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HOW IMPORTANT IS EDUCATION FOR GETTING AHEAD IN SOUTH AFRICA?

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How important is Education for Getting Ahead in South Africa?

Malcolm Keswell
Laura Poswell

The impact of education on the process of development relies crucially on what can be assumed about the way it is rewarded. Standard human capital theory assumes diminishing marginal returns to education. The purpose of this paper is to examine the empirical relevance of this assumption. We find that the standard approach to estimating this relation is not well supported by virtually all of the available evidence for South Africa. Indeed, the marginal rate of return to education is extremely high for tertiary levels of education and small (approaching zero) for lower levels of education. If human capital accumulation is an important determinant of wealth accumulation, this implies that educational reforms in the form of small policy interventions will not have any significant impact on the distribution of income and wealth, as long as key features of labour markets that govern the manner in which education is rewarded, remains unaltered.

1. Introduction

The relevance of education for the process of development relies crucially on what can be assumed about the way it is rewarded. In a recent survey of 1300 school students between the ages of 13-18, over 90% agreed with the statement that "To get ahead in South Africa, one must have a good education" (Burns, 2003). That young people believe this is unsurprising, given that much of the social and political rhetoric surrounding issues such as poverty focus on the importance of effort and ability in overcoming one's circumstances. But there is another way in which their response could be read: to get ahead in life, simply having *some* education is insufficient. One either has to have a great deal of education (or a great deal of money). But this is at odds with the standard human capital representation of how education is rewarded. The theoretical literature in economics now contains two widely different views of this process. What can be termed as the

Walrasian approach adopts the view that human capital, like physical capital, exhibits diminishing returns at the margin. Typically in this world view, initial conditions do not matter. The so-called concavity in the return structure of education ensures that private incentives for the acquisition of education exist so that all individuals, even the extremely poor, will eventually acquire enough education, reap the associated rewards and escape poverty.

But what if Burns' high school students are right, that education only matters if one acquires more than an average level of attainment? In other words, what if the rate of return to education is convex? A broad range of theoretical models developed over the last 20 years shows that when the return structure to education is such that it only matters if one acquires a great deal of it, initial conditions can come to play a huge role in who gets ahead and who languishes behind, leading to what economists term *multiple equilbria*. Galor and Zeira (1993) for example model the effects of human capital accumulation on the evolution of income distribution among dynasties, by assuming the existence of both imperfect credit markets and indivisibilities in education (i.e., a non-convexity, or discontinuity, in the production technology of human capital). This assumption is reflected in a strong non-linear pattern in the returns to education. If one does not possess sufficient wealth for the "minimum investment" necessary to acquire education, and if the cost of borrowing is too high, one will remain unskilled, uneducated and poor. Those with higher wealth will be able to invest in education, reap the higher returns and will remain wealthy. Rich and poor dynasties emerge and the unequal distribution of wealth persists. This is bad news for textbook economics, as it implies that individuals can persist in poverty indefinitely even in the presence of public policy designed to achieve the opposite.

The purpose of this paper is to examine the empirical relevance of assumptions about the way in which education is rewarded in the case of South Africa by asking: *how large are the pecuniary benefits of education, and is the available evidence consistent with the view that the returns to education diminish at the margin*? We find that the standard approach to estimating this relation is not well supported by virtually all of the available evidence for South Africa. This is consistent with other emerging evidence on the private benefits of education that show sharp and robust convexities in the return structure (see for example Card (1999) and Belzil and Hanson (2002)). Indeed, the marginal rate of return (i.e., the rate of return to an additional year of education) is extremely high for tertiary levels of education and small (approaching zero) for lower levels of education. Other factors such as school quality undoubtedly account for some of this, but there is evidence to suggest that controlling for these forms of bias would not eliminate the qualitative finding. If convexities remain a robust feature of the data and if human capital accumulation is an important determination of wealth accumulation, educational reforms in the form of small policy interventions can be expected to have a negligible impact on the distribution of income, education and wealth. Indeed, what is needed are large policy interventions or simultaneous focus on policies designed to alter the manner in which the labour market rewards education.

The paper is organised as follows. In section 2, we present a standard analytical framework for measuring the returns to education before turning to a brief review of all the existing evidence we have been able to locate on the subject (that is comparable and representative in some meaningful sense) in section 3. We then turn to our own estimates beginning in section 4, with a discussion of the data we use, followed by a presentation and discussion of our own results in section 5. In section 6, we offer some qualifications to our findings, before concluding in section 7.

2. Measuring Returns to Education

One approach to measuring the pecuniary returns to education is to calculate the so-called *internal rate of return* which is simply the discount rate that equates the present value of costs incurred and the opportunity cost of earnings foregone whilst one is in school, to the present value of earnings arising from the additional education acquired. A popular approximation to this measure, termed the Mincerian return after Jacob Mincer (1974), is given by the coefficient of the schooling term in a log-linear earnings function. The basic idea in this model is to provide a choice-theoretic framework for the accumulation of human capital, where human capital is narrowly defined as one's level of educational attainment. The choice of the optimal level of education is made through a process of comparing the present value of different income streams associated with different levels of schooling (Becker (1964), Hansen (1963), Mincer (1958), (1974), Ben-Porath (1967)). Under the assumption that the time span of earning life is fixed, an equilibrium condition is defined by setting the expected rate of return to schooling investments equal to the discount rate (i.e., the rate at which the individual discounts future benefits of going to school now, relative to the present benefit of working now instead of attending school). Formally, we can define the present value of an individuals lifetime earnings at the start of schooling as:

$$V_s = y\int_s^{s+n} e^{-\beta t}dt = \frac{y}{\beta}e^{-\beta s}(1-e^{-\beta n}) \tag{1}$$

where y refers to the income stream associated with s years of schooling, n is the length of working life, and β is the rate of return to investment in schooling. Likewise, we can define the present value of lifetime earnings in the absence of schooling to be

