Are immigrants so stuck to the floor that the ceiling is irrelevant?

Priscillia Hunt

No 838

WARWICK ECONOMIC RESEARCH PAPERS

DEPARTMENT OF ECONOMICS

THE UNIVERSITY OF WARWICK

Are immigrants so stuck to the floor that the ceiling is irrelevant?

Priscillia Hunt[1 2]

February 2008

Abstract

In this paper, the immigrant-native wage differential is explained through quantile regression estimations. Using repeated cross-sections of the British Labour Force Survey from 1993-2005, we analyse the returns to covariates across the conditional earnings distribution. We estimate a pooled model with an immigrant dummy and separate models for immigrants and natives of the UK. Our results show that the positive wage gap in favour of immigrants is attributed to those at higher quantiles. Returns to education and experience vary wider for natives than for immigrants. We decompose the wage gap in the Blinder-Oaxaca framework and apply quantile regression techniques to see if immigrants simply have more viable labour market characteristics than natives or if there is a preference for immigrant workers (reverse discrimination). Our findings suggest immigrants should actually be earning more and there is sufficient evidence of discrimination. This finding is, however, not symmetric across the conditional wage distribution and immigrants at the bottom face more discrimination than those at the top.

Keywords: immigration, wage differential, quantile regression, Blinder-Oaxaca decomposition

JEL Classification: J31, J61, J71

[1]Address: Department of Economics, University of Warwick, Coventry CV4 7AL, UK. Email: priscillia.hunt@warwick.ac.uk

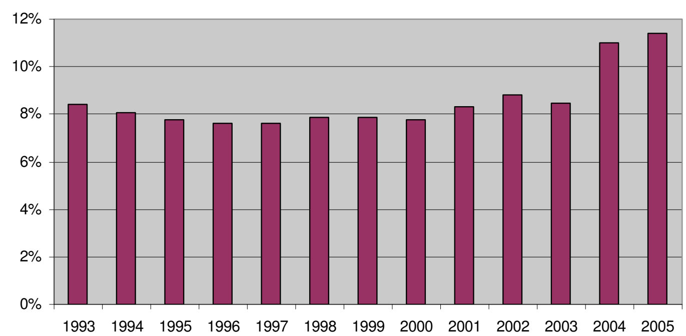
[2]I thank Ian Walker and Dr. Jennifer Smith for their supervision. I am grateful for coding assistance from Vincent O'Sullivan and Dr. Wiji AruIampalam. I would like to acknowledge financial support from the European Commission's Marie Curie Fellowships for EST.

1 Introduction

When immigrants enter a new country to settle and work, there is a period of integration in which the foreign-born must learn a new language, job opportunities, methods of transportation, banking system, laws, and cultural norms. The ability to assimilate into a new economy is important for the economic success of both the existing and next generation of workers. Until recently, immigration to the United Kingdom was of relatively little economic significance because Britain was primarily a region of net emigration (Hatton (2005)). In the last few decades, there has been greater in-migration and less out-migration, resulting in more concern about the state of Britain's labour market (Office of National Statistics 2005[3]).

The proportion of foreign-born workers in Britain remained roughly 8 percent in the early 1990's. As shown in Figure 1, there was a sharp increase to roughly 11 percent in 2004 and 2005. This substantial increase coincides with the EU enlargement of 2004[4], thus we might think the recent increase is mostly due to the heightened flow of Eastern European workers.

Figure 1: Proportion of NonUK-born in UK Labour Force, LFS 1993-2005



Looking at Table 1, we determine region of origin variation for the increased proportion of foreign-born. We see the increase is in fact effectively European in 2005 (+2.46%). There is also some growth, in proportion, from 2004 to 2005 for individuals from China/Hong Kong (+1.02%) and India (+1.89%). For 2004, the distribution for region of origin remained fairly similar to 2003, except we find a drop in workers from the Old Commonwealth & United States (-1.15%). Table 1 illustrates the proportion of immigrants in public- and private-sector employment, thus excluding the self-employed, and there may be origin differences that affect the wage profile for immigrants.

[3] http://www.statistics.gov.uk/cci/nugget.asp?id=1311

[4] Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia.

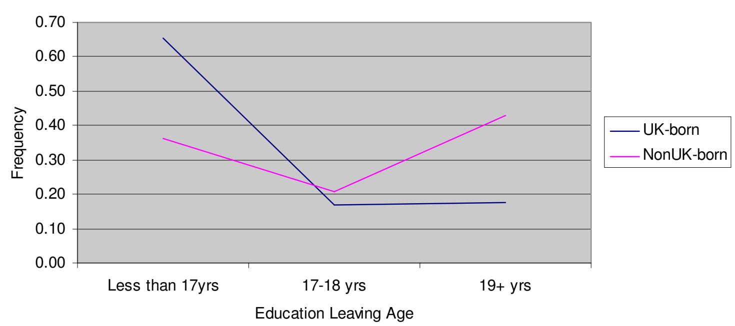
Table 1: Percentage of Employed Immigrants by Region of Origin from 1997-2005

	Ireland	Caribbean & West Indies	China/ HK	Europe	India	Pakistan/ Bang.	Old Common-wealth & US	Rest of the World
1997	13.85%	5.15%	1.42%	21.31%	8.88%	4.62%	12.26%	32.50%
1998	11.79%	5.83%	1.66%	20.11%	10.40%	5.69%	15.26%	29.26%
1999	11.65%	5.12%	1.09%	20.34%	10.25%	5.43%	15.37%	30.75%
2000	11.29%	4.01%	0.89%	19.02%	9.96%	4.61%	16.05%	34.18%
2001	9.02%	4.37%	1.89%	22.85%	8.73%	5.24%	16.16%	31.73%
2002	7.70%	3.65%	1.49%	20.41%	7.30%	5.00%	19.05%	35.41%
2003	8.16%	4.23%	1.96%	22.05%	9.37%	4.23%	18.13%	31.87%
2004	8.65%	4.56%	2.04%	22.01%	9.28%	4.25%	16.98%	32.23%
2005	5.45%	2.53%	3.06%	24.47%	11.17%	4.26%	16.36%	32.71%

Source: Author's LFS Sample, 1997-2005, Employed Men only

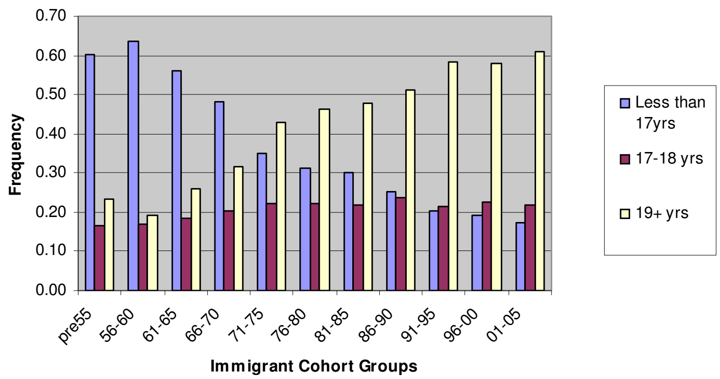
Success in the labour market is determined, in part, to the level of education obtained. Figure 2 shows the educational attainment of immigrant and native workers. It is clear from this illustration that the NonUK-born workers in Britain have relatively more education. Immigrants and natives have roughly the same proportions, 21% and 17% respectively, in the middle education group (leaving age of 17-18yrs). There are stark differences in the lower and higher education groups. 36.2% of immigrants are in the lowest education group (leaving age of 16 yrs or less) and 65.5% of natives are in this lowest education group. Nearly 18% of natives and 43% of immigrants are in the highest education group (leaving age of 19+ yrs). This polarisation of education for immigrants indicates negative and positive observed selection and a potential source of greater wage disparity for immigrants than natives. Since the rate of immigration is increasing, this polarisation will have an effect on overall wage equality.

Figure 2: Education Distribution for Employed Males of Britain, LFS 1993-2005



To observe any cohort trends, we graph the proportions of immigrants in each education category. We are interested to discover what, if any, educational attainment differences there are between immigrants over time. As can be seen in Figure 3, there has been a downward trend in the proportion of low-educated and an upward trend of highly-educated immigrant workers. The proportion of immigrants leaving school at 17 or 18 has been constant. It is beyond the scope of this paper to suggest why this occurred, however, it would be interesting to find what policies and/or economic relationships prompted this trend.

Figure 3: Density of Education leaving age for Immigrant cohorts in the LFS



The differences in observed characteristics and returns to those characteristics may differ across the income distribution for natives and immigrants. Martins and Pereira (2003) perform quantile regression analysis to evaluate conditional returns to education across the earnings distribution and it appears that higher-ability individuals, or those earning a higher hourly wage conditional on education and experience, gain more from education. This result was particularly strong for Britain where OLS estimates suggested a 0.083 premium on education, yet the difference between returns for those in the 10th and 90th percentiles of the earnings distribution are respectively, 0.045 and 0.092. With the findings of Manacorda, Manning, and Wadsworth (2006) in which immigrants depress the wages of other immigrants, we should find the wage gap for immigrants is smaller than for natives. Conversely, the unobserved skills of high-skilled immigrants may be greater than those for low-skilled in such a way that does not exist between low- and high-skilled natives. If we find smaller wage gaps for immigrants than for natives across their respective earnings distributions, then the impacts demonstrated by Manacorda et al (2006) are economically significant.

Our motivation for this research is to provide descriptive analysis of native and immigrant workers in the British labour force and identify sources of wage gaps between these two groups. The main question we want to address is what would immigrants earn if they were natives. We analyse earnings information and apply methods determining the magnitude and sources of an immigrant-native wage gap. The results allow us to discuss the implications of work and wage inequality in Britain.

The remainder of this paper is organised as follows. Section 2 surveys literature looking at sources of immigrant-native wage gaps in Britain and the US. Section 3 introduces our modelling and estimation strategy. Section 4 describes the data set and presents summary statistics. We display our results in Section 5 and the final section concludes with policy implications and areas for further research.

2 Literature

The theoretical framework for immigrant earning profiles was developed in Chiswick (1978, 1980), which argues immigrants cannot immediately compete with natives because they lack human capital exclusive to the destination. As time in the host country labour market progresses, outcomes of foreign-born workers assimilate towards their native counterparts. Chiswick (1980) finds 6 percent wage advantage for white immigrants and 19 percent lower earnings for nonwhite immigrants in the British General Household Survey of 1972. Chiswick's (1980) work revealed a severe pitfall to estimating wage differentials using cross-sectional data- immigrant cohorts changes over time and the 'snapshot' aspect of cross-sections misrepresents the earnings immigrants may expect. In this paper, we include cohort dummies and utilise a repeated cross-sectional data set in order to correctly estimate foreign-born earnings profile.

Since the work of Chiswick (1980), many authors (see the Home Office report (1999)) have investigated immigrant economic outcomes by ethnicity, race, cohort, and intent of entry to uncover what factors put these immigrants at a wage advantage or disadvantage. Bell (1997) examines data from the General Household Survey for the period 1973-1992 and finds UK immigration policy attracted higher-skilled immigrants, even though it did not consider socio-economic characteristics for entrance. White immigrants have an initial advantage over native whites, which eventually dissipates. He also finds ethnic minority immigrants have an initial wage disadvantage that slowly lessens, but does not disappear as they assimilate. Clark and Lindley (2006) examine the 1993-2002 Labour Force Survey and distinguish between education and labour market immigrants to find there is a great deal of variance in labour market success rates based on ethnic differences. There is some indication non-white immigrants have lower earnings due to unemployment rates upon entry (i.e. "scarring effect"). Using the same data set, Dustmann, Fabbri, Preston, and Wadsworth (2003) estimate wage equations for UK- and NonUK-born whites and nonwhites. They find the largest wage gap is between UK whites and nonwhites, whilst the wage differential between UK-born whites and nonwhite immigrants is relatively muted. This paper contributes to the literature by reporting the immigrant-native wage gap across the conditional earnings distribution.

Recent works suggest the immigrant-native wage gap is not due to any nativity differences in returns to characteristics (i.e. discrimination), but rather the wage structure changed over the last decade and this harmed some workers whilst helping others. Manacorda, Manning, and Wadsworth (2006) use the British General Household Survey (GHS) and British Labour Force Survey (LFS) to estimate a CES production function and assess changes to the wage structure. They find the rise in immigration has changed Britain's wage structure and depressed the earnings of immigrants relative to native-born. The wages of native-born workers relative to immigrants can vary over time even with fixed levels of demand and supply and authors indicate immigrants only affect the wages of other immigrants. Since Card and Lemieux (2001) conclude that the return to university education is sensitive to the relative supply of university graduates and because data indicates immigrants are better-educated than natives, immigration will have reduced the return to education. Through simulation techniques, Manacorda et al. (2006) determine imperfect substitutability and small immigrant sizes eliminated the immigrant effect on native wages. The Blinder-Oaxaca decomposition allows us to separate the differences in native and immigrant earnings due to differing characteristics and to discrimination (Blinder (1973); Oaxaca (1973)).

In Britain, Martins and Pereira (2003) find returns to education are greater for high-ability workers. They utilise the quantile regression technique to estimate parameters across the earnings distribution of a basic Mincer earnings equation. Butcher and DiNardo (1998) find returns to education increased in the United States and immigrants to the US possessed less education resulting in an increasing wage gap. This lead to the work of Chiswick, Le, and Miller (2006) who perform the first quantile analysis on the immigrant-native wage gaps for the US. This allows them to analyse returns to education across the conditional earnings distribution. They use the method proposed in Albrecht, Björklund, and Vroman (2003), which allows for quantile regression techniques to estimate Blinder-Oaxaca decompositions of wage gaps between two groups. The procedure involves random samples repeatedly drawn from the database and observations sorted into each percentile based on wages. This is then repeated to find average characteristics of individuals in each percentile and coefficients for the quantile of interest are determined. In Chiswick et al. (2006), differences in returns to skills between nativity groups (i.e. natives, English-speaking immigrants, and nonEnglish speaking immigrants) are observed across the quantiles. They find immigrants from nonEnglish-speaking countries experience higher earnings with increasing length of stay in the host country; English-speaking immigrants do not. Authors attribute this to the high degree of transferability of skills into the U.S. labour market for individuals from English-speaking countries. They also find the schooling payoff gap between natives and immigrants increases at higher percentiles of the earnings distribution. Chiswick et al. (2006) use a single cross-section (individuals in the 2001 Census data) and we use repeated cross-sections, which we anticipate will produce more robust results.

