The Role of Levels of Numeric Competence and School Quality in the South African Wage Function

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Numeric competence, confidence and school quality in the South African wage function: towards understanding pre-labour market discrimination[1]

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ABSTRACT

Highly convex estimates of average returns to education commonly found in South Africa are usually rationalised as being the result of a surplus of unskilled workers and a shortage of skilled workers in the economy (Keswell & Poswell, 2004). However, due to the absence of appropriate micro level data in the past, unbiased estimation of these returns has been difficult. This paper investigates potential sources of estimation bias using the NIDS 2008 survey, one of the first to contain concurrent information on individual labour market outcomes, numeric proficiency and quality of education received (which is highly diverse and unequal across the population).

We compare naïve estimates in all relevant sub-samples with estimates that attempt to correct for the sample selection on numeracy (as the test was voluntary), as well as selection into employment. We also correct for (and exploit information on) the choice of test difficulty given to respondents, an option which was not intended in the design stage of the survey. This feature allows rough estimates of the influence of respondents' confidence in their abilities on wages. More importantly, the sample selection adjustments allow us to control for numeracy and school quality, which influence the classic problem of ability bias in returns to education. We estimate the bias in returns to education as well as the extent of racial labour market discrimination that can be accounted for by schooling outputs rather than other features of the labour market. We assess whether convex returns to education can be explained by an unequal distribution of school quality, or whether conventional explanations (such as labour demand) remain the main explanation.

Suggested remedies for selection on the endogenous numeracy measure include instrumental variables and a "Double Heckman" approach. Typical instrumental variables used in labour market analysis are poorly captured and restrict sample sizes to the extent that estimates often become nonsensical. The latter (non-standard) adjustments for sample selection issues show some promise but further evaluation and tests are required to fully rely on these results.

Convex returns to education remain strongly present in the African population (after accounting for inequalities in schooling outputs), while they are concave for the white population. Bias in these returns is unreliably estimated for whites and Asians, but is highest for the more educated at a peak of 4.55 and 5.84

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percentage points for the African and coloured populations respectively. Returns to numeracy, when more reliably identified, are convex. School outputs (measured in numeracy test scores and historical school performance) constitute a sizable part of discrimination estimates, accounting for between 18% and 36% of unexplained racial wage premia.

Keywords School quality, Labour Market Discrimination, Returns to Education, South Africa, Affirmative Action, Cognitive Skills
JEL codes: C21, I21, J78

1 Introduction

The largest single item in South Africa's government budget is spending on the public education system. The government acknowledges the severe skills shortage in the labour market as a binding constraint to growth and has prioritized the development of relevant human resources. This task has deep-rooted challenges, given South Africa's legacy of both institutionalized labour market discrimination and a segregated, poorly performing education system. South Africa's school children consistently achieve disappointing results in standardized international tests (even within the group of developing countries), and the largest backlogs remain in the former African schooling system (Van der Berg, 2007). Given an education system that seems unable to address the shortage and unequal distribution of skills in the labour market, it is relevant to understand the magnitude of the role that the schooling system plays in labour market inequalities. A firm understanding of the specific impact of the schooling system is essential, as South Africa is also plagued by other labour market rigidities such as strict labour regulations and politically powerful organized labour institutions. Ideally, the impacts of these very different constraints should be separated to enable prioritisation of policy interventions.

First we wish to uncover the role of ability in the South African wage function. Severe convexity in the returns to education may be driven by vast differences in competencies (which are in turn a product of an unequal schooling system). Estimates do not confirm the validity of this hypothesis, suggesting that traditional explanations for convex returns remain dominant. Competencies in this context are defined as labour market participants' natural abilities combined with the value added by formal learning. Both concepts together are most conveniently measured by administering standardized tests to individuals in the job market (in the case of this study, a numeracy test). The value added by formal learning may be isolated by quality measures identified at the school level: those individuals who benefitted from the favoured section of apartheid's schooling system should have developed better competencies (even if their natural abilities may not be superior to other groups), and this would carry greater rewards in the labour market. This study attempts to quantify the bias commonly found in earnings functions as a result of the omission of ability (competency) in regression models. It is evident that standard returns to education are overstated by as much as 5.84 percentage points and that this bias is concentrated amongst the most educated individuals. We also attempt to understand whether the variation in numeracy scores can explain unexplained racial inequalities in the labour market that remain after controlling for a standard set of productivity characteristics. Further, we study a similar hypothesis, but related to systematic differences that may be attributed to separate racial educational streaming in the apartheid era – and focus only on the value that was (or was not) added in schools with historically high (low) success in the matric examinations. Estimates show that about 18 to 36 per cent of unexplained racial wage premia are accounted for by either numeracy scores or indicators of school quality.

In addition, estimates attempt to not only capture the impact of *actual* abilities, but try to understand whether respondents' *perceptions* of their abilities have a role to play in labour market success. This is done by studying respondent choices in voluntary testing procedures and relating these outcomes to the labour market. Some evidence points towards a positive labour market premium for confident individuals (who choose to write tests that are more difficult than suggested benchmarks).

Consequently, what is often proposed as an *ability* bias in wage functions, also contains a more nuanced component that is driven by individuals' *perceptions* of their abilities. This suggests that success in the labour market is not only determined by levels of education and the productive value added by schooling quality, but also by how confident individuals are to convert their given schooling attainment and abilities into higher earning jobs.

The rest of this paper is structured as follows. Section 2 provides a brief review of South African earnings studies, the structure of the labour market and the potential role of the schooling system in each of these factors. It also considers the various biases that prevail in earnings studies. Section 3 describes the data used and identifies some of its limitations, along with proposed solutions. Section 4 discusses various estimates of the returns to education and the role of numeric competency and school quality. Section 5 concludes.

2 Returns to education and numeracy in South Africa

The concurrent shortage of skilled workers and apparent excess supply of unskilled labour in the South African labour market is one of the most perverse outcomes of the racially inequitable distribution of education under apartheid (Mariotti & Meinecke, 2009, p.1; Burger & Von Fintel, 2009). Moreover, the existence of unemployment (albeit less severe) even among those at the upper end of the educational attainment distribution suggests that a large part of South Africa's education sector is failing to instil the type and quality of skills that are valued in the labour market (Pauw et al., 2008, pp.46-47). Given the extent of the apparent mismatch between labour supply and demand and the strong racial dimension of this mismatch, differential returns to education between race groups and convexity in the general structure of educational returns in South African are common empirical findings in the earnings function literature (Daniels, 2007, p.29; Keswell & Poswell, 2004).[5]

Numerous studies have investigated South African returns to education, producing marginal return estimates ranging from as low as 0% for primary schooling to as high as 100% for tertiary education (Mariotti & Meinecke, 2009, pp.1-2). These widely varying estimates raise concerns regarding their reliability as a true reflection of the underlying processes modelled. Obtaining unbiased and robust estimates for the marginal return from schooling from a cross-section survey is difficult for a variety of reasons established in the literature, such as omitted variable bias (Parsons & Bynner, 2005) and sample selection bias (Heckman, 1979). In the South African context an additional concern is vast differences in quality of schooling obtained from "formerly White" as opposed to "formerly Black" schools. We provide a brief discussion of each of the three concerns and how one may address them with the data available in the first wave of NIDS study.

2.1 Omitted Variable Bias and measures of ability

In theory, the omission of a measure of ability in earnings functions biases OLS estimates of the returns to education upwards if higher ability is causally associated with both higher educational attainment and

[5] See (Keswell & Poswell, 2004) for a summary of studies providing evidence of increasing marginal returns to educational attainment in South Africa.

earnings (Keswell & Poswell, 2004, p.846). The notion that ability is positively correlated with educational attainment is theoretically supported by both the human capital and sorting hypotheses (Blackburn & Neumark, 1993, p.522). If this relationship is unaccounted for, the regression coefficient(s) on the education variable(s) in earnings functions would capture not only the marginal effect of incremental educational attainment on earnings, but also the marginal effect of higher ability levels. Because of the limited scope of historically available micro level data on natural abilities and labour market outcomes in South Africa, very little research has been conducted to establish the potential extent of ability bias in South African education returns estimates. The most recent study to investigate this in South African earnings functions is that of Mariotti & Meinecke (2009), who estimate nonparametric bounds to the marginal earnings returns to education for Black males in South Africa. Controlling for sample selectivity and accounting for omitted ability in their estimates[6], the authors find that omission of ability from normal parametric earnings function estimations may bias the marginal returns to high school education upwards by between 3 and 5 percentage points. In a previous study, (Moll, 1998, p.275) finds that the inclusion of a measure of cognitive skill in the South African earnings function reduces the marginal return to education by between 6 and 12 percentage points.

The type of micro level labour market data available for earnings function estimation seldom includes direct measures of cognitive ability. For this reason, researchers often have to rely on proxy measures such as IQ, literacy, and/or numeracy test scores that are supposed to be reflective of, though not necessarily commensurate to, cognitive ability. The use of numeric competency in earnings estimations, in particular, has grown rapidly in the international literature on labour market returns to education. McIntosh and Vignoles (2001, pp.453 - 454) emphasise numeracy, alongside literacy, as one of the most basic and essential skills necessary to function in modern-day labour markets.

Using data from two British panel surveys, Parsons & Bynner (2005, pp.4 - 7) show that numeracy is at least as important as literacy for success in the labour market and that individuals with low levels of numeracy are not only less likely to progress to higher levels of educational attainment, but also have poorer employment and earnings prospects than those with high levels of numeracy. Similarly, McIntosh & Vignoles (2001, pp.471 - 473) find significant earnings returns to numeric competency in Britain, even after controlling for educational attainment and family background. These findings suggest that numeracy is not only an important component of cognitive ability, but that it is also a component that is highly valued in the labour market. This value is recognized in policy circles: the South African government has identified numeracy as one of the most critical and demanded skills in the South African labour market (Daniels, 2007, p.2).

The dataset used in this study specifically included a test of numeracy, the results of which will be used to attempt to address these concerns. To the extent that numeracy is reflective of ability, its inclusion in earnings regressions may serve to mitigate the extent of the bias in education return estimates which would otherwise arise from omission of a direct measure of ability. Moreover, given the emphasis on the value of this specific skill in the South African labour market, the inclusion of numeracy would allow for evaluation of its true value in generating labour market returns.

[6] They apply techniques developed by Manski & Pepper (2000).

Since we still do not have a perfect proxy for ability, some endogeneity may remain in both our education and numeracy measures. We therefore employ those instrumental variables that have been suggested in the literature[7] to establish such bounds on our estimates as the data permits. Instrumentation (and other methods) are also important to account for endogenous sample selection bias resulting from the fact that numeracy tests were administered on a voluntary basis, and non-random response patterns were evident in the data under consideration. This is discussed in the next sub-section.

2.2 Sample Selection Bias

In the context of earnings regressions, classic sample selection bias obtains when one fails to control for systematic but unobserved differences between those individuals for whom the outcome variable, (earnings/wages), is observed and those individuals for whom it is not (Heckman, 1979). Standard methods exist that allow for the consistent estimation of parameters when there is censoring of the dependent variable, and a variety of extensions have been proposed for more complicated situations (Schnedler, 2005).

In this paper, we have potentially serious selection issues: within the scope of the survey design, respondents were classified in one of four labour market categories (employed, searching unemployed, discouraged unemployed and economically inactive) and were furthermore given the choice of whether or not to take the numeracy test. Each of these selection processes is non-randomly determined. A further complication arose due to inadequate enumeration: the numeracy test was designed in four tiers of increasing difficulty, each to be administered based on the highest official level of mathematics taken during school education. In practice, respondents were allowed to choose which test they wished to take after having acceded to taking the test. More detail on the nature of the test-taking will be presented in section 3 and some of the econometric estimates in section 4. Furthermore, several different approaches to dealing with these concerns are presented.