$$V_0 = \alpha\int_0^{n} e^{-\beta t}dt = \frac{y}{\beta}e^{-\beta 0}(1-e^{-\beta n})e^{-\beta(0)} = \frac{y}{\beta}(1-e^{-\beta n}) \tag{2}$$

where α refers to the income stream associated with s years of schooling. Assuming that the only cost to schooling is forgone earnings and individuals do not earn while in school, then equating V_s to V_0 establishes the first order condition for maximisation of lifetime earnings, and therefore the equilibrium choice of schooling. Thus,

$$1 = \frac{ye^{-\beta s}(1-e^{-\beta n})}{\alpha(1-e^{-\beta n})} \tag{3}$$

Taking the natural logarithm and rearranging terms, we get,

$$\ln y = \ln\alpha + \beta s \tag{4}$$

This is the canonical earnings function usually attributed to Mincer (1974). Note that individual sub-scripts, though applicable, have been suppressed to reduce notational clutter.

The constant term α accounts for expected earnings in the absence of other factors, where the other factors in this model, relate only to schooling. The schooling coefficient β is the marginal "private" rate of return on education. This coefficient is interpreted as the marginal *internal rate of return* on education where the costs of education are accounted for, both in terms of direct costs (tuition etc.), as well as indirect costs, in terms of earnings foregone during the time spent acquiring education (Rosen (1992)).

Since earnings is also likely to be independently influenced by experience, (4) is conventionally augmented with a measure of "potential experience" to account for the importance of on-the-job learning. But because this proxy is measured with considerable error in cases where grade repetition is high and spells of unemployment are long (both of which are true for South Africa), we choose not to follow convention here. Instead, we use age, as opposed to the more standard proxy for "potential experience" as is common in the literature on returns to education.

$$\ln y = \ln \alpha + \beta S + \xi_1 Age + \xi_2 Age^2 + u \tag{5}$$

as our baseline earnings function, where the last term in the expression is simply a random shock, which is assumed to average out over the population (i.e., the mean is zero). Several observations about (5) are worth drawing attention to: First, while it is explicitly derived from a model where individuals choose the optimal level of schooling that maximises their utility, it could also be treated as a reduced form representation of an income-generating function. Second, the (assumed) relation between log income and schooling is linear, implying that the rate of return to an additional year of education is the same for all individuals (less and more educated alike). Third, a standard finding about the effects of age is that marginal increases in age lead to marginal increases in income, but these increases diminish as one gets older. Thus, the age-earnings profile is said to be concave.

In what follows, we present estimates of (5) and then alter the model in several important ways. One standard test of the hypothesis of non-linear returns to education is to re-write (5) so that

$$\ln y = \ln \alpha + \beta_1 s + \beta_2 s^2 + \xi_1 Age + \xi_2 Age^2 + u \tag{6}$$

The returns to education then become:

$$\frac{\partial \ln y}{\partial s} = \beta_1 + 2\beta_2 s \tag{7}$$

Thus, an important implication of measuring the returns to education in this way is that the rate of return is now allowed to vary by level of education. A sufficient test of the hypothesis that all individuals experience the same rate of return, independent of the level of education would be to find β_2 to be insignificantly different from zero.

Finally, we extend (6) even further to account for intercept effects of race, gender and location (all captured in the vector X shown in equation (8) below). Moreover, to allow for the possibility that age does not operate independently of education, we also include age-education interaction terms. This controls for the differing average educational attainment of various age groups, and allows an evaluation of the rate of return of education, conditional on one's age. In addition, we introduce a cubic polynomial in education, based on the notion that since we actually do not know the true functional form of the reward structure, it is appropriate to tease out the underlying functional form by introducing higher order polynomials in the spirit of a Taylor series approximation. Thus (6) is transformed to:

$$\begin{aligned} \ln y = \ln \alpha + \beta_1 s + \beta_2 s^2 + \beta_3 s^3 + \xi_1 Age + \xi_2 Age^2 + \\ \delta_1 (Age \times s) + \delta_2 \left(Age \times s^2\right) + \delta_3 \left(Age \times s^3\right) + \Omega \mathbf{X} + u \end{aligned} \tag{8}$$

We can therefore write the returns to education as:

$$\frac{\partial \ln y}{\partial s} = \beta_1 + 2\beta_2 s + 3\beta_3 s^2 + \delta_1 Age + 2\delta_2 (Age \times s) + 3\delta_3 (Age \times s^2) \tag{9}$$

How will rates of return to education affect inequality? One standard measure of this is given by the coefficient of determination – the R^2 – which measures the fraction of the variation in log earnings explained by the particular combination of explanatory variables in question. In a model like (4) the R^2 measure is a useful indication of the fraction of earnings inequality explained by schooling. By taking variances of the basic earnings equation (4) we can also arrive at a measure of the distribution of earnings as a linear function of the distribution of schooling:

$$
\begin{aligned}
\operatorname{var}(y) &= \operatorname{var}(\alpha + \beta s + u) \\
&= \beta^2 \operatorname{var}(s) + \operatorname{var}(u) + 2\beta \operatorname{cov}(s,u) \\
\frac{\partial \operatorname{var}(y)}{\partial \beta} &= 2\beta \operatorname{var}(z) + 2\beta \operatorname{cov}(s,u) \\
&= 2 \operatorname{cov}(s,y)
\end{aligned} \tag{10}
$$

Differentiating the resulting expression with respect to the rate of return, as shown in equation (10), we can derive an analytical expression that shows that inequality necessarily must increase when the rate of return increases, as long as there is a positive relationship between earnings and education. If the variance decomposition were applied to (6), it would become obvious that convexity in the returns to education implies a more skewed distribution of earnings.

