052	0.922
	(0.072)	(0.069)	(0.069)	(0.633)	(0.642)	(1.382)	(0.358)	(0.222)	(0.859)
$GradSH_{j,t-1}$	0.019	-0.004	-0.004	-1.017***	-1.650***	-0.458**	0.155	0.106	-0.020
	(0.023)	(0.025)	(0.025)	(0.159)	(0.289)	(0.180)	(0.105)	(0.091)	(0.123)
$ImmSH_{j,t-1}$	0.065**	-0.004	-0.004	1.178***	1.009**	0.462	-0.726**	-0.260	-0.237
	(0.027)	(0.049)	(0.049)	(0.299)	(0.463)	(0.369)	(0.29)	(0.165)	(0.258)
N	372	186	186	371	186	185	372	186	186

Notes: The dependent variables are changes in the log of the overall, graduate and non-graduate population. Panel A shows RSH estimates for the univariate regression, Panel B shows RSH estimates conditioning on the relative shares of graduates and immigrants. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of the national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 3.10: Conditioning on Local Labour Supply Changes, 2SLS

	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
Panel A. Non-graduate routine employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.488***	-0.499***	-0.454	-0.478***	-0.510***	-0.350
	(0.108)	(0.106)	(0.278)	(0.094)	(0.102)	(0.262)
$\Delta\ GradSH_{j,t-1}$				-0.064***	-0.121***	-0.060**
				(0.021)	(0.026)	(0.027)
$\Delta\ ImmSH_{j,t-1}$				-0.006	0.065	-0.075
				(0.042)	(0.069)	(0.049)
1Stage						
P-K F-test	48.906	46.989	17.751	48.568	46.315	16.018
Panel B. Non-graduate non-routine manual employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.270***	0.242**	0.332	0.252***	0.261**	0.317
	(0.081)	(0.118)	(0.287)	(0.082)	(0.123)	(0.290)
$\Delta\ GradSH_{j,t-1}$				-0.031**	-0.044	-0.051***
				(0.015)	(0.033)	(0.016)
$\Delta\ ImmSH_{j,t-1}$				0.070	-0.066	0.031
				(0.069)	(0.131)	(0.079)
1Stage						
P-K F-test	48.906	46.989	17.751	48.686	45.455	16.963
Panel C. Graduate non-routine cognitive employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.194	0.089	0.416	0.182*	0.094	0.272
	(0.152)	(0.172)	(0.392)	(0.108)	(0.127)	(0.288)
$\Delta\ GradSH_{j,t-1}$				0.220***	0.437***	0.191***
				(0.058)	(0.038)	(0.069)
$\Delta\ ImmSH_{j,t-1}$				-0.015	-0.343**	0.177
				(0.153)	(0.172)	(0.148)
1Stage						
P-K F-test	48.906	46.989	17.751	48.672	46.648	17.079

Notes: As a robustness check RSH is now measured extending the set of routine-intensive occupations to the top employment-weighted 40% of the RTI index. All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regressions. Standard errors in parentheses are clustered by TTWA in the stacked regressions, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Table 3.11: Robustness Check: Routine-intensity Measure (Top 40% of RTI Measure), 2SLS