The labour market choice is accounted for by a standard Heckman selection model, while the endogenous selection into the test requires additional attention. Wooldridge (2002) suggests that sample selection of explanatory variables can be dealt with using standard instrumentation techniques in combination with standard methods to account for the selection on the dependent variable. Preliminary Monte Carlo simulations (not shown here[8]), testing the type of approach suggested by Wooldridge as well as a number of other alternatives, have proved to be very sensitive to minor changes to the parameter set or selection mechanism imposed, which suggests that the problem may be severe.

Below we propose and implement a "double Heckman" estimator. Two inverse Mill's ratios are added to the earnings function: one from a probit estimated on positive earnings (the dependent variable), the other from a probit estimated on whether or not the respondent chose to take the censored numeracy test (the independent variable we use to control for ability bias). Results show that this correction is

[7] As yet, the only reasonable instrument in the NIDS dataset is a variable capturing mother's educational attainment.

[8] Full robustness checks and detailed results of Monte Carlo studies employed will be presented in the future versions of this paper.

more stable than instrumentation, purely due to data constraints on instruments. Further investigation of full information maximum likelihood estimators is therefore necessary to confirm the validity of these estimates.

The numeracy test selection process is extensively analysed in Van Broekhuizen & von Fintel (2010). Briefly, it is evident that more confident and educated individuals were likely to participate in the test. Opportunity costs of time and peer effects were also relevant. These and other factors are included to model this particular Inverse Mills Ratio. Convexity of returns to education in South Africa suggests that this implied censoring at the bottom of the education distribution will deliver a sample with higher returns to education on average.

2.3 School Quality

It is an unpleasant but undeniable fact that one of the legacies of the apartheid regime that has persisted during the 17 years under full democracy is the difference in quality of education provided by those schools that were formerly part of the privileged part of society and those that were not. This fact has severe consequences for the interpretability and generality of results from regression estimates of the average marginal return to an extra year of schooling.

If only a small fraction of schools add significantly to initial ability of their students, returns to education are likely to be high only for this small section of the population and comparatively low for those who receive poorer quality schooling. Not accounting for the unequal distribution of schooling quality is likely to bias the estimates of the average marginal return of schooling.

This inequality may even be one of the sources of the convexity of educational returns in South Africa: If only the small fraction who receive a high quality education have the necessary background to be successful in further/higher education and they earn a premium on their quality of education, there may appear to be increasing returns if there is no way to distinguish between the two types. This may happen even if there are diminishing returns to education within the group that receives high quality education.

Figure 1 illustrates these propositions. The blue dashed line represents the diminishing returns from a high quality school, the red line the diminishing returns from a low quality school. If the data points observed (black dots) cannot be attributed to schools of differing quality and a simple polynomial is fitted (solid green line), it may show overall convex returns. In principle, both school quality and individual ability should be accounted for jointly in estimates of the returns to education. However, very little overlap between those who took numeracy tests and those for whom we have school quality data to make this feasible. However, we estimate the impact of each separately.

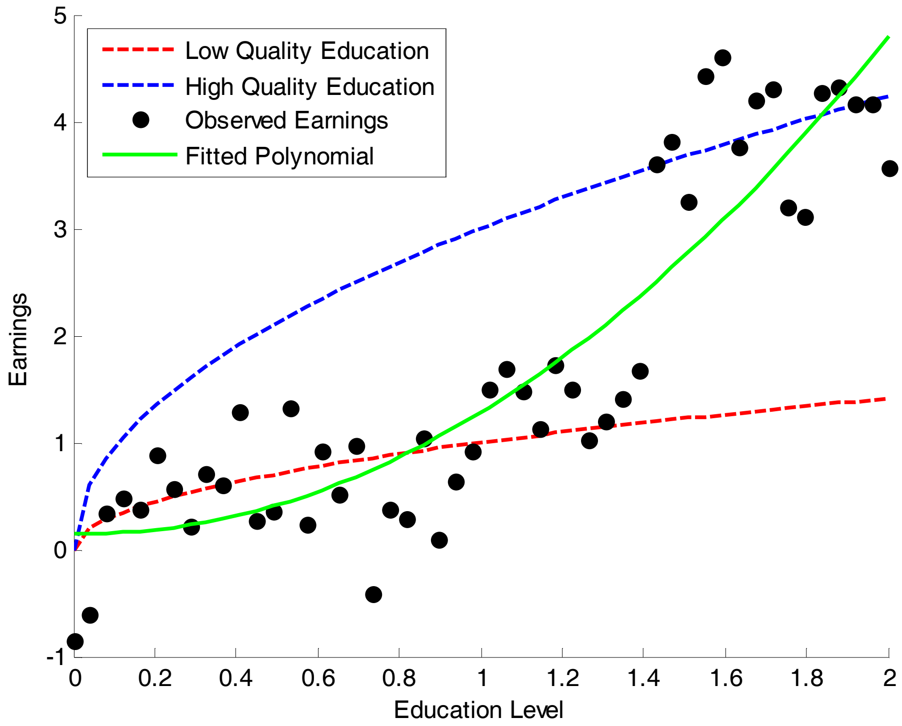


Figure 1: Convex Returns estimates from two concave functions

Burger and Van der Berg (2011) estimate the "school quality component" in standard labour market discrimination measures, by using historical matric data as a proxy (with certain assumptions about the distribution of ability) in South Africa's Labour Force Survey data. They find that the variation in their proxy for school quality accounts for a large portion of labour market discrimination. We provide additional evidence of this using the NIDS dataset, where school characteristics can be connected to individuals in the labour market explicitly and without making distributional assumptions about school quality.

Similar sampling issues arise as with the numeracy test. Naturally, individuals who had not yet entered any form of secondary education could not answer questions relating to which high school they attended., As a result, most respondents are of higher education levels relative to that of the average population. Response rates also decline with age: those who are still in education or who recently exited the school system were more likely to provide information on the school that they attended. This may be a result of better memory – both of respondents, but also of the availability historical official education records to identify specific schools (perhaps no longer registered as active schools) that were attended by individuals from older generations.

3 Data and Descriptive Analysis

Most South African labour market indicators are collected by the official statistical agency, Statistics South Africa, in the form of its (Quarterly) Labour Force Surveys. This particular survey has been redesigned in recent years, so that fewer questions are enumerated on a more regular basis. The trade-off is, however, that higher frequency data has been favoured above detailed micro level information. Statistics South Africa (2008: 10-11) proposed to shorten questionnaire length and to supplement micro level information with auxiliary and existing household surveys. Yet it is not possible, for instance, to connect the many socioeconomic dimensions measured in the General Household survey at the individual level with the Quarterly Labour Force Survey. The consequence of all these changes is that earnings analysis is no longer possible using South Africa's primary labour market survey instrument[9].

The alternative is the National Income Dynamics Study (NIDS) which was launched in 2008 by National Presidency and the Southern African Development Research Unit (SALDRU) and will in time form a panel that will be enumerated every two years. The first wave of the data contains detailed information on household welfare, individual labour market characteristics and incorporates (for the first time since the SALDRU 1993 survey) a module that gives respondents the option to respond to a numeracy test. Other work (van Broekhuizen & von Fintel, 2010) investigates the psychological and demographic response patterns associated with this voluntary test. This study intends to maximally exploit this rich data source to estimate the effect that controlling for numeracy scores has on returns to education.

A number of issues arise before we can proceed with estimates of returns to education: The numeracy test in NIDS was initially targeted at voluntary respondents within the subsample of 12 to 72 year olds (Griffin, Leibbrandt, Pavlovic, & Zuze, 2010). However, it is evident from response patterns that 12 to 59 year olds were the only relevant age range within which people were in practice asked to complete the test. This does not correspond entirely to the definition of the working age population (15 to 65). Hence, most of our estimates in this paper focus more narrowly on the sample aged from 15 to 59.

Van Broekhuizen & von Fintel (2010) extensively investigate the response patterns associated with the NIDS numeracy test. First, only 22% of eligible survey respondents within the relevant age range were willing to complete the test. It is evident that individuals with higher returns to education took the test, so that numeracy scores are apparently censored on the latent ability variable for which they are a proxy. Second, clear job market dimensions arise, in that individuals at the margin of the labour market (those most likely to enter or exit the workplace) were motivated to answer the test. These socioeconomic dimensions had clear racial differences associated with them. The study also reveals that individual level motivation and confidence in reading and writing abilities play a large role in explaining why some groups were more likely to respond to the numeracy test. These elements are, however, also by assumption important components of the earnings data generating process.

Controlling for numeracy in earnings function estimates in the NIDS dataset reduces the sample size to approximately one fifth of the original, and this sample selection is non-random. Furthermore, the

[9] Statistics South Africa recently released one quarter of micro level earnings data for 2010Q3. Other earnings data seems to be available, but only for sub-samples of the data.

censoring is correlated with typical omitted variables in earnings functions. As a result, the attempt to reduce ability bias by controlling for this feature may in fact introduce other forms of bias. Wooldridge (2002) shows that endogenous sample selection on the explanatory variables may not be as serious as selection on the dependent variable, if valid instruments are available. However, our results suggest that such estimates are biased , in that education returns are higher for the sample that responded to the numeracy test. A number of remedial measures for the selection on numeracy are compared below, including instrumentation and a "double Heckman" correction. Additionally, we also study estimates that exploit the numeracy response patterns (in terms of difficulty levels chosen), which may indirectly capture respondents' confidence in their abilities to answer tests. In effect, the particular omitted variable (perceptions of ability and, by implication, respondent motivation) is at least partially accounted for.

Numeracy tests were conducted on a voluntary basis within the respondent households. Four different tests were constructed in consultation with the Assessment Research Centre at Melbourne University. Each test was aimed at a different mathematical attainment level, and was linked to the required competencies of different scholastic stages in the South African school curriculum[10]. The fifteen multiple choice test questions were designed to take ten minutes to complete, and examined broad topics such as numeration, algebra, measurement, space and data analysis (Griffin, Leibbrandt, Pavlovic, & Zuze, 2010). Each of the question scores was calibrated by item response theory to construct a standardized test score[11] for the entire sample, so that comparisons between individuals should presumably be invariant to the difficulty level at which the respondent wrote the test (Griffin, Leibbrandt, Pavlovic, & Zuze, 2010).

Table 1 shows that of the 3498 individuals who agreed to take the test, 1109 respondents did not take the "appropriate" test level according to their mathematical attainment. In the higher education categories, respondents were more likely to write the correct tests: 76% of respondents were supposed to take levels 3 and 4 according to the benchmark[12], and 74% of individuals chose this option. More clearly, 36% of those who were supposed to write the easiest test stuck to that option (the rest chose more difficult tests), while 78% who were supposed to write the most difficult test did so (with the others choosing tests that were easier than this benchmark). In consultation with the NIDS team, it became clear that enumerators were encouraged to allow respondents to choose their own test levels in order to increase response rates and positive respondent attitude towards the entire survey instrument. The natural tendency for individuals to be over-confident in their abilities is only partially

[10] Another caveat is important to mention here. While basic concepts were tested, the tests were administered to individuals from different generations who, by implication, had completed their schooling not only in different education systems, but also studied mathematics curricula with different emphases. Most of the material covered in the tests was generalized so that these generational knowledge differences should not have been a problem. However, some questions did require such specific knowledge (such as recalling formulae for the calculation of volumes of various shapes), that individuals who had not studied mathematics for a number of years may have experienced difficulties in answering them.

[11] While such a standardized score should have a mean of zero and a standard deviation of one, the sample under consideration deviates from this slightly, with the mean being -0.518 and the standard deviation 1.094.

[12] This high figure suggests another bias that is discussed by van Broekhuizen & von Fintel (2010): most of the test respondents were drawn from better-educated cohorts.

reflected here (Dunning, Meyerowitz, & Holzberg, 1989, p. 1082): while 51% of the sample took the appropriate test, 24% chose to take a test that was meant to be too easy according to their benchmarked level and 25% of respondents took a test that was too difficult (by the benchmark).

