Università degli Studi di Modena e Reggio Emilia
Dipartimento di Economia Politica

Materiali di discussione

\\ 621 \\

Assimilation and discrimination effects among the UK migrant labour force

di

Sara Flisi

September 2009

Università di Modena e Reggio Emilia
Dipartimento di Economia Politica
Via Berengario, 51
41100 Modena, Italy
e-mail: sara.flisi@unimore.it

Assimilation and discrimination effects among the UK migrant labour force

Sara Flisi*

September 2009

Abstract

This paper analyses the performance of foreign born male individuals on the British labour market. Using data from the Quarterly Labour Force Survey over the period 1992-2009, we find consistent evidence of positive economic assimilation of immigrants, with their labour market outcomes improving with duration of stay in the country. We also find that the performance of individuals who came to the UK to complete their education is significantly higher than that experienced by labour market entrants.

Keywords Immigrants, Earnings, Employment

JEL classification J15, J23, J61

* University of Modena and Reggio Emilia
Via Berengario, 51
41100 Modena, Italy
e-mail: flisi.sara@unimore.it

1. Introduction

Immigration has always been a highly debated and very sensitive issue. With the steady growth of international human capital movements, natives seem to call more and more for restrictive immigration policies, while on the other side, economic considerations generally think about migrants as a resource. The friction between economic and political concerns can be somehow limited, increasing the capability of migrants to positively contribute to the host economy; this contribution is strongly linked to their performance on the labour market, and on their ability to support themselves. It is therefore in the interest of the host country to facilitate the process of economic assimilation of the foreign born population.

Following this line of research, this paper investigates the labour market performance of foreign born male individuals in the UK over the period 1992-2009, using data from the Quarterly Labour Force Survey (QLFS).

2. Literature review

The framework for the research concerning the earnings and labour market behaviour of immigrants is generally provided by human capital theory, where workers' performance in the labour market reflects their human capital endowment. The basic hypothesis is that migrants experience an initial labour market disadvantage, due to the imperfect transferability across countries of knowledge and skills acquired at home, which may include education, training, cultural characteristics, language proficiency, labour market information. This provides incentives for the migrant to invest in country-specific skills, or to increase transferability of those previously acquired. In both cases, the result will be that with duration of stay in the destination country, the outcomes of the foreign born gradually adjust towards those of native workers, through human capital enhancement.

The degree of economic assimilation of migrants has been heavily researched, starting from the 1970s with the path-breaking work of Chiswick (1978), who investigated the pattern of convergence of immigrant earnings in the U.S. to those of the native population. The evidence he provides suggests the existence of a positive assimilation process, with immigrants' earnings eventually overtaking those of the native workers at a later stage of the migration cycle. This result of an economic assimilation is confirmed by several other cross-sectional studies of the time, including Borjas (1982). This type of analysis, however, can be very sensitive to changes in the initial position of migrants who arrive at different points in time, i.e. to unmeasured quality differentials among subsequent immigrant cohorts. This makes it crucial to carefully distinguish the true assimilation pattern from these 'cohort effects', an issue that becomes particularly relevant when relying on multiple cross-sections to estimate what is actually a longitudinal effect. This is exactly the concern that pressed Borjas (1985) to move on to a revised methodology, which involves the decomposition of the standard cross-section growth of earnings in two parts, where the first element is the 'within-cohort' growth (i.e. the growth of immigrant earnings of a cohort over time, which measures the convergence or divergence to the earnings profiles of the natives), and the second one is the 'across-cohort' growth (i.e. the growth in earnings experienced by different cohorts at the same point of their life cycle in the host country). The study, which is therefore carried out *within* immigrant cohort, shows that the assimilation rates were in fact heavily overestimated in the early studies due to a decreasing quality of successive arrival cohorts; the growth rate of immigrants' earnings is generally found to be not high enough to allow foreign-born individuals to fill the initial gap.

This interpretation, and the findings of decreasing immigrant quality and slower assimilation, have been questioned by a number of studies though; analyses that followed individuals or cohorts over time showed that the assimilation profiles of immigrants actually resembled those indicated by the first cross-sectional estimates. Duleep and Regets (1997), using data from the U.S. Current Population Survey that allows them to follow individuals for one year, find that the wage growth of the foreign-born does exceed that of natives, and that the actual wage growth of migrants relative to natives is close to that predicted by a cross-sectional analysis. Lalonde and Topel (1992) use data from the 1970 and 1980 Census of Population to reexamine the evidence on intragenerational assimilation of immigrants in the U.S. and changes in the cohort quality; following cohorts over time, they find again a strong evidence of assimilation, with estimates resembling those from the cross-sectional analysis, and therefore conclude that no relevant evidence of declining quality of successive immigrant cohorts can be found for the immigrant groups they study[1]. Using longitudinal data for Australia, Chiswick et al. (2005) show that cross-sectional and longitudinal analyses generate similar findings.

[1] They point out, however, that the *overall* quality of immigrants did actually decline, because of the shift in the ethnic composition of the new immigrants to the U.S.

Studies on the economic assimilation profiles of immigrants have been carried out not only for the U.S., but also for a number of other countries. Hayfron (1998) finds for Norway results that are similar to those of Borjas (1985) for the U.S. Aguilar and Gustafsson (1991) and Hammarstedt and Shukur (2006) show that the assimilation profiles in Sweden vary widely between different immigration cohorts and between migrant groups coming from different regions. Amuedo-Dorantes and de la Rica (2007) and Fernández and Ortega (2008) find the same result for Spain. Antecol et al. (2006) compare Australia, Canada and the U.S., concluding that assimilation is more likely to take place through quantities (i.e. employment) in Australia, while through prices (i.e. earnings) in the U.S., with Canada falling in between. Chiswick et al. (2005), on the other hand, find evidence of a positive earnings assimilation in Australia as well.

Baker and Benjamin (1994) indentify very small assimilation effects for immigrants on the Canadian labour market, and in some cases even a negative assimilation. This result is somehow confirmed by Bloom et al. (1995), who find that while assimilation took place for earlier cohorts, it has been slower or even negative for more recent ones. Using panel data, Hum and Simpson (2004) find evidence suggesting that immigrants never fill the negative wage gap they experience upon entry in the host country.

The evidence of a negative immigrant assimilation is not uncommon in the literature, despite the strong empirical support for the standard model. Bell (1997) finds this result for white immigrants in the UK. Dustmann et al. (2003) find the same for Irish and Europeans. Clark and Lindley (2009) find negative assimilation for earnings of all foreign-born individuals, and for the employment probability of white immigrants. Chiswick and Miller (2008) try to outline the conditions under which this unexpected result can still fall within the traditional assimilation model; they argue that ‘where countries are of approximately equal economic standing, and skills are highly transferable internationally, international migration will typically occur where the individual experiences a favourable draw from the distribution of wages offers in the potential destination relative to the wage available in the country of origin […]. A relatively high wage offer that attracts the immigrant need not persist indefinitely. With the passage of time, a ‘regression to the mean’ would be expected, which will be captured by a negative relationship between earnings and duration of residence in the destination’. Other papers suggest that this evidence can be explained by factors related to the labour market, for example a reduced capacity to absorb particular groups of individuals, especially the low skilled (Bloom et al., 1994). Family migration models have been developed to try to answer this question: Baker and Benjamin (1997) find evidence in favour of the ‘family investment model’, according to which ‘wives in immigrant families take on ‘dead-end’ jobs to finance their husbands’ investment in human capital’, but then they reduce participation or even drop out of the labour market as the husbands’ economic outcomes improve.

A part of the literature has focused on the UK as well. Both Chiswick (1980) and Bell (1997) find an earnings disadvantage for black immigrants, but while the former finds no evidence of assimilation with duration of stay, the latter – relying on a larger dataset – does, despite concluding that a gap remains throughout their working lives. Neither of these studies finds that white immigrants experience any economic disadvantage. The conclusion that race matters more than being born in the country or elsewhere is drawn by several studies. Dustmann and Fabbri (2005) and Dustmann et al. (2003) conclude that employment and participation rates of immigrants from ethnic minority groups are considerably lower than those of natives, with Pakistanis and Bangladeshis – especially women – suffering a particular disadvantage, while the patterns for white immigrants tend to be more similar to those of the natives. However, Dustmann et al. (2003) find that there is some assimilation process taking place for minority immigrants. Evidence of assimilation is found by Wheatley Price (2001) as well. Using decomposition analysis, Blackaby et al. (1994) find substantial employment and earnings differentials even between whites and British-born ethnic minorities[2], confirming that nonwhite minorities appear to face substantial discrimination; they show that the position of these groups declined further between the 1970s and 1980s, while Blackaby et al. (1998) demonstrate that it improved slightly in the 1990s, with Indians performing better than Pakistanis and Blacks.

A different assimilation profile for white and nonwhite immigrants is highlighted by Shields and Wheatley Price (1998) and Clark and Lindley (2009) as well. They also investigate whether the return to education changes depending on where it has been acquired, the UK or abroad; Shields and Wheatley Price (1998) find that education obtained in a foreign country tends to be less valuable on the labour market; Clark and Lindley (2009) show that highly qualified nonwhite immigrants who hold a British qualification have labour market outcomes that are comparable to those of white immigrants, while those who do not have a significant performance gap with respect to their white counterparts.

[2] According to Blackaby et al. (2005), though, this might partly be due to these groups adopting a ‘taste for isolation’, rather than only be the consequence of some discrimination on the labour market.

3. Data

The data used for our analysis are drawn from the Labour Force Survey (LFS), a continuous sample survey of households living at private addresses in Great Britain which has been carried out since 1973. We choose to use data from 1992, when the survey took its current form of a quarterly survey (Quarterly Labour Force Survey, or QLFS). The sample includes about 59,000 responding addresses per quarter, with 138,000 individuals responding. Each address is interviewed for five waves, with interviews taking place every three months, thereby having the last interview one year after the first one. This of course introduces a panel component in the survey, but it is not possible to follow individuals over time. Information about income is collected only in the fifth wave until winter 1996, and in the first and fifth waves from spring 1997. We therefore choose to consider only individuals who are being interviewed in Wave 5[3], ending up with a pooled cross-section covering the period 1992-2009[4], allowing us to ignore any panel data issue.

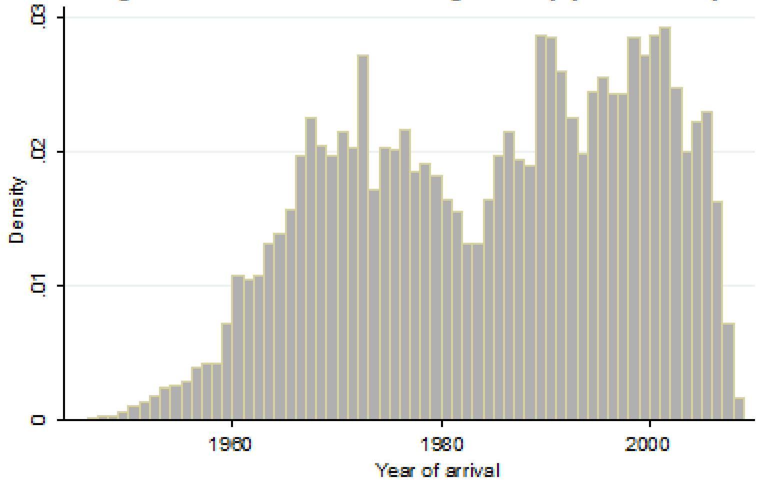
For our analysis, we focus on male individuals in the labour force aged 20-45. This selected sample includes about 265,000 individuals, 8.87% of which are foreign-born[5].

[3] No data about income seem to be available in the first quarter of 2004 though; for this reason, we choose to include in the sample also Wave 1 from January-March 2003, which covers the same individuals we would find in Wave 5 in the data about January-March 2004.

[4] We created the variables we use in the analysis building on the available QLFS data. However, the content of the interviews, as well as the names and coding of the variables in the surveys, changed over time, so that it was impossible to rely on the same variables throughout the whole period. We took this into account while generating our own variables, to ensure that information on which our study is built is reliable.

[5] According to the estimates of the Annual Population Survey, in the year to December 2008 11% of the UK population was born outside the UK.

Figure 1. Distribution of immigrants by year of entry



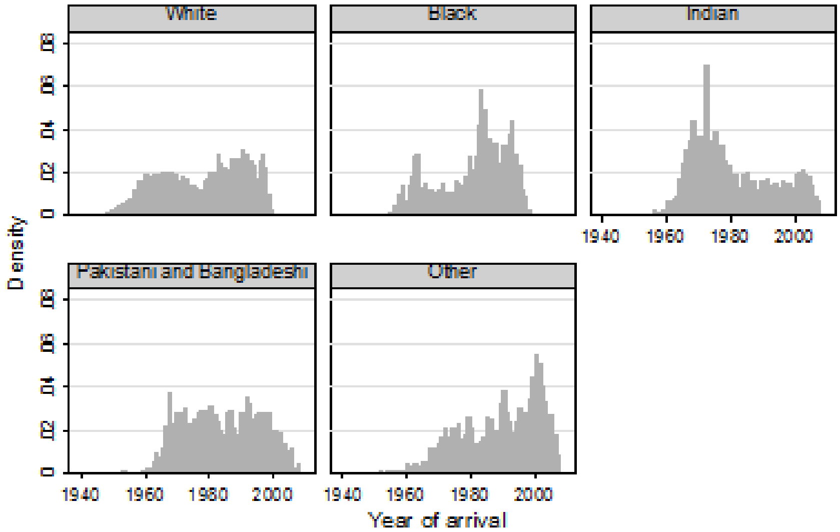
Source: LFS 1992-2009.

Figure 1 shows the historical pattern of arrival of the immigrants in the sample. Only 3.18% of the foreign-born individuals arrived before 1960; 30% of our sample arrived between the mid-1960s and the early 1980s. We can see, however, that a large part of the sample we consider is made up of relatively recent arrivals, as above 40% of the immigrants studied arrived in the 1990s and early 2000s[6].

As emerges from Figure 2, the first immigrants, who started to arrive shortly after the end of the war, were mainly whites, who continued to come to the UK quite constantly. Individuals of other ethnic groups prevalently arrived after 1960, with a peak for blacks in the early 1960s. In the 1970s, we find a migration wave coming from India, followed by a wave of blacks again. The arrival of Pakistanis and Bangladeshis started only in the late 1960s, but has remained steady since then.

[6] We need to remember that this figure does not show exactly what we can consider an historical pattern of inflows, as for this purpose we would need to take into account mortality and outmigration as well. Instead, it shows the pattern of foreign-born residents.

Figure 2. Distribution of immigrants by year of entry and ethnic group



Source: LFS 1992-2009.

We now compare a range of characteristics of foreign- and native-born individuals in our sample, highlighting some of the main figures about the various groups. For this purpose, we also split the groups into whites and nonwhites, and compare some statistics at the beginning and at the end of the time span we cover in the analysis, 1993 and 2008[7]. The figures are presented in Table 1.

As we can see in Panel A, the share of immigrants in the labour force in our sample has doubled from 1993 to 2008. The share of nonwhites in the sample has increased from 5.29 to almost 10% over these 15 years.

The median age has seen a small decline for the immigrants, while has increased for the natives (in particular for the nonwhites).

In 1993, the share of highly educated individuals was much higher for migrants than for the natives; this confirms the well-known fact that immigrants tend to be on average more skilled than the natives. Over the period, all groups have seen an increase in the share of individuals holding a degree; however, this increase has been very small for white immigrants, quite significant for nonwhite immigrants and white natives, but also incredibly high for nonwhite natives, going from 16.55 to above 37%.

[7] We prefer to use these years than 1992 and 2009 as these do not have data for all four quarters.

Table 1. Descriptive statistics of separate samples of individuals (men, age 20-45)

Panel A

		Native born		Foreign born	
		Whites	Nonwhites	Whites	Nonwhites
Percentage of the total sample					
	1993	90.88	1.51	3.82	3.78
	2008	82.66	3.14	7.58	6.62
Median age					
	1993	33	27	34	35
	2008	34	32	33	34
Median n. of years since migration					
	1993			20	17
	2008			11	11
Median age at arrival					
	1993			14	18
	2008			21	23
Share of individuals holding a					
	1993	0.1567	0.1655	0.2393	0.2043
	2008	0.2483	0.3705	0.2497	0.2778
Employment rate					
	1993	0.8887	0.7230	0.8783	0.8173
	2008	0.9503	0.8774	0.9653	0.9140

Panel B

	1960s	*1970s*	*1980s*	*1990s*	*2000s*
% of education entrants	95.36	77.95	40.25	13.89	5.07

Source: LFS 1992-2009.

For both the foreign and the native born, the employment rate is constantly lower for nonwhites; the performance of all whites is similar, starting from around 88% at the beginning of the period, to go over 95% in 2008; nonwhites started from a lower level, but while nonwhite immigrants have only slightly narrowed the gap with white immigrants, nonwhite natives have gone from -17% to -7%.

In 1993, the average white and nonwhite immigrant had already spent 20 and 17 years respectively in the UK; in 2008, for both groups, only 11 years. On the other hand, the median age at arrival has significantly increased over time.

This is somehow confirmed by the share of education entrants (i.e. individuals who arrive to complete their education in the country and enter the labour market only after that) in the foreign-born population, as opposed to labour market entrants (i.e. individuals who arrive in the UK to enter the labour market), share that we present in Panel B. In our sample, the percentage of education entrants – who of course tend to arrive at an earlier age – in our sample who arrived in the 1960s was incredibly high; cohort after cohort, however, the share has been steadily declining. Given that our sample is composed of individuals who are in the labour force already, the share of the last two cohorts is probably underestimated, since a part of the immigrants who arrived in those decades might still be studying, therefore being excluded from our analysis. Even so, the historical pattern is quite clear, and can be explained by the different dynamics in the migration patterns and motivations that developed over time.

4. Model

The analysis carried out in the paper relies on the standard assumptions of the human capital literature, and needs to deal with the major shortcomings in data availability that this kind of study always faces. One of the assumptions that might turn out to be less credible is that labour market experience isn't accrued until education is complete; the type of data available generally does not allow to ascertain whether this is the case or not; we try to limit the extent to which the first problem can bias our estimates by dropping observations for which the age at which full-time education was left is implausibly high (above 45). Analogously, data do not allow to identify true labour market experience, which in the literature is practically measured by potential experience. Surely, there are groups of individuals whose labour force participation tends to be more continuous over the life cycle, in which case the use of potential experience should not represent a major concern. This needs not be true for everybody though: for example, it's a well known fact that women tend to have a more fragmented employment history than males. For this reason, we decide to limit our analysis to the male population, like several studies do (Bell, 1997; Wheatley Price, 2001; Clark and Lindley, 2009; and many others)

We investigate two labour market outcomes of migrants, namely employment (i.e. the occurrence that the survey respondent is in paid employment at the time of the interview[8]) and earnings (measured as gross hourly wage, and expressed in logarithms). The sample includes only male individuals who are part of the labour force.

The basic model we consider to be relevant for the analysis is the following one:

[8] The definition of employment used in the QLFS variable considered, which follows the ILO definition, includes individuals who are employees, self-employed, engaged in government employment and training programmes, and unpaid family workers. This last category accounts for only 0.10% of the sample though.

$$Z_i = x_i\beta + \gamma EXPERIENCE_i + \delta YSM_i + \sum_t \phi_t D_{it} + \varepsilon_i \quad , i = 1,..., N, \; t = 1940s, 1950s, ..., 2000s$$

where Z_i is the measure of labour market outcome taken into consideration (either employment or earnings) for individual *i*, x_i is a vector of socioeconomic variables we will explain in more detail later, *YSM* is the number of years since migration, *exper* is the (potential) working experience, and D are cohort dummies indicating whether the immigrant arrived in a particular decade (*d40*, *d50*, *d60*, *d70*, *d80*, *d90* and *d00*).

Years since migration (*YSM)* is the measure of the time spent in the British labour market by the foreign-born individual, and is typically used to identify the assimilation effect. This variable needs to be handled carefully though: while simply meant to capture the effect of the duration of residence in the destination country, it can generate an estimation bias arising from two different types of problems, both connected to the 'use of a cross-section regression model to explain a dynamic series of events', as Borjas (1985) explains.

First of all, we need to consider that a selective out-migration can occur; if the most successful immigrants tend to remigrate, there will be a downward bias on the estimated assimilation profiles; on the other hand, if immigrants performing worse in the labour market are those who decide to leave the country, the coefficient of the *YSM* variable might be biased upward. In any case, given the lack of emigration data, this is an issue for which very little can be done.

Secondly, we have what Borjas (1985) calls the problem of the 'dynamic interpretation of the cross-section coefficient' of *YSM*, with its 'implicit assumption that the average 'quality' of successive cohorts of immigrants is not changing over time'. Again, an estimation bias may arise, upwardly if the quality of immigrants arriving in the UK is decreasing, and downwardly if for example more selective migration policies lead to higher quality entries. We include a set of arrival cohort dummies to control for this issue.

