HETEROGENEITY IN THE WAGE IMPACTS OF IMMIGRANTS

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Abstract

This paper analyses impacts of immigration on individual wages. The empirical analysis is based on the British Labour Force Survey from 1993 to 2005. In addition to mean regression methods, this paper applies a semi-parametric procedure to measure covariates at quantiles of the wage distribution. Results indicate the substitutability of immigrant workers depends on the combination of education and experience attained. Our main finding is university educated immigrants with the least experience expand wages of all UK-born workers. We also find positive wage impacts between workers with the same skill sets and these effects are stronger for immigrants than natives.

JEL Classifications: J31, J61, C33

Keywords: Immigration, wage impacts, quantile regression

1. Introduction

According to the International Migration report[1] for 2005, the foreign-born comprised 9.1% of the United Kingdom's population. Compared to Western Europe or the United States, the UK has a relatively low immigrant population (11.9% and 12.9% respectively). Regarding nations of Europe, the migrant stock[2], as a percentage of the population, was greater in France (10.7%), Germany (12.3%), Ireland (14.1%), Spain (11.1%) and Sweden (12.4%). On the other hand, Britain maintained a larger proportion of immigrants than Greece (8.8%), Italy (4.3%), Norway (7.4%), and Portugal (7.3%). Although there is a moderate stock of migrants in the UK, the rate of growth of foreign-born in Britain has increased considerably. The overseas-born as a percentage of the UK population, through 1951 to 1991, grew at rates ranging from 0.46 to 0.87% per decade.[3] Through 1991-2001, the rate jumped to 1.64%. Most recently, 2000-2005, the annual growth rate of foreign-born as a percentage of the UK population was 2.3%. The UK growth rate of foreign-born was greater than France (1.0%) and Italy (2.1%), but lower than Germany (2.7%), Ireland (9.8%), and Spain (10%). The increasing rate at which immigrants are entering the UK causes concern for academics, policy-makers, and the general public, as they seek to determine the changes immigrants have on life in Britain.

Immigration has changed the profile of Britain's labour market. Unlike other countries, such as the United States, immigrants to the United Kingdom have relatively more education than natives. In Table 1, we illustrate the proportion of immigrants and natives within particular education groups. Immigrants and natives have roughly the same proportions, 21% and 17% respectively, in the middle education group (leaving age of 17-18yrs). Interestingly, 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

[1] United Nation's Department of Economic and Social Affairs, Population Division, 2006.
[2] Mid-year estimate of the number of people living in one country who are born outside the country.
[3] Censuses, Office for National Statistics; General Register Office for Scotland; Northern Ireland Statistics and Research Agency

are in this lowest education group. Roughly 18% of natives and 43% of immigrants are in the highest education group (leaving age of 19+ yrs).

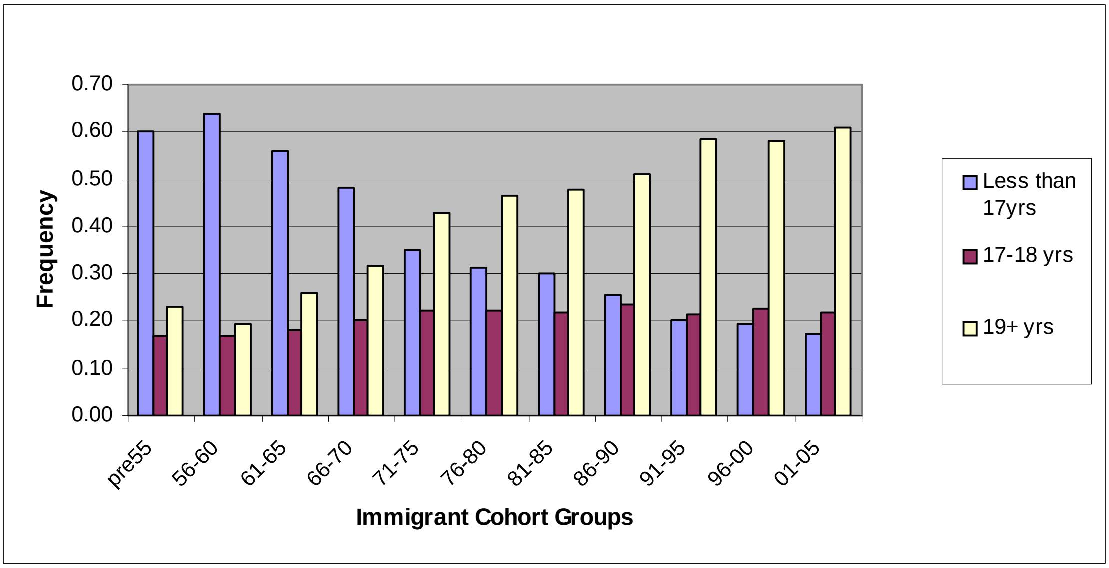
Table 1: Educational Attainment Distribution

	UK-born	NonUK-born
Less than 17yrs	0.655	0.363
17-18 yrs	0.169	0.209
19+ yrs	0.176	0.428

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

The educational attainment of immigrants has been changing over the years. By grouping immigrants into 5-year cohorts (based on year of entry into the UK), we observe a gradual decline in entrants leaving education before 17 years of age. The entrants leaving education after 18 years old has been increasing over time, whilst the immigrants leaving between 17 and 18 years of age has remained constant (see Figure 1).

Figure 1: Educational Attainment of NonUK-born Workers, by cohort of entry



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

In summary, the proportion of immigrants was increasing and their skills were changing, so we anticipate impacts on the labour market. Overseas-born workers may improve wages for some UK-born workers and harm others, potentially causing wage inequalities. In order to suggest whether immigrants were `good' or `bad' for the economy, it is necessary to make judgments about the ranking of importance for particular outcomes. Of course, this is not the work of economist but for politicians and the voting public. To improve their decision-making process, however, we seek to shed light on the issue of wage inequality. The result has sociological and economic implications that we hope will enrich the immigration debate of Britain.

The remainder of this paper is organised as follows. Section 2 surveys prior literature analysing wage impacts of immigrants. Section 3 discusses the theoretical framework and Section 4 introduces our data set. Section 5 develops empirical strategies employed throughout the paper. Section 6 presents the main results and the final section concludes with policy implications and areas for further research.

2. Literature

The economic investigation of immigrant impacts is a growing body of work reporting how the labour market functions with differentiated labour inputs. In their detailed survey, Gaston and Nelson (2001) show that area studies and factor proportions analysis typifies the labour market approach. Area analyses find the change in earnings from a change in immigration within a particular geographical area, whilst factor proportions approach examines how alterations of the skill distribution leads to native outcome changes. Gaston and Nelson (2001) suggest that the main issue for a researcher involved in either type of investigation is to discern an accurate level of analysis. Both natives and immigrants make location decisions and it may not be entirely clear what geographical boundaries to select. Several authors (Filer (1992), Borjas (1997), Frey (1995), Card and Dinardo (2000), Hatton and Tani (2005)) find mixed results regarding the relationship between native migration patterns and immigration rates. It is generally understood, however, the greater the area of analysis, the less possibility of biased results because mobility is more fully accounted. We model individual wages in the national labour market and control for region of inhabitance, which accounts for any general equilibrium effects in terms of mobility.

In a comparison of the area and factor proportions approaches, Borjas, Freeman, and Katz (1996) detect effects of the immigrant-to-native ratio on the supply of native labour and native wages in the relevant region. Using 1980 and 1990 Public Use Microdata Sample (PUMS) US Census data and Current Population Survey (CPS), Borjas et al. (1996) discover that the greater the geographical region, the less positive or more negative becomes the immigrant impact. This is because when the geographical region under investigation is too small, it does not factor in the location decisions of natives and exaggerates the immigrant supply in the immigrant-to-natives ratio. Borjas et al. (1996) conclude that immigrants and trade had the most depressive effect, -.039 log points, on relative weekly wages of high school dropouts to other workers and -0.016 points for log(high-school/college equivalents).

Two well cited area studies are Card (1990) and Friedberg (2001) looking at the US and Israel, respectively. Card (1990) exploits the Mariel Boatlift operation in which Cubans were granted permission to immigrate and increased the population of Miami, Florida by nearly 7%. Card (1990) found no effect on wages or employment on non-Cuban workers.[4] Friedberg (2001) investigates the 1990-1994 emigrations from the Soviet Union into Israel, which increased Israel's population by 12%. OLS regressions indicate a depressive wage and employment effect, but IV regressions suggest immigrants were in occupations of falling wages already and there was no evidence immigrants impacted wages.

There is some work investigating the periods of EU enlargement to uncover immigrant impacts. Portes and French (2005) evaluate unemployment changes in Britain from the introduction of the European free movement of workers. They use Worker Registration Services data and Social Insurance administration data for the UK from 2003 through 2004. They find significant results in their unrestricted OLS and an OLS on agriculture and fishing registrations only. Their

[4] Angrist and Krueger (1999) provide evidence contradicting Card's results.}

main finding is there are higher unemployment rates amongst natives in the local authorities with greater immigration, albeit very small. These rates of unemployment are mean reverting, and the speed of mean reversion increases the further away it travels. They suggest the mean reversion is due to relatively flexible labour market of the UK, welfare-to-work intervention, and/or mobility of factors of production. In another work using the change in labour market openness, Blanchflower, Saleheen, and Shaforth (2007) evaluate the impact of the flow of A8 European Union enlargement workers into Britain. They examine relationships between unemployment rates and other structural developments across regions. The basic theoretical framework is immigrants are consumers and producers so they affect both aggregate supply and demand. Consequently, there is a relative change in demand and supply. Plus, the natural rate of unemployment declines when the proportion of individuals in the population with high propensities for unemployment declines. Blanchflower et al. (2007) find A8 immigration increased supply more than demand, but it also increased labour market flexibility and likely lowered the natural rate of unemployment and the NAIRU.

There are few immigrant population shocks like that found in Card (1990) and Friedberg (2001), thus researchers make use of empirical strategies to uncover immigrant impacts. Borjas (2003) developed a new framework to directly examine the impact of immigration. In effect, he constructs `skill cells', which are combinations in the levels of education and experience. His approach allows workers with the same education but different levels of work experience to be imperfect substitutes. Borjas's (2003) findings are consistent with competitive labour market theory, where immigrants reduce wages of competing natives. Interestingly, however, Borjas (2003) finds college graduate immigrants have a positive effect on similarly educated natives and argues this may be due to changing wage structure. Since he is unable to control for experience-period interactions, the positive coefficient is most likely the result of increasing returns to education for the highest education group. This result is consistent with Card and Lemieux's (2001) findings that returns to education for those in the highest education group have been increasing relative to other education groups.

A recent work by Ottaviano and Peri (2006) stresses the importance of the general equilibrium framework and argues that estimates should take skill distribution and substitutability into account. Building on Borjas's (2003) strategy of education and experience determining skill groups, Ottaviano and Peri (2006) derive the demand for differentiated labour from a CES production function and generate measures of immigrant impacts. They use the integrated Public Use Microdata Samples (IPUMS) of the US Census to study impacts of immigration from 1980-2000. Ottaviano and Peri (2006) conclude the overall wage impact of immigration was a 2.0-2.2% with the least positive, potentially negative, impact on the lowest education group. Following Ottaviano and Peri's (2006) technique, Manacorda, Manning, and Wadsworth (2006) use the British General Household Survey (GHS) and LFS to estimate a CES production function and assess changes to the wage structure. Their main finding is immigrants do not effectively compete with natives in wages. Manacorda et al. (2006) argue the wages of native-born workers relative to immigrants can vary over time even with fixed levels of demand and supply. The methodology uses observed wage bill shares and estimated elasticities of substitution to compute the changes in wages for each cell in response to different hypothetical changes in the number and composition of immigrants. This specific framework was developed in Ottaviano and Peri (2006), which itself is an augmented version of the modelling strategy in Borjas (2003). Imperfect substitutability is permitted to arise from different abilities, occupational choices, or unobserved characteristics of workers. Manacorda et al. (2006) find the rise in immigration has changed Britain's wage structure. Immigration has depressed the earnings of immigrants relative to native-born. Since immigrants had relatively more university education than natives and returns to education are sensitive to the relative supply of university graduates (Card and Lemieux (2001)), there would be an effect on both migrants and natives. Since the immigrant share is relatively low, the size of the effect on natives, they argue, is negligible.

