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COBUS BURGER AND SERVAAS VAN DER BERG

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COBUS BURGER
DEPARTMENT OF ECONOMICS
UNIVERSITY OF STELLENBOSCH
PRIVATE BAG X1, 7602
MATIELAND, SOUTH AFRICA
E-MAIL: COBUSBURGER@SUN.AC.ZA

SERVAAS VAN DER BERG
DEPARTMENT OF ECONOMICS
UNIVERSITY OF STELLENBOSCH
PRIVATE BAG X1, 7602
MATIELAND, SOUTH AFRICA
E-MAIL: SVDB@SUN.AC.ZA

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Modelling cognitive skills, ability and school quality to explain labour market earnings differentials[1]

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ABSTRACT

Attempts to explain wage differences between race groups in South Africa are constrained by the fact that quality of education is known to differ greatly between groups, thus the unexplained portion of the wage gap may be much affected by such differences in education quality. Using a simulation model that utilises school-leaving (matric) examination results and educational attainment levels to generate estimates of education quality, we find that much of the wage gap can indeed be explained by differences in education quality. Thus the unexplained residual, often identified with labour market discrimination, usually greatly over-estimates such discrimination. This emphasises even more strongly the need for greater equity in educational outcomes, particularly in the often unobserved quality of education.

Keywords: South Africa, education quality, wages, labour market, Oaxaca-Blinder decomposition, discrimination, economics of education
JEL codes: J7, J24, J31

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1. Introduction

Racial differentials in labour market outcomes (employment and wages) in South Africa have remained stubbornly large after the advent of democracy (Burger & Jafta 2006). To measure whether these gaps in earnings between population groups are warranted by productivity-related attributes, economists often compare the level of education and experience among the labour force participants. However, educational quality differs widely across race groups. In terms of outcomes, the South African school system performs much the same as during apartheid, with most historically black schools (despite vast improvements in resources) still performing abysmally in terms of cognitive outcomes and most historically white schools (despite significantly reduced funding and now also containing many black children) largely performing as successfully as in the past (Van der Berg and Burger, 2003). Given these differences in the quality of school education between groups, it is doubtful whether a year of schooling in a former white school and in a former black school will bring about the same cognitive gains and hence gains in productivity. Failing to control for these difference in educational quality introduces a bias to decompositions of wage estimates.

This paper attempts to correct for this disparity between white and black schools by utilising simulations based on the results of the 2003 matric exams, a nationwide test that is administered in the last year of formal schooling, and educational attainment data. Using this method we find that differences in schooling quality explain away almost half of the hitherto unexplained part of the wage gap found in conventional models. The fact that this unexplained component – often interpreted as labour market discrimination – is thus reduced does not change the fact that coloured and black workers still earn disproportionately less than their white counterparts. It simply shows that some of the racial discrepancies – and perhaps discrimination – mistakenly attributed to the labour market actually originate at school level, where black and coloured learners are generally still being equipped with far fewer skill and abilities than their white and Indian counterparts.

2. Existing Evidence

Several studies have attempted to quantify the degree of racial discrimination present within the South African labour market. Most decompose the mean wage differential in the model in a counterfactual manner, enabling one to see what part of it can be "explained" by differences in productive characteristics (education and experience) and what part cannot. The latter, the "unexplained" residual term, is then used as a measure for the extent of discrimination possibly present in the labour market, i.e. as an upper bound to discrimination. The most popular of these techniques was proposed by Blinder (1973) and Oaxaca (1973) and will be introduced in the following section.

Using 1993 data, Mwabu and Shultz (1998) attributed almost half of the difference in the log of wages in South Africa to differences in years of education between whites and others in their sample. Their results showed that level of education (educational attainment) explained 52 percent of the wage gap between black and white men and 56 percent of the wage gap between black and white women. Interestingly, they also found that despite the lower quality of education for blacks, the relative gains attributed to a further year of schooling were higher for blacks than for whites.

A comparable study by Rospabé (2002) measured the extent of employment, occupational and earnings discrimination by comparing the characteristics and employment outcomes of a black and white sample of labour market participants for 1993 and 1999. Depending on the type of inequality being measured, she found that between 60 and 70 percent of the racial gap could be explained by differences in observed characteristics, while the residual 30 to 40 percent of the gap was due to discrimination, unobserved traits or a combination of the two. Throughout it appears as if this unexplained residual, taken to be discrimination, had decreased over this interval.

Burger and Jafta (2006) analysed the discrimination faced by all four race groups in three different labour market outcomes (employment, occupation and wage) for every year from 1995 to 2004. Their results confirmed that labour market change had been slow, with little change in the level of discrimination over time. This upper-bound estimate of the level of discrimination ranged between 15 and 30 percent, depending on what outcome measure and group one measured it for. Although we recognise that the term "discrimination" for this unexplained residual is not accurate, we shall follow convention in much of the literature by calling it by that term, though qualifying it from time to time.

Using 1994 data, Kingdon and Knight (2001a) found a 35 percentage point gap between the likelihood of black and white unemployment. They proceed to decompose this gap using the Gomulka and Stern (1990) method, an adaptation of the Oaxaca-Blinder method, and found that, once they controlled for employment-enhancing characteristics, the model was able to explain 14 percentage points (40% percent) of the employment probability differential. Thus, the remaining 21 percentage points (60%) were unexplained and could thus potentially be due to racial discrimination. In another paper by the same authors (Kingdon and Knight, 2004), they attributed roughly 75 percent of the employment gap between blacks and whites to differences in the productive characteristics between these two groups. The remaining 25 percent was left unexplained. As with the other papers, the authors were hesitant to attribute the remaining 25 percent to employer discrimination, since they recognised that a large section of the residual could be due to unobserved differences in schooling quality between blacks and whites. In another paper they had warned that "*racial differences in education and location do not explain the whole of the black-white gap in unemployment incidence. The unexplained part of the racial gap may well be due to prelabour market discrimination in the schooling system rather than due to employer discrimination in the labour market*" (Kingdon & Knight, 2001b: 15)

Case and Deaton (1999) and Case and Yogo (1999) attempted to control for the effect that quality may have on school-level outcomes and earning by including the pupil-teacher-ratio of magisterial districts in their respective models. They found that learners in schools with more favourable pupil-teacher ratios stayed in school longer, did better in tests and earned more in the labour market. The use of pupil-teacher ratios as measure of school quality is, however, problematic, considering what international studies have shown about the weak translation of school inputs into cognitive outcomes. In South Africa, too, the increase in teacher resources in formerly disadvantaged schools after 1994 did not bring about the expected improvements in educational outcomes (Van der Berg: 2001).

The 2007 Community Survey provides some evidence of the impact of education quality on employment. The survey provides information on three broad categories of Matric (Grade 12) exam achievement, namely: attempted and failed Matric; passed Matric; and passed Matric with university exemption or endorsement (a measure of quality that indicates the candidate could continue to university studies). Focusing on black workers only so as not to conflate the effects of race and education quality, the survey shows that those who had attempted but failed Matric faced an unemployment rate of almost 48%. In contrast, those who had passed Matric but failed to obtain university exemption had a lower unemployment rate of 42%. In comparison, pupils who passed Matric with a university exemption (but did not continue to further studies) had a considerably lower unemployment rate of 36%.

Performance in the Matric exam (based on these categories) also affected wages earned for those who did find employment: Those black workers who had no higher qualifications than matric but who indicated that they had achieved a university exemption in matric received wages almost twice as high as those who had failed matric (94% higher), and almost a third (30%) higher than those who had passed matric but did so without university exemption. Clearly, the quality of the matric counted. Analysis for other race groups showed similar, though somewhat more muted, effects of the quality of matric results on both employment and earnings.

In an exploratory study, Chamberlain and Van der Berg (2002) tried to overcome the shortcomings of earnings function models that ignored school quality by experimenting with a whole range of weights. They tested what the effect of education quality might have been on labour market outcomes if a year of black education was worth less than a year of white education. Using such a sensitivity testing approach, they showed that education quality probably accounted for a large portion of the disparity between employment likelihoods and expected wages. Although this paper gives an indication regarding the *direction* of the bias in current models, it still could not establish the *size* of this bias in the absence of a valid measure of education quality. In the following section we try to construct such a measure using actual South African school data.

3. Data and Methodology

Measuring Discrimination

The most popular method for measuring the degree of discrimination in labour market outcomes between two groups is the one popularised by Blinder (1973) and Oaxaca (1973). As discussed above, using this technique one is able to decompose the mean wage differential in the model in a counterfactual manner a to ascertain the size of the two separate components: an explained component (i.e. a component that can be explained by differences in productive characteristics) and an unexplained component (i.e. a component that arises from discrimination or differences in how the same productive characteristics are remunerated across groups).

The decomposition starts off with an Ordinary Least Squares (OLS) wage regression

$$y_{it} = b_t x_{it} + u_{it} \qquad \textbf{(1)}$$

where y_{it} is the log of the hourly wage of individual i belonging to group t, x_{it} is a vector of productive characteristics, b_t is vector of parameters and u_{it} is an error term (Oaxaca, 1973). Thus, the sample average outcome y_{it} for group t is

$$\bar{y}_t = \bar{x_t} b_t \;, \quad \text{where} \quad \bar{y}_t = \sum y_{it} \text{ and } \bar{x_t} = \sum x_{it}. \quad \textbf{(2)}$$

Equation 3 below estimates the outcome for individuals belonging to group n:

$$y_{in} = b_t x_{in} + u_{in} \quad \textbf{(3)}$$

where y_{in} is the log of the hourly wage of individual i belonging to group n , x_{in} is a vector of productive characteristics, b_n is vector of parameters and u_{in} is an error term. The mean outcome y is therefore

$$\bar{y}_n = \bar{x}_n b_n \;, \quad \text{where} \quad \bar{y}_n = \sum y_{in} \quad \text{and} \quad \bar{x}_n = \sum x_{in} \quad \textbf{(4)}$$

The difference between the mean outcomes for group t and group n is thus

$$\bar{y}_t - \bar{y}_n = \bar{x}_t (b_t - b_n) + b_n(\bar{x}_t - \bar{x}_n) \quad \textbf{(5)}$$

where the difference in wages resulting from differences in the way in which productive characteristics are remunerated between group t and group n is represented by $\bar{x}_t (b_t - b_n)$ and is referred to as the “unexplained” component, and difference in wages resulting from differences in the productive characteristics between group t and group n are represented by $b_n(\bar{x}_t - \bar{x}_n)$ and are referred to as the “explained” component (Oaxaca, 1973).

All labour market analysis in this paper uses the nationally representative September 2007 Labour Force Survey dataset, taking its survey design into account. Using this data, wage earnings were derived by dividing earnings by total hours worked. These wage earnings values were then logged to derive the log wage earnings, our variable of interest. The years of education index was derived by allocating one year to each grade attained of normal schooling and estimating the equivalent years required to complete other degrees or certificates. Diplomas or certificates following upon Matric were set to 13 years of education, Bachelor's degrees to 15, and Master's degrees to 17.

4. The Conventional Model

Using the Oaxaca-Blinder approach, the magnitude of discrimination within the current job market for young employed individuals was tested by comparing the wages earned between different race groups over three different age-cohorts, viz. 20-24, 25-29 and 30-34. Since experience is defined in terms of age, these narrow cohorts have the added benefit of lessening the role of experience on our results.

In our first model, wages were regressed on education and potential experience – a simple Mincerian function. This simple model did not control for some basic explanatory variables found in many Mincerian earnings functions, such as unionisation, industry, sector, province and gender. Neal and Johnson (1996) argue that including these might distort estimates of the full effect of race on wages, since these variables may reflect *responses* to labour market discrimination. As a result, they argue that models which include these variables fail to capture the 'full effect' of race discrimination, since some of the effect is lost through the correlation with these variables. The simpler model was thus used in an effort to isolate the channels through which education quality influences earnings.