At first glance then, response patterns of the numeracy test could reveal how participants rate their numeracy skills. Moreover, this pattern in itself could serve as a proxy for motivation or confidence in numerical abilities – these variables are typically also caught up in the error term of earnings functions, leading to potential omitted variable bias. This form of confidence is different to the measures used in van Broekhuizen & von Fintel (2010) to explain response patterns: in that paper response patterns were explained by how well individuals rated their own reading and writing abilities; here, however, this information is revealed by respondent behaviour (in their choice of test difficulty), rather than explicitly being enumerated based on a survey question on self-perceptions. Supposedly, respondents who take tests that should be too difficult for them do not lack confidence in their own ability and vica versa. A confounding possibility, which is still to be addressed, is that those who took a test that was too easy may not have doubted their abilities, but could have done so to avoid the additional response burden associated with taking a more difficult test.

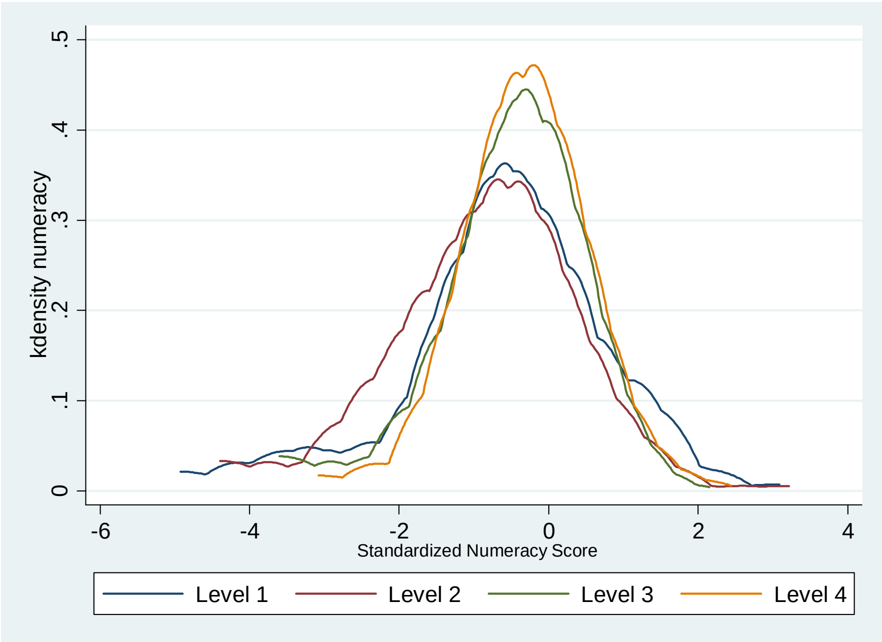
Table 1 Mean Numeracy Test - by test level taken and suggested test level (Source: Own Calculations from NIDS, 2008)

			Test Level Recommended					
			level 1	**level 2**	**level 3**	**level 4**	**Unknown**	**Total**
Test Level Taken by Respondent	**level 1**	Mean	**-0.63449**	-0.49596	0.102567	1.045667	-0.90322	-0.32057
		St. Dev.	**1.42298**	1.429694	1.207077	1.203556	2.045139	1.504114
		N	**118**	64	71	24	25	302
	level 2	Mean	-0.9329	**-0.89124**	-0.45712	-0.05074	-0.91098	-0.70003
		St. Dev.	0.983124	**1.302227**	1.30191	1.085839	1.049643	1.272745
		N	64	**297**	184	51	29	625
	level 3	Mean	-0.76142	-0.60878	**-0.5339**	-0.15658	-0.79331	-0.51561
		St. Dev.	1.067474	0.920386	**1.017998**	0.960671	1.23823	1.024462
		N	59	71	**1045**	143	40	1358
	level 4	Mean	-0.61752	-0.58422	-0.62424	**-0.32549**	-0.53207	-0.42286
		St. Dev.	0.655356	0.761062	0.82342	**0.826269**	1.019935	0.828703
		N	87	47	244	**798**	37	1213
	Total	Mean	-0.71105	-0.76643	-0.50976	-0.25554	-0.76655	-0.49956
		St. Dev.	1.113692	1.235209	1.046485	0.896367	1.334775	1.068245
		N	328	479	1544	1016	131	3498

NOTES: Figures are not weighted. The sample here is larger than the number of observations included in earnings functions, as some covariates in those tables have missing values. The test score should have a mean of 0 and standard deviation of 1 across all observations on which the item response theory was applied.

The implication of respondents' test level choices is clear in Table 1. The "off-diagonal" mean values of the numeracy measure represent the average test scores of individuals who did not take the appropriate test level. Those above the diagonal took tests that were too easy, and, on average, performed better than those who took the correct test level. Similarly, those below the diagonal took tests that were too difficult according to the benchmark and consequently results were comparatively poor in some instances.

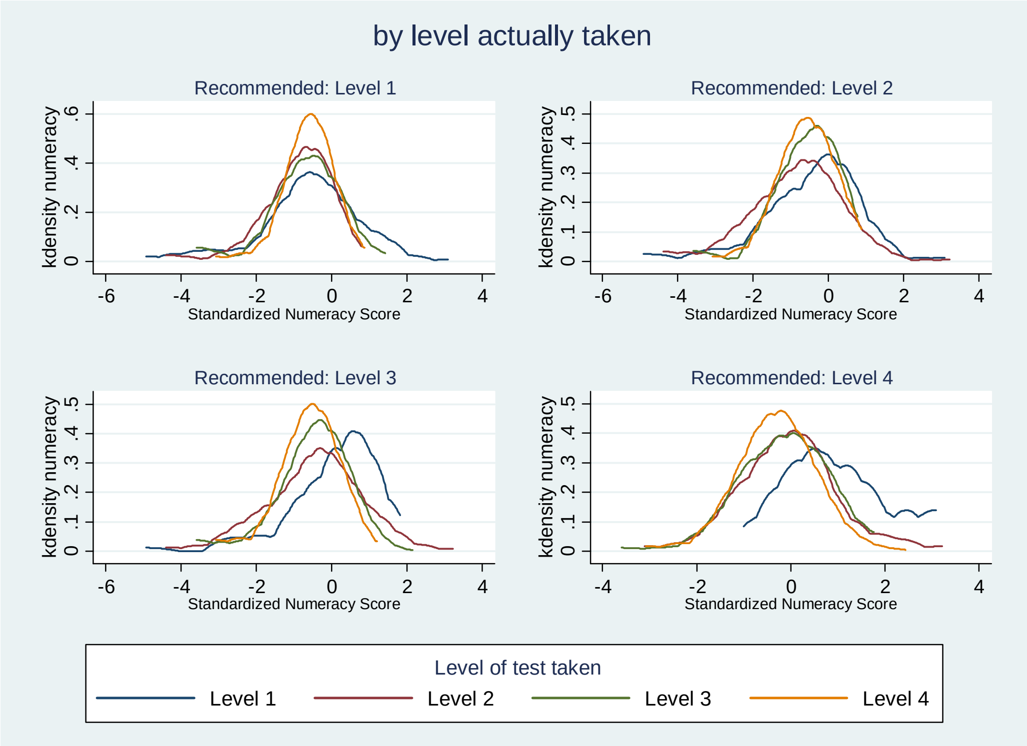
Figure 2 Kernel Density Estimates of Calibrated Numeracy Score - for those who took the appropriate test (Source: Own Calculations from NIDS, 2008)



NOTES: Sample only includes those that took the appropriate test level (within the working age population). Estimates are not weighted. An Epanechnikov kernel with bandwidth 0.5 was implemented.

Figure 2 considers the distributions of numeracy scores for only those individuals who took the appropriate test level. It is evident that the modal test scores are fairly close to each other for each of the test levels. The densities for test levels 3 and 4 match each other very closely, so that the calibration procedure appears to have successfully eliminated differences in test difficulty for the top benchmarks. The greater spread that arises as the test level drops does not suggest that the calibration was incorrect, but that it is likely that, in a country such as South Africa (where attainment levels are particularly low for previously disadvantaged groups from older generations as a result of institutionalized discrimination (Louw, van der Berg, & Yu, 2007)), both high and low ability individuals dropped out of mathematics education at an early level. For the first group the low attainment levels may not be reflective of true numeric ability (hence the relatively long upper tail in the numeracy score), but is a function of discrimination within the apartheid education system. This initial picture suggests that calibration between test levels was successful, and that the numeracy score is reflective of numerical ability for the entire population.

Figure 3 Kernel Density Estimates of Calibrated Numeracy Score – By Recommended Test Level Benchmark and Test Level Taken (Source: Own Calculations from NIDS, 2008)



NOTES: Sample includes all individuals that answered the test (within the working age population). Estimates are not weighted. An Epanechnikov kernel with bandwidth 0.4 was implemented. Each frame represents a set of estimates for the test level that respondents were supposed to take. Within each frame, the respective densities are compared by the actual test level taken.

Figure 3 draws further comparisons. In each frame the density of the numeracy score for the appropriate test level is repeated, and compared to the densities for those who did not take the correct test levels. Each frame represents the test level that respondents were supposed to take, while separate densities within frames represent actual test levels taken. At lower benchmark test levels (Frames 1 and 2), comparisons are inconclusive due to small sample sizes. At test benchmark levels 3 and 4 a higher number of "under and over confident" individuals responded to the test. It is clear from both these sets of estimates that individuals who chose to take the easiest test performed substantially better, with a higher mode and a pronounced upper tail. Under-confident (or possibly "lazy") individuals therefore excelled at the test, likely as a result of choosing a test that was too easy. This discrepancy has clearly not been fully overcome by calibrating test scores; these are likely a false reflection of what at, face value, appears to be exceptional numeric ability. The discrepancy in the distribution of the test scores for over-confident individuals is not as pronounced, though the mode of the numeracy distribution for those who took the most difficult test (and were supposed to take level 3 or level 2) is slightly lower than that of the sample that took the appropriate level.

The test score distribution narrows for the overconfident (see frames 3 and 4). This indicates that the lower mean is a result of a shorter upper tail (which can be ascribed to the choice of a test that is too difficult), but that the generally poorest performing individuals also do not fall within this category, suggesting that the overconfident are at least partially realistic in their expectations (in contrast to the underconfident who performed markedly better in absolute value than their counterparts). In sum, those who chose easy tests generally performed better, while those who chose difficult tests were only marginally disadvantaged (relative to the former magnitude). Overconfident respondents also did not have as long lower tails as underconfident respondents. This suggests that comparing participants' perceived test level and their benchmark test level does indeedreflect real information regarding confidence and/or motivation. It does, however, also indicate that the calibration of the numeracy score does not entirely eliminate differences between test levels. The implications of this are discussed in the results below. Estimates are conducted using various sub-samples to highlight how sampling affects returns to education.

To expose the implications of restrictions placed on the sample by including covariates with low response rates, we estimate simple returns to education in various scenarios. Because education returns are often found to be highly convex in South Africa (Keswell & Poswell, 2004), we estimate earnings functions with a cubic in education. Throughout, we implement the Heckman (1979) maximum likelihood estimator to correct for sample selection bias that arises from the non-random observation of wages for the employed only[13].

4 Methodology and Results

Two primary objectives are pursued by the results that follow. First, the focus falls on estimating reflective returns for each of the race groups. Most estimates include a cubic polynomial in education to capture initially increasing marginal returns to education, which could be followed by a flattening earnings-education profile at very high levels of education. In this set of estimates, we also interact the education specification with a full set of racial dummies. The objective is to consider whether different subpopulations have different returns structures, or whether conventional constituent shapes of different groups can explain the overall convexity in earnings (as in Figure 1). While Figure 1 postulates suggests that such patterns should be driven by education quality more explicitly, race is still strongly related to education quality in South Africa (Van der Berg, 2007). To make this more explicit, estimates also control for numeracy test scores and school quality. Here the intention is again two-fold. In the first case, the objective is to remove the ability bias in education returns estimates. In the second instance, should controlling for school quality and numeric ability still yield a highly convex returns structure across all race groups, the argument put forth in Figure 1 fails. Consequently we would be able to discount the assertion that convexity results from inequality in schooling system outputs; rather it could be the result of long term demand-side shifts in the labour market, which has resulted in a shortage of skilled workers who are rewarded well (Bhorat & Hodge, 1999).

