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THE DISTRIBUTION OF DISCRIMINATION IN IMMIGRANT EARNINGS - EVIDENCE FROM BRITAIN 1974-93*

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Abstract:

This paper uses the General Household Survey data for the UK to study earnings discrimination between natives and migrants. The key result is that the main source of discrimination is ethnicity rather than migrant status *per se*. This paper differs from the conventional focus in studies of earnings discrimination, which focus on mean wage differences. In contrast we study the entire distribution of the wage gap, and incorporate distributionally sensitive measures of the wage gap reflecting different levels of aversion to discrimination. Our results are consistent with previous studies for the UK that find that non-white immigrants are the most widely discriminated in terms of their labour market returns. Moreover this discrimination on the basis of colour is also present in the sub-sample of natives.

* The authors acknowledge the comments of Patrick Geary, Stephen Jenkins and Dorren McMahon on earlier versions of this paper. The usual disclaimer applies. Material from the General Household Survey is used with permission of the Office for Population Censuses and Surveys and made available through the Data Archive at the University of Essex. The providers bear no responsibility for the calculations contained herein nor for any interpretation made by the authors. Corresponding author: Kevin Denny, Department of Economics, University College Dublin, Belfield, Dublin 4, Ireland. Phone (+353 1) 7068399. Fax (+3531) 2830068. E-mail `kevin.denny@ucd.ie`.

INTRODUCTION

This paper looks at the distribution of wage differences between migrants and natives in Britain over the period 1974-1993. Unlike than the conventional 'Blinder-Oaxaca' decomposition, we consider the complete distribution of the mean wage gap. In addition we calculate measures of the degree of discrimination based on this distribution and show how these may depend on alternative levels of aversion to discrimination.

The literature is rich in studies exploring the issue of migrant wage discrimination in various forms in the labour market. Recent contributions, largely led by the work of Borjas (1995) have been based on large-scale microeconomic datasets typically using US census data. Papers by Blackaby *et al* (1995) and Bell (1997) explores the issue for the United Kingdom using the General Household Survey (GHS) pooled over a 20 year period and finds that non-white immigrants are the most widely discriminated against in terms of their labour market returns. Several studies have explored the issue for the UK using single cross sections of microdata (typically GHS) such as Chiswick (1983), McNabb and Psacharopoulos (1981) or Stewart (1983).

Using the more general set of measures proposed by Jenkins (1994) we find evidence of discrimination, results which are consistent with those of Bell (1997). Our findings suggest that the discrimination is concentrated by ethnicity and not necessarily driven by migrant status in itself. Section I outlines our approach in terms of earnings discrimination indices. Section II presents our findings based on the GHS pooled from 1974-1993. Section III discusses limitations to our approach. Section IV concludes.

I EARNINGS DISCRIMINATION INDICES

We examine whether discrimination between migrants and natives is present by first estimating standard earnings regressions of the form:

(1) $\log(y_i) = \mathbf{X_i}\ \boldsymbol{\beta}^{\mathbf{n}} + u_i^n\ ,\ \forall\, i\ \in\ N\ ,$

(2) $\log(y_i) = \mathbf{X_i}\ \boldsymbol{\beta}^{\mathbf{m}} + u_i^m\ ,\ \forall\, i\ \in\ M\ ,$

where M is the set of migrants, N is the set of natives, y_i is the hourly wage of person i, $\mathbf{X_i}$ is a vector of person-specific explanatory variables, the β's are parameter vectors and the u_i's are random error terms. Evidence of discrimination (in terms of the approach of Oaxaca, 1973) is usually based on comparing the predicted wage of one group, migrants for example, with their predicted reference wage. The predicted reference wage of migrants (denoted $\hat{r}$) is defined as the wage they would receive if all the migrants' attributes had the same rate of return as the native group. Thus, the predicted reference and actual wages are calculated as:

(3) $$\left.\begin{aligned} \hat{r}_i &= \exp\left(\mathbf{X_i}\ \hat{\beta}^N\right) \\ \hat{y}_i &= \exp\left(\mathbf{X_i}\ \hat{\beta}^N\right) \end{aligned}\right\}\ i\ \in\ M\ ,$$

$$\hat{r}_i\ = \exp\left(\mathbf{X}_i\ \hat{\beta}^N\right)\ i\ \in\ N\ .$$

The conventional summary measure of wage discrimination is the mean log wage gap, expressed in percentage terms,

(4) $$\begin{aligned} D_F\ &\equiv\ 100 \bullet \left[\exp\left(\underset{i\in M}{\text{mean}}\left[\log(\hat{r}_i) - \log(\hat{y}_i)\right]\right)\right] \\ &\approx\ 100 \bullet \left[\exp\left(\underset{i\in M}{\text{mean}}\left[(\hat{r}_i\ -\ \hat{y}_i)\ /\ \hat{y}_i\right]\right)\right] \end{aligned}\ .$$

While the approximation indicated in (4) provides an intuitive interpretation of the measure as the mean proportionate difference in the wages of the reference groups, it is inexact to the extent that the variances differ between groups[1].