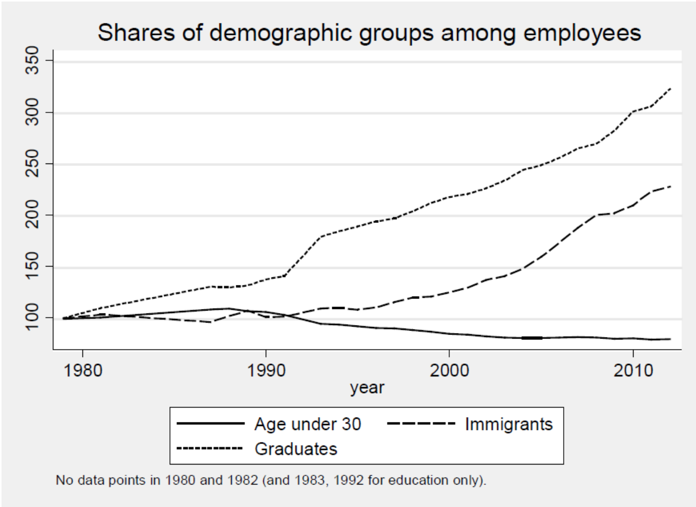
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
Panel A. Non-graduate routine employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.237*	-0.322*	-0.129	-0.150	-0.296	-0.049
	(0.138)	(0.177)	(0.265)	(0.151)	(0.185)	(0.313)
$GradSH_{j,t-1}$				0.030	-0.041	0.029
				(0.059)	(0.103)	(0.089)
$ImmSH_{j,t-1}$				-0.143*	-0.054	-0.090
				(0.080)	(0.120)	(0.129)
1st Stage						
K-P F-stat	40.990	24.354	30.424	58.246	34.968	28.300
Panel B. Non-graduate non-routine manual employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.333***	0.190	0.511***	0.307***	0.152	0.537
	(0.070)	-0.118	(0.159)	(0.076)	(0.114)	(0.182)
$GradSH_{j,t-1}$				0.065**	0.040	0.104*
				(0.033)	(0.063)	(0.057)
$LowImmSH_{j,t-1}$				0.063	0.086	0.008
				(0.057)	(0.095)	(0.107)
1st Stage						
K-P F-stat	40.990	24.354	30.424	57.457	35.739	30.158
Panel C. Graduate non-routine cognitive employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.145	-0.027	-0.295	-0.216	-0.046	-0.446
	(0.135)	-0.192	(0.271)	(0.140)	(0.168)	(0.313)
$GradSH_{j,t-1}$				-0.124**	-0.253**	-0.122
				(0.049)	(0.104)	(0.097)
$HighImmSH_{j,t-1}$				0.806***	1.522***	0.878***
				(0.110)	(0.451)	(0.332)
1st Stage						
K-P F-stat	40.990	24.354	30.424	61.975	39.755	28.885

Notes: All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level.

Figures

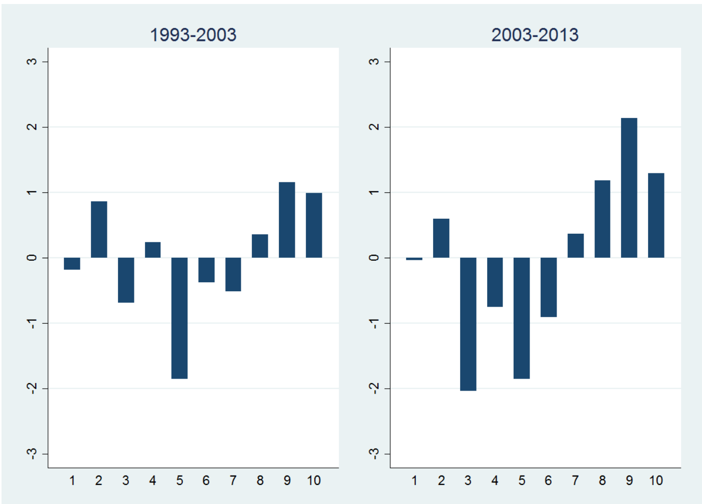
Figure 3.1: Demographic Groups' Working Shares (%) for Employees, 1979-2012



Source: Salvatori [2015] (Figure 1).

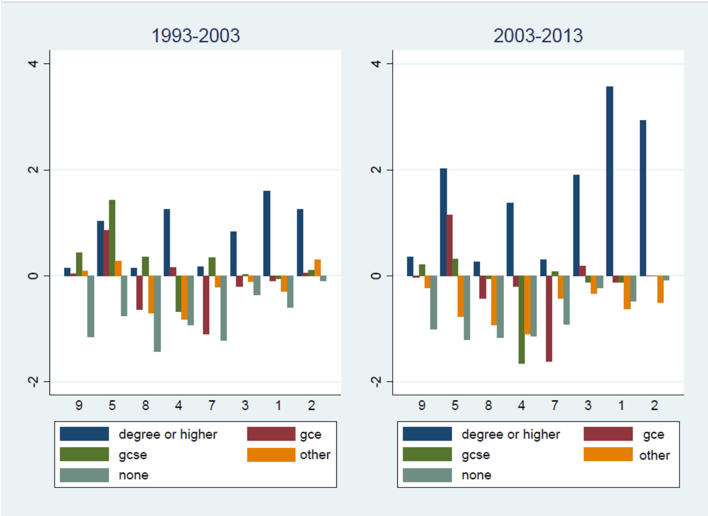
Notes: The figure shows the shares of individuals under 30 years of age, immigrants and graduates among employees in the UK. The shares are normalized with respect to their 1980 levels.