Our second objective is to produce estimates that focus more narrowly on unexplained racial differences in wages (abstracting from returns to education and other factors). More clearly, we study

[13] In cases where we run double Heckman estimators or 2SLS, we use a manual two-step estimator as opposed to the maximum likelihood variant.

the racial wage premia before and after controlling for ability and school quality respectively. Because estimates of racial dummies are sensitive to interaction structures, we limit the discussion of these results to a simpler specification that estimates returns to education for the whole population, while only the intercepts are varied by race. In essence, we answer a similar question to Burger & van der Berg (2010), who incorporated simulated school quality distributions into earnings functions. They find that school quality can explain much of what is traditionally measured as labour market discrimination between races. The approach here is somewhat different, in that measures for numeric ability and school quality are explitly available in the NIDS data.

As an auxilliary hypothesis, we investigate the role of respondents' revealed confidence in wage determination. While some evidence for a positive association between confidence and earnings exists, results are not robust. Nevertheless, simple estimates are presented here to illustrate these propositions and to illuminate the rest of the discussion.

To illustrate the biases present in earnings functions we compare multiple sub-samples. In most instances, the first set of estimates considers a naïve Heckman maximum likelihood estimate of the returns to education for the entire working age population, controlling only for the standard sample selection bias[14]. Following this, the sample is progressively limited: firstly, to only those who were eligible to take the numeracy test; secondly, only individuals that actually wrote the numeracy test (or provided school data in the case of school quality estimates) were included. Here estimates with and without controls for numeracy (or school quality) are presented to evaluate the impact of these factors on wages and to gauge the extent of the bias in the returns to schooling. However, because the conclusion on bias is in itself based on a sample selected on the clearly non-random selection into the numeracy test, further corrections are necessary.

The first proposal is to instrument for both education and numeracy as per Wooldridge (2002). Mothers' education is used to isolate exogenous variation in respondent education and numeracy, while respondents' self-reported happiness categories add an additional set of instruments for numeracy scores. Happiness variables capture respondents' self-reported happiness levels in the week prior to the survey. Given that the numeracy test was only conducted towards the end of the survey instrument, personal well-being at the time of the survey could influence how meticulously the numeracy test was completed and consequently influence the results. Current happiness should not, however, be correlated with the wage error term, as wages are set up contractually and long-term happiness could provide an indicator of individuals' motivation and performance in the labour market[15]. As noted below, the instrumentation strategy fails largely due to yet another limitation in the sample size. Alternatively,

[14] Results of the selection equations are not shown, but are available from the authors on request. Controls in that stage include quadratics in education and age, gender, area and marital status dummies, as well as controls for the number of children in the household, whether the respondent was the household head, the number of unemployed individuals residing in the household, household income from grants and household income from remittances.

[15] Admittedly, current well-being may be strongly related to long-term well-being, so that this variation could be potentially endogenous to wages. For instance, people who generally have a negative emotional disposition may always perform poorly in the labour market, but would also likely report unhappiness in the most recent reference period.

a so-called "double Heckman" procedure is estimated. Here an Inverse Mills Ratio (in addition to the maximum likelihood estimation of the employment selection process) is included to account for the selection into writing the numeracy test. Though it is not yet clear what the statistical implications of this procedure are, these estimates appear to be more well-behaved than the IV estimates.

To account for the possibility that individuals' freedom to choose too easy or too difficult tests may have biased numeracy scores, each of the estimates outlined above are compared to an identical set of estimates, but now limiting the sample to only those individuals who wrote the correct test. The reason for this is that the calibration of numeracy test scores appeared to have been done most successfully for those who chose the appropriate test level. However, this further limits sample sizes.

A similar empirical strategy is followed for separate estimates controlling for school quality rather than numeracy test scores. While more individuals provided school data than answered the numeracy test[16], similar issues are at play. The overlap between the two samples is itself very small, so that one might expect estimates of education returns to be very different in the two subpopulations. Therefore a separate analysis is conducted for school quality, but with similar motivations. In this case instrumental variables for school quality include indicators of socioeconomic quintiles of schools. While these variables should have no direct influence on labour market outcomes, the education production function literature underscores the importance of socioeconomic status in schooling outcomes. Similar difficulties with the IV estimates as noted above are experienced in this setting. However, no double Heckman procedure is pursued here as an alternative remedy.

4.1 Revealed Confidence

Before commencing with the analysis of the primary hypotheses described above, we first discuss results relating to respondents revealed confidence. Figure 4 provides estimates of wage distributions for different types of test writers. It is evident that those who wrote an easier test than recommended (the potentially under confident) earned the lowest modal incomes, while those who chose the correct test and the confident individuals who wrote a test that was more difficult than recommended earned more on average. The latter group, however, has a high dispersion of wages. One group performs remarkably well in the labour market, presumably experiencing a return to their confidence. Another, however, performs worse than the rest of the labour market, which indicates that revealed confidence has a non-linear impact on wages. This sub-group potentially represents those who are unjustifiably confident in their abilities.

[16] This is not surprising, given the effort levels associated with answering the numeracy tests.

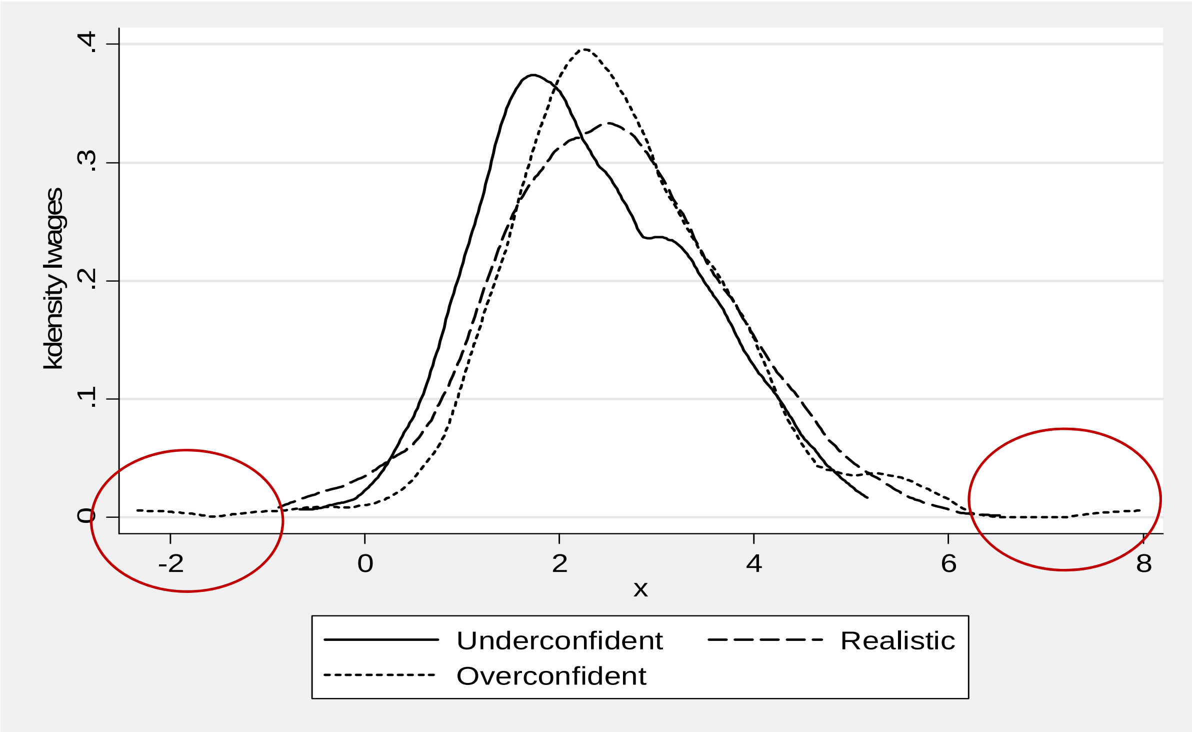


Figure 4 log(Wage) distributions by revealed confidence (Source: Own Calculations from NIDS, 2008)

Table 2 presents estimates that uncover these features. All estimates are unweighted and obtained by OLS rather than the Heckman estimator[17]. Column (b) confirms the finding from Figure 4 and suggests a statistically significant premium for those who wrote appropriate and difficult tests relative to those who wrote easy tests. Evidently, some form of confidence is at play. Column (a) shows estimates of a standard earnings function. Education coefficients are not significant, though this may be the result of the very specific sample used. Column (c) augments this specification with the confidence dummy variables. Now confidence does not provide significant explanations for earnings differences and education returns decline somewhat (as is evident in the smaller coefficient on the quadratic). This suggests that revealed confidence is positively correlated with education levels, so that education does not only enhance ability, but bolsters individuals' *confidence* in their abilities. Both effects of education are rewarded in the labour market.

Column (d) suggests that numeracy scores significantly influence wages positively. In contrast to controlling for education, however, the impact remains when also accounting for revealed confidence. Furthermore, revealed confidence remains strongly positively related to earnings (Column (e)). This different result suggests that confidence and ability (both captured in the educational attainment measure), can be more clearly distinguished from each other by numeracy scores and the test level measures. However, education apparently accounts for both effects simultaneously.

[17] Because the sample is in itself limited to a very specific sub-sample, weighting will not be reflective of the entire population either way. Sample selection bias is, naturally, very important. Results presented here are not robust to accounting for this issue, but are presented here as a further descriptive tool.

To account for the non-linear impact of overconfidence on earnings, we also wish to make the confidence effects depend on the levels of numeracy. Supposedly people who have inflated confidence levels are only successful in the labour market if this is complemented by actual high levels of ability; conversely, those with high confidence in their abilities, but without good numeracy scores, should perform below expectations in the wage distribution. Column (f) augments the previous specification with a set of interactions between numeracy and revealed confidence to test these hypotheses. None of these impacts are statistically significant, so that the reason for the dispersion in wages of the overconfident remains unexplained.

Columns (g) and (h) present fuller models. While numeracy remains a significant predictor of wages, the correlation between this quantity, confidence and education becomes clear (in that the impact is largely reduced with the full set of controls). Racial and gender differences remain remarkably robust in significance and magnitude.

In summary, this section reveals (though not robustly) that returns to education not only capture ability (in this case proxied by numeracy scores) but also confidence in these abilities (revealed willingness to answer difficult tests). These preliminary indicators will be exposed in more detail where relevant below.

4.2 Robustness and Bias of Marginal Returns to Education

While the previous section already shows that an interrelationship between numeracy scores and education exists, this section more explicitly investigates the bias that the omission of ability has on the returns to schooling. The role of school quality on bias is also investigated in a separate section. As noted above, relatively complex interaction structures between a cubic in education and racial dummies is specified. Unless otherwise specified, Heckman maximum likelihood estimates accounting for selection into employment are presented.

4.2.1 Numeracy

First, we investigate the more traditional strategy of controlling for numeracy test scores. This strategy introduces a proxy for omitted ability in the text book sense. In all applicable cases we estimate a quadratic in numeracy, based on preliminary descriptive analysis. Test scores represent the culmination of individuals' innate ability and the value added to this by schools, and therefore supposedly measures a more composite version of ability. Tables 3 and 4 present a full set of results (though they omit all first stage estimates).