In the first endeavour to estimate wage and employment impacts from immigrants into Britain, Dustmann, Fabbri, and Preston (2005) use the British Labour Force Survey (LFS) to determine employment, unemployment, participation, and wages effects on 17 UK regions for the period 1983-2000. They estimate OLS, Difference, and IV-Difference models for outcomes of a region using a ratio of immigrant to natives to determine effects. In order to account for native responses and identify the model, they include a vector of natives' skills. Dustmann et al. (2005) do not find statistically significant impacts of immigrants on regional outcomes. Although when they group natives by education group, they do find weakly determined results on the intermediate level. There is a 17.9 percent reduction in employment, 9.8 percent increase in unemployment, 10.8 percent decrease in participation; wages were insignificant, but they find a 15.3 increase for natives. This paper produces some puzzling results. According to the factor price equalisation theory that they state as their theoretical framework, when the skill distribution of natives is unlike that for immigrants a wage effect should occur. So even though immigrants tend to have more education and returns to education are sensitive at higher levels (Card and Lemieux (2001)), they find no effect on natives' earnings.

There are several methodological strategies a researcher can choose to extract information about immigrant effects. The spatial correlations method evaluates average regional wage changes over time and exploits geographical differences in immigrant settlement to find for impacts. Natural experiment approach compares affected and unaffected regions of immigrant flow shocks to make an impact assessment. One last methodology, simulations methods, calculates the impact of variations in the quantities of factors of production on their prices. One feature is similar in all of these methodologies; they focus on mean aggregate outcomes. Koekner and Hallock (2001) suggest that empirical economics is well justified to concentrate on the tails of the distribution. Tannuri-Pianto (2002) performs, to our knowledge, the first and only quantile regression focusing on immigrants to determine effects across the wage distribution. She uses Machado and Mata's (2005) method to decompose changes in native-immigrant skills and changes in the return to skills in the United States over the period 1970-1990. The technique allows Tannuri-Pianto (2002) to perform a counterfactual analysis to suggest what would have happened if the distribution of explanatory variables had remained as in a previous period. It appears natives' earnings grew relative to immigrants from 1970 to 1990 because of differing effects of return to skills for natives and changing workers' characteristics. However, the changing wages structure, which harmed low and middle-income immigrants more than natives and improved high-income immigrants more than natives, diminished the wage gap. A potential weakness is this approach does not take into account any general equilibrium effects. We also perform quantile regressions, as a robustness check on the mean regression estimates.

3. Theory

In the simplest of frameworks, equating the supply and demand for labour and setting prices at marginal cost determine wages and output. The price of marginal productivity from labour is the wage; hence, increasing an individuals' productivity (i.e. further education, more experience) increases their wage. This is the crux of human capital theory formalised by Becker (1975). However, employers cannot observe all productivity characteristics, so they reward personal characteristics that proxy for productive attributes. For example, marital status suggests dependability or loyalty, which is positively rewarded in the labour market. Therefore, we can estimate a wage received by an individual as a function of his or her personal and productive characteristics, such as work experience and education. Mincer (1974) initiated this line of work to estimate the schooling premium in which log earnings are regressed on years of education to determine the returns to education[5].

Immigration has implications for the productivity of an individual and thus, his or her wages. Foreign-born workers bring knowledge and creativity from differing

[5] Heckman, Lochner, and Todd (2005) argue this type of estimation is actually the price of schooling in a hedonic market wage equation and not an internal rate of return to education.

systems, which may improve the ability of native workers to do their job. A basic analysis suggests immigrant workers are a labour supply shock, which shifts the supply curve out and exerts downward pressure on wages. However, this relationship between price and quantity of labour only exists when immigrants substitute for native labour. Immigrants can expand the productivity of native workers and increase returns to labour. This indicates complementarity, which leads to upward pressure on wages. Differing skill sets between immigrants and natives is the key factor in determining how immigrants affect native productivity (wages), so we will define our foreign variables of interest as ratios of immigrants-to-natives. Specifically, the variables will be ratios of immigrants-to-natives possessing the same skill set of education and experience. Categories of skill are the basis for competitiveness and thus, a channel through which immigrants affect native wages. In order to determine what groups of immigrants exert upward or downward pressure on native wages, it is essential to explain the definition of 'skills'. We derive skill categories, or cells, from the combinations of education levels and years of experience in a fashion similar to Borjas (2003). This allows us to calculate which immigrants increase, decrease, or have a null effect on native wages. If immigrants increase natives' productivity, we will find for a positive coefficient on our foreign variable in the wage equation. This is consistent with immigrants acting as complements to natives in production. In contrast, if immigrants are substitutes, we will observe a negative coefficient on the immigrant skill category. Temporal variation of immigrant-native skill ratios provides an opportunity to examine how foreign workers absorb into the British labour market.

The substitutability of immigrants to natives depends not only on observable skills, but unobservable factors as well and estimating an overall wage impact may be misleading. Some natives will find themselves better off, whilst others are harmed. Specifically, we determine how immigrants influence wages of low- to high-ability individuals through the quantile regression (QR) technique. A quantile regression calculates coefficients based on least absolute deviation from the quantile, or percentile, of interest. Thus, we can loosen restrictions on the error term and estimate coefficients for groups of individuals with low- and high-unobservables separately. The quantile analysis ensures OLS estimates capture the true effect of immigrants and unobserved heterogeneity is not driving our findings. In addition, we can make statements about the effect of immigrants on natives with particular abilities and form conclusions about immigrant impacts on wage inequality.

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[6]; 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.[7] 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

[6] The LFS was carried out on a biennial basis from 1973 to 1983.
[7] We do not use the year and quarter in the survey because that relates to the period in which the respondent entered the survey.

the UK Retail Price Index[8] (RPI). 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. Quantile regression estimates are simultaneously estimated for quintiles- .10, .25, .50, .75, .90- using Stata 9.2.

4.a. Summary Statistics

In Table 2, 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, £12.18 and £11.05 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 are 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 is 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.

Table 2: Summary Statistics, 1993-2005

Variable	*UK-born*		*NonUK-born*	
	Mean	SD	Mean	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				

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

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 (by leaving age)				
Less than 17yrs old	0.586		0.276	
17-18	0.193		0.223	
19 +	0.221		0.501	
Potential Experience				
Less than or equal to 5yrs	0.095		0.117	
5-15 yrs	0.248		0.318	
16 +	0.657		0.564	
Education-Experience Groups				
LL	0.028		0.009	
LM	0.114		0.048	
LH	0.443		0.220	
ML	0.024		0.014	
MM	0.057		0.068	
MH	0.112		0.141	
HL	0.043		0.094	
HM	0.077		0.203	
HH	0.101		0.203	
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.

Since we will use education and experience groups as the factor of substitutability, we are particularly interested in differences between the foreign-born and natives. 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.

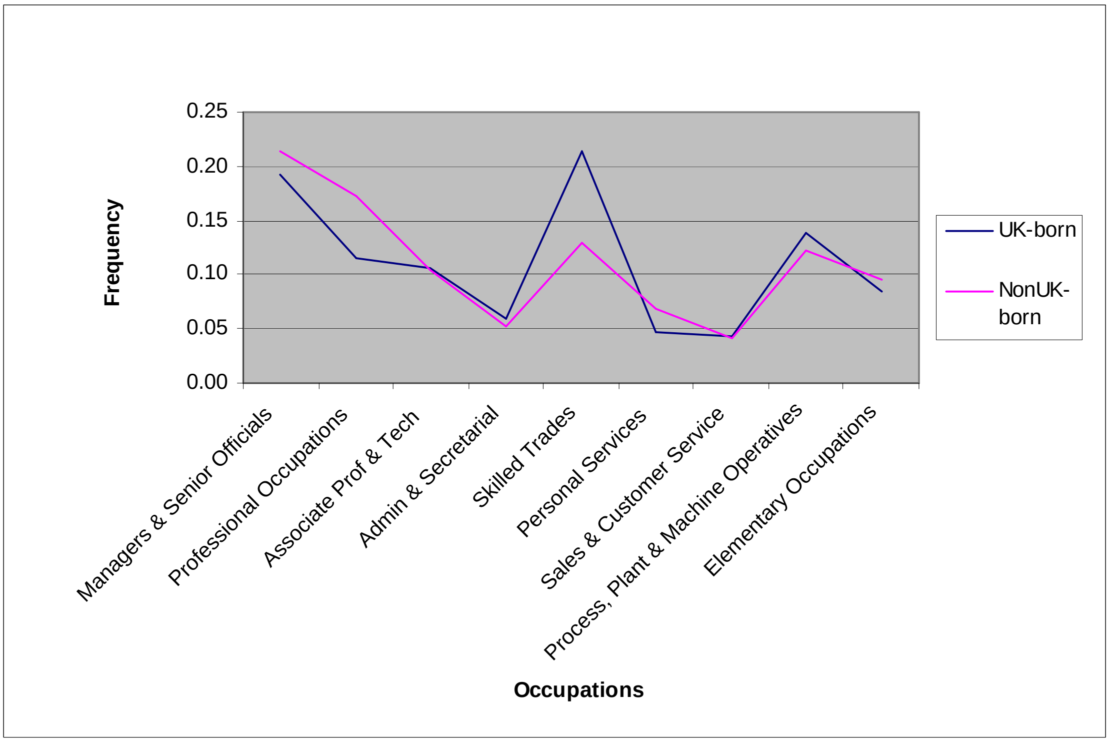
To observe any cohort education trends, we graph the proportions of immigrants in each education category. We are interested to discover what, if any, educational attainment differences there are between immigrants over time. As can be seen in Figure 1, there has been a downward trend in the proportion 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.

We are interested to find out which occupations[9] immigrants accept and whether this is different from natives. In Figure 2 we illustrate the distribution of occupations chosen by immigrants and natives with positions of authority descending from left to right. One of the most noticeable differences is between immigrants and natives in the skilled-trades. There are significantly larger proportions of natives than immigrants in skilled-trades. Generally, immigrants

[9] See Appendix for LFS Occupation definitions.

are more smoothly distributed in occupations and more immigrants than natives are in higher positions. We find there are relatively few differences in occupational choice for natives and immigrants.

Figure 2: Occupational Distribution of British Labour Force, by nativity



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

Immigrants may have lower reservation wages due to less alternative sources of income or lack of borrowing options. This is important because if it leads to immigrants accepting positions for which they are over-qualified, our skill definition, education-experience, is an inaccurate term of comparison. Immigrants and natives would not compete for jobs in terms of their education and experience, but on some other definition of skill. In Table 3, we present immigrant occupations within each of the education-experience cells. In essence, we cross-tab occupations with skill groups and as Table 3 illustrates, we do not find evidence of mismatching occupations to education-experience. Within the lower skill cells, proportions to the Low-educated immigrants, of all experience levels, are mostly involved in skilled-trades rather than other occupations. The bottom, right-hand of Table 3 shows that highly educated immigrants are filling professional roles rather than accepting positions for which they are over-qualified. For example, nearly 61% of highly educated, mid- and highly-experienced immigrants are in professional and managerial/senior roles. Comparing this to natives, in Table 4, we find similar results. Natives are more likely than immigrants of the same education-experience group to be in higher occupations, but the differences are minor. There are some significant differences in the lowest education-experience category, LL, in which LL immigrants are more evenly distributed in Sales & Customer Service, Personal Services, and Skilled Trades. There are 15% more LL natives than LL immigrants in Skilled Trades. On the other end of the spectrum, HH natives are more likely than HH immigrants to be Associate Professionals & Technicians, Professionals, and Managers & Senior Officials. In regression estimates, we allow all education-experience groups to affect an individual's wage and yet, we can see in Table 3 and Table 4 that LL immigrants are not competing for the same positions as HH natives. For example, the lowest five occupations employ 10% of HH natives whilst these occupations employ nearly 85% of LL immigrants and 85% of LL natives. Therefore, it is more consistent with the descriptive evidence that HH natives manage LL workers and do not compete with one another. This leads us to believe there are immigrant skill share groups that do not substitute nor complement through competition. Instead, the lowest skill cells work for the highest skill cells. Coefficients on immigrant shares may be interpreted as the productivity (wage) impact of immigrant compared to native employees.