3. Existing Evidence

The most influential work (from a policy perspective) on collating and comparing international estimates of the returns to education are the cross-country analyses by Psacharopoulos (1973, 1985, 1994) and most recently, Psacharopoulos & Patrinos (2002). Over a period of 30 years, he has compiled and compared estimates of the rates of return to education for a vast number of countries – the latest review is for a sample of 98 countries covering all major geographic regions of the world. The central claims of each of these studies has been that the returns to education, however they may be measured, decline by level of education within countries, becoming less important over the course of economic development. Table 1 reproduces these results and purports to show this pattern for Mincerian rates of return, averaged over region. Since countries in poorer regions trend to have higher rates of return coupled with lower average attainment figures, this (at least in the previous reviews) was taken as evidence that spending priorities of poor countries should focus on primary education. However, more recent evidence (Bils and Klenov (1999), Psacharopoulos & Patrinos (2002)) does not show a consistent pattern of diminishing returns. Moreover, various problems plague this sort of analysis. Differences abound in the type of data used, much of which is derived from employer surveys rather than household surveys. Indeed, Bennel (1996) argues convincingly that much of the evidence presented for Sub-Saharan Africa in these reviews are of highly questionably quality and thus the enormous rates of return to primary schooling typically claimed, as evidence in table 2, cannot be treated as reliable. These factors, coupled with the recent divergence in aggregate patterns, have highlighted the need for caution in interpreting evidence on rates of return to education, particularly in terms of their policy relevance.

A common alternative approach, relied on heavily in macroeconomic policy debates about the role of education, is to study the so-called *social rate of return*. The distinguishing feature of this method is to include some measure of social spending on education (or sometimes average attainment by type of education) in cross country growth regressions, aggregated at the country or regional level where per capita GDP (or some such aggregate measure of welfare) is the object of interrogation. Table 3 shows an example of this from the reviews mentioned above. Barring obvious problems with this approach[1], the most recent evidence in favour of concavity in the returns to education is at best mixed. For example, in the more recent review undertaken by Psacharopoulos & Patrinos (2002), the pattern does no hold for the lesser-developed regions in Europe/ Middle East/ North Africa and

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[1] Growth accounting models of the returns to education are highly sensitive to the measure of welfare used – GDP per capita (adjusted for purchasing power parity), unemployment rate, poverty rate, GINI coefficients – these are just a sampling of the available choices. Then there are questions of how to define education: if educational expenditures are used, how does one account for structural breaks in expenditure within countries?

for OECD countries. Moreover it has also been agued that in the case of the Middle East and Africa in general, evidence in favour of social returns to education of any kind simply do not exist (Pritchett, 2001).

These and other problems of aggregation (see Bennel, 1996) perhaps account for the much more guarded approach taken in the latest review by Psacharopoulos and Patrinos, with the authors themselves stating that these patterns should no longer be treated as prescriptions for policy – a statement quite at odds with the tone of earlier reviews. Indeed, closer inspection of Psacharopoulos' results shows that many findings are extremely dated and many countries are excluded from the analysis altogether. Consideration of just a handful of these recent studies (all subject to peer review) reveals some interesting patterns. Siphambe (2000) for example, finds that in Botswana, the Mincerian returns to primary schooling are quite small, followed by lower secondary, tertiary, and then upper secondary schooling. Skyt and Westergård (1998) find a similar result for Zambia for urban men and woman. Likewise, Teal (2001), Wahba (2000) and Appleton, Hoddinott and Mackinnon (1996) find evidence of strongly increasing private returns to education in Ghana, Egypt, Côte d'Ivoire, Kenya and Tanzania.

Neither is the phenomenon peculiar to Africa. Carnoy (1995) for example shows that a pattern of increasing returns emerges when studying changes in rates of returns over time for countries as diverse as the USA, Columbia, Hong Kong, Kenya and Korea. He argues that in periods of rapid industrialization, combined with increased access to primary and secondary education, the rates of return to schooling appear to decline over time with the largest decreases affecting the returns to primary education. On the whole, a strong pattern of increasing returns therefore emerges, with tertiary education ending up with the highest rates of return.[2]

These broad results are also consistent with what is known about rates of return for South Africa. Table 4 summarises the key results of studies that have incorporated some form of education variable into semi-log earnings functions (appendix A provides more details on each of the studies

[2] See also Card (1999) and Belzil and Hanson (2002) for more recent evidence on convexities.

considered[3]). The estimates presented in the table are derived from the listed studies by converting those estimates reported by the authors into a linear spline function (the most common approach used in the reviewed studies)[4]. The results are therefore to be interpreted as the average private rate of return to an additional year of primary, secondary or tertiary education. We then take the average across the spline as an approximation to an ordinary least squares estimate of the Mincerian return.

Several patterns emerge from comparing these studies. First, in virtually every case considered, the returns to education are clearly increasing, by level of education[5]. Second, in every study the returns to an additional year

[3] The relevant studies are Mwabu and Shultz (1993), Rospabe (2001), Bhorat (2000), Michaud and Vencatachellum (2001), Bhorat and Leibbrandt (2001), Lam (1999), Moll (1996), Hofmeyer (2001), Hosking (2001), Kingdon and Knight (1999), Erichsen and Wakeford (2001). Earlier studies such as Joubert (1974), Archer and Moll (1980), and Pillay (1991) are not explicitly considered as all of these studies were not based on representative datasets.

[4] This was done so as to make estimates roughly comparable since some of the studies differed markedly in terms of the data, sampling algorithms, definitional conventions, and estimation techniques. For example, some studies explicitly separate out the effects of race and gender by estimating separate regressions for each of these catagories. Still, other studies consider different forms of employment ranging from full time, part time, and self-employment, spanning formal and informal sector workers.