The expected earnings gap between whites and other population groups were measured and decomposed for the three different age cohorts. The results can be viewed in the Appendix (Table A4, A7 and A10 respectively). Education together with experience explained between 30 and 50 percent of the log wage differential, depending on which racial groups and age cohorts were considered. The remaining 50 to 70 of the wage gap is left unexplained, and this has traditionally been referred to as discrimination. We return to some of the results later after expanding the model by adding education quality.

Since the current models make no distinction between a year of schooling achieved by members of different groups, they implicitly assume that schooling quality is identical across race groups. Assuming education quality to be similar across groups is a heroic assumption, but it is nevertheless often implicitly made because of the lack of a reliable indicator of the quality of education of different groups. However given the unequal distribution of school resources under apartheid and the large and systematic differences across the school system in educational quality (as measured by cognitive skills and shown by international and national tests), this assumption is unlikely to be a sound one. School surveys show that black pupils tend to receive an education of a lower quality than white pupils and therefore the omission of quality would overestimate the size of the unexplained residual. The next sections apply a methodology that allows us to relax this assumption that school quality is identical across race groups.

5. Modelling School Quality

In the following section a cognitive performance measure is constructed to control for the level of disparity in school quality and home background between members of different race groups. Despite being recognised as a crucial determinant of labour market earnings, the school quality measure is often omitted from conventional models due to the lack of information and difficulty of generating reliable estimates.

The school quality measure constructed here is an index that provides an indication of the expected matric results students would be likely to obtain (or would have obtained had they not dropped out prior to grade 12), given their race and years of educational attainment. It is thus one measure of productive characteristics one is likely to posses in the labour market. Although correlated with an individual's innate ability, it is also likely to be influenced by other factors such as home background, school quality, motivation, etc. It is thus in some sense a concept closer to "manifest ability" rather than "innate ability", in the sense that Hansen, Heckman & Mullen (2004) use these terms. These authors (2004: 39) point to "*two widely held and mutually inconsistent conceptions of* *ability and scholastic achievement tests*", viz. one that sees these tests as simply reflecting innate ability that remains roughly fixed from about age 8, while the second considers test results as being much influenced by schooling. The rest of this section introduces and discusses our measure and proceeds to calculate estimates.

Matric Scores

A dataset containing the marks of all pupils who wrote matric in November 2003 was used to derive a racially unbiased approximation of the skills obtained by individuals in the schooling system. The distribution of marks for each race is shown below.

Figure 1: Kernel-density curves of matric aggregates by race

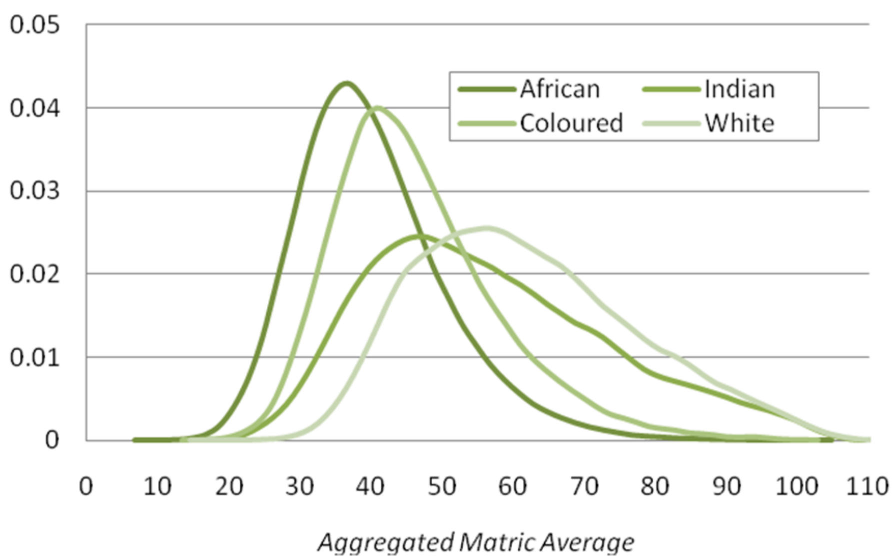

Table 1: Matric results by race

	n	Mean	std dev	Minimum	Maximum
Black	340832	40.2	10.5	7.5	104.0
Coloured	31843	46.4	11.7	14.6	101.7
Indian / Asian	16868	56.7	16.9	16.8	107.1
White	46434	61.9	15.3	16.2	111.0
Other	3909	54.5	15.7	18.8	109.1
Total	440396	43.7	13.6	7.5	111.0

Figure 1 and Table 1 show the large differences in matric results across race groups. Although these descriptive summaries provide some indication of the magnitude of the quality gap between different race groups at the end of grade 12, they do not provide any information about the quality gap at educational levels prior to and beyond this point. Furthermore, matric scores were not a fair reflection of differences in cognitive performance, since the proportion of drop outs in and the mechanisms and signals governing drop out and continuation in school differ substantially by race. The sub-sample of students in each race group who made it to matric and were able to sit the exams is likely to be dissimilar to the group who did not make it to matric, but there are also important differences in this relationship across races. This applied especially for the black and coloured sample, as roughly 46 percent of coloureds and 43 percent of blacks in the relevant age cohorts dropped out before grade 12. Ignoring these students who dropped out of school is likely to bias estimates. If failure and grade repetition were indeed major causes for discontinuing one's education (Motala, 1992), students that ended up dropping out was likely to have performed weaker than their classmates. Consequently, using average matric marks over different race groups leads one to underestimate differences in educational quality.

Therefore, an alternative approach was adopted: starting off with an underlying distribution of expected future matric[2] results for an entire race cohort (which includes all future dropouts), one would expect it to look similar to the distributions found above in Figure 1. Given these underlying distributions, the model ran the larger sample of students through a fictional education attainment process, stretching from grade 1 to 12. At each grade a portion of the sample was assumed to drop out. Finally, the distribution

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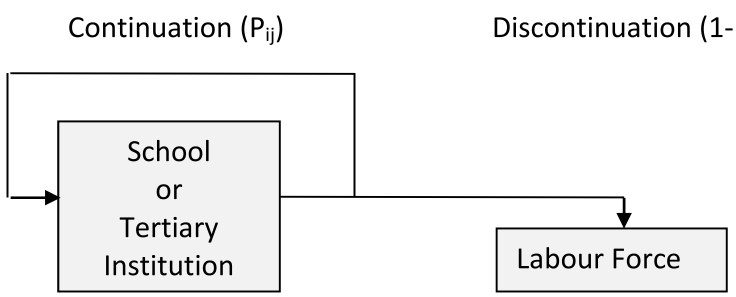
[2] *Factors such as innate ability, persistence, socio-economic status, quality of schooling, etc. all could have played a role, but were not modelled explicitly.*

of matric scores of those students that remained still in our constructed sample in matric was compared to the actual matric scores observed for 2003 to assess what initial estimate of the distribution of cognitive ability fared best.

Modelling the Education Attainment Process

Data from the LFS datasets from 2004 to 2008[3] were used to obtain education attainment figures for the age cohorts concerned (see Figures A1 in the Appendix). These figures, which denote the likelihood of staying in school by grade, were introduced into a Markov-Chain-like model that simulated the education attainment process. This is illustrated in Figure 2 below.

Figure 2: Simulation of choice faced at end of each grade



If the decision whether to stay in school or not was not correlated with students characteristics, then the likelihood of continuation, P_{ij}, would have been the same for all students at each grade, since $P_{ij} = \frac{\text{Number of individuals with at least grade i}}{\text{Number of individuals with at least grade i}-1}$. But students who performed worse were more likely to drop out of school. Consequently, the

[3] The pooled dataset delivered more reliable estimates of educational attainment for the smaller race groups within the age cohorts considered. Note, as indicated above, that in this study all tertiary qualifications that did not culminate in a university degree were considered to be 13 years of attainment.

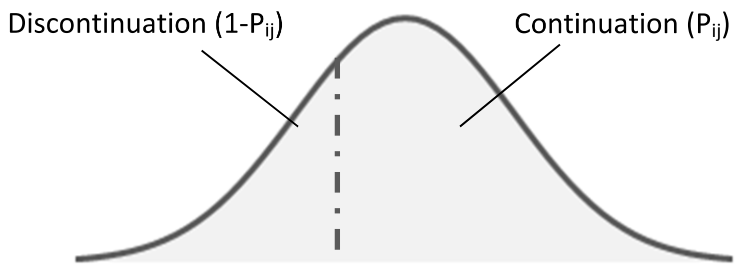
continuation likelihood will be lower for weaker performing students and higher for better performing ones.

Conceptually, this would be similar to letting all students write a test at the end of each grade. If the results attained for this test are correlated with the true matric score, students are likely to use these marks to guide their expectation of future exam scores and their decisions on whether or not to continue their schooling.

Modelling Survival Bias

Intuitively, one would expect students at the lower end of the distribution in grade exams to drop out and students at the top of the distribution to progress. In its simplest form the distribution can be depicted as in the figure below: all the students below a certain threshold drop out, while all those above it stay in school. This threshold can then be adjusted until the proportion of students who fail agrees with the observed proportion in the labour force data.

Figure 3: Simulated distribution of marks in grade tests



However, the cut-off between students who drop out and those who remain in school is unlikely to be this clear and 'clean'. Imperfect information and differences in the way students discount their future achievement may distort the results. It is also unlikely that the grade tests would be perfectly correlated with the final matric scores. As a result, a model which allows for differences between the expected matric score obtained by students and their actual score attained in lower grades was constructed. The model, shown below, allows for these distortionary effects by adding a "noise term" to the equation.

$$realised\ score = expected\ score\ + e$$

where $expected\ score$ has mean μ_a and variance δ_a^2 and e has mean μ_e and variance δ_e^2 .

In short, the score a learner obtains at any period is the sum of two components: the expected score and an error component. The variance within the error component will determine the extent to which the results of these repeated tests are likely to differ from one another and from the final matric exam. In this original model δ_e^2 is allowed to vary in such a way as to maintain a correlation of 0.75. The choice of this seemingly arbitrary value will be made clear later when we discuss the correlation among tests.

Building on the assumption that students face an implicit test at the end of each grade, it can be shown that the test scores achieved for these annual grade tests provide students with an unbiased ($\mathrm{E}[\mu_e] = 0$) estimate of their future expected matric scores. Consequently, it seems plausible that students might use these results in guiding their decision regarding whether or not to stay on in school.

Similarly, a bias might exist regarding the choice of continued studies after high school. Our dataset does not provide any data regarding the likelihood of specific students continuing their studies beyond matric. Academic results are hardly the only barrier that prevent student from furthering their studies. Other constraints include the attractiveness of immediately joining the labour market and the high costs associated with tertiary education. However, grade 12 scores will still be highly correlated with tertiary enrolment, both because universities and other tertiary institutions use matric marks to determine eligibility for further studies and because scholarships or loans for further studies are often contingent on matric performance.

Simulations

In order to estimate the true parameters of the sample as a whole, the error component and the true cognitive ability score (and thus also the achieved score) were assumed to be normally distributed. Using Monte-Carlo-like simulations, a range of values for the underlying population parameters (μ_a and δ_a^2) were tested in order to find the set of parameters that most often produced results that best fitted the true 2003 matric results for each race. Applying a simple grid search method, numerous values were tested. The set of parameters that came out best are contained in the table below. Table A1 (in the Appendix) shows how closely these values obtained from these underlying populations resembled that of the true population.

