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The impact of immigration on occupational wages: evidence from Britain

Stephen Nickell and Jumana Saleheen

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Stephen Nickell[1] and Jumana Saleheen[2]

Abstract

This paper asks whether immigration to Britain has had any impact on average wages. There seems to be a broad consensus among academics that the share of immigrants in the workforce has little or no effect on native wages. These studies typically have not refined their analysis by breaking it down into different occupational groups. Our contribution is to extend the existing literature on immigration to include occupations as well. We find that the immigrant to native ratio has a small negative impact on average British wages. This finding is important for monetary policy makers, who are interested in the impact that supply shocks, such as immigration, have on average wages and overall inflation. Our results also reveal that the biggest impact of immigration on wages is within the semi/unskilled services occupational group. We also investigate if there is any differential impact between immigration from the EU and non-EU, and find that there is no additional impact on aggregate UK wages as a result of migrants arriving specifically from EU countries. These findings accord well with intuition and anecdotal evidence, but have not been recorded previously in the empirical literature.

Key words: Immigration, occupation, wages.

JEL classification: J6.

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1. Introduction

The recent rise in UK immigration has been a hotly debated and politically charged topic. The debate increased at the time of EU expansion in 2004, when the UK granted nationals from the new member states immediate free access to the UK labour market, and has intensified further ahead of a British referendum on EU membership. At the heart of this debate is the widespread belief by the general public and policymakers that immigration has large effects on the labour market in general and employment and wages in particular.[1] The stereotype of the Polish plumber — used widely as a symbol of cheap labour — encapsulates the commonly held belief that immigration in Britain has pushed down wages in the most affected jobs. However, the balance of the research on this issue suggests that the share of immigrants in the workforce has had little or no impact on the pay rates of the indigenous population. Nevertheless, there is a continuing controversy, exemplified by the influential works of Borjas (2003) and Card (2005).

In an earlier paper, Card (1990) examined the impact of the Mariel Boatlift of Cubans into the Miami labour market and found little impact on the wages of natives. Borjas (2003) argues that such an analysis gives a misleading impression because regional labour markets are not self-contained. Thus, as immigrants move into a region, natives move out, thereby attenuating local wage effects. So he considers the impact of immigrants on wages in national age/education groups and finds a significant impact on wages in the United States: an immigrant inflow of 10 percent of the labour force lowers the wages of natives by 3 or 4 percent.

But other research that takes account of native mobility is unable to confirm the Borjas (2003) results. For example, Card (2005), in an analysis of U.S. cities, finds first that increases of immigrants into localities have generated significant rises in the proportion of low-skilled workers (high school dropouts) and second, that these large shifts in the proportions of the low-skilled have had minimal effects on the low-skill wage relative to their effect on the

[1] Its importance for monetary policy is highlighted in a speech by Governors of the Bank of England, see Carney (2015) and King (2007).

higher-skill wage.[2] Ottaviano and Peri (2012), who build and extend the Borjas framework, also conclude that the immigration has had a small impact on the wages of native workers. Evidence for the United Kingdom is consistent with the findings of Card (2005), suggesting that the impact of immigration on the wages of natives is minimal (see Dustmann et al. (2005, 2012) and Manacorda et al. (2012), for example). Both Ottaviano and Peri(2012) and Manacorda et al. (2012) conclude that the more recent immigration has the biggest negative effect on the wages of previous immigrants.

The contribution of this paper to the existing literature is twofold.

First it considers the impact of immigration on *average* wages, rather than on *native* wages— which is the focus of much of the existing literature. This is because for the purposes of monetary policy, central banks are interested in whether supply side shocks (like immigration) alter the level of average wage growth consistent with their inflation target. This paper reports figures direct interest to such monetary policymakers. To do this, this paper draws on the Labour Force Survey (LFS) and the Annual Survey of Hours and Earnings (ASHE) data. The latter is the best source for historic hourly wage data but it has not been previously been exploited to study the impacts of migration on wages.

Second, while much of the existing research has concentrated on looking for wage effects of immigration among the low-skilled, where skill levels are defined in terms of education, this paper makes a novel contribution to the literature by considering skills in as measured by occupation. Given the change in occupational classifications in 2001, we devise a methodology to create a consistent definition of occupations across time.[3] We think our approach of segmenting the labour market by occupations is more suited to the study of immigration because when it comes to the measurement of education levels of migrants one finds that it is often very tricky to accurately compare education qualifications across countries. Furthermore, for a variety of reasons, many immigrants who come to the United

[2] This would appear to be at variance with standard economics based on supply and demand. The most convincing explanation is that there is a weaker adoption of advanced technology, which is complementary to skilled labour, in the presence of larger numbers of the unskilled. This would offset the wage effects of shifts in the proportion of unskilled workers. See Lewis (2004, 2005) and Beaudry et al. (2006), for evidence in favour of this explanation.

[3] Details of the proportional mapping methodology used to construct a consistent occupational classification are set out in Appendix II.

Kingdom with high qualification levels work in low-skill occupations. This may tend to corrupt an analysis that depends on using education levels to partition the data. One advantage of this approach is that it focuses the analysis on the various groups in the labour market, such as plumbers, agricultural workers, nurses, waiters, etc., who have been the subject of much of the public discussion.

Some occupations see a very heavy influx of immigrants. For example, in Britain, over 30 percent of health professionals (for example, doctors and dentists) are immigrants, compared with around 5 percent of those in skilled agricultural trades (for example, farmers and gardeners). *A priori*, it seems unlikely that a substantive rise in immigration in a particular region and occupation has had absolutely no impact on pay in that region and occupation. Our purpose is to find out more about this.

While there is a great deal of anecdotal discussion on the impact of immigration in specific occupations like agriculture and construction, we feel it would be helpful to present some harder data on this subject. For this reason, section II of this paper is about occupations. We consider some novel stylised facts about which occupations tend to see a higher share of immigrants, how this has changed over time, the role of immigration from the newest EU member countries, and what has happened to pay in these occupations.

Section III sets out the theoretical framework and Section IV describes the data and the empirical analysis of the relationship between immigration and average wages. The key challenge here, as in much of the literature, is that of identification as immigration is unlikely to be exogenous to wages. We follow a similar approach to Card and Altonji (1991) and Dustmann et al (2005), among others, by instrumenting immigration by its lagged value. Section V considers differences among EU and non-EU migrants and Section VI concludes.

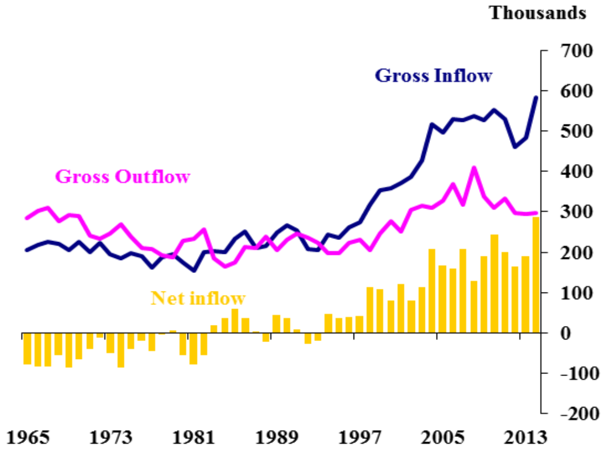
We find that that once the occupational breakdown is incorporated into a regional analysis of immigration, the immigrant-native ratio has a statistically significant, small, negative impact on the average occupational wage rates of the regions.

2. Immigration across occupations: some facts

Immigration to the United Kingdom has risen dramatically over the past two decades. This can be seen clearly from the charts below. Figure 1, panel a, shows that according to the

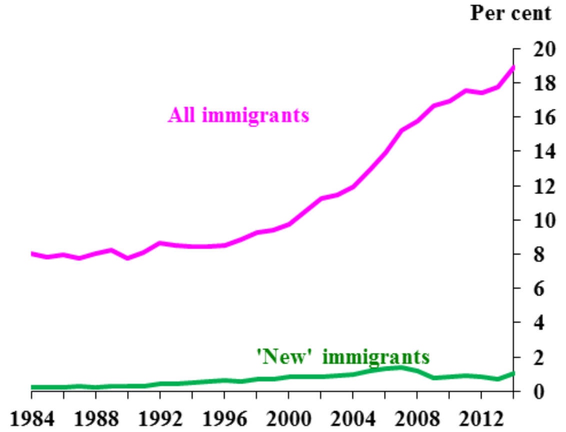
Figure 1: UK immigration

Panel a: Immigration into and out of the United Kingdom



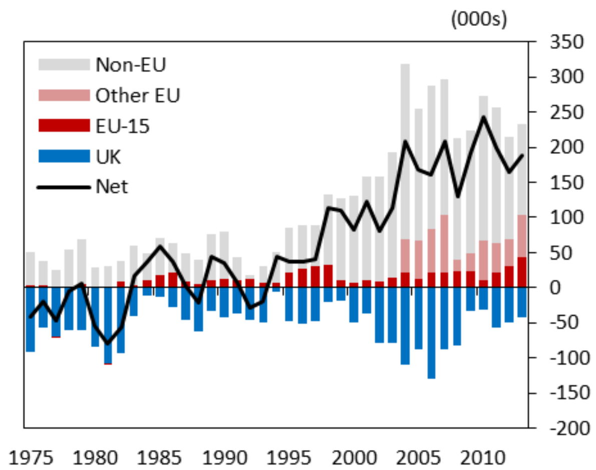
Sources: ONS International Passenger Survey 1975-2014.
1. The number of people (all ages) entering/leaving the UK with the intention of staying/leaving for at least 1 year.

Panel b: The immigrant native ratio



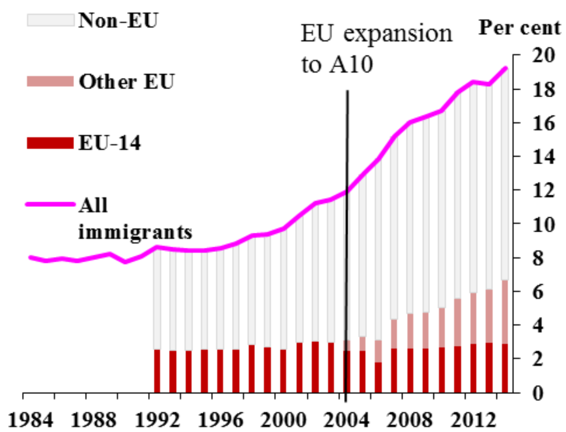
Source: Labour Force Survey (LFS) and authors' calculations.
1. The immigrant native ratio measures the number of 16–64 year olds born outside the UK divided by the number born in the UK.
2. New immigrants are the subset of immigrants who entered the UK in the LFS survey year or one year prior.
3. Dotted lines depict the pre-2004 average for each line.

Panel c: Net migration flows: EU 15, A10 and non-EU



Sources: ONS International Passenger Survey

Panel d: Immigrant native ratio: EU, A10 and non-EU



Source: Labour Force Survey (LFS) and authors' calculations.