Differences between the reference and actual wages for the migrant grouping would indicate discrimination is present. Jenkins (1994) argues that this summary approach ".....may be consistent with very different distributions of discrimination experience". For example, suppose that in 1974 and 1993 the average wage gap is estimated to be 5% in favour of natives. In 1974 the average wage gap could be due to all migrants getting paid 5% less than natives, while in 1993 the average wage gap could be due to half the migrants getting the same wage and the other half getting 10% less than natives. The presence of heterogeneity in discrimination across a distribution of individuals seems likely given the findings of Stewart (1983), who shows that while the median differential in earnings by race was about 12% against non-whites in the UK the differential for those in the upper quartile of earnings falls to 3% and at the lower quartile the gap widens to almost 20%.

Jenkins (1994) proposes some methods for analyzing the joint distribution of the two groups. The first of these measures is based on the Lorenz curve and the associated Gini coefficient. We order the migrants in ascending order of the observed wage and plot the cumulative predicted wage per capita against cumulative sample share for each member of the migrant sample. In a similar fashion we summarize the predicted reference wage by plotting the cumulative predicted reference wage per capita against the cumulative sample share *ranked in the same order as for the Lorenz Curve*. In Jenkins (1994) terminology these two plots are the Generalized Lorenz Curve (GLC) and Generalized Concentration Curve (GCC). If there is no discrimination the curves will coincide, but there will be discrimination if the predicted reference and predicted actual wages are not equal. In this instance the GCC curve will lie everywhere above the GLC curve. An aggregate discrimination index that is analogous to the

Gini coefficient (in the sense of using the area between the curves as a measure of discrimination) is given as:

$$(5) \qquad C = \left(1 + \frac{1}{2n_m}\right)\left(\frac{\bar{r}^m - \bar{y}^m}{\bar{y}^m}\right) - \left(\frac{1}{n_m}\right)^2 \bullet \sum_{i \in M} i \left(\frac{\hat{r}_i - \hat{y}_i}{\bar{y}^m}\right)$$

where the "bar" terms denote means. This measure takes the differences in means as in a traditional 'decomposition' measures of discrimination but also incorporates a term which is the wage gap weighted by the rank in the predicted earnings distribution.

The second measure of overall discrimination suggested by Jenkins (1994) is:

$$(6) \qquad J_\alpha = \sum_{i \in M} \omega_i \left(1 - d_i^{-\alpha}\right) = 1 - \sum_{i=1}^{n_m} \omega_i \, d_i^{-\alpha} \, ,$$

where

$$\omega_i = \frac{\hat{y}_i}{n_m \, \bar{y}^m}$$

$$d_i = 1 + \frac{|\ \hat{r}_i - \hat{y}_i\ |}{\bar{r}^m}$$

$$\alpha > 0$$

Here ω_i is a migrants wage share and d_i is a normalized wage gap (the gap for the migrant individual relative to the mean of the reference distribution). If the wage gap equals 1 (in the no discrimination case where the predicted reference and actual wage are equal) the J_α is equal to zero. This measure allows for the wage gaps to be aggregated in different ways, with the parameter α interpreted as "the degree of discrimination aversion, with higher values for α corresponding to greater aversion" (Jenkins, 1994). With this interpretation the aversion parameter is the increase in wages required to compensate an individual for a small increase in

the wage gap (or discrimination) – large values of α suggest a large aversion to discrimination. It is somewhat analogous to the familiar "Atkinson Aversion to Inequality" parameter.

This index (unlike the Lorenz Curve based *C* Index) has the desirable property that it is additively decomposable: that is one can write the aggregate discrimination against migrants (say) into a weighted sum of the discrimination indices pertaining to two sub groups: black migrants and white migrants.[2] The *J* index is a concave function of proportionate wage gaps: a given percentage wage gap receives a lower weight the higher it occurs in the wage distribution reflecting the view that one cares less about discrimination against the relatively well off. One could, of course, argue for a convex function on the basis that a given wage gap corresponds to a greater absolute amount of discrimination the higher it occurs in the wage distribution. With some fairly plausible assumptions about the underlying Social Welfare Function (see Jenkins, 1991) one can write welfare for the group of interest (i.e. those for whom we are measuring discrimination against) as

(7) $$W = \bar{y}^{w}\left(1 - J_{\alpha}\right)$$

which makes explicit the welfare cost of discrimination in terms of average wages of the group.

II. RESULTS

Using the pooled sample

We estimate a simple earnings function using GHS data for the 1974-93 period using the log real wage (in 1974 prices) where the GHS nominal wage is divided by the consumer price index. Our set of characteristics include age, age squared and years of education, as well as sets of dummy variables to control for regional, occupational and industry effects as well as year dummies from 1975-1993 (1974 is the reference year).[3]

Our total sample size is 98,839, of which 92,726 are natives and 6,133 are migrants defined in the GHS by country of birth. The classification of 'non-white' for the purposes of this paper is defined explicitly within the GHS questionnaire. The interviewer must observe the respondent and classify accordingly. Thus non-white is not defined arbitrarily by virtue of specific countries of origin. Migrant status is therefore separate to white/non-white status. While the GHS is a representative survey it is possible that recent migrants are under-represented since they are less likely to be in the sampling frame[4]. We confine our analysis to employed males.