3 Empirical Strategy

3.1 Modelling

The competitive model framework assumes there are so many firms that no single firm has enough demand to affect wages. Profit-maximising firms set prices of labour (wage) equal to marginal productivity of labour, since any more or less reduces profits. Typical skills contributing to an individual's productivity are schooling and experience, however, levels of education and years of experience alone do not induce technological progress nor build customer relationships. Behavioural traits also contribute to the manufacture and sale of firm goods and services and influence the working environment. Thus, firms are willing to pay a premium for positive unobservable qualities as well. Green, Machin, and Wilkinson (1998) learn that British employers consider motivational, attitudinal, and social skills an important contributing factor to the 'skills shortage'. Moreover, these attributes have an ethnic dimension in which Bauder (2006) finds clear differences in work attitudes between national origin groups. Hence, observable and unobservable qualities are important factors to consider in the analysis of wage disparities between natives and immigrants. All models include standard variables for human capital (i.e. years of education, potential experience), industry and region dummies, and personal characteristics (i.e. Non-white, Married status, Non-English as first language).[5] The single model with a foreign dummy variable is the following:

$$wage = f(EXP, EDYRS, MIG, NONW, MARC, ENG, \\ INDUS, URESMC).$$

In order to develop a framework of comparison, we must understand what factors enter the wage integration process and make assumptions about how it all works. The basic conjecture is assimilation in Britain occurs over time (Dustmann et al (2003)). The more time workers spend in the host country, the more they adapt to their environment. Thus, we include a variable accounting for the number of years spent in the host country. We do not presume, however, the speed of adjustment is similar for all immigrants. An important consideration for integration in the UK labour market is country of origin. Due to historical ties, many countries are relatively similar, such as the Ireland and UK, and skills will easily transfer from home to host country. High degrees of skill transferability reduces assimilation time of the worker and improves overall earnings. Generally, immigrants can easily transport their skills if they move to a country that speaks the same language. We use national language to proxy for skill transferability since English-speaking immigrants will gather more information about job prospects and communicate their abilities more effectively to employers and customers. To estimate separate models for immigrants and natives, there are variables in the immigrant that clearly cannot be included for natives. The model for natives is as above and for immigrants includes covariates accounting for the assimilation process:

[5] See Appendix A for full details of variables in the model.

$$wage = f(EXP, FORx, EDYRS, UKed, NONW, MARC, ENG, INDUS, \\ URESMC, REGOB, AGEAIM, YRSSIN).$$

Lastly, we estimate a decomposition model established by Blinder-Oaxaca (Blinder (1973); Oaxaca (1973)). The Blinder-Oaxaca decomposition is a useful tool to estimate the nature of our immigrant-native wage gap . The basic idea is to break down the earnings gap between two groups as the difference in observable characteristics and difference in the benefits to those characteristics. Let k represent natives and m for immigrants and suppose the wage equation takes the form:

$$\ln w_i^k = \boldsymbol{\beta}^k \mathbf{x}_i^k + \varepsilon_i^n \tag{1}$$

where w_i^k are wages for a native individual i and $\mathbf{x}_i^k$ is a vector of observable characteristics for a native individual i, $\boldsymbol{\beta}^k$ denotes the vector of parameters to be estimated and ε_i^n is a normally distributed disturbance term with zero mean. In the same fashion, we will have for immigrants:

$$\ln w_i^m = \boldsymbol{\beta}^m \mathbf{x}_i^m + \varepsilon_i^m. \tag{2}$$

The difference of these two equations is:

$$\ln w_i^k - \ln w_i^m = (\boldsymbol{\beta}^k \mathbf{x}_i^k - \boldsymbol{\beta}^m \mathbf{x}_i^m) + (\varepsilon_i^k - \varepsilon_i^m). \tag{3}$$

We can calculate the difference between the *mean* wage logarithms for the two groups and add and subtract $\hat{\boldsymbol{\beta}}^k \bar{\mathbf{x}}^m$ to get:

$$\ln \bar{w}^m - \ln \bar{w}^k = \hat{\boldsymbol{\beta}}^k (\bar{\mathbf{x}}^m - \bar{\mathbf{x}}^k) + (\hat{\boldsymbol{\beta}}^m - \hat{\boldsymbol{\beta}}^k) \bar{\mathbf{x}}^m, \tag{4}$$

where $E(\varepsilon^k) = E(\varepsilon^m) = 0$. The first term of the decomposition, $\hat{\boldsymbol{\beta}}^k (\bar{\mathbf{x}}^k - \bar{\mathbf{x}}^m)$, indicates the "explained" component of wage differences between natives and immigrants or the part of the wage gap which can be attributed to differences in average observable characteristics of the individuals in each group. The second term, $(\hat{\boldsymbol{\beta}}^m - \hat{\boldsymbol{\beta}}^k) \bar{\mathbf{x}}^m$, can be interpreted as the "unexplained" component of the wage gap in which immigrants experience a difference in returns to characteristics due to mere association with the 'immigrant group'.

Clearly, we could add and subtract $\hat{\boldsymbol{\beta}}^m \bar{\mathbf{x}}^k$ instead, which is the crux of the standard 'index number' problem (see Oaxaca and Ransom (1999)). It is not a problem in the summation of the wage gaps, but we will find different estimates of the wage gap at each covariate when there are dummy covariates. We, therefore, perform estimations with natives as the reference group, then immigrants as the reference group, and lastly, as suggested in Cotton (1988), we assign population proportion weights. Results for natives as the reference group are presented in the body of the paper.[6]

[6] Other specifications are found in the Appendix.

3.1.1 Participation Selection

As with any wage equation, there is a danger of selectivity bias where only those who are working are included in the sample. Ideally, we would like to include the unemployed who are effectively choosing zero wages, but are left out of the model. There are no parental variables in the LFS and we were not able to find a suitable instrument. Thus, we conclude that there is potential upward bias in our parameter estimates should the participation effect be significant.

3.2 Estimation

3.2.1 Quantile Regression

In addition to standard OLS estimations, we take a further step to encapsulate any unobserved heterogeneity in the individual wage equations. Following Koenker and Bassett (1978) and Buchinsky (1998), we let (y_i, x_i), $i = 1, ..., N$, be the LFS random sample of the UK population. x_i is a $K \times 1$ vector of observable characteristics to individual i and y_i is the dependent variable, log real hourly wages. The conditional quantile of y_i, conditional on the vector of explanatory variables x_i, is $Quant_\theta(y_i|x_i) = \mathbf{x}_i^{\prime}\boldsymbol{\beta}_\theta$. We assume the conditional error term at each quantile is $Quant_\theta(u_{\theta i}|x_i) = 0$. Then, the model is simply

$$y_i = \mathbf{x}_i^{\prime}\boldsymbol{\beta}_\theta + e_{\theta i} \tag{5}$$

The estimation process is similar to OLS in that parameter estimates are derived through minimisation of the errors. OLS measures least distance for the sum of the squared errors, whilst QR measures least distance of weighted absolute values of the error. Generally speaking, the 'weights' are percentiles that can take on the various values for which the researcher is interested. For example, the weighted least absolute deviation estimator for the median regression is the result when $\theta = .5$. An advantage of the quantile regression approach is that outliers are not given extra weight of the OLS procedure, which squares the errors. We will see that this is particularly important in terms of the LFS sample, which has some extreme values reported for weekly wages and weekly hours worked.

Since quantile functions do not specify how variance changes are linked to the sample mean, it is not necessary to specify the parametric distributional form of the error. Although as we indicated above, the error term at each quantile is zero. Thus, the θ^{th} quantile regression estimator for β is defined as:

$$\min_\beta \left\{ \sum_{i:y \geq \mathbf{x}_i^{\prime}\boldsymbol{\beta}} \theta \ |y_i - \mathbf{x}_i^{\prime}\boldsymbol{\beta}| \quad + \sum_{i:y < \mathbf{x}_i^{\prime}\boldsymbol{\beta}} (1-\theta)|y_i - \mathbf{x}_i^{\prime}\boldsymbol{\beta}| \right\} \tag{6}$$

3.2.2 Blinder-Oaxaca QR Decomposition

The Blinder-Oaxaca framework was extended to the quantile regression technique in Albrecht et al. (2003), with formalisation of the technique in Machado and Mata (2005). The estimation procedure involves generating the UK-born log wage density that would arise if natives were given immigrant's labour market characteristics but continued to be "paid like natives" (i.e. $\hat{\boldsymbol{\beta}}^k \bar{\mathbf{x}}^m$). In order to estimate this marginal density, Machado and Mata (2005) indicate we first find which quantiles that should be estimated. Then, we estimate parameters in each of those quantiles for immigrants and natives separately. Next, we must randomly draw natives (with replacement) to determine the distribution of covariates and use this with the estimated coefficients in each quantile to determine the counterfactual density. There are several methods we can choose to perform this final step. The difference in approaches come down to whether to construct average characteristics in each quantile, $\bar{\mathbf{x}}_\theta^m$, (Machado and Mata (2005), Albrecht et al. (2003)) or average characteristics of the whole sample, $\bar{\mathbf{x}}^m$, (Montenegro (2001), Blaise (2005)). We follow Machado and Mata (2005), which entails using the distribution of immigrant characteristics to decompose the wage gap at quantiles of interest. In practice, this requires performing a bootstrap sample of size 100 and ordering each observation into percentile one, percentile two, and so forth. After 500 repetitions, we utilise covariate means at percentiles, or quantiles, of interest in the decompositions. Formally, the steps are the following:

1. Draw on the native data from the LFS to estimate the quantile regression coefficient vectors, $\hat{\beta}_\theta^k$, for $\theta = .10, .25, .50, .75, .90$.

2. Make 100 draws at random with replacement from the immigrant data from the LFS and sort by earnings.

3. Repeat 500 times to obtain $\bar{x}_\theta^m$ for $\theta = .10, .25, .50, .75, .90$

4. The counterfactual density is then generated as $\{\ln \hat{w}_\theta = \hat{\boldsymbol{\beta}}_\theta^k \bar{\mathbf{x}}_\theta^m\}$.

We follow Machado and Mata (2005) almost identically, except they suggest a first step should be to determine the quantiles, $\theta_j \epsilon [0, 1]$ for $j = 1, ...n$. We predetermine the quantiles of interest as 0.10, 0.25, 0.50, 0.75, and 0.90. We want to eliminate any possibilities of violating the assumption of monotonicity in the estimated conditional quantile functions and ensure enough variation across the subsamples. Koenker and Bassett (1982) argue the less dense are the set of $\theta' s$ in $[0, 1]$, the less likely we violate this presumption. It is also the case that the larger the sample size becomes, the less likely one violates monotonicity; however, the immigrant small size is arguably still small. Hence, we estimate at these five quantiles. The Blinder-Oaxaca decomposition for quantile regression becomes:

$$\ln \bar{w}_\theta^m - \ln \bar{w}_\theta^k = \hat{\boldsymbol{\beta}}_\theta^k (\bar{\mathbf{x}}_\theta^m - \bar{\mathbf{x}}_\theta^k) + (\hat{\boldsymbol{\beta}}_\theta^k - \hat{\boldsymbol{\beta}}_\theta^m) \bar{\mathbf{x}}_\theta^m.$$

4 Data

The British Labour Force Survey (LFS) is based on a systematic random sample design, which makes it representative of the entire UK. An LFS year is composed of four seasonal-quarters: Spring (March-May), Summer (June-August), Autumn (September-November), and Winter (December-February). Each quarter samples 125,000 individuals from approximately 60,000 households. Not all questions are posed to a household at once. The questions are posed over five successive quarters, which are called 'waves'. Therefore, in each quarter 12,000 households are in their wave 1, 12,000 are in wave 2, etc. The LFS is released quarterly and there are variables indicating the interviewee's wave, as well as the quarter and year the individual entered the survey. Quarters of the LFS were seasonal until January 2006; the survey was then switched to calendar-quarters in order to fulfil European Union regulations. The survey has been carried out annually in its current form since 1983[7]; however, earnings information is only available since 1992. The earnings question is asked in wave 5 from 1992 onwards and then also in wave 1 from 1997 onwards. For consistency, we use wave 5 wages whenever possible. We only use wave 1 earnings for those persons with positive wages in wave 1 and non-response in wave 5. When we inflate wages, we use the index corresponding to the year and quarter when the respondent gave their earnings details.[8] Wages are reported in terms of weekly earnings, so we derive hourly wages by dividing (gross) weekly earnings into weekly hours worked. To account for inflation and determine real wages, we use the UK Retail Price Index (RPI)[9]. We use 2005Q4 prices as the base period to inflate all prior earnings observations. We pool cross-sections of the LFS from 1993Q1 to 2005Q4. The data used for this estimation includes men aged 16-64 in full-time employment. Earnings are not reported for the self-employed.

4.1 Summary Statistics

In Table 3, we present a summary of statistics characterising the sample we use for wage analysis. The data is from 1993 to 2005 and descriptive statistics are aggregated data of individual level responses from the LFS data set. Results show that foreign-born workers earn more than UK-born, £14.51 and £12.85 respectively. Foreign-born workers are on average the same age as native workers, roughly 38 years old. Average age at immigration is 19 years old and average years in the UK is 20 years. There are significantly more non-whites in the immigrant population than in the native population. Less than 2% of working age, employed males born in the UK are non-white, whilst 39% of the immigrant workforce are non-white. The geographical dispersion of UK-born workers is much greater for natives than immigrants. The greatest regional concentration of UK-born working males is in the South East (21%), 2-9% concentration in the other regions of England, and 10% living in Scotland. Immigrants, on the other hand, are highly concentrated in London (33%) and the South East (23%). Roughly the same proportion of natives and immigrants are married or living together as a couple, 50% and 54% respectively.

[7] The LFS was carried out on a biennial basis from 1973 to 1983.

[8] We do not use the year and quarter in the survey because that relates to the period in which the respondent entered the survey.

[9] From the Office of National Statistics. http://www.statistics.gov.uk/StatBase/tsdataset.asp?vlnk=7173

Table 2: Summary Statistics

Variable	UK-born Mean	UK-born SD	NonUK-born Mean	NonUK-born SD
Dependent variable				
Log of gross real hourly pay	2.403	0.549	2.500	0.585
Independent variable				
Age	38.839	11.141	38.588	10.392
Race				
Non-white	0.012		0.389	
Region				
Tyne & Wear	0.020		0.008	
Rest of Northern Region	0.037		0.011	
South Yorkshire	0.023		0.011	
West Yorkshire	0.040		0.033	
Rest of Yorks & Humberside	0.031		0.015	
East Midlands	0.078		0.055	
East Anglia	0.040		0.038	
Inner/Outer London	0.080		0.328	
Rest of South East	0.214		0.230	
South West	0.090		0.067	
West Midlands (met county)	0.041		0.055	
West Midlands	0.055		0.029	
Greater Manchester	0.041		0.029	
Merseyside	0.018		0.007	
Rest of North West	0.042		0.020	
Wales	0.046		0.020	
Scotland	0.104		0.045	
Marital status				
Living as a couple (cohabiting)	0.503		0.538	
Foreign-specific variables				
Years since Immigrated			20.302	14.791
Age at Immigration			19.809	11.560
Education				
Years of education	12.327	2.598	14.467	3.762
(Leaving age groups)				
Less than 17yrs old	0.586		0.276	
17-18	0.193		0.223	
19 +	0.221		0.501	
Potential Experience				
Years of experience	21.511	11.834	19.099	11.515
(Experience groups)				
Less than or equal to 5yrs	0.095		0.117	
5-15 yrs	0.248		0.318	
16 +	0.657		0.564	
Industries				
Agriculture & Fishing	0.012		0.005	
Energy & Water	0.024		0.013	
Manufacturing (omitted)	0.013		0.010	
Construction	0.293		0.235	
Hotels, Restaurants & Distribution	0.128		0.142	
Transportation & Communication	0.085		0.054	
Banking, Finance & Insurance	0.143		0.192	
Public admin, Education & Health	0.163		0.204	
Other Services	0.138		0.145	
N	130,558		8,282	

Source: Author's LFS sample, 1993-2005. Employed males only.