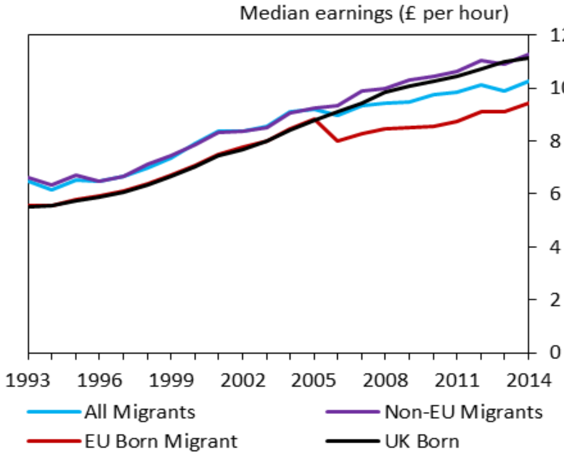
official migration statistics, the net inflow of immigrants to the United Kingdom each year has risen from around 50,000 individuals in 1995 to just under 300,000 in 2014. The gross outflow has grown as well, but by increasingly less than the gross inflow, and as a result, the net inflow of immigrants has risen dramatically since the mid-1990s. Figure 1, panel b, shows how immigrants—defined as foreign-born workers—have become a larger share of the U.K. working age population. Having been stable at around 8 percent between 1984 and 1995, it has grown to nearly 20 percent by 2014. And the share of "new" immigrants — those who arrived in the UK in the previous two years—has also increased since 1995, peaking just before the financial crisis at 1.4% in 2007, before stabilising to around 0.8% in recent years. This latter measure could be interpreted as a measure of the flow of migration.

Given the recent interest on immigration from the EU, Figure 1c and d set out how immigration from this sub-group has changed with immigration policy. Immigration from the EU-14 countries has been pretty stable in recent decades, with immigration from the new EU member states, the so called A10 countries —Czech Republic, Cyprus, Estonia, Slovakia, Slovenia, Lithuania, Hungary, Poland, and Malta — rising recently. That rise is undoubtedly related to the expansion of the EU to include the new A10 countries in 2004. Until the mid-1990s it was standard practice for all EU countries to grant free movement of labour to new EU member states at the time they joined the EU. But the 2004 expansion saw many countries change their approach and delay labour market access - the UK, Ireland and Sweden were the only EU-15 countries to grant full labour market access to the new A10 countries in 2004. Other countries delayed access by 2-6 years.[4] Later when Bulgaria and Romania joined the EU in 2007, the UK changed its approach and opted - like other high income EU countries - to delay labour market access of nationals from these countries until 2014. While the immigration policy of the UK and other countries in Europe, undoubtedly played a role in shaping the trends in immigration, macro factors such as the relative economic growth of the UK compared to Europe would also have played an important role. Whatever the determinants, chart 5 shows that this new wave of immigration looks to have had a noticeable downward impact on the average wages of EU immigrants in the UK around the year of Accession, some of which will undoubtedly reflect the occupations these immigrants move into and the potentially lower reservation wages of these workers.

[4] This evolution in migration policy across EU countries is summarised in Figure A1 in Appendix I.

This rise in immigration to the United Kingdom in recent years has been well documented in past studies. But very little has been said about the occupations in which immigrants end up. In this section, we explore the key facts about immigration across occupations. In particular, we document which occupations attract the most immigrants and whether this has changed over time. We also document the trends in wages in the different occupations.

Figure 2: Hourly Earnings



Source: Labour Force Survey (LFS) and authors' calculations

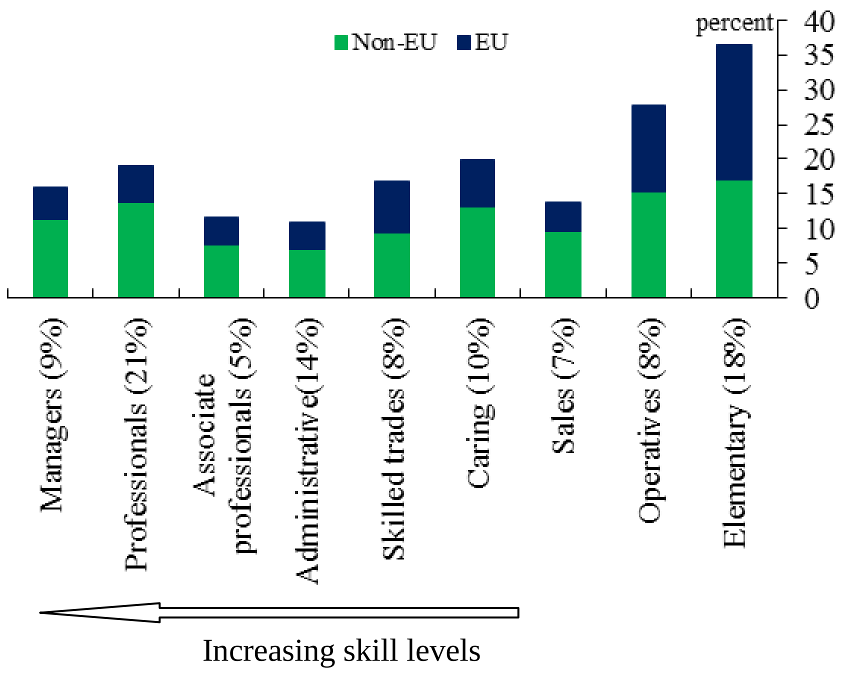
To consider how immigration and wages have changed in each occupation one needs a consistent definition of occupations over time. Since the standard occupational classification changed from SOC 1990 to SOC 2000 at the turn of the century, it is necessary to devise a consistent classification over the time period we consider in this paper, 1992–2014. We do this by transforming the SOC 1990 codes into SOC 2000 codes. More details are given in the data appendix.

2.1. Immigration across occupations

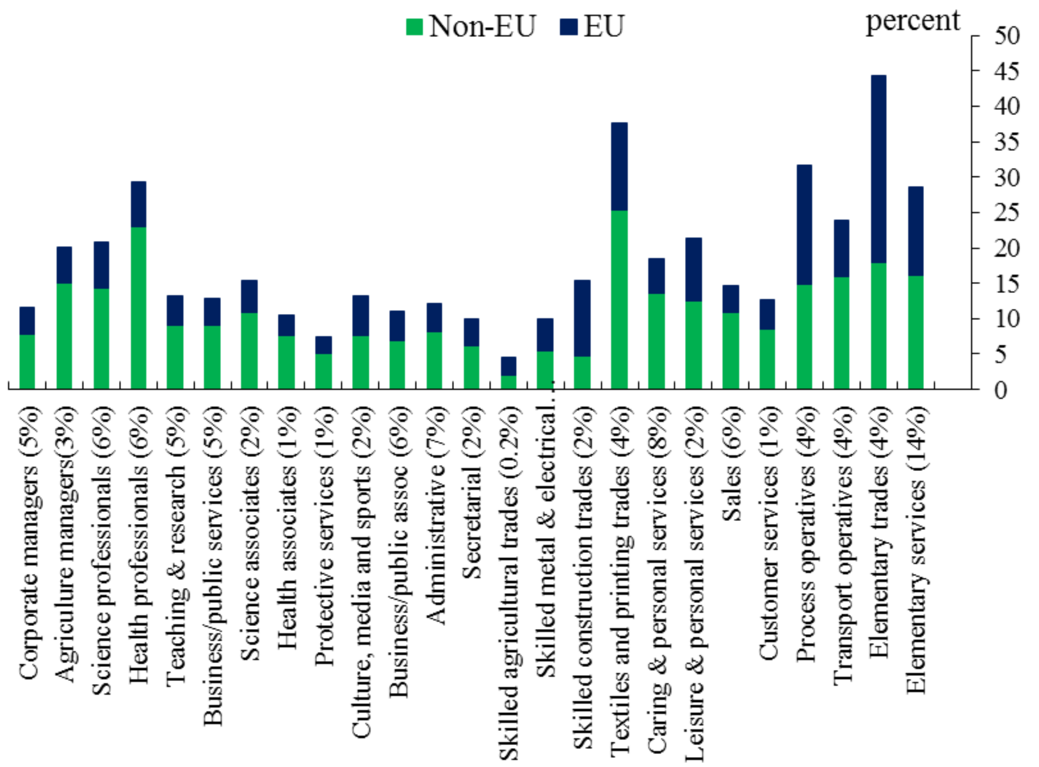
Which occupations attract the most immigrants? Figure 3a shows the ratio of immigrants to natives in each broadly defined occupation group — measured at the SOC 2000 1-digit level. It shows that the immigrant-native ratio varies considerably across broad occupations. It is highest for elementary workers (for example, cleaners and labourers) and operatives (clothing cutters, plastic wood and machine operatives): in these occupations 1 in 3 workers are immigrants. The immigrant native ratio is also high for professional workers (e.g. engineers): 1 in 5 workers are immigrants. And the ratio tends to be lowest in

Figure 3: Immigrant native ratio by occupation

Panel a: by 1-digit occupation (2012-14)



Panel b: by 2-digit occupation (2012-2014)



Source: Labour Force Survey (LFS) and authors' calculations.

Notes: Figures on the x-axis label in parenthesis show the share of immigrants in each occupation.

administrative occupations (secretaries, call centre staff); importantly, although the immigrant to native ratio is lowest here, it should be noted that 15% of all immigrants in 2012-2014 were in administrative occupations.

The chart also shows the split of by immigrants from the EU countries and elsewhere. What stands out here is that EU migrants are most predominant in the low skilled Elementary and Operative occupations (examples of these jobs given above, with further examples in Table A1 of the Appendix).

Figure 3b shows the immigrant-native ratio at a more detailed, 2-digit level. The picture is now one of greater variability, with no strong patterns. A very high proportion of U.K. health professionals are immigrants, and very few immigrants work in protective services (for example as security guards) and skilled agricultural trades (farmers).

Earlier it was noted that overall immigration to the United Kingdom has risen rapidly since the middle of the 1990s. An important question here is whether that rise has affected all occupations proportionately or has it been more heterogeneous?

We consider how the immigrant-native ratio across occupation has evolved over four sub time periods that reflect the start and end of our sample, and the period just after EU Accession and before the Global Financial Crisis – 92-94, 98-00, 04-06 and 2012-14. Figure 4 makes evident that immigration has grown across most occupations, with the sharpest rise in the lowest skill occupations (Elementary jobs). To give a sense of this relativity, the immigrant-native ratio for managers grew by 6 percentage points between 1992–94 and 2012–14, whereas it grew by 28 percentage points in elementary jobs over the same period. These changes mean the pattern of immigration across occupations has changed dramatically over the past two decades. In the early 1990s, we described the pattern of immigration across occupation as having a shallow U-shape, being high at the top and bottom skill levels than in middle skilled occupations. But in recent years, the pattern of immigration across occupations tends to be higher in lower skilled jobs.