In addition to analyzing the discrimination between total natives and migrants we can divide the total into white and nonwhite sub groups. In Table 1 we present summary statistics for the migrant wage distribution for the total, white and non-white groups. The raw wage gap between predicted reference and actual wages is always positive for each group and is relatively large for the non-white group, supporting the conclusions of Bell (1997).

Table 1

Summary statistics for migrant wage distributions 1974-93

	Statistic	**Total**	**White**	**Non-white**
Predicted reference wages	Mean	1.176	1.166	1.212
	Median	1.098	1.078	1.187
Predicted wages	Mean	1.078	1.144	1.005
	Median	1.006	1.038	0.968
Raw wage gaps (r^M-y^M)	Mean	0.098	0.022	0.207
	Median	0.077	0.024	0.199

It is also informative to illustrate the complete distribution of discrimination using the Generalized Lorenz and Generalized Concentration Curves. An appealing feature of the diagrammatic approach in the context of this paper is that it illustrates the complete distribution of the degree of discrimination. In Figure 1A we present the GLC (light line) and GCC (heavy

line), estimated using the total sample of natives and migrants. The GCC lies everywhere above the GLC, which indicates wage discrimination, is present over the whole distribution. This is not as evident when we examine the case of white migrants versus white natives (see Figure 1B), but is very evident when we examine the case of non-white migrants versus non-white natives (see Figure 1C). From this it appears that it is the non-white migrant group that are being discriminated against and this is reflected in the results for the total sample.