We include among the explanatory variables socio-demographic indicators, regional dummies and time effects (dummies for quarter when interview took place, to control for seasonality).

The first group includes marital status (*married*), dummies for the presence of children aged 0-4, 5-9 and 10-15 (*dkid04*, *dkid59*, *dkid1015*), and education. Earnings regressions include a dummy, *pt*, equal to 1 if the individual works part-time.

We decide to control for education (and hereby for human capital) including dummies for the level of the highest educational qualification attained. The exact type of qualification is generally traceable in the datasets, and the variable is normally reliable for natives and education entrants. There is a problem involving labour market entrants though, since foreign qualifications are generally coded as 'other qualifications' whatever their level[9]. For this reason, in this case and when data on higher qualification are missing due to seasonal-to-calendar quarter change[10], the level of higher qualification has been inferred starting from years of schooling. Although this is surely not an exact measure, we believe that years of schooling – another measure of human capital often used in the literature – would not be either, since this variable is just computed as age when completed full time education -5, and therefore it does not really prove that a particular educational level has been achieved. For this reason, using years of schooling for all the individuals would imply a loss of exact information for those for whom we do have data collected in the QLFS; we therefore choose to rely on this corrected version of the highest qualification variable. Following Dustmann and Fabbri (2005), we include in the model three dummy variables, *degree* (indicating whether the individual has a first or higher degree or other degree-level qualification), *a_level* (if the individual's highest qualification is below degree level, i.e. A-level or equivalent), and *o_level* (if the individual has O-levels or equivalent, or other professional-vocational qualifications).

We choose not to include among the socio-demographic characteristics in the immigrants' regression an age variable, since a problem of multicollinearity would arise, given the contemporaneous presence of a variable capturing experience[11].

As explained in Section 2, different studies have resorted to different methodologies to analyse the assimilation pattern of immigrants. The key variable is generally the number of years of residence in the country, and several methods have been used to make sure that it captures a true assimilation effect. We believe that different groups of individuals show different employment and earnings behaviours, and different responses to the range of characteristics affecting labour market performance. We therefore try to control for this heterogeneity of the immigrant population by introducing more flexibility, running

[9] When considering the variables included over time in the QLFS about the higher qualification achieved, we find that the percentage of natives and education entrants holding 'other qualifications' is around 6-7%, but the share is much higher, above 40%, for labour market entrants, sign that in many cases foreign qualifications are not recorded as the equivalent British one.

[10] The QLFS operated on a seasonal quarter basis at the beginning; in May 2006, in accordance with EU legislation for data for Eurostat, a switch from seasonal to calendar quarters took place; this also allowed to enhance comparability with other surveys mostly conducted on this basis. Following the 2007 LFS Reweighting Project, all previous calendar versions of QLFS have been adjusted accordingly.

[11] In our sample, there is a 93.72% correlation between age and experience.

regressions on subsamples of individuals, so that we can achieve an increased homogeneity within each group. We generally disaggregate immigrants along two different dimensions, where the first one is always ethnicity (white and nonwhite[12]). This is a standard division that many studies on this topic use. A subsequent subdivision is done either by level of education (where highly educated individuals are defined as those who have a higher education qualification, either at degree or below degree level), or on marital status[13].

A relevant issue that is critical to the subject is that immigrants can differ in a fundamental aspect, that is the age of arrival in the UK. About 40% of our immigrant sample arrived in the country when aged 16 or below. This surely entails different adaptation processes, as individuals who came as children have probably been able to seize different types of opportunities when compared to adult immigrants, first of all because they participated in the British educational system. This might determine for example wage patterns that are closer to those of the native population.

Several studies do not take this aspect into consideration (for example, Bell, 1997; Borjas, 1985). Other papers have dealt with the issue in different ways. Antecol et al. (2006) simply exclude individuals for whom entry in the destination country is supposed to have taken place before the age of 16. Dustmann et al. (2003) include in the regression a dummy for the immigrant being 16 or below when entering the country. Wheatley Price (2001) uses regressors that separate education and working experience acquired in the UK and abroad.

Following Clark and Lindley (2009) (and, partially, Wheatley Price, 2001), we therefore make the additional distinction between labour market and education entrants. To do this, the sample of foreign-born individuals is divided according to whether the migrant left full time education before or after arrival in the UK. Labour market entrants will have both foreign experience and experience acquired in the UK, while they completed education in the country of origin. On the other hand, education entrants will have work experience accrued only in the UK, and their highest educational qualification will be a British one. Due to sample size, we make this distinction only on white and nonwhite subsamples.

The attempt to work on more homogeneous samples is also one of the reasons why we choose to limit our analysis to individuals aged 20-45; on the other side, this choice allows to rule out the possibility that issues such as early retirement affect our estimates.

[12] Any further disaggregation among non white individuals (e.g. between Indian, Pakistani, Bangladeshi and other non whites) would generate samples that are too small to provide significant results.

[13] Again, given that the group of immigrants in the sample is made up of about 23,500 individuals only, we cannot run regressions on samples with a higher level of disaggregation.

We run regressions on the native sample as a term of comparison.

Different econometric methods have been used in the literature to analyse the employment propensity of individuals. Since the dependent variable is binary and its relationship with the explanatory variables is non-linear, a simple Linear Probability Model would be inappropriate as it would provide predicted probabilities of employment that lie outside the interval (0,1), and because it would create problems for testing hypothesis, as the disturbance terms are by definition not normal[14]. We choose to use Probit regressions to analyse the employment propensity of individuals, so that the conditional expectation is bounded between zero and one.

As far as the analysis of earnings is concerned, an issue that arises is that we have to deal with a potential sample selection problem. While data on the explanatory variables is available for the entire sample, we have information on wages only for individuals in paid employment, and this subsample is potentially non-random. This is obviously a case of truncation, and in particular of incidental truncation, where the observability of the dependent variable is the result of the outcome of another variable; in the specific case, the occurrence of being in paid employment (*emp*=1), as of course wages are not observed for non-working individuals. This would imply the presence of a sample selection bias, and a simple linear regression would generate non consistent estimators for the parameters[15].

We choose to deal with these issues by using the Heckman Selectivity Model, a procedure suggested by Heckman (1979) to obtain consistent (although not efficient) estimates of the parameters of the Selectivity model.

Starting from a structural relationship for the Selectivity model in terms of a latent relationship of the form

$$wage_i^* = x_i'\beta + u_i$$

with an additional latent relationship for the observability of $wage_i$ as

$$emp_i^* = z_i'\gamma + v_i$$

where x_i are the regressors for the earnings equation and z_i are the explanatory variables for the latent variable equation for employment, and given the observability criterion

$$wage_i = wage_i^* .1(emp_i^* > 0)\ ,$$

[14] Another issue concerning disturbance terms is that they would be heteroskedastic by construction, but this is a problem that could be easily dealt with simply using heteroskedasticity robust standard errors.

[15] ‘Wage or earnings functions estimated on selected samples do not, in general, estimate population (i.e. random sample) wage functions’ (Heckman, 1979).

the conditional expectation for the Selectivity model can be represented as

$$
\begin{aligned}
E(wage_i \mid wage_i > 0) = E(wage_i \mid emp_i^* > 0) = \\
&= x_i'\beta + E(u_i \mid emp_i^* > 0) = \\
&= x_i'\beta + E(u_i \mid v_i > -z_i'\gamma) = \\
&= x_i'\beta + \frac{\sigma_{uv}}{\sigma_u}\lambda(z_i'\gamma)
\end{aligned}
$$

where $\lambda(z_i'\gamma) = \dfrac{\phi(z_i'\gamma)}{\Phi(z_i'\gamma)}$ is the Inverse Mills ratio (IMV), or hazard rate.

Building on this, Heckman (1979) suggests a two-stage estimation procedure, where in the first step a Probit regression is used on the entire sample to model the discrete choice in the selection equation (in our case, employment or unemployment). The estimated parameters are then used to obtain the IMV, the sample selection correction term, which is included as an additional explanatory variable in a second-stage linear regression estimation of the structural relationship on the selected sample of non-censored observations, i.e. in the estimation of our wage equation. This allows to make sure that the error has zero mean, so that a simple OLS regression for the wage equation will yield consistent estimates. Without the inclusion of this additional variable, an omitted variable bias would occur.

5. Results

We run regressions starting from the base model, and then progressively including a quadratic in both *exper* and *YSM* (rescaled dividing by 100), and interaction terms of these variables (again divided by 100). We show here regressions where we use five combinations of these key measures, namely equations including (A) *exper* and *YSM*; (B) *exper*, *YSM* and *YSM*exper*; (C) *exper*, $exper^2$ and *YSM*; (D) *exper*, $exper^2$, *YSM*, *YSM*exper* and $YSM*exper^2$; (E) *exper*, $exper^2$, *YSM*, YSM^2, *YSM*exper*, $YSM*exper^2$ and $YSM^2*exper^2$.

We then perform Likelihood Ratio, Wald and F-tests to decide among the different specifications. In particular, we test exclusion restrictions of the coefficients of *YSM*exper* and $YSM*exper^2$ in Model (D) and of YSM^2, *YSM*exper*, $YSM*exper^2$ and $YSM^2*exper^2$ in Model (E), to compare them to Model (C).

5.1 Employment

The main result of this part of the analysis is the clear and robust pattern of the coefficient of *YSM*, which is positive and significant throughout the different combinations of variables and interactions included, although generally losing significance – as all the other measures – when the full set of interactions between the variables and their quadratics are used. Given that we control for cohort quality[16], this is a remarkable result, which corroborates the hypothesis of a positive economic assimilation of migrants with residence in the destination country.

As we can see in Tables 2-3, the marital status is always relevant in explaining the employment rates of immigrants. Married individuals consistently show a better performance on the labour market.

Altogether, having children appears to reduce the probability of employment, probably because it affects the participation rate of individuals. This seems to be true especially for immigrants who have children aged 0-4 and to affect low-educated individuals in particular. This result is somewhat counterintuitive, since we are studying the performance of male individuals only, and we would expect that having children – in particular in pre-school age – negatively affects the participation decision of women, while potentially rising that of men. However, only an analysis of the participation decision within the household would be able to give us a greater insight into the mechanisms that are at work here.

[16] The evidence concerning the cohort effect is somewhat more contradictory. The problem here is that the coefficients of the dummies surely depend on the reference cohort, which is generally set to be the first one, the cohort of individuals who arrived before 1950. This is, however, a rather small and potentially highly selected group. Furthermore, given the disaggregation is subsamples that we use in our analysis, the dummies are sometimes dropped in the regressions because no individuals in the particular sample belong to one of the cohorts included; this is a particularly relevant issue for non white immigrants, who seem to have arrived in the UK later than whites. All these concerns make the interpretation and comparison of cohort dummies coefficients between different samples quite difficult.

Table 2. Probit estimates - Dependent variable: employment - Whites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated
exper	0.0027	-0.006 *	-0.0025	-0.0111 **	0.0267	0.0072	0.0109	0.0034	-0.0266	0.0189
	(0.0065)	(0.0035)	(0.0103)	(0.0051)	(0.0185)	(0.0119)	(0.0313)	(0.0177)	(0.0444)	(0.0220)
expersq/100					-0.1006	-0.0436	-0.083	-0.0614	0.0473	-0.12
					(0.0723)	(0.0373)	(0.1334)	(0.0608)	(0.2019)	(0.0785)
YSM	0.0227 ***	0.0388 ***	0.0183 *	0.0317 ***	0.0232 ***	0.039 ***	0.0095	0.0213 **	-0.0804 **	0.0491
	(0.0077)	(0.0052)	(0.0102)	(0.0074)	(0.0077)	(0.0052)	(0.0124)	(0.0103)	(0.0382)	(0.0310)
YSMsq/100									0.3298 **	-0.0970
									(0.1348)	(0.1241)
YSM_x_exper/100			0.031	0.0375			0.1604	0.1414	1.1153 **	-0.226
			(0.0483)	(0.0279)			(0.1566)	(0.1083)	(0.5657)	(0.3446)
YSM_x_expersq/100							-0.0035	-0.0021	-0.0316	0.0097
							(0.0057)	(0.0031)	(0.0220)	(0.0102)
YSMsq_x_exper/100									-0.0343 **	0.0117
									(0.0168)	(0.0118)
YSMsq_x_expersq/100									0.0009 *	-0.0003
									(0.0006)	(0.0003)
married	0.5358 ***	0.5158 ***	0.5383 ***	0.5128 ***	0.5244 ***	0.51 ***	0.5254 ***	0.4978 ***	0.5219 ***	0.4988 ***
	(0.0901)	(0.0546)	(0.0902)	(0.0546)	(0.0905)	(0.0548)	(0.0906)	(0.0552)	(0.0909)	(0.0552)
dkid04	-0.0178	-0.1817 ***	-0.0163	-0.1741 ***	-0.029	-0.1902 ***	-0.0318	-0.1851 ***	-0.0285	-0.1843 ***
	(0.1058)	(0.0585)	(0.1058)	(0.0587)	(0.1064)	(0.0589)	(0.1064)	(0.0590)	(0.1066)	(0.0591)
dkid59	-0.0259	-0.1161 *	-0.0258	-0.1125 *	-0.0309	-0.1223 **	-0.0368	-0.1245 **	-0.0251	-0.125 **
	(0.1145)	(0.0602)	(0.1144)	(0.0603)	(0.1145)	(0.0605)	(0.1147)	(0.0606)	(0.1150)	(0.0607)
dkid1015	-0.0744	-0.1953 ***	-0.0814	-0.2 ***	-0.0449	-0.1852 ***	-0.0466	-0.1847 ***	-0.0345	-0.1929 ***
	(0.1328)	(0.0640)	(0.1332)	(0.0641)	(0.1345)	(0.0646)	(0.1345)	(0.0647)	(0.1347)	(0.0650)
d50	-3.7593 ***	-4.2949 ***	-3.741 ***	-4.2413 ***	-3.7567 ***	-4.3267 ***	-3.7210 ***	-4.2993 ***	-3.7285 ***	-4.4238 ***
	(0.3852)	(0.2434)	(0.3874)	(0.2455)	(0.3883)	(0.2486)	(0.4099)	(0.2607)	(0.4283)	(0.2687)
d60	-3.8075 ***	-3.9908 ***	-3.7473 ***	-3.8875 ***	-3.8523 ***	-4.0436 ***	-3.7646 ***	-3.9587 ***	-3.7314 ***	-4.1165 ***
	(0.2995)	(0.1993)	(0.3162)	(0.2100)	(0.3106)	(0.2108)	(0.3299)	(0.2214)	(0.3561)	(0.2330)
d70	-3.7714 ***	-3.7064 ***	-3.6977 ***	-3.5822 ***	-3.8079 ***	-3.7547 ***	-3.6771 ***	-3.6141 ***	-3.5689 ***	-3.7818 ***
	(0.2474)	(0.1599)	(0.2761)	(0.1797)	(0.2583)	(0.1723)	(0.2925)	(0.1951)	(0.3294)	(0.2115)
d80	-3.3976 ***	-3.3087 ***	-3.3322 ***	-3.1962 ***	-3.4267 ***	-3.3571 ***	-3.3086 ***	-3.2348 ***	-3.1475 ***	-3.3982 ***
	(0.2017)	(0.1285)	(0.2297)	(0.1480)	(0.2134)	(0.1438)	(0.2518)	(0.1697)	(0.3005)	(0.1897)
d90	-3.1714 ***	-2.9746 ***	-3.1204 ***	-2.8848 ***	-3.1987 ***	-3.0200 ***	-3.1175 ***	-2.9392 ***	-3.0200 ***	-3.0872 ***
	(0.1781)	(0.1071)	(0.1986)	(0.1212)	(0.1904)	(0.1237)	(0.2228)	(0.1476)	(0.2649)	(0.1653)
d00	-2.9062 ***	-2.7253 ***	-2.8641 ***	-2.6459 ***	-2.9303 ***	-2.7679 ***	-2.8687 ***	-2.7058 ***	-2.8383 ***	-2.8453 ***
	(0.1819)	(0.1054)	(0.1964)	(0.1162)	(0.1933)	(0.1210)	(0.2215)	(0.1426)	(0.2571)	(0.1588)
_cons	4.5653	3.9382	4.57	3.9242	4.4964	3.9109	4.5556	3.9447	4.7817	4.0012
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
N	4557	7386	4557	7386	4557	7386	4557	7386	4557	7386
LR test on Model C: p-value							0.3264	0.0673	0.1146	0.1979
Wald test on Model C: p-value							0.3242	0.0656	0.1284	0.1906

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A1 - Appendix

Table 3. Probit estimates - Dependent variable: employment - Nonwhites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated
exper	0.0053	-0.0046	0.0117	-0.003	0.0447 ***	0.0133	0.015	-0.0146	0.0282	-0.0251
	(0.0055)	(0.0033)	(0.0093)	(0.0050)	(0.0165)	(0.0114)	(0.0288)	(0.0188)	(0.0406)	(0.0253)
expersq/100					-0.1597 **	-0.0583	-0.0379	0.0278	-0.1273	0.0685
					(0.0626)	(0.0354)	(0.1181)	(0.0631)	(0.1701)	(0.0876)
YSM	0.0299 ***	0.0393 ***	0.0354 ***	0.0415 ***	0.0306 ***	0.0396 ***	0.0209 *	0.0218 **	0.0368	0.0043
	(0.0068)	(0.0046)	(0.0094)	(0.0070)	(0.0068)	(0.0046)	(0.0121)	(0.0109)	(0.0383)	(0.0345)
YSMsq/100									-0.05	0.0646
									(0.1363)	(0.1389)
YSM_x_exper/100			-0.0421	-0.0121			0.2036	0.2431 **	0.0444	0.4672
			(0.0489)	(0.0298)			(0.1676)	(0.1234)	(0.5783)	(0.4142)
YSM_x_expersq/100							-0.0077	-0.0068 *	0.0027	-0.0144
							(0.0061)	(0.0035)	(0.0213)	(0.0123)
YSMsq_x_exper/100									0.0040	-0.0077
									(0.0182)	(0.0147)
YSMsq_x_expersq/100									-0.0002	0.0002
									(0.0006)	(0.0004)
married	0.3579 ***	0.6117 ***	0.3568 ***	0.6130 ***	0.3289 ***	0.6064 ***	0.3293 ***	0.6058 ***	0.3294 ***	0.6044 ***
	(0.0804)	(0.0537)	(0.0804)	(0.0538)	(0.0814)	(0.0538)	(0.0815)	(0.0541)	(0.0815)	(0.0542)
dkid04	-0.0638	-0.1714 ***	-0.068	-0.1736 ***	-0.0832	-0.1818 ***	-0.0851	-0.1806 ***	-0.0867	-0.1808 ***
	(0.0781)	(0.0467)	(0.0783)	(0.0470)	(0.0786)	(0.0472)	(0.0787)	(0.0473)	(0.0788)	(0.0473)
dkid59	0.1687 **	-0.061	0.1651 **	-0.0627	0.1536 *	-0.068	0.1477 *	-0.0742	0.1479 *	-0.0726
	(0.0837)	(0.0461)	(0.0838)	(0.0463)	(0.0840)	(0.0463)	(0.0842)	(0.0466)	(0.0843)	(0.0466)
dkid1015	-0.052	-0.0258	-0.0489	-0.0242	-0.0073	-0.0142	-0.0142	-0.0208	-0.0206	-0.0168
	(0.0960)	(0.0508)	(0.0960)	(0.0509)	(0.0976)	(0.0513)	(0.0979)	(0.0514)	(0.0981)	(0.0517)
d50		-1.4513 ***								-1.4715 ***
		(0.2826)								(0.2898)
d60	-0.8186 ***	-1.0014 ***		0.4404 *		0.4419 *	-0.8212 ***	0.4286 *		-1.0004 ***
	(0.2224)	(0.1367)		(0.2439)		(0.2428)	(0.2233)	(0.2449)		(0.1376)
d70	-0.6631 ***	-0.7401 ***	0.1312	0.6932 ***	0.1544	0.6934 ***	-0.666 ***	0.6882 ***	0.0843	-0.7317 ***
	(0.1627)	(0.1075)	(0.1343)	(0.2512)	(0.1316)	(0.2476)	(0.1651)	(0.2525)	(0.1487)	(0.1130)
d80	-0.6749 ***	-0.4538 ***	0.1198	0.9789 ***	0.1402	0.9819 ***	-0.6767 ***	0.9901 ***	0.0730	-0.4307 ***
	(0.1173)	(0.0802)	(0.1690)	(0.2644)	(0.1666)	(0.2605)	(0.1201)	(0.2655)	(0.1857)	(0.0888)
d90	-0.3557 ***	-0.2029 ***	0.4478 **	1.2335 ***	0.4591 **	1.2345 ***	-0.3563 ***	1.2394 ***	0.4216 **	-0.1902 ***
	(0.0979)	(0.0637)	(0.1986)	(0.2757)	(0.1977)	(0.2734)	(0.0989)	(0.2765)	(0.2068)	(0.0659)
d00			0.8149 ***	1.4385 ***	0.8151 ***	1.4394 ***		1.4374 ***	0.8029 ***	
			(0.2228)	(0.2843)	(0.2228)	(0.2826)		(0.2851)	(0.2254)	
_cons	1.278 ***	0.773 ***	0.4066	-0.6857 **	0.3119	-0.7636 **	1.2565 ***	-0.5827 *	0.4033	0.9151 ***
	(0.1779)	(0.1457)	(0.2930)	(0.3204)	(0.2921)	(0.3240)	(0.2189)	(0.3387)	(0.3434)	(0.2111)
N	4178	7096	4178	7096	4178	7096	4178	7096	4178	7096
LR test on Model C: p-value							0.4484	0.1424	0.6182	0.4663
Wald test on Model C: p-value							0.4456	0.1424	0.5999	0.4695