Table 3: Occupational Distribution of Education-Experience Groups, Immigrants

	LL	LM	LH	ML	MM	MH	HL	HM	HH
Elementary Occupations	19.26%	17.20%	12.42%	22.26%	12.91%	7.90%	8.83%	6.08%	5.12%
Process, Plant & Machine Operatives	14.25%	19.15%	23.31%	8.70%	12.09%	12.35%	4.71%	4.96%	5.69%
Sales & Customer Service	13.98%	5.71%	3.39%	10.96%	6.56%	3.83%	7.13%	3.46%	2.76%
Personal Services	13.72%	12.46%	8.61%	14.96%	11.94%	6.87%	5.83%	4.65%	2.99%
Skilled Trades	23.22%	21.64%	22.46%	13.91%	14.40%	14.24%	4.90%	6.31%	6.16%
Admin & Secretarial	5.80%	5.90%	3.34%	12.52%	8.15%	6.38%	8.20%	5.00%	4.57%

Associate Prof & Tech	3.69%	5.59%	5.36%	8.70%	12.70%	12.46%	16.89%	14.03%	11.33%
Professional Occupations	1.58%	1.58%	3.03%	2.09%	6.66%	9.14%	30.85%	31.91%	31.23%
Managers & Senior Officials	4.49%	10.76%	18.10%	5.91%	14.60%	26.82%	12.66%	23.62%	30.15%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 4: Occupational Distribution of Education-Experience Groups, UK-born

	LL	LM	LH	ML	MM	MH	HL	HM	HH
Elementary Occupations	19.81%	12.48%	10.08%	14.73%	6.02%	3.58%	5.60%	1.87%	0.98%
Process, Plant & Machine Operatives	13.62%	19.79%	19.85%	8.52%	8.87%	6.44%	2.99%	2.10%	1.79%
Sales & Customer Service	8.05%	5.10%	3.31%	15.12%	6.46%	3.89%	7.99%	2.98%	1.64%
Personal Services	5.09%	5.99%	4.79%	7.86%	7.35%	4.16%	4.48%	2.39%	1.21%
Skilled Trades	38.17%	31.02%	27.36%	17.86%	15.78%	11.44%	6.17%	5.57%	5.05%
Admin & Secretarial	7.93%	6.88%	4.51%	16.02%	11.25%	6.68%	12.74%	4.89%	2.77%
Associate Prof & Tech	3.76%	6.48%	7.46%	9.89%	16.61%	16.70%	20.56%	20.07%	14.20%
Professional Occupations	1.28%	2.91%	4.93%	3.37%	7.90%	14.06%	26.47%	33.39%	40.74%
Managers & Senior Officials	2.29%	9.35%	17.72%	6.62%	19.76%	33.05%	12.99%	26.73%	31.61%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

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

Table 5 demonstrates the average wages for UK- and NonUK-born workers in each skill group. There are some significant differences in the wages between UK- and NonUK-born of the same skill groups, although we are cautious about the statistical validity of the descriptives because the number of immigrants in a couple of the categories is very small. Nevertheless, we see that in the skill groups of high-experience, with any level of education, immigrants earn less on average than natives. In contrast, in groups with Low-experience and any level of education, immigrants earn more on average than natives.

Table 5: Mean real wage of Education-Experience groups, by nativity

	UK-born	NonUK-born
LL	5.626	6.443
LM	9.639	9.023

LH	11.603	11.069
ML	6.821	7.325
MM	11.567	11.304
MH	15.799	13.689
HL	10.756	12.565
HM	16.938	17.702
HH	20.684	19.761

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

6. Empirical Strategy

In order to estimate returns to skills or human capital, individual earnings equations are commonly used because results are fairly straightforward to interpret. Regression procedures determine the coefficients on variables of interest and may be interpreted as the marginal impact on earnings. We model wages for an individual as a function of her personal and productivity-related characteristics and immigrant shares. The human capital variables[10] include age, potential experience, education, marital status, race, and region. The LFS does not ask about past unemployment spells, so we must use "potential experience" as the number of years from when an individual left full-time education to the LFS year of questioning. For the education variable, we would like to use the highest qualification attained to measure the marginal effect of obtaining the next level of education. However, the response to this question is inconsistent between immigrants and natives. Immigrants tend to answer `I don't know' when they are unable to transfer the type of degree they obtained from their home country into the UK version. When comparing leaving age of education to highest qualification, immigrants left schooling at a much higher age than natives who respond with `I don't know', which indicates that the transferability of qualifications is a problem and an unreliable estimate of education. In order to account for any industrial or skill-biased technological changes (SBTC) in wage, we include industry dummies. Card and DiNardo (2002) find that SBTC cannot explain the various shifts in wage structure for the US; we want to be certain that this is not influencing any returns to immigration and include industry controls.

[10] See the Appendix for derivation of variables.

Similar to other works of immigrant impacts on wages (Borjas (2003), Dustmann et al. (2005)), our foreign variables are ratios of immigrants to natives. We, however, add an element in which the ratios are based on the same skill level. The skill level is an interaction of education and potential experience. We construct three categories of education indicating low (L), middle (M), and high (H) levels of educational attainment. These are based on standard leaving ages from education institutions: ≤16, 17-18, 19+. We construct three experience groups in a similar fashion[11], so we have low (L), middle (M), and high (H) with the following years of potential experience: ≤5 years, 6-15 years, 16+years. We then interact these two groups to construct nine education-experience dummies: LL, LM, LH, ML, MM, MH, HL, HM, and HH. To detect immigrant impacts, we use the ratios of immigrants to natives with the same skills combination (LL, LM, LH, etc…). Since ratios in each skill cell change over time, we are able to calculate the wage effect of a relative change in skills.

In Borjas (2003) and Dustmann et al. (2005), the left-hand side variable is the mean outcome for native men within each skill cell of a particular region so that wage equations are estimated separately for each education-experience group. We, however, interact immigrant-native skill ratios with a vector of skill dummies for natives. This produces different coefficients for natives of each education-experience group and yet includes all information to estimate the rest of the parameters. We consider this an attractive aspect of our procedure because we are able to include more information, which generates more accurate coefficient estimates. There is potential weakness in our estimation strategy where we have not accounted for temporal variation in wages of skill groups. Since we utilise repeated cross-sections and identify immigrant impacts for skill groups through dummies, it may be necessary to control for time effects common to skill groups. We consider this an avenue for improvement.

The model we are interested in estimating is:

[11] Although somewhat arbitrary, we consider the experience levels demanded by employers in job offers.

$$y_{it} = \alpha + \boldsymbol{\beta}\mathbf{x}_{it} + \pi m_t^j + u_{it} ,$$

for $i=1,\ldots N$, $t=1,\ldots T$, $j=LL, LM, LH,\ldots HH$, where y_i is the real hourly wage for UK-born individual i at time t, α is a constant of the mean national wage, $\mathbf{x}_{it}$ is a vector of personal characteristics (including potential experience, education, industry dummies, etc.) for individual i at time t, m_t^j is the ratio of immigrants to natives with education-experience combination j at time t, and u_{it} is the error term. α, $\boldsymbol{\beta}$, and π are the parameters to be estimated.

When we perform the quantile regression, the model is specifically:

$$y_{it} = \alpha_\theta + \boldsymbol{\beta}_\theta\mathbf{x}_{it} + \pi_\theta m_t^j + u_{\theta it}. \quad (1)$$

Since we control for personal attributes, productivity-related characteristics, and cyclical and technological/industrial changes, the coefficient on the immigrant variable, π, may be interpreted as the immigrant skill-group effect on the quantile of interest. Performing a quantile regression produces within group effects. Suppose π_θ<0 for $j=LL$ and θ=0.10, low-education/low-experience immigrants substitute for low-ability natives. On the other hand, if π_θ >0, then LL immigrants are complements and the LL immigrants exert upward pressure on wages for average native workers in the lowest quantile. Estimating equation (1) will indicate whether transferability of immigrant skills affect wages of high-ability natives dissimilarly from low-ability natives. Standard errors are estimated by boostrapping with 20 resamples.

We also compare the immigrant effect between native education-experience groups. To compare across skill groups, we introduce a dummy on the foreign term in equation (1) and estimate:

$$y_{it} = \alpha + \boldsymbol{\beta}\mathbf{x}_{it} + \gamma(m_t^j * D_i) + u_{it}. \quad (2)$$

The foreign variable of interest here is the interaction term of the vector of skill-group immigrant shares, m_t^j, with education-experience dummies D for natives i.

Estimation of γ gives us some insight into how each skill-type of native interacts in production with each immigrant skill-type. We carry out estimation of this model with quantile regression technique as well.

6.a. Endogeneity, Selectivity, Measurement error

The spatial correlations approach faces an endogeneity problem on foreign variables because immigrants locate in regions with economic growth and the foreign variables are no longer exogenous. In such a case, the model is not identified and coefficients are upward bias, making it seems as though foreigners increase wages; when in fact, wages were increasing already. We minimise this issue since our foreign variable, immigrant-native ratio, is at the national level and based on skill cells. It may be argued that rising wages for particular skills in Britain encourages immigrants, but there are obstacles to entering the UK and working legally.

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.

The problem of measurement error is compounded by the fact that our dependent variable, hourly wage, is derived from weekly wages and weekly hours worked. This could present an obstacle to accuracy since we find extreme observations for income. For example, there are manual labourers reporting very high wages and professionals reporting very low wages. However, we perform a quantile regression, so unlike mean regressions, parameter vector estimates are robust to outliers (Buchinsky (1998)). Formally, if the residual is positive, $y_i - x_i'\beta_\theta > 0$, then the hourly wage, y_i, can be increased towards ∞ without altering our solution $\hat{\beta}_\theta$ (Buchinsky (1998)).

6.b. Quantile Regression

Following Koenker and Bassett (1978) and Buchinsky (1998), we let $(y_i,\ x_i)$, $i=1,\ldots N$, be the LFS random sample of the UK population. x_i is a $Kx1$ 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 $Quant_\theta(y_i\ |x_i)=\ x_i'\beta_\theta$. We assume the conditional error term at each quantile is $Quant_\theta(u_{\theta i}\ |x_i)=0$. Then, the model is simply:

$$y_i = \mathbf{x}_i'\boldsymbol{\beta}_\theta + u_{\theta i}\ .$$

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 $\theta=0.5$. An advantage of the quantile regression approach is that outliers are not given extra weight, as in the OLS procedure that 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:

$$\min_{\beta}\left\{\sum_{i:y_i\geq \mathbf{x}_i'\beta}\theta\,|y_i-\mathbf{x}_i'\beta| + \sum_{i:y_i<\mathbf{x}_i'\beta}(1-\theta)\,|y_i-\mathbf{x}_i'\beta|\right\}$$

To avoid misinterpretation of the coefficients from the quantile regression, we provide an illustration. Suppose an immigrant covariate in our OLS regression generates a positive coefficient so it increases average wages. This would mean when there was a lower number of those immigrants, a native worker in the top quantile had much lower earnings than would be predicted. In the bottom quantile, the earnings difference between those working with a lower number of those immigrants compressed earnings relative to natives in a labour market with higher numbers of immigrants. In other words, relative to the low-ability, the high-ability natives encounter wage gains with larger numbers of immigrants. This education-experience group of immigrants actually complement high-ability natives.

7. Results

7.a OLS Estimations

7.a.1 Effect of immigration on UK-born workers

We perform OLS regressions on various model specifications (see Table 6 below) to discover how introducing more controls affects the calculation of our foreign variables. We find statistically significant immigrant effects on wages and very few differences across models. In model (1), we estimate individual wages conditional only on immigrant skill groups. Although this model is economically unappealing and the extremely low R^2 indicates a poorly fitted model, it is a good starting point. Generally speaking, this model suggests the highest skilled immigrants have a positive effect on native wages. Model (2) conditions on education, potential experience, and a quadratic in experience. Results indicate that increasing the ratio of HL, HM, and HH immigrants to natives by 1% increases natives' wages by 0.004, 0.006, and 0.005 log points respectively. Native wages decrease by 0.029 and 0.007 log points if increasing the immigrant to native ratio of the LM and MH skill groups. In Model (3), we further control for personal characteristics that contribute to wages. Several foreign variables lose significance- ML and MH- whilst the rest of the immigrant shares remain similar.

The final Model (4) includes all controls and is the specification we use in the remainder of this paper (see Table 12 in the Appendix for full results). In this model, positive impacts are at the polar ends of skill distribution. The lower end (LL) and upper end (HL, HM, and HH) skill groups expand native wages, such that an increase in those ratios by 1% increases the average native wage between 0.004-0.10 log points. By contrast, increasing the ratio of immigrants to natives in either the LM and ML skill cells by 1% decreases the average wage by nearly 0.023 and 0.003 log points respectively.

Table 6: OLS Regression Estimates of impacts from Immigrant shares on UK-born

Dependent variable: log real hourly pay	**(1)**	**(2)**	**(3)**	**(4)**
Constant	2.113**	0.364**	0.238**	0.591**
	(52.20)	(10.23)	(6.58)	(13.98)
Foreign variables				
LL	0.013**	0.004	0.001	0.006**
	(5.40)	(1.93)	(0.31)	(2.71)
LM	-0.029**	-0.029**	-0.030**	-0.023**
	(4.46)	(5.20)	(5.10)	(3.92)
LH	0.012	0.021*	0.027**	-0.010
	(0.97)	(2.04)	(2.61)	(-0.88)
ML	-0.004**	-0.003*	0.00	-0.003*
	(-3.28)	(-2.29)	(0.29)	(-2.36)
MM	0.015**	0.009**	0.005**	0.005**
	(11.30)	(8.06)	(4.14)	(4.51)
MH	-0.013**	-0.007**	0.001	-0.001
	(-5.43)	(-3.56)	(0.69)	(-0.28)
HL	0.007**	0.004**	0.009**	0.010**
	(6.64)	(4.60)	(8.59)	(9.73)
HM	0.009**	0.006**	0.003**	0.004**
	(10.72)	(8.15)	(4.04)	(4.55)
HH	0.004**	0.005**	0.006**	0.005**
	(2.64)	(3.88)	(5.02)	(4.01)
Observations	130,558	130,512	125,428	120,650
R-squared	0.01	0.27	0.31	0.33
Experience, Education	N	Y	Y	Y
Personal characteristics	N	N	Y	Y
Regional dummies	N	N	Y	Y
Industry dummies	N	N	N	Y

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%
Source: Author's LFS sample, 1993-2005. Employed males only.