Figure 1A Discrimination between Migrants and Natives - Total Sample

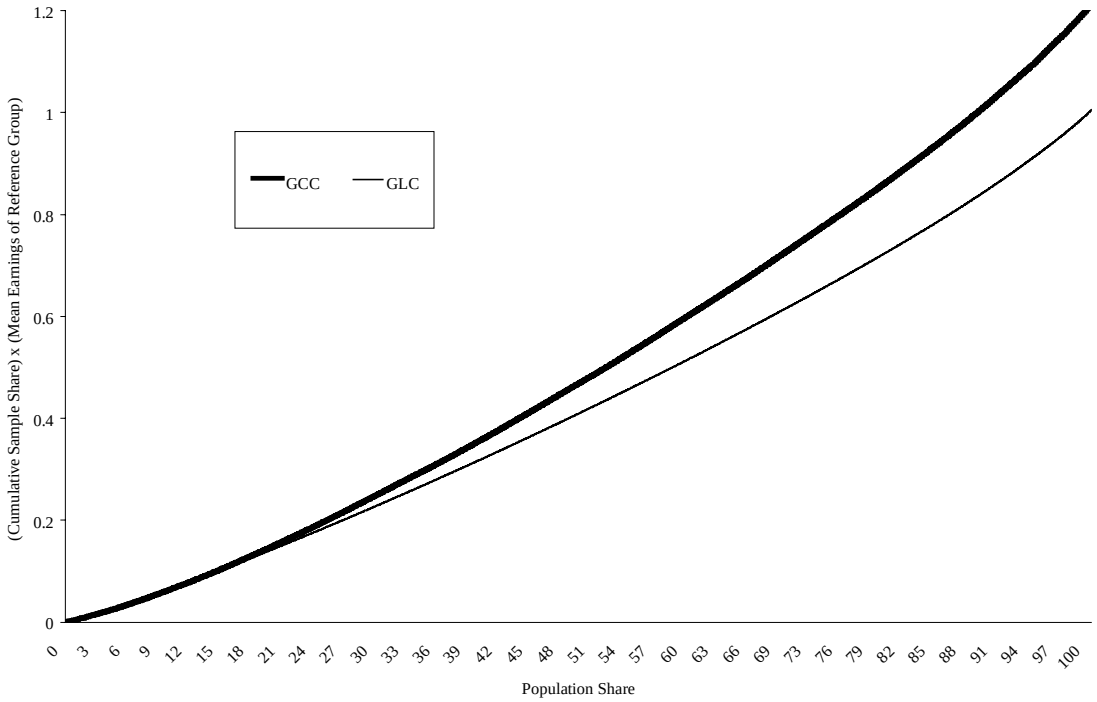


Figure 1B Discrimination between Migrants and Natives - White Sample

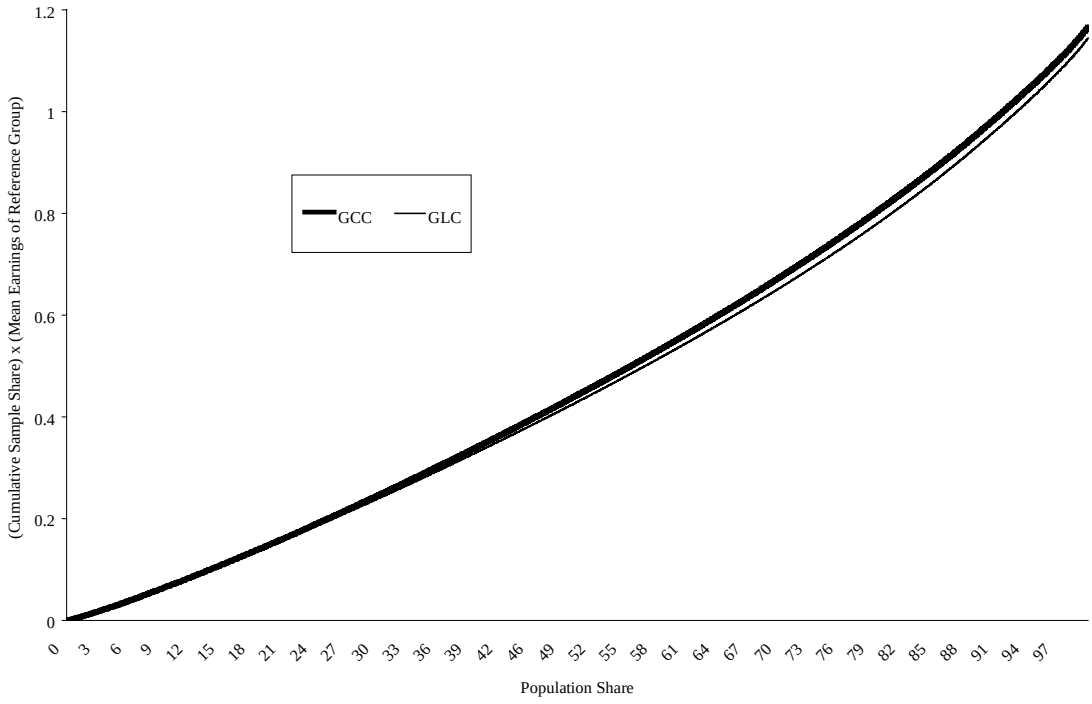
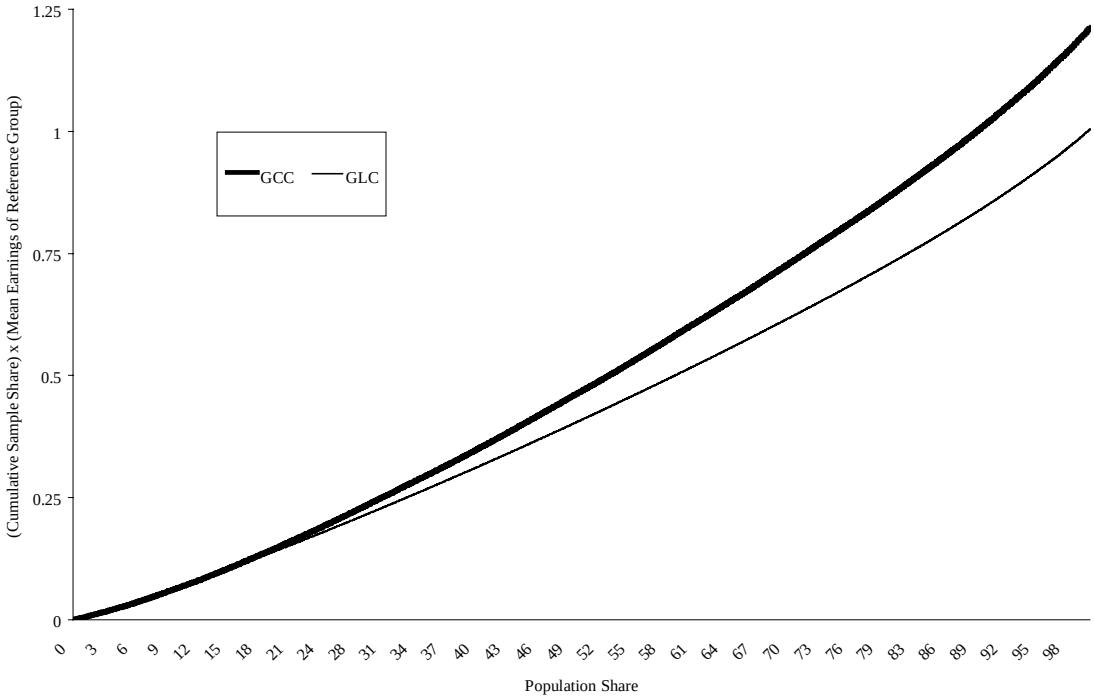


Figure 1C Discrimination between Migrants and Natives - NonWhite Sample



In order to throw further light on these findings we repeat our analysis but this time we examine the distribution of discrimination experiences between white and non-white groups. We find that there is some degree of colour discrimination in the total sample (see Figure 1D) which is not due to discrimination in the native sample (see Figure 1E) but reflects discrimination in the migrant sample (see Figure 1F). It is also noteworthy that whereas in most of the diagrams the curves grow further apart as we move to the right, in Figure 1E, the two converge. This suggests that there is little discrimination in the native sample between blacks and whites at the *upper end of the distribution*.