Figure 3.2: Changes in Employment Shares (%) by Deciles, 1993-2013



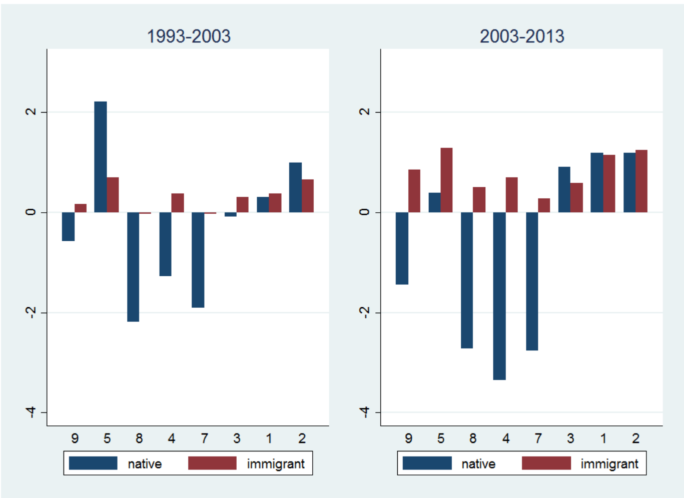
Notes: The figure shows the percentage changes in the employment shares by deciles. Occupations are grouped into employment-weighted deciles of the 1993 wage distribution.

Figure 3.3: Changes in Major Occupational Groups' Employment Shares (%) by Educational Qualification, 1993-2013



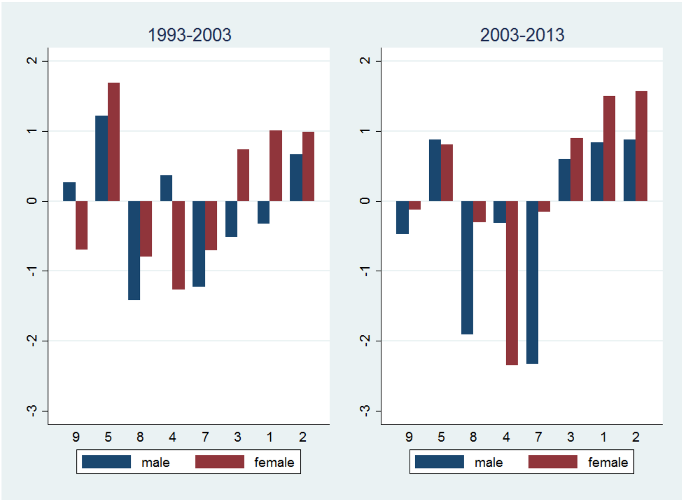
Notes: The figure shows the percentage changes in the employment shares by educational qualifications, ranked by average log hourly wages. Graduate qualifications are indicated by "degree or higher", non-graduate qualifications are distinguished into (ranked from high to low) "gce" (general certificate of education), "gcse" (general certificate of secondary education), "none".

Figure 3.4: Changes in Major Occupational Groups' Employment Shares (%) by Immigration Status, 1993-2013



