The impact of immigration on occupational wages: British evidence

Stephen Nickell* and Jumana Saleheen**

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Abstract

This paper asks whether immigration has any impact on wages. There seems to be a broad consensus among academics that the share of immigrants in the workforce has little or no affect on the pay rates of the indigenous population. But these studies have typically not refined their analysis by breaking it down into different occupational groups. In this paper we find that once the occupational breakdown is incorporated into a regional analysis of immigration, the immigrant-native ratio has a significant, small, negative impact on the average wages. Closer examination reveals that the biggest impact is in the semi/unskilled services sector. This finding accords well with intuition and anecdote, but does not seem to have been recorded previously in the empirical literature.

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*Nuffield College Oxford.
** Federal Reserve Bank of Boston and Bank of England.
Email: jumana.saleheen@bos.frb.org

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1. Introduction

The rise in immigration experienced in the UK over the past 10 years is widely believed by the general public and policymakers to have had large effects on the labour market in general and wages in particular. The stereotype of the Polish plumber encapsulates the commonly held belief that immigration 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 little or no impact on the pay rates of the indigenous population. Nevertheless, there is a continuing controversy exemplified by 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 finds 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 US. An immigrant inflow of 10% of the labour force lowers the wages of natives by 3 or 4%.

But further research which takes account of native mobility is unable to confirm the Borjas (2003) results. For example, Card (2005), in an analysis of US cities finds first that increases of immigrants into localities have generated significant rises in the proportion of low skilled (high school dropouts) and second, these large shifts in the proportions of low skilled have had minimal effects on the low skill wage relative to that of the higher skilled.[1] Evidence for the UK is consistent with the findings of Card (2005), suggesting that the impact of immigration on the wages of natives is minimal (see Dustman et al., (2005) and Manacorda et al. (2006), for example).

Much of the research in this area has concentrated on looking for wage effects of immigration among the low skilled, where skill levels are defined in terms of education. Unfortunately, however, the measurement of the education levels of migrants is often very tricky because of the difficulty of comparing education qualifications across countries. Furthermore, for a variety of reasons, many immigrants who come to the UK with high qualification levels work in low skill occupations. This may tend to corrupt an analysis which depends on using education levels to partition the data.

So here we take a different approach, segmenting the labour market by occupation. One advantage of this is that it focuses the analysis on the various groups in the labour market such as plumbers, agricultural workers, nurses, waiters, etc., which have been the subject of much of the public discussion.

Some occupations see a very heavy influx of immigrants. For example, over 30% of Health Professionals (e.g. doctors and dentists) are immigrants, compared to around 5% of those in Skilled Agricultural Trades (e.g. farmers and gardeners). *A priori*, it

[1] 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 the unskilled workers. See Lewis (2004, 2005) and Beaudry et al. (2006), for evidence in favour of this explanation.

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.

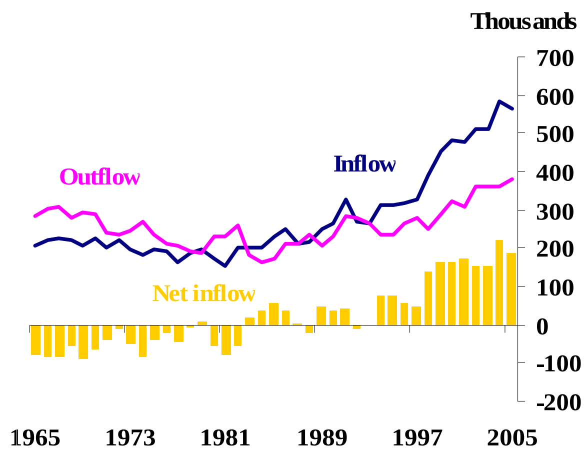
While there is a great deal of anecdotal discussion on the impact of immigration in specific occupations like agriculture and construction, we feel it would be helpful to present some harder data on that subject. For that reason the first part of this paper is about occupations. We consider some facts about which occupations tend to see a higher share of immigrants and how this has changed over time and what has happened to pay in those occupations.

The paper then moves on to a more formal empirical analysis of the relationship between migration and wages. It finds that once the occupational breakdown is incorporated into a regional analysis of immigration, the immigrant-native ratio has a significant and negative impact on the average occupational wage rates of that region.