In summary, every specification indicates that university educated immigrants expand the average British wage. When controlling for personal characteristics and industry of the worker, it becomes clearer that the lower skilled immigrants have a depressive effect on the average British wage.

Next, we introduce interaction terms that allow us to discuss how each skill-type of native responds to each skill-type of foreign worker. Rather than running separate regressions for each native skill group, we interact the immigrant shares with a vector of native education-experience dummies and keep information from the entire data set. As we anticipate, the impact of foreign skill groups varies across native skill groups. There are some interesting results in terms of complements and substitutes and the relative experience of natives. In Table 7 below, we present the results of the interaction terms (see Table 13 in the Appendix for full results). The omitted skill group in the native skill vector is Low education-High experience, thus results are relative to LH natives. Even when we interact the immigrant shares with natives' skills, it is still the case that low-skilled immigrants have a negative effect and higher skilled immigrants have a positive effect. More specifically, we can see that the immigrants with low-education and over 10 years of work experience and the mid-educated with less than 5 years experience have a negative effect on natives of all skill-types. The statistically significant results show LH immigrants reduce wages between 0.02 to 0.14 log points. Conversely, the HL immigrant share has a statistically positive effect of 0.005 to 0.017 log points on wages of natives with any skill. When we examine across the rows to uncover the immigrant experience of each skill-type of native, we find the lowest skilled incur the greatest roller coaster of effects. Considering only statistically significant impacts, the range of immigrant effects on LH natives is -0.14 to 0.028 log points. These lowest-skilled native workers, LL, experience the same positive wage gain from LL and MM immigrants (+0.028 log points).

Table 7: OLS Regression Estimates of impact from Immigrant shares on UK-born skill cells

UK-born, by skill cell	Immigrant shares, by skill cell								
	LL	LM	LH	ML	MM	MH	HL	HM	HH

LL	0.028*	-0.049	-0.14**	-0.013	0.028**	-0.039**	0.015**	0.015**	0.006
	(2.55)	(-1.48)	(-4.18)	(-1.81)	(4.29)	(-3.65)	(2.94)	(3.40)	(1.03)
LM	0.014*	-0.007	-0.048**	-0.011**	0.006	-0.008	0.009**	0.005	0.006
	(2.43)	(-0.42)	(-2.94)	(-2.87)	(1.65)	(-1.54)	(3.66)	(1.95)	(1.78)
LH (omitted)									
ML	0.021	-0.064	-0.135**	-0.008	0.023**	-0.021	0.017**	0.015**	0.005
	(1.84)	(-1.85)	(-3.59)	(-1.09)	(3.42)	(-1.79)	(3.17)	(3.11)	(0.81)
MM	0.00	-0.025	-0.02	0.001	0.005	0.005	0.008*	0.002	0.002
	(0.00)	(-1.08)	(-0.87)	(0.16)	(1.06)	(0.71)	(2.22)	(0.51)	(0.54)
MH	0.007	-0.036*	-0.052**	-0.006	0.004	0.003	0.011**	0.003	0.01**
	(1.38)	(-2.37)	(-2.98)	(-1.92)	(1.41)	(0.52)	(4.45)	(1.21)	(3.30)
HL	0.004	-0.033	-0.061*	-0.004	0.012*	-0.006	0.011**	0.004	0.007
	(0.53)	(-1.33)	(-2.16)	(-0.71)	(2.49)	(-0.65)	(2.74)	(1.25)	(1.41)
HM	0.004	0.004	-0.03	-0.002	0.002	0.007	0.005	0.003	0.006
	(0.61)	(0.20)	(-1.43)	(-0.59)	(0.62)	(1.08)	(1.67)	(1.29)	(1.54)
HH	-0.003	-0.037*	-0.059**	-0.006	0.006	0.008	0.013**	0.005*	0.005
	(-0.59)	(-2.30)	(-3.17)	(-1.82)	(1.82)	(1.32)	(4.96)	(2.05)	(1.54)

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

In summary, we are able to specify the groups that exert positive and negative forces on native wages. Unlike previous works, we do not find all groups of immigrants have a negative impact on low-skilled natives. For the lowest skilled natives, it appears that the lowest immigrants complement, the mid-skilled immigrants compete, and the higher skilled immigrants improve productivity. In addition, there are low-skilled groups of immigrants that have negative effects on high-skilled natives, which indicates that natives would prefer a larger ratio of natives with low skills. Although the labour market reacts to supply shocks with wage and employment impacts, our estimates only determine the price effects and any workers that leave employment do not influence parameter estimates. Therefore, there may be larger effects that we are unable to capture.

7.a.2 Effect of immigration on NonUK-born workers

We perform OLS regressions on various model specifications to observe how the addition of more controls affects the coefficients on our foreign variables. In order to account for any assimilation effects bias our estimates, we include foreign characteristic variables[12] in Model (4) and Model (5) (see Table 8). By including the assimilation variables, we find the coefficient on immigrant share LL\ becomes significant at the 5% level. In Model (5) with all controls, increasing the ratio 1% of immigrants-to-natives with skill level ML or MH reduces the average immigrant's wages by 0.089 and 0.025 log points, respectively. On the other hand, a 1% increase in the immigrant-native ratio with MM or HM skills expands the average immigrant worker's wage by 0.018 and 0.013 log points (see Table 16 in Appendix for full results).

Table 8: OLS Regression Estimates of impacts from Immigrant shares on NonUK-born

Dependent variable: log real hourly pay	(1)	(2)	(3)	(4)	(5)
Constant	2.072**	0.782**	0.495**	0.635**	0.791**
	(11.63)	(4.78)	(3.07)	(3.40)	(3.76)
Foreign Variables					
LL	0.010	0.007	0.007	0.014	0.019*
	(0.95)	(0.74)	(0.81)	(1.51)	(1.99)
LM	-0.107**	-0.106**	-0.114**	-0.100**	-0.089**
	(-4.06)	(-4.48)	(-4.65)	(-4.10)	(-3.72)
LH	0.057	0.055	0.055	0.074	0.066
	(1.06)	(1.13)	(1.18)	(1.59)	(1.31)
ML	-0.01	-0.007	-0.006	-0.004	-0.006
	(-1.83)	(-1.40)	(-1.24)	(-0.78)	(-1.21)
MM	0.024**	0.021**	0.018**	0.020**	0.018**
	(4.36)	(4.27)	(3.66)	(3.76)	(3.65)
MH	-0.024*	-0.020*	-0.016	-0.022*	-0.025**
	(-2.38)	(-2.17)	(-1.83)	(-2.51)	(-2.83)
HL	0.005	0.004	0.009*	0.009*	0.009*
	(1.02)	(0.96)	(2.02)	(2.11)	(2.17)
HM	0.018**	0.014**	0.014**	0.014**	0.013**
	(5.01)	(4.22)	(3.78)	(3.50)	(3.32)
HH	0.015*	0.011	0.014*	0.013*	0.010
	(2.39)	(1.86)	(2.53)	(2.30)	(1.79)
Observations	8,283	8,263	7,921	7,883	7,614
R-squared	0.01	0.19	0.26	0.28	0.33
Experience, Education	N	Y	Y	Y	Y
Personal characteristics	N	N	Y	Y	Y
Foreign particular char.	N	N	N	Y	Y
Region dummies	N	N	Y	Y	Y

[12] Age at immigration, Years since immigrated squared, Region of Birth, Cohort of entry. See Appendix for definitions of these terms.

Industry dummies	N	N	N	N	Y

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%
Source: Author's LFS sample, 1993-2005. Employed males only.

Comparing immigrant and native responses, the results in Model (5) for immigrants (see Table 8) and Model (4) for natives (see Table 6) indicate that immigration to Britain has only a slightly different impact on immigrant and native workers. Generally, it appears that natives absorb the wage impact more than immigrants. The ratio of LH immigrants has a -0.089 log point effect on average immigrant wage and a -0.023 log point on the average native's wages. On the positive spectrum, the effects are 0.004 and 0.013 log points for natives and immigrants, respectively.

Between skill group regression analysis reveals there are only a couple of skill groups that experience a differential impact of immigration (see Table 15 for full results). The results below (Table 9) indicated upward pressure on wages from LL immigrant share and we discover here that the statistically significant groups to receive this benefit are LL, MM, and MH immigrants. It seems rather odd the LL immigrant share has a more positive impact on LL immigrants than those with LH skills. However, when we look at the higher-skilled immigrants it once again appears that there are positive effects associated with similarly skilled immigrant shares. It is possible that there are network effects between workers with similar skills and this is stronger for immigrants than natives. This would be an interesting avenue of research, however it is beyond the scope of this paper to determine the validity of our suggestion.

Table 9 OLS Regression Estimates of impact from Immigrant shares on NonUK-born skill cells

	Immigrant share, by skill								
Immigrants, by skill	LL	LM	LH	ML	MM	MH	HL	HM	HH
LL	0.176*	0.284	0.06	-0.028	0.058	0.018	0.018	-0.058	-0.097
	(2.04)	(1.20)	(0.22)	(0.53)	(1.32)	(0.19)	(0.48)	(-1.79)	(-1.81)
LM	0.065	0.102	0.015	0.004	0.010	-0.042	-0.003	-0.014	-0.001
	(1.79)	(0.96)	(0.14)	(0.18)	(0.47)	(-1.19)	(-0.17)	(-0.90)	(-0.06)
LH (omitted)									
ML	-0.035	-0.119	-0.027	-0.012	-0.017	-0.067	0.062*	0.023	-0.011

	(-0.59)	(-0.60)	(-0.12)	(-0.28)	(-0.47)	(-0.87)	(1.96)	(0.85)	(-0.31)
MM	0.066*	-0.09	0.115	-0.009	0.023	-0.082**	0.029*	-0.011	0.007
	(2.31)	(-1.07)	(1.18)	(-0.49)	(1.45)	(-2.73)	(2.02)	(-0.92)	(0.38)
MH	0.041*	-0.011	0.059	0.001	0.001	-0.035	0.006	0.000	-0.001
	(2.05)	(-0.19)	(0.84)	(0.05)	(0.08)	(-1.57)	(0.65)	(0.05)	(-0.04)
HL	0.017	0.019	0.01	-0.007	0.001	0.001	0.002	0.011	-0.016
	(0.69)	(0.27)	(0.12)	(-0.49)	(0.10)	(0.03)	(0.18)	(1.07)	(-1.05)
HM	0.019	-0.066	0.120*	0.002	0.030**	-0.052**	-0.005	0.013	0.000
	(1.12)	(-1.42)	(2.00)	(0.18)	(3.14)	(-2.81)	(-0.59)	(1.91)	(0.03)
HH	0.011	-0.129**	0.02	0.005	0.02*	-0.022	0.007	0.007	0.018
	(0.69)	(-2.76)	(0.33)	(0.48)	(2.15)	(-1.16)	(0.83)	(1.00)	(1.68)

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Between group effects also show that immigrants face statistically significant impacts from only one or two immigrant skill groups. For example, immigrants with LL skills incur a 0.176 log point increase by increasing the ratio of immigrants-to-natives with the LL skills by 1 log percentage point. All models of the initial regressions (see Table 8) indicate downward pressure on wages due to the share of MH immigrants. Through the following regression analysis, we can be more explicit and specify a great deal of the disadvantage, -0.082 and -0.052 log points, is on immigrants with skill set MM and HM.

The range of techniques and specifications we implement provides a more complete picture of immigrants in the British workforce. Results indicate that the OLS estimates are fairly accurate across the earnings distribution for most immigrant skill groups. Nevertheless, we do find some differences in the LM immigrant share where coefficients decrease further across the quantiles. This indicates with a larger share of LH immigrants, individuals in the upper 10 percent of UK earnings have lower earnings than would be expected. Another way of stating this is that individuals in a labour market with higher ratios of LH immigrants whom are in the bottom quantile of earnings, their earnings difference is compressed relative to those in the median group. In addition, the HH immigrant share has a more positive effect across the earnings distribution. Comparing this with OLS results, we see that HH immigrant share increases average earnings. Therefore, we can interpret QR results to mean that a larger share of HH immigrants expands earnings for individuals with greater ability.