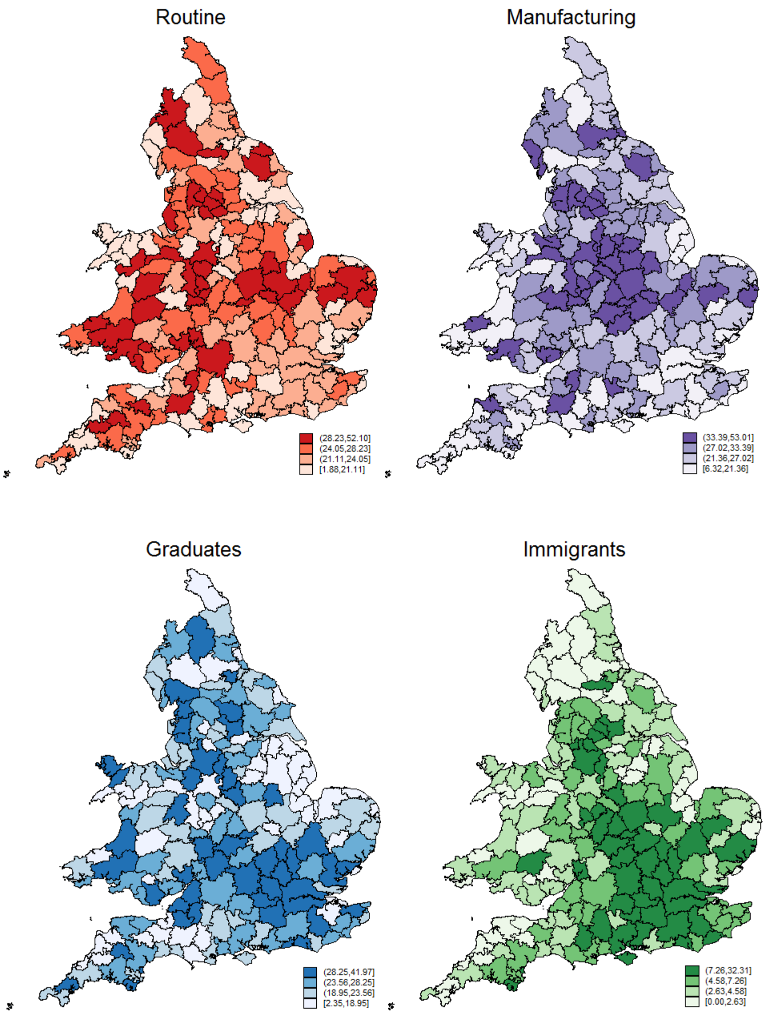
Notes: The figure shows the percentage changes in the employment shares by immigration status, ranked by average log hourly wages.

Figure 3.5: Changes in Major Occupational Groups' Employment Shares (%) by Gender, 1993-2013



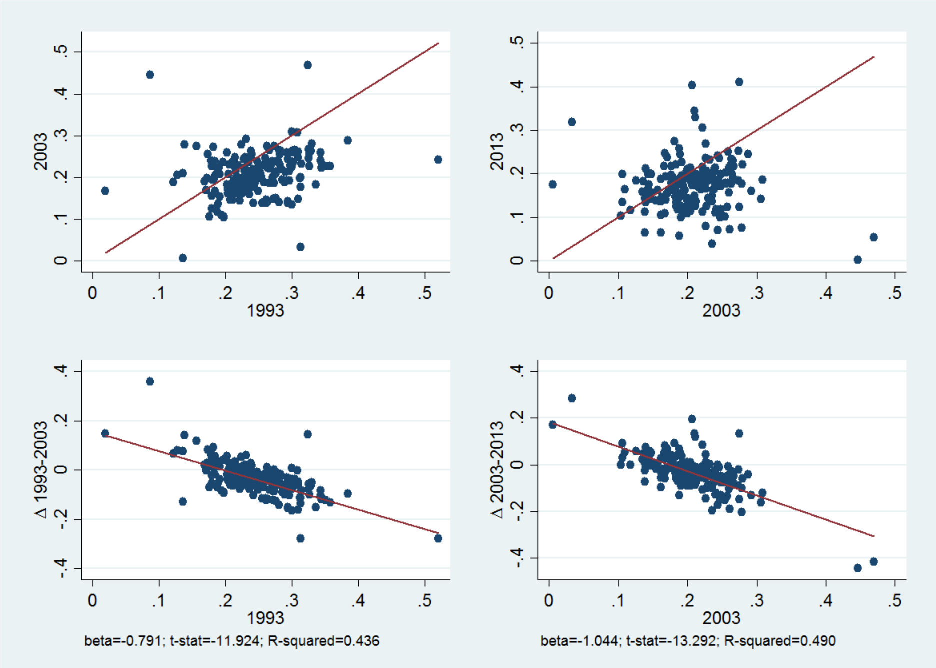
Notes: The figure shows the percentage changes in the employment shares by gender, ranked by average hourly wages.

Figure 3.6: Geographical Distribution of Routine Employment, Graduate and Immigrant Labour Supply Shares (%) in 1993



Notes: The figure plots the choropleth maps of England and Wales TTWAs for the 1993 percentage share levels of the following variables: Routine employment, Manufacturing employment, Graduate and immigrant relative labour supply (with respect to the non-graduate population). Darker coloured TTWAs have higher concentration levels.