Table 2: Estimated parameters for the entire age-cohort

	$\widehat{\mu_a}$	$\hat{\delta}_a$
Black	35.46	8.82
Coloured	40.16	9.83
Indian	53.40	14.33
White	59.04	12.3

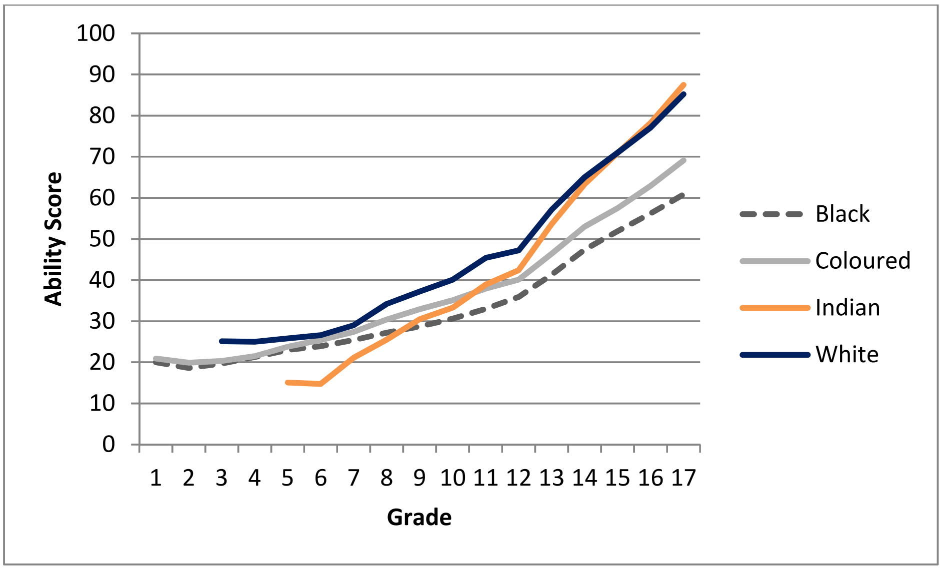
Considering the entire age-cohort (including dropouts), the expected mean aggregate matric results were the lowest for blacks, followed closely by the coloured population, with values of 35 and 40 respectively. Results for Indians and whites were considerably higher, with a mean of 53 and 59 respectively. The standard errors followed a similar trend to that of the means, increasing as the mean increases, although the standard error for the coloured sample was much higher than that of the black sample.

The Homogenous Index

The model explained above was used to gauge the average productive capacity of each student across race groups by disaggregating their expected scores by grade. Figure A2 (appendix) displays the distribution of potential matric scores for each grade for our black sample at each level of educational attainment. A similar process was applied to the other race groups. The average matric scores expected for each grade is presented in Table A2 in the Appendix, and illustrated in Figure 4 below.

For lower grades the expected cognitive scores were highest for black students. Although this may seem counterintuitive at first, reflection shows that this makes good sense. A much larger section of the black population fell within this part of the sample than was the case for any other race (as Figure A1 suggests). As a result, it contained a smaller part of the tail or extreme values than was the case with the Indian and white samples. Also, amongst whites, those who did not achieve higher levels of education were a far greater adversely selected group.

Figure 4: Average expected matric scores for each race group at each grade attainment level



Apart from the Indian curves, the other three race groups' estimated scores initially started relatively close together at the start of primary school and then gradually separated as grade 11 was approached.[4] From grade 12 onwards there was a visible increase in the dispersion of the average matric scores at each grade. At the higher end of the grade distribution, the expected score for each grade followed the usual ordering, with those of whites and Indians being highest (and almost identical) followed by the scores of the coloured students. Black scores were the lowest.

[4] *Note that if we compare Table A1 and A2 in the Appendix we find that the expected matric result for students with grade 11 only is higher than the realised scores in our simulation. This is not an error. Although we are dealing with the same sample of students, their average estimated matric scores and those they attained on the matric run is bound to differ due to the error term in our model. It is likely that the sample might contain some students who on average would achieve a passing grade, but did not do so on the grade 12 run and therefore had Grade 11 as their highest attainment level. If this group of students who failed matric were to write it again, they would be expected to perform better.*

The Heterogeneous Index

Thus far it has been assumed that the error component in the model was unaffected by a pupil's grade or school. According to Lam, Ardington & Leibbrandt (forthcoming), however, this assumption of homogeneity need not necessarily hold true. Using data from the Cape Area Panel Study, they showed that results obtained by students attending black schools tended to be much 'noisier' than those of students attending coloured (and presumably also white and Indian) schools. This was demonstrated by comparing the literacy and numeracy evaluation (LNE) (administered to all youths in the sample during its first wave) with the attainment of grades over the following four years. The effect of these scores on grade attainment differed substantially between the black and coloured samples. For the black sample, the marginal impact of the LNE score on the probability of passing was small and often insignificant for grade 9, 10 and 11, but large and significant for the standardised grade 12 exam and between 3 and 6 times larger than it was for the earlier grades. This stands in stark contrast to the coloured sample, for which the effect of LNE scores did not differ substantially between grade 9, 10 and 11 and the subsequent standardised grade 12 exam. The poor link between LNE and grade attainment that blacks face during earlier grades of high school is indicative of a system where there is "*a weak link between learning and evaluation for blacks in grades prior to grade 12*" (Lam, Ardington & Leibbrandt, forthcoming).

Even more concerning, it appears from their study that the LNE test provided students with a better indication of future grade 12 achievements than did regular grade 11 exams – despite numerous shortcoming of the LNE tests, including that it was very short (it took only 20 minutes to administer) and was usually conducted a number of years before grade 12. The weak feedback signals that students received with regard to their progression through the schooling system may seriously limit their ability to make informed decisions regarding whether to stay in school or not. This may explain why black students were less likely to drop out of school than coloured students, despite performing weaker.

In an attempt to more closely quantify the size of this ‘noise’ component in the underlying model, results from the 2005 externally assessed matric examinations and the associated continuous assessments (CASS), set and marked within schools, were compared. (These have been more fully discussed in Van der Berg & Shepherd 2010.) It was assumed that schools where continuous assessments results were similar to the external exam results provided students with a fairly accurate idea of how well they were expected to do in the exams. On the other hand, if these scores differed substantially, testing within those schools was uninformative.

The following table shows the average correlation coefficients between the continued assessment marks and the final exam marks. The results were disaggregated by subject (only for subjects taken by more than 40 000 students) and race.

The table shows that the correlation between the school level assessment and assessment at the national level differed considerably between race groups. For all subjects except History, black students had the lowest correlation between school level assessment and assessment at a national level. Similarly, the correlation between coloured students’ marks was consistently lower than that for both Indian and white students. The variation in continued assessment results and the final matric exam marks between Indian and white students appeared to be fairly similar. Although Table 5 confirms Lam et al.’s assessment regarding the performance of black schools relative to coloured schools, it also indicates that continuous assessment results in coloured schools may also be considered quite ‘noisy’.

Table 3: Correlation between continuous assessment marks and final exam marks within race groups

	Black	Coloured	Indian	White
Non-Language Subjects				
Biology	0.54	0.61	0.79	0.77
Mathematics	0.73	0.81	0.85	0.84
Geography	0.49	0.60	0.70	0.67
Business economics	0.54	0.55	0.67	0.70
Physical science	0.57	0.71	0.77	0.79
Accounting	0.62	0.75	0.82	0.81
Economics	0.44	0.51	0.57	0.61
History	0.51	0.49	0.59	0.69
Agricultural science	0.51	0.68	..	0.73
Language Subjects				
Afrikaans 1st language	0.67	0.62	0.72	0.78
Afrikaans 2nd language	0.60	0.77	..	0.85
English 1st language	0.65	0.72	0.77	0.75
English 2nd language	0.63	0.69	..	0.77
Isixhosa 1st language	0.51	..	..	..
Isizulu 1st language	0.53	..	..	..
Sepedi 1st language	0.49	..	..	..
Sesotho 1st language	0.44	..	..	..
Setswana 1st language	0.58	..	..	..
Non-Language Subjects	0.53	0.62	0.73	0.71
Language Subjects	0.56	0.70	0.75	0.79

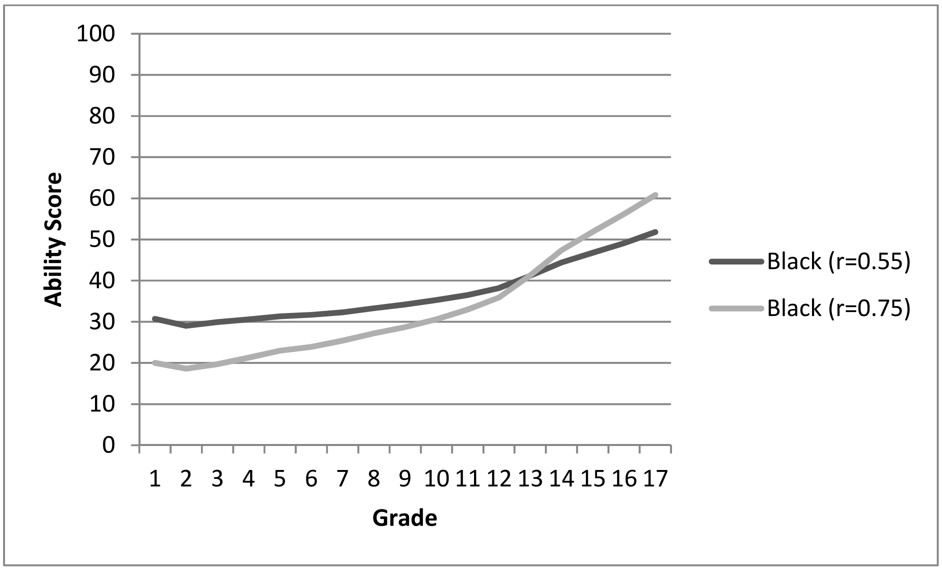
Note: Coefficient only reported if at least 100 students in the race group took the subject

In the 'homogenous model' used thus far, a 75% level of accuracy (correlation between actual cognitive skills and assessment of cognitive skills for grade progression) was assumed to apply within each race group, i.e. it was implicitly assumed that 'noise' did not differ systematically across Indian, white, black and coloured schools. This does not appear appropriate for predominantly coloured and black schools, where the correlation appeared to be around 65% and 55%, respectively. As a result, the model was re-specified with the degree of correlation being allowed to differ. We refer to this as the *heterogeneous model*, where the heterogeneity lies in the different correlations assumed between marks in the externally assessed matric and those in the school-based grade tests.

For both the coloured and black sample, an increase in the estimated mean and a subsequent decrease in the standard error of the underlying parameter of the population distributions were observed within the re-specified models. In the initial model the black population had a mean of 35.5 and a standard error of 8.8, but in the re-specified model the group mean was 37.9, with a standard error of 5.8. Similarly, the coloured sample's mean increased from 40.2 to 41.4, while the standard error declined by 2 points to 7.8.

The effect of the re-specification can be seen more clearly in Figure 5 below. It shows the difference in the expected matric score for blacks at each grade before and after the re-specification. Figure A3 in the Appendix shows the difference in the matric score for coloured learners before and after re-specification.

Figure 5: Average expected matric scores for blacks for homogenous and heterogenous models



An increase in the noise component would make it more difficult for students to assess their true future matric scores, resulting in a greater dropout among relatively good students at early grades and a lower expected mean score among those that remained in the education system. Figure 5 confirms this interpretation. The two curves pivot around the same point at grade 12 – the one point at which the simulated data touches the true dataset.

There is one other option that should also be considered: The models specified here assume that the racial differences in the quality of primary and secondary schooling are maintained at higher education levels. However, an argument can be made that this would exaggerate what is likely to occur in tertiary studies, where all students first have had to pass the criteria for endorsement set in the matric exam, and are then subject to similar learning processes often in the same tertiary institutions. Thus a third model, based on the heterogeneous one, would allow for a narrowing of the race gap in steps until it is completely eliminated at the level of master's degree studies. Although such estimates were derived and tested, the final models did not differ all that much from those obtained in the heterogeneous model, thus they will not be reported here.

6. Comparing our cognitive skills estimates to alternative estimates

There have been few studies that directly allow for a comparison of their results to those obtained here. Moses (2011) provides an overview of these as well as of the literature on the effect of education quality on economic outcomes. Moll (1998) used the test data linked to the 1993 PSLSD survey to investigate the link between education, cognitive skills and wages, focusing largely on the black population. Table 4 shows scores out of 14 literacy questions by race and broad schooling category for adults aged 18 to 59. As can be observed, there were large differences in scores between members of different population groups within the same broad educational attainment categories. Though some of the sample sizes were small and therefore not all the results should be interpreted too finely, the extremely weak performance of the black population, for whom sample size was not an issue, is clear. Even black people who were matriculated and had a degree still barely passed the test, while there were large differences between race groups for the bulk of those sampled, viz. those with incomplete secondary education.