Figure 4: Immigrant-native ratio by 1-digit occupation (2012-14)

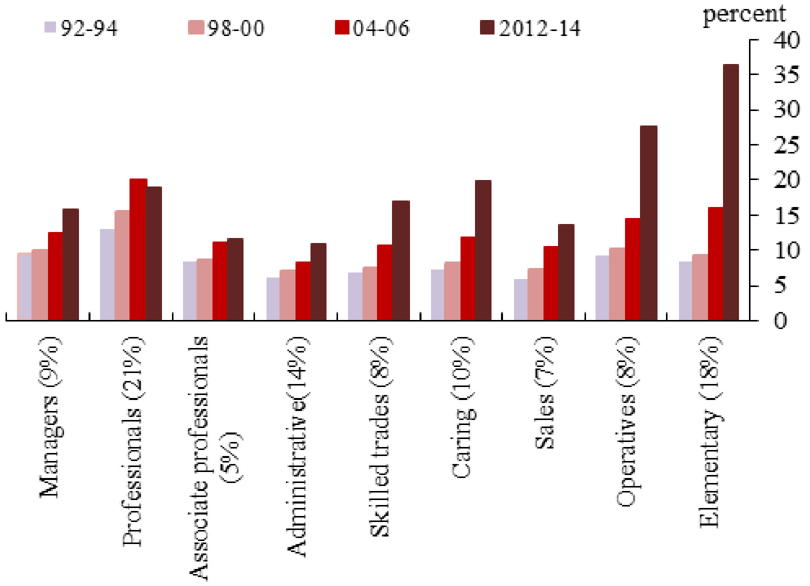
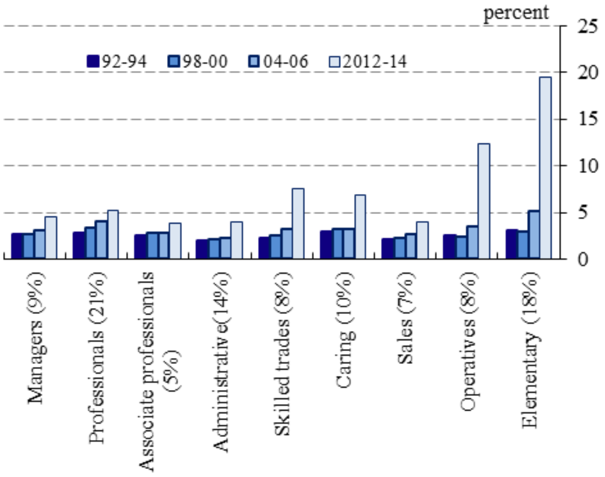


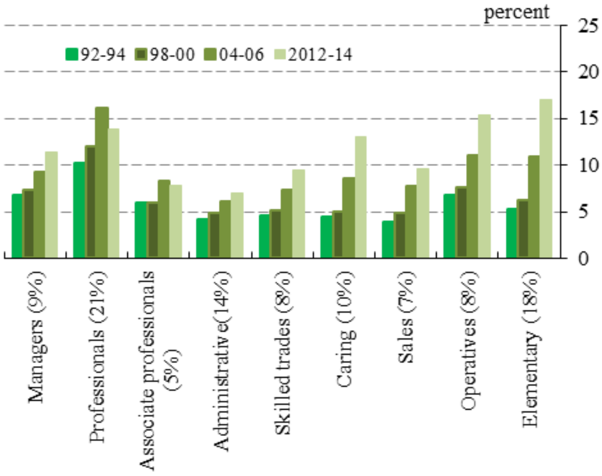
Figure 5: Immigrant native ratio: EU vs Non-EU by occupation

Panel a: EU immigrant/native ratio



Source: Labour Force Survey (LFS) and authors' calculations.

Panel b: Non-EU immigrant/native ratio



Source: Labour Force Survey (LFS) and authors' calculations.

Figure 5 breaks the rise in immigration down into immigration from the EU and non-EU. The pace of rise in immigration from outside of the EU appears to have been steady over time, but growing fastest in low skilled jobs (Elementary and Operatives). In contrast the EU immigrant-native ratio appears to have been rather stable until 2006, rising rapidly thereafter notably in low skilled jobs.

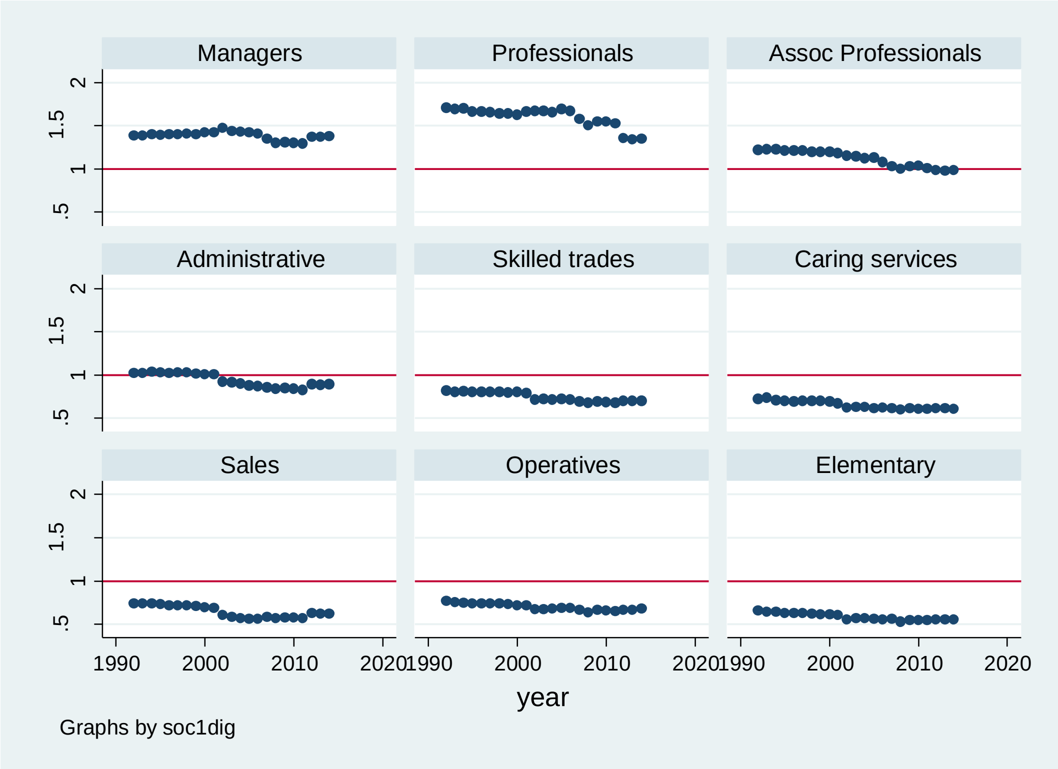
The pattern of immigration across occupations has changed noticeably over time, in the early 1990s immigration was spread across high and low skilled occupations, but more recently there is a greater abundance of immigration in low skilled jobs, particularly from EU countries. These changes in the structure of immigration across occupations are, at least in part, related to the expansion of the European Union to include many Central and Eastern European countries in 2004 and the immigration policy of the UK. The Euro Area crisis and related macro weakness in Europe will also drive these trends, but an analysis of those global factors is a topic for future research.

2.2. Wage movements across occupations

This section documents the changes in pay across occupations in recent years. Pay is defined here as the nominal hourly wage rate of full-time workers as captured by the Annual Survey of Hours and Earnings (ASHE) – a comprehensive survey of employers (see the data appendix for more details).[5] Figure 6 shows how the average wage in each occupation, has evolved relative to the average wage across all occupations.[6] The horizontal line at 1 is a benchmark that illustrates the occupation where wages are higher than the national average, and which are lower. Two things stand out. First, high-skilled jobs (managers, professionals) earn more than the average wage, and low-skilled jobs (operatives and elementary occupations) earn below the average. Managers earn nearly 1.5 times the average wage, and Elementary workers earn around 50% of the average wage. Second, we see that relative wages have fallen in some occupations and have been flat to rising for other groups. That relative wages have increased for some groups and decreased for others is a well-documented fact in the literature on U.K. wage inequality (see, for example, Machin (2003)). For example, the relative wages for Professionals and Associate Professionals (which included teaching and research staff) has fallen noticeably over time, with smaller declines over time seen in Sales and Elementary occupations. There has been more stability in wages for other skills such as for Managers and Administrative staff. So there has been some heterogeneity in changes in relative wages across occupations.

[5] Of course immigrants may typically work longer hours than natives, and our analysis of hourly wages does not incorporate those differences.
[6] Each dot in the chart represents the average wage for each occupation divided by the average wage for all occupations.

Figure 6: Wages in each occupation relative to the average wage



To summarize, this section has documented some facts about how wages and immigration vary across different occupations. It finds that immigrants in recent years are most predominant in low-skill occupations, with a significant presence amongst high-skilled occupations as well. And while the immigrant-native share has continued to increase in all occupations since the mid-1990s, in recent years the rise has been greatest in low-skill occupations. The concentration of EU immigrants has been substantially higher in low-skilled jobs in recent years, compared to non-EU immigrants where the spread is more variable across occupations. Low-skill occupations, of course, pay wages that are below the average wage rate. But there has been some heterogeneity in the evolution of relative wage rates across occupations over time.

3. Theoretical background

Since we are going to undertake an empirical analysis of occupational wage changes, it is helpful to develop a theoretical framework to enable us to interpret the results.

Suppose each region has an aggregate production function of the form

$$Y_{rt} = F(N_{1rt},..., N_{Irt,}, s_{1rt},..., s_{Irt}, K_{rt}, A_{rt}), \tag{1}$$

where Y=output, N_i=employment in occupation *i*, *i*=1…I, s_i=share of immigrants in occupation *i*, K=fixed capital, A=technical change factor, *r*=region, and *t*=time. The role of the share of immigrants is to capture the possibility that immigrants are more or less productive than natives or, at least, are thought to be so by the owners of firms. The demand for regional output is given by

$$Y_{rt} = (P_{rt} / P_t)^{-\eta_{rt}} D_{rt}, \tag{2}$$

where P_{rt} = the price of regional output, P_t = the aggregate price level, and D_{rt} = the regional demand index, which captures the extent to which aggregate demand in a particular region may rise or fall.

If the occupational wages are W_i, and K and A are predetermined, employment is determined by solving

$$\max_{N_i,P,Y} P_{rt}Y_{rt} - \sum_{i=1}^{I} W_{irt}N_{irt},$$

subject to (1) and (2). Note that, within occupations, we assume that firms are unable to pay different wages to natives and immigrants, an assumption consistent with current U.K. anti-discrimination legislation.[7]

The first-order conditions are given by

[7] Of course, in practice, we would have to split employees into age/education groups within occupations to make this assumption totally realistic. These factors are controlled for in the empirical analysis.

$$(1-\tfrac{1}{\eta_{rt}})p_{rt}F_i(N_{1rt},...,N_{Irt,},s_{1rt},...,s_{Irt},K_{rt},A_{rt}) = w_{irt}\,, \tag{3}$$

where i=1,..I, and $p_{rt} = P_{rt}/P_t$, $w_{rt} = W_{irt}/P_t$ are real prices and real wages, respectively. If we make a log-linear approximation of the I equations in (3) and solve for $n_{irt} = \ln N_{irt}$, all *i*, we have

$$n_{irt} = \alpha_0 - \alpha_1 \ln w_{irt} + \sum_{\substack{j=1\\ j\neq i}}^{I} \alpha_{1j} \ln w_{jrt} - \alpha_2 s_{irt} + \sum_{\substack{j=1\\ j\neq i}}^{I} \alpha_{2j} s_{jrt} + \alpha_3 \ln(p_{rt}(1-\tfrac{1}{\eta_{rt}})) + \alpha_4 \ln K_{rt} + \alpha_5 \ln A_{rt} + v_{irt} \tag{4}$$

where *i*=1,…I. Note that we have written these I equations with identical coefficients, with any differences absorbed into the error. This "assumption" is ultimately dropped in our empirical analysis when we estimate models that differ across occupations.

Suppose the cross effects are not large and may be approximated by

$$\sum_{\substack{j=1\\ j\neq i}}^{I} (\alpha_{1j} \ln w_{jrt} + \alpha_{2j} \ln s_{jrt}) = \alpha^{'}_{ir} + \alpha^{'}_{rt} + \alpha^{'}_{it} + v^{'}_{irt}\ .$$

So we end with a simple regional-occupation labour-demand equation of the form

$$n_{irt} = \alpha_{ir} + \alpha_{rt} + \alpha_{it} - \alpha_1 \ln w_{irt} - \alpha_2 s_{irt} + v^{1}_{irt}\,, \tag{5}$$

where $\alpha_3 \ln(p_{rt}(1-\tfrac{1}{\eta_{rt}})) + \alpha_4 \ln K_{rt} + \alpha_5 \ln A_{rt}$ are absorbed into α_{rt}. Then the cross effects, output prices, capital, and technical change are all captured by the occupation/region effects, α_{ir}; the region/time effects, α_{rt}; and the occupation/time effects, α_{it}. The impact of the immigrant share is negative (α_2>0) if immigrants are less productive than natives, and positive (α_2<0) if they are more productive.