Figure 3.7: Changes in Routine Employment Share by TTWA, 1993-2013

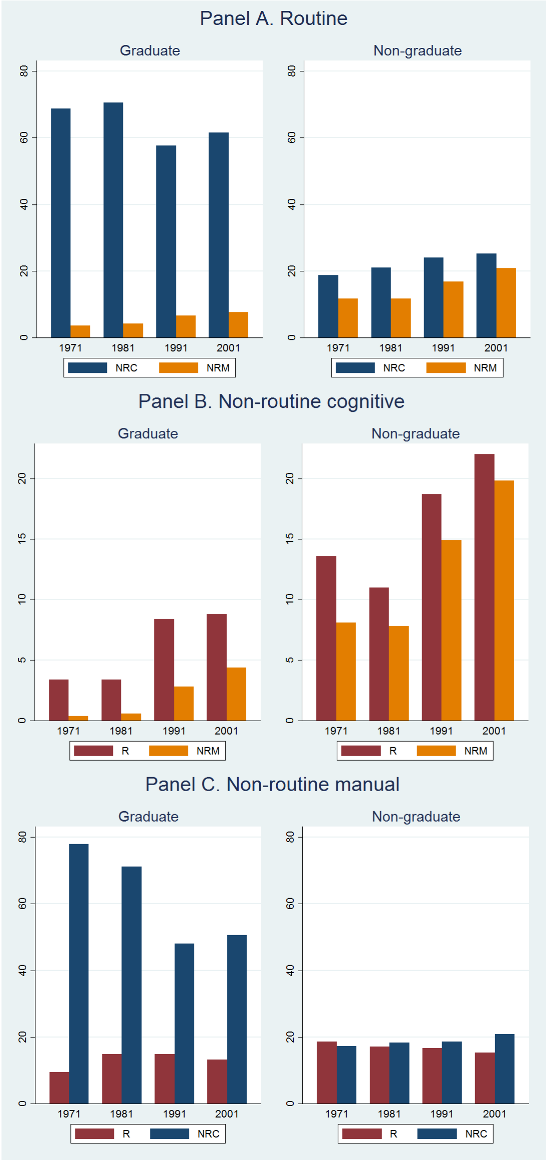


e

Notes: The figure plots routine employment share levels and changes across TTWAs by decade. The top panels depict the start-of-the-period routine employment share (x-axis) against the next period routine employment share (y-axis), while superimposing the 45 degree line. The bottom panels depicts the fitted line from an OLS regression of the change in the routine employment share throughout the period (y-axis) on the start-of-the-period routine employment share (x-axis).

N=186 x period. Observations are weighted by the start-of-the-period TTWA share of national population.

Figure 3.8: Exit Occupational Probabilities (%), 1971-2011



Notes: The figure shows the exit probabilities for graduate vs non-graduate workers in each decade for each occupational group category, i.e. Routine (Panel A), Non-routine cognitive (Panel B), Non-routine manual (Panel C).

In 1991 census, missing values cannot be distinguished from "no qualifications" in the records for highest qualification. Non-graduate values are imputed for individuals that reported having no degree or higher qualifications in 2001. However, general results do not alter if all individuals with missing values in 1991 are imputed as having no degree qualifications.

Appendix

Table 3.12: Levels and Changes in Employment Shares (2-digit) by Sector, 1993-2013