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A2 - Appendix

Table 4. Probit estimates - Dependent variable: employment - Whites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried
exper	-0.0092 *	0.0000	-0.0111 *	-0.0002	0.0064	0.0321 **	-0.0124	0.0467 **	0.0003	0.0322
	(0.0047)	(0.0044)	(0.0064)	(0.0068)	(0.0159)	(0.0128)	(0.0232)	(0.0209)	(0.0298)	(0.0268)
expersq/100					-0.0495	-0.1183 ***	-0.0047	-0.205 **	-0.1	-0.1462
					(0.0481)	(0.0442)	(0.0767)	(0.0798)	(0.1012)	(0.1076)
YSM	0.0483 ***	0.0163 **	0.0454 ***	0.016 *	0.0483 ***	0.0168 **	0.0266 *	0.0122	-0.036	-0.0069
	(0.0062)	(0.0065)	(0.0091)	(0.0085)	(0.0062)	(0.0065)	(0.0137)	(0.0102)	(0.0434)	(0.0289)
YSMsq/100									0.2811 *	0.0659
									(0.1522)	(0.1073)
YSM_x_exper/100			0.0148	0.0019			0.2296	-0.0319	0.4731	0.2798
			(0.0342)	(0.0344)			(0.1407)	(0.1132)	(0.4845)	(0.3746)
YSM_x_expersq/100							-0.0054	0.0031	-0.0011	-0.0078
							(0.0039)	(0.0037)	(0.0138)	(0.0125)
YSMsq_x_exper/100									-0.0171	-0.0096
									(0.0152)	(0.0118)
YSMsq_x_expersq/100									0.0002	0.0003
									(0.0004)	(0.0003)
degree	0.3559 ***	0.3861 ***	0.3609 ***	0.3868 ***	0.3535 ***	0.39 ***	0.366 ***	0.4133 ***	0.369 ***	0.4176 ***
	(0.0758)	(0.0826)	(0.0768)	(0.0835)	(0.0759)	(0.0827)	(0.0772)	(0.0845)	(0.0771)	(0.0848)
a_level	0.2276 ***	0.2197 ***	0.2283 ***	0.22 ***	0.2271 ***	0.2138 ***	0.2269 ***	0.2229 ***	0.2402 ***	0.2266 ***
	(0.0677)	(0.0743)	(0.0677)	(0.0745)	(0.0677)	(0.0744)	(0.0677)	(0.0748)	(0.0681)	(0.0753)
o_level	-0.0327	0.0033	-0.0308	0.0036	-0.0355	-0.0108	-0.0335	-0.0069	-0.0083	-0.0077
	(0.0990)	(0.1002)	(0.0991)	(0.1003)	(0.0990)	(0.1004)	(0.0992)	(0.1006)	(0.0995)	(0.1019)
dkid04	-0.1087 **	-0.4704 ***	-0.1064 *	-0.4697 ***	-0.1176 **	-0.4879 ***	-0.116 **	-0.4692 ***	-0.1163 **	-0.4681 ***
	(0.0541)	(0.1615)	(0.0543)	(0.1620)	(0.0549)	(0.1614)	(0.0549)	(0.1622)	(0.0550)	(0.1623)
dkid59	-0.0886	-0.1354	-0.0868	-0.1355	-0.0988 *	-0.1371	-0.1049 *	-0.1401	-0.1045 *	-0.1388
	(0.0556)	(0.1913)	(0.0558)	(0.1913)	(0.0566)	(0.1912)	(0.0567)	(0.1915)	(0.0569)	(0.1916)
dkid1015	-0.1843 ***	-0.1046	-0.186 ***	-0.1047	-0.1806 ***	-0.08	-0.1897 ***	-0.0758	-0.1896 ***	-0.0619
	(0.0660)	(0.1477)	(0.0661)	(0.1477)	(0.0662)	(0.1482)	(0.0665)	(0.1483)	(0.0667)	(0.1493)
d50	-4.0841 ***	-4.5059 ***	-4.064 ***	-4.3283 ***	-4.1161 ***	-4.4272 ***	-4.1794 ***	-4.3191 ***	-4.2953 ***	-4.2488 ***
	(0.2839)	(0.2758)	(0.2868)	(0.3113)	(0.2938)	(0.3137)	(0.3152)	(0.3243)	(0.3378)	(0.3317)
d60	-3.7517 ***	-4.3745 ***	-3.7153 ***	-4.1936 ***	-3.8005 ***	-4.3749 ***	-3.8501 ***	-4.1652 ***	-4.0246 ***	-4.072 ***
	(0.2358)	(0.2060)	(0.2481)	(0.2566)	(0.2531)	(0.2563)	(0.2733)	(0.2641)	(0.3019)	(0.2726)
d70	-3.4504 ***	-4.2217 ***	-3.4089 ***	-4.0398 ***	-3.4976 ***	-4.2082 ***	-3.5164 ***	-3.9732 ***	-3.6446 ***	-3.8748 ***
	(0.1933)	(0.1590)	(0.2130)	(0.2200)	(0.2131)	(0.2101)	(0.2439)	(0.2299)	(0.2791)	(0.2454)
d80	-2.9241 ***	-3.9348 ***	-2.8867 ***	-3.7534 ***	-2.9754 ***	-3.9122 ***	-3.0054 ***	-3.6963 ***	-3.0542 ***	-3.5924 ***
	(0.1554)	(0.1200)	(0.1748)	(0.1848)	(0.1817)	(0.1767)	(0.2151)	(0.1996)	(0.2544)	(0.2210)
d90	-2.6055 ***	-3.6346 ***	-2.5737 ***	-3.4546 ***	-2.6538 ***	-3.6123 ***	-2.6988 ***	-3.4346 ***	-2.7516 ***	-3.3399 ***
	(0.1303)	(0.0928)	(0.1466)	(0.1507)	(0.1588)	(0.1512)	(0.1940)	(0.1687)	(0.2322)	(0.1850)
d00	-2.3585 ***	-3.3323	-2.3309 ***	-3.1525 ***	-2.4016 ***	-3.3056 ***	-2.4612 ***	-3.1333 ***	-2.5367 ***	-3.0451 ***
	(0.1263)	(.)	(0.1387)	(0.1470)	(0.1527)	(0.1487)	(0.1859)	(0.1650)	(0.2223)	(0.1784)
_cons	3.9966	4.7841 ***	3.9936	4.6069	3.9503	4.6131	4.166	4.4222	4.3109	4.3915
	(.)	(0.1388)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
N	7900	4043	7900	4043	7900	4043	7900	4043	7900	4043
LR test on Model C: p-value							0.2174	0.2354	0.0486	3.7600
Wald test on Model C: p-value							0.2100	0.2328	0.0493	0.5847

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A3 - Appendix

Table 5. Probit estimates - Dependent variable: employment - Nonwhites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried
exper	-0.0028	0.0006	-0.0003	0.0055	0.026 **	0.0393 ***	0.0001	0.0259	-0.0151	0.0204
	(0.0038)	(0.0045)	(0.0057)	(0.0073)	(0.0131)	(0.0140)	(0.0214)	(0.0239)	(0.0293)	(0.0332)
expersq/100					-0.0904 **	-0.1483 ***	-0.0146	-0.1056	0.0297	-0.0736
					(0.0393)	(0.0506)	(0.0703)	(0.0919)	(0.0987)	(0.1311)
YSM	0.0408 ***	0.0228 ***	0.0443 ***	0.0277 ***	0.0412 ***	0.024 ***	0.0219 *	0.0178	0.0137	-0.0234
	(0.0048)	(0.0069)	(0.0076)	(0.0088)	(0.0048)	(0.0069)	(0.0125)	(0.0110)	(0.0393)	(0.0345)
YSMsq/100									0.0198	0.164
									(0.1431)	(0.1292)
YSM_x_exper/100			-0.0191	-0.0349			0.2384 *	0.1079	0.5464	0.2852
			(0.0327)	(0.0398)			(0.1390)	(0.1436)	(0.4699)	(0.5135)
YSM_x_expersq/100							-0.0064	-0.0033	-0.0158	-0.0086
							(0.0039)	(0.0048)	(0.0137)	(0.0180)
YSMsq_x_exper/100									-0.0089	-0.0084
									(0.0156)	(0.0168)
YSMsq_x_expersq/100									0.0003	0.0002
									(0.0004)	(0.0005)
degree	0.4492 ***	0.5151 ***	0.4436 ***	0.5095 ***	0.4434 ***	0.5362 ***	0.4499 ***	0.5359 ***	0.4567 ***	0.5356 ***
	(0.0601)	(0.0849)	(0.0608)	(0.0850)	(0.0602)	(0.0855)	(0.0612)	(0.0865)	(0.0615)	(0.0864)
a_level	0.1934 ***	0.11	0.1903 ***	0.1097	0.187 ***	0.1131	0.1878 ***	0.1096	0.1917 ***	0.1238
	(0.0547)	(0.0772)	(0.0550)	(0.0771)	(0.0548)	(0.0772)	(0.0550)	(0.0774)	(0.0553)	(0.0780)
o_level	0.1129	-0.1088	0.11	-0.1072	0.1055	-0.1116	0.1052	-0.1148	0.1102	-0.0915
	(0.0814)	(0.0997)	(0.0815)	(0.0997)	(0.0815)	(0.0997)	(0.0817)	(0.0998)	(0.0819)	(0.1008)
dkid04	-0.1546 ***	0.3124	-0.1577 ***	0.3111	-0.1689 ***	0.2917	-0.1661 ***	0.2855	-0.1687 ***	0.2921
	(0.0413)	(0.2031)	(0.0416)	(0.2032)	(0.0418)	(0.2031)	(0.0419)	(0.2032)	(0.0419)	(0.2034)
dkid59	-0.0144	-0.0195	-0.0174	-0.0202	-0.031	-0.011	-0.0343	-0.0137	-0.0378	-0.0038
	(0.0416)	(0.1677)	(0.0419)	(0.1679)	(0.0423)	(0.1680)	(0.0424)	(0.1681)	(0.0425)	(0.1684)
dkid1015	-0.0334	-0.1022	-0.0316	-0.1011	-0.0305	-0.068	-0.0395	-0.068	-0.0429	-0.062
	(0.0506)	(0.1234)	(0.0507)	(0.1234)	(0.0507)	(0.1237)	(0.0511)	(0.1238)	(0.0512)	(0.1241)
d50		-0.8896 **	-1.5432 ***	-0.8344 *	-1.5441 ***	-0.8238 *	-1.5392 ***	-0.8341 *	-1.4906 ***	
		(0.4343)	(0.3181)	(0.4387)	(0.3179)	(0.4345)	(0.3219)	(0.4388)	(0.3241)	
d60	0.4531	-0.8564 ***	-1.1036 ***	-0.8397 ***	-1.0997 ***	-0.8399 ***	-1.1023 ***	-0.8515 ***	-1.1056 ***	0.0891
	(0.2784)	(0.2069)	(0.1415)	(0.2079)	(0.1414)	(0.2076)	(0.1415)	(0.2086)	(0.1420)	(0.3941)
d70	0.705 **	-0.5692 ***	-0.8624 ***	-0.5885 ***	-0.8618 ***	-0.5814 ***	-0.8576 ***	-0.5773 ***	-0.9 ***	0.4449
	(0.2826)	(0.1577)	(0.1101)	(0.1593)	(0.1094)	(0.1580)	(0.1102)	(0.1596)	(0.1157)	(0.4161)
d80	0.9472 ***	-0.4353 ***	-0.6201 ***	-0.453 ***	-0.6209 ***	-0.4421 ***	-0.6112 ***	-0.4359 ***	-0.6599 ***	0.6256
	(0.2961)	(0.1143)	(0.0830)	(0.1160)	(0.0821)	(0.1145)	(0.0830)	(0.1164)	(0.0904)	(0.4313)
d90	1.2352 ***	-0.1758 **	-0.3277 ***	-0.1851 **	-0.3279 ***	-0.184 **	-0.3226 ***	-0.1799 **	-0.3433 ***	0.8338 *
	(0.3075)	(0.0870)	(0.0675)	(0.0876)	(0.0673)	(0.0871)	(0.0675)	(0.0877)	(0.0693)	(0.4416)
d00	1.5599 ***									0.9627 **
	(0.3164)									(0.4487)
_cons	-0.1869	0.8718 ***	1.3445 ***	0.8222 ***	1.2071 ***	0.6872 ***	1.3849 ***	0.7561 ***	1.4585 ***	-0.1237
	(0.3435)	(0.2068)	(0.1488)	(0.2143)	(0.1575)	(0.2158)	(0.1906)	(0.2346)	(0.2315)	(0.5226)
N	8448	2847	8448	2847	8448	2847	8448	2847	8448	2847
LR test on Model C: p-value							0.2297	0.7492	0.3948	0.3928
Wald test on Model C: p-value							0.2278	0.7493	0.3909	0.4035

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A4 - Appendix

Tables 4-5 show evidence of a higher employment rate for individuals the higher the education qualification they have. Quite intuitively, having a qualification at degree level seems to give the greatest and most robust employment advantage, since the effect is always strongly significant. A qualification below degree level (or at A-level or equivalent) gives a premium as well if compared to lower qualifications, but the effect appears to be less robust, in particular for nonwhite immigrants[17].

No clear and consistent regional pattern emerges from the regressions (estimates of these parameters can be found in the Appendix, Tables A1-A4). There seems to be an employment disadvantage in the North West and West Midlands for low-educated immigrants, both white and nonwhite. An advantage for low-educated white immigrants appears in the South East and East of England. Unmarried whites show a disadvantage in Yorkshire and the Humber, while married whites seems to have an advantage in the East of England. When disaggregated by marital status, nonwhite immigrants appear to have lower employment rates in the West Midlands, while the rate seems to be higher for unmarried individuals in the South East and for married individuals in the South West.

To give an idea of the employment assimilation profiles, we compute marginal effects of the regressions for an individual with the characteristics of the average immigrant, i.e. 15 years of experience, married, with at least one child aged 4 or below, living in the London area (interviewed in quarter 2). We compute the employment probability of an immigrant with YSM=5, 10 and 15, arrived in the 1970s and in the 1990s, and compare it to the employment probability of a native with the same characteristics and coming from the same ethnic group. We use equation (C) for this purpose, as both LR and Wald tests reported in Tables 2-5 show that any additional combination of the variables *exper* and *YSM* is not relevant for the model .
We can see that for both whites and nonwhites, and high- and low-educated immigrants, the % employment probability differential is much lower the longer the residence in the destination country. The performance gap is higher for nonwhites than for whites, and the disadvantage experienced by low-educated individuals is higher than that of the higher educated. In every case, however, the gap that we observe decreases as YSM increase, as the assimilation theory would predict. There seems to be a performance differential also among different cohorts. We report here the estimated probabilities for individuals with the same

[17] For nonwhite immigrants, the effect seems to be limited to the group of married individuals, while it is not significant for the unmarried ones.

characteristics, but arrived at different points in time, and we see that the performance of the more recent cohort is better, with low-educated immigrants who even seem to perform better than natives after 10 and 15 years of residence in the country.

Table 6. Predicted employment probability differences wrt natives, using model C from Tables 2-3

		Whites			Nonwhites		
	YSM	5	10	15	5	10	15
	Arrival cohort						
High-educated	1970s	-8.0393	-6.2936	-4.8192	-13.2413	-10.0044	-7.3094
	1990s	-1.5874	-0.9678	-0.4802	-7.30947	-5.1286	-3.3841
Low-educated	1970s	-17.9441	-12.2446	-7.4480	-22.0294	-15.2483	-9.2859
	1990s	-1.1717	1.2719	3.0546	-5.5115	-1.1606	2.2771

5.2 Earnings

We use the Heckman procedure for earnings, thereby estimating a model of the probability of being in paid employment using a probit for *emp*, and then a linear regression model for *wage*, in which we include $\lambda(z_i'\gamma)$ to control for truncation. Of course an identification problem arises here for the hazard rate, so that we have to include in the employment equation at least one exogenous variable that does not enter the structural relationship. We therefore include variables which are supposed to capture a particular motivation to obtain a paid job, but which should not be relevant for the level of wage earned by the individual; we identify these characteristics in variables about particular family circumstances, i.e. marital status and the dummies relative to the presence of children.

Using the Heckman Selectivity Model also makes it relatively easy to test for the existence of sample selection, with a simple t-test on the estimated parameter of lambda (the hazard rate). What we observe in our results is that the coefficient of the lambda is always significant in the regressions we run on samples disaggregated by educational level, but less so in those for samples disaggregated by marital status[18]. This implies that sample selection is a problem more when we use groups of individuals divided by educational level. Whenever significant, the coefficients of the lambda are negative; as Chiswick et al. (2005) point out, this ‘indicates

[18] In this second case, the parameters are significant only for married nonwhites individuals.

that there is a negative correlation between the error terms in the selection equation determining whether the immigrant is in paid employment and the earnings equation. That is, immigrants with an above average probability of being in paid employment, given their observed characteristics, have a lower than average expected earnings, again given their observed characteristics. In other words, there is negative selection into paid employment', which seems to point in the direction of a situation where immigrants move to other labour markets because they need to work, more than for a comparative advantage in the type of jobs offered in the labour market of the destination country, which would assure higher earnings.

Results are presented in Tables 7-10. The estimates of the Probit regressions for the first stage, produced in the Appendix (Tables A9-A12), show that the over-identifying restrictions used (marital status and dummies for the presence of children) are statistically significant, which allows us to rightfully rely on the Heckman procedure for the analysis.

The estimates again show a clear and consistent pattern as far as *YSM* is concerned, with positive and significant coefficients with any specification of the model (although again the estimate loses significance when too much structure is added to the model as for the two main variables *exper* and *YSM*). So once again, the hypothesis of a positive economic assimilation seems to be confirmed by evidence.

Using Heckman allows us to directly read and interpret the coefficients of the variables – something we obviously could not do with estimates from Probit regressions – and this can be particularly useful if we want to say something about the unobserved quality of successive arrival cohorts. However, the same issues we needed to consider for these variables in analysing the employment regressions are valid even here, in particular the consideration about the lack of individuals in some of the early cohorts and the cohort of reference, which can be the first or the last one depending on which one is dropped in the regression. However, the picture that emerges shows that the unobserved quality of cohorts seems to increase over time, as the performance of each cohort is better than that of the previous one and worse than that of the following one[19]. The result is highly significant and robust to different model specifications. Only for highly-educated whites no clear pattern is indentified.

Our estimates of the earnings equations also provide evidence of positive but decreasing returns to (potential) working experience of the individual, although this result is more robust to different specifications for whites than for nonwhites.

---

[19] One needs to note that this conclusion is drawn from coefficients that might be different in sign: when the reference cohort is the first one available (either before 1950, or 1950-1959), the coefficients are positive and increasing with subsequent arrival cohorts; when the reference cohort is the last one (2000-2009), the sign is negative with decreasing coefficients.