Turning to region/occupation labour supply, we suppose an equation of the form

$$n_{irt} = \gamma_{ir} + \gamma_{rt} + \gamma_{it} + \gamma_1 \ln w_{irt} - \gamma_2 u_{irt-1} + \gamma_3 s_{irt-1} + \gamma_4 X_{irt} + v^{2}_{irt}\,, \tag{6}$$

where *u* is the unemployment rate and *X* are other exogenous variables. The idea here is that labour is attracted into region *r* if wages are higher than those elsewhere (captured in the occupation/time effect, γ_{it}), if relative unemployment is lower, and if high immigrant proportions tend to attract mobile workers (γ_3>0). If immigrants have a lower reservation wage than natives, then labour supply will be higher, given wages, when the share of immigrants is higher. This is another reason why γ_3 may be positive. It is, of course, possible that high immigrant proportions are a disincentive to move to work in region *r* and that immigrants have higher reservation wages than natives (γ_3<0). Similarly, the immigrant proportion in region *r* depends on the attractiveness of the region; thus,

$$s_{irt} = \beta_{ir} + \beta_{rt} + \beta_{it} + \beta_1 \ln w_{irt} - \beta_2 u_{irt-1} + \beta_3 s_{irt-1} + \beta_4 X_{irt} + v^3_{irt}. \tag{7}$$

The structure is similar to the labour supply equation, (6), although $\beta_3 > 0$ is almost certainly positive because it is known that immigrants have a tendency to cluster.

Our analysis concentrates on wage movements, so we consider the wage equation obtained by using (6) and (7) to eliminate n_{irt}, s_{irt} from (5). This yields an equation of the following form:

$$\ln w_{irt} = \omega_{ir} + \omega_{rt} + \omega_{it} + \omega_2 u_{irt-1} - \omega_3 s_{irt-1} + \omega_4 X_{irt} + \omega_{irt}. \tag{8}$$

In particular, the coefficients on u and s are $(\gamma_2 + \alpha_2\beta_2)/(\gamma_1 + \alpha_1 + \alpha_2\beta_1)$ and $-(\gamma_3 + \alpha_2\beta_3)/(\gamma_1 + \alpha_1 + \alpha_2\beta_1)$, respectively. Overall, occupation/region wages are driven by basic factors such as regional productivity, regional labour market slack, regional product demand, national occupation demand, and unchanging occupation/region characteristics. All these are captured by the three types of interaction dummies, ω_{ir}, ω_{rt}, and ω_{it}. The impact of the lagged immigrant share on pay is negative if $(\gamma_3 + \alpha_2\beta_3)$>0. γ_3 is positive, if occupation/region labour supply is enhanced by the presence of existing immigrants, or if immigrants have a lower reservation wage than natives, and, since β_3 is almost certainly positive, as we have already noted, $\alpha_2\beta_3$ is positive if immigrants are, or are thought to be, less productive than natives in the same occupation. So these are the conditions that will tend to generate a negative impact of the pre-existing immigrant share on wages. Finally, note that we are taking account of the feedback effect of wages on the immigrant share by substituting out the current immigrant share using equation (7).

Turning to the unemployment effect, this will be positive if $(\gamma_2 + \alpha_2\beta_2)>0$. γ_2 and β_2 are almost certainly positive, because this depends on the uncontroversial notion that high unemployment makes regions less attractive to potential employees. α_2 is positive if migrants are less productive than natives, as noted above. Overall, we would expect this unemployment effect to be positive. It is worth commenting on how this relates to the standard negative "wage curve" effect of unemployment on wages. This has been absorbed into the region/time dummy, which already captures local labour market slack. What remains is the second-round effect, whereby local occupation-specific unemployment makes the region less attractive, reducing local occupational labour supply and raising pay.

So equation (8) is the basis for our empirical investigation. The analysis in this section has been fundamentally static. In practice, because of adjustment costs we would not expect instantaneous adjustment, so we also consider dynamic versions of (8). Finally, equation (8) has the same coefficient for all occupations, any differences being absorbed into the error. To pursue this further, we also investigate models of the same form as (8), except we estimate them separately for different groups of occupations.

4. Data and results

The purpose of this section is to investigate whether the lagged immigrant-native ratio in a particular region and occupation has any impact on the average pay rate of that region and occupation. We do this by estimating various forms of equation (8), which we derived in the section above. The primary sources of data for our analysis are the British Labour Force Survey (LFS) and the Annual Survey of Hours and Earnings (ASHE)/New Earnings Survey (NES).[8] To estimate these equations we use a panel dataset that we have created in which each observation covers three dimensions: region, occupation, and time. This panel contains information on 11 U.K. Government Office Regions and 25 occupations, based on the 2-digit

[8] For more details see the data appendix.

SOC 2000 occupational classification, over 23 years (1992–2014. Based on this level of disaggregation, our dataset has a maximum of 6325(=23x11x25) observations.[9]

In Section 2, we mentioned that the change in the standard UK occupational classification at the turn of the century introduces a discontinuity in the definitions of occupation within the duration of our dataset. We are able to deal with this discontinuity by transforming, or converting, the old SOC 1990 classification into the new SOC 2000 classification — that is by creating a consistent definition of occupations throughout our dataset. Details of the methodology used are set out in the Data Appendix.

For each observation, relating to a particular region, occupation, and year cell, our dataset contains information about the hourly pay rate, the unemployment rate, the ratio of immigrants to natives, and age and education level controls. We follow the literature and define an immigrant on the basis of their country of birth – if they are born outside the UK, they are classified as an immigrant. The age controls include the average age of natives and the average age of immigrants in each region, occupation, and year cell. And the education controls include the skill level of the native population in each cell is measured by the share of the native population who have a degree, who have completed secondary school qualifications, those who have incomplete secondary schooling and those who are students. These qualifications are derived according to the length of time individuals have spent in full-time education because of the difficulties described above of not having comparable data on the level of qualifications across countries.[10] People still in full-time education are classified as *students*, those who left full-time education before 16 are classified as having *incomplete schooling,* and those who left after age 21 as having *a degree*. Individuals who left full-time education between the ages of 16 and 20 are classified as having *completed secondary school*.

Table 1 shows the mean and standard deviations for these key variables over all time periods, regions, and occupations. Over our entire dataset the average hourly wage is £10.93, the average unemployment rate is 5.1 percent, and the average immigrant-native

[9] If there is no observation relating to a particular region, occupation, and year cell, that cell will be empty and the sample size will be smaller than this maximum.
[10] For more information on this measure of skill, and the problems it helps overcome, see Saleheen and Shadforth (2006) or Manacorda, Manning, and Wadsworth (2012).

ratio is 12.5 percent. Most of these immigrants arrived more than two years ago—the ratio of old immigrants to natives is 11.7 percent; the ratio of new immigrants to natives is just below 1 percent. The average age of both immigrants and natives is just over 39 years of age, although there is a great deal more variation in the age of immigrants. Eighteen percent of the native population have a degree, with 61.5 percent having completed school, 2.5 percent still in education, and 17.9 percent having incomplete schooling. The standard deviations capture the extent to which each variable varies across our region, occupation, and year dataset. Figure A2 in the appendix shows that the education controls vary considerably across occupations and over time, so are in important factor to control for in our empirical work.

4.1. Pooled specification

We begin with the pooled estimation of equation (8), where we implicitly assume that the impact of immigration on wages is identical across all occupations. Later, we relax this assumption and allow the impact of immigration on wages to differ by occupation.

In equation (8), the dependent variable refers to log real wages. In practice, we use log nominal wages with the price normalization being absorbed into the region/time dummies. The question of focus is: does the lagged immigrant-native ratio have any impact on wages? In Table 2, column 1, we present the basic results, and these show that the immigrant proportion has a significant negative impact on pay. The scale of this impact suggests that if the proportion of immigrants working in a particular occupation rises by 10 percentage points, the occupational wage falls by around 0.3 percent. This is a relatively small effect.

Given the ongoing controversy in the literature of the impact of immigration on wages, it is important to ask, how reliable are these findings? The reliability of these results depends on the accuracy of the data and the appropriateness of the method of estimation.[11] A common problem faced by most empirical studies that try to estimate the impact of immigration on wages is that the increase in immigration to any particular region or occupation is not clearly exogenous. In particular, if immigrants are likely to be attracted to areas with strong

[11] For a discussion of the accuracy of immigration data see the box on page 376–377 of Saleheen and Shadforth (2007).

demand, then any empirical relationship relating the immigrant-native ratio to wages will tend to pick up a spurious positive correlation that will result in the an upwardly biased coefficient of the immigration-native ratio. Our theoretical model takes some account of these channels and delivers an equation in which wages are related to the lagged immigrant-native ratio. But even the lagged immigrant ratio may not be clearly exogenous. Shocks that hit a region and occupation are likely to be correlated over time. This leads to serially correlated errors in the presence of which the lagged immigrant-native ratio will be correlated with the error term. In that case the coefficient on the lagged immigrant-native ratio reported under OLS may continue to be biased upwards. To deal with this issue we follow a similar approach to Altonji and Card (1991) and Dustmann et al (2005) to instrument the lagged immigrant-native ratio with lagged values of the immigrant-native ratio. Our econometric specification considers up to 4 lags. The results reported in Table 2 column 4, are of a similar magnitude to the OLS results.

The remainder of Table 2 sets out a range of other econometric specifications. It highlights a clear result: the coefficient of interest (the lagged immigrant native ratio) is generally negative and significant taking on values between -0.03 and -0.09. We also note the positive impact of the unemployment rate, as expected (see Section 3).

Weighting occupation cells by the employment level of that occupation region cell (columns 2 and 5), helps us to down-weight smaller cells with large sampling errors; and doing this increases the coefficient a little above our basic result reported in column I. We also allow errors within region-occupation cell to be correlated over time, and report standard errors that are heteroskadasticity robust and clustered by region-occupation in column 3 and 6. This naturally pushes up the standard errors, and in the OLS case, enough to make the coefficient of interest turn insignificant. This is no surprise, as we are pushing the data quite hard, because we are estimating an equation with region, time and occupation dummies as well as region-by-time, occupation-by-time and regions-by-occupation fixed effects – that is we are estimating 1162 fixed effects with 5600 observations — so a very large part of the panel variation is absorbed by the fixed effects.[12] This means large standard errors of 0.04 are being used identify a coefficient that is estimated in the neighbourhood of -0.04. We are

[12] This point is also made by Aydemir and Borjas (2010) and Ottaviano and Peri (2012).

reassured that our preferred specification — the weighted IV regression (Table 2, column 5) – illustrates that 10% rise in immigration lowers average wages by just under 1%.

We also investigate whether there is any difference between the inflow of new immigrants (arrived in the last two years) and old immigrants (the remainder). We find that the impact of immigration on wages is driven by the stock of total immigrants, not by the inflow of new ones.

Turning to estimates of dynamic versions of equation 8, these are presented in Table 3. With 23 time periods, the standard bias on the lagged dependent variable coefficients when estimating fixed effects models is small, so we ignore this problem (see Nickell 1981). The overall picture from the dynamic specification is similar to that of the static specification. The impact of immigration on wages exhibits some persistence, but the long-run coefficient is similar to the static model. For example in column (3) where we include two lags of immigration, the long run coefficient is -0.035 (that is, (-0.022+0.001)/(1-0.41)), which is similar to the corresponding static coefficient in Table 2 (-0.033). We experiment with adding further lags of the exogenous variables, but we do not find these to be significant. They may be in other specifications.