2. Immigration across occupations: some facts

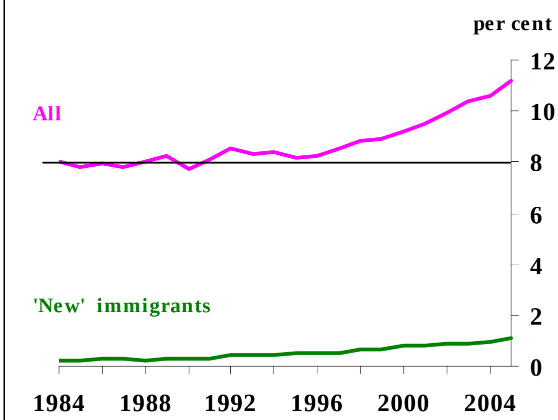
Immigration to the UK has risen dramatically over the past decade. This can be seen clearly from the charts below. Chart 1 shows that according to the official migration statistics, the net inflow of immigrants to the UK each year has risen from around 50,000 individuals in 1995 to 220,000 in 2005. The 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 90s. Chart 2 shows how immigrants – defined as foreign born workers – have become a larger share of the UK working age population. Having been stable at around 8% between 1984 and 1995, it has grown to nearly 12% by 2006 (Chart 2).

Chart 1: Immigration into and out of the United Kingdom



Source: Data are mainly from the International Passenger Survey (IPS). From 1991, the ONS supplement the IPS with administrative data on asylum seekers and their dependents, and estimates of the migrant flow between the United Kingdom and the Irish Republic; the ONS also make other adjustments to account for those whose intended length of stay changes (from less than a year to more than a year, and vice versa). The IPS sampling methodology was also changed in 1999.
1. The number of people (all ages) entering/leaving the United Kingdom with the intention of staying/leaving for at least 1 year.

Chart 2: The foreign-born share of the population aged 16 to 64



Source: Labour Force Survey (LFS).
1. The number of 16-64 year olds born outside the United Kingdom as a proportion of the total population aged 16-64.
2. 'New' immigrants are those who entered the United Kingdom in the survey year or the (calendar) year before the survey was carried out.
3. Average share of foreign born individuals in the UK population between 1985 and 1995.

This rise in immigration to the UK 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.

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, 1992-2005. 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? Chart 3 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 rather modestly across broad occupations. It is highest for Professional workers (e.g. engineers), Associate Professional workers (e.g. science and IT technicians) and those in Elementary occupations (e.g. cleaners, and labourers). It is lowest among skilled tradesmen (e.g. plumbers and electricians) and administrative occupations. In other words, there is a slight tendency for immigrants to be predominant in jobs at the top end of the occupational classification (or high skilled jobs) and those at the bottom end of the occupational (or low skilled jobs) classification with fewer in the middle – so that chart 3 traces out a shallow U-shaped pattern. This reflects the fact that there are many different types of immigrants that come to the UK. For example, some immigrants come to the UK having already secured a high-skilled job. While others come in search of work and a better standard of living, but end up in occupations at the very bottom end of the occupational distribution, possibly because they lack knowledge of the local labour market and face language difficulties.