Table 7. Heckman Selectivity Model - Dependent variable: log hourly wage - Whites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated
exper	0.0216 ***	0.0128 ***	0.0352 ***	0.0147 ***	0.0745 ***	0.0395 ***	0.0855 ***	0.0393 ***	0.1073 ***	0.045 ***
	(0.0057)	(0.0020)	(0.0086)	(0.0030)	(0.0143)	(0.0062)	(0.0227)	(0.0090)	(0.0311)	(0.0115)
expersq/100					-0.2079 ***	-0.0901 ***	-0.2403 **	-0.1055 ***	-0.3043 **	-0.1168 ***
					(0.0537)	(0.0202)	(0.0954)	(0.0322)	(0.1384)	(0.0432)
YSM	0.0127	0.0101 ***	0.0252 **	0.0129 ***	0.0162 **	0.0123 ***	0.0222 **	0.0043	0.0511 *	0.0059
	(0.0083)	(0.0038)	(0.0099)	(0.0048)	(0.0065)	(0.0036)	(0.0093)	(0.0053)	(0.0292)	(0.0156)
YSM2/100									-0.1026	-0.0011
									(0.1041)	(0.0619)
YSM_x_exper/100			-0.0786 **	-0.0143			-0.0832	0.0649	-0.5878	-0.0837
			(0.0395)	(0.0157)			(0.1119)	(0.0546)	(0.4195)	(0.1755)
YSM_x_expersq/100							0.0024	-0.0009	0.0172	0.0032
							(0.0039)	(0.0015)	(0.0156)	(0.0053)
YSM2_x_exper/100									0.0157	0.0038
									(0.0120)	(0.0059)
YSM2_x_expersq/100									-0.0005	-0.0001
									(0.0004)	(0.0001)
pt	-0.3868 **	-0.553 ***	-0.3714 **	-0.5524 ***	-0.3541 ***	-0.5404 ***	-0.3535 ***	-0.5359 ***	-0.3577 ***	-0.5417 ***
	(0.1663)	(0.0472)	(0.1580)	(0.0474)	(0.1280)	(0.0428)	(0.1263)	(0.0409)	(0.1292)	(0.0413)
d50	0.3858	-0.5683 ***	0.3165		0.3135		0.3118		0.3469	
	(1.0164)	(0.1574)	(0.9637)		(0.7826)		(0.7710)		(0.7908)	
d60	0.6341	-0.4658 ***	0.4755	0.0837	0.4765	0.0625	0.4705	0.0861	0.5318	0.1006
	(1.0113)	(0.1254)	(0.9615)	(0.0714)	(0.7796)	(0.0616)	(0.7700)	(0.0622)	(0.7940)	(0.0648)
d70	0.8129	-0.3706 ***	0.6083	0.1693 *	0.6599	0.169 **	0.6375	0.2223 ***	0.7188	0.2626 ***
	(1.0175)	(0.0981)	(0.9697)	(0.0915)	(0.7843)	(0.0765)	(0.7760)	(0.0804)	(0.8031)	(0.0862)
d80	0.9051	-0.2493 ***	0.7327	0.2951 **	0.8089	0.3128 ***	0.7885	0.3641 ***	0.8456	0.4053 ***
	(1.0315)	(0.0655)	(0.9816)	(0.1189)	(0.7942)	(0.1036)	(0.7854)	(0.1048)	(0.8130)	(0.1106)
d90	1.1353	-0.0246	1.0135	0.5306 ***	1.0697	0.5597 ***	1.0615	0.5916 ***	1.1035	0.6005 ***
	(1.0461)	(0.0412)	(0.9936)	(0.1473)	(0.8052)	(0.1321)	(0.7948)	(0.1287)	(0.8190)	(0.1312)
d00	1.1301		1.0372	0.5606 ***	1.0964	0.6011 ***	1.0947	0.6279 ***	1.1261	0.6214 ***
	(1.0577)		(1.0038)	(0.1586)	(0.8139)	(0.1434)	(0.8029)	(0.1384)	(0.8249)	(0.1400)
_cons	1.2041	2.093 ***	1.1543	1.5078 ***	0.9679	1.3207 ***	0.9037	1.3203 ***	0.7623	1.3028 ***
	(1.0769)	(0.0701)	(1.0205)	(0.1932)	(0.8318)	(0.1846)	(0.8227)	(0.1784)	(0.8426)	(0.1833)
lambda	-1.737 ***	-0.7951 ***	-1.6461 ***	-0.7982 ***	-1.337 ***	-0.721 ***	-1.3165 ***	-0.6797 ***	-1.3456 ***	-0.6942 ***
	(0.5619)	(0.1454)	(0.5314)	(0.1458)	(0.4508)	(0.1347)	(0.4433)	(0.1311)	(0.4465)	(0.1321)
N	2962	4428	2962	4428	2962	4428	2962	4428	2962	4428
F-test on Model C: p-value							0.7319	0.1148	0.764	0.1986

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A5 - Appendix

Table 8. Heckman Selectivity Model - Dependent variable: log hourly wage - Nonwhites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated	High-educated	Low-educated
exper	0	-0.0001	0.0026	-0.0019	0.0317 ***	0.0157 **	0.036 ***	0.0121	0.0472 **	0.0203
	(0.0031)	(0.0017)	(0.0052)	(0.0026)	(0.0095)	(0.0064)	(0.0133)	(0.0100)	(0.0185)	(0.0133)
expersq/100					-0.1161 ***	-0.0494 **	-0.1435 ***	-0.0579 *	-0.1514 **	-0.0787 *
					(0.0329)	(0.0192)	(0.0515)	(0.0329)	(0.0751)	(0.0450)
YSM	0.03 ***	0.0263*** ***	0.0326 ***	0.0237 ***	0.0325 ***	0.0269 ***	0.0315 ***	0.0133 **	0.0572 ***	-0.0076
	(0.0048)	(0.0030)	(0.0062)	(0.0041)	(0.0040)	(0.0030)	(0.0060)	(0.0064)	(0.0187)	(0.0187)
YSM2/100									-0.1029	0.1026
									(0.0653)	(0.0731)
YSM_x_exper/100			-0.0166	0.0141			-0.0101	0.1162 *	-0.3864	0.0223
			(0.0255)	(0.0152)			(0.0763)	(0.0702)	(0.2707)	(0.2215)
YSM_x_expersq/100							0.0010	-0.0019	0.0087	0.0022
							(0.0026)	(0.0019)	(0.0096)	(0.0064)
YSM2_x_exper/100									0.0137	-0.0008
									(0.0084)	(0.0076)
YSM2_x_expersq/100									-0.0003	-0.0001
									(0.0003)	(0.0002)
pt	-0.5329 ***	-0.3411 ***	-0.5303 ***	-0.3410 ***	-0.5252 ***	-0.3375 ***	-0.5268 ***	-0.3358 ***	-0.5235 ***	-0.3345 ***
	(0.0533)	(0.0292)	(0.0513)	(0.0292)	(0.0434)	(0.0292)	(0.0434)	(0.0292)	(0.0432)	(0.0291)
d50	-0.932 ***	-1.0014 ***	-0.919 ***	-1.0155 ***		-1.0042 ***			-1.0549 ***	-1.1147 ***
	(0.2531)	(0.1825)	(0.2437)	(0.1832)		(0.1817)			(0.2070)	(0.1841)
d60	-0.8611 ***	-0.847 ***	-0.8664 ***	-0.8488 ***	0.0348	-0.8561 ***	0.0535	0.1845	-0.8986 ***	-0.8564 ***
	(0.1518)	(0.0889)	(0.1465)	(0.0890)	(0.1623)	(0.0888)	(0.1635)	(0.1484)	(0.1289)	(0.0896)
d70	-0.6331 ***	-0.699 ***	-0.6477 ***	-0.6922 ***	0.2668	-0.716 ***	0.2964 *	0.3502 **	-0.622 ***	-0.6352 ***
	(0.1161)	(0.0704)	(0.1150)	(0.0707)	(0.1640)	(0.0708)	(0.1672)	(0.1538)	(0.1089)	(0.0730)
d80	-0.333 ***	-0.5255 ***	-0.3489 ***	-0.5172 ***	0.5677 ***	-0.5418 ***	0.5977 ***	0.5358 ***	-0.3355 ***	-0.4271 ***
	(0.0974)	(0.0488)	(0.0979)	(0.0496)	(0.1737)	(0.0494)	(0.1769)	(0.1647)	(0.0967)	(0.0526)
d90	-0.1355 **	-0.2667 ***	-0.1437 **	-0.263 ***	0.7908 ***	-0.2745 ***	0.8163 ***	0.7944 ***	-0.1468 **	-0.2236 ***
	(0.0625)	(0.0342)	(0.0620)	(0.0344)	(0.1847)	(0.0343)	(0.1866)	(0.1749)	(0.0590)	(0.0350)
d00					0.965 ***		0.9866 ***	1.0604 ***		
					(0.1990)		(0.1998)	(0.1821)		
_cons	2.5228 ***	1.9393 ***	2.4877 ***	1.9643 ***	1.3516 ***	1.8346 ***	1.3265 ***	0.8334 ***	2.2393 ***	1.9103 ***
	(0.1154)	(0.0902)	(0.1244)	(0.0940)	(0.2500)	(0.1013)	(0.2490)	(0.2261)	(0.1378)	(0.1187)
lambda	-0.794 ***	-0.1917 **	-0.7641 ***	-0.191 **	-0.5574 **	-0.1733 **	-0.5534 **	-0.1477 *	-0.639 ***	-0.1625 *
	(0.2653)	(0.0871)	(0.2597)	(0.0871)	(0.2362)	(0.0883)	(0.2368)	(0.0886)	(0.2450)	(0.0893)
N	2461	3883	2461	3883	2461	3883	2461	3883	2461	3883
F-test on Model C: p-value							0.6492	0.0143	0.2595	0.0000

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A6 - Appendix

Table 9. Heckman Selectivity Model - Dependent variable: log hourly wage - Whites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried
exper	0.0073 ***	0.017 ***	0.0124 ***	0.0162 ***	0.0583 ***	0.0498 ***	0.0646 ***	0.0554 ***	0.0605 ***	0.0737 ***
	(0.0020)	(0.0021)	(0.0027)	(0.0033)	(0.0053)	(0.0066)	(0.0084)	(0.0110)	(0.0110)	(0.0122)
expersq/100					-0.1681 ***	-0.1309 ***	-0.2103 ***	-0.1949 ***	-0.1904 ***	-0.2906 ***
					(0.0168)	(0.0262)	(0.0292)	(0.0504)	(0.0402)	(0.0548)
YSM	0.0278 ***	0.019 ***	0.033 ***	0.0182 ***	0.0287 ***	0.0218 ***	0.0242 ***	0.0129 ***	-0.0033	0.0184
	(0.0038)	(0.0041)	(0.0042)	(0.0045)	(0.0037)	(0.0040)	(0.0047)	(0.0046)	(0.0137)	(0.0123)
YSM2/100									0.0935 **	-0.0025
									(0.0471)	(0.0478)
YSM_x_exper/100			-0.0312 ***	0.0052			0.017	0.0466	0.1733	-0.2488
			(0.0111)	(0.0155)			(0.0456)	(0.0479)	(0.1650)	(0.1658)
YSM_x_expersq/100							0.0007	0.0008	-0.0036	0.0157 ***
							(0.0013)	(0.0017)	(0.0050)	(0.0058)
YSM2_x_exper/100									-0.0061	0.0059
									(0.0048)	(0.0052)
YSM2_x_expersq/100									0.0001	-0.0003 **
									(0.0001)	(0.0002)
degree	0.4903 ***	0.3492 ***	0.4734 ***	0.351 ***	0.475 ***	0.3732 ***	0.4956 ***	0.3959 ***	0.4897 ***	0.3768 ***
	(0.0331)	(0.0591)	(0.0335)	(0.0606)	(0.0324)	(0.0564)	(0.0331)	(0.0609)	(0.0330)	(0.0632)
a_level	0.0557 *	0.0448	0.0479	0.0456	0.0507 *	0.0461	0.0614 **	0.0511	0.0643 **	0.0437
	(0.0301)	(0.0423)	(0.0301)	(0.0427)	(0.0296)	(0.0402)	(0.0298)	(0.0410)	(0.0301)	(0.0429)
o_level	-0.0729 **	-0.1153 **	-0.0752 **	-0.1152 **	-0.0773 **	-0.1346 ***	-0.0746 **	-0.1383 ***	-0.0679 *	-0.123 **
	(0.0361)	(0.0496)	(0.0359)	(0.0496)	(0.0356)	(0.0480)	(0.0359)	(0.0477)	(0.0362)	(0.0488)
pt	-0.5501 ***	-0.4454 ***	-0.5488 ***	-0.4464 ***	-0.5365 ***	-0.4327 ***	-0.5357 ***	-0.4358 ***	-0.5422 ***	-0.4352 ***
	(0.0480)	(0.0475)	(0.0480)	(0.0476)	(0.0475)	(0.0470)	(0.0473)	(0.0468)	(0.0474)	(0.0468)
d50	0.4116		0.406		0.4461		0.4552		0.4998	
	(0.3408)		(0.3383)		(0.3360)		(0.3402)		(0.3377)	
d60	0.6167 *	0.289 ***	0.5748 *	0.2979 ***	0.5867 *	0.1975 **	0.6324 *	0.2891 ***	0.7023 **	0.2169 **
	(0.3397)	(0.0806)	(0.3375)	(0.0866)	(0.3349)	(0.0772)	(0.3395)	(0.0855)	(0.3377)	(0.0945)
d70	0.8173 **	0.4771 ***	0.7545 **	0.4896 ***	0.7877 **	0.413 ***	0.8589 **	0.553 ***	0.961 ***	0.4731 ***
	(0.3419)	(0.1001)	(0.3402)	(0.1111)	(0.3371)	(0.0918)	(0.3424)	(0.1118)	(0.3413)	(0.1306)
d80	1.1587 ***	0.6066 ***	1.0999 ***	0.6178 ***	1.1373 ***	0.5765 ***	1.2077 ***	0.7039 ***	1.3143 ***	0.6274 ***
	(0.3493)	(0.1335)	(0.3474)	(0.1430)	(0.3442)	(0.1223)	(0.3495)	(0.1434)	(0.3480)	(0.1655)
d90	1.538 ***	0.9057 ***	1.4919 ***	0.9135 ***	1.5297 ***	0.9076 ***	1.5895 ***	0.9891 ***	1.6496 ***	0.9098 ***
	(0.3572)	(0.1814)	(0.3551)	(0.1878)	(0.3519)	(0.1659)	(0.3568)	(0.1813)	(0.3536)	(0.1978)
d00	1.6616 ***	1.0611 ***	1.6222 ***	1.0679 ***	1.6749 ***	1.0838 ***	1.7326 ***	1.1547 ***	1.76 ***	1.0675 ***
	(0.3627)	(0.2052)	(0.3605)	(0.2110)	(0.3574)	(0.1887)	(0.3619)	(0.2032)	(0.3576)	(0.2160)
_cons	0.3466	0.8491 ***	0.336	0.8489 ***	0.0458	0.6502 **	-0.0261	0.6022 **	0.0119	0.6725 **
	(0.3782)	(0.2750)	(0.3756)	(0.2777)	(0.3754)	(0.2688)	(0.3780)	(0.2911)	(0.3739)	(0.2979)
lambda	0.1941	-0.328	0.1325	-0.3259	0.1675	-0.1758	0.2636	-0.1648	0.2002	-0.2585
	(0.2408)	(0.3067)	(0.2412)	(0.3105)	(0.2340)	(0.2915)	(0.2315)	(0.2996)	(0.2272)	(0.3080)
N	4869	2521	4869	2521	4869	2521	4869	2521	4869	2521
F-test on Model C: p-value							0.0127	0.0041	0.0008	0.0002

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A7 - Appendix

Table 10. Heckman Selectivity Model - Dependent variable: log hourly wage - Nonwhites

	Model A		Model B		Model C		Model D		Model E	
	1	2	3	4	5	6	7	8	9	10
	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried	Married	Unmarried
exper	-0.0005	0.0085 ***	0.0008	0.0047	0.0217 **	0.0394 ***	0.0365 ***	0.0229 *	0.0628 ***	0.0151
	(0.0020)	(0.0026)	(0.0032)	(0.0040)	(0.0086)	(0.0111)	(0.0112)	(0.0137)	(0.0187)	(0.0170)
expersq/100					-0.0698 ***	-0.1158 ***	-0.1292 ***	-0.0985 *	-0.1976 ***	-0.0684
					(0.0265)	(0.0394)	(0.0373)	(0.0544)	(0.0628)	(0.0682)
YSM	0.0205 ***	0.0273 ***	0.0218 ***	0.0238 ***	0.019 ***	0.0316 ***	0.0239 ***	0.0153 **	0.0522 **	-0.0146
	(0.0053)	(0.0070)	(0.0062)	(0.0074)	(0.0059)	(0.0073)	(0.0068)	(0.0070)	(0.0242)	(0.0189)
YSM2/100									-0.0986	0.1103
									(0.0850)	(0.0757)
YSM_x_exper/100			-0.0088	0.0256			-0.0688	0.1897 **	-0.6652 **	0.335
			(0.0175)	(0.0211)			(0.0722)	(0.0849)	(0.3051)	(0.2702)
YSM_x_expersq/100							0.0028	-0.0038	0.0193 **	-0.0072
							(0.0020)	(0.0027)	(0.0090)	(0.0092)
YSM2_x_exper/100									0.0181 *	-0.0076
									(0.0095)	(0.0086)
YSM2_x_expersq/100									-0.0005 *	0.0002
									(0.0003)	(0.0003)
degree	0.4869 ***	0.5328 ***	0.4796 ***	0.5376 ***	0.4575 ***	0.624 ***	0.4951 ***	0.6267 ***	0.4643 ***	0.5474 ***
	(0.0679)	(0.1413)	(0.0703)	(0.1415)	(0.0741)	(0.1461)	(0.0611)	(0.1466)	(0.0742)	(0.1364)
a_level	0.0738	0.1344 **	0.0697	0.1349 **	0.0537	0.1683 **	0.0768 *	0.162 **	0.0598	0.1456 **
	(0.0496)	(0.0642)	(0.0512)	(0.0642)	(0.0548)	(0.0660)	(0.0447)	(0.0653)	(0.0541)	(0.0654)
o_level	-0.0496	-0.1009	-0.0523	-0.1051 *	-0.0657	-0.1051	-0.0508	-0.1216 *	-0.0638	-0.0974
	(0.0537)	(0.0632)	(0.0554)	(0.0633)	(0.0606)	(0.0640)	(0.0494)	(0.0644)	(0.0596)	(0.0621)
pt	-0.4144 ***	-0.3393 ***	-0.4154 ***	-0.3448 ***	-0.4127 ***	-0.3271 ***	-0.4102 ***	-0.34 ***	-0.4105 ***	-0.3441 ***
	(0.0307)	(0.0429)	(0.0317)	(0.0431)	(0.0354)	(0.0427)	(0.0289)	(0.0427)	(0.0346)	(0.0427)
d50				-1.3134 ***		-1.4158 ***	-0.697 ***	-1.4959 ***		-1.3845 ***
				(0.3490)		(0.3475)	(0.2308)	(0.3584)		(0.3558)
d60	-0.0954	0.3932 *	-0.1054	-0.8993 ***	-0.1143	-1.0198 ***	-0.7658 ***	-1.0464 ***	0.0001	-0.9139 ***
	(0.1526)	(0.2039)	(0.1581)	(0.2579)	(0.1748)	(0.2578)	(0.1494)	(0.2626)	(0.1764)	(0.2458)
d70	0.0583	0.5446 **	0.0417	-0.7219 ***	0.0188	-0.8512 ***	-0.6092 ***	-0.8019 ***	0.1982	-0.6779 ***
	(0.1633)	(0.2225)	(0.1705)	(0.1905)	(0.1856)	(0.1966)	(0.1216)	(0.1908)	(0.1913)	(0.1695)
d80	0.2155	0.7406 ***	0.1961	-0.5245 ***	0.1594	-0.6362 ***	-0.4545 ***	-0.5809 ***	0.341	-0.4456 ***
	(0.1870)	(0.2435)	(0.1948)	(0.1537)	(0.2106)	(0.1578)	(0.0879)	(0.1512)	(0.2144)	(0.1262)
d90	0.4307 **	0.946 ***	0.4103 *	-0.3269 ***	0.3632	-0.379 ***	-0.2332 ***	-0.3513 ***	0.501 **	-0.2841 ***
	(0.2181)	(0.2974)	(0.2262)	(0.0777)	(0.2437)	(0.0807)	(0.0516)	(0.0773)	(0.2434)	(0.0662)
d00	0.6504 **	1.2807 ***	0.6292 **		0.5757 **				0.6828 **	
	(0.2534)	(0.3464)	(0.2620)		(0.2815)				(0.2787)	
_cons	1.6102 ***	0.5313	1.6236 ***	1.844 ***	1.5933 ***	1.52 ***	2.0452 ***	1.651 ***	1.2609 ***	1.8668 ***
	(0.3480)	(0.5641)	(0.3582)	(0.2658)	(0.3976)	(0.3051)	(0.1347)	(0.2862)	(0.3787)	(0.2507)
lambda	-0.7156 **	-0.0319	-0.7375 **	-0.0263	-0.8251 ***	0.2202	-0.6716 ***	0.2087	-0.8037 **	-0.0427
	(0.2930)	(0.4250)	(0.3017)	(0.4249)	(0.3191)	(0.4313)	(0.2595)	(0.4299)	(0.3141)	(0.3990)
N	4646	1698	4646	1698	4646	1698	4646	1698	4646	1698
F-test on Model C: p-value							0.1569	0.0075	0.0225	0.1005

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A8 - Appendix

Tables 9-10 show that holding a higher educational qualification, especially at degree level, yields strong and consistent wage premiums (the coefficients on *degree* range from 0.35 to 0.63, according to the specification used), which appear to be higher for nonwhites. Higher qualifications below degree level, or A-level or equivalent, seem to provide an earning advantage as well, but the effect is not as robust as the previous one. Holding a qualification at O-level or equivalent appears to produce a wage disadvantage when compared to individuals with a qualification at an even lower level; this result is generally more significant for whites than for nonwhites.