How should one interpret these findings? The model outlined above suggests certain conditions that must hold in order for the impact of the immigrant-native ratio on wages to be negative. These include: (i) that firms believe (rightly or wrongly) that immigrants are less productive than natives and (ii) that immigrants have lower reservation wages than natives or that occupation/region labour supply is likely to be enhanced by the presence of existing immigrants. Our findings cannot tell us anything about any of the above conditions in isolation, rather they suggest that either both conditions are true or that only one is true but its impact is large enough to dominate.

What should monetary policymakers make of these findings? The UK Monetary Policy Committee (MPC) cares about migration because changes in the level of immigration can alter the demand and supply of labour, and hence the level of wages consistent with the inflation target.[13] While immigration clearly increases the supply of labour, immigrants are

[13] See MPC minutes in July 2015.

consumers too and so the demand for goods and labour rise too. Here we have found immigration to have a small, significant, negative impact on UK average wages. This suggests that the supply effects dominate over our sample period. And while the MPC takes these factors into account when setting monetary policy, the small overall impact of immigration on wages has not prevented the MPC from achieving its price stability objective.

4.2. Occupational-level specification

So while immigration appears to have a negative impact on occupational pay, the overall average effect is relatively small. It is natural to ask whether we can find bigger effects in particular occupations. To do this, we divide the 25 2-digit occupations into four groups: managers and professionals, skilled production workers, semi/unskilled production workers, and semi/unskilled services workers.[14]

There is no particular reason to expect the parameters in the theoretical model to be the same across occupations. Rather, one might expect there to be heterogeneity across occupations. This heterogeneity probably reflects a variety of factors. It may be the case that immigrants may be perceived as being more productive than natives in some occupations but not in others. It may be that different occupations have been hit by different shocks or that different occupations have been hit by the same shocks but to differing degrees. For example, it may be the case that immigrants entering skilled jobs have done so primarily as a result of a positive demand shock. Faced with shortages of these skilled workers, firms may need to be more active in recruitment and offer competitive wages to attract foreign workers. At the other end of the spectrum, it may also be the case that immigrants entering semi/unskilled service jobs have done so primarily as a result of supply shocks (such as the EU Accession). In this case, their reservation wages may be lower than those of natives, reflecting the lower wage rates they might earn in their home countries. These examples highlight how potential differences in immigrant and firm behaviour across occupations can show up as differences in the impact of immigration on wages across occupations.

[14] Details may be found in the data appendix.

Estimates across these four broad occupation groups are reported in Table 4.[15] For each occupation, the static equation results are reported in the first row and the dynamic equation results in the second row. Panel A reports the results under OLS, and Panel B under IV. All equations are weighted by employment of each occupation-region cell. The OLS and IV findings are broadly similar, so we focus on our preferred IV method of estimation.

Not surprisingly, the results show that there are clear differences, in the impact of immigration on wages, across occupations. The static results suggest that the statistically significant negative effects of immigration on wages are concentrated among skilled production workers, and semi/unskilled service workers. In the latter cases, the coefficients indicates that a 10 percentage point rise in the proportion of immigrants working in semi/unskilled services — that is, in care homes, bars, shops, restaurants, cleaning, for example — leads to a 1.88 percent reduction in pay.

What should we make of this finding? Our earlier investigation into the facts about immigration unveiled that low-skill occupations, such as semi-unskilled services, had witnessed the largest increases in immigration in recent years. If immigrants in these occupations earn less than natives, the 1.88 percent negative impact of immigration on wages reported above could simply reflect compositional changes within the occupation, towards a higher share of (lower paid) immigrants. The compositional effect will be determined by the wage differential between immigrants and natives within occupations.[16] A simple hourly wage equation suggests that, in semi/unskilled services, immigrants earn 5.4 percent less than natives (Table 6).[17] In other words a 10% rise in immigration alone, would lead to a 0.54 percent fall in wages — that is the size of the compositional effect. It is striking that the compositional effect is small when compared to the large impact of 1.88

[15] Estimates based on each of the detailed 25 occupations can also be seen in Table A3 (for the static model) and Table A4 (for the dynamic model). Note that the average of the coefficients reported in Table A3 - that is the average across the 25 occupational equations - is -0.07, within the range of results obtained from estimating the pooled model that is reported in Table 2.

[16] The wage data that we have used thus far (from the NES) are not broken down into immigrant and native sub-groups. But the LFS survey that we have used for data on immigration does have individual information on wages and so can by split by natives and immigrants. The LFS wage data comes from a smaller sample and so is of a lower quality than NES wage data, nevertheless it is useful in indicating whether immigrants earn more or less than natives.

[17] Across all occupations immigrants earn 7 percent less than natives (Table 5).

percent reported above. From this we conclude that the impact of immigration on wages in semi/unskilled services is much larger than can be accounted for by purely compositional effects, suggesting that the vast majority of this effect refers to the impact on native workers.

The same cannot be said for skilled production workers. Here a 10% rise in immigration lowers wages by 1.68%, but the compositional effect is in the same ball park, around 1.13%. So for skilled production workers the impact of immigration on wages can largely be accounted for the compositional effect.

4.3. EU vs non-EU specification

Given the recent rise in immigration from the EU, and particularly from the new EU countries, and the ongoing debate about the UK's membership in the EU it is natural to ask if the impact of immigration on wages is different for EU and non-EU immigrants. In other words, does the impact on wages depend on where the immigrant comes from?

There are many different econometric specifications that would allow us to test for such a differential effect. Our preferred specification is to do this via the ratio of EU to non-EU immigrants. But we also report the findings of including the EU immigrant to native ratio, and the non-EU immigrant to native ratio as two separate variables.

We find that the ratio of EU to non-EU immigrants has a very small impact on wages, and is only significant in the dynamic model (Table 6). The table tells us that a 10% rise in immigration, and constant EU/non-EU immigrant ratio, would lower overall wages by 0.33%. But if a 10% rise in immigration was such that the EU/non-EU immigrant share also rose by 10%, overall wages would likely fall by 0.31%. These differences are tiny. It tells us that impact of immigration on wages is driven mainly by the overall total stock of immigration, with its composition — EU vs non-EU — having a second order impact.

Does this result hold within different occupations? Broadly yes. Table 7 shows that the EU immigrant share is only significant for semi/unskilled services. This means that if the immigrant share in this occupational group was to rise by 10%, with a corresponding 10% rise in the share of EU immigrants, the downward impact on wages would be 1.8% as opposed to 2.1% if there were no change in the EU share. This differential impact between an EU and non-EU immigrants on wages is larger for the semi/unskilled services sector that the aggregate figures, but nevertheless these are relatively small differences.

6. Conclusions

This paper asks whether immigration has any impact on wages. It answers this question by considering the variation of wages and immigration across regions, occupations, and time. Occupations turn out to be a relatively important dimension. Once the occupational breakdown is incorporated into a regional analysis of immigration, the immigrant-native ratio has a significant small impact on the average occupational wage rates of that region. Closer examination reveals that the biggest effect is in the semi/unskilled services sector, where a 10 percentage point rise in the proportion of immigrants is associated with a 2 percent reduction in pay. Where immigrants come from — EU or non-EU — appears to have no impact on our economy wide results; with the impact within the semi/unskilled services sector being small. These findings accord well with intuition and anecdotal evidence, but do not seem to have been recorded previously in the empirical literature.

Table 1: Means of variables

	Mean	Standard deviation
Dependent variable		
w_{irt} (£'s)	10.93	5.08
ln w_{irt}	2.30	0.42
Independent variables		
immigrant/native ratio $_{irt}$	0.125	0.185
new immigrant/native ratio $_{irt}$	0.008	0.015
old immigrant/native ratio $_{irt}$	0.117	0.174
EU immigrant/native ratio $_{irt}$	0.039	0.059
non-EU immigrant/native ratio $_{irt}$	0.086	0.137
unemployment rate $_{irt}$	0.051	0.039
age controls		
mean immigrant age $_{irt}$ (years)	39.63	4.29
mean native age $_{irt}$ (years)	39.63	3.08
skill controls		
share of native population		
- with degree	0.182	0.213
- with completed school	0.615	0.151
- still in education	0.025	0.039
- with incomplete schooling	0.179	0.119

Source: LFS and ASHE/NES.

Table 2: The Impact of Immigration on Wages, Static Model (Eq. 8)

	Dependent Variable, Ln W_{irt-1}					
	(1) Not weighted	(2) Weighted	(3) Weighted, robust S.E.s	(4) Not weighted	(5) Weighted	(6) Weighted, robust S.E.s
	OLS			IV		
(Immigrant/native ratio)$_{irt-1}$	-0.033***	-0.057***	-0.057	-0.043***	-0.093***	-0.093*
	(0.010)	(0.008)	(0.040)	(0.016)	(0.012)	(0.050)
Unemployment rate $_{irt-1}$	0.070*	0.076*	0.076	0.059*	0.048	0.048
	(0.037)	(0.039)	(0.052)	(0.035)	(0.037)	(0.048)
Sample Size	5,930	5,930	5,930	5,655	5,655	5,655
Adjusted R^2	0.993	0.996	0.996	0.993	0.996	0.996

Notes:

(i) Equations in column (1), (2) ad (3) are estimated using ordinary least squares (OLS), with columns (3), (4) and (5) being estimated using instrumental variables, where the lagged immigrant native ratio is instrumented with the 2 year lag.

(ii) Standard errors are reported in parenthesis; those in columns (3) and (6) are heteroskedasticity-robust, clustered over the 275 regions-occupation groups.

(iii) In specifications 2, 3, 5 and 6 we weight each cell by its employment.

(iv) Each equation also contains age controls (mean immigrant age, mean native age), skill controls (share of native population with degree, with completed school, still in education) and a full set of region/year, occupation/year and region/occupation interaction dummies.

(v) t = time (23 years, 1992–2014), i = occupation (25 2-digit occupations), r = region (11 Government Office Regions). This implies a maximum of 6325 (23X25X11) observations. The table shows fewer observations because some cells have have missing information.

(vi) ***=significance at 1% level; **=significance at 5% level; *=significance at 10% level.

Source: LFS and ASHE/NES.

Table 3: The Impact of Immigration on Wages, Dynamic Model (Eq. 8)

	Dependent Variable, Ln W_{irt}					
	(1)	(2)	(3)	(4)	(5)	(6)
		Not weighted			Weighted	
Ln W_{irt-1}		0.411***	0.403***		0.493***	0.482***
		[0.013]	[0.013]		[0.013]	[0.013]
(Immigrant/native ratio)$_{irt-1}$	-0.033***	-0.020**	-0.022**	-0.057***	-0.024***	-0.008
	[0.010]	[0.009]	[0.011]	[0.008]	[0.007]	[0.010]
(Immigrant/native ratio)$_{irt-2}$			0.001			-0.022**
			[0.011]			[0.010]
Unemployment rate $_{irt-1}$	0.070*	0.02	0.011	0.076*	0.043	0.032
	[0.037]	[0.034]	[0.035]	[0.039]	[0.034]	[0.035]
Unemployment rate $_{irt-2}$			0.032			0.03
			[0.036]			[0.036]
Sample Size	5,930	5,912	5,600	5,930	5,912	5,600
Adjusted R^2	0.993	0.995	0.994	0.996	0.997	0.997

Notes:

(i) Notes (iv)–(vi) from Table 2.

(ii) Equations in column (1), (2) ad (3) are estimated using OLS. Columns (4), (5) and (6) are also estimated using OLS and by weighting each cell by employment.

(iii) All equations are estimated using ordinary least squares (OLS). Results in columns (1)-(3) are based on un-weighted regressions, with those in (4)-(6) being weighted by the employment level of each region occupation cell.