Table 4: Mean test scores (out of 14) by educational level and race, adults 18-59 years

	No schooling-Gr.6	Gr.7-11	Gr.12 and tertiary
Blacks	**3.1**	**5.7**	**7.5**
(s.e. of mean); N	(0.1); 470	(0.1); 768	(0.2); 109
Indians	9.5	**10.0**	10.7
(s.e. of mean); N	(1.5); 2	(0.7); 27	(0.6); 15
Coloureds	5.2	**8.2**	10.9
(s.e. of mean); N	(1.2); 12	(0.5); 37	(1.1); 7
Whites	9.4	**9.0**	**11.3**
(s.e. of mean); N	(1.3); 10	(0.4); 48	(0.3); 41

Note: Estimates based on at least 20 observations in bold faced font
Source: Moll (1998: 273, Table 2.)

Fuller, Pillay & Sirur (1995) also investigated this same dataset, with a focus also on the black population. A summary of the test results by race is presented in Table 5. Van der Berg, Wood 7 Le Roux (2002: 291, footnote to Table 1) indicate that mother-tongue literacy was tested on a four-point scale, English language literacy on a further four-point scale, and numeracy on a six-point scale. The combined score was thus out of 14. The difference in mean score of around 5 points out of 14 between whites and blacks is equivalent to almost ten years of education for the black population (derived from Simkins 2001), a fact also remarked upon by Case and Deaton. Interesting, also, is the exceptional performance of the Indian population. Comparisons between numeracy and literacy scores are not valid, yet it is interesting that the racial patterns are similar across literacy and numeracy.

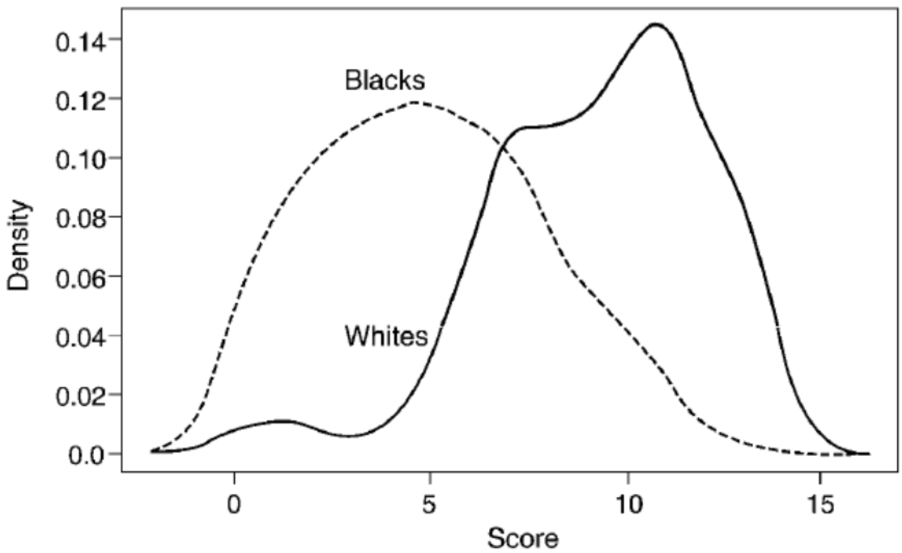
Table 5: Literacy and numeracy test results, 1993-94

	Blacks	Coloureds	Indians	Whites
Number of respondents	1 647	209	72	212
Total score: Males (max 14)	5.0 (36%)	7.5 (54%)	10.5 (75%)	9.8 (70%)
Total score: Females (max 14)	4.8 (34%)	6.9 (49%)	10.5 (75%)	9.6 (69%)
Numeracy score: Males (max 6)	1.9 (32%)	2.8 (46%)	4.2 (70%)	3.9 (65%)
Numeracy score: Females (max 6)	1.8 (30%)	2.4 (40%)	4.1 (68%)	3.9 (65%)
Years of schooling: Males	5.2	5.8	8.3	8.1
Years of schooling: Females	5.6	5.3	7.6	7.7

Source: Fuller, Pillay and Sirur (1995): Table 2, as presented in Simkins (2001: Table 12)

Figure 6 shows the test score (literacy plus numeracy, i.e. out of 14) for white and black teenagers, again from the PSLSD. The large differences in scores are reminiscent of the more recent differentials in matric results shown in Figure 1.

Figure 6: Test scores of white and black teenagers (literacy plus numeracy), 1993

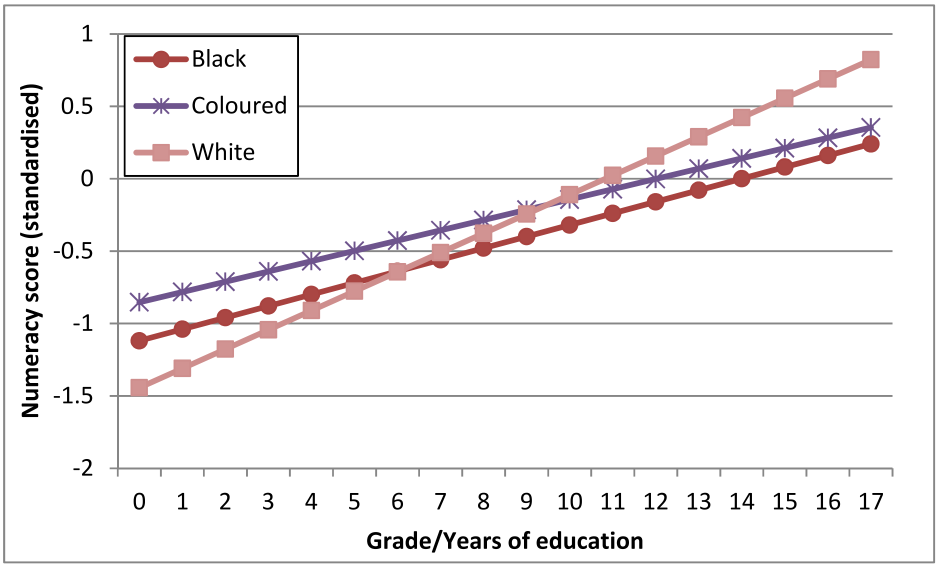


Source: Van der Berg, Wood & Le Roux (2002: 293, Figure 3)

Figure 7 below shows, for the black population, linear regression lines for three population groups of the scores on a numeracy module included with Wave 1 of the

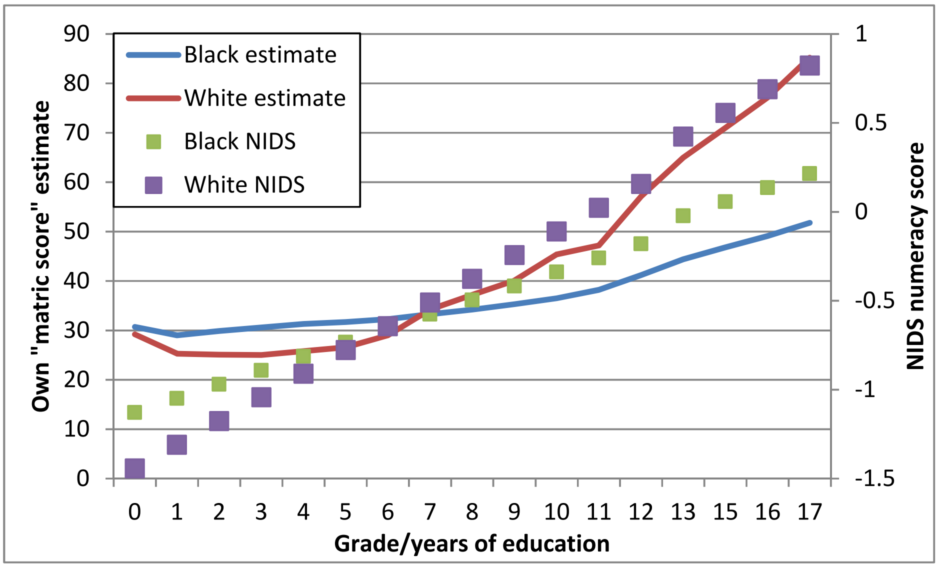
National Income Dynamics Survey (NIDS) of 2008, taken from De Vos (2011). The lower part of the curve for whites should be interpreted with caution, as there are few members of this group with so little formal education. (There are severe selection problems into participation in this test, discussed in detail in Van Broekhuizen & Von Fintel (2010).) At higher education levels, there clearly is a white advantage in cognitive skills over the other two groups shown (the sample for Indians was too small to use). The shape of the white-black differential is similar to those found in this study, so they are shown together in Figure 8, though with different y-axes to allow for scale differences. The shapes may well have looked even more similar to the estimates from our study if the De Vos study had used non-linear regressions.

Figure 7: Regression lines by race of cognitive test performance by educational attainment in NIDS



Note: This graph is based on a linear regression model that allows for interaction effects between race group and years of education. Lines shown are for 25 year old male residents of formal housing areas and with a household income of R25 000 per year.
Source: Own calculations from De Vos (2011, regression 6).

Figure 8: Regression lines of cognitive test performance by educational attainment in NIDS versus estimates from this study



It thus appears that the estimates obtained from the simulation model are not intuitively out of line with what little we know of the relationship between race, educational attainment and cognitive scores from other studies. Accordingly, we now present results from re-estimating the racial wage gaps, after including the simulation results obtained above.

9. Results: Re-estimating the unexplained residual wage gap

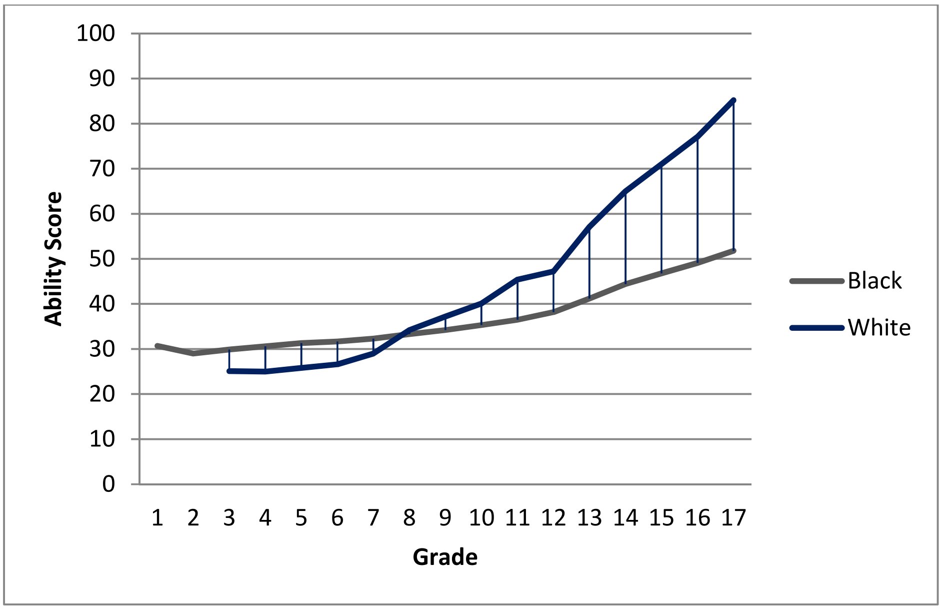
The Oaxaca-Blinder decompositions in Section 3 are now replicated, again comparing the log wage gaps between whites and each of the other three groups. This time, however, the model also allows for different levels of education quality. Each of these pairs of wage gaps will first be introduced in isolation, to consider the influence of education quality on each. In each case the unexplained residual under the conventional model will be compared to that found under the augmented model, which allows for difference in school quality. Discrimination for each race will be measured compared to the white population. Any change in the explained-unexplained ratio of the wage gap will be attributed to school quality.