[5] Two exceptions to this finding are Bhorat and Leibbrandt (2001), and Michaud and Vencatachellum (2001). In the case of the latter study, the returns to education for union-members are convex, whereas this is not the case for non-union members. There are two probable reasons for this. Firstly, the sample of non-unionised African males with tertiary education is particularly small. Secondly the regressions are run including a significant ‘skilled-employment’ dummy. This dummy is likely to be highly correlated with tertiary education and probably accounts for why the pattern does not emerge for this group.
In the case of Bhorat and Leibbrandt (2001), the authors use what they term a “three stage sample selection model” for which coefficients on the education splines are reported for each stage. They begin by estimating separate probit equations for labour market participation and employment. Using the estimated inverse of the Mills ratio computed in the second equation, they then proceed to estimate an earnings function. They find that in the employment probit, the coefficients are as expected. The spline for tertiary education is significant in influencing the probability of having a job and is much higher than for secondary and primary returns. In the earnings equation, however, the coefficients on tertiary education are insignificant. The authors comment that this implies that although tertiary education is important in raising the probability of employment, it is not relevant as a predictor of the level of earnings for Africans. This result is in direct contrast with at least two other studies focusing on the sample of African individuals in nationally representative data sets, namely Moll (1996) and Keswell (2003).

of primary education are low and below 10%. The median across studies is in fact a mere 4%. Many authors have commented on reasons for the relatively low returns to primary education in South Africa. Moll (1996) postulates that poor schooling quality for Africans is likely to be the major cause of low returns. While this surely must be an important part of the explanation, in other work it has been shown that a large piece of the puzzle rests on understanding the changing racial patterns of rewards and returns in the labour market (Keswell, 2003).

The above results suggest that the weight of the available evidence for South Africa at least does not support the long held view of diminishing returns to education. However, owing to the various problems of comparability and interpretation across these studies, it is difficult to make a serious judgement about robustness of the evidence. The literature reviewed here suggest strong reasons to expect convexities to be a robust phenomenon of the data, but this can only be rigorously established if many of the comparability problems highlighted above are dealt with in some systematic manner. The remainder of the paper is devoted to dealing with some of these problems in the hope of being able to ascertain the robustness of the convexities result. Our approach is straightforward in the sense that we apply common definitions, functional forms and estimation techniques in estimating the returns to education, using on four nationally representative datasets for South Africa.

4. Data

The data used in this paper are drawn from the *Project for Statistics Living Standards and Development* (PSLSD) conducted in 1993, the *October Household Surveys* (OHS) of 1995 and 1997, and *the Labour Force Survey* (LFS), conducted in September 2000[6].

[6] Other available micro data was not used primarily for differences in data coverage and measurement. For example, the OHS 1996 was excluded primarily due the nature of the income data which was only reported in intervals. The 1996 sample is also least comparable with other data as its sample size is approximately half that of the other years of the OHS and its enumerator areas are based on a different sampling frame. See also appendix B for more on this point.

In all surveys considered, the distribution of education is not systematically related to the non-reporting of incomes – those that did not report their income did not report statistically different levels of educational attainment from those who did report income. This implies that the incidence of missing data for earnings is independent of a respondent's schooling level. We therefore choose to ignore cases of missing data generally[7].

Table 5 shows the mean characteristics of the sample drawn from each of the four surveys to be used in the analysis to follow. All estimates are for individuals and not households.

We use age, as opposed to the more standard proxy for "potential experience" as is common in the literature on returns to education. This is because factors such as grade repetition, low educational attainment, and job insecurity (problems which typify South Africa) will likely produce overestimates of the effect of potential experience.[8] Table 5 shows that average age of all full time employees rises from about 36 years in 1993 to 39 years in 2000. The average age of those without any form of paid employment (i.e., the censored observations) remains fairly constant across the surveys at about 31 years, while mean educational attainment (measured as years of schooling attained) of the censored observations increases by 1 ½ years.

Income earners are restricted to full time workers between the ages 15 – 65. Earnings are measured as gross monthly pay including overtime and bonuses[9]. Self-employment is excluded from the analysis as it is poorly

[7] In the case of the October household surveys, one can do this with less confidence because the frequency of missing income data is potentially not exogenously determined in at least one known way: questionnaire designs, particularly of the most recent surveys, allowed respondents to report their income brackets as opposed to their actual income. Thus, it becomes important to know if the complete distribution of incomes (which we have no precise way of knowing) is systematically different to the distribution of reported incomes. Appendix B details the manner in which we tried to address this problem.

[8] "Potential experience is usually proxied by the formula: Age – Years of Education – 6. For obvious reasons, whenever self-selection of any kind is at work, this proxy is a poor measure of job tenure, on-the-job learning, and other such factors, about which "potential experience" is usually meant to shed light on.

[9] The choice of using monthly as opposed to hourly earnings is largely due to differences in the way this variable is measured across surveys. As our sample of interest is limited to full time formal sector workers, we do not see this as particularly problematic. Furthermore, if one

defined in both the PSLSD and the LFS thus rendering any meaningful comparisons of this group impossible. Moreover, even in the absence of these problems, including these categories would compound the opposing effects of seasonality (where measurement error is systematic and therefore predictable) and inter-temporal fluctuations due to the transitory nature of many types of self-employment in the informal sector.

Excluding these categories of paid employment has the consequence of overstating the implied degree of unemployment. Thus, the fraction of the sample where individuals have zero earnings is best interpreted as the degree of censoring and not the rate of unemployment. Appendix C provides further details of the construction of the dependent variable in the analysis to follow.

Table 5 shows that the extent of censoring is substantially lower in 1995 than in other years. This necessitates that some systematic approach be adopted to account for this, if we are to make reliable comparisons across the various surveys. The econometric literature is divided on precisely how to deal with this issue (see Madalla (1983) and Deaton (1997) for opposing views). However, the practice of simply treating zeros as missing values (which all except one of the reviewed studies does) results in biased estimates (see appendix D). Moreover including the zeros and not adjusting the estimator used can have consequences, especially if the goal is to compare estimates across surveys where the degree of censoring differs substantially. Since the degree of censoring in the 1995 OHS differs by a magnitude of 10-15% compared to the other surveys, the cross-sectional comparisons made in this paper depends crucially on a systematic treatment of this problem. We therefore present estimates based on two different approaches –ordinary least squares (where no adjustments are made) and Tobit estimates (where we do adjust for the inclusion of the unemployed). Further details concerning this estimation technique are outlined in Appendix E. The results are reported in tables 6-10.