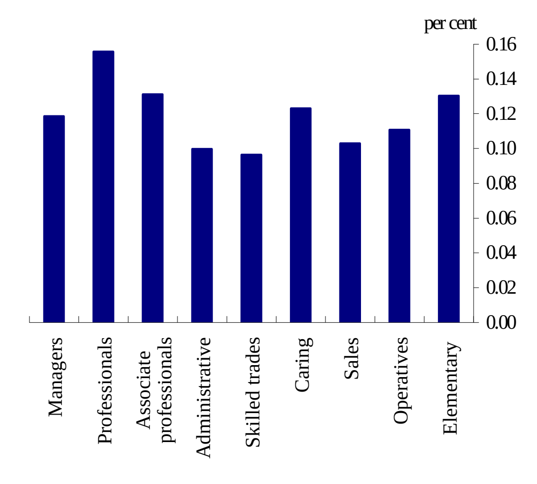
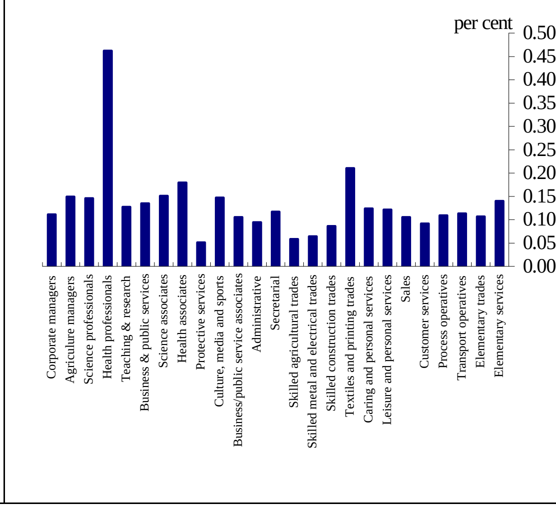
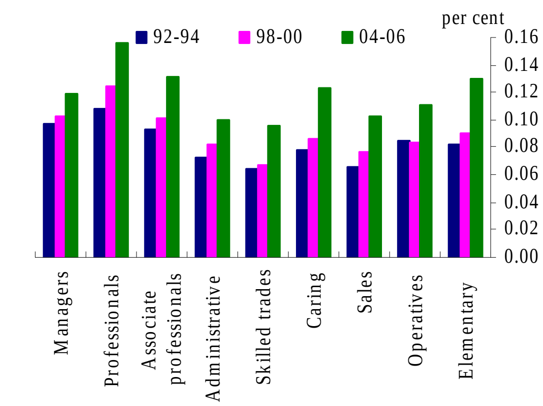
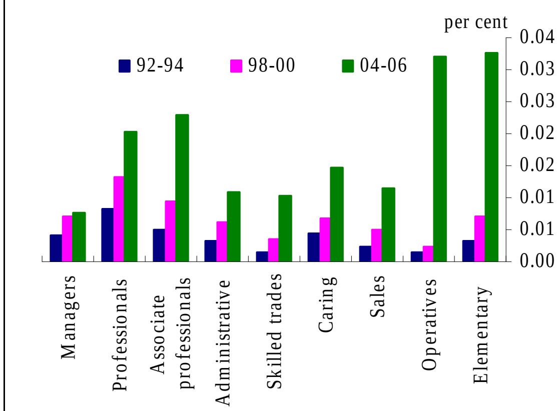
Chart 3: Immigrant-native ratio at 1 digit classification (2004- 2006)	Chart 4: Immigrant-native ratio at 2 digit classification (2004- 2006)
	

Chart 4 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 UK Health Professions are immigrants and very few immigrants work as Security Guards.

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

Chart 5 shows the immigrant-native ratio in each occupation for three time periods, 1992-94, 1998-00 and 2004-06. A shallow U-shaped pattern is evident for all three periods: the ratio is highest among Professional and Elementary workers and lowest for those in Skilled Trades. It is also evident that the immigrant-native ratio has risen for all occupations over time. Importantly, however, the rise has been biggest in Elementary (low skilled) occupations. For example, the immigrant-native ratio for

Managers grew by 2 percentage points between 1992-94 and 2004-06, whereas it grew by 5 percentage points for Elementary workers over the same period.

Chart 5: Immigrant-native ratio over time	**Chart 6: New immigrant-native ratio over time**
	

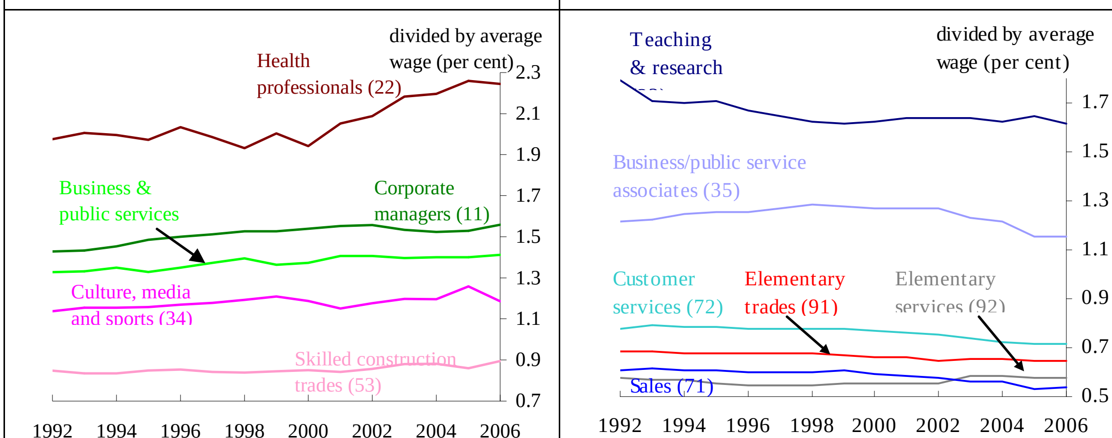
The fact that the immigration has risen by proportionately more in lower occupations, particularly in Elementary and Operatives occupations, is clearer from Chart 6. This chart reports the ratio of ‘new’ immigrations to natives, where ‘new’ immigrants are defined as those immigrants who entered the UK in the past two years. During the periods 1992-94 and 1998-00 the new immigrant-native ratio for Elementary and Operatives were among the lowest, but in 2004-06 it was among the highest. In other words, a larger fraction of new immigrants enter low skilled occupations now than they did in the past. The influx of immigrants into Professional and Associate Profession occupations were among the highest in 1992-94, and though it remains high in recent years it is no longer the highest. These changes in structure are, at least in part, related to the expansion of the European Union to include many East European countries in 2004.