Figure 1D Discrimination between Non Whites and Whites - Total Sample

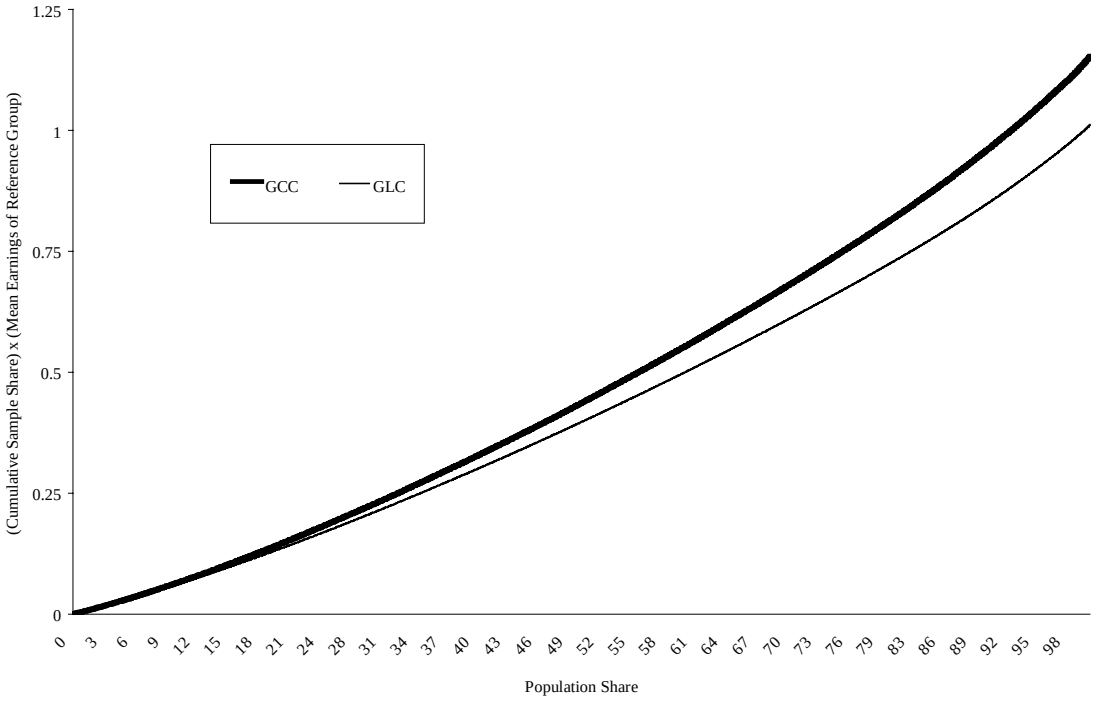


Figure 1E Discrimination between Non Whites and Whites - Native Sample

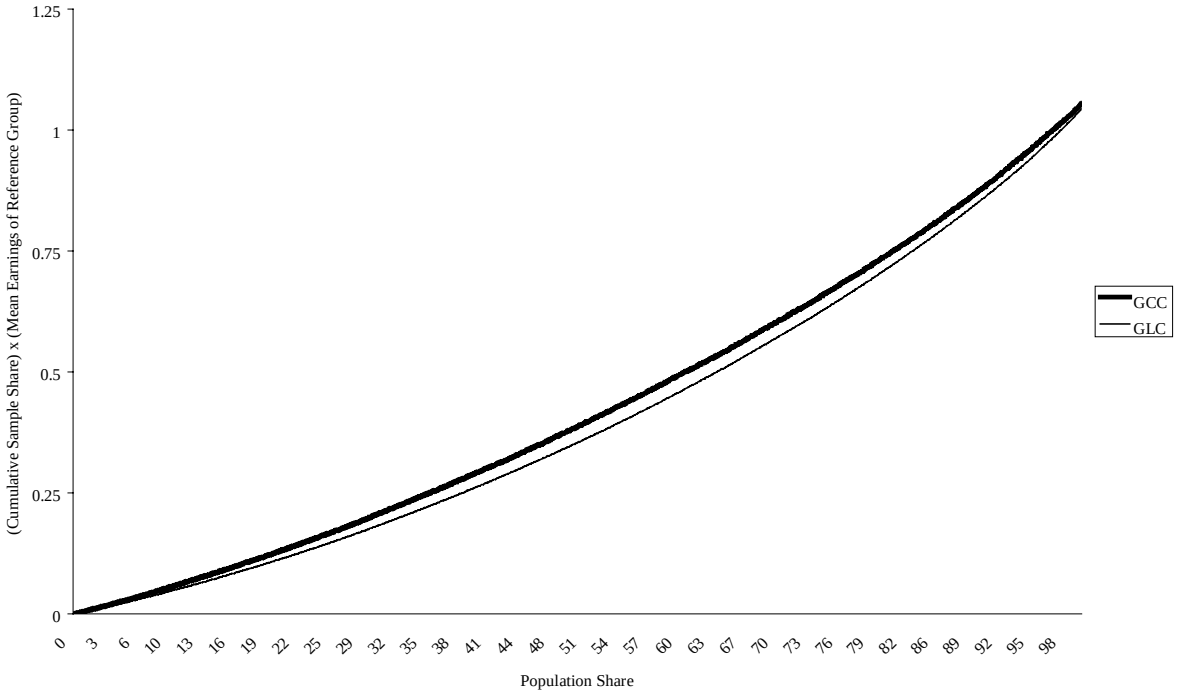
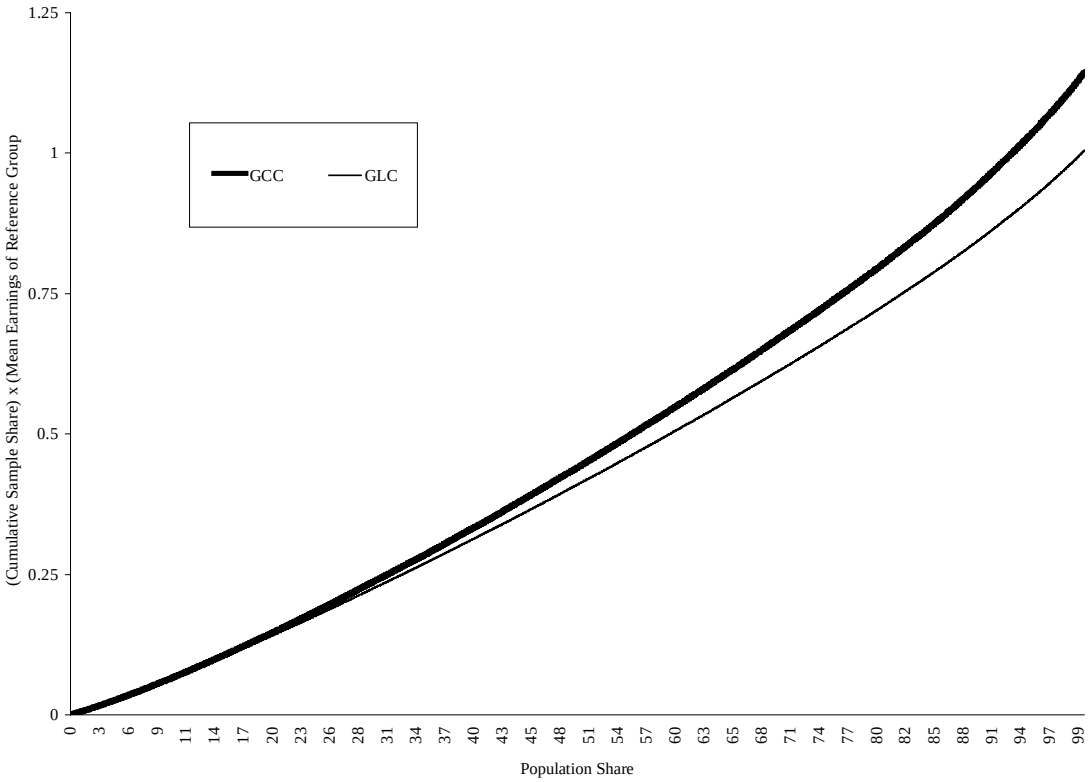