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assumes that the pattern of hours worked over the lifecycle is fixed exogenously, it makes little difference what measure of earnings is used, be it hourly, weekly, monthly or annual. (Willis, 1986)

5. Empirical Estimates

Tables 6 and 7 shows OLS and Tobit estimates of equation (5) – the standard Mincerian earnings function. Accounting for censoring, the rate of return to education for full time wage earners lies between 15–26 percent. The non-linear model (equation (6)) represented in tables 8-9 show that the Mincerian model does not fit the data well – the quadratic specification for education is highly significant for all years under consideration. Both sets of results however, suggest remarkably higher rates of return at all levels of education than is typical (see section 3). Several factors account for this. First, only full time wage earners are considered. Second, owing to the large degree of censoring, the rate of return is overstated[10]. Third, the results obscure the effects of race – i.e., in addition to the non-linear effects by education, a further dimension of (omitted) heterogeneity is the effect of race on the rate of return to education. Indeed, further estimates (not reported here) indicate that race accounts for a substantial fraction of the large returns indicated in tables 6-9. For example, when including race dummies, the estimated Mincerian rate of return in all years considered is less than half that indicated in tables 6-7. Keswell (2003) considers this question in more detail and finds an extremely large increase in the racial income gap between Africans and whites emerges over the period 1993-2000 – this increase being driven largely by a sharp increase in the rates of return accruing to whites.

Tables 10 and 11 present estimates of the effect of a cubic polynomial in schooling (as in equation (8)) controlling for intercept differences by race and region, as well as slope differences in rates of return to education by age. The results show a particularly robust fit of the cubic model – the coefficients on all the educations terms are significant in all years considered. Note though that given the non-linearity introduced through schooling, the rates of return implied by these estimates are not obvious. However, by making use of equation (9) the marginal effect of education can

[10] The consequence of including the zeros is to make the predicted earnings-education mapping steeper than it would otherwise be, if one were to use OLS. The Tobit can be thought of as a intermediate estimate between the relatively flat fitted regression line that would result were the zeros excluded, and the relatively steep fit were the zeros included and estimated via ordinary least squares (notice that the estimated coefficients of the Tobit are consistently smaller than the corresponding OLS estimates).

then be calculated – though as is evident from resulting expression, the rate of return depends on one's age and level of schooling. Thus to find the actual rates of return we need to substitute in the relevant information for each individuals age and level of education. Table 12 shows such a calculation for a 40 year old individual with 7, 10, 12 and 15 years of education respectively. In order to facilitate comparison with the existing evidence, we need to also calculate the pseudo splines referred to earlier. The estimates referred to as "average returns" in table 12 show this calculation. The new evidence reported here is quite consistent with what was inferred from existing studies. Specifically, the average rate of return per year of primary schooling is exceptionally low, with a strong pattern of increasing returns present (consistent with the derived estimates from other South African studies summarised in table 4).

An alternative way of depicting this finding is shown in figure 2. This figure simply represents a plot of the fitted values generated by estimating equation (8) against the corresponding years of education for our sample of individuals in each dataset. The slope of the plots reflect how predicted earnings change with each level of education (i.e., the flatter the slope at a particular point, the smaller the associated rate of return at that point). Like the parametric estimates discussed above (table 12), it shows a sharply convex relationship between education and predicted earnings. The huge returns to tertiary education are quite striking in each of the 4 datasets, as indicated by the large steepness of the slope of the fitted line. Equally striking is the flatness of the slope of predicted earnings for virtually all of primary education, confirming the low (close to zero) returns that are generally suggested by the existing evidence (see table 4).

An interesting finding is the apparent downward sloping portion of the fitted lines in figure 2. This is quite a robust feature of the data. While a substantial fraction of this effect is probably generated by reporting errors in schooling, if those individuals with only a few years of education are adults, this introduces the possibility that the apparently higher expected earnings of individuals with less than three years of education may have more to do with age or experience effects, rather than education. Setting aside the potential problems with the experience proxy, Using the PSLSD data, Hertz (2001) finds that controlling explicitly for potential years of experience eliminates the apparent trade-off between experience and schooling at the bottom of education distribution. We perform the same test for our two datasets in which the downward-sloping effect is most severe. Figure 3 shows that this reverses the negative slope, but also serves to pronounce the sharpness of the convexity – the returns are constant up until approximately 12 years, increase substantially around this point, and thereafter are fairly constant but at a much higher level, suggesting two regimes within the data. Such a pattern might be described as "lumpy" or discontinuous. For example, the pictures show that one could invest for 10 years, with practically zero marginal return, or invest for more than 13 years and receive a high return. Both figures 2 and 3 show that at least one of the preconditions for the generation of poverty traps (convex returns) might be a robust feature of the data, suggesting a strong causal role for education in the perpetuation of inequality (Ljungqvist (1993), Galor & Zeira (1993), Hertz (2001), Mookherjee and Ray (2002)).

6. Some Qualifications

Several forms of potential biases plague any estimate of the rate of to education. These include the omission of ability, family background, school quality, as well as error stemming from the mis-measurement of the schooling variable itself. Though no attempt is made to correct for any of these potential biases in the estimates we report (primarily because of the lack of adequate data on these variables in the sources we have used) it is worth briefly considering what is known about these effects elsewhere, and what can be inferred from the limited work in this area using South African data.