Starting with table 3, the full NIDS sample is implemented. Coefficients are discussed here, but changes in returns to education will be illuminated with a graphical analysis. Column (a) displays a naïve set of estimates using the whole population of working age. This column only accounts for employment selection bias (though the hypothesis that selection is insignificant is not rejected) and not for any form of ability or quality bias. Though it is not immediately clear from the complex specification, it is evident that returns to schooling differs significantly by race. Racial premia are large in magnitude, but are imprecisely estimated due to the specification of the equation. Column (b) limits the sample to 15-59 year-olds to reflect the eligibility criteria for writing the numeracy test. Visual inspection of the coefficients suggests that this sample limitation does not substantially affect the results, so that one can refer to this sub-population and the working age population almost interchangeably. However, columns (c) to (f) further limit the sample size (reducing it to less than a quarter of the original observations), by including only those who wrote the numeracy test. It is immediately evident that - even without additional controls – the educational returns structure changes somewhat for most race groups. As noted by van Broekhuizen & von Fintel (2010), this limited group displayed higher returns to education, suggesting that censoring occurred along individual ability. This discrepancy is accounted for with the IV and Double Heckman estimates. First, however, column (d) adds numeracy to the specification. It displays a significant convex relationship with wages, and the coefficients on education change yet again. This suggests that some form of ability bias exists – though the magnitude thereof is unclear, because of the additional bias introduced by the censoring along ability itself. IV estimates in column (e) attempt to correct for this. However, the sample size reduces to nearly 10% of the original sample. Results of other coefficients are furthermore clearly out of line with other estimates. The Double Heckman estimator attempts to fill this gap in column (f). While the sample size does not remain intact, the explanatory variables used in the numeracy selection process overlap more readily with the covariates in the equation of interest.

Figure 5 sheds light on the magnitudes with respect to education returns for the African population based on these estimates. Marginal returns are quadratic as a result of the cubic specification. Firstly it is evident that returns are highly convex and approach a value of 80-100 per cent for advanced levels of education. At high levels of education (particularly for those with tertiary qualifications), returns to education are higher for the test writing population. Because this holds true despite not controlling for numeracy, the result confirms that high ability individuals chose to write the test. Even though numeracy was highly statistically significant in the wage equation, its inclusion does not affect the returns profile of Africans. Instrumentation also does not change the results for those with undergraduate degrees and higher. However, below this level decreasing returns are realised. This is probably not a reflection of reality, but rather of the introduction of additional biases which we wish to eliminate. The Double Heckman estimates appear to achieve this. It is evident that the upward bias that stems from a "high return" group writing the numeracy test is eliminated. However, this procedure does not only bring us back to where we started, it reduces the returns to schooling relative to the original naïve estimates. This is particularly true for the range of 8-15 years of education, which includes secondary school and undergraduate degrees. This section of the profile represents the bulk of South Africans, and hence suggests that educational returns are biased by ability. However, the magnitude does not appear very large at first sight. As was evidenced in the estimates which first conditioned for numeracy, its impact on schooling returns does not appear noteworthy. However, the magnitude is reduced by about 0.45 percent at the lowest levels of schooling up to a maximum reduction of 4.55 percent at 12 years of schooling for the African Population. The latter figure compares well with estimates of the bias found by Mariotti & Meinecke (2009). Interestingly the largest bias for African individuals is registered for those who completed their matric, suggesting that earnings functions overvalue this school leaving certificate. Given that this (matric) is usually the quoted "turning point" in the education-earnings profile, this overvaluation could possibly suggest that the marginal impact of tertiary education should carry greater weight in the policy debate than the much publicised matriculation results. This may, however, be a function of many other factors and requires further investigation.

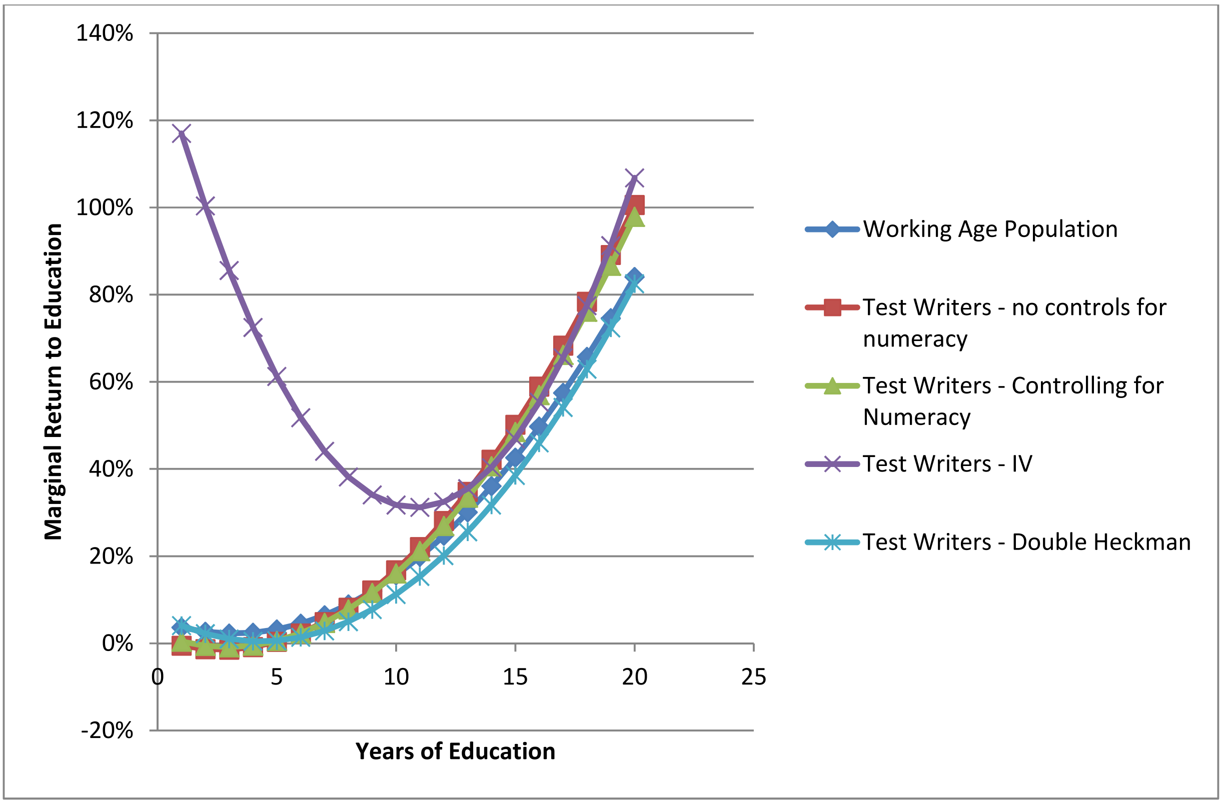


Figure 5 Marginal Returns to Education - African Population

A similar analysis for the white population is presented in Figure 6. Here, a concave rather than convex returns structure is observed. Small sample sizes at some education levels could be driving part of this analysis. This is particularly true over the upper range, where negative returns to education realise. Further, no white individuals in the sample have attainment levels below secondary school. Shifting the focus to relevant levels of education shows that the limited (test-responding) sample did not display markedly different returns to schooling compared to the entire working age population for individuals with post-secondary attainment. However, returns are higher for those with secondary schooling. Controlling for numeracy removes the convexity in returns. However, diminishing marginal returns (with earnings still increasing with education) still hold. This suggests that, once removing the effects of numeracy, the white population displays a more textbook earnings-schooling profile. IV estimates raise estimates of marginal returns substantially, while the Double Heckman procedure alters the structure entirely. Consequently, the corrections for selection into numeracy are not deemed satisfactory for the white subpopulation.

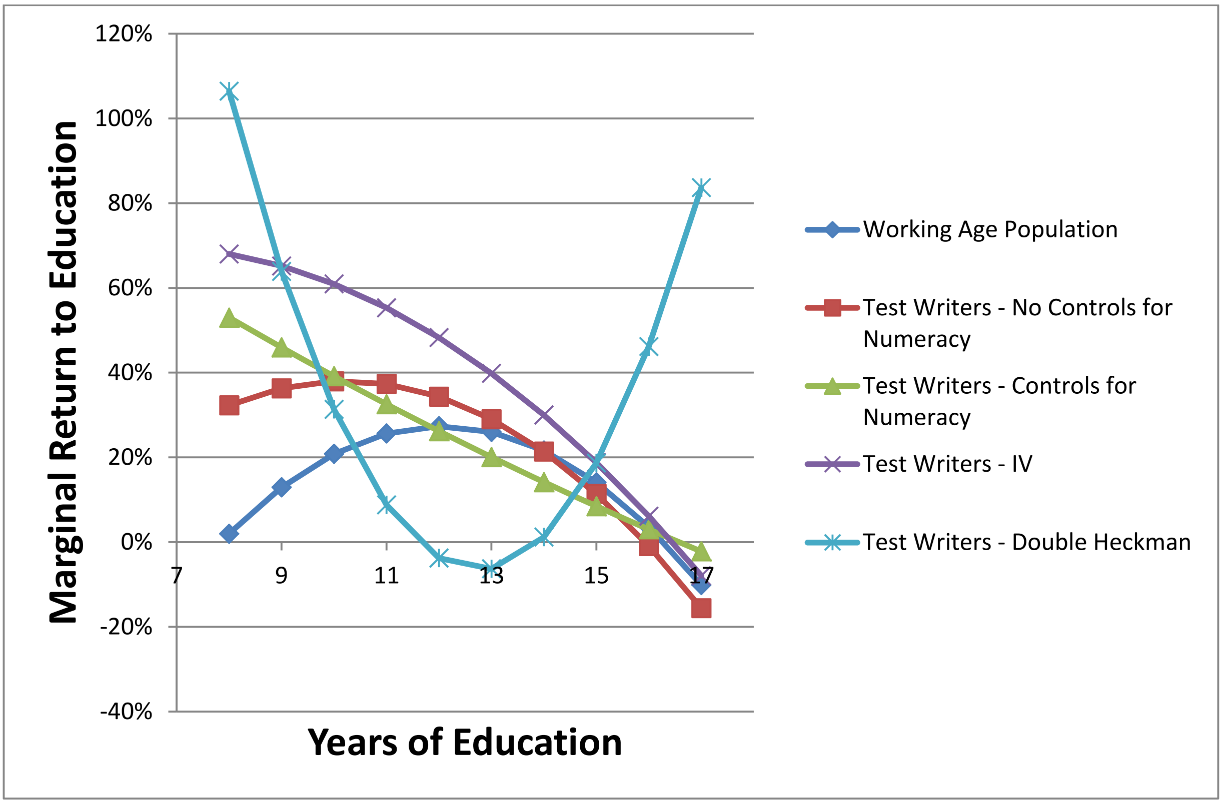


Figure 6 Marginal Returns to Education - White Population

While results for all race groups are not discussed, Figure 7 summarises the magnitudes of bias at various levels of schooling. Bias here is defined as the difference between the naïve single Heckman estimates of educational returns and those of the Double Heckman procedure. Only attainment levels at which sufficient numbers of respondents wrote the numeracy test are depicted. In reality, the number of test writers within the entire white and Asian cohorts is very small, which makes an analysis of bias infeasible. Hence, the very large numeracy biases indicated on the right axis for these groups are probably not an accurate reflection of reality, but are driven by the limitations of the sample. An analysis of African and coloured bias is, however, warranted. As noted before, bias peaks at 12 years of education with a magnitude of 4.55 percentage points for the African population. A similar picture holds true for the coloured group, though the greatest bias is noticed at 10 years of education at 5.84 percentage points. Together these estimates suggest that numerate individuals (after accounting for variable response patterns) are concentrated around upper secondary attainment levels. Small sample sizes at tertiary levels are probably the reason why this same phenomenon is not traced in that region. Most importantly, however, is that the marginal value of upper secondary education is most likely to be overstated in the South African earnings function.