		Manufacturing				Non-manufacturing			
		Level			Delta	Level			Delta
Occupations	Code	1993	2003	2013	1993-2013	1993	2003	2013	1993-2013
Top									
PMES professionals[1]	21	9.14	10.25	11.57	2.43	8.92	9.61	11.63	2.71
Corporate managers	12	6.1	6.68	8.99	2.89	4.23	5.15	5.97	1.74
Other professionals	24	1.54	1.96	1.1	-0.44	4.64	4.79	5.49	0.85
Life, science and health professionals	22	0.33	0.6	0.62	0.29	4.39	4.59	5.32	0.93
PMES associate professionals[2]	31	2.8	2.55	3.25	0.45	2.36	1.92	2.07	-0.29
Other associate professionals	34	3.99	4.43	4.41	0.42	5.45	5.86	6.43	0.98
General managers	13	6.73	8.61	8.95	2.22	8.75	8.05	8.55	-0.2
Middle									
Metal, machinery and related trades workers	72	14.25	15.01	15.41	1.16	5.13	4.14	3.47	-1.66
Stationary plant and related operators	81	2.96	2.42	1.88	-1.08	0.33	0.12	0.13	-0.2
Extraction and building trade workers	71	2.07	3.04	3.13	1.06	3.08	3.59	2.67	-0.41
Life science and health professionals	32	0.07	0.11	0.4	0.33	1.81	1.82	2.52	0.71
Precision, handicraft, printing and related trades workers	73	3.9	3.42	2.6	-1.3	0.32	0.22	0.24	-0.08
Office clerks	41	10.79	9.77	9.58	-1.21	16.56	15.89	12.88	-3.68
Drivers and mobile plant operators	83	3.51	3.99	3.62	0.11	5.2	5.32	4.13	-1.07
Machine operators and assemblers	82	18.69	15.51	13.64	-5.05	0.89	0.65	0.7	-0.19
Labourers in MCMT[3]	93	4.77	5.08	5.33	0.56	2.15	1.9	1.67	-0.48
Customer service clerks	42	0.63	0.56	0.46	-0.17	4.32	3.32	2.76	-1.56
Bottom									
Personal and protective service workers	51	0.68	0.58	0.7	0.02	10.82	12.23	13.75	2.93
Other craft and related trades workers	74	5.48	3.59	2.48	-3	0.62	0.41	0.39	-0.23
Sales and services elementary occupations	91	1.27	1.24	1.12	-0.15	5.06	4.64	4.15	-0.91
Models, salespersons and demonstrators	52	0.3	0.6	0.76	0.46	4.94	5.76	5.08	0.14

Notes: The table reports the levels and changes in employment shares by 2-digit ISCO-88 occupation, distinguishing between manufacturing/non-manufacturing sector. Occupations are ranked by median log hourly wages. Average log hourly wages are computed across all the years in the period 1993-2013 and then adjusted using the 2015 Consumer Price Index (CPI). The wage distribution for the period 1993-1996 is taken from respondents at the fith interview (instead of first) because of data limitation.

[1−2] PMES stands for Physical, Mathematical and Engineering Science.

[3] MCMT stands for Mining, Construction, Manufacturing and Transport.

Table 3.13: Occupational Transitions (%), 1971-2011

Panel A. 1971-1981					Panel C. 1991-2001				
		NRC	R	NRM			NRC	R	NRM
	NRC	96.2	3.4	0.4		NRC	88.9	8.4	2.8
Graduate	R	68.8	27.7	3.6	Graduate	R	57.6	35.7	6.7
	NRM	77.9	9.5	12.6		NRM	48	14.9	37.1
			N=3985					N=12485	
		NRC	R	NRM			NRC	R	NRM
	NRC	78.3	13.6	8.1		NRC	66.3	18.7	14.9
Non-	R	18.8	69.4	11.8	Non-	R	24.1	59	16.9
graduate	NRM	17.3	18.6	64.1	graduate	NRM	18.7	16.7	64.6
			N=82567					N=116288	
Panel B. 1981-1991					Panel D. 2001-2011				
		NRC	R	NRM			NRC	R	NRM
	NRC	96	3.4	0.6		NRC	86.9	8.8	4.4
Graduate	R	70.6	25.1	4.2	Graduate	R	61.6	29.7	7.7
	NRM	71.2	14.9	13.9		NRM	50.6	13.2	36.3
			N=6964					N=41692	
		NRC	R	NRM			NRC	R	NRM
	NRC	81.2	11	7.8		NRC	58.3	22	19.8
Non-	R	21.1	67.2	11.7	Non-	R	25.3	53.9	20.9
graduate	NRM	18.4	17.2	64.4	graduate	NRM	20.9	15.4	63.8
			N=76819					N=130178	

Notes: Each panel reports the decade-specific transition probabilities between any occupational group (non-routine cognitive (NRC), routine (R), non-routine manual (NRM)) pair for graduate and non-graduate employees.

In 1991 census data, missing values cannot be distinguished from "no qualifications" in the records for highest qualification. Non-graduate values are imputed for individuals that reported having no degree or higher qualifications in 2001. However, general results do not alter if all individuals with missing values in 1991 are imputed as having no-degree qualifications.

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