Figure 1F Discrimination between Non Whites and Whites – Migrant Sample



These results are also evident when we calculated distributional discrimination index estimates. The standard D_f and Jenkins' (1994) C and various J_α indices are calculated for native/migrant (see Table 2) and white/non-white (see Table 3) wage discrimination. The degree of migrant discrimination using any of these indices is always higher for the non-white group. The degree of non-white discrimination using any of these indices is always higher for the migrant group. Thus over the 1974-93 period non-white migrants appeared to be subject to real wage discrimination. The first column in Table 2 compares all migrants against all natives. The second column compares migrants who are white against natives who are white and so on. The first row gives the conventional mean wage gap and the second is the Gini based measure. We can use equation (7) to interpret the various J indices. Table 2 implies that for $\alpha = 0.25$, the welfare cost to migrants of discrimination is equivalent to the welfare loss caused by reducing their average wages by about 2.4%. For purposes of comparison we include estimates of male/female discrimination

from Jenkins (1994) which suggest that our estimates of discrimination against non-whites are of similar magnitude to that experienced by females in the labour market.

The finding that colour is the key distinction contrasts with the results of Heath & McMahon (1997b) who find in a study of occupational attainment that first generation Irish immigrants to Britain – the bulk of the white immigrants- experience an "ethnic penalty" in much the same manner as other immigrant groups.

Table 2 Distributional Discrimination Index: Natives versus Migrants

	Total	White	Non-white	Males vs Females (Jenkins)
Df	8.141	2.116	17.812	21.5
C	0.032	0.011	0.072	0.094
J_α α=**0.25**	0.024	0.013	0.043	0.041
J_α α=**0.5**	0.047	0.026	0.084	0.080
J_α α=**1**	0.090	0.050	0.158	0.152
J_α α=**2**	0.167	0.100	0.283	0.279
J_α α=**5**	0.341	0.214	0.527	0.546
J_α α=**10**	0.519	0.360	0.720	0.776

Table 3 Distributional Discrimination Index: White and Non-white Groups

	Total	Natives	Migrants
Df	12.450	3.327	11.566
C	0.048	0.023	0.041
J_α α=**0.25**	0.032	0.021	0.032
J_α α=**0.5**	0.062	0.042	0.062
J_α α=**1**	0.117	0.081	0.118
J_α α=**2**	0.213	0.152	0.213
J_α α=**5**	0.415	0.320	0.410
J_α α=**10**	0.601	0.500	0.587