Table 2 reports immigrants have relatively more workers leaving education at 19 years old or later (50%) than natives (22%). Conversely, natives are more concentrated (59%) in the lowest education group than natives (28%). Immigrants and natives have similar proportions, 19% and 22% respectively, in the middle education group of 17-18 years leaving age. Regarding years of experience, immigrants have less overall than natives. Nearly 66% of natives are in the highest experience group, whilst 56% of immigrants are within this category.

In Table 3, we present the distributions for the regions of birth[10] and countries of birth for immigrants in the UK for 1993-2005. The first column illustrates the proportion of immigrant males in the UK immigrant male population. The second column presents the proportion of immigrant males in the UK immi-

[10] As defined by the United Nations.

grant work force. By contrasting these two tables, we observe ethnic differences in employment and we find there are several significant ethnic differences. The top of the table demonstrates quite clearly that South Asian males are a significant proportion of the population (24%), but they are less prevalent in the labour force (17%). By disaggregating the immigrant population into areas of interest[11], we find the weak employment propensities for South Asian males are mostly due to Pakistanis and Bangladeshis. This confirms reports of high self-employment propensities and/or low participation rates for Pakistani and Bangladeshi males (Dustmann et al (2005)). The top part of the table illustrates lower proportions in the second (employed) column for Central American & Caribbean, Eastern Asia, Eastern Europe, Middle Africa, Northern Africa, South America, South Asia, Southern Europe, Western Asian, and Central Asia. It is beyond of the scope of this paper to suggest why this exists, however, one must consider these results do not include the self-employed or those outside legal employment.

Table 3: Region of Birth Distribution for UK Immigrants

Regions of the World	Percentage in population	Percentage employed*
Australia/New Zealand	3.41	5.66
Central America & Caribbean	4.03	3.87
Eastern Africa	9.29	10.13
Eastern Asia	3.87	2.93
Eastern Europe	2.21	1.89
Middle Africa	1.29	0.88
Northern Africa	1.96	1.65
Northern America	3.87	5.19
Northern Europe	13.76	14.8
South America	1.55	1.28
Southern Asia	24.42	16.84
South-eastern Asia	3.05	3.94
Southern Africa	3.28	4.97
Southern Europe	6.47	5.83
Western Africa	3.3	3.52
Western Asia	5.58	3.89
Western Europe	7.41	12.22
Central Asia	1.24	0.52
By specific countries		
Ireland	6.97	8.14
Caribbean&West Indies	3.32	3.46
China/HK	2.45	1.72
Europe	14.10	16.77
India	7.98	7.50
Pakistan/Bangladesh	9.00	3.77
Old Commonwealth & US	8.30	12.77
Rest of the World	47.87	45.87

Source: Author's LFS Sample, 1993-2005, Males only

*- Excluding self-employed

[11] From 1993-1996, the LFS limits responses for 'origin of birth' to- Ireland, Hong Kong, China, and Other.

5 Results

5.1 Pooled Regressions with Foreign Dummy

This model demonstrates the "return to being foreign", holding all else equal. Results are displayed in Table 9 in Appendix B. OLS regression estimates indicate a 0.042 premium to foreign status; however, it is clear from the QR estimates that these returns are not homogeneous across the conditional wage distribution. In the 10th percentile, coefficients are not statistically different from zero. In the 25th percentile, the coefficient on foreign status increases to 0.029, but is still not statistically significant. At the median, results become significant and the coefficient is +0.30 log point. This increases to 0.052 and 0.091 log points for the 75th and 90th percentiles, respectively. Therefore, we can say that relative to the low-ability immigrants, the high-ability immigrants encounter wage gains associated with being an immigrant. Put another way, workers of low-ability earn the same whether an immigrant or native. Higher ability workers earn more as an immigrant than a native.

We find the years of education and experience increase only slightly across the wage distribution. The coefficient on nonwhite varies considerably from the lowest to highest quantiles. The average effect appears to be a -0.144 log point decrease in wages, whereas the effect for those in the 10th percentile is -0.156 and in the 90th percentile it is less at -0.105 log points. We separate out the language effect from migrant status and find a decreasing negative effect across the conditional distribution. The impact of a different mother tongue than English is -0.16 log point reduction in wages for the least (10th percentile) able workers and approximately -0.12 for the most (50th, 75th, and 90th percentile) able workers. There is evidence, therefore, the highest ability workers are able to persevere through the language barrier somewhat, but not entirely. It has a real negative impact on the wage potential of even the most ambitious and loyal workers.

Lastly for this model specification, we discuss the average returns and returns across the quantiles in the industrial sector of choice. Results are reported in comparison to the omitted sector of Manufacturing. Not surprisingly, it appears that premiums in certain industries have results that are similar to quantile regression analysis of union-nonunion and private-public sector wages. Specifically, the evidence indicates returns in the Public administration/Education/Health industry fall across the conditional distribution. The coefficient for the average worker in this sector (compared to the average in Manufacturing) is -.007 log points. Earnings at the bottom of the distribution expand for being in this industry, whilst those beyond the median incur losses. In Banking/Finance/Insurance, wages increase across the quantiles. The average worker's premium for being in this industry, as opposed to Manufacturing, is 0.123 log points. For individuals in the bottom 10th percentile of conditional wages, the wage gain is only 0.022 log points. For those in the top 90th percentile, the wage gain for being in Finance, instead of Manufacturing, increases to a 0.216 log points return.

The second regression model includes an interaction term between foreign status and year dummies. We can see in Table 4 below (full results are in Table 10 of Appendix B), the immigrant effect becomes statistically insignificant with the inclusion of interaction terms. The interaction terms are the effect of being foreign in a particular year compared to being foreign in 1993. All are statistically insignificant and fail to show any pattern or trend for the signs. The positive effect of 'foreignness' we found in the first model (0.042 log points) remains the case here (0.073 log points), but becomes statistically insignificant.

Table 4: OLS & QR Results of Pooled Model, with Immigrant-Year interactions

	OLS	Quantile Regression				
Dependent variable: Log real hourly wage		.10	.25	.50	.75	.90
Immigrant dummy	0.073	0.015	0.047	0.058	0.042	0.007
	(1.17)	(0.19)	(0.50)	(1.71)	(0.52)	(0.05)
Foreign*1994	0.045	0.03	-0.041	0.004	0.155	0.299*
	(0.57)	(0.23)	(-0.33)	(0.07)	(1.94)	(1.99)
Foreign*1995	-0.095	-0.051	-0.038	-0.046	-0.149	0.022
	(-1.17)	(-0.55)	(-0.29)	(-0.64)	(-1.41)	(0.13)
Foreign*1996	0.001	0.033	0.061	0.024	0.001	0.065
	(0.01)	(0.28)	(0.62)	(0.42)	(0.01)	(0.52)
Foreign*1997	-0.073	-0.042	-0.058	-0.057	-0.049	0.035
	(-1.11)	(-0.51)	(-0.60)	(-1.24)	(-0.55)	(0.22)
Foreign*1998	-0.074	-0.045	-0.075	-0.089*	-0.024	0.057
	(-1.13)	(-0.49)	(-0.70)	(-2.13)	(-0.27)	(0.38)
Foreign*1999	-0.042	-0.015	-0.056	-0.04	0.008	0.079
	(-0.64)	(-0.17)	(-0.57)	(-1.22)	(0.10)	(0.53)
Foreign*2000	-0.072	-0.072	-0.021	-0.041	-0.013	0.047
	(-1.11)	(-0.75)	(-0.19)	(-1.03)	(-0.16)	(0.33)
Foreign*2001	0.046	0.051	0.039	0.059	0.09	0.241
	(0.69)	(0.67)	(0.37)	(1.47)	(1.12)	(1.80)
Foreign*2002	0.012	0.018	-0.005	0.033	0.076	0.153
	(0.18)	(0.25)	(-0.05)	(0.68)	(0.88)	(1.09)
Foreign*2003	-0.034	0.009	-0.005	-0.033	-0.007	0.086
	(-0.52)	(0.11)	(-0.05)	(-0.90)	(-0.08)	(0.62)
Foreign*2004	-0.073	-0.056	-0.076	-0.062	-0.031	0.069
	(-1.11)	(-0.66)	(-0.82)	(-1.64)	(-0.35)	(0.47)
Foreign*2005	-0.035	0.016	-0.028	-0.025	0.014	0.072
	(-0.54)	(0.19)	(-0.27)	(-0.51)	(0.16)	(0.51)
Observation	126,877					126,877
Pseudo R-squared	0.33	0.17	0.20	0.22	0.22	0.21

t statistics in parentheses. * significant at 5%; **

5.2 Regressions by Nativity

UK-born We examine the wage equation for immigrants to discover what, if any, changes we find across the conditional wage distribution and compare these results to OLS estimates (see Table 11). The OLS estimate indicate a 0.80 log point increase in returns for each additional year of schooling. Although, it appears those with higher unobservable skills earn greater returns and those with the least ability earn less than OLS estimates from education. Workers in the 10th percentile earn an additional 7.7 log percentage points, whilst those in the 90th percentile gain 8.4 log percentage points form each additional year of schooling. The results on experience suggest OLS estimates are fairly accurate, yet earnings do increase consistently across quantiles. OLS estimates demonstrate there is a 0.055 log point premium for each additional year of work experience. Quantile regression analysis indicate this is an accurate estimate for all workers since the difference between the 10th and 90th quantile is 0.009 log points The human capital variables appear to increase across the quantiles indicating higher returns to experience and education for high-ability workers.

OLS estimates indicate a 0.043 log point increase in each additional year of work experience. This ranges steadily from 0.031 log points for the bottom 10th percentile of workers to 0.055 for the top 10 percentile of workers. We find a 0.061 log point premium to each additional year of education.

The influence of personal characteristics on earnings varies only slightly across the conditional wage distribution. Holding all else equal, OLS estimates a -0.069 log point reduction in wages for nonwhites. This negative effect bounces around across the conditional distribution, ranging from estimates of -0.063 to -0.080 log points. The positive effect of the marriage/cohabiting variable decreases across the conditional earnings distribution. There is an average effect of 0.086 log point increase on real hourly wages, as determined through OLS. Quantile regression tells us this effect is actually more positive at the lower quantiles- 0.096 and 0.088 log points at the 10th and 25th quantiles, respectively and 0.79 log points at both the 75th and 90th quantiles.

The impact of working in particular industries, compared to manufacturing, is heterogenous across the conditional wage distribution. Construction yields greater returns for those with high unobservable skills, 0.075 log points at the 90th quantile. Estimates show returns are not significantly different from zero (i.e. 0.027, yet statistically insignificant) at the 10th quantile. Similarly, returns are consistently less and less negative across the distribution for workers in Distribution, Hotels & Restaurants. Workers in Banking, Finance & Insurance at the top of the distribution earn 0.211 log point premium, whilst those at the bottom earn 0.015 log point premium for working in Banking rather than Manufacturing. We find the most striking differences across the distribution to be in Public Administration, Education & Health. OLS estimates an average decrease in earnings as -0.011 log points in real hourly wages, compared with average Manufacturing wages. Rates of return are not significantly different from zero or positive below the 50th quantile. There is a strong depressive effect on wages for high ability individuals, -0.014 and -0.046 log points at the 75th and 90th quantiles.

Regarding the regions of inhabitancy in the UK, all estimates are in comparison to the South East. Only London yields a positive effect on hourly wages relative to the South East. Quantile regression analysis indicates the average positive effect from OLS, 0.073 log point, is an accurate estimate since coefficients across the quantiles range from 0.074 to 0.082.

NonUK-born Next, we examine the wage equation for immigrants to discover what, if any, changes we find across the conditional wage distribution and compare these results to OLS estimates (see Table 12). Firstly, the human capital variables appear to increase across the quantiles indicating higher returns to experience and education for high-ability workers. OLS estimates indicate a 0.043 log point increase in each additional year of work experience. This ranges steadily from 0.031 log points for the bottom 10th percentile of workers to 0.055 for the top 10 percentile of workers. We find a 0.061 log point premium to each additional year of education. Workers in the bottom quantile earn 0.048 for each additional school year, which is nearly identical to the findings of Martins and Pereira (2003) for the entire British labour force. Unlike their results, we find the highest ability workers do not earn such a premium from education (0.076 log points at the 90th percentile). These results appear to confirm the findings that immigrants compress the earnings of other immigrants, particularly at the top of the conditional earnings distribution. The dummy variables for foreign experience and UK education produce some interesting results. In particular, individuals with some education in a British institution have greater wages than those who do not, as else equal. Although the estimates are weakly significant, the greatest return to UK education is at the median (0.079 log points). This falls to roughly a 0.60 log points at the 25th, 75th, and 90th percentiles. Interestingly, for those in the 10th percentile, the return to UK education is far below the other quantiles (0.013 log points). Perhaps more intriguing is the finding that returns switch from negative to positive across the quantiles for the possession of foreign experience.

The influence of personal characteristics on immigrant earnings varies only slightly across the conditional wage distribution. OLS estimates a 0.192 reduction in wages for nonwhite immigrants relative to white immigrants, ceteris peribus. This negative effect diminishes across the conditional distribution, but does not dissipate entirely. The marriage/cohabiting variable is correctly estimated through the OLS regression technique for those in the 10th, 25th, and 75th percentiles (0.07 log points). It appears the highest ability workers do not earn a wage premium through marriage or cohabitation. OLS estimates a depressive effect, -0.098 log point, of immigrating from a nonEnglish-speaking versus an English-speaking country. The impact is actually greater for the lowest ability individuals, -0.114 at the 10th percentile, and lessens to -0.083 log points for the highest ability individuals.

We are interested in the impact of working in particular industries and regions because immigrants are more concentrated in certain sectors and areas of Britain than natives. Relative to manufacturing, OLS results indicate a premium to working in Energy & Water (0.161 log point) and Banking, Finance, & Insurance (0.196 log point) sectors. Quantile regression estimates break down the returns to these industries and we find dissimilar results between the two industries. Within the Energy & Water industry, the 10th, 25th, and 50th percentile workers earn more than those at the top of the conditional distribution. For those in Banking, Finance, & Insurance, we find increasing wages across the conditional wage distribution. This is not alike the results we would find for public-private sector or union-nonunion quantile estimates in which the protection of governments and unions increase the wages of the lowest-ability individuals and private firms reward high ability workers.