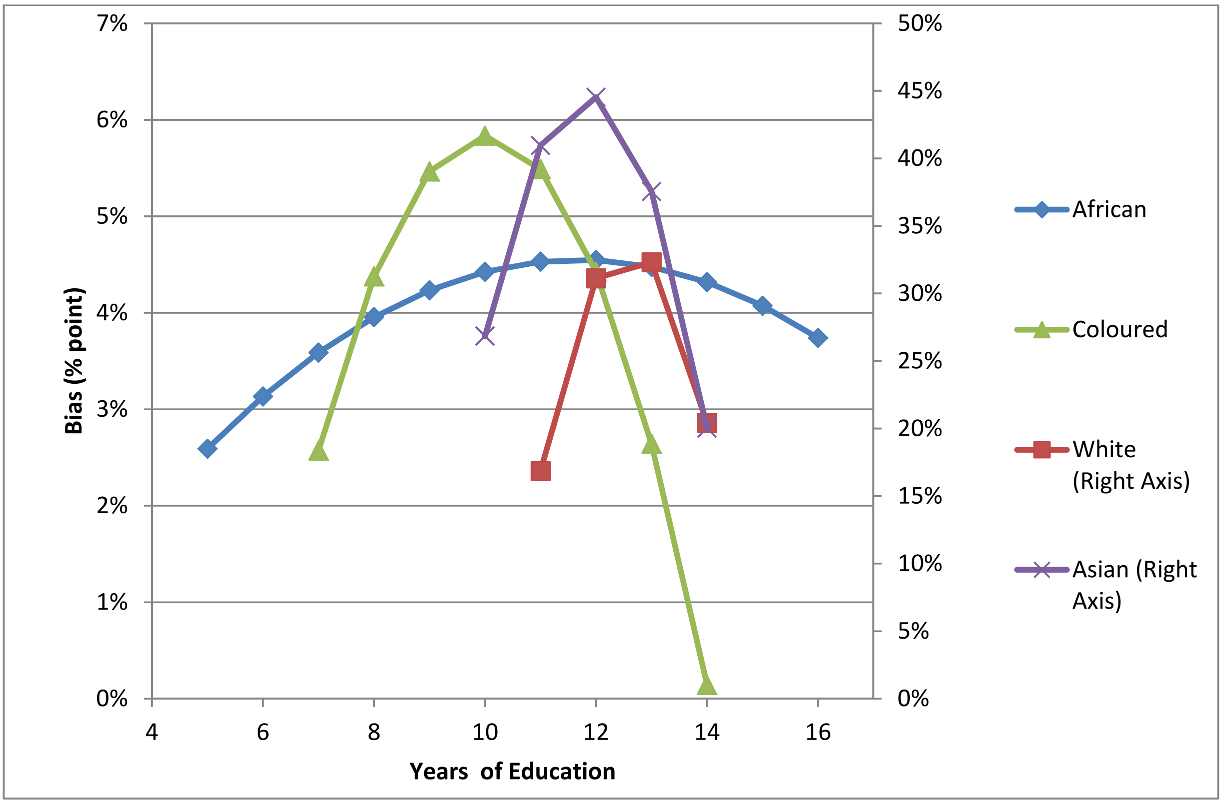


Figure 7 Bias in Returns to Education (Source: Own Calculations from NIDS, 2008)

How are these results impacted by the potentially incorrect calibration of test scores for those individuals that chose easy and difficult numeracy tests? Table 4 repeats the same exercise completed in Table 3, but the estimates in columns (c) – (e) are only for those individuals who wrote the test at the recommended level. The number of uncensored observations now reduces from 922 to 590. Given that most of the coefficients are statistically insignificant, a detailed discussion is not warranted. However, the differences in returns to education are again analysed graphically. Figure 8 depicts estimates of the marginal returns to education for the African population. The profile for all test writing individuals (with controls for numeracy) is repeated, with estimates again ranging from about 0 per cent for those with no education to around 100 per cent for those with advanced degrees. The same estimates within the limited sample (only those who wrote the correct test) decline markedly for the upper range of educational attainment. At the extreme, the drop is from a return of about 60 per cent to approximately 45 per cent. This decline can only be attributable to the fact that the sample has been limited to individuals that have not written tests that were too easy or difficult, and suggests that there is indeed an “overconfidence” component in the marginal returns to education. This is particularly apposite for the most educated African individuals.

Numeracy does not affect the returns dramatically and IVs alter the returns structure unrealistically. Double Heckman estimates are omitted here. We do not observe similar effects for the white population: all estimates are very close to each other (except for the IVs which are again apparently unsuccessful in estimating truly reflective returns to education), suggesting that neither a revealed numeric confidence nor a numeric ability premium is discernable within this subpopulation.

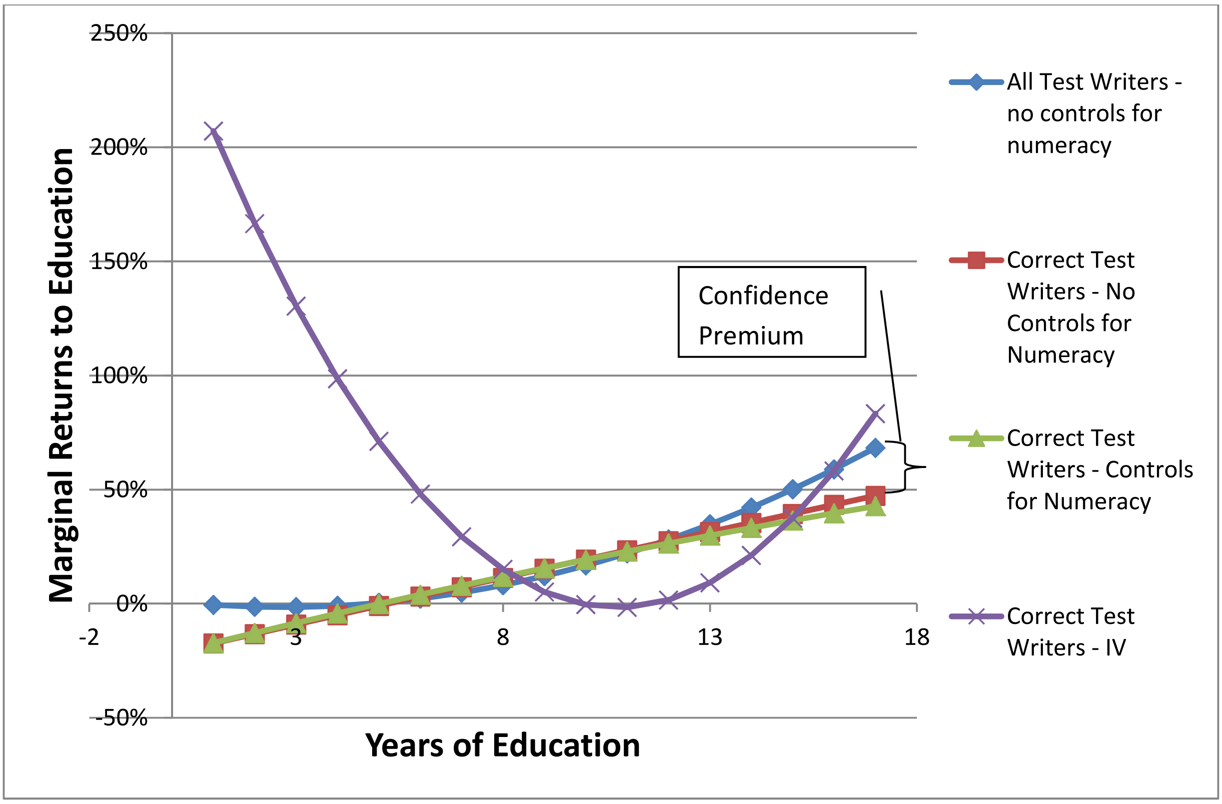


Figure 8 Marginal Returns to Education - African Population

In summary, this section has shown that numeracy scores do play an important role in the South African wage function. They have significant predictive power throughout. More importantly, at their largest impact, they account for about a 4.5 (5.84) percentage point bias in returns to schooling for the African (Coloured) sub-populations. Further investigation shows that some of the bias that is usually ascribed to "ability" can partially be attributed to "confidence in abilities" (for the African population). The analysis in the previous subsection on confidence suggests that education does have some role to play in creating actual value added (in terms of returns to numeric abilities), but that it also fosters the confidence required to succeed in the labour market.

The sample selection issues that are addressed in quite some detail here require further investigation. The validity of Double Heckman estimates needs to be tested. Future work will consider full information maximum-likelihood estimates of all the selection processes at play.

4.2.2 School Quality

A similar analysis is conducted using school level information on quality, rather than individual numeracy scores. While sample sizes on school quality measures are also small in relation to the overall sample size, the response rate was much higher for this group. Furthermore, rather than relying on a potentially noisy numeracy score, using historic school level information on quality allows more direct analysis of what specific schools would have added to earnings potential.

Results are presented in Table 5. It is evident from the large changes in magnitudes from column (a) to column (b) (with sign changes occurring frequently) that the sample that provided school information was very different from the entire working population. This response selection process has only been analysed superficially at this stage, so that no Double Heckman estimates are constructed here. It is evident in Figure 9 that at higher levels of African education returns are higher for the limited sample, suggesting that a higher ability sample provided schooling information.

When controlling for school quality (without instrumentation) in column (c), it is clear that coefficients are only slightly altered from the previous set, and that school quality is not statistically significant. Figure 9 confirms that returns to African education are not noticeably altered by controlling for school quality. However, as is evident in column (j) of Table 6, school quality plays a large role in changing the coefficients on education, and is in itself highly significant when racial controls are omitted. Its impact again disappears once racial controls are introduced in column (l) of Table 6. Clearly school quality is highly collinear with race. We interpret this as evidence that supports the contention that labour market outcomes are a function of apartheid-era segregation within the education system – school quality is a factor that is still largely indistinguishable from racial membership. These results do not show that school quality is directly responsible for racial disparities once individuals enter the labour market (as evidenced by the persistently highly significant racial dummies). More careful analysis is required to understand the lines of causality between inequalities in school output, racial segregation and labour market inequality. However, as the results of Burger and van der Berg (2011) suggest, much of what is often measured as direct labour market discrimination can rather be attributed to school quality differentials between race groups. We return to this in the next section.

Instrumental variables for education and school quality are also implemented to account for the absence of Double Heckman results: these are the school quintile and happiness levels. However, the sample size again drops to low levels, with coefficients changing substantially. Figure 9 reveals that the returns structure is again altered dramatically by applying this estimator.

Results for other population groups do not add to the discussion and are omitted here for the sake of brevity.

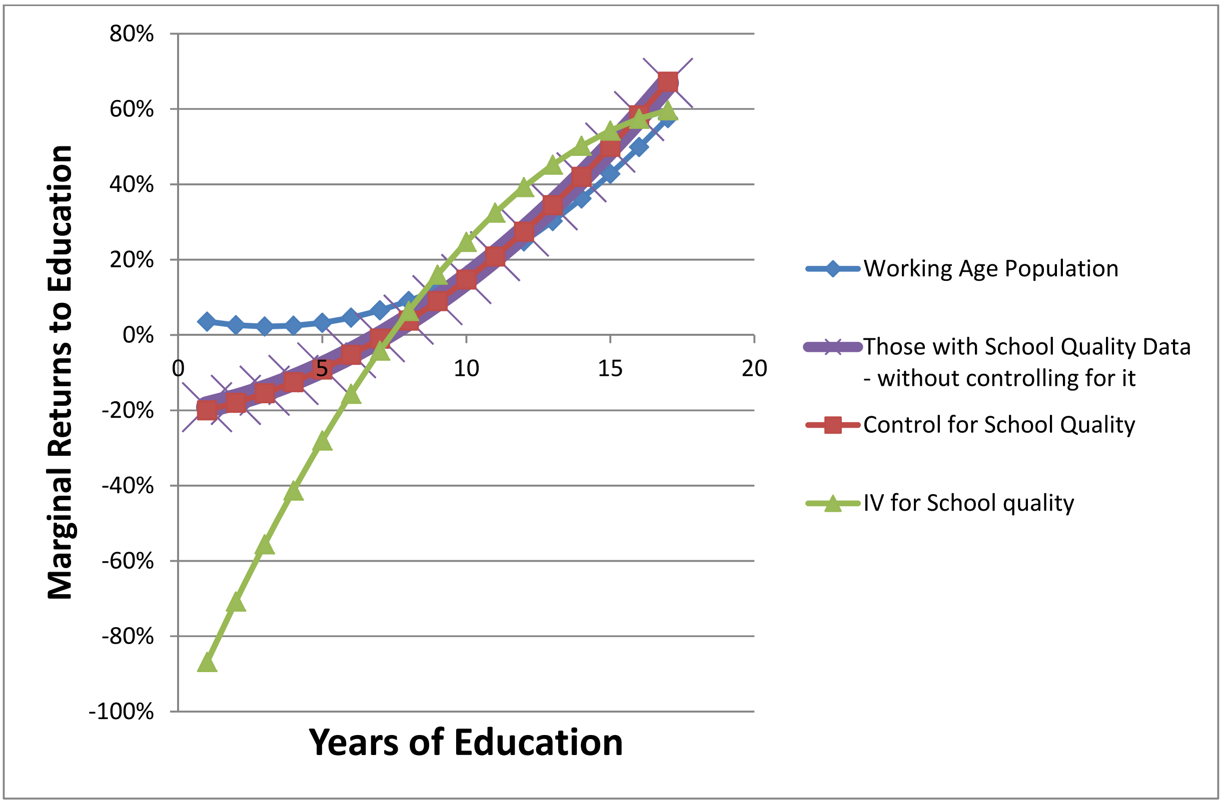


Figure 9 Marginal Returns to Education - African Population

4.3 The School Quality Component of Racial Premia

Burger and van der Berg (2011) perform Oaxaca-Blinder decompositions after simulating and incorporating school quality distributions into earnings functions. They find that what is traditionally measured as labour market discrimination can to a large degree be accounted for by the pre-labour market disparities in education quality. These differences are analysed more directly in Table 6. No racial interactions with education are introduced; the simpler specification is suited to an analysis of pure racial premia in the sense of a shift of the intercept.