The time pattern of discrimination

In this section we briefly consider the evolution of discrimination indices over the 1974-1993 period. We estimate the earnings functions for each year of the GHS sample for each year and graph the J index for $\alpha = 1$ in Figure 2A comparing total natives with total migrants as well as making the same comparison for the whites and non-whites. Consistent with Table 2 and Table 3 we find positive levels of discrimination with a much higher level against non-whites in all but one year. Figure 2B plots the same discrimination index for non-whites versus whites within the whole sample. This backs up the story in Figure 2A: when we distinguish between natives and migrants there is very little difference, the three lines move together, except for the years 1976-1978.[5] In general it is difficult to detect a time pattern in the discrimination indices, apart from a slight upward tendency over the latter part of the period. This also holds if we plot the D_f or C indices over time where the increase is more pronounced. Indeed the stability of the measures is rather striking considering the changes in the British labour market throughout the 1980's. One might expect the large fluctuations in unemployment and an increasingly de-regulated and less unionised labour market to have had some influence on the level of discrimination, although economic theory provides few, if any, predictions as to the effect on discrimination. Moreover there has been an increase in income inequality over the 1980's so one might expect that to have had some impact.[6] If so, it is not apparent.

To test this more formally we regressed our time series measures of discrimination against a number of indicators of aggregate activity including unemployment, GDP and inflation[7]. In general no robust results emerge although there is weak evidence of a negative effect of unemployment on some of the discrimination measures.

Figure 2A Native-Migrant 'J' Discrimination Index (α = 1)

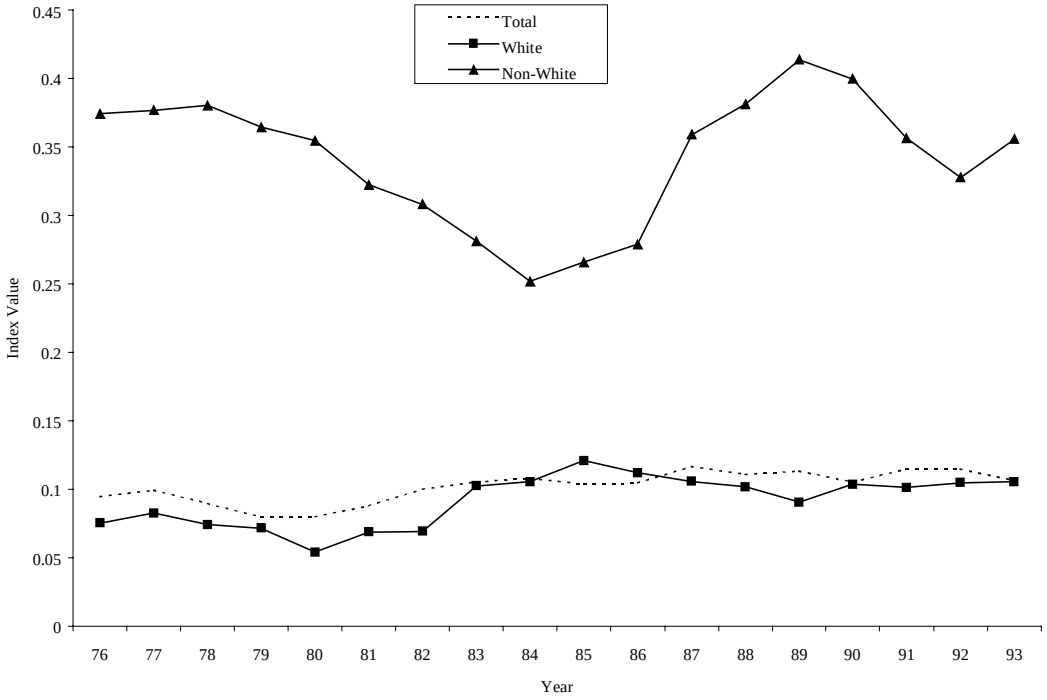
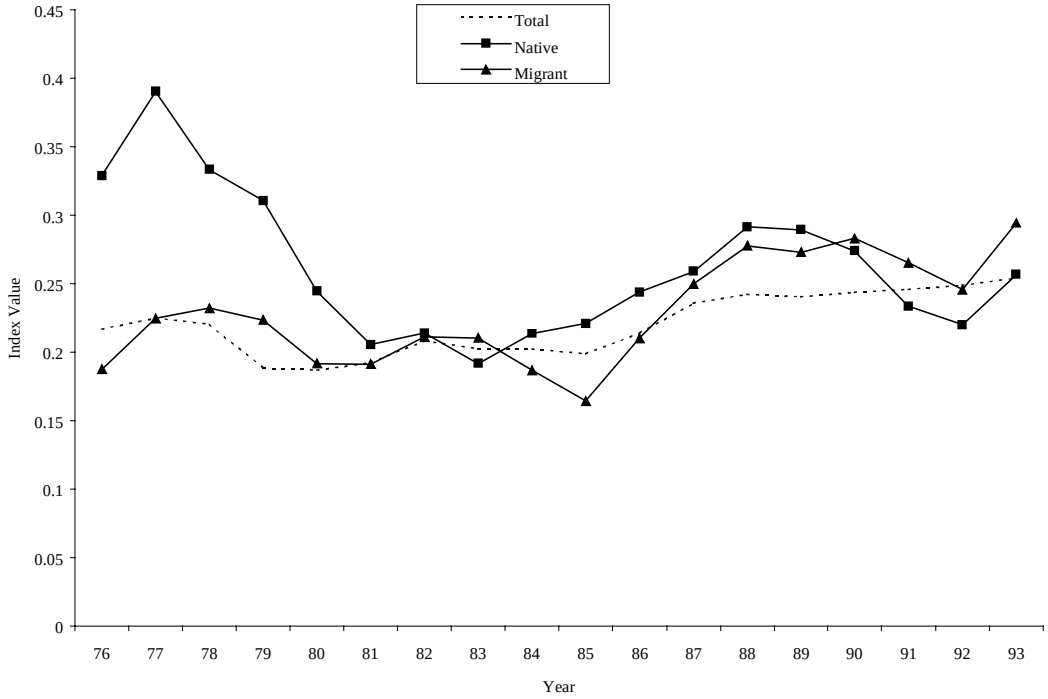