Omission of "ability" from the earnings function is one potential cause of bias. If there is a positive correlation between education and ability, so that those who have greater ability tend to stay in schooling longer, then earnings that are attributed to higher levels of schooling may rather be a function of higher ability. When ability is unobserved and omitted from earnings functions, the estimate of the rate of return to education will be biased upwards. Attempts to quantify ability biases have used instrumental variable approaches and data on twins to control for ability differences (see Ashenfelter and Rouse (2000) and Bowles and Gintis, 2002)). Another approach is to attempt to control for "observable" ability using test scores such as IQ as a measure of cognitive ability. Empirical evidence on the magnitude of ability bias measured in terms of (omitted effects of) test scores tends to suggest that it is relatively small, typically around 10-12 percent (Griliches and Mason (1972), Card (2001)) with the direction of the bias sometimes being indeterminate (Griliches (1977)). In a survey of studies on investments in education, Schultz (1988) places the figure as most likely falling between 5 and 15 percent.

Little is known about this form of bias for South Africa owing to the lack of reliable data on measures of cognitive skill. However, one recent estimate implies that the fraction of the rate of return to schooling accounted for by cognitive skill is about 33% for individuals with primary and secondary schooling, and about 6% for those with tertiary education (Moll, 1998). This pattern suggests that although ability biases might be large compared to what is typically observed in richer countries (see for example Bowles and Gintis (2001)), the inclusion of cognitive skill as a proxy for ability will not have a marked impact on the convex nature of the returns to education. Indeed, Moll's (1998) results, while not representative, shows quite strong convexities even after controlling for reporting errors using robust estimators.[11]

Omitting family background variables, such as parental education, may also result in biased coefficients, either due to the potential correlation between genetics and ability or through the possibility that wealthier and "better socially connected" parents will secure more education for their children, as well as high-paying jobs. In a comprehensive review of recent studies of returns to education, Card (1999) concludes that the biases that arise in OLS estimates upon the inclusion of controls for family background (such as a parent's or sibling's education) are of a similar order of magnitude to the biases in OLS estimates that omit family background indicators altogether. This however, does not suggest that these factors are unimportant – parental

[11] Molls estimates are based on a sample of 133 African male workers that have regular employment and from whom literacy test results were obtained. This by itself does not render the estimates unreliable. However, the literacy tests were only administered in 1 in 6 households visited, and of these, only a small fraction of the working sample was captured, thus rendering this group a non-random sample, even of African male workers that have regular employment. See Case and Deaton (1998) for more on this.

income and one's neighbourhood of residence will be highly correlated with one's own educational attainment (see for example Burns (2001)) and therefore might cause bias in the rate of return. However, the opposing effects of the various forms of bias could mask both the overall importance of these variables, as well as their indirect operation made possible through the likely correlation between parental and off-spring characteristics *in general*. Indeed, recent evidence suggests that the *direct* influence of these variables on an individual's income generation is perhaps more important (see for example Bowles and Gintis (2002)).

Finally, if there is a high correlation between the quality and quantity of education attained, and the quality variable is omitted from the earnings function, the estimated rate of return to education might be biased, though this depends largely on how quality is measured – measuring school quality in terms of the relationship between test scores and wage rates, for example, often does not give very different estimates of the return to education than if one were to exclude the measure altogether (Schultz (1988:590); Card and Krueger (1992:1)). Research using other indicators of school quality however, such as teacher qualification and teacher-pupil ratios, suggests significant biases in estimated rates of return. In a study of Brazilian males aged 15 to 35, Behrman and Birdsall (1983) use district-average teacher education as a proxy for schooling quality. On comparing OLS estimates of standard earnings functions with estimates that include the omitted quality variable, they find substantial upward bias in the returns to education – on the order of about 75 percent. Likewise, Card and Krueger (1992) find that in the USA, men schooled in states with higher quality education systems (measured by relative teacher pay, average term length, pupil-teacher ratios and the like), have greater returns to education. Case and Yogo (1999) find some corroborative evidence of this for black South African males though little can be deduced about the magnitude of the bias involved owing to the approach used.

Whereas omission of ability, family background and school quality are most likely to bias OLS estimates in an upward direction, measurement error resulting from individuals misreporting their educational attainment will, in most cases, bias results downwards. Using data on identical twins Ashenfelter and Krueger (1994) find that that measurement error in reported schooling biases results downwards significantly. Card (1999) finds that the downward bias in conventional Mincerian schooling coefficients due to measurement error is probably on the order of 10%. When family background effects are controlled for, the bias is more likely to be in the region of 15%. Recent work by Kane, Rouse and Staiger (1999) however cautions about the implications of measurement error when the measurement error is non-classical. This might occur as those with the lowest level of schooling cannot underreport and those at the highest level cannot over-report their educational attainment. They find that those with completed college education have a higher probability of reporting schooling levels correctly than those with less than completed college and that OLS estimates of the returns to education will tend to be understated for incomplete college and overstated for college completion.

We know little of the true extent of these potential biases in the returns to education in South African owing to lack of reliable data. However, if the emerging consensus in richer countries is anything to go by, we might expect these various forms of bias to have little net effect, if not on the estimated rates of return, then on the generalised convex nature of the relationship between education and earnings. Indeed, Griliches (1977) finds that the biases resulting from measurement error and omitted variables appear to offset each other. Likewise, Deardon (1999) finds that the effects of measurement error and self-selection biases almost directly offset the impact of omitted ability and family background bias. Likewise, the available evidence on the effects of ability suggests little impact on the convexity of the returns to education, as evidenced in Moll (1998).

7. Conclusion

Contrary to the assumptions of conventional human capital theory, the weight of the available evidence (old and new) for South Africa, indicates, a strong convex relationship between education and earnings, the implication being that rates of returns to schooling increase with the level of education attained. The discontinuity found in the large gap in the returns between primary and higher education, could even be described as non-convex.