7.b Quantile Results, A Robustness Check

7.b.1 Effect of immigration on UK-born workers

Quantile regression estimates demonstrate the effect of immigrants on natives' wages depends on the ability of natives. In order to compare OLS and QR results, Table 10 presents quantile estimates and the previously determined OLS estimates (see Table 13 in Appendix B for full quantile regression results). The most striking result is to find OLS results hide the impact of LH immigrants on low-ability natives. In OLS estimates, the LH ratio is statistically insignificant; however, QR estimates show that this group has a negative impact (-0.034 log points) on the conditional wages of low-ability natives. Coefficients on LH become increasingly positive, yet statistically insignificant, across the quantiles. Therefore, LH immigrants have a smaller impact on earnings at the upper quantiles of the earnings distribution. This indicates that the share of LH immigrants have no effect on average wages, yet individuals in the bottom 10 percent of UK earnings have lower earnings than would be expected for a larger ratio of immigrants with LH skills.

Table 10: OLS & QR Regression Estimates of impact from Immigrant shares on UK-born skill cells

	OLS	Quantiles				
UK-born, by skill share		0.10	0.25	0.50	0.75	0.90
LL	0.006**	0.009**	0.004*	0.004*	0.001	0.00
	(2.71)	(3.65)	(2.26)	(2.39)	(0.42)	(0.10)
LM	-0.023**	-0.008	-0.022**	-0.016**	-0.024**	-0.014
	(3.92)	(-1.11)	(-3.52)	(-3.41)	(-3.83)	(-1.63)
LH	-0.010	-0.034*	-0.01	0.001	0.014	0.007
	(-0.88)	(-2.55)	(-0.76)	(0.10)	(1.24)	(0.34)
ML	-0.003*	-0.004*	-0.004*	-0.003*	-0.001	-0.002
	(-2.36)	(-2.07)	(-2.41)	(-2.17)	(-0.56)	(-0.82)
MM	0.005**	0.006**	0.004**	0.003*	0.005**	0.005*
	(4.51)	(2.65)	(2.75)	(2.46)	(3.71)	(2.57)
MH	-0.001	-0.002	0.001	0.002	-0.001	0.003
	(-0.28)	(-0.69)	(0.65)	(1.14)	(-0.24)	(0.91)
HL	0.010**	0.01**	0.01**	0.009**	0.007**	0.008**
	(9.73)	(6.69)	(10.46)	(8.58)	(6.58)	(4.23)
HM	0.004**	0.002	0.004**	0.003**	0.005**	0.003**
	(4.55)	(1.45)	(5.57)	(5.09)	(5.38)	(2.68)

	OLS					
HH	0.005**	0.002	0.005**	0.005**	0.006**	0.005**
	(4.01)	(1.47)	(3.71)	(5.47)	(4.75)	(3.30)
Observations	120,650					120,650
Pseudo R-squared	0.33	0.181	0.207	0.221	0.219	0.207

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

7.b.2 Effect of immigration on NonUK-born workers

In a final calculation of the immigrant effect, we perform a quantile regression on Model (5)[13] and investigate the impact of immigration on immigrants across the wage distribution. Coefficients on the foreign variables are displayed in Table 11 (for full results, see Table 17 in the Appendix). Results show the OLS estimates do not capture the entire story regarding immigrant impacts on other immigrants. Beginning with the immigrant share of LL workers, OLS estimates report 0.204 log point increase in average wages. Quantile estimates indicate conditional wages of higher skilled workers, those in the top 25% of conditional wages (or in the .75 and .90 quantiles), reduce the positive effect of LL immigrants; coefficient estimates are 0.191 for the 75th percentile and 0.065 for the 90th percentile as opposed to 0.272 for the 10th percentile. Increasing the ratio of LH immigrants-to-natives has a less negative effect on the highest ability immigrants. More importantly, quantile regression estimates illustrate how the OLS technique misrepresents the downward pressure of LH immigrants on wages. OLS estimates indicate a wage reduction of -0.116 log points with a 1% increase in the ratio of LH immigrants-to-natives, whilst QR results show that the effect of this ratio is greater at the 10th (-0.177) and 50th (-0.175) percentiles. We do find, however, the OLS technique accurately estimates the effect of ML immigrants, such that the QR estimates are similar across the quantiles.

Table 8: OLS & QR Regression Estimates of impact from Immigrant shares on NonUK-born skill cells

Immigrant share, by skill	OLS	Quantiles 0.10	0.25	0.50	0.75	0.90
LL	0.019*	0.015	0.021	0.017	0.018	0.007

[13] From Table 8

	(1.99)	(0.79)	(1.44)	(1.68)	(1.51)	(0.42)
LM	-0.089**	-0.067*	-0.084*	-0.102**	-0.106**	-0.125*
	(-3.72)	(-1.97)	(-2.70)	(-4.43)	(-2.94)	(-2.36)
LH	0.066	0.114	0.044	0.098*	0.074	-0.009
	(1.31)	(1.47)	(0.73)	(2.21)	(1.16)	(-0.09)
ML	-0.006	0.003	0.001	-0.002	-0.013	-0.022
	(-1.21)	(0.28)	(0.07)	(-0.52)	(-1.95)	(-1.90)
MM	0.018**	0.014	0.012	0.018**	0.018**	0.017*
	(3.65)	(1.76)	(1.92)	(3.57)	(3.15)	(2.23)
MH	-0.025**	-0.03*	-0.019*	-0.016	-0.027*	-0.012
	(-2.83)	(-2.43)	(-2.17)	(-1.22)	(-2.52)	(-0.71)
HL	0.009*	0.003	0.011*	0.007	0.015**	0.02**
	(2.17)	(0.42)	(2.01)	(1.48)	(2.93)	(2.73)
HM	0.013**	0.011*	0.008*	0.014**	0.014*	0.021**
	(3.32)	(2.22)	(1.98)	(3.36)	(2.51)	(3.16)
HH	0.010	0.003	0.005	0.009	0.019*	0.023*
	(1.79)	(0.35)	(0.58)	(1.47)	(2.37)	(2.03)
Observations	7,614					7,614
Pseudo R-squared	0.33	0.155	0.197	0.221	0.221	0.228

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Quantile regression results indicate the OLS estimates are accurate. Excluding a few skill groups, the OLS and QR are very similar and suggest there is no unobserved heterogeneity affecting results. In other words, the ability to absorb immigrant workers is largely from matching skill needs in terms of education-experience. Native and immigrant unobserved ability to interact with immigrants is not the force behind wage impacts of immigrants in the workforce.

8. Conclusion

In March 2007, former Federal Reserve Chairman Alan Greenspan suggested the United States reduce wage inequality by encouraging in-migration of high-skilled workers.[14] The theory is there will be relatively more high-skilled workers competing for fewer jobs and wages will fall relative to low-skilled workers. This is a rather simplistic interpretation of the labour market and does not take into

[14] http://www.bloomberg.com/apps/news?pid=newsarchive\&sid=aDWi3n1erxT8. Accessed on 28/03/07.

account nuances of worker relationships. The numbers of high-skilled immigrants it would take to begin pushing down wages of the most educated and experienced individuals is beyond any amount the public and its government would allow. High-skilled workers are able to take advantage of the opportunities brought about by immigrant workers and expand earnings potential. Lower-skilled workers take the available, low paying jobs.

This paper does not support the broad hypothesis that high-skilled immigrants will drive down high-skilled wages. In fact, highly educated NonUK-born workers with limited experience push up the wages of all native workers. There is a great deal of complementarity between high-skilled, low-experience foreign workers and other skill types of workers. It appears they are a very adaptable group of workers and positively influence the productivity of natives across the earnings distribution. Policies encouraging the in-migration of these workers do not reduce wage inequality, but do improve wages for all workers.

In contrast, highly educated immigrants with more than five years work experience increase wages for all but the lowest ability native workers. This has the consequence of increasing wage inequality. However, it is important to reiterate that this is only one way to interpret results. It is highly probable that the influx of immigrants with high education and experience increase trade and growth, which can positively yet indirectly affect low wage earners. What we calculate here is the direct effect on an individual's marginal productivity.

We find immigrants with similar skill set to natives improve the wages of their counterparts. We offer a couple of explanations for this. Firstly, there are network effects in force where people communicate with other workers of similar skill levels, exchange information, and push up wages. This may be why we find positive effects between same skill cells are stronger for immigrants. Another possibility is this finding is the result of positive competition between workers, which improves productivity or wages. Lastly, we must consider these positive findings may be attributed to uncontrolled selectivity.

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10. Appendix A (*Variable Definitions*)

Dependent Variable

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. 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 that 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.

Personal and Productivity Variables

Education- is equal to leaving age minus 5 (to account for the age of starting school).

Experience- is potential labour market experience in that it is derived from the respondents' 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 legal leaving age from education.

Full-time- we create a dummy equal to 1 if the response to USUHR is greater than 30. It is equal to 0 if the response is 30 hours or less.

Industry- this 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.

Married- 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, zero otherwise.

Nonwhite- there are several ethnicity variables over time, ETH01, ETHCEN15, ETHCEN6, which are 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.

Region- 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.

Immigrant ratio {LL-HH}- the vector of education groups is derived from `leaving age from education', EDAGE. The groups are: (Low) ≤16 leaving age, (Mid) 17-18, (High) 19+. The vector of experience groups is created by potential experience of age minus education leaving age: (Low) ≤5 years, (Mid) 6-15, (High) 16+. These dummies are interacted to create the nine skill groups. The number of immigrants in each skill cell is divided into the number of natives in the same skill cell per year.