When we compare the results of the native and immigrant models, we find the returns to human capital (education and experience) variables to be quite similar. The effect of personal variables, such as nonwhite, are noticeably different between the two groups. Since we control for English-speaking region and many other characteristics, we are concerned that even the highest ability individuals experience wage depression for being nonwhite. See Table 13 for a comparison in OLS results of immigrants and natives.

5.3 Blinder-Oaxaca Decomposition

5.3.1 OLS

The pooled model and separate estimations make it clear there is a wage premium to immigrant status, yet differential returns to characteristics for immigrants and natives. We are still unclear about the source of wage advantage and disadvantages. We still need to illustrate whether the observed differential treatment of immigrants and natives in the workforce is due to labour market differences or discrimination. We utilise OLS and QR techniques to the break down of equation(4), otherwise known as the Blinder-Oaxaca decompositions.

In Table 5, we present OLS estimates of the decompositions, which consists of running regressions on each of the groups and then comparing results in the Blinder-Oaxaca framework. The table illustrates differences in labour market characteristics (E) and rewards to those characteristics (C+U). There is a fair bit of difference between the raw differential (10.8 log percentage points) and the adjusted differential (-7.7 log percentage points) because there is a sizable difference in endowments between native and immigrant workers. Put another way, the raw wage gap is 10.8 log percentage points, a gain to immigrants that seems to be largely made up of the shift parameter (46.4 log percentage points). When considering immigrants have 18.5 log percentage gain from greater endowments than natives, there are losses to being an immigrant. When removing the component of this wage gap due to labour market characteristics, the wage gap turns in favour of natives. It appears immigrants should earn more than they do and discrimination of immigrants is 71.1 log percentage points of the total raw differential in wages.

Table 5: Summary of Decomposition Results (as %), OLS Estimation

Amount attributable:	-35.6
- due to endowments (E):	18.5
- due to coefficients (C):	-54.0
Shift coefficient (U):	46.4
Raw differential (R) {E+C+U}:	10.8
Adjusted differential (D) {C+U}:	-7.7
Endowments as % total (E/R):	171.1
Discrimination as % total (D/R):	-71.1

U = unexplained portion of differential (difference between model constants)
D = portion due to discrimination (C+U)

The full results of the OLS Blinder-Oaxaca decompositions are in Table 14, which we examine more closely to discuss factors of the wage gap. Immigrant workers have higher constants reflected in the 46.4 log percentage points advantage in U (the shift coefficient). Immigrant workers have greater wages due to more education and less years of (quadratic) work experience. Since many more immigrants live in London, where wages are greater than in other parts of Britain, immigrants earn greater wages than natives. However, the size of the education and experience coefficients are such as to offset the wage gain from endowments, leaving immigrant workers with a net disadvantage (D) of -7.7%. We can see in Table 14 that the greatest source of this discrimination is in the years of experience in which natives earn a return of 0.055 log points for each additional year and immigrants earn 0.043. This results in 23.5 log percentage points greater returns to experience for natives. When considering how much more experience natives possess, 37.2 log percentage points of the wage gap is attributable to experience discrimination. natives. The second source of discrimination is in returns to education. Table 14 shows immigrants earn an additional 0.06 log points for an additional year of schooling, whilst natives earn 0.08 for an additional year. Hence, the return to education is 28.8 log percentage points greater for natives. Since immigrant attain more education, the wage gap due to discrimination in returns to education is 11.1 log percentage points of the attributable wage gap.

5.3.2 QR

When examining the two components ("explained and unexplained") of the immigrant-native wage gap, we find interesting differences across the conditional wage distribution (see Table 15 for full results in Appendix). Looking at the summary of decomposition results in Table 6, we learn the raw wage gap favours natives at the bottom and immigrants at the top of the conditional wage distribution. However, discrimination against immigrants does not completely die out at the top of the distribution. Further scrutiny of Table 6 shows it is primarily differences in endowment of labour market skills of natives and immigrants, which drives changes in the wage gap across the distribution. At the bottom of the wage distribution, immigrants earn approximately 15 log percentage points because of greater labour market characteristics (E). As for those at the top of the conditional distribution, over 20 log percentage points of the wage gap is due to greater allotment of skills. Next, we turn to the shift differential (U), which is the "unexplained" portion of the wage gap. It is simply the differences in constants, presented as a percentage, and may owe to not controlling for more elements or factors in the model of wages. The constant of the wage equation is much greater for immigrants and this difference falls across the distribution. At the 10th quantile, immigrants earn a 68.5 log percentage point gain in the constant of wages over natives in the same quantile. At the 90th percentile, the shift coefficient grants immigrants 20.7 log percentage points greater earnings.

Regarding the terms of discrimination, the adjusted differential (D) indicates that discrimination falls across the conditional distribution. The portion of wage gap due to rewards to characteristics is -21.1 log percentage points loss for being an immigrant at the 10th percentile. This actually increases (-24.5 log percentage points) for those in the 25th percentile and then decreases (-20.6) at the median and across the rest of the distribution (-11.4 and -7.3 at the 75th and 90th percentile, respectively).

Table 6: Summary of Decomposition Results (as %), QR Estimation with Immigrants as reference group

	0.10	0.25	0.50	0.75	0.90
Amount attributable:	-74.5	-61.9	-44.2	-16.2	-5.0
- due to endowments (E):	15.1	14.7	16.5	20.1	23.0
- due to coefficients (C):	-89.6	-76.6	-60.7	-36.3	-28.0
Shift coefficient (U):	68.5	52.1	40.1	24.9	20.7
Raw differential (R) {E+C+U}:	-6.0	-9.8	-4.1	8.7	15.7
Adjusted differential (D) {C+U}:	-21.1	-24.5	-20.6	-11.4	-7.3

U = unexplained portion of differential (difference between model
D = portion due to discrimination

positive number indicates advantage to immigrants, negative number indicates advantage to natives

Comparing these results with those above in the OLS decomposition, we find mean regression analysis covers up an important story. The OLS results show the raw differential is an immigrant gain of 10.8 log percentage points and a -7.7 log percentage point loss to immigrants due to discrimination. Quantile regression analysis shows a large part of the discrimination burden is on low-ability immigrants. The raw differential favouring immigrants is because of greater labour market skills and smaller differences in the shift coefficients of workers above the 50th percentiles.

The full quantile regression results of the decomposition indicate the differences in skills and returns to those skills vary across the quantiles (see Table 15 in Appendix). Firstly, the endowment of years of education variable increases along the distribution. This indicates the greater ability immigrants gain more education than greater ability natives. The differences in coefficients on this variable illustrates a preference for natives over immigrants in providing returns to education. Likewise with potential experience, immigrants earn less than natives, all else equal, and this discrimination reduces across the quantiles. Yet, immigrants possess less work experience across the distribution, unlike in education. This is primarily because those individuals stay longer in education.

We present summaries and full results of decompositions with natives as the reference groups (Table 16 and Table 17) and population weighted reference (Table 18 and Table 19).

5.4 Model Specification Testing

Determining the appropriate model is challenging because there is no definitive method for selecting the best set of regressors. There are certain criteria we can follow to enhance the level of objectivity. We have already determined statistical significance (F- and t-test) and evaluated the coefficient of determination. We would also like to choose the model that minimises the Akaike information criterion (AIC) because this measure takes into account a trade-off between minimising the sum of squared errors (SSE) and limiting any increase in the number of regressors (Burnham and Anderson (2004). In least squares estimation, the AIC formula is:

$$AIC_i = n_i \log\left(\hat{\sigma}_i^2\right) + 2K_i$$

where i indicates the model and $\hat{\sigma}_i^2 = \frac{SSE_i}{n_i}$. We have n is our number of observations for model i and K is the number of parameters, including intercept, in model i. This measurement for the goodness-of-fit is "best" at its lowest value.

Table 7 presents the AIC value for the four models for which we have OLS regression estimates. Although the native and immigrant models cannot tell us anything on their own, the native and immigrant models separately have lower AIC scores than the pooled models. This suggesting it is the "best" model(s) or way of modelling immigrant and native wages. We go on to compare the Model ID 1 and 4. These two are virtually identical with the Model 1 being minimally "better".

Table 7: Model Selection test

Model	Model ID number	SSE	Number of parameters	AIC
Pooled	1	26008.26	31	-87263.8
Native	2	24495.45	29	-83487.4
Immigrant	3	1423.01	42	-3876.8
Pooled with Interactions	4	25896.37	44	-87475.4

The benefit of using the Akaike criterion for model selection, as Koenker (2005) illustrates, is the natural extension for the AIC to quantile regression estimation:

$$AIC_i = \log\left(\hat{\sigma}_i\right) + K_i$$

where $\hat{\sigma}_i = n^{-1} \sum_{i=1}^{n} \rho_{1/2}(y_i - x_i^{\prime}\hat{\beta}_n(1/2))$, which is the minimum sum of deviations for the median regression. In Table 8, we present results for quantile estimations. We find the pooled model outperforms the pooled model with interactions. The fewer parameters in the native model suggests it is the "better" fit, however, it does not give us any indication of the marginal effects for immigrants. Therefore, along with other statistical tests, we find the pooled model to be the more accurate model.

Table 8: Model Selection test

Model	Model ID number	MSD	Number of parameters	AIC
Pooled	1	41700.46	31	30.5
Native	2	39384.63	29	28.5
Immigrant	3	2254.18	42	41.6
Pooled with Interactions	4	41610.05	44	58.2

6 Conclusion

Where a society deems it essential that the standard of living progresses for all its members, research into the achievements of different socio-economic groups is essential. Any disadvantages that arise due to discrimination hold back the integration of a particular group and make it appear as though they are incapable of economic assimilation. This can lead to undue social and political frustrations.

In the UK, immigrants have very polarised levels of education and yet, we do not observe great disparity in wages of immigrants that we do for natives. Card and Lemieux (2002) find that for the highly-educated, returns to education is sensitive to the supply of university graduates. Since immigration only affects other immigrants (Manacorda et al. (2006)) and there are relatively more immigrants graduating from university than natives, we would expect greater depression on the wages of highly-educated immigrants than for natives. This may explain the minimal wage variation we observe for immigrants compared to natives. However, Martins and Pereira (2005) find that high-ability workers gain more from education than low-ability workers. Where high-skilled workers are more likely to gain further education (Harmon and Walker (1998)) and immigrants have relatively higher unobserved qualities, it is ambiguous if and to what extent there are earnings disadvantages for immigrants.

Quantile regression results indicate the higher-ability individuals, or those earning a higher hourly wage conditional on all variables, gain even more from being an immigrant. In other words, immigrants are able to turn their unobserved qualities into wage growth. Those at the bottom of the conditional distribution do not earn any more than natives. Further, we find returns to education are far more sensitive across the immigrant than native conditional earnings distribution. This may be due to the transferability of skills. Employers are not familiar with foreign education systems and do not trust or value foreign education the same as UK education.

Decomposition of immigrant and native earnings shows us the difference in wages favouring immigrants is due to greater endowment of labour market characteristics. In fact, our results show that immigrants should be earning more than they do. OLS results indicate immigrants earn 10.8 log percentage points more than natives because of their characteristics. For simply being a part of the 'immigrant group', however, there is a -7.7 log percentage point loss in wages. Much of the discrimination burden is on low-ability immigrants and increases towards zero across the conditional distribution. Below the median, discrimination reduces wages by about 22 log percentage points; whereas above the median, there is about 10 log percentage point decrease in wages due to discrimination. The difference in endowments of labour market characteristics expands across the quantiles.

This raises some interesting questions as to which immigrants face "more" discrimination. Results show low-skilled immigrants achieve lower wages than comparable natives. Then comparing high-skilled immigrants to their counterparts, we find the wage gap is smaller than for the low-skilled. However, high-skilled immigrants have more labour market skills than their native counterparts. They are, in effect, investing a great deal in their education to overcome discriminatory elements of the labour market. On the other hand, given the amount of work necessary to overcome discrimination, it is inefficient for the low-skilled workers to try. The barriers to wage growth are highly reinforced, such that the "weakest" immigrants succumb to its weight.

7 References

Albrecht, James, Anders Björklund, and Susan Vroman (2003). "Is There a Glass Ceiling In Sweden?" *Journal of Labor Economics*, 21, pp. 145-77.

Bauder, Harald (2006). "Origin, employment status and attitudes towards work: Immigrants in Vancouver, Canada", *Work Employment Society*, 20, pp. 709-29.

Blaise, Melly (2005). "Decomposition of differences in distribution using quantile regression," *Labour Economics*, 12(4), pp. 577-590.

Blinder, Alan (1973). "Wage Discrimination: Reduced Form and Structural Estimates", *The Journal of Human Resources*, 7(4), pp. 436-55.

Borjas, George (1987). "Self-Selection and the Earnings of Immigrants," *American Economic Review*, 77(4), pp. 531-53.

Burnham, Kenneth P. and David R. Anderson (2004). "Multimodel Inference: Understanding AIC and BIC in Model Selection", Sociological Methods & Research, 33(2), pp. 261-304.

Butcher, Kristin F. and John DiNardo. "The Immigrant And Native-Born Wage Distributions: Evidence From United States Censuses," *International Labor Relations Review*, 56, pp. 97-121.

Chiswick, Barry (1978). "The Effect of Americanization on the Earnings of Foreign-born Men", *Journal of Political Economy*, 86(5), pp. 897-921.

Chiswick, Barry (1980). "The Earnings of White and Coloured Male Immigrants in Britain," *Economica*, 47(185), pp. 81-87.

Chiswick, Barry and M.E Hurst (1999). "The employment, unemployment and unemployment compensation benefits of immigrants", Research in Employment Policy, Vol. 2.

Chiswick, Barry, Anh Le, and Paul Miller (2006). "How Immigrants Fare Across the Earnings Distribution: International Analyses", Institute for the Study of Labor, IZA Discussion Paper No. 2405.

Clark, Ken and Joanne Lindley (2006). "Immigrant Labour Market Assimilation and Arrival Effects: Evidence from the UK Labour Force Survey," IZA Discussion Papers 2228, Institute for the Study of Labor (IZA).

Cotton, C. (1988). "On the Decomposition of Wage Differentials", *Review of Economics and Statistics*, 70, pp 236-43.

Denny, K., Harmon, C., Roche, M. (1997). "The Distribution of Discrimination in Immigrant Earnings: Evidence from Britain 1974-93", IFS Working Paper no. W98/3.

Dustmann, Christian, Francesca Fabbri, Ian Preston, and Jonathan Wadsworth (2003). "Labour market performance of immigrants in the UK labour market", Home Office Online Report 05/03.