While our purpose in this paper is not to venture an explanation of this phenomenon, two points concerning interpretation are worth mentioning. First, other work shows that a substantial part of the apparent convexity is attributable to racial differences in the nature of the returns to education, with striking changes having taken place over the last decade concerning in the manner in which the labour market rewards blacks and whites with similar levels of attainment. Specifically, the rate of return to African education has remained unchanged in the decade since the end of Apartheid, but that of White education has witnessed a sharp increase, and no longer displays the convex pattern observed in the aggregate data. In short, the education of Whites, it would appear, is now equally rewarded by level of education, while the reward structure for blacks remains locked in a sharply convex (and thus unequal) pattern (Keswell, 2003).

Second, in the non-linear (read non-Mincerian) approach to estimating the rate of return, including the unemployed in the analysis serves to lower returns at the levels of education for which the highest proportions of the unemployed are found. The major fraction of surplus labour in South Africa is found amongst those who have relatively low levels of education, thus contributing to the strong form of convexity observed.

The pattern of returns has implications for the incentives driving individuals' human capital investment decisions. Increasing returns on the magnitude suggested by the available evidence implies a limited role for publicly provided education to have a measurable impact on inequality, especially in the presence of borrowing constraints. Otherwise talented but poor individuals might quite rationally decide to drop out of schooling at a very low level because the intermediate rewards are so negligible. The expected pattern of the distribution of education would then bifurcate, where previous wealth disparities determine who can and cannot acquire the relevant level of education that *is* rewarded, thus leading to persistence in the distribution of income and wealth. Therefore, when the reward structure is convex, one's initial wealth level matters greatly for long run outcomes. Our estimates suggest that the discontinuity assumption necessary for the generation of theoretical poverty traps as in Galor and Zeira (1993), Ljungqvist (1993), and Mookherjee and Ray (2002) might be a robust empirical phenomenon, but even if this were not the case, the robustness of the increasing returns found in the reward structure suggests little private incentives for the acquisition of education for the overwhelming majority of the labour force. Given this reward structure, educational reforms on their own (especially small interventions) will have a negligible impact on the distribution of income, education and wealth, because the convex pattern of returns (if robust to various controls for omitted variable bias) implies dramatically different incentives for the acquisition of education facing rich and poor – those lucky enough (or smart enough) to attain high levels of education with little cost (in the broad sense) will tend to benefit enormously from educational reforms (that improve access or quality) and will go on and acquire tertiary education and reap the high rewards leaving the vast majority behind. If this scenario were true, one implication is that an education-led development strategy can only work if pursued in conjunction with policies aimed at influencing the way in which the labour market *rewards* such education. The precise nature of these policies is, of course, an open question, depending ultimately on the underlying causes behind these findings.

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Table 1. The Coefficient on Years of Schooling: Mincerian Rates of Return to Education

Region	2002			1994		1985
	Mean per capita ($US)	Mean Years of Schooling	Coefficient	Mean Years of Schooling	Coefficient	Coefficient
Sub-Saharan Africa	974	7.3	11.7	5.9	13.4	13
Latin America/ Caribbean	3 125	8.2	12.0	7.9	12.4	14
Asia*	5 182	8.4	9.9	8.4	9.6	11
Europe/ Middle East/ North Africa*	6 299	8.8	7.1	8.5	8.2	8
OECD	24 582	9.0	7.5	10.9	6.8	9
World	9 160	8.3	9.7	8.4	10.1	11

Source: Psacharopoulos & Patrinos (2002), Psacharopoulos (1994), Psacharopoulos (1985)

Notes.

* These are for Non-OECD countries. The figures for each region comprise simple unweighted averages compiled from the estimates for all countries falling into that region. The specified regions do not represent the same group of countries in each paper. As more country-specific studies have become available, the dataset has increased – the 2002 analysis includes updated estimates on roughly half of the 98 countries considered with a much larger sample size than any of the previous reviews.

Table 2. Average Private Rate of Return to Education

	2002			1994			1985		
Region	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
Sub-Saharan Africa	37.6	24.6	27.8	41.3	26.6	27.8	45	26	32
Latin America/ Caribbean	26.6	17.0	19.5	26.2	16.8	19.7	32	23	23
Asia*	20.0	15.8	18.2	39.0	18.9	19.9	31	15	18
Europe/ Middle East/ North Africa*	13.8	13.6	18.8	17.4	15.9	21.7	17	13	13
OECD	13.4	11.3	11.6	21.7	12.4	12.3	N/A	12	12
World	26.6	17.0	19.0	29.1	18.1	20.3	31 [a]	18	20

Source: Psacharopoulos & Patrinos (2002), Psacharopoulos (1994), Psacharopoulos (1985).

Notes.

* Figures in tables are percentages. These are for Non-OECD countries. The figures for each region comprise simple unweighted averages compiled from the estimates for all countries falling into that region. The specified regions do not represent the same group of countries in each paper. As more country-specific studies have become available, the dataset has increased – the 2002 analysis includes updated estimates on roughly half of the 98 countries considered with a much larger sample size than any of the previous reviews. These studies are not directly comparable with Mincerian returns as they are calculated according to the *extended cost benefit* method. Moreover, the rate of return cannot be read as the marginal increase to an additional year of education as is the case in the Mincerian model. Rather, it is to be interpreted as the rate of return to the relevant level of education (primary, secondary, and tertiary), relative to not having any education at all.

Table 3. Average Social Rates of Returns to Education (calculated according to the "full method")

Region	2002			1994			1985		
	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
Sub-Saharan Africa	25.4	18.4	11.3	24.3	18.2	11.2	26	17	13
Latin America/ Caribbean	17.4	12.9	12.3	17.9	12.8	12.3	26	18	16
Asia*	16.2	11.1	11.0	19.9	13.3	11.7	27	15	13
Europe/ Middle East/ North Africa*	15.6	9.7	9.9	15.5	11.2	10.6	13	10	8
OECD	8.5	9.4	8.5	14.4	10.2	8.7	N/A	11	9
World	18.9	13.1	10.8	18.4	13.1	10.9	23[a]	14	12

Source: Psacharopoulos & Patrinos (2002), Psacharopoulos (1994), Psacharopoulos (1985). Non-OECD

Notes.