11. Appendix B

11.a. Figures

Figure 3: Covariate plots of OLS & QR Estimates for UK-born

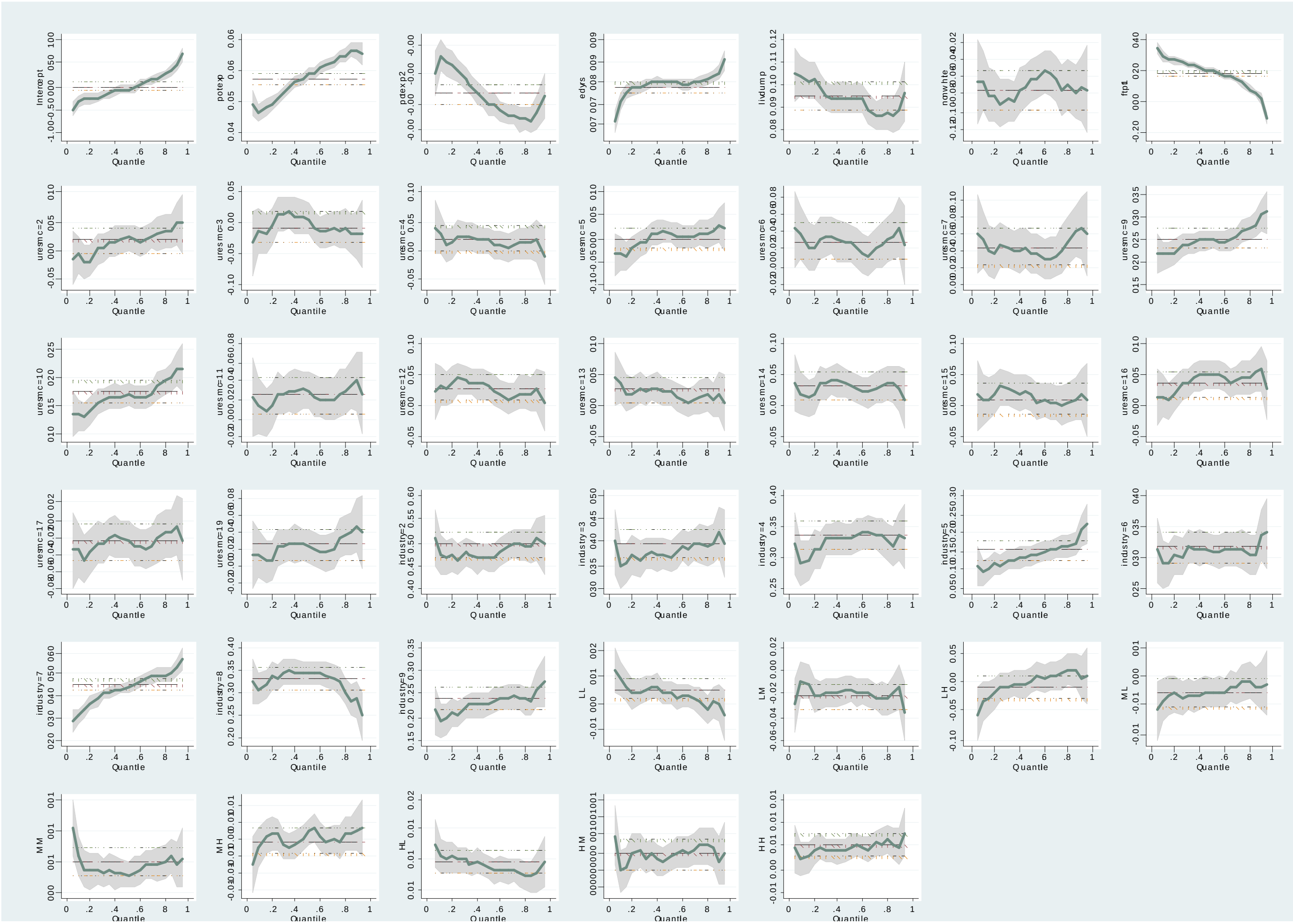
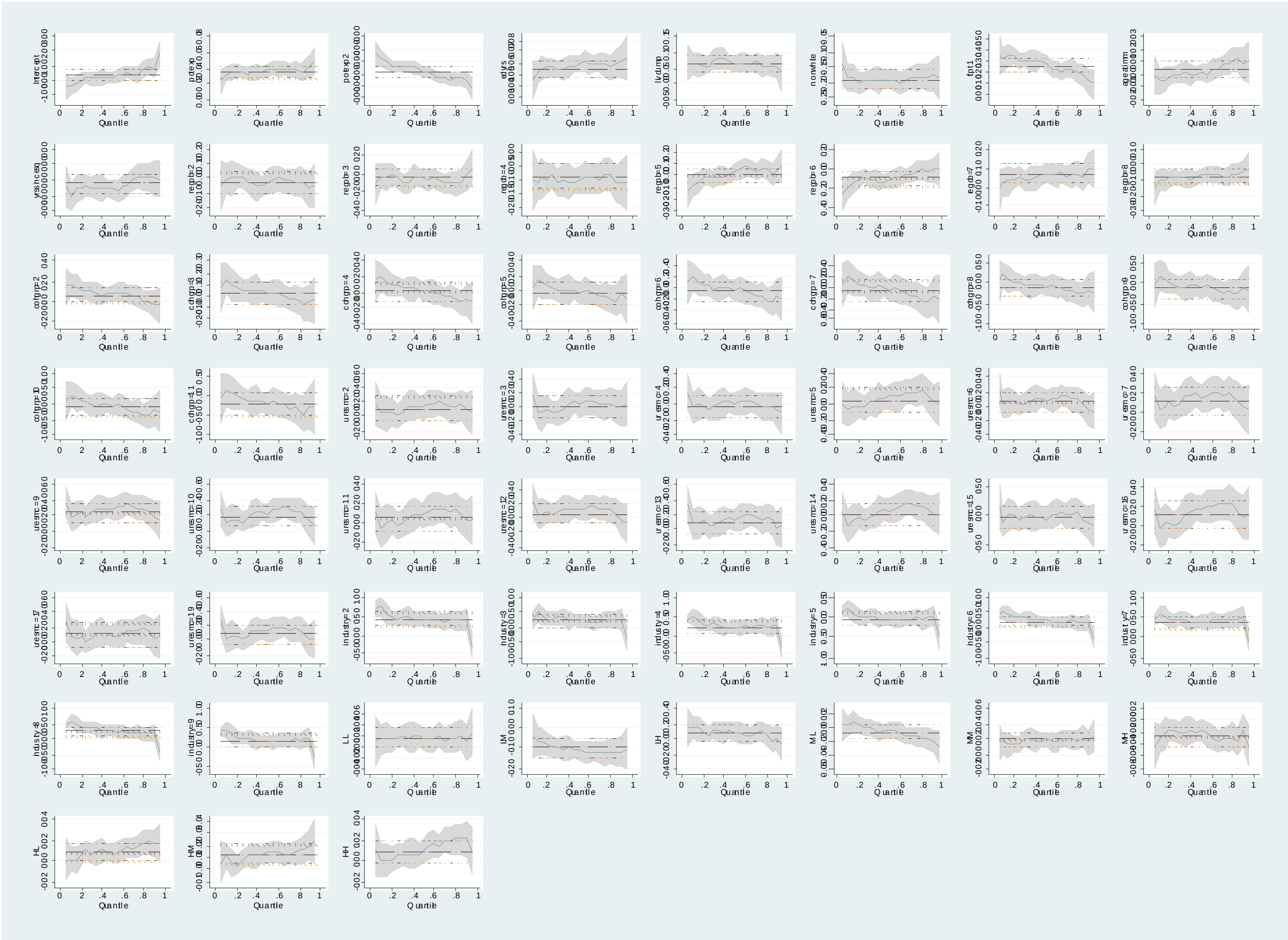


Figure 4: Covariate plots of OLS & QR Estimates for NonUK-born



11.a. Tables

Table 9: OLS Regression Estimates of Immigrant impacts on UK-born wages

Dependent variable: Log real hourly wage	Coefficients
Constant	0.591**
	(13.98)
Potential Experience	0.054**
	(123.15)
Potential Experience Sqrd/1000	-0.001**
	(-104.53)
Years of Education	0.079**
	(136.17)
Married & cohab	0.095**
	(31.27)
Nonwhite	-0.074*
	(-6.31)
Full-time	0.185**
	(20.86)
Region of Residence	
Rest of South East (omitted)	
Tyne & Wear	-0.175**
	(-18.25)
Rest of Northern Region	-0.158**
	(-21.66)
South Yorkshire	-0.182**
	(-20.36)
West Yorkshire	-0.154**
	(-21.83)
Rest of Yorkshire & Humberside	-0.175**
	(-22.08)
East Midlands	-0.145**
	(-26.72)
East Anglia	-0.13**
	(-18.55)
Inner & Outer London	0.079**
	(14.52)
South West	-0.149**
	(-28.99)
West Midlands (Metro)	-0.145**
	(-20.80)
Rest of West Midlands	-0.149**
	(-24.08)
Greater Manchester	-0.141**
	(-20.08)
Merseyside	-0.163**
	(-16.27)

Rest of North West	-0.14**
	(-20.34)
Wales	-0.20**
	(-30.12)
Industries	
Manufacturing (omitted)	
Strathclyde & Rest of Scotland	-0.149**
	(-30.30)
Agriculture & Fishing	-0.397**
	(-23.53)
Energy & Water	0.097**
	(6.67)
Construction	-0.06**
	(-4.87)
Distribution, Hotels & Restaurants	-0.243**
	(-19.26)
Transport & Communication	-0.08**
	(-6.23)
Banking, Finance & Insurance etc	0.054**
	(4.31)
Public admin, Educ & Health	-0.066**
	(-5.25)
Other Services	-0.157**
	(-12.41)
Foreign Variables	
LL	0.006**
	(2.71)
LM	-0.023**
	(-3.92)
LH	-0.01
	(-0.88)
ML	-0.003*
	(-2.36)
MM	0.005**
	(4.51)
MH	-0.001
	(-0.28)
HL	0.01**
	(9.73)
HM	0.004**
	(4.55)
HH	0.005**
	(4.01)
Observations	120,650
Pseudo R-squared	0.33

t-stat reported in parenthesis. **- significant at 1%, *-significant at 5%
Source: Author's LFS sample, 1993-2005. Employed males only.

Table 10: Full OLS Regression Estimates of Immigrant impacts on UK-born wages

Dependent variable: Log real hourly wage	Coefficient
Constant	0.996**
	(40.45)
Potential Experience	0.05**
	(54.68)
Potential Experience Sqrd/1000	-0.001**
	(-54.91)
Years of Education	0.061**
	(44.11)
Married & cohab	0.088**
	(30.03)
Nonwhite	-0.076**
	(-6.47)
Full-time	0.179**
	(20.18)
Region of Residence	
Rest of South East (omitted)	
Tyne & Wear	-0.167**
	(-17.53)
Rest of Northern Region	-0.151**
	(-20.77)
South Yorkshire	-0.177**
	(-19.89)
West Yorkshire	-0.149**
	(-21.15)
Rest of Yorkshire & Humberside	-0.169**
	(-21.44)
East Midlands	-0.141**
	(-26.05)
East Anglia	-0.128**
	(-18.30)
Inner & Outer London	0.076**
	(13.99)
South West	-0.147**
	(-28.74)
West Midlands (Metro)	-0.142**
	(-20.47)
Rest of West Midlands	-0.145**
	(-23.52)
Greater Manchester	-0.137**
	(-19.58)

Merseyside	-0.157**
	(-15.70)
Rest of North West	-0.136**
	(-19.83)
Wales	-0.198**
	(-29.95)
Strathclyde & Rest of Scotland	-0.146**
	(-29.85)
Industries	
Manufacturing (omitted)	
Agriculture & Fishing	-0.40**
	(-24.41)
Energy & Water	0.091**
	(6.50)
Construction	-0.067**
	(-5.77)
Distribution, Hotels & Restaurants	-0.248**
	(-20.80)
Transport & Communication	-0.082**
	(-6.70)
Banking, Finance & Insurance etc	0.038**
	(3.14)
Public admin, Educ & Health	-0.073**
	(-6.19)
Other Services	-0.163**
	(-13.72)
Foreign variables	
Native skill / Immigrant share, by skill	
LL / LL	0.028*
	(2.55)
LM	0.014*
	(2.43)
ML	0.021
	(1.84)
MM	0.00
	(0.00)
MH	0.007
	(1.38)
HL	0.004
	(0.53)
HM	0.004
	(0.61)
HH	-0.003
	(-0.59)
LL / LM	-0.049
	(-1.48)
LM	-0.007

		(-0.42)
ML		-0.064
		(-1.85)
MM		-0.025
		(-1.08)
MH		-0.036*
		(-2.37)
HL		-0.033
		(-1.33)
HM		0.004
		(0.20)
HH		-0.037*
		(-2.30)
LL	LH	-0.14**
		(-4.18)
LM		-0.048**
		(-2.94)
ML		-0.135**
		(-3.59)
MM		-0.02
		(-0.87)
MH		-0.052**
		(-2.98)
HL		-0.061*
		(-2.16)
HM		-0.03
		(-1.43)
HH		-0.059**
		(-3.17)
LL	ML	-0.013
		(-1.81)
LM		-0.011**
		(-2.87)
ML		-0.008
		(-1.09)
MM		0.001
		(0.16)
MH		-0.006
		(-1.92)
HL		-0.004
		(-0.71)
HM		-0.002
		(-0.59)
HH		-0.006
		(-1.82)
LL	MM	0.028**
		(4.29)
LM		0.006

		(1.65)
ML		0.023**
		(3.42)
MM		0.005
		(1.06)
MH		0.004
		(1.41)
HL		0.012*
		(2.49)
HM		0.002
		(0.62)
HH		0.006
		(1.82)
LL	MH	-0.039**
		(-3.65)
LM		-0.008
		(-1.54)
ML		-0.021
		(-1.79)
MM		0.005
		(0.71)
MH		0.003
		(0.52)
HL		-0.006
		(-0.65)
HM		0.007
		(1.08)
HH		0.008
		(1.32)
LL	HL	0.015**
		(2.94)
LM		0.009**
		(3.66)
ML		0.017**
		(3.17)
MM		0.008*
		(2.22)
MH		0.011**
		(4.45)
HL		0.011**
		(2.74)
HM		0.005
		(1.67)
HH		0.013**
		(4.96)
LL	HM	0.015**
		(3.40)
LM		0.005

	(1.95)
ML	0.015**
	(3.11)
MM	0.002
	(0.51)
MH	0.003
	(1.21)
HL	0.004
	(1.25)
HM	0.003
	(1.29)
HH	0.005*
	(2.05)
LL HH	0.006
	(1.03)
LM	0.006
	(1.78)
ML	0.005
	(0.81)
MM	0.002
	(0.54)
MH	0.01**
	(3.30)
HL	0.007
	(1.41)
HM	0.006
	(1.54)
HH	0.005
	(1.54)
Observations	120,650
R-squared	0.34

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Table 14: OLS Regression Estimates of Immigrant impacts on NonUK-born wages

Dependent variable: Log real hourly wage	Coefficients
Constant	0.791
	(3.76)**
Potential Experience	0.035**
	(9.05)
Potential Experience Sqrd/1000	-0.001**
	(-18.88)
Education (in yrs)	0.054**
	(14.28)
Married & cohab	0.068**
	(5.25)