Columns (a) to (f) consider only the sample of test writers. In column (c) a white wage premium of approximately 40% relative to Africans is measured (only controlling for education, age and gender). However, once controlling for individual level numeric abilities, this figure drops to about 33% in column (f), suggesting that about 18.7 percent of the premium is explained by differences in test scores. This difference can also be calculated by regressing constructed residuals[18] from columns (a) and (d) (respectively with and without controls for numeracy) on race dummies in columns (b) and (e). Differences in racial premia arise here because we use OLS instead of Heckman estimates on these residuals. Now the premium drops from 30.7% to 25% when controlling for numeracy. This again yields a component of 18.6% explained by differences in numeric ability.

[18] While maximum likelihood estimates conventionally do not have residuals as commonly understood in linear regression analysis, we nevertheless construct these by differencing actual and predicted values.

A similar approach is followed when considering the sample that provided data on school quality. Comparing columns (i) and (l) suggests that the racial premia of both Asians and whites above Africans increase once controlling for school quality. This is counter intuitive, given what is known about the strong correlation between school quality and race in South Africa. Columns (j) and (l) illustrate this particularly clearly, where school quality first has a very large and significant influence on wages before controlling for race – this turns large and (insignificantly) negative once introducing racial dummies. To measure the reduction in racial premia without contending with these correlations we again first run models (g) and (j). It is evident that introducing school quality does not change education coefficients to a large degree. Residuals are again constructed from these regressions and the racial components of these are estimated in (h) and (k). In the latter case school quality has been "purified" from the residuals. The unexplained premium for Asians above Africans drops from 95.1% to 75.2% once controlling for school quality (about a 21% share of the premium is attributable to school quality); for the white population the decline is from 62.8% to 39.7%, so that school quality accounts for a 36.8% share of the unexplained wage difference between whites and Africans. While these figures do not exactly match those of Burger and van der Berg (2011) and many sample selection issues are ignored in these particular estimates, they nevertheless indicate that school quality directly and numeracy scores (in part a function of school quality) account for a large proportion of unexplained racial wage differences.

5 Conclusion

From a policy perspective, monitoring returns to educational *attainment* as well as racial differences in the levels and wage returns to education *quality* are important quantities to measure. They allow us to better understand how the labour market values education, but more importantly describe how much of labour market discrimination can be attributed to inequalities that arise outside the labour market.

In the context of the first objective, numeric ability accounts for as much as 5.8 percentage points of the returns to education. Much of this bias is concentrated at higher levels of education, where the most numerate section of the population is found. This suggests that perhaps part of the convexity in the education-earnings profile in South Africa is accounted for by the fact that individuals with natural ability are concentrated at the top of the wage distribution. However, controlling for numeracy does not eliminate this feature of the wage distribution. Hence, labour demand side issues - such as the structural shift to a demand for skilled workers - still dominate the fact that returns to education are increasing (particularly for the African subpopulation).

The analysis goes on to show that for (particularly) the African population *perceptions* of abilities, and not only measured numeracy scores, play a role in explaining educational returns. While a rudimentary initial analysis indicates that confident respondents earn higher wages relative to the underconfident, it is also evident that Africans (with high levels of education) who volunteered for numeracy tests that were too difficult for them had higher returns to education than those that took correct tests. Together the findings suggest that bias in earnings functions is not only the function of actual ability differences, but whether ability is complemented by confidence in that ability.

The potential noise in the numeracy variables motivates an extension of the study to historical school quality rather than individual cognitive ability. Strong racial inequalities in the South African schooling system have long fed through to South Africa's very high levels of labour market inequality. While school quality is a strong positive predictor of wages, it is again the strong correlation between school quality and race that becomes the salient result. School quality apparently has a minimal impact on the returns to education, though this is only true if results control for race.This strong correlation hints that the racial inequalities in the labour market are largely explained by pre-labour market discrimination (in terms of a formerly segregated education system). However, this asserted causality requires further empirical support.

Finally, this paper quantifies the effect of numeric abilities and school quality on unexplained racial differences in wages. Approximately 18.6 percent of the white-African racial wage gap is accounted for by numeric ability differences, while separate analyses show that school quality accounts for about 36 percent of this measure of discrimination. These figures suggest that labour market discrimination has a large component that is inherited from factors that are already in place before entrants start to work.

In sum, this study suggests that the schooling system has a large role to explain racial disparities within the South African labour market – both by way of the scholastic outputs rewarded by employers and the confidence that a good education instils in students. The riddle of the extent of the ability bias in South Africa (as illustrated by Mariotti & Meinecke (2009)) has been partially isolated within this data, but requires additional work, due to both mismeasurement and sampling issues. While estimates presented here are consistent with other studies that use different methods, the figures can be refined with full information maximum likelihood estimates. What is clear, however, is that the strong racial dimensions of the South African labour market pre-date individuals' and groups' entry into the workplace and that some (though not all) of labour market discrimination should be addressed in that sphere. This draws to attention the growing literature on South African education production functions, which suggests that historically divided school systems still produce diverse outputs despite fiscal equalisation. Increasing the coverage and equalising the distribution of quality education should be emphasised to address the binding constraint of both skills shortages and skills inequalities in South Africa.

Table 2 Earnings Function Estimates - Dependent Variable - log(hourly wages) (Source: Own Calculations from NIDS 2008)

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*	*(h)*
Sample	*Test Writers*							
Estimator	*OLS (no sampling weights)*							
Education	-0.011		0.004				-0.02	0.003
Education^2	0.006		0.004				0.005	0.003
Education^3	0		0				0	0
Age	0.029		0.029				0.03	0.03
Age^2	0		0				0	0
African	Base Group		Base Group				Base Group	Base Group
Coloured	0.107		0.127*				0.097	0.105
Asian	0.775**		0.777**				0.780**	0.794**
White	0.515***		0.527***				0.467***	0.472***
Female	-0.311***		-0.309***				-0.302***	-0.304***
Easy Test		Base Group	Base Group		Base Group	Base Group	Base Group	Base Group
Right Test		0.239**	0.081		0.385***	0.336***	0.122	0.063
Difficult Test		0.311**	0.145		0.542***	0.500***	0.210*	0.221
Numeracy				0.269***	0.322***	0.287***	0.100**	0.091
Numeracy^2				0.023	0.043***	0.022	0.006	-0.016
Easy Test * Numeracy						Base Group		Base Group
Right Test * Numeracy						0.058		0.004
Difficult Test * Numeracy						0.013		0.097
Easy Test * Numeracy^2						Base Group		Base Group
Right Test * Numeracy^2						0.034		0.034
Difficult Test * Numeracy^2						0.009		0.026
Constant	0.836	2.304***	0.729	2.598***	2.236***	2.277***	0.878	0.818
R-squared	0.275	0.006	0.276	0.048	0.065	0.066	0.282	0.284
N	885	886	885	886	886	886	885	885
F statistic	64.594	3.247	54.234	24.039	16.536	10.037	46.226	36.708

NOTES: Significant at *10%, **5% and ***1% respectively. P-values based on robust standard errors. Estimates are not weighted. We do not correct for selection into employment or writing the test. The estimation sample however only includes those who reported wages and who wrote the numeracy test. A further limitation on the sample applies, because the confidence measure requires information on the test level that was actually written and the level that was recommended.

Table 3 Earnings function estimates - Dependent Variable – log(hourly wages) (Source: Own Calculations from NIDS 2008)

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*
Sample	*Entire Working Age Sample*	*Eligible to Take Numeracy Test*	*Test Writing Sample*			
Estimator	*Heckman for Employment Selection*				*IV*	*Double Heckman*
Education	0.052	0.051	0.009	0.021	1.354*	0.066
Education^2	-0.009	-0.009	-0.009	-0.01	-0.097	-0.014
Education^3	0.001***	0.001***	0.001	0.001	0.003	0.001
African	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Coloured	0.289	0.244	-0.912	-0.773	-22.9	-0.564
Asian	4.769	3.555	-78.712	-76.701	319.264	-19.014
White	7.402	7.472	0.99	-6.955	0.004	-32.323*
Education * African	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Education * Coloured	-0.214*	-0.202*	0.214	0.16	7.274	0.074
Education * Asian	-1.401	-0.974	19.117	18.555	-65.58	5.527
Education * White	-2.016	-2.083	-0.848	1.154	-0.953	8.006*
Education^2 * African	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Education^2 * Coloured	0.031**	0.030*	-0.018	-0.013	-0.775	0
Education^2 * Asian	0.145	0.103	-1.498	-1.448	4.35	-0.474
Education^2 * White	0.195	0.203	0.128	-0.035	0.142	-0.624*
Education^3 * African	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Education^3 * Coloured	-0.001**	-0.001*	0.001	0	0.027	0
Education^3 * Asian	-0.005	-0.004	0.038	0.037	-0.092	0.013
Education^3 * White	-0.006	-0.006*	-0.005	-0.001	-0.005	0.016*
Age	0.056***	0.049**	-0.009	-0.009	0.201	0.002
Age^2	-0.001**	-0.000*	0	0	-0.002	0
Female	-0.294***	-0.306***	-0.516***	-0.515***	-0.977**	-0.215**
Numeracy				0.146**	0.437	0.080*
Numeracy^2				0.036*	0.553*	0.003
Constant	0.701	0.809*	2.055*	2.120*	-9.165	2.218**
Number of Censored Observations	10409	9753	9753	9753		10409
Number of Uncensored Observations	4633	4505	922	922	547	865
P-value of H_0: $\rho = 0$	0.405	0.327	0.858	0.784	insignificant	insignificant

NOTES: Significant at *10%, **5% and ***1% respectively. P-values based on robust standard errors. Estimates are weighted. The selection into employment equation was modelled with quadratics in education and age, and gender, area and marital status dummies, as well as controls for the number of children in the household, whether the respondent was the household head, the number of unemployed individuals residing in the household, household income from grants and household income from remittances. In columns (a)-(d) the Heckman maximum likelihood estimator is used. In column (e) a Heckman two-step estimator is used to account for employment selection with another auxiliary first stage to generate the instrumented endogenous regressors; instruments for education and numeracy include respondents' mothers' education and a set of dummy variables indicating respondents' levels of happiness in the week preceding the survey. In column (f) no instruments are used, however an additional Inverse Mills Ratio is generated from a probit model explaining whether individuals took the numeracy test: covariates included whether respondents also volunteered to take biometric measurements shortly before the numeracy test, a measure of self-reported confidence in reading, an emotional index, household response rates to the test and a quadratic in the time elapsed before taking the numeracy test. These factors are discussed in van Broekhuizen & von Fintel(2010).