Glover, Stephen, Ceri Gott , Anaïs Loizillon, Jonathan Portes, Richard Price, Sarah Spencer, Vasanthi Srinivasan and Carole Willis (2001). "Migration: an economic and social analysis", Home Office, RDS Occasional Paper No. 67.

Green, Francis, Stephen Machin, and David Wilkinson (1998). “The Meaning and Determinants of Skill Shortages", *Oxford Bulletin of Economics and Statistics,* 60(2), pp. 165–88.

Harmon, C. and Ian Walker (1995). "Estimates of the economic return to schooling for the United Kingdom", *American Economic Review*, 85, pp.1278-86.

Koenker, Roger (2005). Quantile Regression, Cambridge University Press.

Lee, Sokbae (2007). "Endogeneity in quantile regression models: A control function approach", *Journal of Econometrics*, 141, pp. 1131-58.

Machado, José A. F. and José Mata (2000). "Counterfactual decomposition of changes in wage distributions using quantile regression", *Journal of Applied Econometrics* 20(4), pp. 445-65.

Machado, José A. F. and José Mata (2001). "Earning functions in Portugal: evidence from quantile regressions", *Empirical Economics*, 26(1), pp. 115–134.

Oaxaca, Ronald (1973). “Male-Female Wage Differentials in Urban Labor Market", *International Economic Review*,14(3), pp. 693-709.

Oaxaca, Ronald and Michael Ransom (1999). "Identification in Detailed Wage Decompositions", *The Review of Economics and Statistics*, 81(1), pp. 154-57.

Ottaviano, G. and Peri, G. (2005). “Rethinking the Gains From Immigration: Theory and Evidence from The U.S.", NBER Working Paper No. 11672.

Wooldridge, Jeffrey (2002). Econometric Analysis of Cross Section and Panel Data, MIT Press.

8 Appendix A

LOG REAL HOURLY WAGE- The LFS does not ask income questions to the self-employed. LFS asks all persons 16-69, and those over 70 whom are employed. ‘Gross weekly pay in main job’ (GRSSWK) is asked each quarter, but only to individuals in their 5th wave. From 1997 onwards, the question was asked in the 1st wave as well. For those answering both, we checked for any significant disparities or changes from the 1st to 5th wave; there were none. If GRSSWK is greater than £3,500, or GRSSWK is greater than £1,000 and the respondent is a manual worker, then the LFS does not give an income weight. Non-response to this question is also be zero-weighted. LFS Users Guide indicates standard filters used to calculate average gross weekly earnings are GRSSWK>0. To generate hourly pay, we also filter on ‘usual hours excluding overtime’, USUHR>0. To produce real wages, we use the U.K Retail Price Index to inflate wages based on 2005Q4 prices. We then generate logarithm of the gross real hourly wage.

AGEAIM (Age at immigration)- All individuals report their year of birth (DOBY) and the foreign-born report the year of arrival (CAMEYR) into the UK. We subtract DOBY from CAMEYR to derive AGEAIM. For the native-born, this variable takes on a value of zero.

EDYRS (Years of education)- is equal to the reported education leaving age (EDAGE) minus 5 (to account for the age of starting school).

ENG (Native English-speaker)- is a dummy variable taking a value of 1 if the respondent reports a "typical" English-speaking country of origin. These countries are: England, Wales, Scotland, Ireland, United States, Canada, Australia, New Zealand, South Africa, and any of the Caribbean islands.

EXP (Potential work experience)- is potential labour market experience derived from the respondents' age (AGE) minus leaving age from education (EDAGE) for individuals who responded to EDAGE. If an individual answered (s)he 'never had any education', we use age minus 15. This is because there is a legal working age and leaving age from education.

FTPT (Full-time, Part-time)- We construct this dummy variable from reported usual hours in a week excluding overtime (USUHR). The variable takes a value of 1 if the respondent works less than 30 hours, and a value of zero otherwise.

HEAL(Health status)- is a dummy taking a value of 1 if the respondent answers 'yes' to the question of any health problems lasting more than one year (HEALYR), 0 if answers 'no'.

INDUS (Industries)- is only reported by respondents in employment and not tied to company sponsored college. There are ten categories: (1) Agriculture and fishing, (2) Energy and water, (3) Manufacturing, (4) Construction, (5) Distribution, hotels, and restaurants, (6) Transport and communication, (7) Banking, finance, and insurance, (8) Public administration, education, and health, (9) Other services.

MARC (Married, Cohabiting)- we use the variable 'marital status', MARSTT, and 'living together as a couple', LIVTOG. We move all the responses of 'does not apply' or 'no answer' to missing. Our variable takes a value of 1 if the response is 'married, living with husband or wife' or a 'yes' response to LIVTOG, and 0 otherwise.

NONW (Nonwhite)- There are several ethnicity variables over time (ETH01, ETHCEN15, ETHCEN6), which we recoded for consistency: (1) White, (2) Mixed, (3) Asian or Asian British, (4) Black or Black British, (5) Chinese, (6) Other. We then give a value of 0 to responses of white and 1 otherwise.

REGOB (Region of Birth)- There are several country of origin variables over time (CRY, CRY01, CRYOX, CRYO), which we recoded for consistency. Many country cells had small numbers of respondents, thus we grouped the countries into major regions: (1) Ireland, (2) Caribbean & West Indies, (3) China/HK, (4) Europe, (5) India, (6) Pakistan/Bangladesh, (7) Old Commonwealth & US, (8) Rest of the World.

URESMC (Region of inhabitance)- We create dummies to the response of 'region of usual residence', URESMC. We create one response of inner and outer London, as well as Strathclyde and Rest of Scotland. We drop Northern Ireland.

YRSSIN (Years since immigrated)- We subtract the reported year of arrival (CAMEYR) into the UK from the survey year. For the native-born, this variable is the derived variable (AGE) that comes from subtracting the survey year from the year of birth (DOBY).

FORx (Potential overseas work experience)- if age at immigration (AGEAIM) is greater than leaving age of education (EDAGE), then the respondent has some potential work experience before entering the UK and this variable takes a value of 1.

UKed (UK education)- if the leaving age of education (EDAGE) is greater than the age at immigration (AGEAIM), then the respondent was in the UK education system and this variable takes a value of 1.

9 Appendix B

9.1 Tables

Table 9: OLS & Quantile Regression Results for Pooled Model

	OLS	Quantiles				
Dependent variable: Log real hourly wage		0.10	0.25	0.50	0.75	0.90
Constant	0.914**	0.539**	0.704**	0.884**	1.095**	1.288**
	(97.65)	(27.73)	(64.98)	(73.43)	(90.34)	(80.64)
Potential Experience	0.055**	0.049**	0.052**	0.055**	0.058**	0.059**
	(128.43)	(84.88)	(109.79)	(110.18)	(163.76)	(68.97)
Potential Experience^2	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-108.96)	(-79.74)	(-92.05)	(-96.74)	(-118.42)	(-52.96)
Years of Education	0.079**	0.074**	0.078**	0.08**	0.081**	0.084**
	(142.24)	(77.71)	(124.60)	(112.14)	(89.19)	(68.06)
Nonwhite	-0.144**	-0.156**	-0.158**	-0.137**	-0.109**	-0.105**
	(-16.52)	(-9.14)	(-13.70)	(-12.02)	(-9.86)	(-8.71)
Married & cohab	0.084**	0.094**	0.088**	0.083**	0.077**	0.078**
	(29.77)	(19.05)	(23.11)	(32.80)	(31.78)	(16.71)
NonEnglish Mother tongue	-0.131**	-0.16**	-0.141**	-0.122**	-0.117**	-0.122**
	(-10.37)	(-8.03)	(-8.00)	(-7.62)	(-6.89)	(-4.67)
Immigrant dummy	**0.042****	**0.001**	**0.029**	**0.030****	**0.052****	**0.091****
	(4.11)	**(0.10)**	**(1.55)**	**(3.08)**	**(3.35)**	**(4.93)**
Industries (omit Construction)						
Agriculture & Fishing	-0.336**	-0.301**	-0.322**	-0.331**	-0.332**	-0.326**
	(-27.71)	(-21.21)	(-36.52)	(-23.88)	(-19.68)	(-21.36)
Energy & Water	0.158**	0.181**	0.156**	0.141**	0.163**	0.161**
	(18.40)	(14.00)	(16.95)	(19.11)	(22.95)	(14.19)
Manufacturing	0.045**	0.026	0.041**	0.024	0.053**	0.074**
	(3.98)	(1.17)	(2.79)	(1.91)	(4.31)	(4.70)
Distribution, Hotels & Restaurants	-0.193**	-0.223**	-0.214**	-0.203**	-0.173**	-0.131**
	(-44.77)	(-33.81)	(-54.10)	(-45.87)	(-33.18)	(-15.13)
Transport & Communication	-0.014**	-0.003	-0.01*	-0.018**	-0.012*	0.01
	(-2.87)	(-0.35)	(-2.27)	(-4.43)	(-2.53)	(1.11)
Banking, Finance & Insurance etc	0.123**	0.022**	0.08**	0.118**	0.167**	0.216**
	(28.86)	(2.79)	(-14.42)	(23.87)	(31.67)	(34.56)
Public admin, Educ & Health	-0.007**	0.008	0.023**	0.007*	-0.012**	-0.045**
	(-1.61)	(-1.41)	(5.42)	(2.43)	(-3.61)	(-7.89)
Other Services	-0.094**	-0.104**	-0.106**	-0.103**	-0.087**	-0.065**
	(-22.53)	(-17.86)	(-23.61)	(-21.93)	(-22.49)	(-10.83)
Regions (omit South East)						
Tyne & Wear	-0.175**	-0.14**	-0.156**	-0.166**	-0.185**	-0.202**
	(-18.32)	(-8.38)	(-17.79)	(-18.47)	(-18.72)	(-12.36)
Rest of Northern Region	-0.159**	-0.148**	-0.156**	-0.148**	-0.156**	-0.173**
	(-21.92)	(-11.30)	(-17.01)	(-22.57)	(-19.37)	(-14.05)
South Yorkshire	-0.184**	-0.158**	-0.147**	-0.163**	-0.188**	-0.234**
	(-20.59)	(-10.00)	(-12.52)	(-19.53)	(-19.71)	(-19.23)
West Yorkshire	-0.158**	-0.109**	-0.134**	-0.155**	-0.174**	-0.192**
	(-22.62)	(-13.66)	(-19.50)	(-18.94)	(-23.29)	(-16.38)
Rest of Yorkshire & Humberside	-0.175**	-0.173**	-0.161**	-0.16**	-0.172**	-0.185**
	(-22.26)	(-17.16)	(-17.95)	(-17.88)	(-27.78)	(-17.35)
East Midlands	-0.145**	-0.095**	-0.124**	-0.143**	-0.155**	-0.168**
	(-27.07)	(-12.38)	(-16.25)	(-22.78)	(-22.62)	(-15.64)
East Anglia	-0.13**	-0.087**	-0.108**	-0.126**	-0.144**	-0.155**
	(-18.69)	(-7.23)	(-19.45)	(-19.25)	(-19.89)	(-14.88)
Inner & Outer London	0.07**	0.077**	0.072**	0.075**	0.073**	0.078**
	(13.52)	(8.44)	(14.09)	(11.50)	(10.50)	(10.45)
South West	-0.149**	-0.123**	-0.131**	-0.14**	-0.161**	-0.172**
	(-29.35)	(-17.36)	(-20.05)	(-22.01)	(-24.92)	(-26.32)
West Midlands (Metro)	-0.146**	-0.107**	-0.115**	-0.139**	-0.166**	-0.184**
	(-21.42)	(-11.16)	(-12.02)	(-20.09)	(-23.33)	(-22.17)
Rest of West Midlands	-0.149**	-0.101**	-0.132**	-0.15**	-0.167**	-0.196**
	(-24.20)	(-18.77)	(-22.02)	(-20.81)	(-22.94)	(-19.45)
Greater Manchester	-0.144**	-0.119**	-0.124**	-0.139**	-0.15**	-0.184**
	(-20.73)	(-11.28)	(-14.30)	(-18.94)	(-17.53)	(-14.72)
Merseyside	-0.169**	-0.125**	-0.132**	-0.156**	-0.183**	-0.206**
	(-16.84)	(-6.89)*	(-14.77)	(-16.55)	(-20.22)	(-21.91)
Rest of North West	-0.141**	-0.127**	-0.127**	-0.119**	-0.138**	-0.15**
	(-20.67)	(-15.87)	(-21.75)	(-20.78)	(-16.22)	(-18.14)
Wales	-0.198**	-0.173**	-0.182**	-0.194**	-0.2**	-0.214**
	(-29.98)	(-14.85)	(-25.58)	(-23.00)	(-24.41)	(-18.82)
Strathclyde & Rest of Scotland	-0.147**	-0.123**	-0.135**	-0.146**	-0.153**	-0.163**
	(-30.25)	(-19.51)	(-25.93)	(-28.26)	(-19.81)	(-14.01)
Observations	126,877					126,877
R-squared	0.33	0.17	0.20	0.22	0.22	0.21

Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%

Table 10: Full OLS & Quantile Regression Results for Pooled Model, with Immigrant-Year interactions