To keep the discussion concise, we shall focus on the results attained using the models with heterogeneous noise because this model is seen as more credible, allowing for different levels of noise within different parts of the school system. Discrimination for each race will be measured compared to the white population.

White-black Wage Gap

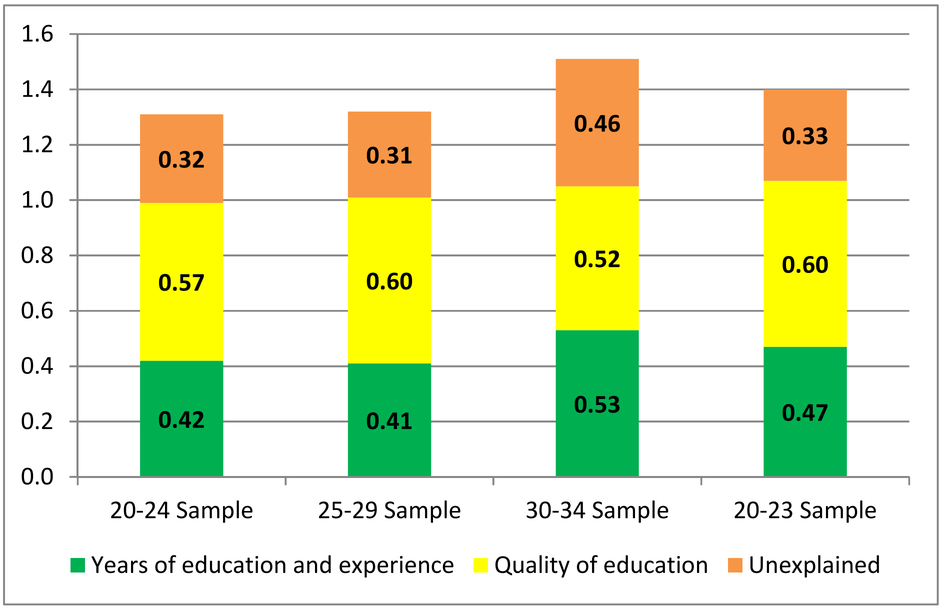
Using our cognitive skills estimates, one can construct a skills-gap measure for people of similar grade attainment by comparing the difference between the average expected matric scores at each grade level. This was done below, where the expected matric score at each grade for blacks was graphed against that of whites. The difference between the two figures at each grade constitutes the skill or productivity gap within a grade.

Figure 9: Skills-gap between whites and blacks



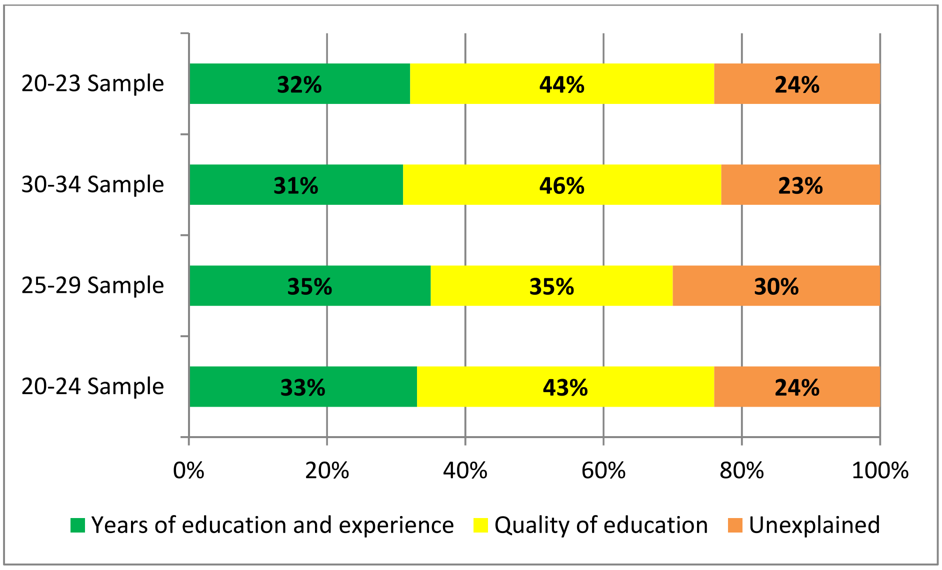
The figure indicates that blacks have a slight skills advantage at the lower end of the grade distribution and a moderate to high disadvantage at the higher end – there is a 33 percentage point gap (in terms of the matric mark metric) between the expected matric scores of whites and blacks at its highest point, grade 17 (i.e. 17 years of education, equivalent to attainment of a Master's degree). The impact of these two curves is shown more clearly in the two figures below. These two figures, which decompose the white-black wage gap for the three different age groups in both absolute and relative terms, was constructed using Tables A3 and A5 in the Appendix.

Figure 10: Oaxaca-Blinder decomposition of wage gap between whites and blacks



While our original model, the conventional Mincerian model without provision for cognitive skills differentials, was able to explain only between 31 and 35 percent of the wage gap between whites and blacks, augmenting the Mincerian model by allowing for education quality was able to explain 69 to 76 percent, depending upon the cohort one focuses on. As a result, the unexplained component fell from round two-thirds to roughly one quarter. This reduction in the unexplained wage gap (also often loosely referred to as discrimination) after the inclusion of school quality indicators is similar to that reported in the work of Chamberlain and Van der Berg (2002). They found that depending on how one weights a year of black education to a year of white education, one is able to explain between 50 and 80 percent of the wage gap. They demonstrated that a model that successfully controls for education quality should explain a greater portion of the wage gap than models that do not, as is indeed seen here.

Figure 11: Oaxaca-Blinder decomposition of wage gap between whites and blacks (% of total gap)



Comparing the results for the homogenous estimates in Table A4 with that of Table A5 in the Appendix, it appears that the homogenous and the heterogeneous noise model delivered similar results. Again, more than 70 percent of the wage gap could be explained by school quality, educational attainment and experience. The similarity in results for the heterogeneous and the homogenous model was unexpected, given the large differences in the average expected black matric score curve for the homogenous and heterogeneous models and their subsequent 'skills gaps' (see Figure 7 above). Further investigation[5] suggests that the decrease in the skills gap at the lower end and an increase of the skills gap at the upper end may have a cancelling out effect.

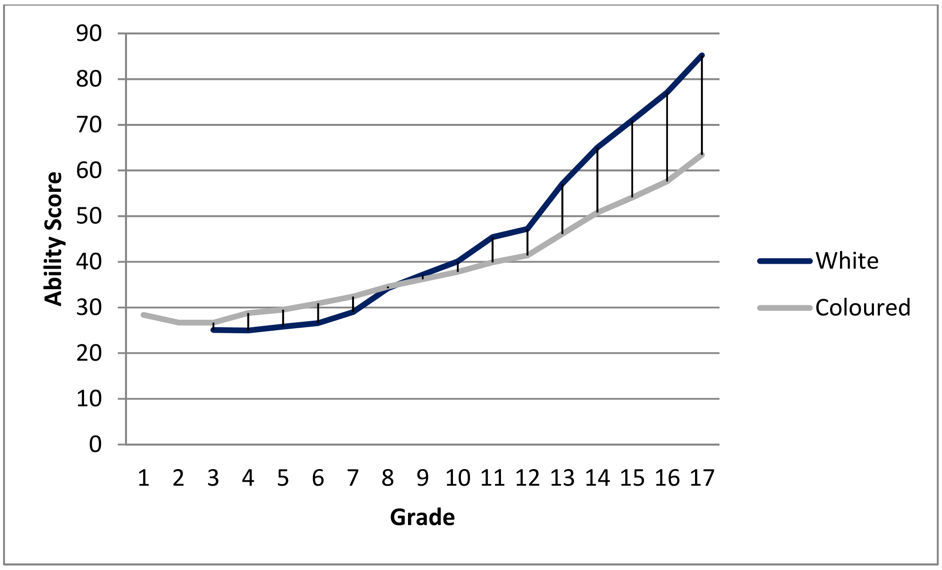
Du Rand, Van Broekhuizen and Von Fintel (2011) also attempted to measure the effect of cognitive skills on wages, but using a numeracy test included in the NIDS survey. Due to major sample selection issues and the weakness of the measuring instrument, they could not arrive at hard answers. However, it is instructive that their results for the black-white wage differential are comparable to those in Figure 19: They found that approximately 31 per cent of the wage differential could be explained by the usual productive characteristics of experience and educational attainment, 29 per cent by differences in the quality of education between white and blacks, and that 40 per cent was left unexplained. Their results, unlike those in the graph shown, are not confined to a specific age cohort.

White-coloured Wage Gap

Since the average expected coloured matric score lies between the scores of blacks and of whites scores, the white-coloured grade-specific skills-gap, shown below, is narrower than the white-black skills-gap. Again the white group enjoys a large advantage at the high end of the grade distribution, a relative advantage for all high school grades and a slight disadvantage for those grades lower than grade 7. Throughout the white-coloured skills gap remains roughly two-thirds of the size of the white-black skills gap.

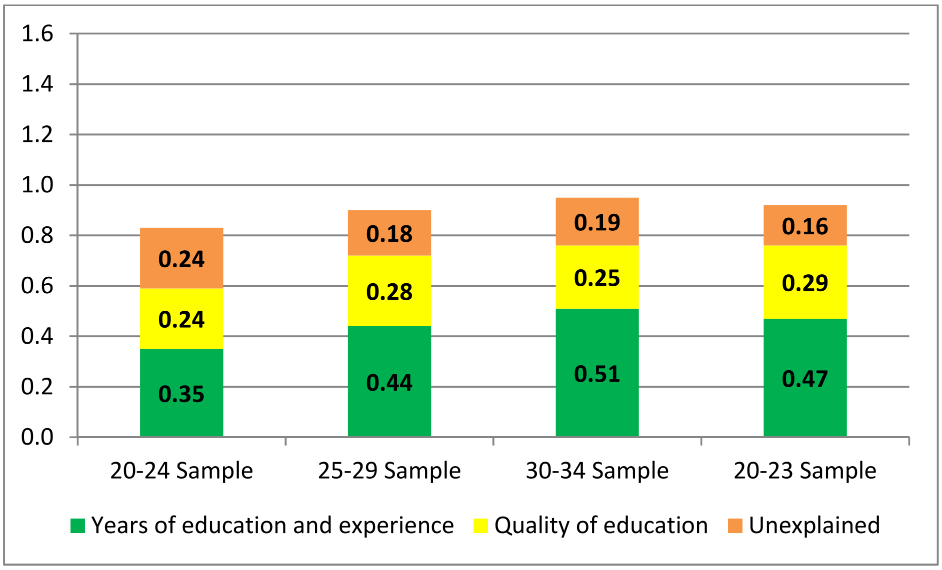
[5] *The same Oaxaca-Blinder decompositions were run on two sub-samples: one containing those individuals who had attained grade 12 or higher and another those who had attained grade 11 or less.*

Figure 12: Skills-gap between whites and coloureds with similar grade attainment



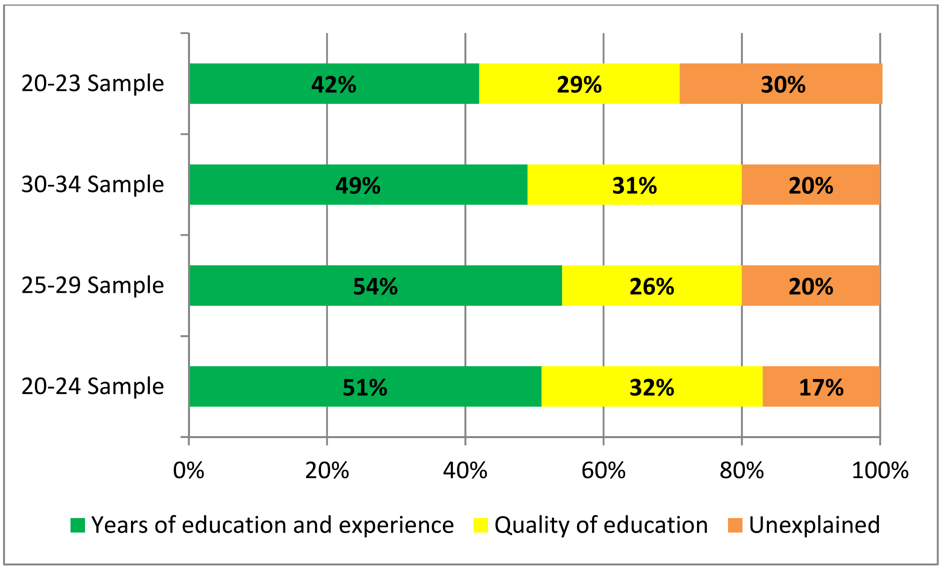
The figures below were constructed using the data obtained from Tables A6 and A8.