Part-time work is associated with a strongly lower hourly wage; the coefficient on *pt* is negative and highly significant in regressions on any subsample and with any model specification.

Our results (reported in the Appendix, Tables A4-A8) show that immigrants living in the East and South East of England, and in London, generally have higher earnings than immigrants living elsewhere. This evidence is more significant for whites than for nonwhites, and, among nonwhites, for low-educated individuals. Some negative earning effect can be found for nonwhite highly educated immigrants in the North of England (Yorkshire and the Humber, North West) and in the East Midlands, but these results are not so robust.

5.3 Labour market and education entrants

Following Clark and Lindley (2009), we now carry out an additional part of analysis using subsamples of individuals based on the distinction between labour market and education entrants (while keeping the disaggregation by ethnic status unchanged). This allows us to ascertain whether there is a difference in labour market and pre-labour market assimilation. Most studies on the topic we are dealing with focus on the former, while the latter is often ignored in the literature. But education entrants generally represent around half the immigrant population (in particular, they make up 45.78% of our sample), so not only are they a far too relevant group to be simply left out of the study, but they can also provide valuable additional information about the mechanisms of economic assimilation. These individuals arrived in the UK at an earlier stage of their life, and therefore they have been exposed to the English language and culture more deeply and for longer than labour market entrants, and their education has been (partially or fully) acquired in the UK. A comparison between the two groups not only allows us to see if education entrants have economic performances that are closer to the natives', but can also give us some insight about the different value that the labour market attaches to national and foreign educational qualifications.

Following the results of the LR and Wald tests in the employment regressions, and of some of the F-tests for the earnings equations[20], we decide to use here Model (C).

Results are presented in Table 11. Once again, the hypothesis of a positive assimilation of migrants is confirmed by evidence, with the coefficient of *YSM* being positive and highly significant for both whites and nonwhites, and for both labour market and education entrants. Work experience yields positive but decreasing returns on earnings for all categories, while it seems to positively affect the probability of being in paid employment more for education entrants than for labour market entrants. The picture that emerges is therefore that for labour market entrants, *YSM* – and therefore experience on the British labour market – is more relevant than the overall working experience, as in the regression for labour market entrants the variable *YSM* obviously captures the additional value that the market attaches to experience in the destination country with respect to that accrued in the home country.

Again, there seems to be some evidence that the unobserved quality of arrival cohorts has risen over time, and this seems to hold especially for education entrants.

As for the other variables, the estimates basically follow the results already noted earlier in the paper. Being married and having children in pre-school age appears to decrease the employment probability of the individual, while there seems to be an earnings disadvantage for working part-time. Living in London, the South-East and the East of England appears to be connected with higher hourly wages[21].

[20] For the earnings equations, however, the results of the tests are less clear-cut. For example, evidence in favour of Model (C) is found in Table 7, in regressions on samples of whites disaggregated by level of education, and for highly educated nonwhites in the following Table, while we find a different result for low-educated whites.

[21] Once again, estimates for the parameters of the regional dummies are shown in the Appendix, Table A13, which also includes the exogenous variables used in the first stage of Heckman, showing the detail about the exclusion restrictions.

Table 11. Education and labour market entrants

	Probit estimates - Dependent variable: employment				Heckman Selectivity Model - Dependent variable: log hourly wage			
	Whites		Nonwhites		Whites		Nonwhites	
	1	2	3	4	5	6	7	8
	Education entrants	LM entrants	Education entrants	LM entrants	Education entrants	LM entrants	Education entrants	LM entrants
exper	0.0426 ***	-0.0168	0.0529 ***	-0.0012	0.0561 ***	0.0643 ***	0.039 ***	0.0271 ***
	(0.0153)	(0.0146)	(0.0143)	(0.0139)	(0.0072)	(0.0072)	(0.0076)	(0.0073)
expersq_div100	-0.135 ***	-0.0073	-0.1763 ***	-0.0279	-0.1345 ***	-0.1797 ***	-0.1016 ***	-0.0885 ***
	(0.0479)	(0.0471)	(0.0453)	(0.0437)	(0.0223)	(0.0245)	(0.0228)	(0.0233)
YSM	0.0307 ***	0.0497 ***	0.0322 ***	0.0464 ***	0.0175 ***	0.0171 ***	0.0331 ***	0.0171 ***
	(0.0071)	(0.0082)	(0.0065)	(0.0065)	(0.0035)	(0.0054)	(0.0031)	(0.0042)
degree	0.4353 ***	0.4207 ***	0.6299 ***	0.4047 ***	0.5204 ***	0.3463 ***	0.7258 ***	0.4919 ***
	(0.0841)	(0.0857)	(0.0779)	(0.0667)	(0.0457)	(0.0432)	(0.0520)	(0.0371)
a_level	0.2753 ***	0.235 ***	0.284 ***	0.1024 *	0.1864 ***	-0.1309 ***	0.2659 ***	0.084 ***
	(0.0759)	(0.0700)	(0.0672)	(0.0613)	(0.0407)	(0.0377)	(0.0402)	(0.0323)
o_level	0.0761	-0.2241	0.1025	0.0368	0.0481	-0.2132 ***	0.0934** **	-0.0846
	(0.0884)	(0.1415)	(0.0809)	(0.1050)	(0.0448)	(0.0755)	(0.0424)	(0.0540)
married	0.6531 ***	0.375 ***	0.5742 ***	0.5006 ***				
	(0.0716)	(0.0634)	(0.0705)	(0.0586)				
dkid04	-0.209 ***	-0.1065	-0.2006 ***	-0.1304 **				
	(0.0789)	(0.0676)	(0.0670)	(0.0507)				
dkid59	-0.0866	-0.0988	0.0418	-0.0548				
	(0.0802)	(0.0709)	(0.0648)	(0.0516)				
dkid1015	-0.1304	-0.1663 **	-0.0145	-0.0107				
	(0.0821)	(0.0814)	(0.0682)	(0.0608)				
pt					-0.3842 ***	-0.5479 ***	-0.4115 ***	-0.3711 ***
					(0.0555)	(0.0490)	(0.0426)	(0.0297)
d50	-4.8315		-1.3183 ***		0.3902		-1.3012 ***	
	(.)		(0.3273)		(0.4084)		(0.1570)	
d60	-4.6278 ***		-1.0538 ***	-1.1284 ***	0.5063		-1.1618 ***	
	(0.1042)		(0.2219)	(0.2076)	(0.4078)		(0.1112)	
d70	-4.3813 ***	0.3645	-0.8746 ***	-0.7727 ***	0.6756 *	-0.1124	-0.9287 ***	-0.0648
	(0.1317)	(0.2311)	(0.2015)	(0.1222)	(0.4099)	(0.1760)	(0.0988)	(0.1085)
d80	-3.961 ***	0.8048 ***	-0.6685 ***	-0.5666 ***	0.8487 **	0.0157	-0.6608 ***	0.0899
	(0.1702)	(0.2481)	(0.1856)	(0.0792)	(0.4143)	(0.1927)	(0.0877)	(0.1178)
d90	-3.6494 ***	1.1353 ***	-0.3212 *	-0.2889	1.1309 ***	0.2677	-0.3651 ***	0.2888 **
	(0.2210)	(0.2690)	(0.1869)	(0.0566)	(0.4212)	(0.2121)	(0.0800)	(0.1301)
d00	-3.5476 ***	1.4215 ***			1.3285 ***	0.3567		0.5308 ***
	(0.3057)	(0.2807)			(0.4358)	(0.2232)		(0.1423)
_cons	4.2441 ***	0.1024	0.6193 **	0.8825 ***	0.5046	1.4751 ***	1.6289 ***	1.4654 ***
	(0.2724)	(0.3126)	(0.2502)	(0.1564)	(0.4422)	(0.2492)	(0.1286)	(0.1870)
lambda					-0.7019 ***	-0.7416 ***	-0.0994	-0.3665 ***
					(0.1400)	(0.2060)	(0.1174)	(0.1193)
N	5714	6229	4930	6365	3732	3658	2685	3659

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time dummies included in the regressions. Coefficients of regional dummies showed in Table A13 - Appendix

Again, we compute marginal effects of the Probit for employment for an individual with the characteristics of the average immigrant, i.e. a higher degree, married, with at least one child aged 4 or below, living in the London area (interviewed in quarter 2). Assuming the individual arrived in the 1970s, we calculate the employment probability of a white and a nonwhite immigrant with different levels of experience and number of *YSM*. For education entrants, we consider individuals who arrived 5 years before starting work, that is individuals with 5 years of education in the UK, who therefore achieved their highest qualification in the country. We compute probabilities for individuals with 5, 10 and 15 years for experience and, respectively, 10, 15 and 20 years of residence in the country. As for labour market entrants, we consider immigrants who worked 5 years before arriving to the UK, and compute probabilities with *exper*=10, 15 and 20, and therefore *YSM*=5, 10 and 15 respectively. We then compare the estimated probabilities to that of a native with the same characteristics and years of experience. The resulting employment probability differentials, reported in Table 12, show that for both education and labour market entrants, the gap with respect to natives of the same ethnic group is reduced as *YSM* increase; however, the gap for education entrants appears to be systematically lower than the one for labour market entrants.

Table 12. Predicted employment probability differences wrt natives, using model C

		Education Entrants		Labour Market Entrants			
exper	*YSM*	White	Nonwhite	White	Nonwhite	*exper*	*YSM*
5	10	-0.0636	-0.0785	-0.0786	-0.1023	10	5
10	15	-0.0342	-0.0441	-0.0518	-0.0716	15	10
15	20	-0.0189	-0.0275	-0.0372	-0.0573	20	15

5.4 Blinder-Oaxaca decomposition

An additional part of the study is carried out using the Blinder-Oaxaca (Blinder, 1973; Oaxaca, 1973) decomposition, a methodology by which differences in a particular outcome between two groups can be decomposed into two components; the first one is a differential that is accounted for by differences in productivity characteristics, for example education or work experience (i.e. different ‘endowments’ across groups); the second one is attributable to differences in the returns to these characteristics (i.e. different ‘coefficients’ for the groups). This second component, which is the ‘unexplained’ part of the gap, is generally used as a measure for discrimination (although it could obviously be connected to differences in unobserved determinants of the outcome considered).

We try to apply this technique to two pairs of groups, the first one being immigrants/natives, the second one white/nonwhite immigrants. It should be pointed out, however, that the model used for the two groups needs to be the same; this implies that in the comparison between the migrant and the native population, we cannot include those variables which are specific to immigrants, i.e. *YSM* and arrival cohort dummies. This of course might bias the results we obtain; nevertheless, we think this methodology can provide some interesting insight, and therefore we try it anyway, still bearing in mind this potential drawback.

The results, presented in Table 13, show a decomposition of each of the four gaps (employment and earnings for immigrant/native and white/nonwhite immigrant) in three parts; as already said, the first term shows the gap component connected to differences in endowments; the second term is related to coefficient differences, and quantifies the change in immigrants' (white immigrants for the second pair of groups) employment probability/wage if they had the same characteristics as the native population (nonwhite immigrants); the third one is an interaction between the first two, accounting for simultaneity of the endowments and coefficients differences between the two groups (Jann, 2008).

Table 13. Predicted employment probability differences wrt natives, using model C

PANEL A - Employment
Immigrants and natives

1. Native - 2. Immigrant			
emp	**Coef.**	**Std. Err.**	**P>z**
Endowments	0.0292	0.0113	0.0100
Coefficients	0.1259	0.0143	0.0000
Interaction	0.0764	0.0122	0.0000
Observed gap	*0.2315*		

PANEL C - Employment
White and nonwhite immigrants

1. Nonwhite immigrant - 2. White immigrant			
Emp	**Coef.**	**Std. Err.**	**P>z**
Endowments	-0.0871	0.0146	0.0000
Coefficients	-0.2517	0.0320	0.0000
Interaction	0.0119	0.0216	0.5800
Observed gap	*-0.3269*		

PANEL B - Earnings
Immigrants and natives

1. Native - 2. Immigrant			
lnhourpay	**Coef.**	**Std. Err.**	**P>z**
Endowments	-0.0717	0.0064	0.0000
Coefficients	-0.1158	0.0220	0.0000
Interaction	0.0477	0.0065	0.0000
Observed gap	*-0.1398*		

PANEL D - Earnings
White and nonwhite immigrants

1. Nonwhite immigrant - 2. White immigrant			
Lnhourpay	**Coef.**	**Std. Err.**	**P>z**
Endowments	0.0302	0.0098	0.0020
Coefficients	-0.2463	0.0392	0.0000
Interaction	-0.0737	0.0117	0.0000
Observed gap	*-0.2898*		

As far as the first pair (immigrants/natives) is concerned, results seem to suggest that there is some discrimination against the foreign-born as for the probability of being in paid employment (as the positive sign of the second component in Panel A indicates), while there appears to be discrimination in the opposite direction for earnings (Panel B). This result is clearly unexpected, and might be explained by the problem discussed earlier, i.e. the impossibility to use a common model for both groups.

The evidence concerning white and nonwhite immigrants is probably more reliable. Both for the employment probability and for earnings, results indicate that a problem of discrimination can arise, as suggested by the negative sign of the second term in Panels C and D. This corresponds to the prior expectation that we can have about the existence of a discrimination against this category of foreign-born individuals, suggested by a large number of studies (and also by some of our previous results).

6. Conclusions

Using data from the British QLFS from 1992 to 2009, we tried to find evidence in support of the theory of migrants' economic assimilation. Our results confirm the hypothesis that labour market outcomes of the foreign-born improve with duration of stay in the UK. We also find that the performance gap suffered by migrants is significantly lower for education entrants when compared to labour market entrants.

There is a considerable evidence in the empirical literature that nonwhite immigrants face a relevant performance gap when compared to their white counterparts: again, our estimates support what appears to be now a well known fact. This is confirmed also by the decomposition analysis, which suggests that the differential is related to some form of discrimination against this ethnic group.

Further studies on the topic could be developed in several directions. It could be interesting to see how second-generation migrants perform relative to the natives and first-generation migrants. Also, an increasing literature shows that migrant networks can provide a wide range of economic benefits at both macro- and micro-levels, smoothing the informational constraints that limit the international flows of goods and capitals on one side, while facilitating the process of job search of recent migrants on the other. A connection between the effects of networks and the performance of the foreign-born on the labour market of the host country might provide some new insight, although data availability might represent a significant problem.

References

Aguilar, R. and B. Gustafsson (1991). The Earnings Assimilation of Immigrants. *Labour*, 5: 37–58.

Amuedo-Dorantes, C. and S. de la Rica (2007). Labour Market Assimilation of Recent Immigrants in Spain. *British Journal of Industrial Relations*, 45 (2): 257-284.

Antecol, H., P. Kuhn and S. J. Trejo (2006). Assimilation via Prices or Quantities? Sources of Immigrant Earnings Growth in Australia, Canada and the United States. *Journal of Human Resources*, 41: 821-840.

Baker, M. and D. Benjamin (1994). The Performance of Immigrants in the Canadian Labor Market. *Journal of Labor Economics*, 12 (3): 369-405.

Bell, B. D. (1997). The Performance of Immigrants in the United Kingdom: Evidence from the GHS. *Economic Journal*, 107: 333-344.

Blackaby, D. H., K. Clark, D. G. Leslie and P. D. Murphy (1994). Black-White Male Earnings and Employment Prospects in the 1970s and 1980s: Evidence for Britain. *Economic Letters*, 46: 273-279.

Blackaby, D. H., D. G. Leslie, P. D. Murphy and N. C. O'Leary (1998). The Ethnic Wage Gap and Employment Differentials in the 1990s: Evidence for Britain. *Economic Letters*, 58: 97-103.

Blackaby, D. H., D. G. Leslie, P. D. Murphy and N. C. O'Leary (2005). Born in Britain: How are Native Ethnic Minorities Faring in the British Labour Market? *Economic Letters*, 88: 370-375.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, 8: 436-455.

Bloom, D. E., G. Grenier and M. Gunderson (1995). The Changing Labour Market Position of Canadian Immigrants. Canadian Journal of Economics, 28 (4b): 987-1005.

Borjas, G. J. (1982). The Earnings of Male Hispanic Immigrants in the United States. *Industrial and Labor Relations Review*, 35 (3): 343-53.

Borjas, G. J. (1985). Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants. *Journal of Labor Economics*, 3 (4): 463-489.

Borjas, G. J. (1995). Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s? *Journal of Labor Economics*, 13 (2): 201-245.

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

Chiswick, B. R. (1980). The Earnings of White and Coloured Male Immigrants in Britain. *Economica*, 47: 81-87.

Chiswick, B. R., Y L. Lee and P. W. Miller (2005). Immigrant Earnings: A Longitudinal Analysis. Review of Income and Wealth, 51 (4): 485-503.

Chiswick, B. R. and P. W. Miller (2008). The 'Negative' Assimilation of Immigrants: A Special Case. IZA Discussion Paper No. 3563.

Clark, K. and J. Lindley (2009). Immigrant assimilation pre and post labour market entry: evidence from the UK Labour Force Survey. *Journal of Population Economics*, 22: 175-198.

Duleep, H. O. and M. C. Regets (1997). Measuring Immigrant Wage Growth Using Matched CPS Files. *Demography*, 34 (2): 239-249.

Dustmann, C., F. Fabbri, I. Preston and J. Wadsworth (2003). Labour Market Performance of Immigrants in the UK labour market. Home Office Online Report 05/03.

Dustmann, C. and F. Fabbri (2005). Immigrants in the British Labour Market. *Fiscal Studies*, 26 (4): 423-470.

Fernández, C. and C. Ortega (2008). Labor Market Assimilation of Immigrants in Spain: Employment at the Expense of Bad Job-Matches? *Spanish Economic Review*, 10: 83-107.

Hayfron, J. E. (1998). The Performance of Immigrants in the Norwegian labour market. *Journal of Population Economics*, 11: 293-303.

Hammarstedt, M. and G. Shukur (2006). Immigrants' Relative Earnings in Sweden – A Cohort Analysis. *Labour,* 20: 285-323.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47 (1): 153-161.

Hum, D. and W. Simpson (2004). Reinterpreting the Performance of Immigrant Wages from Panel Data. Empirical Economics, 29: 129-147.

Jann, B. (2008). A Stata Implementation of the Blinder-Oaxaca Decomposition. ETH Zurich Sociology Working Paper No. 5.

Lalonde, R. J. and R. H. Topel (1992). The Assimilation of Immigrants in the U.S. Labor Market. In G. J. Borjas and R. B. Freeman Eds., *Immigration and the Work Force.* The University of Chicago Press, Chicago.

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labour Markets. *International Economic Review*, 14: 693-709.

Shields, M. A. and S. Wheatley Price (2002). The English Language Fluency and Occupational Success of Ethnic Minority Immigrant Men Living in English Metropolitan Areas. *Journal of Population Economics*, 15: 137-160.

UK Data Archive. Quarterly Labour Force Survey User Guide – Volume 1: Background and Methodology.

Wheatley Price, S. (2001). The Employment Adjustment of Male Immigrants in England. *Journal of Population Economics*, 14: 193-220.

Appendix

We include in the Appendix estimates of the parameters relative to regional dummies in the Probit regressions for the employment probability (Tables A1-A4) and for the Heckman Selectivity Models for the earnings (structural) equation (Tables A5-A8).

We also present the first stage Probit regressions for the Heckman estimates (Tables A9-A12), mainly to show the relevance of the exogenous variables used in the selection equation.

Finally, we provide the same data for the regressions for education and labour market entrants (Table A13).