(iv) With 23 time periods, the standard bias on the lagged dependent variable coefficients when estimating fixed effects models is small, so we ignore this problem (see Nickell, 1981).

Source: LFS and ASHE/NES.

Table 4: Impact of Immigration on Wages: by Occupation Groups

	Ln (wages)$_{irt-1}$		Immigrant/ native ratio)$_{irt-1}$	Robust Standard Errors	Sample Size	Adjusted R-squared
			Panel A: OLS estimation (Weighted)			
Managers & Professionals			-0.242	[0.178]	2576	0.804
	0.940***	[0.016]	-0.058***	[0.021]	2564	0.98
Skilled Production			-0.161***	[0.050]	937	0.87
	0.943***	[0.017]	-0.023***	[0.006]	931	0.983
Semi/unskilled production			0.022	[0.041]	726	0.924
	0.937***	[0.011]	0.003	[0.006]	726	0.99
Semi/unskilled services			-0.159***	[0.033]	1208	0.946
	0.845***	[0.030]	-0.023***	[0.007]	1208	0.984
			Panel B: IV estimation (Weighted)			
Managers & Professionals			-0.276	[0.201]	2455	0.789
	0.912***	[0.019]	-0.040**	[0.019]	2443	0.973
Skilled Production			-0.168***	[0.050]	893	0.86
	0.943***	[0.018]	-0.020***	[0.006]	887	0.981
Semi/unskilled production			-0.011	[0.063]	693	0.909
	0.938***	[0.011]	0.005	[0.008]	693	0.989
Semi/unskilled services			-0.188***	[0.028]	1153	0.925
	0.832***	[0.034]	-0.023***	[0.008]	1153	0.984

Notes:

(i) Each equation also includes lagged unemployment, age controls, skill controls, year dummies, and region dummies.

(ii) Notes (iv)- (vi), Table 2; Note (iii), Table 3.

Source: LFS and ASHE/NES.

Table 5: Wage Equations: All occupations and by Occupational Groups

Dependent variable, ln(hourly wage$_{kt}$)				
	Immigrant/ native ratio)$_{irt-1}$	**Robust Standard Errors**	**Sample Size**	**Adjusted R-squared**
All occupations	-0.076***	[0.002]	710,197	0.486
Managers & Professionals	-0.057***	[0.003]	304,729	0.253
Skilled Production	-0.113***	[0.007]	55,663	0.295
Semi/unskilled production	-0.135***	[0.005]	70,190	0.178
Semi/unskilled services	-0.054***	[0.003]	183,075	0.207

Notes:

(i) All equations are estimated using ordinary lease squares.

(ii) Each equation also contains age, age squared, skill controls (share of native population with degree, with completed school, still in education), region dummies, year dummies and 2-digit occupation dummies.

(iii) t=time (14 years, 2001-2014), the k subscript captures the fact that this is a micro regression of the wages of individuals on their personal characteristics.

Source: LFS.

Table 6: EU vs Non-EU (all skills levels)

Dependent Variable, Ln W_{irt-1}						
	Panel A – Specification I					
	(1) Not weighted	**(2) Weighted**	**(3) Weighted, robust S.E.s**	**(4) Not weighted**	**(5) Weighted**	**(6) Weighted, robust S.E.s**
	OLS			**IV**		
(Immigrant/native ratio)$_{irt-1}$	-0.033*** (0.010)	-0.056*** (0.008)	-0.056 (0.040)	-0.042*** (0.016)	-0.093*** (0.012)	-0.093* (0.050)
(EU/non-EU immigrant ratio)$_{irt-1}$	0.001 (0.001)	0.001** (0.001)	0.001** (0.001)	0.001 (0.001)	0.001** (0.001)	0.001** (0.001)
Unemployment rate$_{irt-1}$	0.075** (0.037)	0.076* (0.039)	0.076 (0.052)	0.062* (0.035)	0.047 (0.037)	0.047 (0.048)
Sample Size	5,889	5,889	5,889	5,614	5,614	5,614
Adjusted R^2	0.993	0.996	0.996	0.993	0.996	0.996
	Panel B – Specification II					
	(1) **Not weighted**	(2) **Weighted**	(3) **Weighted, robust S.E.s**	(4) **Not weighted**	(5) **Weighted**	(6) **Weighted, robust S.E.s**
	OLS			**IV**		
(EU immigrant/native ratio)$_{irt-1}$	-0.012 (0.021)	-0.021 (0.019)	-0.021 (0.035)	0.004 (0.041)	-0.037 (0.034)	-0.037 (0.056)
(Non-EU immigrant/native ratio)$_{irt-1}$	-0.044*** (0.013)	-0.074*** (0.012)	-0.074 (0.051)	-0.072** (0.029)	-0.124*** (0.022)	-0.124* (0.070)
Unemployment rate$_{irt-1}$	0.075** (0.037)	0.086** (0.039)	0.086 (0.054)	0.070* (0.036)	0.060 (0.038)	0.060 (0.051)
Sample Size	5,930	5,930	5,930	5,655	5,614	5,614
Adjusted R^2	0.993	0.996	0.996	0.993	0.996	0.996

Notes:

(i) Notes (iv)–(vi) from Table 2.

(ii) Specification I and II differ because the variable used to control for the composition of EU immigration is different.

Table 7: **EU vs. Non-EU by skill**

Dependent Variable, Ln W_{irt-1}								
				IV estimation (Weighted)				
	ln wirt-1	Robust and clustered S.E.s	Immigrant /native ratio	Robust and clustered S.E.s	EU/non-EU immigrant ratio	Robust and clustere d S.E.s	Sam ple size	$\bar{R}^2$
Managers & Professionals	-		-0.275	(0.200)	0.001	(0.005)	2442	0.79
	0.912***	(0.019)	-0.040**	(0.019)	0.001	(0.001)	2431	0.97
Skilled Production	-		-0.172***	(0.049)	0.000	(0.003)	869	0.86
	0.945***	(0.018)	-0.020***	(0.006)	0.002***	(0.001)	863	0.98
Semi/unskilled production	-		-0.01	(0.063)	0.000	(0.003)	692	0.91
	0.938***	(0.011)	0.00	(0.008)	0.000	(0.001)	692	0.99
Semi/unskilled services	-		-0.188***	(0.028)	0.004	(0.003)	1150	0.93
	0.830***	(0.035)	-0.024***	(0.008)	0.004***	(0.001)	1150	0.98

Notes:

(i) All equations are estimated using IV regressions, and they are all weighted regressions that use the employment in each region occupation cell as weights.

(ii) Each equation also includes lagged unemployment, age controls, skill controls, year dummies, and region dummies.

(iii) Notes (iv) - (vi), Table 2; Note (iii), Table 3.

Source: LFS and ASHE/NES.

References

Altonji, Joseph and **Card, David (1991),** "The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives", in Immigration, Trade and Labor, edited by J.M. Abowd and R. B. Freeman, University of Chicago Press.

Aydemir, Abdurrahman and **Borjas, George (2011),** "Attenuation Bias in Measuring the Wage Impact of Immigration", *Journal of Labour 29*: 69-113.

Baglati, Badi and Qi Li (1995), "Testing AR(1) against MA(1) disturbances in an error component model," *Journal of Econometrics* 68: 133–151.

Beaudry, Paul, Mark Doms, and Ethan Lewis (2006), "Endogenous skill bias in technology adoption: city level evidence from the IT revolution," *Federal Reserve Bank of San Francisco Working Paper* no. 06–24.

Borjas, George (2003), "The labour demand curve is downward sloping," *Quarterly Journal of Economics* 116(4): 463–486.

Borjas, George (2005), *Labour Economics*, Third Edition, McGraw-Hill Irwin publishers.

Borjas, George and Katz, Lawrence (2007), "The Evolution of the Mexican-Born Workforce in the United States," in Mexican Immigration to the United States, edited by George Borjas, National Bureau of Economic Research Conference Report, Cambridge, MA.

Card, David (1990), "The impact of the Mariel Boatlift on the Miami labour market,",*Industrial and Labour Relations Review* 43(2): 245–257.

Card, David and John diNardo (2000), "Do immigrant inflows lead to native outflows?" *American Economic Review, Papers and Proceedings* 90(2): 360–367.

Card, David (2005), "Is the new immigration really so bad?" *Economic Journal* 115(507): 300–323.

Carney, Mark (2015), "The European Union, monetary and financial stability, and the Bank of England" , speech St Peter's College, Cairncross Lecture, Oxford, available from the Bank of England website.

Dustmann, Christian, Francesca Fabbri, and Ian Preston (2005), "The impact of immigration on the British Labour Market," *Economic Journal* 115(507): 324–341.

Dustmann, Christian, Francesca Fabbri, and Ian Preston (2013), "The Effect of Immigration along the Distribution of Wages," *Review of Economic Studies* 80(1): 145–173.

Hatton, Timothy (2002), "Why has UK net immigration increased?" Australian National University, *Centre for Economic Policy Research Discussion Paper* no. 457.

King, Mervyn (2007), Speech to a CBI Dinner in Wales, available from the Bank of England website.

Layard, Richard, Stephen Nickell, and Richard Jackman (1991), *Unemployment: macroeconomic performance and the labour market*, Oxford University Press.

Lewis, Ethan (2004), "Local open economies within the U.S.: how do industries respond to immigration?" *Federal Reserve Bank of Philadelphia Working Paper* no. 04-1.
Lewis, Ethan (2005), "Immigration, skill mix and the choice of technique," *Federal Reserve Bank of Philadelphia Working Paper* no. 05-8.

Machin, Stephen (2003), "Wage inequality since 1975," in R. Dickens, P. Gregg, and J Wadsworth (eds.), *The Labour Market Under New Labour*, Palgrave Macmillan.

Manacorda, Marco, Alan Manning, and Jonathan Wadsworth (2012), "The impact of immigration on the structure of wages: theory and evidence from Britain," *Journal of European Economic Association*, 10(1): 120-151.

Nickell, Stephen (1981), "Biases in dynamic models with fixed effects," *Econometrica* 49(6): 1417–26.

Ottaviano, Gianmarco and Giovanni Peri (2012), "Rethinking the gains from immigration: theory and evidence from the U.S.", *Journal of European Economic Association*, 10(1): 152-197.

Pesaran, Hashem and Ron Smith (1995), "Estimating long-run relationships from dynamic heterogeneous panels," *Journal of Econometrics* 68: 79–113.

Saleheen, Jumana and Chris Shadforth (2006), "The economic characteristics of immigrants and their impact on supply," *Bank of England Quarterly Bulletin*, 2006Q4: 374–385.

Wooldridge, Jeffrey (2002), *Econometric analysis of cross section and panel data*, MIT Press.

Appendix I – Data and definition of variables

The data used for our analysis come from the British Labour Force Survey (LFS) and the Annual Survey of Hours and Earnings (ASHE)/New Earnings Survey (NES). The LFS is a quarterly sample survey of households living at private addresses in Great Britain and is carried out by the Office of National Statistics. The LFS surveys about 100,000 individuals each quarter on a range of issues, including employment characteristics; information on earnings is only collected for 20% of the sample. The ASHE/NES is an annual employee survey that captures the level and distribution of earnings and hours worked by employees in Great Britain. It is based on a 1 percent sample of employees who are members of Pay-As-You-Earn (PAYE) income tax schemes. This survey covers the pay of around 180,000 individuals each year. It is considered the most comprehensive source of earnings information, as for earnings, its' sample is 9 times larger than the LFS; moreover it is based on hard payroll data rather than relying on individual memory of how much they were paid. The ASHE does not cover the earnings of the self-employed, or those who were not paid in the reference period.