Table 4 Earnings function estimates - Dependent Variable – log(hourly wages) (Source: Own Calculations from NIDS 2008)

	(a)	*(b)*	*(c)*	*(d)*	*(e)*
Sample	*Sample Eligible to Take Numeracy Test*	*Test Writing Sample*	*Sample of Individuals Who Wrote Correct Test*		
Estimator	*Heckman for Employment Selection*				*IV*
Education	0.009	0.021	-0.215	-0.217	0.869
Education^2	-0.009	-0.01	0.021	0.023	-0.058
Education^3	0.001	0.001	0	0	0.002
African	Base Group	Base Group	Base Group	Base Group	Base Group
Coloured	-0.912	-0.773	-1.354	-1.274	-68.51
Asian	-78.712	-76.701	-147.983	-139.747	-211.217
White	0.99	-6.955	-1.143	-7.679	-20.6
Education * African	Base Group	Base Group	Base Group	Base Group	Base Group
Education * Coloured	0.214	0.16	0.568	0.562	19.77
Education * Asian	19.117	18.555	35.465	33.492	66.567
Education * White	-0.848	1.154	-0.208	1.436	3.509
Education^2 * African	Base Group	Base Group	Base Group	Base Group	Base Group
Education^2 * Coloured	-0.018	-0.013	-0.068	-0.069	-1.883
Education^2 * Asian	-1.498	-1.448	-2.758	-2.604	-6.662
Education^2 * White	0.128	-0.035	0.068	-0.067	-0.168
Education^3 * African	Base Group	Base Group	Base Group	Base Group	Base Group
Education^3 * Coloured	0.001	0	0.002	0.002	0.059
Education^3 * Asian	0.038	0.037	0.07	0.066	0.214
Education^3 * White	-0.005	-0.001	-0.003	0	0.002
Age	-0.009	-0.009	-0.04	-0.036	0.088
Age^2	0	0	0.001	0.001	-0.001
Female	-0.516***	-0.515***	-0.509***	-0.513***	-0.536
Numeracy		0.146**		0.102	0.486
Numeracy^2		0.036*		0.038	0.580**
Constant	2.055*	2.120*	3.227***	3.147***	-3.851
Number of Censored Observations	9753	9753	1660	1660	
Number of Uncensored Observations	922	922	590	590	352
P-value of H_0: ρ=0	0.858	0.784	0.471	0.458	.

NOTES: Significant at *10%, **5% and ***1% respectively. P-values based on robust standard errors. Estimates are weighted. The selection into employment equation was modelled with quadratics in education and age, and gender, area and marital status dummies, as well as controls for the number of children in the household, whether the respondent was the household head, the number of unemployed individuals residing in the household, household income from grants and household income from remittances. In columns (a)-(d) the Heckman maximum likelihood estimator is used. In column (e) a Heckman two-step estimator is used to account for employment selection with another auxiliary first stage to generate the instrumented endogenous regressors; instruments for education and numeracy include respondents' mothers' education and a set of dummy variables indicating respondents' levels of happiness in the week preceding the survey.

Table 5 Earnings function estimates - Dependent Variable – log(hourly wages) (Source: Own Calculations from NIDS 2008)

	(a)	*(b)*	*(c)*	*(d)*
Sample	*Entire Working Age Sample*	*Sample That Provided School Information*		
Estimator		*Heckman with Selection into Employment*		*IV*
Education	0.051	-0.207	-0.216	-1.039
Education^2	-0.009	0.006	0.007	0.087
Education^3	0.001***	0.001	0.001	-0.002
African	Base Group	Base Group	Base Group	Base Group
Coloured	0.29	-0.875	-0.539	-3.751
Asian	4.75	-0.465	-0.404	15.668**
White	7.435	12.316	11.656	10.983
Education * African	Base Group	Base Group	Base Group	Base Group
Education * Coloured	-0.213*	0.189	0.118	0.981
Education * Asian	-1.394	-0.192	-0.185	-5.485**
Education * White	-2.025	-2.655	-2.468	-2.128
Education^2 * African	Base Group	Base Group	Base Group	Base Group
Education^2 * Coloured	0.031**	-0.008	-0.003	-0.075
Education^2 * Asian	0.145	0.074	0.073	0.601**
Education^2 * White	0.196	0.216	0.201	0.162
Education^3 * African	Base Group	Base Group	Base Group	Base Group
Education^3 * Coloured	-0.001**	0	0	0.002
Education^3 * Asian	-0.005	-0.004	-0.004	-0.020**
Education^3 * White	-0.006	-0.006	-0.006	-0.005
Age	0.059***	0.083**	0.082**	0.112**
Age^2	-0.001**	-0.001*	-0.001*	-0.001**
Female	-0.302***	-0.220***	-0.217***	-0.378***
School Quality			-0.61	1.306
Constant	0.631	1.365	1.481	2.973
N	16521	13457	13457	915
F statistic				30.045
P-value of H_0: ρ=0	0.54	0.771	0.752	

NOTES: Significant at *10%, **5% and ***1% respectively. P-values based on robust standard errors. Estimates are weighted. The selection into employment equation was modelled with quadratics in education and age, and gender, area and marital status dummies, as well as controls for the number of children in the household, whether the respondent was the household head, the number of unemployed individuals residing in the household, household income from grants and household income from remittances. In columns (a) to (c) the Heckman maximum likelihood estimator is used. In column (d) a Heckman two-step estimator is used to account for employment selection with another auxiliary first stage to generate the instrumented endogenous regressors; instruments for school quality include school quintiles and a set of dummy variables indicating respondents' levels of happiness in the week preceding the survey.

Table 6 Earnings function estimates - Dependent Variable – log(hourly wages) (Source: Own Calculations from NIDS 2008)

	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*	*(g)*	*(h)*	*(i)*	*(j)*	*(k)*	*(l)*
Sample	*Test Writers*						*With School Quality Data*					
Estimator	*Heckman*	*OLS*	*Heckman*	*Heckman*	*OLS*	*Heckman*	*Heckman*	*OLS*	*Heckman*	*Heckman*	*OLS*	*Heckman*
Education	-0.224		-0.25	-0.226		-0.244	-0.545*		-0.655**	-0.572**		-0.658**
Education^2	0.028		0.032	0.029		0.032*	0.051*		0.067**	0.057**		0.067**
Education^3	0		-0.001	-0.001		-0.001	-0.001		-0.002**	-0.001		-0.002**
Age	-0.025		-0.007	-0.019		-0.004	0.008		0.074*	0.035		0.072*
Age^2	0.001		0	0.001		0	0		-0.001	0		-0.001
Female	-0.482***		-0.509***	-0.487***		-0.510***	-0.154		-0.208**	-0.181**		-0.205**
Numeracy				0.158**		0.145**						
Numeracy^2				0.036*		0.037*						
School Quality										1.496***		-0.636
African		Base Group	Base Group		Base Group	Base Group		Base Group	Base Group		Base Group	Base Group
Coloured		-0.129	-0.125		-0.168	-0.162		0.061	0.069		-0.014	0.103
Asian		0.384	0.399		0.404	0.413		0.951***	1.005***		0.752**	1.097***
White		0.307**	0.406**		0.250*	0.330**		0.628***	0.689***		0.397***	0.799***
Constant	2.680**		2.442**	2.666**		2.452**	3.857**		2.442	3.085*		2.553*
Number of Censored Observations	9753		9753	9753		9753	11889		11888	11889		
Number of Uncensored Observations	923	922	922	923	922	922	1569	1569	1569	1569	1569	916
P-value of H_0: ρ=0	0.384		0.65	0.389		0.625	0.158		0.629	0.264		0.61

NOTES: Significant at *10%, **5% and ***1% respectively. P-values based on robust standard errors. Estimates are weighted. The selection into employment equation was modelled with quadratics in education and age, and gender, area and marital status dummies, as well as controls for the number of children in the household, whether the respondent was the household head, the number of unemployed individuals residing in the household, household income from grants and household income from remittances. The Heckman maximum likelihood estimator is used throughout, except in columns (d), (e), (h) and (k), where OLS is used. All heckman estimates have *log(wages)* as the dependent variable, while OLS estimates are conducted on constructed residuals from the respective preceding equations.

6 Bibliography

Bhorat, H., & Hodge, J. (1999). Decomposing shifts in labour demand in South Africa. *South African Journal of Economics , 67* (3), 155-168.

Blackburn, M. L., & Neumark, D. (1993). Omitted-Ability Bias and the Increase in the Return to Schooling. *Journal of Labor Economics , 11* (3), 521-544.

Burger, C., & van der Berg, S. (2011). *Modelling cognitive skills, ability and school quality to explain labour market earnings differentials.* Stellenbosch Economics Working Paper 08/11.

Burger, R., & Von Fintel, D. (2009). *Determining the Causes of the Rising South African Unemployment Rate:An Age, Period and Generational Analysis.* Stellenbosch Economic Working Paper 158.

Daniels, R. C. (2007). *Skills Shortages in South Africa: A Literature Review.* Development Policy Research Unit, School of Economics, University of Cape Town, DPRU Working Paper 07/121.

Dunning, D., Meyerowitz, J. A., & Holzberg, A. D. (1989). Ambiguity and Self-Evaluation: The Role of Idiosyncratic Trait Definitions in Self-Serving Assessments of Ability. *Journal of Personality and Social Psychology , 57* (6), 1082 - 1090.

Griffin, P., Leibbrandt, M., Pavlovic, M., & Zuze, T. L. (2010). *Numeric Literacy in South Africa: Report on the NIDS Wave 1 Numeracy Test.* National Income Dynamics Study Technical Paper No. 5.

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

Keswell, M., & Poswell, L. (2004). Returns to Education in South Africa: A Retrospective Sensitivity Analysis. *The South African Journal of Economics , 72* (4), 834-860.

Louw, M., van der Berg, S., & Yu, D. (2007). Convergence of a Kind: Educational Attainment and Intergenerational Social Mobility in South Africa. *South African Journal of Economics , 75* (3), 548-571.

Manski, C., & Pepper, J. (2000). Monotone Instrumental Variables: With an Application to the Returns to Schooling. *Econometrica , 68*, 997-1010.

Mariotti, M., & Meinecke, J. (2009). *Nonparametric Bounds on Returns to Education in South Africa: Overcoming Ability and Selection Bias.* Working Papers in Economics & Econometrics, The Australian National University, Working paper No:510.

McIntosh, S., & Vignoles, A. (2001). Measuring and assessing the impact of basic skills on labour market outcomes. *Oxford Economic Papers , 3* (2001), 453 - 481.

Moll, P. G. (1998). Primary schooling, Cognitive skills, and Wages in South Africa. *Economica , 1998* (65), 263-284.

Parsons, S., & Bynner, J. (2005). *Does Numeracy Matter More.* National Research and Development Centre for adult literacy and numeracy. London: (NRDC).

Pauw, K., Oosthuizen, M., & van der Westhuizen, C. (2008). Graduate Unemployment in the face of Skills Shortages: A Labour Market Paradox. *South Afircan Journal of Economics , 76* (1), 45-57.

Schnedler, W. (2005). Likelihood Estimation for Censored Random Vectors. *Econometric Reviews* , 195-217.

Statistics South Africa (StatsSA). (2008). *Report on the Response by Statistics South Africa to Recommendations of the International Monetary Fund on Improvements to the Labour Force Survey.* Statistics South Africa, Pretoria.

Van Broekhuizen, H., & Von Fintel, D. (2010). *Who Responds to Voluntary Cognitive Tests in Household Surveys? The Role of Labour Market Status, Respondent Confidence, Motivation and a Culture of Learning in South Africa.* Stellenbosch Economic Working Paper 27/10.

Van der Berg, S. (2007). Apartheid's Enduring Legacy: Inequalities in Education. *Journal of African Economies , 16* (5), 849-880.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: The MIT Press.