Nonwhite	-0.191**
	(-11.66)
Full-time	0.269**
	(7.88)
Age at immigration	0.005**
	(1.42)
Years since immigrated sqrd	0.00**
	(2.85)
Regions of Birth	
Ireland (omitted)	
Caribbean&West Indies	-0.022**
	(-0.60)
China/HK	-0.032**
	(-0.68)
Europe	-0.076**
	(-3.30)
India	0.011**
	(0.36)
Pakistan/Bangladesh	-0.091**
	(-2.45)
Old Commonwealth & US	0.086**
	(3.52)
Rest of the World	-0.062**
	(-2.89)
Cohort of Entry to UK	
pre-1955 (omitted)	
1956-1960	0.069**
	(1.79)
1961-1965	0.032**
	(-0.70)
1966-1970	0.011**
	(0.19)
1971-1975	-0.009**
	(-0.13)
1976-1980	-0.039**
	(-0.47)
1981-1985	-0.069**
	(-0.72)
1986-1990	-0.081**
	(-0.74)
1991-1995	-0.111**
	(-0.91)
1996-2000	-0.098**
	(-0.72)
2001-2005	-0.211**
	(-1.42)

Region of Residence	
Rest of South East (omitted)	
Tyne & Wear	-0.187**
	(2.91)
Rest of Northern Region	-0.089**
	(-1.67)
South Yorkshire	-0.204**
	(-3.71)
West Yorkshire	-0.233**
	(-7.10)
Rest of Yorkshire & Humberside	-0.141**
	(-3.03)
East Midlands	-0.16**
	(-6.09)
East Anglia	-0.085**
	(-2.78)
Inner & Outer London	0.049**
	(3.15)
South West	-0.137**
	(-5.69)
West Midlands (Metro)	-0.143**
	(-5.34)
Rest of West Midlands	-0.087**
	(-2.47)
Greater Manchester	-0.17**
	(-4.91)
Merseyside	-0.191**
	(-2.79)
Rest of North West	-0.088**
	(-2.19)
Wales	-0.092**
	(-2.28)
Strathclyde & Rest of Scotland	-0.101**
	(-3.52)
Industries	
Manufacturing (omitted)	
Agriculture & Fishing	-0.203**
	(-2.03)
Energy & Water	0.19**
	(2.54)
Construction	0.00**
	(0.01)
Distribution, Hotels & Restaurants	-0.258**
	(-4.30)
Transport & Communication	0.005**
	(0.08)

Banking, Finance & Insurance etc	0.18**
	(3.00)
Public admin, Educ & Health	0.053**
	(0.89)
Other Services	-0.046**
	(-0.76)
Foreign variables	
LL	0.019*
	(1.99)
LM	-0.089**
	(-3.72)
LH	0.066
	(1.31)
ML	-0.006
	(-1.21)
MM	0.018**
	(3.65)
MH	-0.025**
	(-2.83)
HL	0.009*
	(2.17)
HM	0.013**
	(3.32)
HH	0.010
	(1.79)
Observations	7,614
R-squared	0.33

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Table 15: Full OLS Regression Estimates of Immigrant impacts on NonUK-born wages

Dependent variable: Log real hourly wage	Coefficients
Constant	1.217**
	(9.38)
Potential Experience	0.035**
	(7.50)
Potential Experience Sqrd/1000	-0.001**
	(-10.55)
Education (in yrs)	0.039**
	(9.77)
Married & cohab	0.057**
	(4.46)
Nonwhite	-0.193**
	(-11.73)

Full-time	0.273**
	(8.03)
Age at immigration	0.00
	(0.06)
Years since immigrated sqrd	0.00**
	(2.56)
Regions of Birth	
Ireland (omitted)	
Caribbean&West Indies	-0.005
	(-0.14)
China/HK	-0.028
	(-0.60)
Europe	-0.061**
	(-2.69)
India	0.016
	(0.53)
Pakistan/Bangladesh	-0.074
	(-2.00)
Old Commonwealth & US	0.098**
	(3.99)
Rest of the World	-0.056**
	(-2.59)
Cohort of Entry to UK	
pre-1955 (omitted)	
1956-1960	0.106**
	(2.98)
1961-1965	0.09**
	(2.25)
1966-1970	0.089
	(1.87)
1971-1975	0.089
	(1.57)
1976-1980	0.081
	(1.22)
1981-1985	0.072
	(0.93)
1986-1990	0.077
	(0.88)
1991-1995	0.063
	(0.64)
1996-2000	0.097
	(0.89)
2001-2005	-0.015
	(-0.13)

Region of Residence	
Rest of South East (omitted)	
Tyne & Wear	-0.193**
	(-3.01)
Rest of Northern Region	-0.077
	(-1.44)
South Yorkshire	-0.184**
	(-3.36)
West Yorkshire	-0.226**
	(-6.88)
Rest of Yorkshire & Humberside	-0.13**
	(-2.79)
East Midlands	-0.155**
	(-5.89)
East Anglia	-0.077
	(-2.50)
Inner & Outer London	0.041**
	(2.65)
South West	-0.13**
	(-5.39)
West Midlands (Metro)	-0.139**
	(-5.19)
Rest of West Midlands	-0.083
	(-2.37)
Greater Manchester	-0.174**
	(-5.01)
Merseyside	-0.194**
	(-2.85)
Rest of North West	-0.075
	(-1.86)
Wales	-0.09
	(-2.25)
Strathclyde & Rest of Scotland	-0.099**
	(-3.47)
Industries	
Manufacturing (omitted)	
Agriculture & Fishing	-0.22**
	(-2.25)
Energy & Water	0.18**
	(2.48)
Construction	-0.011
	(-0.19)
Distribution, Hotels & Restaurants	-0.267**
	(-4.66)
Transport & Communication	0.001

		(0.02)
Banking, Finance & Insurance etc		0.162**
		(2.84)
Public admin, Educ & Health		0.039
		(0.69)
Other Services		-0.055
		(-0.95)
Foreign variables		
Immigrant skill	Immigrant share, by skill	
LL	LL	0.176*
		(2.04)
LM		0.065
		(1.79)
ML		-0.035
		(-0.59)
MM		0.066*
		(2.31)
MH		0.041*
		(2.05)
HL		0.017
		(0.69)
HM		0.019
		(1.12)
HH		0.011
		(0.69)
LL	LM	0.284
		(1.20)
LM		0.102
		(0.96)
ML		-0.119
		(-0.60)
MM		-0.09
		(-1.07)
MH		-0.011
		(-0.19)
HL		0.019
		(0.27)
HM		-0.066
		(-1.42)
HH		-0.129**
		(-2.76)
LL	LH	0.06
		(0.22)
LM		0.015
		(0.14)
ML		-0.027
		(-0.12)
MM		0.115

		(1.18)
MH		0.059
		(0.84)
HL		0.01
		(0.12)
HM		0.120*
		(2.00)
HH		0.02
		(0.33)
LL	ML	-0.028
		(0.53)
LM		0.004
		(0.18)
ML		-0.012
		(-0.28)
MM		-0.009
		(-0.49)
MH		0.001
		(0.05)
HL		-0.007
		(-0.49)
HM		0.002
		(0.18)
HH		0.005
		(0.48)
LL	MM	0.058
		(1.32)
LM		0.010
		(0.47)
ML		-0.017
		(-0.47)
MM		0.023
		(1.45)
MH		0.001
		(0.08)
HL		0.001
		(0.10)
HM		0.030**
		(3.14)
HH		0.02*
		(2.15)
LL	MH	0.018
		(0.19)
LM		-0.042
		(-1.19)
ML		-0.067
		(-0.87)
MM		-0.082**

		(-2.73)
MH		-0.035
		(-1.57)
HL		0.001
		(0.03)
HM		-0.052**
		(-2.81)
HH		-0.022
		(-1.16)
LL	HL	0.018
		(0.48)
LM		-0.003
		(-0.17)
ML		0.062*
		(1.96)
MM		0.029*
		(2.02)
MH		0.006
		(0.65)
HL		0.002
		(0.18)
HM		-0.005
		(-0.59)
HH		0.007
		(0.83)
LL	HM	-0.058
		(-1.79)
LM		-0.014
		(-0.90)
ML		0.023
		(0.85)
MM		-0.011
		(-0.92)
MH		0.000
		(0.05)
HL		0.011
		(1.07)
HM		0.013
		(1.91)
HH		0.007
		(1.00)
LL	HH	-0.097
		(-1.81)
LM		-0.001
		(-0.06)
ML		-0.011
		(-0.31)
MM		0.007

	(0.38)
MH	-0.001
	(-0.04)
HL	-0.016
	(-1.05)
HM	0.000
	(0.03)
HH	0.018
	(1.68)
Observations	7,614
R-squared	0.35

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Table 116: Full Quantile Regression Estimates for UK-born

	Quantiles				
Dependent variable: Log real hourly wage	0.10	0.25	0.50	0.75	0.90
Constant	0.183**	0.283**	0.485**	0.785**	1.119**
	(3.24)	(6.00)	(11.14)	(16.25)	(16.17)
Potential Experience	0.048**	0.051**	0.055**	0.057**	0.058**
	(105.51)	(116.32)	(144.06)	(136.85)	(57.63)
Potential Experience Sqrd/1000	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-85.56)	(-118.61)	(-107.68)	(-111.29)	(-46.33)
Years of Education	0.075**	0.079**	0.08**	0.08**	0.083**
	(98.87)	(105.75)	(141.05)	(114.72)	(106.06)
Married & cohab	0.104**	0.099**	0.094**	0.087**	0.09**
	(26.22)	(30.46)	(25.23)	(22.43)	(18.10)
Nonwhite	-0.064**	-0.09**	-0.063**	-0.075**	-0.073**
	(-3.03)	(-5.31)	(-4.76)	(-4.86)	(-3.47)
Full-time	0.295**	0.259**	0.208**	0.127**	0.025**
	(21.29)	(20.55)	(22.45)	(11.13)	(1.06)
Region of Residence					
Rest of South East (omitted)					
Tyne & Wear	-0.134**	-0.158**	-0.169**	-0.184**	-0.214**
	(-7.64)	(-13.33)	(-13.27)	(-18.17)	(-10.73)
Rest of Northern Region	-0.141**	-0.155**	-0.147**	-0.156**	-0.169**
	(-12.42)	(-18.06)	(-20.54)	(-16.36)	(-12.52)
South Yorkshire	-0.145**	-0.142**	-0.163**	-0.195**	-0.234**
	(-13.54)	(-11.08)	(-18.79)	(-24.45)	(-20.14)
West Yorkshire	-0.103**	-0.132**	-0.15**	-0.171**	-0.196**
	(-11.24)	(-14.94)	(-18.62)	(-20.01)	(-17.17)
Rest of Yorkshire & Humberside	-0.165**	-0.167**	-0.157**	-0.172**	-0.186**
	(-12.82)	(-17.57)	(-22.28)	(-18.33)	(-16.45)

East Midlands	-0.094**	-0.126**	-0.143**	-0.159**	-0.17**
	(-11.46)	(-21.83)	(-39.67)	(-30.02)	(-19.68)
East Anglia	-0.079**	-0.112**	-0.133**	-0.143**	-0.149**
	(-9.68)	(-14.68)	(-15.33)	(-11.70)	(-12.50)
Inner & Outer London	0.083**	0.08**	0.081**	0.082**	0.09**
	(8.92)	(11.81)	(14.39)	(11.61)	(9.85)*
South West	-0.119**	-0.131**	-0.14**	-0.158**	-0.174**
	(-14.06)	(-22.55)	(-21.23)	(-20.40)	(-18.43)
West Midlands (Metro)	-0.101**	-0.114**	-0.136**	-0.163**	-0.189**
	(-7.23)	(-13.13)	(-18.69)	(-17.22)	(-15.98)
Rest of West Midlands	-0.098**	-0.13**	-0.148**	-0.17**	-0.196**
	(-13.58)	(-20.12)	(-23.55)	(-24.41)	(-25.78)
Greater Manchester	-0.112**	-0.12**	-0.137**	-0.154**	-0.187**
	(-11.91)	(-14.62)	(-17.21)	(-18.82)	(-19.80)
Merseyside	-0.124**	-0.126**	-0.151**	-0.185**	-0.195**
	(-6.21)	(-12.14)	(-18.03)	(-16.88)	(-14.20)
Rest of North West	-0.117**	-0.121**	-0.119**	-0.138**	-0.154**
	(-9.49)	(-15.07)	(-19.26)	(-26.80)	(-14.45)
Wales	-0.169**	-0.185**	-0.193**	-0.207**	-0.221**
	(-15.13)	(-24.31)	(-32.77)	(-25.08)	(-17.35)
Strathclyde & Rest of Scotland	-0.119**	-0.135**	-0.146**	-0.152**	-0.166**
	(-22.03)	(-21.91)	(-31.70)	(-21.91)	(-19.58)
Industries					
Manufacturing (omitted)					
Agriculture & Fishing	-0.348**	-0.364**	-0.367**	-0.397**	-0.422**
	(-12.69)	(-18.56)	(-18.72)	(-22.74)	(-22.88)
Energy & Water	0.124**	0.099**	0.099**	0.098**	0.085**
	(5.61)	(5.33)	(6.63)	(6.71)	(3.27)
Construction	-0.055**	-0.052**	-0.036**	-0.061**	-0.086**
	(-2.80)	(-3.29)	(-2.65)	(-4.09)	(-4.44)
Distribution, Hotels & Restaurants	-0.254**	-0.25**	-0.229**	-0.232**	-0.217**
	(-13.43)	(-15.83)	(-19.39)	(-17.18)	(-10.93)
Transport & Communication	-0.059**	-0.061**	-0.057**	-0.082**	-0.085**
	(-3.08)	(-3.88)	(-5.05)	(-5.85)	(-4.20)
Banking, Finance & Insurance etc	-0.038**	0.021**	0.077**	0.098**	0.115**
	(-2.26)	(1.47)	(6.18)	(6.11)	(6.59)
Public admin, Educ & Health	-0.04**	-0.031**	-0.026**	-0.074**	-0.138**
	(-2.24)	(-2.02)	(-1.87)	(-5.19)	(-7.38)
Other Services	-0.157**	-0.157**	-0.138**	-0.153**	-0.162**
	(-7.78)	(-9.85)	(-9.88)	(-9.36)	(-6.90)
Foreign Variables					
LL	0.009**	0.004*	0.004*	0.001	0.00
	(3.65)	(2.26)	(2.39)	(0.42)	(0.10)
LM	-0.008	-0.022**	-0.016**	-0.024**	-0.014
	(-1.11)	(-3.52)	(-3.41)	(-3.83)	(-1.63)
LH	-0.034*	-0.01	0.001	0.014	0.007
	(-2.55)	(-0.76)	(0.10)	(1.24)	(0.34)