2.2. Wage movements across occupations

This section documents the changes in pay across occupations in recent years. Chart 7 shows how the occupational wages in selected occupations have evolved relative to the average wage across all occupations. Some occupations have rising relative wages, whereas others have seen falling relative wages. That relative wages have increased for some groups and decreased for others is a well documented fact in the literature on UK wage inequality (see for example Machin (2003)). Chart 7a shows that the relative wages of Health Professionals and Corporate Managers have risen over time. In contrast the relative wages of those in Sales and Customer Services have fallen a little in recent years (Chart 7b). Elementary Trades and Elementary Service workers, on the other hand, have experienced little change in their relative wage rates since 1992. So there has been some heterogeneity in relative wages across occupations.

Chart 7 - Wages in each occupation relative to the average wage

(a) Rising relative wages | **(b) Flat to falling relative wages**



To summarise, this section has documented some facts about how wages and immigration vary across different occupations. It finds that immigrants are most predominant in both high skilled and low skilled occupations and least predominant in middle skilled jobs but the differences are not large. And while the immigrant-native share has continued to increase in all occupations since the mid 90s, in recent years the rise has been greatest in low skilled occupations. Low skilled 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

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

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, *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} =price of regional output, P_t =aggregate price level, D_{rt} =regional demand index.

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).

The first order conditions are given by

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

i=1,..I. $p_{rt} = P_{rt} / P_t$, $w_{rt} = W_{irt} / P_t$ 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

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

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

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

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

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

$$n_{irt} = \alpha_{ir} + \alpha_{rt} + \alpha_{it} - \alpha_1 \ln w_{irt} - \alpha_2 s_{irt} + \nu^1_{irt} \qquad (5)$$

where $\alpha_3 \ln(p_{rt}(1-\frac{1}{\eta_{rt}})) + \alpha_4 \ln K_{rt} + \alpha_5 \ln A_{rt}$ are absorbed into α_{rt}. So the cross effects, output prices, capital, 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

$$n_{irt} = \gamma_{ir} + \gamma_{rt} + \gamma_{it} + \gamma_1 \ln w_{irt} - \gamma_2 u_{irt-1} + \gamma_3 s_{irt-1} + \gamma_4 X_{irt} + \nu^2_{irt} \qquad (6)$$

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 relative to 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). It is, of course, possible that high immigrant proportions are a disincentive to move to work in region r (γ_3 <0). Similarly, immigrant proportion in region r depends on the attractiveness of the region, thus

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

The structure is similar to the labour supply equation, (6), although β_3 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 $\left(\gamma_2 + \alpha_2\beta_2\right)/(\gamma_1 + \alpha_1 + \alpha_2\beta_1)$ and $-\left(\gamma_3 + \alpha_2\beta_3\right)/(\gamma_1 + \alpha_1 + \alpha_2\beta_1)$ 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}, ω_{it}. The impact of the lagged immigrant share on pay is negative if $\left(\gamma_3+\alpha_2\beta_3\right)$>0. γ_3 is positive if occupation/region labour supply is enhanced by the presence of existing immigrants 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 which 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 $\left(\gamma_2+\alpha_2\beta_2\right)$>0. γ_2, 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 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 where 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 we would not expect instantaneous adjustment because of adjustment costs of various kinds, 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) that we derived in the section above. To estimate these equations we use data for 11 UK Government Office Regions and 25 2-digit SOC 2000 occupations over 15 years (1992-2006), giving a panel data set with each observation referring to three dimensions: region, occupation and time. Based on this level of disaggregation our dataset has a potential maximum of 4125 (=15x11x25) observations.[2]

In section 2 we mentioned that the change in the classification of occupation 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 SOC1990 classification into the new SOC 2000 classification – that is by creating a consistent definition of occupations throughout our dataset.