Table A1. Probit estimates - Dependent variable: employment - Whites - Regional dummies (Ref. Table 2)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
North_East	-0.2065	-0.2431	-0.2083	-0.2406	-0.209	-0.2446	-0.2164	-0.2437	-0.2131	-0.2465
	(0.2783)	(0.1611)	(0.2783)	(0.1611)	(0.2778)	(0.1611)	(0.2773)	(0.1611)	(0.2799)	(0.1612)
North_West	-0.1349	-0.1891 *	-0.1357	-0.1912 *	-0.1421	-0.1881 *	-0.1453	-0.1917 *	-0.1367	-0.1891 *
	(0.2026)	(0.1137)	(0.2028)	(0.1138)	(0.2023)	(0.1137)	(0.2027)	(0.1138)	(0.2039)	(0.1139)
Yorks_Hum	-0.2735	-0.0693	-0.2735	-0.0689	-0.2653	-0.0688	-0.2569	-0.0679	-0.2656	-0.0648
	(0.1994)	(0.1185)	(0.1996)	(0.1186)	(0.1995)	(0.1185)	(0.2003)	(0.1187)	(0.2012)	(0.1189)
East_Mids	-0.2058	-0.0341	-0.2088	-0.032	-0.205	-0.0312	-0.2097	-0.025	-0.2189	-0.0232
	(0.2182)	(0.1226)	(0.2183)	(0.1228)	(0.2181)	(0.1226)	(0.2183)	(0.1230)	(0.2186)	(0.1231)
West_Mids	0.0916	-0.2335 **	0.0918	-0.2368 **	0.0919	-0.2316 **	0.099	-0.2357 **	0.0825	-0.2356 **
	(0.2432)	(0.1144)	(0.2435)	(0.1145)	(0.2431)	(0.1144)	(0.2444)	(0.1146)	(0.2443)	(0.1147)
Eastern	-0.1671	0.2025 *	-0.1723	0.1991 *	-0.1608	0.2029 *	-0.1706	0.196 *	-0.1624	0.1977 *
	(0.1793)	(0.1057)	(0.1796)	(0.1058)	(0.1794)	(0.1057)	(0.1796)	(0.1059)	(0.1804)	(0.1059)
London	-0.1719	-0.0841	-0.174	-0.0931	-0.1755	-0.0829	-0.18	-0.1011	-0.1688	-0.1046
	(0.1493)	(0.0874)	(0.1495)	(0.0877)	(0.1491)	(0.0874)	(0.1495)	(0.0878)	(0.1500)	(0.0881)
South_East	-0.142	0.1834 *	-0.144	0.1813 *	-0.1386	0.1847 *	-0.1397	0.1801 *	-0.1291	0.1812 *
	(0.1587)	(0.0980)	(0.1589)	(0.0981)	(0.1586)	(0.0980)	(0.1588)	(0.0982)	(0.1595)	(0.0983)
South_West	0.1151	0.1476	0.1129	0.1464	0.1238	0.1477	0.1268	0.1449	0.1393	0.1467
	(0.2064)	(0.1153)	(0.2068)	(0.1153)	(0.2064)	(0.1153)	(0.2074)	(0.1154)	(0.2081)	(0.1155)
Wales	0.2114	0.0573	0.2094	0.0538	0.2199	0.0578	0.2221	0.0511	0.2204	0.0505
	(0.3305)	(0.1776)	(0.3312)	(0.1775)	(0.3319)	(0.1777)	(0.3349)	(0.1775)	(0.3348)	(0.1777)

Table A2. Probit estimates - Dependent variable: employment - Nonwhites - Regional dummies (Ref. Table 3)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
North_East	-0.3296	-0.2034	-0.3329	-0.2039	-0.3343	-0.2116	-0.3362	-0.2071	-0.3433	-0.2039
	(0.2571)	(0.2074)	(0.2574)	(0.2074)	(0.2575)	(0.2072)	(0.2575)	(0.2073)	(0.2573)	(0.2073)
North_West	0.063	-0.3108 **	0.0600	-0.3113 **	0.0668	-0.3134 **	0.0777	-0.3144 **	0.0727	-0.3114 **
	(0.1946)	(0.1437)	(0.1947)	(0.1437)	(0.1948)	(0.1437)	(0.1951)	(0.1438)	(0.1952)	(0.1439)
Yorks_Hum	0.0444	-0.1881	0.0415	-0.1878	0.0482	-0.1883	0.0535	-0.1877	0.0439	-0.1859
	(0.2059)	(0.1433)	(0.2061)	(0.1433)	(0.2064)	(0.1432)	(0.2064)	(0.1433)	(0.2065)	(0.1434)
East_Mids	-0.108	0.0382	-0.1097	0.037	-0.1136	0.0342	-0.1139	0.0293	-0.1145	0.0312
	(0.2086)	(0.1566)	(0.2086)	(0.1566)	(0.2086)	(0.1566)	(0.2087)	(0.1568)	(0.2087)	(0.1568)
West_Mids	-0.0894	-0.3418 **	-0.0917	-0.3418 **	-0.0924	-0.3431 **	-0.0846	-0.3439 **	-0.0899	-0.3420 **
	(0.1875)	(0.1386)	(0.1876)	(0.1386)	(0.1876)	(0.1386)	(0.1877)	(0.1387)	(0.1877)	(0.1388)
Eastern	0.1646	0.1499	0.1601	0.1498	0.1539	0.1457	0.1592	0.1425	0.1455	0.1444
	(0.2006)	(0.1554)	(0.2008)	(0.1554)	(0.2007)	(0.1554)	(0.2007)	(0.1555)	(0.2009)	(0.1556)
London	-0.0549	-0.171	-0.0579	-0.1711	-0.0588	-0.1752	-0.0588	-0.1786	-0.0691	-0.1766
	(0.1609)	(0.1323)	(0.1611)	(0.1323)	(0.1609)	(0.1322)	(0.1608)	(0.1324)	(0.1610)	(0.1324)
South_East	0.2344	0.1839	0.2343	0.184	0.2276	0.183	0.226	0.1796	0.2222	0.1794
	(0.1856)	(0.1485)	(0.1858)	(0.1485)	(0.1857)	(0.1485)	(0.1855)	(0.1486)	(0.1856)	(0.1486)
South_West	0.3328	0.2159	0.3338	0.2159	0.3204	0.2157	0.3305	0.2144	0.3280	0.2102
	(0.2565)	(0.1915)	(0.2568)	(0.1915)	(0.2561)	(0.1917)	(0.2564)	(0.1920)	(0.2571)	(0.1919)
Wales	-0.0161	0.2004	-0.021	0.2019	-0.0279	0.203	-0.0221	0.1985	-0.0326	0.1967
	(0.2784)	(0.2293)	(0.2784)	(0.2293)	(0.2780)	(0.2293)	(0.2781)	(0.2294)	(0.2782)	(0.2294)

*** 1%, ** 5%, * 10% significant level.

Table A3. Probit estimates - Dependent variable: employment - Whites - Regional dummies (Ref. Table 4)

	Model A		Model B		Model C		Model D		Model E	
	1 - Married	2 - Unmarried	3 - Married	4 - Unmarried	5 - Married	6 - Unmarried	7 - Married	8 - Unmarried	9 - Married	10 - Unmarried
North_East	-0.1421	-0.2608	-0.141	-0.2608	-0.1447	-0.2583	-0.1445	-0.2514	-0.1363	-0.2474
	(0.1863)	(0.2110)	(0.1863)	(0.2110)	(0.1863)	(0.2107)	(0.1866)	(0.2105)	(0.1881)	(0.2107)
North_West	-0.1456	-0.2225	-0.1458	-0.2226	-0.1479	-0.2145	-0.1498	-0.2168	-0.1462	-0.2185
	(0.1308)	(0.1507)	(0.1309)	(0.1507)	(0.1309)	(0.1508)	(0.1310)	(0.1508)	(0.1314)	(0.1509)
Yorks_Hum	0.0822	-0.3257 **	0.0824	-0.3256 **	0.0804	-0.3159 **	0.0818	-0.3093 **	0.085	-0.3081 **
	(0.1445)	(0.1502)	(0.1446)	(0.1503)	(0.1445)	(0.1504)	(0.1447)	(0.1506)	(0.1451)	(0.1505)
East_Mids	-0.0294	-0.0986	-0.0303	-0.0983	-0.0268	-0.0955	-0.0342	-0.0863	-0.0184	-0.0854
	(0.1410)	(0.1656)	(0.1410)	(0.1657)	(0.1411)	(0.1654)	(0.1412)	(0.1657)	(0.1420)	(0.1657)
West_Mids	-0.1026	-0.2475	-0.1042	-0.2475	-0.101	-0.2418	-0.1024	-0.2403	-0.0956	-0.239
	(0.1357)	(0.1546)	(0.1358)	(0.1546)	(0.1357)	(0.1548)	(0.1359)	(0.1549)	(0.1361)	(0.1550)
Eastern	0.2478 **	-0.0484	0.2463 **	-0.0485	0.2462 **	-0.039	0.2417 **	-0.0392	0.251 **	-0.0381
	(0.1227)	(0.1381)	(0.1227)	(0.1381)	(0.1227)	(0.1382)	(0.1230)	(0.1383)	(0.1232)	(0.1382)
London	-0.0566	-0.1579	-0.0585	-0.158	-0.0565	-0.1562	-0.0638	-0.1621	-0.0599	-0.1571
	(0.0991)	(0.1163)	(0.0992)	(0.1163)	(0.0991)	(0.1164)	(0.0995)	(0.1164)	(0.0997)	(0.1166)
South_East	0.1274	0.0848	0.1268	0.0847	0.1256	0.0932	0.1222	0.0959	0.1269	0.098
	(0.1076)	(0.1297)	(0.1076)	(0.1297)	(0.1076)	(0.1298)	(0.1079)	(0.1299)	(0.1080)	(0.1299)
South_West	0.124	0.1794	0.1234	0.1794	0.1225	0.1828	0.1212	0.1855	0.1328	0.1893
	(0.1328)	(0.1525)	(0.1328)	(0.1525)	(0.1328)	(0.1527)	(0.1330)	(0.1527)	(0.1334)	(0.1527)
Wales	0.4061	-0.1626	0.4057	-0.1629	0.406	-0.156	0.4053	-0.1622	0.4036	-0.1606
	(0.2554)	(0.2116)	(0.2552)	(0.2116)	(0.2556)	(0.2120)	(0.2549)	(0.2124)	(0.2542)	(0.2123)

Table A4. Probit estimates - Dependent variable: employment - Nonwhites - Regional dummies (Ref. Table 5)

	Model A		Model B		Model C		Model D		Model E	
	1 - Married	2 - Unmarried	3 - Married	4 - Unmarried	5 - Married	6 - Unmarried	7 - Married	8 - Unmarried	9 - Married	10 - Unmarried
North_East	-0.1875	-0.3824	-0.1879	-0.3846	-0.1979	-0.3792	-0.1927	-0.3786	-0.1941	-0.3702
	(0.1952)	(0.2949)	(0.1952)	(0.2950)	(0.1951)	(0.2944)	(0.1952)	(0.2944)	(0.1956)	(0.2955)
North_West	-0.1626	-0.2656	-0.1652	-0.2644	-0.167	-0.2617	-0.1614	-0.258	-0.1646	-0.244
	(0.1337)	(0.2170)	(0.1338)	(0.2169)	(0.1338)	(0.2169)	(0.1339)	(0.2171)	(0.1341)	(0.2178)
Yorks_Hum	-0.1755	0.0368	-0.1764	0.0365	-0.1754	0.0397	-0.1683	0.0401	-0.1721	0.0626
	(0.1338)	(0.2211)	(0.1338)	(0.2211)	(0.1339)	(0.2210)	(0.1339)	(0.2211)	(0.1342)	(0.2220)
East_Mids	-0.0164	0.115	-0.0198	0.1129	-0.0254	0.1159	-0.026	0.12	-0.0314	0.1264
	(0.1459)	(0.2422)	(0.1461)	(0.2423)	(0.1460)	(0.2424)	(0.1461)	(0.2426)	(0.1463)	(0.2430)
West_Mids	-0.2301 *	-0.3762 *	-0.2325 *	-0.3726 *	-0.2345 *	-0.3643 *	-0.2278 *	-0.3631 *	-0.2342 *	-0.3513 *
	(0.1286)	(0.2107)	(0.1287)	(0.2108)	(0.1287)	(0.2106)	(0.1288)	(0.2107)	(0.1290)	(0.2114)
Eastern	0.0656	0.3565	0.0638	0.3558	0.0586	0.3505	0.0628	0.3515	0.0591	0.3666
	(0.1449)	(0.2288)	(0.1450)	(0.2287)	(0.1451)	(0.2287)	(0.1450)	(0.2288)	(0.1453)	(0.2297)
London	-0.131	-0.1034	-0.1336	-0.1006	-0.1409	-0.0984	-0.1377	-0.0979	-0.1429	-0.0857
	(0.1212)	(0.1916)	(0.1213)	(0.1916)	(0.1214)	(0.1914)	(0.1213)	(0.1916)	(0.1216)	(0.1922)
South_East	0.1364	0.3849 *	0.1338	0.3931 *	0.1285	0.4072 *	0.1313	0.4059 *	0.1279	0.4032 *
	(0.1368)	(0.2181)	(0.1369)	(0.2183)	(0.1370)	(0.2184)	(0.1369)	(0.2186)	(0.1372)	(0.2191)
South_West	0.4187 **	0.1356	0.4161 **	0.1438	0.4074 *	0.1567	0.4084 **	0.1591	0.4058 *	0.1526
	(0.2077)	(0.2494)	(0.2077)	(0.2496)	(0.2080)	(0.2499)	(0.2080)	(0.2503)	(0.2081)	(0.2506)
Wales	0.1186	0.0948	0.1183	0.0987	0.1194	0.0898	0.1236	0.0909	0.1234	0.0983
	(0.2208)	(0.3021)	(0.2209)	(0.3020)	(0.2211)	(0.3011)	(0.2210)	(0.3015)	(0.2212)	(0.3025)

*** 1%, ** 5%, * 10% significant level.

Table A5. Heckman Selectivity Model - Dependent variable: log hourly wage - Whites - Regional dummies (Ref. Table 7)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
North_East	-0.0389	-0.063	-0.0429	-0.0635	-0.061	-0.0678	-0.0583	-0.0671	-0.0622	-0.0635
	(0.2520)	(0.0980)	(0.2388)	(0.0983)	(0.1940)	(0.0889)	(0.1912)	(0.0847)	(0.1953)	(0.0856)
North_West	0.0848	0.0088	0.0817	0.0102	0.051	0.0071	0.0523	-0.0002	0.0513	0.0029
	(0.1749)	(0.0706)	(0.1658)	(0.0709)	(0.1350)	(0.0640)	(0.1330)	(0.0611)	(0.1360)	(0.0618)
Yorks_Hum	0.1243	-0.0671	0.1197	-0.0673	0.0984	-0.0633	0.0953	-0.0686	0.0939	-0.0657
	(0.1797)	(0.0660)	(0.1703)	(0.0662)	(0.1384)	(0.0598)	(0.1362)	(0.0570)	(0.1394)	(0.0577)
East_Mids	0.0969	-0.0031	0.0958	-0.0029	0.0701	0.0126	0.072	0.0102	0.0706	0.0133
	(0.1969)	(0.0679)	(0.1867)	(0.0682)	(0.1517)	(0.0616)	(0.1495)	(0.0587)	(0.1531)	(0.0594)
West_Mids	-0.0082	0.0381	-0.0031	0.0399	-0.0018	0.0436	-0.0034	0.0333	-0.0024	0.0365
	(0.1826)	(0.0684)	(0.1731)	(0.0688)	(0.1406)	(0.0621)	(0.1385)	(0.0592)	(0.1416)	(0.0599)
Eastern	0.1806	0.1159 **	0.1814	0.1171 **	0.1628	0.125 **	0.1651	0.1234 **	0.1605	0.1235 **
	(0.1536)	(0.0576)	(0.1456)	(0.0578)	(0.1183)	(0.0523)	(0.1166)	(0.0498)	(0.1190)	(0.0503)
London	0.438 ***	0.2995 ***	0.4326 ***	0.3034 ***	0.4014 ***	0.3024 ***	0.4005 ***	0.2925 ***	0.3961 ***	0.2987 ***
	(0.1304)	(0.0515)	(0.1236)	(0.0519)	(0.1009)	(0.0467)	(0.0994)	(0.0448)	(0.1012)	(0.0454)
South_East	0.2251 *	0.2068 ***	0.2217 *	0.208 ***	0.2043 **	0.2172 ***	0.2049 **	0.2167 ***	0.1991 *	0.2174 ***
	(0.1331)	(0.0539)	(0.1261)	(0.0541)	(0.1026)	(0.0490)	(0.1010)	(0.0466)	(0.1032)	(0.0472)
South_West	-0.0331	-0.0647	-0.0234	-0.0636	-0.0138	-0.0602	-0.0137	-0.0609	-0.0187	-0.0596
	(0.1604)	(0.0620)	(0.1520)	(0.0622)	(0.1236)	(0.0562)	(0.1217)	(0.0535)	(0.1246)	(0.0541)
Wales	-0.1754	-0.1391	-0.1737	-0.1388	-0.1768	-0.1353	-0.1746	-0.1299	-0.1793	-0.1288
	(0.2367)	(0.0937)	(0.2244)	(0.0941)	(0.1823)	(0.0850)	(0.1795)	(0.0810)	(0.1837)	(0.0819)

Table A6. Heckman Selectivity Model - Dependent variable: log hourly wage - Nonwhites - Regional dummies (Ref. Table 8)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
North_East	-0.1118	0.0989	-0.1197	0.0997	-0.1539	0.0908	-0.1527	0.0913	-0.1471	0.0875
	(0.1573)	(0.1222)	(0.1518)	(0.1221)	(0.1255)	(0.1217)	(0.1253)	(0.1211)	(0.1284)	(0.1208)
North_West	-0.1602	-0.0883	-0.1601	-0.0889	-0.1717 **	-0.0935	-0.175 **	-0.0992	-0.1812 **	-0.0999
	(0.1039)	(0.0824)	(0.1000)	(0.0823)	(0.0817)	(0.0821)	(0.0818)	(0.0816)	(0.0842)	(0.0814)
Yorks_Hum	-0.209 *	-0.0334	-0.2097 **	-0.034	-0.2153 **	-0.0346	-0.2164 **	-0.036	-0.2208 **	-0.0359
	(0.1075)	(0.0775)	(0.1034)	(0.0775)	(0.0845)	(0.0771)	(0.0846)	(0.0767)	(0.0870)	(0.0766)
East_Mids	-0.1675	-0.0042	-0.1662	-0.0028	-0.1725 *	-0.0128	-0.175 **	-0.0136	-0.1816 **	-0.013
	(0.1124)	(0.0824)	(0.1081)	(0.0824)	(0.0884)	(0.0821)	(0.0883)	(0.0816)	(0.0908)	(0.0815)
West_Mids	-0.1165	-0.0075	-0.1178	-0.0079	-0.1291	-0.0116	-0.1308 *	-0.0148	-0.1323	-0.0114
	(0.1000)	(0.0762)	(0.0962)	(0.0762)	(0.0787)	(0.0759)	(0.0786)	(0.0754)	(0.0808)	(0.0753)
Eastern	0.0626	0.1484 *	0.0622	0.1486 *	0.0629	0.1458 *	0.0632	0.1476 *	0.0589	0.1424 *
	(0.1026)	(0.0806)	(0.0987)	(0.0806)	(0.0807)	(0.0802)	(0.0807)	(0.0797)	(0.0830)	(0.0797)
London	0.0608	0.1887 ***	0.0591	0.189 ***	0.0447	0.1844 ***	0.044	0.1831 **	0.0431	0.1848 ***
	(0.0868)	(0.0719)	(0.0835)	(0.0719)	(0.0684)	(0.0716)	(0.0683)	(0.0711)	(0.0703)	(0.0710)
South_East	0.0107	0.2236 ***	0.0116	0.2237 ***	0.0178	0.2209 ***	0.0179	0.2219 ***	0.0115	0.2195 ***
	(0.0962)	(0.0781)	(0.0926)	(0.0781)	(0.0758)	(0.0777)	(0.0758)	(0.0772)	(0.0780)	(0.0771)
South_West	-0.0762	0.0415	-0.0732	0.0417	-0.0646	0.0372	-0.0676	0.0374	-0.0733	0.0167
	(0.1198)	(0.0952)	(0.1154)	(0.0952)	(0.0943)	(0.0947)	(0.0945)	(0.0942)	(0.0973)	(0.0941)
Wales	-0.0356	-0.0894	-0.0366	-0.0879	-0.0546	-0.0901	-0.0562	-0.0832	-0.0435	-0.0803
	(0.1577)	(0.1151)	(0.1518)	(0.1151)	(0.1244)	(0.1145)	(0.1242)	(0.1139)	(0.1280)	(0.1138)