	OLS	Quantile Regression				
Dependent variable: Log real hourly wage		.10	.25	.50	.75	.90
Constant	0.109**	-0.379**	-0.027**	0.195**	0.381**	0.515**
	(2.89)	(-5.41)	(-0.59)	(3.94)	(9.89)	(7.40)
Year trend	0.008**	0.01**	0.008**	0.007**	0.007**	0.008**
	(21.92)	(13.67)	(15.54)	(13.20)	(16.61)	(11.14)
Personal variables						
Potential Experience	0.055**	0.049**	0.052**	0.055**	0.058**	0.059**
	(129.02)	(73.09)	(102.49)	(117.37)	(143.60)	(78.26)
Potential Experience^2	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-109.76)	(-60.58)	(-83.49)	(-87.23)	(-113.71)	(-61.10)
Years of Education	0.077**	0.073**	0.077**	0.079**	0.08**	0.082**
	(139.96)	(100.18)	(121.72)	(111.13)	(102.87)	(86.19)
Nonwhite	-0.149**	-0.162**	-0.164**	-0.14**	-0.114**	-0.112**
	(-17.16)	(-10.25)	(-18.68)	(-16.46)	(-12.55)	(-8.07)
Married & cohab	0.078**	0.088**	0.085**	0.077**	0.070**	0.073**
	(27.20)	(21.57)	(29.82)	(22.32)	(20.52)	(17.59)
NonEnglish Mother tongue	-0.133**	-0.185**	-0.139**	-0.13**	-0.122**	-0.133**
	(-10.30)	(-7.38)	(-7.76)	(-12.23)	(-5.73)	(-7.27)
Foreign variables (omitted 1993)						
Immigrant dummy	0.073	0.015	0.047	0.058	0.042	0.007
	(1.17)	(0.19)	(0.50)	(1.71)	(0.52)	(0.05)
Foreign*1994	0.045	0.03	-0.041	0.004	0.155	0.299*
	(0.57)	(0.23)	(-0.33)	(0.07)	(1.94)	(1.99)
Foreign*1995	-0.095	-0.051	-0.038	-0.046	-0.149	0.022
	(-1.17)	(-0.55)	(-0.29)	(-0.64)	(-1.41)	(0.13)
Foreign*1996	0.001	0.033	0.061	0.024	0.001	0.065
	(0.01)	(0.28)	(0.62)	(0.42)	(0.01)	(0.52)
Foreign*1997	-0.073	-0.042	-0.058	-0.057	-0.049	0.035
	(-1.11)	(-0.51)	(-0.60)	(-1.24)	(-0.55)	(0.22)
Foreign*1998	-0.074	-0.045	-0.075	-0.089*	-0.024	0.057
	(-1.13)	(-0.49)	(-0.70)	(-2.13)	(-0.27)	(0.38)
Foreign*1999	-0.042	-0.015	-0.056	-0.04	0.008	0.079
	(-0.64)	(-0.17)	(-0.57)	(-1.22)	(0.10)	(0.53)
Foreign*2000	-0.072	-0.072	-0.021	-0.041	-0.013	0.047
	(-1.11)	(-0.75)	(-0.19)	(-1.03)	(-0.16)	(0.33)
Foreign*2001	0.046	0.051	0.039	0.059	0.09	0.241
	(0.69)	(0.67)	(0.37)	(1.47)	(1.12)	(1.80)
Foreign*2002	0.012	0.018	-0.005	0.033	0.076	0.153
	(0.18)	(0.25)	(-0.05)	(0.68)	(0.88)	(1.09)
Foreign*2003	-0.034	0.009	-0.005	-0.033	-0.007	0.086
	(-0.52)	(0.11)	(-0.05)	(-0.90)	(-0.08)	(0.62)
Foreign*2004	-0.073	-0.056	-0.076	-0.062	-0.031	0.069
	(-1.11)	(-0.66)	(-0.82)	(-1.64)	(-0.35)	(0.47)
Foreign*2005	-0.035	0.016	-0.028	-0.025	0.014	0.072
	(-0.54)	(0.19)	(-0.27)	(-0.51)	(0.16)	(0.51)
Industry variables (omitted Construction)						
Agriculture & Fishing	-0.335**	-0.30**	-0.314**	-0.332**	-0.337**	-0.333**
	(-27.66)	(15.20)	(26.37)	(24.57)	(33.95)	(16.32)
Energy & Water	0.161**	0.182**	0.16**	0.141**	0.164**	0.167**
	(18.75)	(19.89)	(15.46)	(18.75)	(15.36)	(12.70)
Manufacturing	0.089**	0.082**	0.083**	0.064**	0.092**	0.12**
	(7.69)	(3.26)	(4.66)	(6.32)	(7.36)	(6.69)
Distribution, Hotels & Restaurants	-0.196**	-0.226**	-0.215**	-0.207**	-0.18**	-0.135**
	(-45.53)	(30.93)	(41.89)	(54.71)	(32.33)	(22.65)
Transport & Communication	-0.018**	-0.004	-0.007	-0.018**	-0.018**	0.002
	(-3.59)	(-0.46)	(-1.10)	(3.83)	(3.13)	(-0.25)
Banking, Finance & Insurance etc	0.12**	0.02**	0.079**	0.118**	0.165**	0.208**
	(28.16)	(2.65)	(11.42)	(32.72)	(36.97)	(28.45)
Public admin, Educ & Health	-0.007	0.006	0.021**	0.008**	-0.012**	-0.046**
	(-1.82)	(1.03)	(4.28)	(1.63)	(3.19)	(10.59)
Other Services	-0.098**	-0.109**	-0.107**	-0.105**	-0.091**	-0.07**
	(-23.55)	(16.97)	(19.53)	(20.89)	(18.65)	(11.15)
Regional variables (omitted South East)						
Tyne & Wear	-0.176**	-0.134**	-0.16**	-0.174**	-0.186**	-0.211**
	(-18.51)	(6.82)	(12.66)	(17.22)	(30.54)	(16.93)
Rest of Northern Region	-0.159**	-0.145**	-0.158**	-0.149**	-0.157**	-0.173**
	(-21.94)	(19.12)	(22.01)	(13.02)	(20.85)	(17.03)
South Yorkshire	-0.185**	-0.145**	-0.148**	-0.168**	-0.193**	-0.237**
	(-20.74)	(12.28)	(14.59)	(21.87)	(22.60)	(19.37)
West Yorkshire	-0.16**	-0.113**	-0.137**	-0.158**	-0.177**	-0.194**
	(-22.91)	(10.73)	(14.40)	(25.32)	(26.90)	(18.52)
Rest of Yorkshire & Humberside	-0.176**	-0.169**	-0.169**	-0.162**	-0.174**	-0.186**

	(-22.43)	(15.72)	(16.72)	(21.74)	(22.70)	(12.48)
East Midlands	-0.146**	-0.097**	-0.127**	-0.144**	-0.159**	-0.171**
	(-27.32)	(12.68)	(23.22)	(27.16)	(29.44)	(20.93)
East Anglia	-0.129**	-0.087**	-0.107**	-0.13**	-0.142**	-0.147**
	(-18.62)	(7.54)	(12.29)	(18.95)	(23.40)	(23.21)
Inner & Outer London	0.073**	0.08**	0.074**	0.075**	0.072**	0.084**
	(-14.17)	(8.63)	(11.37)	(11.47)	(11.86)	(11.64)
South West	-0.15**	-0.124**	-0.135**	-0.14**	-0.162**	-0.17**
	(-29.62)	(16.35)	(22.44)	(22.84)	(28.59)	(29.68)
West Midlands (Metro)	-0.145**	-0.101**	-0.114**	-0.141**	-0.164**	-0.182**
	(-21.33)	(8.97)	(16.33)	(19.91)	(21.79)	(21.45)
Rest of West Midlands	-0.149**	-0.098**	-0.134**	-0.151**	-0.166**	-0.194**
	(-24.30)	(10.85)	(22.48)	(24.99)	(26.45)	(26.50)
Greater Manchester	-0.143**	-0.118**	-0.126**	-0.137**	-0.153**	-0.187**
	(-20.66)	(13.21)	(22.09)	(24.73)	(25.54)	(22.28)
Merseyside	-0.167**	-0.123**	-0.131**	-0.155**	-0.182**	-0.206**
	(-16.65)	(8.23)	(12.26)	(15.62)	(16.05)	(17.92)
Rest of North West	-0.14**	-0.124**	-0.125**	-0.119**	-0.137**	-0.15**
	(-20.51)	(10.50)	(18.47)	(15.46)	(18.40)	(21.66)
Wales	-0.199**	-0.167**	-0.186**	-0.195**	-0.202**	-0.213**
	(-30.09)	(21.24)	(26.02)	(31.10)	(26.27)	(30.27)
Strathclyde & Rest of Scotland	-0.149**	-0.12**	-0.139**	-0.146**	-0.154**	-0.164**
	(-30.56)	(14.58)	(20.74)	(25.96)	(39.95)	(23.76)
Observation	126,877					126,877
Pseudo R-squared	0.33	0.17	0.20	0.22	0.22	0.21

t statistics in parentheses. * significant at 5%; ** significant at 1%

Table 11: OLS & Quantile Regression Results for Native Model

Dependent variable: Log real hourly wage	OLS	Quantiles 0.10	0.25	0.50	0.75	0.90
Constant	0.883**	0.491**	0.672**	0.86**	1.084**	1.276**
	(91.22)	(37.32)	(68.43)	(75.67)	(136.13)	(100.26)
Potential Experience	0.055**	0.05**	0.052**	0.056**	0.058**	0.059**
	(127.49)	(101.73)	(150.40)	(124.10)	(106.14)	(78.66)
Potential Experience^2	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-108.00)	(-89.95)	(-115.48)	(-108.19)	(-81.23)	(-62.86)
Years of Education	0.08**	0.077**	0.08**	0.082**	0.082**	0.084**
	(138.73)	(95.37)	(95.30)	(110.54)	(123.08)	(91.05)
Nonwhite	-0.069**	-0.078**	-0.08**	-0.072**	-0.063**	-0.072**
	(-5.85)	(-4.93)	(-6.89)	(-5.13)	(-5.10)	(-2.96)
Married & cohab	0.086**	0.096**	0.088**	0.084**	0.079**	0.079**
	(29.60)	(17.90)	(22.90)	(25.64)	(20.22)	(15.55)
Industries (omit Construction)						
Agriculture & Fishing	-0.337**	-0.297**	-0.323**	-0.333**	-0.331**	-0.328**
	(-27.68)	(-24.42)	(-24.81)	(-27.10)	(-22.42)	(-19.17)
Energy & Water	0.158**	0.178**	0.153**	0.141**	0.164**	0.161**
	(18.20)	(12.94)	(17.99)	(17.66)	(12.05)	(11.68)
Manufacturing	0.047**	0.027	0.041**	0.025*	0.058**	0.075**
	(4.10)	(-1.70)	(3.99)	(2.36)	(5.06)	(4.47)
Distribution, Hotels & Restaurants	-0.188**	-0.218**	-0.21**	-0.197**	-0.169**	-0.128**
	(-42.72)	(-39.09)	(-39.15)	(-34.65)	(-26.60)	(-17.58)
Transport & Communication	-0.014**	-0.004	-0.01*	-0.017**	-0.013	0.012
	(-2.80)	(-0.89)	(-2.22)	(-2.90)	(-1.84)	(-1.12)
Banking, Finance & Insurance etc	0.117**	0.015*	0.073**	0.113**	0.16**	0.211**
	(26.67)	(2.12)	(10.53)	(23.60)	(28.85)	(25.19)
Public admin, Educ & Health	-0.011*	-0.001	0.017**	0.004	-0.014**	-0.046**
	(-2.55)	(-0.18)	(3.48)	(0.83)	(-3.70)	(-6.59)
Other Services	-0.097**	-0.105**	-0.109**	-0.104**	-0.09**	-0.067**
	(-22.71)	(-19.50)	(-19.61)	(-20.42)	(-20.95)	(-8.46)
Regions (omit South East)						
Tyne & Wear	-0.174**	-0.134**	-0.154**	-0.164**	-0.185**	-0.202**
	(-18.14)	(-7.78)	(-16.43)	(-20.18)	(-16.81)	(-11.56)
Rest of Northern Region	-0.16**	-0.148**	-0.156**	-0.147**	-0.16**	-0.173**
	(21.89)	(-12.29)	(-16.38)	(-24.82)	(-21.73)	(-13.82)
South Yorkshire	-0.183**	-0.155**	-0.146**	-0.163**	-0.188**	-0.234**
	(-20.34)	(-11.19)	(-14.91)	(-25.76)	(-18.10)	(-17.12)
West Yorkshire	-0.154**	-0.106**	-0.131**	-0.149**	-0.171**	-0.19**
	(21.62)	(-11.54)	(-15.68)	(-17.73)	(-20.41)	(-15.78)
Rest of Yorkshire & Humberside	-0.175**	-0.17**	-0.161**	-0.158**	-0.174**	-0.186**
	(-22.00)	(-12.90)	(-18.58)	(-21.48)	(-18.13)	(-14.38)
East Midlands	-0.145**	-0.097**	-0.122**	-0.141**	-0.158**	-0.168**
	(-26.51)	(-16.33)	(-17.09)	(-24.41)	(-25.19)	(-17.70)
East Anglia	-0.132**	-0.089**	-0.111**	-0.129**	-0.146**	-0.158**
	(-18.72)	(-9.35)	(-12.05)	(-21.96)	(-18.21)	(-12.74)
Inner & Outer London	0.073**	0.078**	0.074**	0.077**	0.076**	0.082**
	(13.42)	(10.41)	(13.41)	(13.13)	(11.35)	(9.60)
South West	-0.15**	-0.122**	-0.131**	-0.141**	-0.162**	-0.173**
	(-29.02)	(-19.93)	(-31.47)	(-21.45)	(-21.44)	(-22.09)
West Midlands (Metro)	-0.147**	-0.109**	-0.115**	-0.142**	-0.17**	-0.186**
	(-21.07)	(-12.36)	(-14.07)	(-21.83)	(-19.08)	(-16.16)
Rest of West Midlands	-0.15**	-0.103**	-0.131**	-0.15**	-0.169**	-0.196**
	(-24.04)	(-10.50)	(-17.39)	(-21.72)	(-26.66)	(-18.00)
Greater Manchester	-0.143**	-0.117**	-0.123**	-0.138**	-0.151**	-0.185**
	(-20.23)	(-9.91)	(-11.43)	(-21.43)	(-20.98)	(-15.69)
Merseyside	-0.167**	-0.125**	-0.128**	-0.153**	-0.185**	-0.207**
	(-16.54)	(-8.11)	(-13.99)	(-15.18)	(-15.99)	(-17.04)
Rest of North West	-0.142**	-0.128**	-0.126**	-0.12**	-0.142**	-0.153**
	(-20.60)	(-12.85)	(-13.87)	(-12.54)	(-13.69)	(-13.26)
Wales	-0.20**	-0.176**	-0.181**	-0.195**	-0.202**	-0.219**
	(-29.99)	(-24.26)	(-25.89)	(-22.49)	(-26.70)	(-19.31)
Strathclyde & Rest of Scotland	-0.147**	-0.125**	-0.134**	-0.147**	-0.155**	-0.164**
	(-29.95)	(-18.93)	(-21.62)	(-35.35)	(-33.48)	(-16.13)
Observations	120,652					120,652
R-squared	0.33	0.17	0.20	0.22	0.22	0.21

Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%

Table 12: OLS & Quantile Regression Results for Immigrant Model

Dependent variable: Log real hourly wage	OLS	Quantiles				
		0.10	0.25	0.50	0.75	0.90
Constant	1.322**	1.176**	1.193**	1.261**	1.333**	1.483**
	(26.56)	(14.31)	(21.92)	(25.61)	(21.36)	(14.31)
Potential Experience	0.043**	0.031**	0.037**	0.045**	0.052**	0.055**
	(21.02)	(19.31)	(15.81)	(22.92)	(31.40)	(19.31)
Potential Experience^2	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-18.12)	(-15.95)	(-14.87)	(-21.82)	(-27.90)	(-15.95)
Years of Education	0.061**	0.048**	0.054**	0.062**	0.072**	0.076**
	(31.03)	(16.26)	(21.08)	(28.16)	(24.54)	(16.26)
UK education dummy	0.049	0.013	0.065	0.079*	0.06	0.063
	(1.60)	(1.15)	(1.69)	(1.99)	(1.64)	(1.15)
Foreign experience dummy	-0.006	-0.051	-0.019	0.008	0.018	0.059
	(-0.19)	(-0.97)	(-0.54)	(0.23)	(0.54)	(0.97)
Nonwhite	-0.192**	-0.186**	-0.19**	-0.182**	-0.165**	-0.146**
	(-13.37)	(-5.48)	(-10.77)	(-10.14)	(-9.38)	(-5.48)
Married & cohab	0.071**	0.071	0.075**	0.072**	0.073**	0.037
	(5.12)	(1.31)	(3.65)	(5.06)	(4.03)	(1.31)
NonEnglish Mother tongue	-0.098**	-0.114**	-0.109**	-0.095**	-0.095**	-0.083**
	(-6.83)	(-3.45)	(-7.57)	(-7.15)	(-8.13)	(-3.45)
Industries (omit Construction)						
Agriculture & Fishing	-0.194*	-0.484	-0.232	-0.182	-0.202	-0.13
	(-2.03)	(-0.33)	(-1.09)	(-1.78)	(-1.94)	(-0.33)
Energy & Water	0.161**	0.154	0.215*	0.192**	0.088**	0.14
	(2.81)	(1.33)	(2.58)	(5.38)	(2.99)	(1.33)
Manufacturing	0.035	0.136	0.047	0.02	-0.181	-0.225
	(0.32)	(0.36)	(-0.66)	(-0.23)	(-1.25)	(-0.36)
Distribution, Hotels & Restaurants	-0.271**	-0.309**	-0.275**	-0.272**	-0.287**	-0.221**
	(12.95)	(-6.22)	(-11.61)	(-15.42)	(-11.52)	(-6.22)
Transport & Communication	-0.008	0.058	0.02	-0.005	-0.046	-0.04
	(-0.26)	(0.77)	(-0.54)	(-0.16)	(-1.43)	(-0.77)
Banking, Finance & Insurance etc	0.196**	0.087**	0.17**	0.21**	0.244**	0.312**
	(9.92)	(7.81)	(9.21)	(11.56)	(11.18)	(7.81)
Public admin, Educ & Health	0.041*	0.05	0.099**	0.051*	0.00	-0.041
	(2.14)	(1.27)	(4.07)	(2.47)	(0.01)	(-1.27)
Other Services	-0.049*	-0.071	-0.063**	-0.063**	-0.05	0.009
	(-2.35)	(-0.14)	(-2.72)	(-3.01)	(-1.39)	(0.14)
Regions (omit South East)						
Tyne & Wear	-0.158*	-0.123	-0.162	-0.21*	-0.191	-0.094
	(-2.34)	(-0.47)	(-1.50)	(-2.36)	(-1.59)	(-0.47)
Rest of Northern Region	-0.071	-0.049	-0.074	-0.084*	-0.078	-0.104
	(-1.19)	(-0.87)	(-1.21)	(-2.04)	(-1.21)	(-0.87)
South Yorkshire	-0.204**	-0.239	-0.219**	-0.274**	-0.162	-0.185
	(-3.36)	(-1.39)	(-4.06)	(-4.57)	(-1.71)	(-1.39)
West Yorkshire	-0.274**	-0.275**	-0.257**	-0.283**	-0.312**	-0.264
	(-7.58)	(-4.76)	(-5.26)	(-9.03)	(-7.57)	(-4.76)
Rest of Yorkshire & Humberside	-0.176**	-0.204*	-0.204**	-0.188**	-0.139	-0.194*
	(-3.48)	(-1.99)	(-3.96)	(-3.80)	(-1.85)	(-1.99)
East Midlands	-0.17**	-0.148**	-0.141**	-0.184**	-0.159**	-0.175**
	(-5.82)	(-2.70)	(-3.92)	(-7.70)	(-3.63)	(-2.70)
East Anglia	-0.076*	-0.133	-0.055	-0.088**	-0.102	-0.069
	(-2.18)	(-0.89)	(-1.21)	(-3.58)	(-1.82)	(-0.89)
Inner & Outer London	0.046**	0.067	0.057**	0.049*	0.05	0.042
	(2.65)	(1.33)	(-3.31)	(2.32)	(1.72)	(1.33)
South West	-0.138**	-0.176*	-0.16**	-0.163**	-0.098**	-0.112*
	(-5.15)	(-2.38)	(-5.60)	(-7.74)	(-3.28)	(-2.38)
West Midlands (Metro)	-0.147**	-0.108**	-0.113**	-0.142**	-0.132**	-0.181**
	(-4.96)	(-4.08)	(-4.03)	(-5.29)	(-5.17)	(-4.08)
Rest of West Midlands	-0.126**	-0.061	-0.123**	-0.159**	-0.158**	-0.102
	(-3.26)	(-1.60)	(-4.57)	(-3.46)	(-3.16)	(-1.60)
Greater Manchester	-0.176**	-0.245	-0.193**	-0.193**	-0.131**	-0.087
	(-4.60)	(-1.46)	(-5.07)	(-3.83)	(-2.98)	(-1.46)
Merseyside	-0.221**	-0.144	-0.191*	-0.266**	-0.165	-0.119
	(-2.85)	(-0.95)	(-1.98)	(-3.78)	(-1.47)	(-0.95)
Rest of North West	-0.086*	-0.134	-0.173**	-0.119	-0.038	0.004
	(-1.96)	(-0.06)	(-3.44)	(-1.71)	(-0.53)	(0.06)
Wales	-0.105**	-0.10	-0.147**	-0.111**	-0.084	-0.04
	(-2.33)	(-0.55)	(-2.81)	(-2.79)	(-0.99)	(-0.55)
Strathclyde & Rest of Scotland	-0.111**	-0.086*	-0.149**	-0.123**	-0.088*	-0.133**
	(-3.51)	(-2.50)	(-4.38)	(-5.69)	(-2.29)	(-2.50)
Observations	6,225					6,225
R-squared	0.33	0.19	0.20	0.21	0.22	0.23

Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%

Table 13: OLS Estimates used in Decompositions, from separate Immigrant and Native Regressions

OLS Estimates, Natives			OLS Estimates, Immigrants		
Variable	Coefficient	t-stat	Variable	Coefficient	t-stat
Constant	0.883	91.22	Constant	1.346	32.59
Potential Experience	0.055	127.49	Potential Experience	0.043	21.26
Potential Experience^2	-0.001	-108.00	Potential Experience^2	-0.001	-18.48
Years of Education	0.080	138.73	Years of Education	0.060	30.82
NonEnglish mother tongue	(dropped)		NonEnglish mother tongue	-0.090	-6.33
Nonwhite	-0.069	-5.85	Nonwhite	-0.196	-13.73
Married & cohab	0.086	29.60	Married & cohab	0.070	5.03
Tyne & Wear	-0.174	-18.14	Tyne & Wear	-0.157	-2.32
Rest of Northern Region	-0.160	-21.89	Rest of Northern Region	-0.069	-1.15
South Yorkshire	-0.183	-20.34	South Yorkshire	-0.202	-3.32
West Yorkshire	-0.154	-21.62	West Yorkshire	-0.272	-7.51
Rest of Yorkshire & Humberside	-0.175	-22.00	Rest of Yorkshire & Humberside	-0.169	-3.35
East Midlands	-0.145	-26.51	East Midlands	-0.169	-5.79
East Anglia	-0.132	-18.72	East Anglia	-0.077	-2.18
Inner & Outer London	0.073	13.42	Inner & Outer London	0.039	2.27
South West	-0.150	-29.02	South West	-0.133	-4.96
West Midlands (Metro)	-0.147	-21.07	West Midlands (Metro)	-0.145	-4.88
Rest of West Midlands	-0.150	-24.04	Rest of West Midlands	-0.123	-3.19
Greater Manchester	-0.143	-20.23	Greater Manchester	-0.174	-4.56
Merseyside	-0.167	-16.54	Merseyside	-0.215	-2.77
Rest of North West	-0.142	-20.60	Rest of North West	-0.087	-1.98
Wales	-0.200	-29.99	Wales	-0.103	-2.29
Strathclyde & Rest of Scotland	-0.147	-29.95	Strathclyde & Rest of Scotland	-0.108	-3.40
Agriculture & Fishing	-0.337	-27.68	Agriculture & Fishing	-0.193	-2.01
Energy & Water	0.158	18.20	Energy & Water	0.162	2.83
Manufacturing	0.047	4.10	Manufacturing	0.025	0.23
Distribution, Hotels & Restaurants	-0.188	-42.72	Distribution, Hotels & Restaurants	-0.275	-13.11
Transport & Communication	-0.014	-2.80	Transport & Communication	-0.007	-0.23
Banking, Finance & Insurance etc	0.117	26.67	Banking, Finance & Insurance etc	0.199	10.10
Public admin, Educ & Health	-0.011	-2.55	Public admin, Educ & Health	0.042	2.19
Other Services	-0.097	-22.71	Other Services	-0.048	-2.29
Prediction(ln):		2.40	Prediction(ln):		2.51
Prediction(£):		11.04	Prediction(£):		12.30

Table 14: Complete Decomposition Results (as %),
OLS Estimation

Variable	Attributable	Endowment	Coefficient
Potential Experience	-37.2	-13.7	-23.5
Potential Experience^2	18.7	10.1	8.6
Years of Education	-11.1	17.7	-28.8
NonEnglish mother	-6.1	0.0	-6.1
Nonwhite	-7.4	-2.6	-4.9
Married & cohab	-0.3	0.7	-0.9
Tyne & Wear	0.2	0.2	0.0
Rest of Northern	0.5	0.4	0.1
South Yorkshire	0.2	0.2	0.0
West Yorkshire	-0.3	0.1	-0.4
Rest of Yorkshire & Humberside	0.3	0.3	0.0
East Midlands	0.2	0.3	-0.1
East Anglia	0.3	0.1	0.2
Inner & Outer London	0.7	1.8	-1.1
South West	0.4	0.3	0.1
West Midlands (Metro)	-0.2	-0.2	0.0
Rest of West Midlands	0.5	0.4	0.1
Greater Manchester	0.1	0.2	-0.1
Merseyside	0.2	0.2	0.0
Rest of North West	0.4	0.3	0.1
Wales	0.7	0.5	0.2
Strathclyde & Rest of Scotland	1.0	0.9	0.2
Agriculture & Fishing	0.3	0.3	0.1
Energy & Water	-0.2	-0.2	0.0
Manufacturing	-0.1	0.0	0.0
Distribution, Hotels & Restaurants	-1.6	-0.3	-1.3
Transport & Communication	0.1	0.0	0.0
Banking, Finance & Insurance etc	2.3	0.6	1.6
Public admin, Educ & Health	1.0	0.0	1.1
Other Services	0.6	-0.1	0.7
Subtotal	-35.6	18.5	-54.0

Table 15: Complete Decomposition Results (as %), QR Estimation with Immigrants as reference group

	0.10			0.25			0.50			0.75			0.90		
	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.
Potential Experience	-25.7	7.7	-33.4	-27.8	0.4	-28.2	-27.3	-6.1	-21.2	-21.9	-10.4	-11.5	-20.6	-12.9	-7.6
Sqrd/1000	-1.8	-1.8	0.0	2.3	2.3	0.0	5.6	5.6	0.0	8.1	8.1	0.0	9.6	9.6	0.0
Years of Education	-26.7	10.6	-37.3	-21.8	11.9	-33.6	-12.5	14.0	-26.5	2.2	16.0	-13.8	6.0	17.4	-11.3
NonEnglish mother	-8.6	0.0	-8.6	-8.1	0.0	-8.1	-6.7	0.0	-6.7	-6.5	0.0	-6.5	-5.6	0.0	-5.6
Nonwhite	-8.9	-3.7	-5.3	-8.9	-3.7	-5.2	-7.9	-3.1	-4.8	-6.8	-2.5	-4.2	-5.8	-2.8	-3.0
Married & cohab	0.3	1.4	-1.1	0.4	1.0	-0.6	0.0	0.5	-0.6	0.1	0.4	-0.3	-1.9	0.3	-2.2
Tyne & Wear	0.3	0.3	0.0	0.3	0.3	0.0	0.1	0.2	0.0	0.1	0.1	0.0	0.2	0.1	0.1
Rest of Northern Region	0.0	-0.2	0.2	0.1	0.0	0.1	0.2	0.1	0.1	0.3	0.2	0.1	0.3	0.2	0.1
South Yorkshire	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.1	0.0	-0.2	0.1	0.0	0.0	0.1	0.1	0.1
West Yorkshire	1.0	2.3	-1.3	1.4	2.2	-0.9	1.4	2.0	-0.6	1.3	1.9	-0.6	1.6	1.9	-0.3
Humberside	1.0	1.0	-0.1	1.0	1.0	-0.1	1.1	1.2	-0.1	1.4	1.3	0.1	1.4	1.4	0.0
East Midlands	0.1	0.4	-0.3	0.2	0.3	-0.1	0.1	0.4	-0.3	0.7	0.7	0.0	1.0	1.1	0.0
East Anglia	0.1	0.3	-0.2	0.8	0.6	0.2	1.1	0.9	0.2	1.6	1.5	0.2	2.3	1.9	0.3
Inner & Outer London	0.5	0.7	-0.3	0.2	0.6	-0.4	0.1	0.9	-0.8	0.4	1.2	-0.8	0.1	1.4	-1.3
South West	-1.2	-0.8	-0.5	-1.0	-0.8	-0.2	-0.9	-0.7	-0.2	-0.4	-0.8	0.5	-0.4	-0.9	0.4
West Midlands (Metro)	-0.3	-0.3	0.0	-0.4	-0.4	0.0	-0.4	-0.4	0.0	-0.1	-0.4	0.2	-0.3	-0.3	0.0
Rest of West Midlands	0.1	0.0	0.1	0.0	-0.1	0.0	-0.1	-0.1	0.0	0.0	-0.1	0.0	0.2	-0.1	0.3
Greater Manchester	-0.5	0.0	-0.5	-0.3	0.0	-0.3	-0.1	0.1	-0.2	0.2	0.1	0.1	0.5	0.1	0.3
Merseyside	0.4	0.5	0.0	0.4	0.4	-0.1	0.4	0.5	-0.1	0.5	0.5	0.0	0.6	0.6	0.1
Rest of North West	0.7	0.7	0.0	0.6	0.8	-0.1	0.8	0.8	0.0	1.1	0.9	0.2	1.2	0.9	0.3
Wales	0.5	0.3	0.2	0.5	0.4	0.1	0.6	0.4	0.2	0.7	0.4	0.3	0.8	0.4	0.4
Strathclyde & Rest of Scotland	0.2	0.0	0.2	0.0	0.1	-0.1	0.2	0.1	0.1	0.6	0.3	0.3	0.6	0.5	0.1
Agriculture & Fishing	2.3	2.6	-0.3	3.0	2.9	0.1	3.1	3.0	0.1	3.0	2.9	0.1	2.9	2.8	0.1
Energy & Water	-0.6	-0.6	0.0	-0.5	-0.6	0.0	-0.5	-0.5	0.0	-0.6	-0.5	-0.1	-0.5	-0.5	0.0
Construction	0.1	-0.1	0.2	-0.2	-0.2	0.0	-0.1	-0.1	0.0	-0.6	-0.3	-0.3	-0.7	-0.3	-0.4
Distribution, Hotels & Restaurants	-9.3	-6.3	-3.1	-6.8	-5.0	-1.8	-5.0	-3.4	-1.6	-4.2	-2.2	-2.0	-2.8	-1.4	-1.4
Transport & Communication	0.1	0.0	0.2	0.1	0.0	0.1	0.0	-0.1	0.1	-0.2	0.0	-0.2	-0.2	0.0	-0.3
Banking, Finance & Insurance etc	0.9	0.1	0.8	1.5	0.5	1.0	2.0	0.9	1.2	2.8	1.6	1.2	4.2	2.6	1.7
Public admin, Educ & Health	0.5	0.0	0.5	1.0	0.1	0.9	0.7	0.0	0.7	0.1	-0.2	0.3	-0.6	-0.7	0.1
Other Services	0.3	-0.1	0.4	0.2	-0.5	0.7	0.1	-0.5	0.7	0.2	-0.4	0.6	0.8	-0.3	1.1
Subtotal	-74.5	15.1	-89.6	-61.9	14.7	-76.6	-44.2	16.5	-60.7	-16.2	20.1	-36.3	-5.0	23.0	-28.0

positive number indicates advantage to immigrants, negative number indicates advantage to natives