For each observation relating to a particular region, occupation and year cell there is information about: the hourly pay rate, the unemployment rate, the immigrant-native

[2] 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.

ratio and age and education controls. The age controls include the average age of natives and the average age of immigrants in each region, occupation and year cell. And the skill level of the native population in each cell is measured by the share of the native population that have a degree, the share of the native population that are students and the shares of the native population that have incomplete and complete secondary school qualifications. These qualifications are derived according to the length of time individuals have spent in full-time education. 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*.[3]

Table 1 shows the mean and standard deviations for these key variables over all time periods, regions and occupations. Over our entire data set the average hourly wage is £9.47, the average unemployment rate is 5.2% and the average immigrant-native ratio is 10.2%. The average age of both immigrants and natives is around 39 years of age, though there is a great deal more variation in the age of immigrants. 16% of the native population have a degree, with 60% having completed school, 2.5% still in education and 21.2% who have incomplete schooling. The standard deviations capture the extent to which each variable varies across the region, occupation and year data set.

[3] For more information on this measure of skill see Saleheen and Shadforth (2006) or Manacorda, Manning and Wadsworth (2006).

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 normalisation being absorbed into the region/time dummies. So does the lagged immigrant-native ratio have any impact on wages? In Table 2, column1, 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 5 percentage points, the occupational wage falls by around 0.2 percent. This is a relatively small effect. Next, we investigate whether there is any difference between new immigrants (arrived in last two years) and old immigrants (the remainder). It is readily apparent from Table 2, column 2, that there is no difference whatever. Finally, we may note the positive impact of the unemployment rate as expected (see Section 3).

Turning to estimates of dynamic versions of equation 8, these are presented in Table 3. The overall picture remains unchanged. The impact of immigration on wages exhibits some persistence but the long-run coefficient is -0.033 (i.e. (-0.037+0.019)/(1-0.45)) which is similar to the corresponding coefficient in Table 2.

4.2. Occupational level specification

So while immigration appears to have a negative impact on occupations 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 twenty five two-digit occupations into five groups, managers; professionals; skilled production; semi/unskilled production; semi/unskilled services.[4]

Estimates from the static models reported in Table 4 suggest that the negative effects of immigration on wages are concentrated among managers, skilled production workers and semi/unskilled service workers. However, the fact that the lagged dependent variable coefficient in the former group exceeds unity suggests that the managers' effect is spurious. This leaves the skilled production sector and the semi/unskilled service sector as those areas of the economy where immigration has a serious negative impact on pay. In the latter case, the coefficient 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 5.2 percent reduction in pay.

5. 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, occupation and time. Occupations turn out to be a relatively important dimension. Once the occupational breakdown is incorporated into a regional analysis of

[4] Details may be found in the Data Appendix.

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 5 percent reduction in pay. This finding accords well with intuition and anecdotal evidence, but does not seem to have been recorded previously in the empirical literature.

Table 1

Means of Variables

	Mean	Standard deviation
Dependent variable		
w_{irt} (£'s)	9.48	4.08
ln w_{irt}	2.17	0.39
Independent variables		
immigrant/native ratio $_{irt}$	0.102	0.140
unemployment rate $_{irt}$	0.052	0.039
age controls		
mean immigrant age $_{irt}$ (years)	38.67	4.29
mean native age $_{irt}$ (years)	39.00	2.74
skill controls		
share of native population		
- with degree	0.166	0.204
- with completed school	0.600	0.144
- still in education	0.025	0.039
- with incomplete schooling	0.216	0.122

Table 2

The impact of Immigration on Wages, Static Model (Eq. 8)

	Dependent variable, ln wirt (1)	(2)
(immigrant/native ratio)$_{irt-1}$	-0.039	
	[2.04]	
(new immigrant/native ratio)$_{irt-1}$		-0.040
		[2.08]
(old immigrant/native ratio)$_{irt-1}$		-0.040
		[2.10]
(unemployment rate) $_{irt-1}$	0.096	0.096
	[2.42]	[2.42]
Sample size	3771	3771
$\overline{R}^2$	0.990	0.990

Notes:

(i) 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), region/year dummies, occupation/year dummies, region/occupation dummies.