*** 1%, ** 5%, * 10% significant level.

Table A7. Heckman Selectivity Model - Dependent variable: log hourly wage - Whites - Regional dummies (Ref. Table 9)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
North_East	-0.0917	-0.0702	-0.0917	-0.0703	-0.1026	-0.0755	-0.1051	-0.0734	-0.1	-0.0661
	(0.0694)	(0.0985)	(0.0690)	(0.0985)	(0.0685)	(0.0944)	(0.0691)	(0.0939)	(0.0685)	(0.0954)
North_West	0.0018	-0.0231	0.0047	-0.0242	-0.0047	-0.0345	-0.0107	-0.0442	-0.0103	-0.0292
	(0.0494)	(0.0736)	(0.0492)	(0.0738)	(0.0488)	(0.0704)	(0.0492)	(0.0706)	(0.0488)	(0.0717)
Yorks_Hum	-0.0157	-0.0011	-0.0171	-0.0016	-0.0234	-0.0088	-0.0225	-0.0069	-0.0263	0.0011
	(0.0474)	(0.0739)	(0.0472)	(0.0739)	(0.0468)	(0.0701)	(0.0472)	(0.0692)	(0.0468)	(0.0702)
East_Mids	0.0154	-0.0226	0.0191	-0.023	0.0286	-0.0132	0.0263	-0.0059	0.0256	-0.0067
	(0.0494)	(0.0704)	(0.0491)	(0.0703)	(0.0487)	(0.0673)	(0.0492)	(0.0666)	(0.0488)	(0.0677)
West_Mids	0.0456	-0.0526	0.0508	-0.0537	0.0595	-0.0634	0.0549	-0.0687	0.0574	-0.0693
	(0.0484)	(0.0729)	(0.0482)	(0.0729)	(0.0478)	(0.0697)	(0.0483)	(0.0692)	(0.0479)	(0.0704)
Eastern	0.1792 ***	0.1452 **	0.1778 ***	0.1443 **	0.1751 ***	0.1484 ***	0.1776 ***	0.1436 **	0.1752 ***	0.1434 **
	(0.0423)	(0.0591)	(0.0420)	(0.0592)	(0.0416)	(0.0564)	(0.0418)	(0.0561)	(0.0415)	(0.0569)
London	0.2711 ***	0.3504 ***	0.2763 ***	0.3499 ***	0.2783 ***	0.3366 ***	0.2725 ***	0.3305 ***	0.2779 ***	0.3343 ***
	(0.0363)	(0.0546)	(0.0361)	(0.0548)	(0.0357)	(0.0518)	(0.0361)	(0.0522)	(0.0358)	(0.0527)
South_East	0.2908 ***	0.1204 **	0.2894 ***	0.1203 **	0.2842 ***	0.1319 ***	0.2857 ***	0.1327 ***	0.2831 ***	0.1273 **
	(0.0372)	(0.0532)	(0.0370)	(0.0532)	(0.0367)	(0.0511)	(0.0369)	(0.0511)	(0.0366)	(0.0522)
South_West	-0.0054	0.0236	-0.0053	0.0232	-0.0084	0.0361	-0.0084	0.033	-0.0112	0.0243
	(0.0439)	(0.0632)	(0.0436)	(0.0633)	(0.0433)	(0.0606)	(0.0437)	(0.0606)	(0.0433)	(0.0622)
Wales	-0.0913	-0.0715	-0.0988	-0.0719	-0.1018	-0.0827	-0.0927	-0.0886	-0.0922	-0.0787
	(0.0682)	(0.0911)	(0.0678)	(0.0910)	(0.0671)	(0.0871)	(0.0677)	(0.0867)	(0.0671)	(0.0882)

Table A8. Heckman Selectivity Model - Dependent variable: log hourly wage - Nonwhites - Regional dummies (Ref. Table 10)

	Model A		Model B		Model C		Model D		Model E	
	1 - Married	2 - Unmarried	3 - Married	4 - Unmarried	5 - Married	6 - Unmarried	7 - Married	8 - Unmarried	9 - Married	10 - Unmarried
North_East	-0.0322	-0.1262	-0.0309	-0.1183	-0.0333	-0.1663	-0.0535	-0.1283	-0.0446	-0.0715
	(0.1178)	(0.1978)	(0.1214)	(0.1976)	(0.1360)	(0.2002)	(0.1106)	(0.1978)	(0.1324)	(0.1895)
North_West	-0.0863	0.019	-0.0844	0.0205	-0.0823	-0.0234	-0.1002	-0.0054	-0.0955	0.0345
	(0.0801)	(0.1296)	(0.0826)	(0.1294)	(0.0922)	(0.1321)	(0.0749)	(0.1297)	(0.0895)	(0.1247)
Yorks_Hum	-0.0931	-0.0935	-0.092	-0.0885	-0.0929	-0.0904	-0.1024	-0.0718	-0.0984	-0.0666
	(0.0748)	(0.1116)	(0.0771)	(0.1116)	(0.0863)	(0.1140)	(0.0702)	(0.1135)	(0.0840)	(0.1112)
East_Mids	-0.1003	-0.0533	-0.1014	-0.0494	-0.1114	-0.0456	-0.1071	-0.0294	-0.1114	-0.0334
	(0.0799)	(0.1225)	(0.0823)	(0.1224)	(0.0920)	(0.1252)	(0.0749)	(0.1250)	(0.0897)	(0.1216)
West_Mids	-0.0422	-0.0525	-0.0416	-0.0542	-0.0437	-0.0917	-0.0538	-0.0767	-0.0486	-0.0236
	(0.0727)	(0.1416)	(0.0749)	(0.1415)	(0.0837)	(0.1424)	(0.0680)	(0.1406)	(0.0815)	(0.1331)
Eastern	0.0985	0.1541	0.0964	0.16	0.0839	0.1932	0.0912	0.2114	0.0802	0.1753
	(0.0785)	(0.1329)	(0.0810)	(0.1332)	(0.0901)	(0.1348)	(0.0735)	(0.1363)	(0.0880)	(0.1327)
London	0.1198 *	0.187 **	0.1195 *	0.1892 **	0.1132	0.1851 *	0.109 *	0.1968 **	0.1108	0.2077 **
	(0.0666)	(0.0946)	(0.0686)	(0.0945)	(0.0768)	(0.0967)	(0.0625)	(0.0960)	(0.0748)	(0.0936)
South_East	0.0998	0.2178	0.0975	0.2157	0.0834	0.2816 **	0.0916	0.2777 **	0.083	0.2254 *
	(0.0753)	(0.1331)	(0.0777)	(0.1329)	(0.0863)	(0.1390)	(0.0704)	(0.1378)	(0.0844)	(0.1298)
South_West	-0.0313	0.0373	-0.0347	0.0362	-0.0617	0.0658	-0.0436	0.0735	-0.0641	0.0625
	(0.1018)	(0.1255)	(0.1049)	(0.1254)	(0.1156)	(0.1296)	(0.0941)	(0.1293)	(0.1129)	(0.1254)
Wales	-0.0701	-0.1812	-0.0721	-0.1804	-0.0826	-0.1766	-0.078	-0.1732	-0.07	-0.161
	(0.1167)	(0.1555)	(0.1203)	(0.1554)	(0.1345)	(0.1588)	(0.1095)	(0.1576)	(0.1311)	(0.1541)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses.

Table A9. Heckman Selectivity Model - First stage - Dependent variable: employment - Whites (Ref. Table 7)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
emp										
exper	-0.0018	-0.0129 ***	-0.0075	-0.0203 ***	0.0185	0.0058	0.0033	0.0011	-0.041	0.0126
	(0.0070)	(0.0041)	(0.0111)	(0.0058)	(0.0199)	(0.0134)	(0.0336)	(0.0200)	(0.0474)	(0.0250)
expersq					-0.0856	-0.0624	-0.069	-0.0923	0.0955	-0.1253
					(0.0781)	(0.0426)	(0.1436)	(0.0695)	(0.2167)	(0.0911)
YSM	0.0314 ***	0.0516 ***	0.0267 **	0.0409 ***	0.0319 ***	0.052 ***	0.0186	0.0257 **	-0.0818 **	0.0317
	(0.0086)	(0.0061)	(0.0112)	(0.0086)	(0.0086)	(0.0061)	(0.0134)	(0.0117)	(0.0414)	(0.0348)
YSM2									0.3666 **	-0.015
									(0.1472)	(0.1405)
YSM_x_exper			0.0341	0.0551 *			0.1548	0.208 *	1.2478 **	-0.066
			(0.0518)	(0.0315)			(0.1688)	(0.1220)	(0.6106)	(0.3891)
YSM_x_expersq							-0.0033	-0.0031	-0.037	0.0052
							(0.0062)	(0.0035)	(0.0237)	(0.0117)
YSM2_x_exper									-0.0388 **	0.0076
									(0.0182)	(0.0133)
YSM2_x_expersq									0.0011 *	-0.0002
									(0.0006)	(0.0003)
married	0.5717 ***	0.6054 ***	0.575 ***	0.6033 ***	0.5619 ***	0.5971 ***	0.5645 ***	0.5825 ***	0.56 ***	0.5847 ***
	(0.0967)	(0.0616)	(0.0969)	(0.0617)	(0.0972)	(0.0619)	(0.0973)	(0.0622)	(0.0977)	(0.0623)
dkid04	0.0095	-0.1972 ***	0.011	-0.1867 ***	-0.0012	-0.2091 ***	-0.0051	-0.2034 ***	0.0032	-0.2017 ***
	(0.1134)	(0.0656)	(0.1133)	(0.0659)	(0.1140)	(0.0661)	(0.1140)	(0.0663)	(0.1144)	(0.0664)
dkid59	-0.0305	-0.1534 **	-0.03	-0.1487 **	-0.0348	-0.1625 **	-0.0411	-0.1671 **	-0.0226	-0.168 **
	(0.1238)	(0.0680)	(0.1238)	(0.0681)	(0.1240)	(0.0683)	(0.1244)	(0.0685)	(0.1249)	(0.0686)
dkid1015	-0.1115	-0.2274 ***	-0.1195	-0.2332 ***	-0.0864	-0.2136 ***	-0.0882	-0.2114 ***	-0.0742	-0.2137 ***
	(0.1432)	(0.0725)	(0.1438)	(0.0726)	(0.1450)	(0.0731)	(0.1452)	(0.0733)	(0.1457)	(0.0738)
d50	-3.7554 ***	-1.9554 ***	-3.7258 ***	-1.9878 ***	-3.7718 ***	-1.9437 ***	-3.7413 ***	-1.9872 ***	-3.6528 ***	-1.9936 ***
	(0.4236)	(0.2515)	(0.4257)	(0.2527)	(0.4260)	(0.2517)	(0.4475)	(0.2533)	(0.4665)	(0.2549)
d60	-3.7311 ***	-1.5366 ***	-3.6537 ***	-1.4924 ***	-3.7881 ***	-1.5581 ***	-3.7047 ***	-1.5184 ***	-3.5515 ***	-1.4977 ***
	(0.3282)	(0.1993)	(0.3453)	(0.2006)	(0.3385)	(0.2000)	(0.3579)	(0.2018)	(0.3854)	(0.2049)
d70	-3.6751 ***	-1.1489 ***	-3.581 ***	-1.0733 ***	-3.7285 ***	-1.1644 ***	-3.5999 ***	-1.0388 ***	-3.3632 ***	-0.9782 ***
	(0.2692)	(0.1525)	(0.3002)	(0.1584)	(0.2802)	(0.1527)	(0.3166)	(0.1586)	(0.3548)	(0.1700)
d80	-3.235 ***	-0.6234 ***	-3.1504 ***	-0.5688 ***	-3.2813 ***	-0.6336 ***	-3.1659 ***	-0.5358 ***	-2.8666 ***	-0.4779 ***
	(0.2188)	(0.1092)	(0.2490)	(0.1136)	(0.2304)	(0.1095)	(0.2708)	(0.1144)	(0.3229)	(0.1280)
d90	-2.9019 ***	-0.1564 *	-2.834 ***	-0.1395 *	-2.9485 ***	-0.1613 *	-2.8709 ***	-0.1318	-2.651 ***	-0.1145
	(0.1913)	(0.0823)	(0.2131)	(0.0829)	(0.2044)	(0.0824)	(0.2381)	(0.0830)	(0.2820)	(0.0855)
d00	-2.6531 ***		-2.5938 ***		-2.6972 ***		-2.6355 ***		-2.4877 ***	
	(0.1979)		(0.2138)		(0.2098)		(0.2395)		(0.2765)	
_cons	4.1302	0.8623 ***	4.1232	0.9557 ***	4.0964	0.7649 ***	4.1532	0.8998 ***	4.2921	0.8487 ***
	(.)	(0.1180)	(.)	(0.1297)	(.)	(0.1352)	(.)	(0.1596)	(.)	(0.1772)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time and regional dummies included.

Table A10. Heckman Selectivity Model - First stage - Dependent variable: employment - Nonwhites (Ref. Table 8)

	Model A		Model B		Model C		Model D		Model E	
	1 - High ed.	2 - Low ed.	3 - High ed.	4 - Low ed.	5 - High ed.	6 - Low ed.	7 - High ed.	8 - Low ed.	9 - High ed.	10 - Low ed.
exper	0.0076	-0.0051	0.0143	-0.0065	0.0493 ***	0.0121	0.0137	-0.0214	0.0194	-0.0307
	(0.0062)	(0.0039)	(0.0104)	(0.0059)	(0.0186)	(0.0134)	(0.0323)	(0.0220)	(0.0452)	(0.0297)
expersq_div100					-0.1679 **	-0.0559	-0.0237	0.0365	-0.0929	0.0807
					(0.0705)	(0.0416)	(0.1315)	(0.0737)	(0.1870)	(0.1025)
YSM	0.0382 ***	0.0471 ***	0.0439 ***	0.0451 ***	0.0387 ***	0.0474 ***	0.0268 *	0.0197	0.0333	-0.0121
	(0.0079)	(0.0056)	(0.0106)	(0.0084)	(0.0079)	(0.0056)	(0.0139)	(0.0132)	(0.0439)	(0.0406)
YSM2/100									-0.0146	0.1292
									(0.1576)	(0.1633)
YSM_x_exper/100			-0.0436	0.0113			0.2451	0.3343 **	0.2419	0.5553
			(0.0548)	(0.0351)			(0.1881)	(0.1471)	(0.6602)	(0.4884)
YSM_x_expersq/100							-0.0092	-0.0086 **	-0.0029	-0.0161
							(0.0067)	(0.0042)	(0.0242)	(0.0146)
YSM2_x_exper/100									-0.0014	-0.0091
									(0.0210)	(0.0173)
YSM2_x_expersq/100									-0.0001	0.0003
									(0.0007)	(0.0005)
married	0.3971 ***	0.6951 ***	0.3951 ***	0.6939 ***	0.3623 ***	0.6905 ***	0.3629 ***	0.6877 ***	0.3636 ***	0.6819 ***
	(0.0905)	(0.0639)	(0.0906)	(0.0640)	(0.0918)	(0.0640)	(0.0919)	(0.0644)	(0.0921)	(0.0646)
dkid04	-0.0768	-0.1462 ***	-0.0805	-0.1442 ***	-0.0957	-0.1561 ***	-0.0982	-0.1514 ***	-0.1005	-0.1494 ***
	(0.0872)	(0.0551)	(0.0873)	(0.0555)	(0.0876)	(0.0556)	(0.0878)	(0.0558)	(0.0878)	(0.0558)
dkid59	0.1702 *	-0.0776	0.1653 *	-0.0759	0.154	-0.0847	0.1449	-0.0911 *	0.1441	-0.0846
	(0.0938)	(0.0542)	(0.0940)	(0.0545)	(0.0941)	(0.0545)	(0.0945)	(0.0549)	(0.0945)	(0.0550)
dkid1015	-0.1112	-0.0646	-0.1089	-0.0659	-0.061	-0.0554	-0.0676	-0.0631	-0.0702	-0.0534
	(0.1090)	(0.0597)	(0.1091)	(0.0598)	(0.1112)	(0.0601)	(0.1115)	(0.0602)	(0.1116)	(0.0606)
d50						-1.8642 ***	3.7211			
						(0.3471)	(.)			
d60	-4.4428 ***	0.5975 **	-4.48 ***	0.608 **	-4.4411 ***	-1.2789 ***	-1.0999 ***	0.5762 *	-4.6996 ***	0.714 **
	(0.3270)	(0.2977)	(0.3329)	(0.2996)	(0.3332)	(0.1663)	(0.2589)	(0.3005)	(0.3897)	(0.3151)
d70	-4.2494 ***	0.864 ***	-4.3157 ***	0.8828 ***	-4.2524 ***	-1.0236 ***	-0.9118 ***	0.8556 ***	-4.5984 ***	1.042 ***
	(0.2677)	(0.3037)	(0.2851)	(0.3094)	(0.2753)	(0.1312)	(0.1901)	(0.3106)	(0.3499)	(0.3325)
d80	-4.1878 ***	1.256 ***	-4.2549 ***	1.2756 ***	-4.1949 ***	-0.6304 ***	-0.8515 ***	1.2686 ***	-4.5357 ***	1.4651 ***
	(0.2288)	(0.3209)	(0.2493)	(0.3267)	(0.2382)	(0.0952)	(0.1375)	(0.3275)	(0.3289)	(0.3480)
d90	-3.7922 ***	1.6216 ***	-3.8502 ***	1.638 ***	-3.8019 ***	-0.2628 ***	-0.4556 ***	1.6242 ***	-4.1062 ***	1.7822 ***
	(0.2083)	(0.3364)	(0.2258)	(0.3404)	(0.2187)	(0.0744)	(0.1111)	(0.3410)	(0.3077)	(0.3549)
d00	-3.3388 ***	1.8825 ***	-3.384 ***	1.8968 ***	-3.3416 ***			1.8736 ***	-3.6194 ***	2.0019 ***
	(0.1985)	(0.3471)	(0.2109)	(0.3500)	(0.2083)			(0.3507)	(0.2886)	(0.3613)
_cons	4.2905	-1.6942 ***	4.2791	-1.6903 ***	4.1397	0.0947	0.9514 ***	-1.5386 ***	4.5558	-1.5907 ***
	(.)	(0.3918)	(.)	(0.3921)	(.)	(0.1893)	(0.2429)	(0.4145)	(.)	(0.4364)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time and regional dummies included.