Figure 2B White-NonWhite 'J' Discrimination Index (α = 1)



III DISCUSSION

There are many other aspects to the study of discrimination, which we have not explored. Firstly, race is literally and figuratively not a black and white distinction. We have for example eschewed distinguishing between Asian, African and Caribbean immigrants although there is considerable research in the sociology literature which suggests that this distinction is important. These differences arise not just because there may be intrinsic differences between the ethnic groups but also because they will have arrived at different times reflecting changes in both the economic circumstances of the receiving and sender country and changes in immigration policy[8]. We have also assumed that the distinction between migrant and native is clear cut: however the process of assimilation may mean that long term migrants have more in common with natives than with recently arrived migrants. The role of assimilation has been widely studied by sociologists but less so by economists[9].

As pointed out by Stewart (1983) research such as this considers only discrimination within the labour market; in particular it takes characteristics of individuals such as education as exogenous and identifies discrimination as arising for differences in the returns to these characteristics. If, for example, the return to schooling for a particular group is low then we might expect them to respond by participating relatively less. There is evidence that schooling is endogenous and that controlling for this using instrumental variables procedures affects the estimated return. [10] However finding a suitable instrument for both native and migrant groupings in this instance is problematic. So we do not study discrimination which may influence access to education or employment status itself.

The interpretation of differences in returns across demographic groups as discrimination is, of course, debatable. The estimates of the returns are conditional on the specification of the equations and holding other things equal. We have controlled for education in the standard way

(years of schooling) but it is possible that the quality of schooling differs between migrants or natives or that employers *perceive* this to be the case. There is some evidence that the human capital of immigrants is "less portable"[11]. It may be possible to get further evidence on the extent to which discrimination is colour based by distinguishing between first generation migrants (those who actually migrate) and second generation migrants (their off-spring, born after migration occurred) since any disadvantage arising from migrants status *per se* should not apply to the second generation.

Finally we have not attempted to deal with sample selection issues which could arise if the nature of migration to Britain was non random. It is difficult to see how one could implement any correction for this potential problem given that we are unable to model structurally the migration process, as no information as to the reasons for migration is in the dataset. However evidence for the United States shows that variations in the decision to migrate are attributable to economic and political circumstances in the home countries and that this affects the labour market "quality" of immigrants.[12]

IV CONCLUSIONS

This paper applies the methods of Jenkins (1994) to examine the issue of discrimination against migrants in the UK labour market. The innovation of this approach is that it changes the focus away from simply looking at the average level of discrimination and considers the entire distribution of wage discrimination.

Using GHS data pooled over the years 1974-1993 our findings support recent research on the UK labour market experiences of migrant workers and suggest that the discrimination present may be racial rather than due to migrant status alone. Across the broad migrant/native split the migrant sample appear discriminated against, but comparing white native to white migrant does not support any strong presence of discrimination practices. However

examination of the data for non-white migrants shows clear adverse differences for this sample against white natives and even against non-white natives.

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Notes

[1] If $\log(y) = \mathbf{X\beta} + u, u \sim N(0, \sigma^2)$ then $E(y) = \exp(\mathbf{X\beta} + \sigma^2/2)$. Our thanks to Steve Jenkins for this point.

[2] This decomposition is not pursued here in the present paper.

[3] Full summary statistics and estimates are available from the authors on request. See studies such as Blanchflower and Oswald (1995) for more detailed descriptions of the GHS dataset.

[4] See Goyder(1987). This happens because they are likely to be more "footloose" .

[5] Both graphs are 3 year moving averages.

[6] See, for example, Goodman and Webb(1994).

[7] This method was used by Nolan(1988/89) to investigate macroeconomic patterns in aggregate inequality in the UK.

[8] For example Heath and McMahon(1997a, 1997b) for the UK, Farley(1990) or Treiman and Lee(1996) for American evidence.

[9] But see Borjas(1995) for the US and Bell(1997) for Britain.

[10] See, for example, Harmon and Walker (1996) for consideration of the issue of endogenous schooling in the GHS data.

[11] See Friedberg(1996).

[12] See Borjas(1987).