(ii) Asymptotic t-ratios in parenthesis.

(iii) t = time (15 years, 1992-2006), i = occupation (25 two-digit occupations), r = region (11 Government Office Regions). Observations are missing because some of the cells have missing information.

Table 3

The impact of Immigration on Wages, Dynamic Model Eq.8)

	Dependent variable, ln wirt	
	(1)	(2)
ln w_{irt-1}	0.45	0.45
	[25.35]	[25.28]
(immigrant/native ratio)$_{irt-1}$	-0.037	
	[1.84]	
(immigrant/native ratio)$_{irt-2}$	0.019	
	[0.85]	
(new immigrant/native ratio)$_{irt-1}$		-0.037
		[1.87]
(new immigrant/native ratio)$_{irt-2}$		0.021
		[0.94]
(old immigrant/native ratio)$_{irt-1}$		-0.037
		[1.83]
(old immigrant/native ratio)$_{irt-2}$		0.017
		[0.78]
(unemployment rate) $_{irt-1}$	0.071	0.072
	[1.76]	[1.78]
(unemployment rate) $_{irt-2}$	-0.003	-0.003
	[0.08]	[0.06]
Sample size	3468	3468
$\overline{R}^2$	0.99	0.99

Notes:

(i) As in Table 2

(ii) With fifteen 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)

Table 4

Impact of Immigration on Wages: Occupational Groups

Dependent variable, ln wirt

	ln w_{irt-1}	t-ratio	immigrant/native ratio	t-ratio	Sample size	$\bar{R}^2$
Managers	-		-0.391	[2.43]	308	0.88
	1.02	[46.05]	0.036	[0.65]	308	0.99
Professionals	-		0.036	[0.96]	1336	0.83
	0.95	[87.28]	0.033	[2.31]	1330	0.98
Skilled Production	-		-0.238	[4.39]	594	0.74
	0.91	[50.64]	-0.054	[2.31]	588	0.95
Semi/unskilled production	-		0.076	[1.88]	308	0.95
	0.90	[34.44]	0.017	[0.96]	308	0.99
Semi/unskilled services	-		-0.521	[10.32]	769	0.90
	0.88	[50.47]	-0.070	[2.72]	769	0.98

Notes:

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

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

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Data Appendix

This paper uses data from a variety of sources to form a panel dataset that has three dimensions: time, region and occupation. In other words, for each year of the 15 years (1992-2006) of data that that we consider, there are observations for each of the 11 UK 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 data set will have a maximum of 4125 (=15x11x25) observations. If there is no observation for a given cell, then that data point is missing. A typical static regression has 3771 observations.

Region:

Standard Government Office Regions (GORs).

Occupation:

In our panel dataset occupations are classified according to SOC2000 throughout. An important data problem encountered was that the variables required were not available on the SOC2000 basis through time. 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 methodology to transform SOC1990 into SOC 2000.

Transforming SOC1990 to SOC2000

The Office of National Statistics (ONS) does not provide a match between SOC1990 and SOC2000. 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 SOC1990 and SOC2000 occupations, it is unlikely that all the people from a single category of SOC1990 will end up in the same single category of SOC2000. Instead individuals from one category of SOC 1990 are likely to end up in multiple categories of SOC2000.

To transform SOC 1990 to SOC 2000 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. LFS 2000Q4 survey coded occupations based on SOC1990 and the LFS 2001Q1 survey coded occupations based on SOC2000. 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.

This matrix of dual occupation codes allows us to map individuals from SOC1990 to SOC2000. The matrix relates to one point in time and so is time invariant. As the mapping is not 1:1 (the off diagonal cells are non-zero) a “proportional” mapping method is used. Proportional mapping is one in which a given proportion of individuals in SOC1990 are assigned to one category in SOC2000, with another proportion being assigned to another category in SOC2000 and so on. The proportions that need to be assigned to each category are determined from the elements of the matrix. For example assume that there are only two categories of SOC1990 and SOC2000. And that 70% of individuals in category 1 of SOC1990 fall into category 1 of SOC2000, and 30% fall into category 2. Then the proportions of SOC 1990 going to categories 1 and 2 will be 0.7 and 0.3. In the paper 3 digit SOC 1990 (371 categories) is mapped into 2-digit SOC2000 (25 categories)

The mapping of occupations allows any variable that is defined on the SOC1990 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 variable that are derived from ASHE/NES, the occupational codes change in 2002.