Figure 13: Oaxaca-Blinder decomposition of wage gap between whites and coloureds



As with the skills gap, the wage gap between coloureds and whites was also narrower than it was between whites and blacks. It again constitutes roughly two-thirds of the size of the white-black gap.

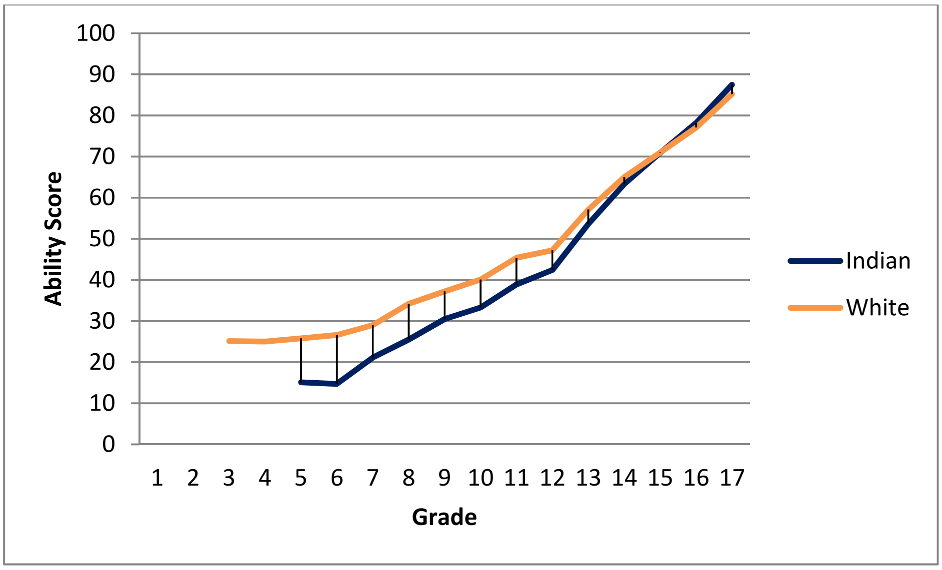
Figure 14: Oaxaca-Blinder decomposition of wage gap between whites and coloureds (% of total gap)



Since the skills gap and wage gap follow a similar trend as for the black-white decomposition, the decomposition of this wage gap also shows similar results. While productive characteristics only explained about 50 percent of the wage gap in the original Mincerian model, this value jumps to between 70 and 80 percent when controlling for differences in the expected school quality between these two groups. Thus the different quality of schooling contributes roughly 30 percent of the wage gap. The unexplained remaining wage gap was thus more than halved – dropping from 50 percent to between 20 and 30 percent. As with the white-black wage gap, there were no great differences among the results attained using the homogenous (see Table A7) and those attained using heterogeneous indices (see Table A8).

White-Indian Wage Gap

Figure 15: Skills-gap between whites and Indians with similar grade attainment



Unlike the two previous skill gaps, the white-Indian skill gap shows an advantage for whites at the lower grades. The 10 percentage point advantage that white students enjoy over the Indian population at grade 5, however, erodes towards the higher end of the grade distribution. But this gap is somewhat misleading, since very few employed individuals in either of these two groups do not have at least a grade 10 qualification.

A clear trend is visible, despite the omission of the sample containing individuals between the age of 25 and 30 due to the irregularities brought about by the high proportion of high earners present in that relative small Indians cohort. The remaining two samples and the larger total sample show that the wage gap between whites and Indians is much smaller than the wage gaps between whites and either coloureds or blacks.

Figure 16: Oaxaca-Blinder decomposition of wage gap between whites and Indians

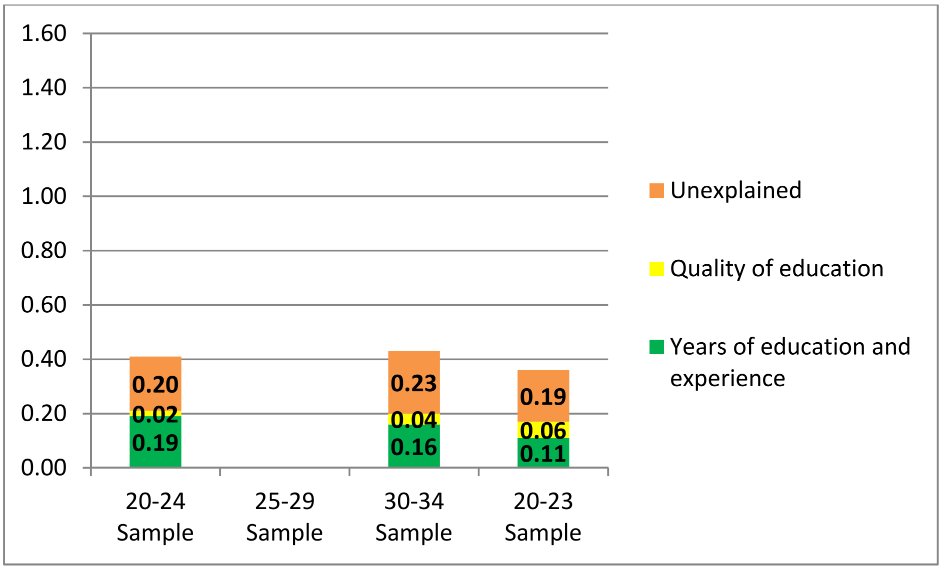
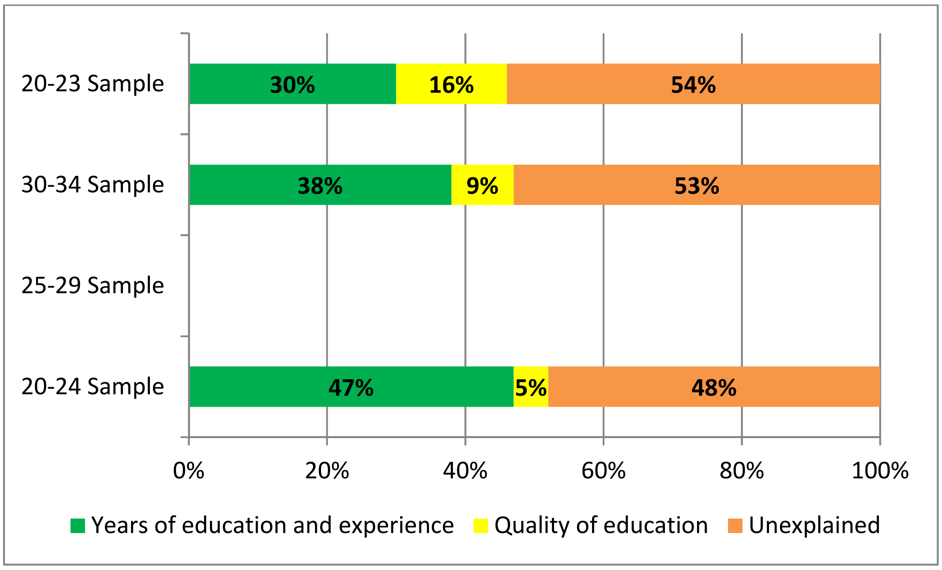


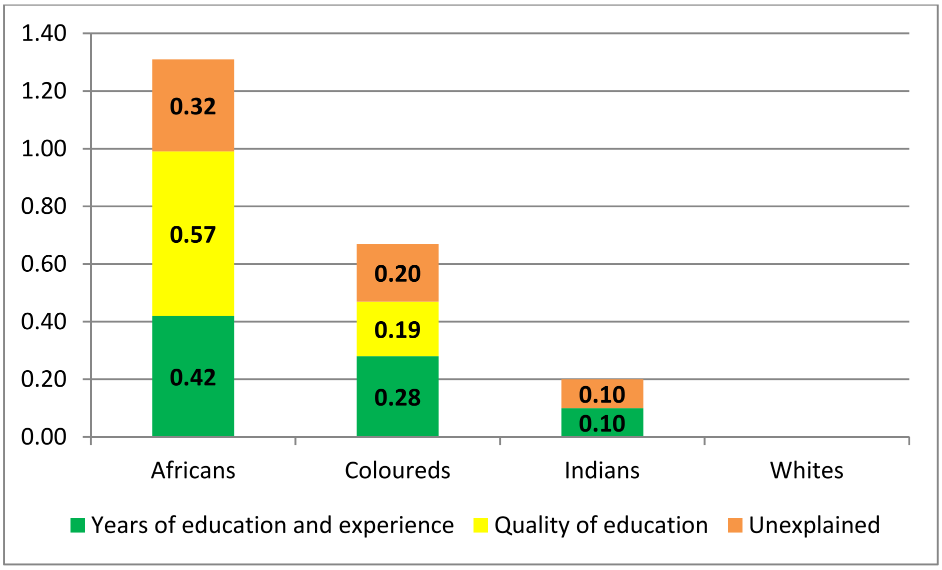
Figure 17: Oaxaca-Blinder decomposition of wage gap between whites and Indians (% of total gap)



Although the wage gap between the white and Indian sample is much smaller in absolute terms, a larger portion of this gap was due to discrimination. After including a proxy for school quality the unexplained portion of the wage gap shrunk and appeared to be much smaller than it was in either of the previous cases.

Comparing Wage Gaps

Figure 18: Oaxaca-Blinder decomposition of wage gap for all race groups, age group 20-24



The graph above indicates the difference in the magnitude of the wage gap between whites and the three other groups. The log wage gap between blacks and whites is nearly double the size of the coloured-white gap, while the Indian-white gap is much smaller. The white-white gap, which obviously takes a value of zero, was included to remind readers that all discrimination is being measured relative to this group which, by definition, is assumed to face no discrimination.

A large portion of the wage gap could be explained by differences in years of education and experience. These values ranged from 32 percent (between blacks and whites) to 47 percent (between Indians and whites).

In all three cases, the inclusion of a proxy for school quality substantially reduced the level of measured discrimination. This is in line with the earlier statement that conventional models that fail to control for educational quality tend to overestimate the level of labour market discrimination.