We use data from these two sources to form a panel dataset that has three dimensions: time, region, and occupation. In other words, for each year of the 23 years (1992–2014) of data that we consider, there are observations for each of the 11 U.K. standard Government Office Regions, and within each region there is information on each of the 25 occupations defined at the 2-digit SOC 2000 classification. In total, in the absence of missing observations, the dataset will have a maximum of 6325 (=23x11x25) observations. If there is no observation for a given cell, then that data point is missing. A typical static regression has 5,600 observations.

Region:

Standard Government Office Regions (GORs).

Occupation:

In our panel dataset, occupations are classified according to SOC 2000 throughout.

Table A1 set out some example occupations for each 2-digit occupation category. The 1 digit category can be derived by considering the first digit of each figure in the middle column.

In Table 5, results are presented on various groups of occupations. The 2-digit occupations we use are set out in Table A1. The groups used in Table 5 are managers (11, 12), professionals (21, 22, 23, 24, 31, 32, 35), skilled production workers (51, 52, 53, 54) semiskilled/unskilled production workers (81, 82, 91), and semiskilled/unskilled services workers (61, 62, 71, 72. 92).

Wages:

Nominal hourly wage rates of all full-time workers by region and occupation. Based on adult rates for those whose pay was not affected by absence during the week in which the survey was carried out.

Source: ASHE 2002-2006 published data files from Table 3.6a based on SOC 2000. Prior to 2002, these data are constructed from the NES (1992–2001) micro data files, where occupations are defined at the 3-digit SOC 1990 level.

Employment:

Individuals aged 16–65 who report being in employment by region and occupation.

Source: LFS 1992–20134 seasonal quarters.

Unemployment:

The unemployment rate is measured by taking the number of individuals aged 16–65 who are unemployed according to the LFS definition and dividing by the total number of individuals aged 16–65 who are employed and unemployed. The unemployment rate is constructed for each occupation and region cell. To compute unemployment rates by occupation we need to use information on individuals' last job - that is the occupation that the individual was employed in prior to becoming unemployed.

Source: LFS 1992–2014 seasonal quarters.

Table A1 – Occupations – what types of jobs do they include?

Corporate **managers**	11	Senior officials in national government, managers in construction, marketing and sales. IT managers
Managers and proprietors in agri and services	12	Farming managers, hotel managers, hairdressing and beauty salon managers
Science and technology **professionals**	21	Physicists, civil engineers, chemists
Health **professionals**	22	Doctors, dentists, vets
Teaching and research **professionals**	23	Higher education teachers
Business and public service **professionals**	24	Solicitors, lawyers, chartered accountants, librarians
Science and technology **associate professionals**	31	Technicians in labs, IT, building and civil engineering
Health and social welfare **associate professionals**	32	Nurses, pharmacists, physicians
Protective services (**associate professionals**)	33	Police, prison and fire services
Culture, media &sports (**associate professionals**)	34	Artists, actors, sports players
Business and public service (**associate professionals)**	35	Train drivers, estate agents, insurance underwriters
Administrative occupations	41	Credit controllers, data assistants, clerks
Secretarial and related (**admin**)	42	Medical, legal, company secretaries,
Skilled trades (agricultural)	51	Farmers, gardeners
Skilled trades (metal and electrical)	52	Electricians, telecoms engineers , computer maintenance
Skilled trades (construction and building)	53	Plumbers, carpenters, bricklayers, roofers, plasterers
Skilled trades (textiles and printing)	54	Tailors, upholsters
Caring personal service occupations	61	Child-minders, nursery nurses, animal care assistants
Leisure and other personal service (**caring**)	62	Housekeepers, travel agents/assistants, caretakers,
Sales occupations	71	Sales assistants, check-out staff
Customer service occupations	72	Call centre staff
Process, plant & machine **operatives**	81	Clothing cutters, tyre fitters, coal mine operatives, plastic process operatives
Transport, mobile machine drivers & **operatives**	82	Crane drivers, taxi drivers, air/rail transport operatives
Elementary trades, plant and storage	91	Packers, labourers, goods storage
Elementary admin and service occs	92	Postmen, shelf fillers, car park attendants, cleaners road sweepers, bar staff, porters, waiters

Immigrant-native ratio

The number of foreign born individuals (or "immigrants") aged 16–65 divided by the number of individuals aged 16–65 who were born in the United Kingdom ("natives"). This ratio is constructed for each occupation and region cell.

Source: LFS 1992–2014 seasonal quarters.

EU immigrant-native ratio:

EU migrants are defined as those individuals who report being born in an EU country, and the UK has allowed that country access to the UK labour market. The set of countries that form part of the EU will therefore vary over time. This information is captured in Chart A2 below.[18] If you follow the UK row- the year each column sets out whether the citizen of that country is counted as part of the EU in our definition. So for example, Estonia, Latvia, Lithuania, Poland, Hungary Czech Republic, Slovakia and Slovenia all joined the EU migrant's category in 2004, whereas Bulgaria and Romania joined in in 2012.

New immigrant-native ratio:

"New" immigrants are defined as those immigrants (foreign-born workers) who arrived in the United Kingdom in the year of the survey or the previous calendar year. The "new" immigration-native ratio takes the number of new immigrants aged 16–65 in each occupation and region and divides it by the number of natives aged 16–65 in that same occupation and region.

Old immigrant-native ratio:

"Old" immigrants are defined as those immigrants (foreign-born workers) who are not new immigrants. They are defined as the difference between the total number of immigrants and the number of new immigrants. The "old" immigration-native ratio takes the number of old immigrants aged 16–65 in each occupation and region and divides it by the number of natives aged 16–65 in that same occupation and region.

[18] Credit for this Chart goes to Thomas Smith.

Figure A1: Years when EU member states granted labour market access to other EU member states

Citizens of => / Can Work in:	Italy	France	Germany	Belgium	Netherlands	Luxembourg	Denmark	Ireland[a]	United Kingdom[a]	Greece	Portugal	Spain	Austria	Finland	Sweden	Cyprus	Malta	Estonia	Latvia	Lithuania	Poland	Hungary	Czech Republic	Slovakia	Slovenia	Bulgaria	Romania	Croatia
Date of EU Membership:	1957	1957	1957	1957	1957	1957	1973	1973	1973	1981	1986	1986	1995	1995	1995	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2007	2007	2013
Italy		1958	1958	1958	1958	1958	1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2006	2006	2006	2006	2006	2006	2006	2006	2012	2012	2015
France	1958		1958	1958	1958	1958	1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2008	2008	2008	2008	2008	2008	2008	2008	2014	2014	2015
Germany	1958	1958		1958	1958	1958	1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2011	2011	2011	2011	2011	2011	2011	2011	2014	2014	2015
Belgium	1958	1958	1958		1958	1958	1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2009	2009	2009	2009	2009	2009	2009	2009	2014	2014	2015
Netherlands	1958	1958	1958	1958		1958	1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2007	2007	2007	2007	2007	2007	2007	2007	2014	2014	2018
Luxembourg	1958	1958	1958	1958	1958		1973	1973	1973	1981	1986	1986	1994	1994	1994	2004	2004	2007	2007	2007	2007	2007	2007	2007	2007	2014	2014	2015
Denmark	1973	1973	1973	1973	1973	1973		1973	1973	1981	1986	1986	1994	1954	1954	2004	2004	2009	2009	2009	2009	2009	2009	2009	2009	2009	2009	2013
Ireland[a]	1973	1973	1973	1973	1973	1973	1973		1973	1981	1986	1986	1994	1994	1994	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2012	2012	2013
United Kingdom	1973	1973	1973	1973	1973	1973	1973	1973		1981	1986	1986	1994	1994	1994	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2014	2014	2018
Greece	1981	1981	1981	1981	1981	1981	1981	1981	1981		1986	1986	1994	1994	1994	2004	2004	2006	2006	2006	2006	2006	2006	2006	2006	2009	2009	2015
Portugal	1986	1986	1986	1986	1986	1986	1986	1986	1986	1986		1986	1994	1994	1994	2004	2004	2006	2006	2006	2006	2006	2006	2006	2006	2009	2009	2013
Spain	1986	1986	1986	1986	1986	1986	1986	1986	1986	1986	1986		1994	1994	1994	2004	2004	2006	2006	2006	2006	2006	2006	2006	2006	2009	2014	2015
Austria	1994	1994	1994	1994	1994	1994	1994	1994	1994	1994	1994	1994		1994	1994	2004	2004	2011	2011	2011	2011	2011	2011	2011	2011	2014	2014	2018
Finland	1994	1994	1994	1994	1994	1994	1954	1994	1994	1994	1994	1994	1994		1954	2004	2004	2006	2006	2006	2006	2006	2006	2006	2006	2007	2007	2013
Sweden	1994	1994	1994	1994	1994	1994	1954	1994	1994	1994	1994	1994	1994	1954		2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2007	2007	2013
Cyprus	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2004	2004	2004	2004	2004	2007	2007	2015
Malta	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2004	2004	2004	2004	2014	2014	2018
Estonia	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2004	2004	2004	2007	2007	2013
Latvia	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2004	2004	2007	2007	2013
Lithuania	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2004	2007	2007	2013
Poland	2006	2007	2007	2007	2007	2007	2007	2004	2004	2006	2006	2006	2007	2006	2004	2004	2004	2004	2004	2004		2004	2004	2004	2004	2007	2007	2013
Hungary	2006	2008	2009	2009	2007	2007	2009	2004	2004	2006	2006	2006	2009	2006	2004	2004	2004	2004	2004	2004	2004		2004	2004	2004	2009	2009	2013
Czech Republic	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2004	2007	2007	2013
Slovakia	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2004	2007	2007	2013
Slovenia	2006	2007	2007	2007	2007	2007	2007	2004	2004	2006	2006	2006	2007	2006	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004		2007	2007	2018
Bulgaria	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007		2007	2013
Romania	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007		2013
Croatia	2015	2015	2015	2015	2018	2015	2013	2013	2018	2015	2013	2015	2018	2013	2013	2015	2018	2013	2013	2013	2013	2013	2013	2013	2018	2013	2013	

Average Age:

The average age of natives and immigrants aged 16–65 by region and occupation.

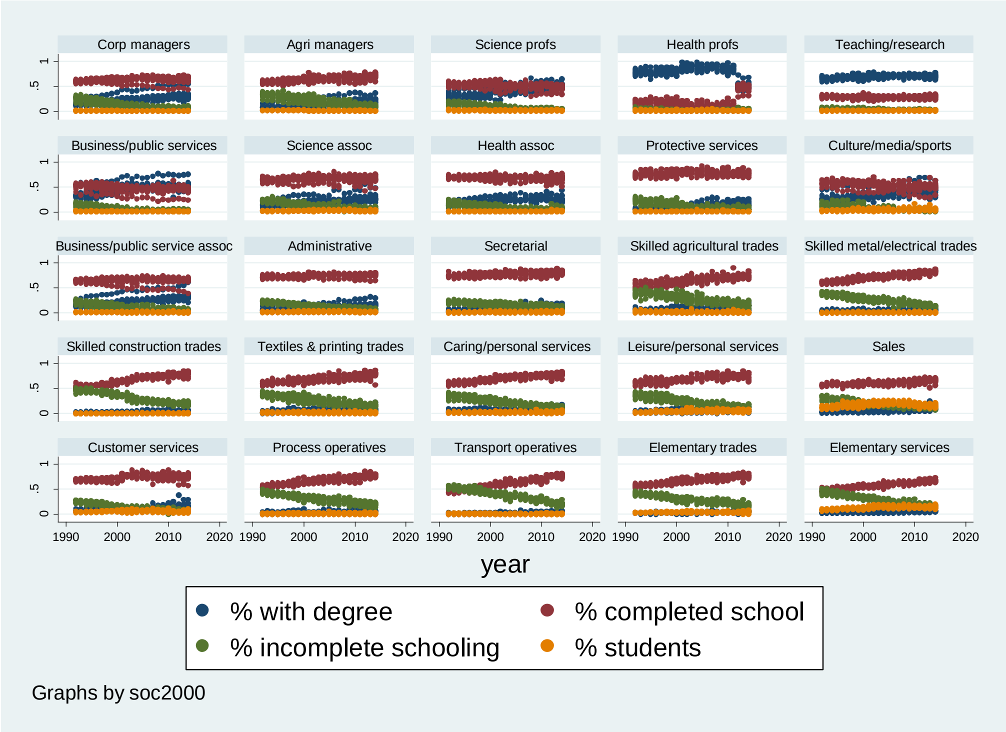
Source: LFS 1992–2014 seasonal quarters.