This transformation is successful for the majority of regions and occupations but less successful for a handful of cells. Success is determined if the transformed variable (i.e. wage rate, employment rate, immigrant-native ratio) does not jump up or down in the year in which the new occupational classification is introduced, i.e. the data break point (2001 for LFS source variables and 2002 for the ASHE/NES source variables). The discontinuity (or jump) is not noticeable for the vast majority of observations, but it is clearly an issue for some. To deal with this jump, whether big or small, the transformed data are spliced on to the data for the earlier years: crudely speaking this involves a level shift in the data after the data break point. The splicing takes place by taking the average growth rate of each variable in the three years before the break point and projecting this growth rate forward to link the data on either side of the break point. For consistency purposes, we do this for all cells and all variables excluding the average age of natives and immigrants. The default strategy in the paper is to report all results based on all the spliced variables and the non-spliced average age variables.

The reason for not splicing the average age variables is as follows. As will be noted below the average age refers to the average age of individuals aged between 16 and

65. But as the sample of immigrants is small, on a handful of occasions the act of splicing (and projecting forward past growth rates) resulted in average ages in certain regions and occupations that were larger than 65. Using the spliced average age variables thus seemed inappropriate.

In Table 4, results are presented on various groups of occupations. The two digit occupations we use are set out in Table A2. The groups used in Table 4 are Managers (11, 12), Professionals (21, 22, 23, 24, 31, 32, 35), Skilled Production (51, 52, 53, 54) Semiskilled/Unskilled Production (81, 82, 91) and Semiskilled/Unskilled Services (61, 62, 71, 72. 92).

Wages:

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 1992-2006 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.

Source: LFS 1992-2006 seasonal quarters.

Immigrant-native ratio

The number of foreign born individuals (or 'immigrants') aged 16-65 divided by the number of individuals aged 16-65 who are born in the UK ('natives). This ratio is constructed for each occupation and region cell.

Source: LFS 1992-2006 seasonal quarters.

New immigrant-native ratio:

'New' immigrants are defined as those immigrants (foreign born workers) who arrived in the UK 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 aged16-65 in that same occupation and region.

Source: LFS 1992-2006 seasonal quarters.

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.
Source: LFS 1992-2006 seasonal quarters.

Average Age:

The average age of natives and immigrants aged16-65 by region and occupation.
Source: LFS 1992-2006 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; 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 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 is 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 who are still in full-time education. As defined the sum of these four skill shares will sum to 1.
Source: LFS 1992-2006 seasonal quarters.

Table A2

Immigrant Proportions in Two Digit Occupations

	SOC2000	92-94	98-00	04-06
11	Corporate managers	0.090	0.096	0.111
12	Agriculure managers	0.119	0.125	0.149
21	Science professionals	0.089	0.111	0.146
22	Health professionals	0.285	0.345	0.462
23	Teaching & research	0.095	0.109	0.127
24	Business & public services	0.105	0.111	0.135
31	Science associates	0.071	0.084	0.151
32	Health associates	0.134	0.134	0.179
33	Protective services	0.061	0.048	0.051
34	Culture, media and sports	0.118	0.141	0.147
35	Business/public service associates	0.079	0.087	0.105
41	Administrative	0.071	0.081	0.094
42	Secretarial	0.075	0.088	0.117
51	Skilled agricultural trades	0.028	0.036	0.058
52	Skilled metal and electrical trades	0.056	0.054	0.064
53	Skilled construction trades	0.051	0.048	0.086
54	Textiles and printing trades	0.119	0.137	0.211
61	Caring and personal services	0.080	0.085	0.124
62	Leisure and personal services	0.073	0.087	0.121
71	Sales	0.065	0.076	0.105
72	Customer services	0.067	0.078	0.091
81	Process operatives	0.095	0.093	0.109
82	Transport operatives	0.067	0.070	0.113
91	Elementary trades	0.067	0.071	0.107
92	Elementary services	0.090	0.100	0.140