Figure 19: Oaxaca-Blinder decomposition of wage gap for all race groups, age group 20-24 (% of total gaps)

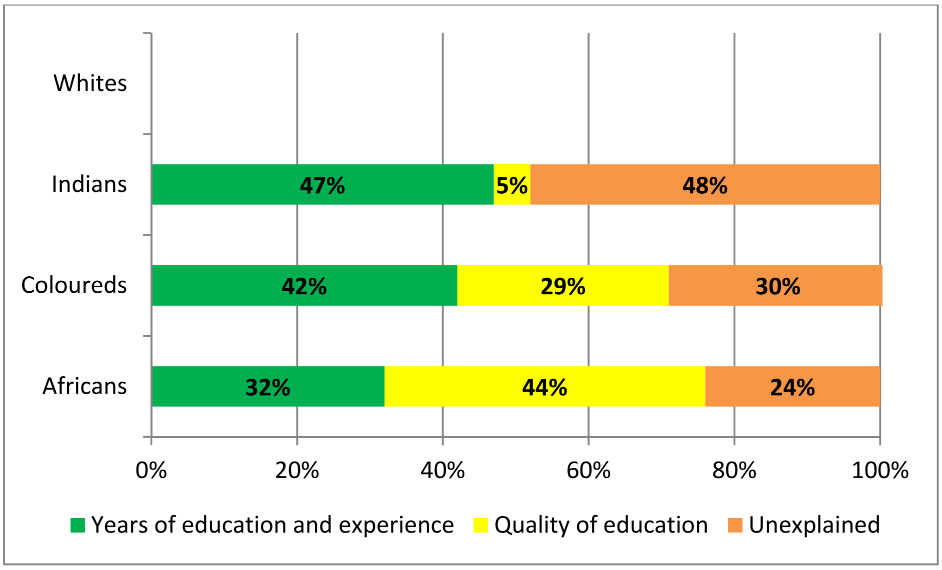
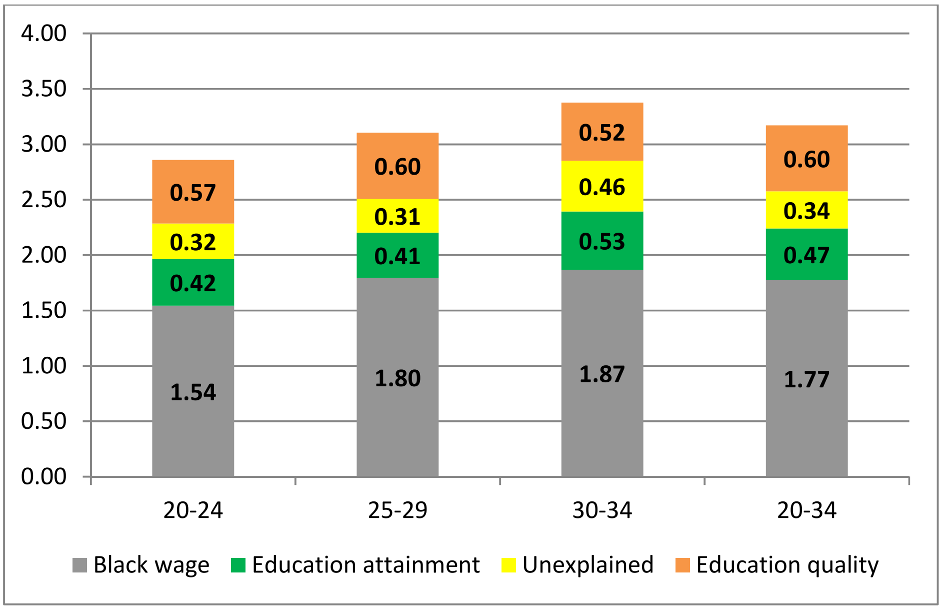


Figure 20 below shows the decomposed white-black log wage differential for each of the three cohort groups considered, and the three combined. The estimates are quite stable over different cohorts and wages rise with age, as would be expected. This figure demonstrates that even when all other sources of differences between white and black wages were to be eliminated, the effect of education quality differences still remains substantial.

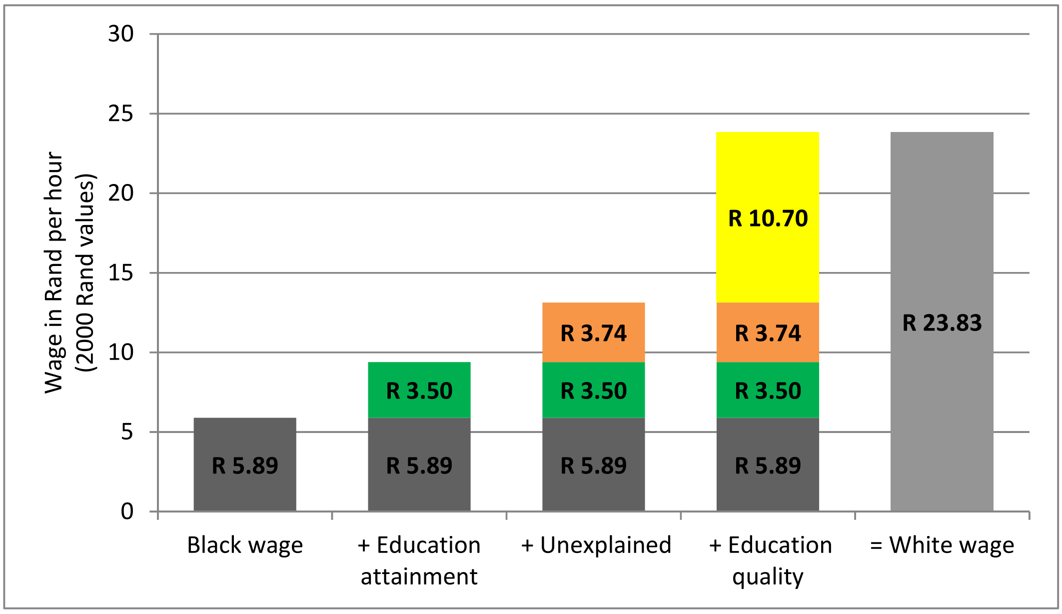
Figure 20: Decomposition of the white/black differences for different age cohorts in the log of average hourly wages



Note: lof of white wage = lkog of black wage + effect of education attainment and experience + effect of educational quality + unexplained residual

Figure 21, this time showing actual hourly wages rather than its logged form, makes this even more apparent for the three cohorts combined. It shows the monetary magnitude of each of the sources of wage differences and that, even if all other wage differences were eliminated, black people would still earn more than R10 per hour (in 2000 Rand terms) less than their white counterparts, due to educational quality differences.

Figure 21: Potential effect of education on the hourly white/black wage differential for the age group 20-34 (all three cohorts)



7. Conclusion

This paper discussed the role that school quality has on our preconceived notion of labour force discrimination, arguing that a large portion of the observed wage-gap between different race groups may be due to the different qualities of education that these two groups attained. Although most researchers acknowledge this possibility, they usually proceed to assume it away, due to the lack of any proper quantifiable measures for these differences in school quality.

Such an index was proposed, formulated, derived and fitted. The index and the results it delivered when added to an Oaxaca-Blinder model were in line with what theory predicted: The index affirmed the different degrees of human capital accumulation between different schools, while the modelling showed that models that fail to account for school quality tend to overestimate the degree of discrimination.

On average, about a half of the unexplained part of the wage gap that remained after controlling for education and experience can be explained by differences in school quality between whites and other groups. If these results are valid, then most of what is often perceived to be labour market discrimination may result from events prior to job market entry – the varying quality of education received by members of different population groups. These differences are likely to persist and keep feeding into the labour market as long as good schools that produce high quality education remain beyond the reach of the majority of children. This highlights the urgent need for change in the education system.

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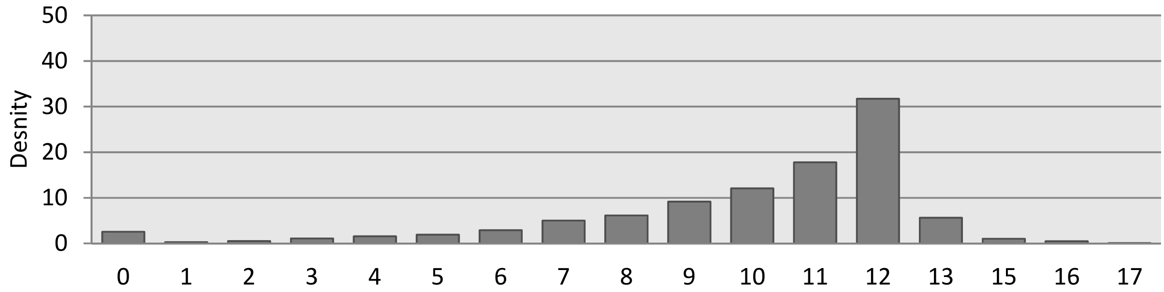
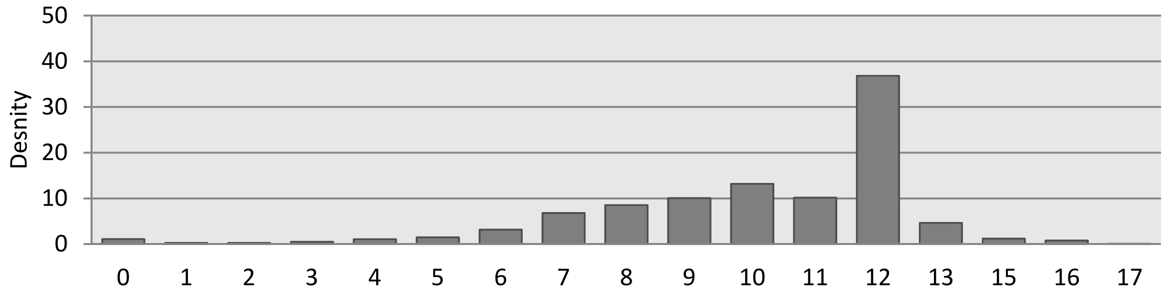
Appendix

Figure A1: Years of Educational Attainment by Race:

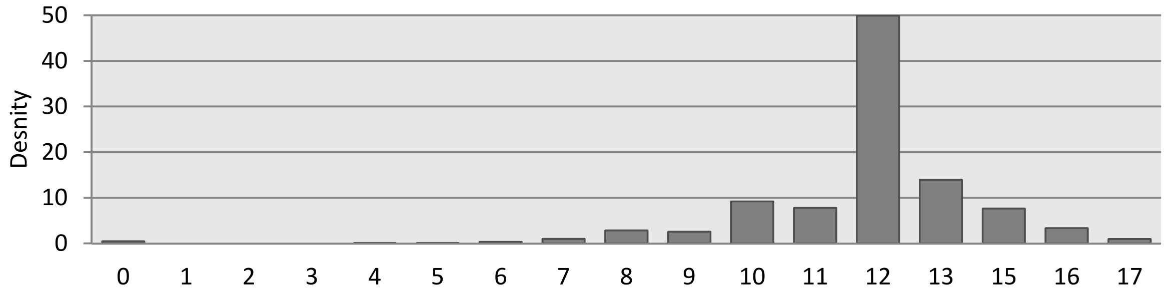
Black



Coloured



Indian



White

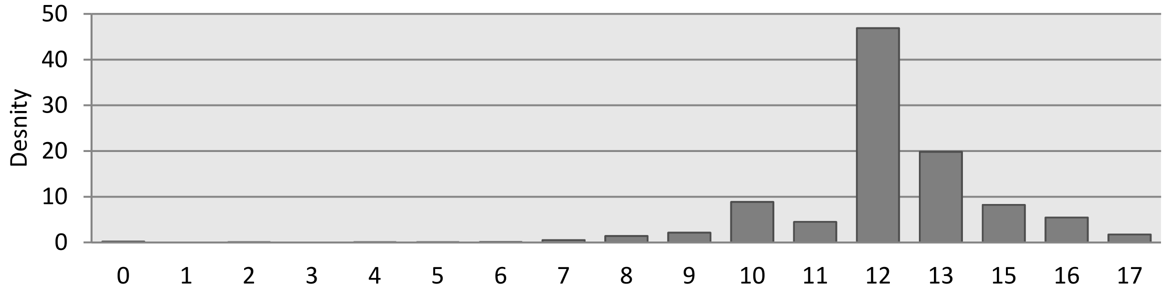


Figure A2: Kernel-density curves of the expected matric score for each grade

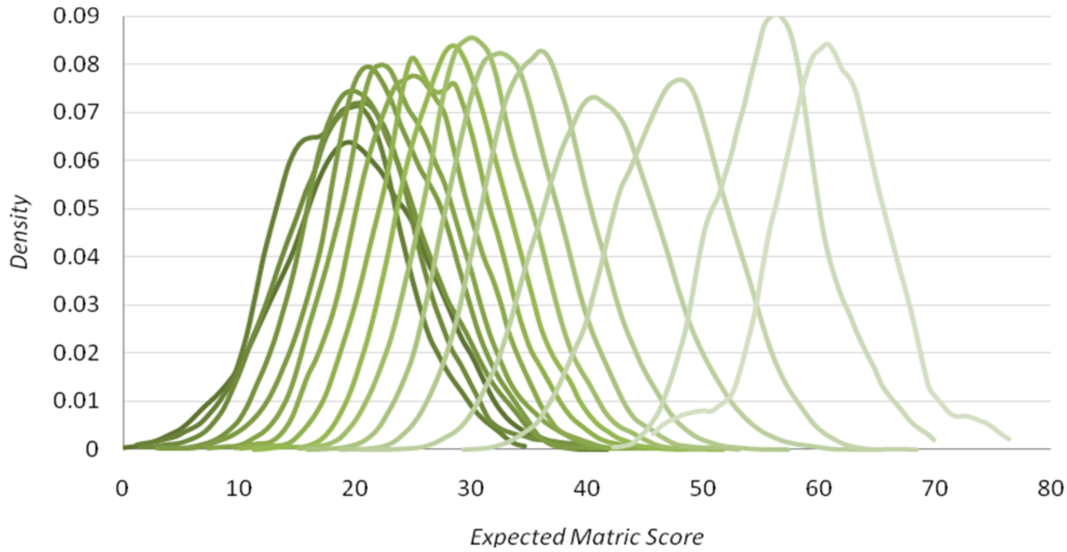


Figure A3: Average expected matric scores for coloureds for homogenous and heterogenous models