Education:

The skill level of each region and occupation cell is measured by the level of education held by the native inhabitants aged 16–65 in each region and occupation cell. Four levels of education are defined and used in this paper: those who have a degree; those who have completed school; those who have incomplete or no schooling; and those who are still in full-time education. These educational variables are defined according to the age at which the worker left full-time education. Completing education at the age of 21 is used to proxy completion of a degree. If education was completed before the age of 16, it is taken to proxy incomplete schooling; and if education was completed between the ages of 16 and less than 21, it is taken to imply that schooling has been completed (see Saleheen and Shadforth 2006 for details). The skill control variables take the form of the share of natives who hold a degree, have completed school, have incomplete schooling, or are still in full-time education. As defined, the sum of these four skill shares will sum to 1. Chart A2 below shows how that the educational level varies considerably across occupations, with trends changing over time as well, which is why controlling for the average level of skill within region occupation group is important.

Source: LFS 1992–2014 seasonal quarters.

Chart A1: **Average education levels of the population by occupation**



Appendix II – Creating a consistent occupational classification

An important data problem encountered was that the variables required were not available on the SOC 2000 basis through our sample period 1992-2015. This is because there has been a major change in the classification of occupations from SOC 1990 to the SOC 2000 classification in 2001/2002. This paper therefore devises a novel methodology to transform old occupational classification (SOC 1990) into the new classification (SOC 2000).

Transforming SOC 1990 to SOC 2000

The Office of National Statistics (ONS) does not provide a match between SOC 1990 and SOC 2000. Indeed, they argue that there is no "formula" that will allow one simply to match the two classifications. In other words, if one were to classify 100 people into the SOC 1990 and SOC 2000 occupations, it is unlikely that all the people from a single category of SOC 1990 would end up in the same single category of SOC 2000. Instead, individuals from one category of SOC 1990 are likely to end up in multiple categories of SOC 2000.

To find a mapping from SOC 1990 to SOC 2000 we first calculate a matrix that allocates the same people to both sets of codes is derived. Such a dual coding of occupations for the same people is obtained from the panel component of neighbouring LFS surveys. The LFS 2000:Q4 survey coded occupations based on SOC 1990. and the LFS 2001:Q1 survey coded occupations based on SOC 2000. Taking the individuals who were surveyed in both quarters and who did not change jobs during that time, one is able to obtain 55,000 individuals with dual occupational codes. It is important to note that one drawback of our method is that the matrix we have relates to one point in time and so is time invariant.

This matrix of dual occupation codes is the key building block that allows us to derive a mapping of individuals from SOC 1990 to SOC 2000. As the mapping is not one-to-one (the off diagonal cells are non-zero), a "proportional" mapping method is used. Proportional mapping is a method in which a given proportion of individuals in each old occupational category (SOC 1990) is assigned to one category in the new occupational classification (SOC 2000), with another proportion being assigned to another category in SOC 2000, and so on. The proportions that need to be assigned to each category are determined by the elements of the matrix. For example, assume that there are only two categories of SOC 1990 and SOC

2000. And assume that 70 percent of individuals in category 1 of SOC 1990 fall into category 1 of SOC 2000, and 30 percent fall into category 2. Then, the proportions of SOC 1990 individuals going to categories 1 and 2 will be 0.7 and 0.3, respectively. In the paper, 3-digit SOC 1990 (371 categories) is mapped into 2-digit SOC 2000 (25 categories)

The mapping of occupations allows any variable that is defined on the SOC 1990 basis to be transformed into the SOC 2000 basis. This transformation has to be applied to all the variables that are used in our dataset. For variables that are derived from the LFS, the occupational codes change in 2001, and for variables that are derived from ASHE/NES, the occupational codes change in 2002.

Table A2

Immigrant Proportions in 2-Digit Occupations

	SOC2000	1992-94	1998-00	2004-06	2012-14
11	Corporate managers	0.090	0.096	0.106	0.137
12	Agriculture managers	0.119	0.125	0.165	0.202
21	Science professionals	0.089	0.111	0.155	0.239
22	Health professionals	0.285	0.345	0.454	0.285
23	Teaching & research	0.095	0.109	0.126	0.144
24	Business & public services	0.105	0.111	0.164	0.178
31	Science associates	0.071	0.084	0.115	0.158
32	Health associates	0.134	0.134	0.168	0.116
33	Protective services	0.061	0.048	0.060	0.075
34	Culture, media and sports	0.118	0.141	0.156	0.173
35	Business/public service associates	0.079	0.087	0.109	0.142
41	Administrative	0.071	0.081	0.090	0.131
42	Secretarial	0.075	0.088	0.097	0.115
51	Skilled agricultural trades	0.028	0.036	0.042	0.044
52	Skilled metal and electrical trades	0.056	0.054	0.058	0.087
53	Skilled construction trades	0.051	0.048	0.072	0.127
54	Textiles and printing trades	0.119	0.137	0.208	0.331
61	Caring and personal services	0.080	0.085	0.114	0.173
62	Leisure and personal services	0.073	0.087	0.122	0.205
71	Sales	0.065	0.076	0.105	0.141
72	Customer services	0.067	0.078	0.088	0.122
81	Process operatives	0.095	0.093	0.125	0.244
82	Transport operatives	0.067	0.070	0.106	0.217
91	Elementary trades	0.067	0.071	0.131	0.366
92	Elementary services	0.090	0.100	0.145	0.255

Table A3
Impact of Immigrant on Wages: 25 Occupations (Static Model)

Dependent variable is ln wirt	Soc 2000 2-digit code	immigrant/native share $_{irt-1}$	t-stat	sample size	$\bar{R}^2$
Corporate managers	11	0.596***	[0.118]	242	0.991
Managers and proprietors in agri and services	12	0.090*	[0.049]	242	0.966
Science and technology profs	21	0.011	[0.038]	241	0.992
Health professionals	22	-0.041	[0.044]	202	0.944
Teaching and research profs	23	-0.045	[0.096]	242	0.979
Business and public service profs	24	-0.091	[0.139]	239	0.983
Science and technology associate profs	31	-0.144***	[0.038]	241	0.987
Health and social welfare associate profs	32	-0.029	[0.048]	240	0.991
Protective service occs	33	0.046	[0.086]	227	0.982
Culture, media and sports occs	34	-0.144	[0.234]	218	0.905
Business and public service assoc profs	35	-0.364***	[0.067]	242	0.987
Administrative occupations	41	-0.291***	[0.040]	242	0.994
Secretarial and related occs	42	-0.118	[0.077]	241	0.994
Skilled agricultural trades	51	-0.111	[0.079]	218	0.919
Skilled metal and electrical trades	52	-0.091**	[0.039]	242	0.992
Skilled construction and building trades	53	-0.033**	[0.012]	235	0.985
Textiles, printing and other skilled trades	54	-0.112***	[0.013]	242	0.976
Caring personal service occupations	61	-0.301***	[0.020]	242	0.979
Leisure and other personal service occs	62	0.036	[0.040]	241	0.975
Sales occupations	71	-0.163***	[0.047]	242	0.985
Customer service occupations	72	-0.274***	[0.044]	241	0.962
Process, plant and machine operatives	81	-0.032*	[0.018]	242	0.991
Transport and mobile machine drivers and operatives	82	0.070***	[0.020]	242	0.992
Elementary trades, plant and storage	91	-0.074***	[0.010]	242	0.99
Elementary admin and service occs	92	-0.136***	[0.016]	242	0.993

Notes: (i) All equations are estimated using OLS. Each equation also includes lagged unemployment, age controls, skill controls, year dummies and region dummies.
(ii) See notes (iii), (iv), Table 2; Note (ii), Table 3.

Table A4
Impact of Immigrant on Wages: 25 Occupations (Dynamic Model)

Dependent variable is ln wirt	Soc 2000 2-digit code	ln w_{irt-1}	Robust SEs	immigrant/native share $_{irt-1}$	Robust SEs	Sample size	$\bar{R}^2$
Corporate managers	11	0.604***	(0.060)	0.219**	(0.105)	242	0.994
Managers and proprietors in agri and services	12	0.500***	(0.065)	0.017	(0.058)	242	0.973
Science and technology profs	21	0.511***	(0.055)	0.007	(0.028)	240	0.994
Health professionals	22	0.349***	(0.071)	-0.033	(0.046)	202	0.951
Teaching and research profs	23	0.578***	(0.054)	-0.028	(0.062)	242	0.987
Business and public service profs	24	0.482***	(0.063)	-0.100	(0.082)	239	0.987
Science and technology associate profs	31	0.608***	(0.055)	-0.057*	(0.030)	241	0.992
Health and social welfare associate profs	32	0.417***	(0.063)	-0.029	(0.030)	240	0.993
Protective service occs	33	0.272***	(0.068)	0.009	(0.060)	227	0.983
Culture, media and sports occs	34	0.357***	(0.075)	-0.039	(0.186)	207	0.925
Business and public service assoc profs	35	0.465***	(0.065)	-0.210***	(0.064)	242	0.989
Administrative occupations	41	0.408***	(0.066)	-0.169***	(0.057)	242	0.995
Secretarial and related occs	42	0.384***	(0.065)	-0.069	(0.058)	241	0.995
Skilled agricultural trades	51	0.122	(0.076)	-0.076	(0.147)	217	0.919
Skilled metal and electrical trades	52	0.583***	(0.060)	-0.038	(0.037)	242	0.995
Skilled construction and building trades	53	0.247***	(0.070)	-0.015	(0.024)	230	0.987
Textiles, printing and other skilled trades	54	0.376***	(0.065)	-0.073***	(0.019)	242	0.979
Caring personal service occupations	61	0.182***	(0.069)	-0.253***	(0.045)	242	0.98
Leisure and other personal service occs	62	0.555***	(0.064)	-0.014	(0.033)	241	0.982
Sales occupations	71	0.631***	(0.058)	-0.036	(0.036)	242	0.99
Customer service occupations	72	0.535***	(0.059)	-0.132***	(0.037)	241	0.973
Process, plant and machine operatives	81	0.352***	(0.070)	-0.012	(0.020)	242	0.992
Transport, machine drivers/operative	82	0.298***	(0.066)	0.052***	(0.019)	242	0.992
Elementary trades, plant and storage	91	0.524***	(0.065)	-0.038***	(0.011)	242	0.993
Elementary admin & service s	92	0.313***	(0.067)	-0.087***	(0.019)	242	0.994

Notes: (i) All equations are estimated using OLS. Each equation also includes lagged wages, lagged unemployment, age controls, skill controls, year dummies, and region dummies.

(ii) See notes (iii), (iv), Table 2; Note (ii), Table 3.