Table 16: Summary of Decomposition Results (as %), QR Estimation with Natives as reference groups

	0.10	0.25	0.50	0.75	0.90
Amount attributable:	74.5	61.9	44.2	16.2	5.0
- due to endowments (E):	2.6	1.6	-3.0	-8.0	-11.2
- due to coefficients (C):	71.9	60.3	47.2	24.2	16.2
Shift coefficient (U):	-68.5	-52.1	-40.1	-24.9	-20.7
Raw differential (R) {E+C+U}:	6.0	9.8	4.1	-8.7	-15.7
Adjusted differential (D) {C+U}:	3.4	8.2	7.1	-0.7	-4.5

U = unexplained portion of differential (difference between model constants)
D = portion due to discrimination
positive number indicates advantage to natives, negative number indicates advantage to immigrants

Table 17: Complete Decomposition Results (as %), QR Estimation with Natives as reference group

	0.10			0.25			0.50			0.75			0.90		
	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.
Potential Experience	25.7	-4.8	30.5	27.8	-0.3	28.1	27.3	4.9	22.4	21.9	9.3	12.6	20.6	12.1	8.5
Potential Experience Sqrd/1000	1.8	1.8	0.0	-2.3	-2.3	0.0	-5.6	-5.6	0.0	-8.1	-8.1	0.0	-9.6	-9.6	0.0
Years of Education	26.7	-6.6	33.3	21.8	-8.0	29.8	12.5	-10.6	23.1	-2.2	-14.0	11.8	-6.0	-15.7	9.7
NonEnglish mother tongue	8.6	8.6	0.0	8.1	8.1	0.0	6.7	6.7	0.0	6.5	6.5	0.0	5.6	5.6	0.0
Nonwhite	8.9	8.8	0.2	8.9	8.7	0.2	7.9	7.8	0.1	6.8	6.7	0.1	5.8	5.7	0.1
Married & cohab	-0.3	-1.0	0.7	-0.4	-0.8	0.5	0.0	-0.5	0.5	-0.1	-0.3	0.3	1.9	-0.1	2.0
Tyne & Wear	-0.3	-0.3	0.0	-0.3	-0.3	0.0	-0.1	-0.2	0.1	-0.1	-0.1	0.0	-0.2	-0.1	-0.1
Rest of Northern Region	0.0	0.1	-0.1	-0.1	0.0	-0.1	-0.2	0.0	-0.1	-0.3	-0.1	-0.2	-0.3	-0.1	-0.2
South Yorkshire	0.1	0.0	0.1	0.1	-0.1	0.1	0.1	0.0	0.2	-0.1	0.0	0.0	-0.1	0.0	-0.1
West Yorkshire	-1.0	-6.0	5.0	-1.4	-4.4	3.0	-1.4	-3.8	2.5	-1.3	-3.4	2.1	-1.6	-2.6	1.0
Rest of Yorkshire & Humberside	-1.0	-1.2	0.3	-1.0	-1.3	0.4	-1.1	-1.4	0.3	-1.4	-1.1	-0.3	-1.4	-1.4	0.1
East Midlands	-0.1	-0.6	0.5	-0.2	-0.4	0.2	-0.1	-0.5	0.4	-0.7	-0.7	0.0	-1.0	-1.1	0.1
East Anglia	-0.1	-0.5	0.4	-0.8	-0.3	-0.5	-1.1	-0.6	-0.5	-1.6	-1.0	-0.6	-2.3	-0.8	-1.4
Inner & Outer London	-0.5	-0.6	0.2	-0.2	-0.5	0.3	-0.1	-0.6	0.5	-0.4	-0.8	0.4	-0.1	-0.7	0.6
South West	1.2	1.1	0.1	1.0	1.0	0.1	0.9	0.9	0.0	0.4	0.5	-0.1	0.4	0.6	-0.1
West Midlands (Metro)	0.3	0.3	0.0	0.4	0.4	0.0	0.4	0.4	0.0	0.1	0.3	-0.2	0.3	0.3	0.0
Rest of West Midlands	-0.1	0.0	-0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.0	-0.2	0.0	-0.2
Greater Manchester	0.5	-0.1	0.6	0.3	0.0	0.3	0.1	-0.1	0.2	-0.2	-0.1	-0.1	-0.5	-0.1	-0.4
Merseyside	-0.4	-0.5	0.1	-0.4	-0.6	0.3	-0.4	-0.8	0.4	-0.5	-0.5	-0.1	-0.6	-0.3	-0.3
Rest of North West	-0.7	-0.7	0.0	-0.6	-1.0	0.4	-0.8	-0.8	0.0	-1.1	-0.2	-0.8	-1.2	0.0	-1.2
Wales	-0.5	-0.2	-0.3	-0.5	-0.3	-0.2	-0.6	-0.2	-0.4	-0.7	-0.2	-0.5	-0.8	-0.1	-0.7
Strathclyde & Rest of Scotland	-0.2	0.0	-0.2	0.0	-0.1	0.1	-0.2	-0.1	-0.1	-0.6	-0.2	-0.4	-0.6	-0.4	-0.2
Agriculture & Fishing	-2.3	-4.2	1.9	-3.0	-2.1	-0.9	-3.1	-1.6	-1.5	-3.0	-1.8	-1.2	-2.9	-1.1	-1.8
Energy & Water	0.6	0.5	0.1	0.5	0.8	-0.3	0.5	0.7	-0.2	0.6	0.3	0.3	0.5	0.4	0.1
Manufacturing	-0.1	0.6	-0.6	0.2	0.2	0.0	0.1	0.1	0.0	0.6	-0.8	1.4	0.7	-1.0	1.7
Distribution, Hotels & Restaurants	9.3	8.9	0.4	6.8	6.5	0.3	5.0	4.7	0.3	4.2	3.7	0.5	2.8	2.4	0.4
Transport & Communication	-0.1	0.0	-0.1	-0.1	0.0	-0.1	0.0	0.0	0.0	0.2	0.2	0.1	0.2	0.2	0.1
Banking, Finance & Insurance etc	-0.9	-0.6	-0.3	-1.5	-1.1	-0.4	-2.0	-1.6	-0.4	-2.8	-2.4	-0.4	-4.2	-3.8	-0.4
Public admin, Educ & Health	-0.5	-0.1	-0.3	-1.0	-0.5	-0.5	-0.7	-0.5	-0.3	-0.1	0.0	-0.1	0.6	0.6	0.0
Other Services	-0.3	0.1	-0.4	-0.2	0.3	-0.5	-0.1	0.3	-0.4	-0.2	0.2	-0.4	-0.8	0.0	-0.8
Subtotal	74.5	2.6	71.9	61.9	1.6	60.3	44.2	-3.0	47.2	16.2	-8.0	24.2	5.0	-11.2	16.2

positive number indicates advantage to natives, negative number indicates advantage to immigrants

Table 18: Summary of Decomposition Results (as %), QR Estimation with weighted reference groups

	0.10	0.25	0.50	0.75	0.90
Amount attributable:	60.3	48.9	33.4	6.5	-4.4
- due to endowments (E):	-13.4	-13.0	-15.2	-18.9	-21.8
- due to coefficients (C):	73.6	62.0	48.5	25.4	17.4
Shift coefficient (U):	-68.5	-52.1	-40.1	-24.9	-20.7
Raw differential (R) {E+C+U}:	-8.2	-3.2	-6.7	-18.4	-25.1
Adjusted differential (D) {C+U}:	5.1	9.9	8.4	0.5	-3.3

U = unexplained portion of differential (difference between model

D = portion due to discrimination

positive number indicates advantage to natives, negative number indicates advantage to immigrants

Table 19: Complete Decomposition Results (as %), QR Estimation with population weights on groups

	0.10			0.25			0.50			0.75			0.90		
	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.	Attribut.	Endow.	Coeff.
Potential Experience	23.3	-7.4	30.7	27.7	-0.3	28.1	28.3	6.0	22.3	22.8	10.3	12.5	21.3	12.9	8.4
Potential Experience Sqrd/1000	1.8	1.8	0.0	-2.3	-2.3	0.0	-5.6	-5.6	0.0	-8.1	-8.1	0.0	-9.6	-9.6	0.0
Years of Education	23.5	-10.2	33.7	18.7	-11.5	30.2	9.8	-13.6	23.4	-3.8	-15.8	12.0	-7.4	-17.2	9.8
NonEnglish mother tongue	1.7	0.9	0.9	1.6	0.8	0.8	1.3	0.7	0.7	1.3	0.7	0.7	1.1	0.6	0.6
Nonwhite	4.9	4.2	0.7	4.8	4.2	0.7	4.2	3.5	0.6	3.5	3.0	0.5	3.5	3.1	0.4
Married & cohab	-0.6	-1.3	0.8	-0.5	-1.0	0.5	0.0	-0.5	0.5	-0.1	-0.4	0.3	1.8	-0.3	2.1
Tyne & Wear	-0.3	-0.3	0.0	-0.2	-0.3	0.0	-0.1	-0.2	0.1	-0.1	-0.1	0.0	-0.2	-0.1	-0.1
Rest of Northern Region	0.1	0.1	-0.1	0.0	0.0	-0.1	-0.2	-0.1	-0.1	-0.3	-0.2	-0.2	-0.4	-0.2	-0.2
South Yorkshire	0.1	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.2	-0.1	0.0	0.0	-0.1	-0.1	-0.1
West Yorkshire	2.0	-2.7	4.7	0.3	-2.5	2.8	0.1	-2.2	2.3	-0.1	-2.0	2.0	-1.0	-1.9	0.9
Rest of Yorkshire & Humberside	-0.8	-1.0	0.2	-0.7	-1.1	0.3	-0.9	-1.2	0.3	-1.6	-1.3	-0.3	-1.3	-1.4	0.1
East Midlands	0.1	-0.4	0.5	-0.2	-0.3	0.2	0.0	-0.4	0.4	-0.7	-0.7	0.0	-1.0	-1.1	0.1
East Anglia	0.0	-0.3	0.4	-1.1	-0.6	-0.5	-1.3	-0.9	-0.4	-2.0	-1.4	-0.6	-3.1	-1.8	-1.3
Inner & Outer London	-0.5	-0.7	0.2	-0.3	-0.6	0.3	-0.4	-0.9	0.5	-0.7	-1.1	0.4	-0.7	-1.4	0.6
South West	0.9	0.8	0.2	0.9	0.8	0.1	0.8	0.8	0.1	0.6	0.8	-0.2	0.7	0.8	-0.2
West Midlands (Metro)	0.3	0.3	0.0	0.4	0.4	0.0	0.4	0.4	0.0	0.2	0.4	-0.2	0.3	0.3	0.0
Rest of West Midlands	-0.1	0.0	-0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.0	-0.1	0.1	-0.2
Greater Manchester	0.5	0.0	0.6	0.3	0.0	0.3	0.1	-0.1	0.2	-0.2	-0.1	-0.1	-0.5	-0.1	-0.4
Merseyside	-0.4	-0.5	0.1	-0.2	-0.4	0.2	-0.1	-0.5	0.4	-0.6	-0.5	-0.1	-0.8	-0.5	-0.3
Rest of North West	-0.6	-0.7	0.0	-0.4	-0.8	0.4	-0.8	-0.8	0.0	-1.6	-0.8	-0.8	-1.9	-0.8	-1.1
Wales	-0.6	-0.3	-0.3	-0.5	-0.4	-0.1	-0.8	-0.4	-0.4	-0.9	-0.4	-0.5	-1.1	-0.4	-0.7
Strathclyde & Rest of Scotland	-0.2	0.0	-0.2	0.0	-0.1	0.1	-0.3	-0.1	-0.1	-0.7	-0.3	-0.4	-0.7	-0.5	-0.2
Agriculture & Fishing	-1.0	-2.7	1.7	-3.7	-2.9	-0.9	-4.2	-2.8	-1.3	-3.9	-2.8	-1.1	-4.3	-2.7	-1.7
Energy & Water	0.7	0.6	0.1	0.3	0.6	-0.2	0.3	0.5	-0.2	0.8	0.5	0.3	0.6	0.5	0.1
Manufacturing	-0.4	0.2	-0.6	0.2	0.2	0.0	0.1	0.1	0.0	1.4	0.2	1.3	1.8	0.2	1.6
Distribution, Hotels & Restaurants	7.2	6.5	0.7	5.6	5.1	0.5	4.0	3.5	0.5	3.0	2.3	0.7	2.0	1.5	0.5
Transport & Communication	-0.1	0.0	-0.1	0.0	0.0	-0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.0	0.1
Banking, Finance & Insurance etc	-0.5	-0.2	-0.4	-1.0	-0.5	-0.5	-1.4	-0.9	-0.5	-2.1	-1.7	-0.5	-3.3	-2.7	-0.6
Public admin, Educ & Health	-0.4	0.0	-0.4	-0.7	-0.1	-0.5	-0.4	-0.1	-0.3	0.1	0.2	-0.1	0.7	0.7	0.0
Other Services	-0.3	0.1	-0.4	-0.1	0.4	-0.5	0.0	0.5	-0.5	0.0	0.4	-0.4	-0.6	0.3	-0.8
Subtotal	60.3	-13.4	73.6	48.9	-13.0	62.0	33.4	-15.2	48.5	6.5	-18.9	25.4	-4.4	-21.8	17.4

positive number indicates advantage to natives, negative number indicates advantage to immigrants