Table A11. Heckman Selectivity Model - First stage - Dependent variable: employment - Whites (Ref. Table 9)

	Model A		Model B		Model C		Model D		Model E	
	1 - Married	2 - Unmarried	3 - Married	4 - Unmarried	5 - Married	6 - Unmarried	7 - Married	8 - Unmarried	9 - Married	10 - Unmarried
exper	-0.0164 ***	-0.0045	-0.0171 **	-0.009	0.0045	0.0301 **	-0.0192	0.0532 **	-0.0126	0.0365
	(0.0052)	(0.0050)	(0.0071)	(0.0078)	(0.0177)	(0.0142)	(0.0259)	(0.0237)	(0.0336)	(0.0306)
expersq/100					-0.067	-0.1307 ***	-0.0038	-0.2814 ***	-0.0701	-0.2099
					(0.0543)	(0.0500)	(0.0861)	(0.0939)	(0.1153)	(0.1284)
YSM	0.0628 ***	0.0241 ***	0.0617 ***	0.0197 **	0.063 ***	0.025 ***	0.0403 ***	0.0148	-0.0438	-0.0243
	(0.0071)	(0.0075)	(0.0103)	(0.0096)	(0.0071)	(0.0075)	(0.0151)	(0.0113)	(0.0481)	(0.0320)
YSM2/100									0.3533 **	0.1449
									(0.1692)	(0.1192)
YSM_x_exper/100			0.0059	0.0285			0.2547 *	-0.0252	0.6336	0.3857
			(0.0378)	(0.0387)			(0.1532)	(0.1249)	(0.5444)	(0.4140)
YSM_x_expersq/100							-0.0064	0.0046	-0.0067	-0.0087
							(0.0043)	(0.0041)	(0.0158)	(0.0142)
YSM2_x_exper/100									-0.0217	-0.0144
									(0.0170)	(0.0129)
YSM2_x_expersq/100									0.0003	0.0004
									(0.0004)	(0.0004)
degree	0.4421 ***	0.4531 ***	0.444 ***	0.4637 ***	0.4401 ***	0.4562 ***	0.4506 ***	0.5001 ***	0.454 ***	0.5052 ***
	(0.0828)	(0.0913)	(0.0838)	(0.0926)	(0.0828)	(0.0915)	(0.0843)	(0.0938)	(0.0841)	(0.0941)
a_level	0.2799 ***	0.211 **	0.2803 ***	0.2151 **	0.2792 ***	0.2055 **	0.2771 ***	0.2207 ***	0.2929 ***	0.2296 ***
	(0.0760)	(0.0839)	(0.0761)	(0.0841)	(0.0760)	(0.0841)	(0.0761)	(0.0846)	(0.0765)	(0.0851)
o_level	0.0652	-0.0114	0.0657	-0.0081	0.0633	-0.0279	0.0639	-0.0223	0.0891	-0.0123
	(0.1074)	(0.1122)	(0.1074)	(0.1123)	(0.1075)	(0.1125)	(0.1076)	(0.1128)	(0.1081)	(0.1144)
dkid04	-0.1109 *	-0.4948 ***	-0.11 *	-0.4857 ***	-0.1237 **	-0.5085 ***	-0.1235 **	-0.4795 ***	-0.1215 **	-0.4717 **
	(0.0601)	(0.1834)	(0.0604)	(0.1840)	(0.0611)	(0.1833)	(0.0611)	(0.1844)	(0.0613)	(0.1849)
dkid59	-0.1094 *	-0.1336	-0.1087 *	-0.1329	-0.1231 *	-0.1451	-0.1304 **	-0.1425	-0.1298 **	-0.1392
	(0.0621)	(0.2188)	(0.0622)	(0.2189)	(0.0632)	(0.2191)	(0.0634)	(0.2199)	(0.0636)	(0.2197)
dkid1015	-0.2195 ***	-0.0956	-0.2202 ***	-0.0955	-0.2143 ***	-0.0716	-0.2251 ***	-0.0586	-0.2208 ***	-0.0334
	(0.0744)	(0.1667)	(0.0745)	(0.1667)	(0.0746)	(0.1673)	(0.0750)	(0.1677)	(0.0753)	(0.1690)
d50	-3.6311 ***	-1.3738 ***	-3.6299 ***		-3.6103 ***		-3.5538 ***	-1.4266 ***	-3.5738 ***	
	(0.3217)	(0.3174)	(0.3256)		(0.3328)		(0.3566)	(0.3233)	(0.3805)	
d60	-3.1728 ***	-1.1951 ***	-3.1649 ***	0.2303	-3.1761 ***	0.0758	-3.1167 ***	-1.1622 ***	-3.1414 ***	0.3249
	(0.2667)	(0.2381)	(0.2823)	(0.1940)	(0.2867)	(0.1857)	(0.3096)	(0.2413)	(0.3398)	(0.2133)
d70	-2.7993 ***	-0.9609 ***	-2.7894 ***	0.4815 **	-2.8007 ***	0.3255	-2.7077 ***	-0.8612 ***	-2.6362 ***	0.6627 ***
	(0.2174)	(0.1825)	(0.2420)	(0.2266)	(0.2406)	(0.2103)	(0.2763)	(0.1896)	(0.3136)	(0.2515)
d80	-2.0829 ***	-0.6306 ***	-2.0751 ***	0.8033 ***	-2.0871 ***	0.6722 ***	-2.0068 ***	-0.5463 ***	-1.8617 ***	0.9949 ***
	(0.1734)	(0.1381)	(0.1964)	(0.2621)	(0.2029)	(0.2514)	(0.2409)	(0.1451)	(0.2845)	(0.2812)
d90	-1.6344 ***	-0.2102 **	-1.6293 ***	1.2025 ***	-1.6341 ***	1.0922 ***	-1.5689 ***	-0.2027 *	-1.4718 ***	1.2961 ***
	(0.1426)	(0.1051)	(0.1612)	(0.3014)	(0.1749)	(0.2990)	(0.2150)	(0.1057)	(0.2577)	(0.3086)
d00	-1.3866 ***		-1.3833 ***	1.4074 ***	-1.3794 ***	1.3087 ***	-1.3297 ***		-1.2775 ***	1.4701 ***
	(0.1394)		(0.1534)	(0.3209)	(0.1691)	(0.3193)	(0.2064)		(0.2470)	(0.3259)
_cons	2.7904	1.1529 ***	2.7971	-0.2162	2.6634	-0.3063	2.7962	0.9811 ***	2.8597	-0.4057
	(.)	(0.1536)	(.)	(0.3514)	(.)	(0.3531)	(.)	(0.1819)	(.)	(0.3738)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time and regional dummies included.

Table A12. Heckman Selectivity Model - First stage - Dependent variable: employment - Nonwhites (Ref. Table 10)

	Model A		Model B		Model C		Model D		Model E	
	1 - Married	2 - Unmarried	3 - Married	4 - Unmarried	5 - Married	6 - Unmarried	7 - Married	8 - Unmarried	9 - Married	10 - Unmarried
exper	-0.003	0.0031	-0.002	0.0018	0.0273 *	0.039 **	0.0037	0.0167	-0.0169	0.0118
	(0.0044)	(0.0054)	(0.0065)	(0.0085)	(0.0151)	(0.0161)	(0.0244)	(0.0280)	(0.0335)	(0.0387)
expersq/100					-0.0954 **	-0.1369 **	-0.0328	-0.0878	0.0276	-0.0661
					(0.0455)	(0.0581)	(0.0804)	(0.1065)	(0.1131)	(0.1524)
YSM	0.0461 ***	0.0296 ***	0.0474 ***	0.0283 ***	0.0464 ***	0.0308 ***	0.0252 *	0.0151	-0.0145	-0.0419
	(0.0057)	(0.0082)	(0.0087)	(0.0105)	(0.0057)	(0.0083)	(0.0144)	(0.0130)	(0.0453)	(0.0401)
YSM2/100									0.1462	0.2324
									(0.1658)	(0.1497)
YSM_x_exper/100			-0.0076	0.0089			0.2422	0.2149	0.7509	0.4384
			(0.0375)	(0.0464)			(0.1588)	(0.1664)	(0.5454)	(0.5909)
YSM_x_expersq/100							-0.0061	-0.0053	-0.0202	-0.0098
							(0.0045)	(0.0055)	(0.0160)	(0.0207)
YSM2_x_exper/100									-0.0177	-0.0117
									(0.0182)	(0.0192)
YSM2_x_expersq/100									0.0005	0.0002
									(0.0005)	(0.0006)
degree	0.6016 ***	0.6858 ***	0.5992 ***	0.6875 ***	0.5926 ***	0.7037 ***	0.6031 ***	0.7135 ***	0.6057 ***	0.7101 ***
	(0.0681)	(0.1000)	(0.0691)	(0.1004)	(0.0683)	(0.1005)	(0.0693)	(0.1020)	(0.0695)	(0.1020)
a_level	0.3406 ***	0.219 **	0.3393 ***	0.2195 **	0.3331 ***	0.2195 **	0.3356 ***	0.2159 **	0.3386 ***	0.236 **
	(0.0626)	(0.0908)	(0.0629)	(0.0908)	(0.0627)	(0.0908)	(0.0630)	(0.0912)	(0.0632)	(0.0921)
o_level	0.2451 ***	-0.0513	0.244 ***	-0.052	0.2376 **	-0.0562	0.2403 **	-0.0696	0.2429 ***	-0.0411
	(0.0932)	(0.1188)	(0.0933)	(0.1188)	(0.0933)	(0.1188)	(0.0935)	(0.1192)	(0.0938)	(0.1202)
dkid04	-0.1321 ***	0.2887	-0.1334 ***	0.2876	-0.147 ***	0.2718	-0.143 ***	0.2543	-0.1432 ***	0.2587
	(0.0478)	(0.2414)	(0.0482)	(0.2414)	(0.0484)	(0.2411)	(0.0485)	(0.2412)	(0.0486)	(0.2413)
dkid59	-0.0178	-0.0079	-0.0191	-0.0079	-0.0352	0.0058	-0.0377	0.005	-0.0382	0.0211
	(0.0483)	(0.1972)	(0.0488)	(0.1971)	(0.0491)	(0.1977)	(0.0494)	(0.1977)	(0.0495)	(0.1983)
dkid1015	-0.0604	-0.1234	-0.0597	-0.1233	-0.0587	-0.0926	-0.0681	-0.0864	-0.0656	-0.0789
	(0.0585)	(0.1459)	(0.0586)	(0.1459)	(0.0586)	(0.1462)	(0.0589)	(0.1463)	(0.0591)	(0.1467)
d50	-1.8762 ***				-1.8507 ***				-1.8761 ***	
	(0.3672)				(0.3690)				(0.3819)	
d60	-1.4001 ***	0.1681	0.4692	0.1758	-1.3877 ***	0.1528	0.4666	0.1943	-1.3921 ***	0.3293
	(0.1704)	(0.4503)	(0.3195)	(0.4520)	(0.1705)	(0.4509)	(0.3248)	(0.4535)	(0.1714)	(0.4711)
d70	-1.1509 ***	0.4789	0.7137 **	0.4959	-1.1557 ***	0.4366	0.7138 **	0.5444	-1.1515 ***	0.7824
	(0.1314)	(0.4580)	(0.3287)	(0.4664)	(0.1314)	(0.4589)	(0.3342)	(0.4682)	(0.1379)	(0.4991)
d80	-0.7948 ***	0.63	1.0696 ***	0.6467	-0.8033 ***	0.5943	1.0718 ***	0.7061	-0.7894 ***	1.0034 *
	(0.0952)	(0.4774)	(0.3470)	(0.4853)	(0.0953)	(0.4783)	(0.3519)	(0.4872)	(0.1053)	(0.5191)
d90	-0.4007 ***	1.0119 **	1.4653 ***	1.0264 **	-0.4046 ***	0.9747 *	1.4631 ***	1.0729 **	-0.3948 ***	1.3107 **
	(0.0765)	(0.5011)	(0.3603)	(0.5067)	(0.0765)	(0.5018)	(0.3650)	(0.5082)	(0.0789)	(0.5317)
d00		1.3072 **	1.8672 ***	1.319 **		1.2799 **	1.8589 ***	1.3585 ***		1.5281 ***
		(0.5161)	(0.3699)	(0.5198)		(0.5167)	(0.3746)	(0.5211)		(0.5394)
_cons	0.907 ***	-0.9324	-0.9713 **	-0.9326	0.7383 ***	-1.0821 *	-0.9469 **	-1.0259 *	1.0579 ***	-1.075 *
	(0.1631)	(0.5748)	(0.3992)	(0.5748)	(0.1815)	(0.5785)	(0.4326)	(0.5887)	(0.2648)	(0.6224)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses. Time and regional dummies included.

Table A13. Education and labour market entrants - 1. Regional dummies 2. First stage of Heckman Selectivity Model (Ref. Table 11)

	Probit estimates - Dependent variable: employment				Heckman Selectivity Model - Dependent variable: log hourly wage			
	Whites		Nonwhites		Whites		Nonwhites	
	1 Education entrants	2 LM entrants	3 Education entrants	4 LM entrants	5 Education entrants	6 LM entrants	7 Education entrants	8 LM entrants
North_East	-0.1172	-0.307	-0.3118	-0.2279	-0.0981	-0.0079	-0.0271	-0.0853
	(0.1749)	(0.2323)	(0.2806)	(0.1987)	(0.0833)	(0.1146)	(0.1322)	(0.1093)
North_West	-0.1244	-0.2567	-0.2354	-0.1922	-0.0299	0.1018	-0.0563	-0.1156
	(0.1271)	(0.1580)	(0.2039)	(0.1376)	(0.0598)	(0.0812)	(0.0913)	(0.0721)
Yorks_Hum	0.0183	-0.2645 *	-0.1168	-0.1426	-0.0474	0.0064	-0.1437	-0.0688
	(0.1361)	(0.1563)	(0.2042)	(0.1389)	(0.0592)	(0.0758)	(0.0887)	(0.0688)
East_Mids	-0.0328	-0.0697	-0.1073	0.0836	-0.0363	0.0745	-0.1175	-0.0466
	(0.1397)	(0.1698)	(0.2132)	(0.1579)	(0.0638)	(0.0756)	(0.0899)	(0.0780)
West_Mids	-0.004	-0.356 **	-0.3553 *	-0.2135	-0.0227	0.119	-0.0245	-0.0812
	(0.1380)	(0.1532)	(0.1955)	(0.1338)	(0.0622)	(0.0764)	(0.0851)	(0.0675)
Eastern	0.1052	0.1203	0.0214	0.2192	0.1088** **	0.155 **	0.0918	0.1406 **
	(0.1207)	(0.1409)	(0.2151)	(0.1508)	(0.0532)	(0.0606)	(0.0887)	(0.0711)
London	0.0165	-0.2319 **	-0.1649	-0.1273 *	0.2447 ***	0.3886 ***	0.135 *	0.1199 **
	(0.1073)	(0.1142)	(0.1879)	(0.1222)	(0.0485)	(0.0554)	(0.0801)	(0.0602)
South_East	0.1368	0.0625	0.0943	0.2678 *	0.1282 ***	0.3036 ***	0.1233	0.1349 **
	(0.1095)	(0.1287)	(0.2049)	(0.1424)	(0.0477)	(0.0554)	(0.0851)	(0.0676)
South_West	0.2548 **	0.0007	0.1244	0.3291	-0.062	0.0046	-0.0484	0.0499
	(0.1293)	(0.1610)	(0.2581)	(0.1921)	(0.0541)	(0.0714)	(0.1009)	(0.0847)
Wales	0.1001	0.0534	0.1073	0.1113	-0.1051	-0.1773 *	-0.07	-0.0703
	(0.2007)	(0.2438)	(0.2971)	(0.2232)	(0.0852)	(0.0974)	(0.1206)	(0.1124)
					Exogenous variables used in the first stage			
dkid04					-0.1806 **	-0.1284 *	-0.1725 **	-0.1078 *
					(0.0855)	(0.0763)	(0.0791)	(0.0584)
dkid59					-0.1036	-0.1293	0.0335	-0.0571
					(0.0880)	(0.0805)	(0.0764)	(0.0597)
dkid1015					-0.1324	-0.2135 **	-0.0562	-0.0407
					(0.0899)	(0.0940)	(0.0807)	(0.0701)

Notes: *** 1%, ** 5%, * 10% significant level. Standard errors in parentheses.

RECENTLY PUBLISHED "Materiali di Discussione"

N. 620 - *Politiche industriali per i distretti, politiche di sviluppo ispirate dai distretti. La lezione di Sebastiano Brusco,* by Margherita Russo e Anna Natali [September 2009].

N. 619 - *Innovative interventions in support of innovation networks. A complex system perspective to public innovation policy and private technology brokering*, by Federica Rossi, Margherita Russo, Stefania Sardo and Josh Whitford, [September 2009].

N. 618 - *Returning and Sharing Memories Genesi e sviluppo di un progetto per l'uso del "passato comune" italo-etiope (1935-1941),* by Paolo Bertella Farnetti [September 2009].

N. 617 - *The skew pattern of implied volatility in the DAX index options market*, by Silvia Muzzioli [July 2009].

N. 616 - *Political institutions and central bank independence revisited*, by Davide Ferrari, Barbara Pistoresi and Francesco Salsano [July 2009].

N. 615 - *Industrial districts in a globalizing world: A model to change, or a model of change*, by Margherita Russo and Josh Whitford [July 2009].

N. 614 - *Brokeraggio tecnologico nel settore metalmeccanico in Emilia-Romagna: dal Parco Scientifico Tecnologico ex-SIPE a CRIT srl*, by Stefania Sardo [May 2009].

N. 613 - *The Officina Emilia Initiative: Innovative Local Actions to Support Education and Training Systems,* by Paola Mengoli and Margherita Russo [May 2009].

N. 612 - *Strategia di Lisbona per l'inclusione sociale e politica agricola comune: un esempio della difficile coerenza tra azioni di policy europee*, by Paola Bertolini and Marco Montanari [April 2009].

N. 611 - *The recent reforms of the Italian personal income tax: distributive and efficiency effects,* by Massimo Baldini and Daniele Pacifico [March 2009].

N. 610 - *La City di Torino. Alla ricerca del quartiere finanziario della città a metà Ottocento,* by Simone Fari [March 2009]

N. 609 - *Which European model for elderly care? Equity and cost-effectiveness in home based care in three European countries,* by Francesca Bettio and Giovanni Solinas [February 2009]

“Materiali di Discussione” LATER PUBLISHED ELSEWHERE

N. 546 - M. Murat and B. Pistoresi, *Emigrants and immigrants networks in FDI*, Applied Economics letters, April 2008, **http://www.informaworld.com/ /content~content=a789737803~db=all~order=author** (electronic publication), **WP No. 546 (December 2006).**

N. 545 - M.Brunetti and C. Torricelli, *The Population Ageing in Italy:Facts and Impact on Household Portfolios*, in M. Balling & E. Gnan & F. Lierman (eds.), Money, Finance and Demography: The Consequences of Ageing, Vienna, Suerf, **WP No. 545 (November 2006).**

N. 532 – M: Montanari, Between European Integration and Regional Autonomy: The Case of Italy from an Economic Perspective, Constitutional Political Economy, Vol. 17, 4, pp. 277-301, **WP No. 532 (March 2006).**

N. 529 - M. Montanari, Knocking on the EU’s door: the Political Economy of EU-Ukraine Relations, Journal of Contemporary European Research, Vol.3,1, pp.64-78, **WP No. 529 (February 2006).**

N. 518 - M.Brunetti and C. Torricelli, *Economic Activity and Recession Probabilities: information content and predictive power of the term spread in Italy*, Applied Economics, 2008, in press, **WP No. 518 (December 2005).**

N. 517 - M. Murat and S. Paba (2006), *I distretti industriali tra immigrazioni e internazionalizzazione produttiva*, in B. Quintieri (ed.) I distretti italiani dal locale al globale, Rubbettino, **WP No. 517 (December 2005).**

N. 491 - V. Moriggia, S. Muzzioli and C. Torricelli, *On the no arbitrage condition in option implied trees*, European Journal of Operational Research, forthcoming (doi: 10.1016/j.ejor.2007.10.017), **WP No. 491 (May 2005).**

N. 482 - G. Di Lorenzo and G. Marotta, *A less effective monetary transmission in the wake of EMU? Evidence from lending rates passthrough*, ICFAI Journal of Monetary Economics, Vol. 4, 2, pp. 6-31, **WP No. 482 (February 2005).**

N. 472 - M.Brunetti and C. Torricelli, *The internal and cross market efficiency in index option markets: an investigation of the Italian market*, Applied Financial Economics, Vol. 17, 1, pp. 25-33, **WP No. 472 (November 2004).**

N. 466 - G. Marotta, *La finanza del settore non profit tra ritardi nei pagamenti e Basilea 2*, Banca Impresa Società, Vol. XXIV, 1, pp. 35-51, **WP No. 466 (September 2004).**

N. 453 - Pederzoli and C. Torricelli, *Capital requirements and Business Cycle Regimes: Forward-looking modelling of Default Probabilities* , Journal of Banking and Finance, Vl. 29, 12, 2005, pp. 3121-3140, **WP No. 453 (February 2004).**

N. 448 - V. Moriggia, S. Muzzioli, C. Torricelli, *Call and put implied volatilities and the derivation of option implied trees*, Frontiers In Finance and Economics, vol.4, 1, 2007, pp. 35-64, **WP No. 448 (November 2003).**

N. 436 - M.Brunetti and C. Torricelli, *Put-Call Parity and cross-market efficiency in the Index Options Markets: evidence from the Italian market*, International Review of Financial Analysis, Vl.14, 5, pp. 508-532, **WP No. 436 (July 2003).**

N. 429 - G. Marotta, *When do trade credit discounts matter? Evidence from Italian Firm-Level Data*, Applied Economics, Vol. 37, 4, pp. 403-416, **WP No. 429 (February 2003).**

N. 426 - A. Rinaldi and M. Vasta, *The Structure of Italian Capitalism, 1952-1972: New Evidence Using the Interlocking Directorates Technique,* Financial History Review, vol, 12, 2, pp. 173-198, **WP No. 426 (January 2003).**

N. 417 - A. Rinaldi, *The Emilian Model Revisited: Twenty Years After*, Business History, vol. 47, 2, pp. 244-226, **WP No. 417 (September 2002).**

N. 375 - G. Marotta, *La direttiva comunitaria contro i ritardi nei pagamenti tra imprese. Alcune riflessioni sul caso italiano*, Banca, Impresa, Società, Vol. XX, 3, pp. 451-71, **WP No. 375 (September 2001).**

N. 303 - G. Marotta and M. Mazzoli, *Fattori di mutamento nella domanda di prestiti ed effetti sulla trasmissione della politica monetaria*, in P. ALESSANDRINI (ed.) Il sistema finanziario italiano tra globalizzazione e localismo, Bologna, Il Mulino, pp. 223-260, **WP No. 303 (April 2000)**

N. 131 - G. Marotta, *Does trade credit redistribution thwart monetary policy? Evidence from Italy*, Applied Economics, Vol. 29, December, pp. 1619-29, **WP No. 131 (1996).**

N. 121 - G. Marotta, *Il credito commerciale in Italia: una nota su alcuni aspetti strutturali e sulle implicazioni di politica monetaria*, L'Industria, Vol. XVIII, 1, pp. 193-210, **WP No. 121 (1995)**

N. 105 - G. Marotta, *Credito commerciale e "lending view"*, Giornale degli Economisti e Annali di Economia, Vol. LIV, 1-3, gennaio-marzo, pp. 79-102; anche in G. Vaciago (a cura di) *Moneta e finanza*, Bologna, Il Mulino, **WP No. 105 (1994).**