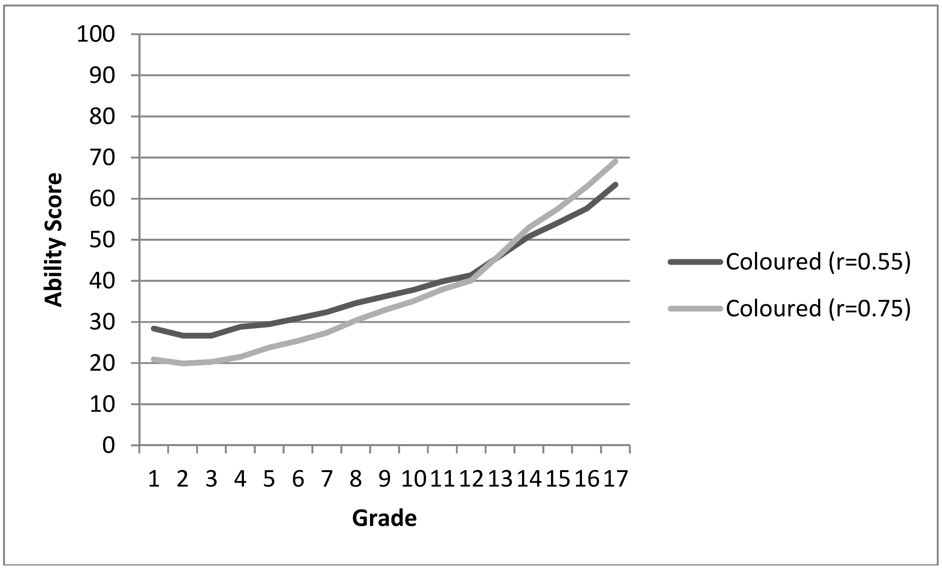


Table A1: Comparison of true score distribution with estimated score distribution

	True Population		Simulated Sample	
	μ_a	δ_a	$\hat{\mu}$	$\hat{\delta}_a$
Black				
Fail grade 12	29.99	(4.35)	29.20	(5.08)
Pass grade 12	45.20	(8.83)	45.93	(7.35)
Coloured				
Fail grade 12	30.83	(3.49)	30.51	(4.87)
Pass grade 12	48.54	(10.75)	50.03	(8.81)
Indian				
Fail grade 12	31.65	(4.36)	29.94	(5.59)
Pass grade 12	58.61	(15.95)	59.82	(13.64)
White				
Fail grade 12	34.04	(4.53)	32.37	(5.01)
Pass grade 12	62.23	(15.05)	63.17	(13.32)

Table A2: Index of school quality, not allowing for heterogeneity

Grade	Black		Coloured		Indian		White	
	Mean	se	Mean	se	Mean	se	Mean	se
0	20.0	(6.3)	20.9	(6.8)	18.4	(8.9)	29.2	(7.9)
1	18.6	(5.0)	19.9	(6.4)	16.4	(8.0)	25.3	(7.9)
2	19.7	(5.3)	20.3	(5.8)	16.0	(7.8)	25.1	(7.0)
3	21.3	(5.0)	21.5	(5.8)	15.5	(7.6)	25.0	(6.0)
4	23.0	(5.1)	23.8	(5.7)	15.1	(7.4)	25.8	(6.8)
5	23.9	(4.9)	25.4	(5.6)	14.7	(7.2)	26.6	(7.5)
6	25.4	(4.8)	27.4	(5.8)	21.1	(7.8)	29.0	(8.5)
7	27.2	(4.9)	30.4	(5.8)	25.5	(7.4)	34.2	(7.6)
8	28.7	(4.8)	32.9	(5.7)	30.5	(7.6)	37.2	(7.4)
9	30.6	(4.8)	35.1	(5.6)	33.3	(7.3)	40.1	(7.0)
10	33.0	(4.8)	37.9	(5.5)	38.9	(7.5)	45.4	(7.5)
11	35.9	(4.8)	40.1	(5.2)	42.4	(7.1)	47.2	(6.7)
12	41.3	(5.4)	46.4	(6.2)	53.6	(8.7)	57.1	(8.0)
13	47.4	(5.1)	53.0	(5.7)	63.3	(7.7)	65.0	(7.3)
15	51.9	(4.5)	57.5	(5.2)	70.9	(7.1)	71.0	(6.6)
16	56.2	(4.3)	62.9	(5.5)	78.2	(6.9)	77.1	(6.5)
17	60.8	(4.8)	69.1	(5.2)	87.5	(7.5)	85.2	(6.9)

Table A3: Revised augmented index of school quality, allowing for heterogeneity

Grade	Black		Coloured	
	Mean	se	Mean	se
0	30.7	(8.9)	28.4	(7.9)
1	29.0	(8.0)	26.7	(7.9)
2	29.9	(7.8)	26.7	(7.0)
3	30.6	(7.6)	28.8	(6.0)
4	31.3	(7.4)	29.5	(6.8)
5	31.7	(7.2)	30.9	(7.5)
6	32.3	(7.8)	32.4	(8.5)
7	33.3	(7.4)	34.6	(7.6)
8	34.2	(7.6)	36.2	(7.4)
9	35.3	(7.3)	37.8	(7.0)
10	36.5	(7.5)	39.9	(7.5)
11	38.2	(7.1)	41.4	(6.7)
12	41.2	(8.7)	46.1	(8.0)
13	44.4	(7.7)	50.8	(7.3)
15	46.8	(7.1)	54.1	(6.6)
16	49.1	(6.9)	57.6	(6.5)
17	51.8	(7.5)	63.4	(6.9)

Table A4: Oaxaca-Blinder decomposition of white-black wage gap using conventional model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Blacks	1.544	(0.001)	1.795	(0.001)	1.868	(0.001)	1.774	(0.000)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.419	(0.001)	-0.407	(0.001)	-0.526	(0.001)	-0.466	(0.001)
Unexplained	-0.896	(0.002)	-0.904	(0.001)	-0.982	(0.001)	-0.931	(0.001)
Difference	-1.315	(0.002)	-1.311	(0.001)	-1.508	(0.001)	-1.397	(0.001)

Table A5: Oaxaca-Blinder decomposition of white-black wage gap using homogenous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Blacks	1.544	(0.001)	1.795	(0.001)	1.868	(0.001)	1.774	(0.000)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.988	(0.002)	-0.992	(0.002)	-1.037	(0.001)	-1.037	(0.001)
Unexplained	-0.327	(0.002)	-0.318	(0.002)	-0.470	(0.002)	-0.360	(0.001)
Difference	-1.315	(0.002)	-1.311	(0.001)	-1.508	(0.001)	-1.397	(0.001)

Table A6: Oaxaca-Blinder decomposition of white-black wage gap using heterogeneous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Blacks	1.544	(0.001)	1.795	(0.001)	1.868	(0.001)	1.774	(0.000)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.993	(0.002)	-1.005	(0.002)	-1.050	(0.002)	-1.062	(0.001)
Unexplained	-0.322	(0.002)	-0.305	(0.002)	-0.458	(0.002)	-0.335	(0.001)
Difference	-1.315	(0.002)	-1.311	(0.001)	-1.508	(0.001)	-1.397	(0.001)

Table A7: Oaxaca-Blinder decomposition of white-coloured wage gap using conventional model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Coloureds	2.033	(0.001)	2.213	(0.001)	2.431	(0.002)	2.243	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.346	(0.001)	-0.435	(0.001)	-0.511	(0.001)	-0.474	(0.001)
Unexplained	-0.480	(0.002)	-0.457	(0.002)	-0.434	(0.002)	-0.454	(0.001)
Difference	-0.826	(0.002)	-0.892	(0.002)	-0.944	(0.002)	-0.928	(0.001)

Table A8: Oaxaca-Blinder decomposition of white-coloured wage gap using homogenous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Coloureds	2.033	(0.001)	2.213	(0.001)	2.431	(0.002)	2.243	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.577	(0.002)	-0.717	(0.002)	-0.762	(0.002)	-0.762	(0.001)
Unexplained	-0.250	(0.002)	-0.176	(0.003)	-0.183	(0.002)	-0.166	(0.001)
Difference	-0.826	(0.002)	-0.892	(0.002)	-0.944	(0.002)	-0.928	(0.001)

Table A9: Oaxaca-Blinder decomposition of white-coloured wage gap using heterogeneous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Coloureds	2.033	(0.001)	2.213	(0.001)	2.431	(0.002)	2.243	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.582	(0.002)	-0.715	(0.002)	-0.756	(0.002)	-0.769	(0.001)
Unexplained	-0.244	(0.002)	-0.178	(0.003)	-0.188	(0.002)	-0.159	(0.001)
Difference	-0.826	(0.002)	-0.892	(0.002)	-0.944	(0.002)	-0.928	(0.001)

Table A10: Oaxaca-Blinder decomposition of white-Indian wage gap using conventional model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Indians	2.448	(0.002)	2.894	(0.002)	2.945	(0.002)	2.816	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.193	(0.001)	0.031	(0.002)	-0.162	(0.001)	-0.105	(0.001)
Unexplained	-0.218	(0.003)	-0.242	(0.002)	-0.269	(0.002)	-0.250	(0.001)
Difference	-0.411	(0.003)	-0.211	(0.003)	-0.431	(0.002)	-0.355	(0.002)

Table A11: Oaxaca-Blinder decomposition of white-Indian wage gap using homogenous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Indians	2.448	(0.002)	2.894	(0.002)	2.945	(0.002)	2.816	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.214	(0.001)	-0.040	(0.002)	-0.203	(0.001)	-0.162	(0.001)
Unexplained	-0.197	(0.003)	-0.171	(0.002)	-0.228	(0.002)	-0.193	(0.001)
Difference	-0.411	(0.003)	-0.211	(0.003)	-0.431	(0.002)	-0.355	(0.002)

Table A12: Oaxaca-Blinder decomposition of white-Indian wage gap using heterogeneous model

	20 - 24 sample		25 -29 sample		30 - 34 sample		20 - 34 sample	
Indians	2.448	(0.002)	2.894	(0.002)	2.945	(0.002)	2.816	(0.001)
Whites	2.859	(0.001)	3.105	(0.001)	3.376	(0.001)	3.171	(0.001)
Explained	-0.214	(0.001)	-0.040	(0.002)	-0.203	(0.001)	-0.162	(0.001)
Unexplained	-0.197	(0.003)	-0.171	(0.002)	-0.228	(0.002)	-0.193	(0.001)
Difference	-0.411	(0.003)	-0.211	(0.003)	-0.431	(0.002)	-0.355	(0.002)