ML	-0.004*	-0.004*	-0.003*	-0.001	-0.002
	(-2.07)	(-2.41)	(-2.17)	(-0.56)	(-0.82)
MM	0.006**	0.004**	0.003*	0.005**	0.005*
	(2.65)	(2.75)	(2.46)	(3.71)	(2.57)
MH	-0.002	0.001	0.002	-0.001	0.003
	(-0.69)	(0.65)	(1.14)	(-0.24)	(0.91)
HL	0.01**	0.01**	0.009**	0.007**	0.008**
	(6.69)	(10.46)	(8.58)	(6.58)	(4.23)
HM	0.002	0.004**	0.003**	0.005**	0.003**
	(1.45)	(5.57)	(5.09)	(5.38)	(2.68)
HH	0.002	0.005**	0.005**	0.006**	0.005**
	(1.47)	(3.71)	(5.47)	(4.75)	(3.30)
Observations					120,650
Pseudo R-squared	0.181	0.207	0.221	0.219	0.207

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

Table 12: Full Quantile Regression Estimates for NonUK-born

	Quantiles				
Dependent variable: Log real hourly wage	0.10	0.25	0.50	0.75	0.90
Constant	0.185	0.625**	0.597**	0.863**	1.151**
	(0.62)	(3.03)	(2.67)	(3.21)	(2.91)
Potential Experience	0.033**	0.035**	0.039**	0.039**	0.043**
	(4.89)	(10.11)	(9.66)	(9.32)	(6.88)
Potential Experience Sqrd/1000	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(-9.09)	(-14.80)	(-18.16)	(-16.44)	(-11.07)
Education (in yrs)	0.053**	0.055**	0.058**	0.058**	0.061**
	(7.06)	(14.32)	(11.55)	(10.84)	(8.57)
Married & cohab	0.071**	0.068**	0.065**	0.057**	0.062*
	(3.29)	(4.29)	(4.45)	(2.76)	(2.01)
Nonwhite	-0.195**	-0.197**	-0.187**	-0.188**	-0.179**
	(-9.14)	(-10.68)	(-11.29)	(-7.89)	(-7.32)
Full-time	0.325**	0.303**	0.263**	0.225**	0.115**
	(4.38)	(7.87)	(6.25)	(3.97)	(1.85)
Age at immigration	-0.006**	-0.001**	0.002**	0.01**	0.011**
	(-0.95)	(-0.28)	(0.42)	(2.60)	(1.98)
Years since immigrated sqrd	0.00	0.00**	0.00	0.00**	0.00*
	(0.06)	(2.64)	(1.29)	(3.14)	(2.17)
Regions of Birth					
Ireland (omitted)					
Caribbean&West Indies	0.026	0.015	-0.02	-0.009	-0.076
	(0.68)	(0.54)	(-0.54)	(-0.17)	(-1.56)
China/HK	-0.006	-0.044	-0.036	-0.085	-0.043
	(-0.07)	(-1.00)	(-0.91)	(-1.46)	(-0.57)

Europe	-0.091*	-0.081**	-0.088**	-0.062	-0.11**
	(-2.48)	(-3.37)	(-5.54)	(-1.86)	(-2.88)
India	-0.066*	-0.003	0.033	0.071	0.048
	(-2.26)	(-0.07)	(1.24)	(1.72)	(0.85)
Pakistan/Bangladesh	-0.187**	-0.067	-0.105**	-0.008	-0.002
	(-3.07)	(-1.46)	(-2.75)	(-0.18)	(-0.03)
Old Commonwealth & US	0.036	0.070*	0.083**	0.08**	0.106*
	(1.00)	(2.37)	(2.95)	(2.75)	(2.47)
Rest of the World	-0.077*	-0.071**	-0.058**	-0.055	-0.041
	(-2.13)	(-3.03)	(-3.06)	(-1.82)	(-0.95)
Cohort of Entry to UK					
pre-1955 (omitted)					
1956-1960	0.154**	0.097**	0.079	0.052	0.005
	(3.12)	(2.53)	(1.94)	(1.16)	(0.08)
1961-1965	0.161*	0.046	0.034	-0.024	-0.045
	(2.36)	(0.88)	(0.85)	(-0.40)	(-0.51)
1966-1970	0.229**	0.086	0.036	-0.05	-0.10
	(2.70)	(1.53)	(0.66)	(-0.59)	(-1.04)
1971-1975	0.179*	0.054	0.010	-0.062	-0.043
	(2.00)	(0.85)	(0.16)	(-0.73)	(-0.40)
1976-1980	0.242*	0.051	-0.002	-0.125	-0.152
	(2.04)	(0.62)	(-0.02)	(-1.17)	(-1.31)
1981-1985	0.237	0.022	-0.022	-0.159	-0.183
	(1.64)	(0.24)	(-0.23)	(-1.20)	(-1.20)
1986-1990	0.256	0.025	-0.059	-0.179	-0.213
	(1.57)	(0.25)	(-0.52)	(-1.27)	(-1.43)
1991-1995	0.249	-0.003	-0.069	-0.231	-0.17
	(1.23)	(-0.03)	(-0.53)	(-1.53)	(-0.92)
1996-2000	0.329	0.06	-0.041	-0.236	-0.269
	(1.49)	(0.48)	(-0.29)	(-1.42)	(-1.40)
2001-2005	0.23	-0.04	-0.167	-0.346	-0.347
	(0.97)	(-0.30)	(-0.98)	(-1.81)	(-1.52)
Region of Residence					
Rest of South East (omitted)					
Tyne & Wear	-0.112	-0.126**	-0.226**	-0.251**	-0.132**
	(-0.88)	(-3.35)	(-4.68)	(-3.14)	(-0.89)
Rest of Northern Region	-0.069	-0.114	-0.105*	-0.141**	-0.058
	(-0.96)	(-1.63)	(-2.21)	(-2.81)	(-0.72)
South Yorkshire	-0.20**	-0.224**	-0.214**	-0.233**	-0.148
	(-3.39)	(-3.28)	(-3.98)	(-2.95)	(-1.14)
West Yorkshire	-0.173**	-0.208**	-0.232**	-0.287**	-0.216**
	(-2.81)	(-5.01)	(-5.78)	(-6.63)	(-3.84)
Rest of Yorkshire & Humberside	-0.174*	-0.163**	-0.15**	-0.079	-0.112
	(-1.98)	(2.61)	(2.96)	(-1.27)	(-1.33)
East Midlands	-0.114*	-0.117**	-0.162**	-0.17**	-0.184**
	(-2.50)	(-3.22)	(-8.37)	(-4.54)	(-4.05)

East Anglia	-0.087	-0.065	-0.08*	-0.078	-0.071
	(-1.16)	(-1.48)	(-2.53)	(-1.77)	(-1.28)
Inner & Outer London	0.062**	0.069**	0.052**	0.052**	0.056**
	(2.45)	(3.27)	(3.79)	(2.80)	(1.65)
South West	-0.153**	-0.138**	-0.143**	-0.122**	-0.096*
	(-2.62)	(-5.11)	(-7.40)	(-2.99)	(-1.99)
West Midlands (Metro)	-0.092**	-0.08*	-0.141**	-0.127**	-0.166**
	(-3.00)	(-2.25)	(-5.38)	(-3.84)	(-3.53)
Rest of West Midlands	-0.03	-0.071*	-0.101**	-0.11**	-0.099
	(-0.66)	(-1.96)	(-2.99)	(-3.08)	(-1.49)
Greater Manchester	-0.248**	-0.197**	-0.16**	-0.114**	-0.104
	(-4.02)	(-7.05)	(-4.43)	(-2.69)	(-1.22)
Merseyside	-0.184*	-0.175**	-0.255**	-0.172	-0.22
	(-1.97)	(-4.01)	(-2.65)	(-1.55)	(-1.86)
Rest of North West	-0.121	-0.145**	-0.08	-0.048	-0.043
	(-1.80)	(-2.68)	(-1.65)	(-0.69)	(-0.51)
Wales	-0.057	-0.099	-0.152**	-0.094	-0.066
	(-0.96)	(-1.87)	(-4.93)	(-1.47)	(-0.73)
Strathclyde & Rest of Scotland	-0.095*	-0.117**	-0.106**	-0.093	-0.108
	(-2.01)	(-3.06)	(-3.61)	(-1.88)	(-1.83)
Industries					
Manufacturing (omitted)					
Agriculture & Fishing	-0.467**	-0.318**	-0.225*	-0.182	-0.225
	(-2.85)	(-2.59)	(-2.08)	(-1.47)	(-0.84)
Energy & Water	0.261*	0.137	0.194**	0.213**	0.152**
	(1.97)	(1.46)	(2.76)	(2.85)	(1.84)
Construction	-0.035	-0.062	-0.02	0.036	0.021
	(-0.27)	(-0.71)	(-0.37)	(-0.78)	(-0.54)
Distribution, Hotels & Restaurants	-0.297*	-0.31**	-0.266**	-0.231**	-0.201**
	(-2.11)	(-3.58)	(-4.61)	(-4.28)	(-4.63)
Transport & Communication	0.012	-0.003	-0.006	0.013	-0.042
	(0.09)	(-0.04)	(-0.11)	(0.24)	(-0.76)
Banking, Finance & Insurance etc	0.068	0.113	0.171**	0.258**	0.293**
	(0.55)	(1.28)	(2.86)	(5.06)	(5.73)
Public admin, Educ & Health	0.068	0.058	0.058	0.043	-0.028
	(0.51)	(0.70)	(1.08)	(0.93)	(-0.54)
Other Services	-0.063	-0.102	-0.074	-0.011	0.004
	(-0.45)	(-1.27)	(-1.23)	(-0.20)	(0.09)
Foreign variables					
LL	0.015	0.021	0.017	0.018	0.007
	(0.79)	(1.44)	(1.68)	(1.51)	(0.42)
LM	-0.067*	-0.084*	-0.102**	-0.106**	-0.125*
	(-1.97)	(-2.70)	(-4.43)	(-2.94)	(-2.36)
LH	0.114	0.044	0.098*	0.074	-0.009
	(1.47)	(0.73)	(2.21)	(1.16)	(-0.09)
ML	0.003	0.001	-0.002	-0.013	-0.022
	(0.28)	(0.07)	(-0.52)	(-1.95)	(-1.90)

MM	0.014	0.012	0.018**	0.018**	0.017*
	(1.76)	(1.92)	(3.57)	(3.15)	(2.23)
MH	-0.03*	-0.019*	-0.016	-0.027*	-0.012
	(-2.43)	(-2.17)	(-1.22)	(-2.52)	(-0.71)
HL	0.003	0.011*	0.007	0.015**	0.02**
	(0.42)	(2.01)	(1.48)	(2.93)	(2.73)
HM	0.011*	0.008*	0.014**	0.014*	0.021**
	(2.22)	(1.98)	(3.36)	(2.51)	(3.16)
HH	0.003	0.005	0.009	0.019*	0.023*
	(0.35)	(0.58)	(1.47)	(2.37)	(2.03)
Observations					7,614
Pseudo R-squared	0.155	0.197	0.221	0.221	0.228

t-stat reported in parenthesis. **- significant at 1%, *- significant at 5%

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

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