* Figures in tables are percentages. These are for Non-OECD countries. The figures for each region comprise simple unweighted averages compiled from the estimates for all countries falling into that region. The specified regions do not represent the same group of countries in each paper. As more country-specific studies have become available, the dataset has increased – the 2002 analysis includes updated estimates on roughly half of the 98 countries considered with a much larger sample size than any of the previous reviews. The average rate of return is calculated according to the "full method" using the following formula:

$$\sum_{t=-s}^{0} (c+w)_t (1+r)^{-t} = \sum_{t=1}^{n} (w_s - w_0)_t (1+r)^{-t}$$

where s = years of schooling, c = the costs incurred in acquiring s years of schooling and w = the earnings foregone in this period. w_S = the wages earned by someone with s years of schooling and w_0 = the wages earned by someone with 0 years of schooling. r is the internal rate of return to s years of schooling that equates the present value of the costs of s years of schooling with the present value of the benefits for a working life of n years. (Adapted from Psacharopoulos (1973))

Table 4. Rates of Return to Education for South Africa1

Study	Survey	Sample considered	Years of Education			
			7	12	15	Mean
Mwabu and Schultz (2000)	PSLSD, 1993	All races and genders[2]	0.05	0.21	0.37	0.21
Kingdon and Knight (1999)	PSLSD, 1993	All races and genders	0.04	0.09	0.13	0.09
Erichsen and Wakeford (2001)	PSLSD, 1993	All races and genders[2]	0.04	0.12	0.17	0.11
Erichsen and Wakeford (2001)	PSLSD, 1993	All races (male)	0.05	0.14	0.19	0.13
Erichsen and Wakeford (2001)	OHS, 1995	All races and genders[2]	0.05	0.12	0.17	0.11
Erichsen and Wakeford (2001)	OHS, 1995	All races (male)	0.05	0.14	0.19	0.13
Lam (2001)	OHS, 1995	All races (male)	0.09	0.25	0.26[3]	0.11
Rospabe (2001)	OHS, 1999	All races and genders[2]	0.03	0.10	0.18	0.10
Mean (studies using all races)			0.05	0.15	0.18	0.12
Michaud and Vencatachellum (2001)		African (male)	0.05	0.12	0.12	0.10
Moll (1996)	CSS/HSRC, 1990	African (male)	0.02	0.11	0.16[3]	**0.04**
Moll (1998)	PSLSD, 1993	African (male)	0.03	0.09	0.60	**0.24**
Hertz	PSLSD, 1993	African (both genders)				0.11[4]
Mean (studies using African data)			0.05	0.13	0.13	0.10

Notes.

1. To make the reported estimates in each study roughly comparable, the estimates in each study were translated into pseudo splines where the relevant thresholds are set at 7 years (primary), 12 years (secondary) and 15+ years (tertiary). The coefficient on the spline measures the average rate of return to an additional year of the given level of education. When the dependent variable is in natural logarithm form, the marginal effect is computed by taking the antilog of the spline coefficient minus 1 (see Halvorsen and Palmquist (1980)). For studies that attempt to capture non-linearities by specifying dummy variables for each year of education, the marginal effect is calculated by subtracting the coefficient of a given year from the coefficient of the previous or following year. The average rate of return from, for example, 8 years to 10 years is calculated by subtracting the coefficient on the 8 year dummy from that on the 10 year dummy and then dividing by the difference, in this case 2. For studies that introduce higher order polynomials in education, the marginal rate of return is simply the derivative with respect to schooling evaluated at the relevant level of schooling. In all cases, once the marginal returns are calculated they are then averaged for primary, secondary and tertiary levels to calculate the pseudo spline.
2. The reported coefficients in these studies apply to sub-samples so coefficients are first weighted by their relevant sample proportions before applying the relevant marginal effect calculation.
3. The use of dummy variables to capture non-linearities complicates the calculation of marginal returns to tertiary education. Since tertiary education varies in length of study and qualification, one needs to make assumptions about the number of years spent in acquiring a diploma or degree. Two estimates were calculated – one based on the assumption that average length to completion of a course of study at the tertiary level is 3 years, and another based on the assumption of 2 years. The figure reported in the table is the average of the two estimates
4. The construction of the pseudo spline was not possible in this case. The estimates are not directly comparable because included are zero values for the unemployed and the relevant equations are estimated in levels as opposed to the usual log-linear form.

Table 5. Mean Sample Characteristics of Surveys Used

	PSLSD, 1993	OHS, 1995	OHS, 1997	LFS, 2000	Actual EAP
Sample Size	8495	31777	30956	29949	N/A
African	76.14	70.22	79.61	79.76	72
Coloured	10.18	14.70	14.32	12.48	11
Indian	3.64	3.71	1.84	2.16	3
White	10.04	11.37	4.23	5.60	14
Male	52.48	56.06	49.44	49.51	54
Female	47.52	43.94	50.56	50.49	46
Rural	77.93	42.74	44.07	39.07	36
Urban	22.07	57.26	55.93	60.93	64
Non-Unionised Full Time Wage Earners	71.2	67.59	62.14	60.97	N/A
Unionised Full Time Wage Earners	28.8	32.41	37.86	39.03	N/A
Mean Age	32.88	34.90	34.07	34.18	N/A
	(11.10)	(11.09)	(10.63)	(11.16)	N/A
Mean Age of Censored Sample	30.12	31.25	31.34	30.56	N/A
	(10.64)	(10.31)	(9.96)	(10.33)	N/A
Mean Age of Full Time Wage Earners	35.70	37.41	37.19	38.52	N/A
	(10.85)	(10.90)	(10.51)	(10.54)	N/A
Mean Educational Attainment	7.58	8.23	7.82	8.50	N/A
	(3.99)	(3.99)	(3.97)	(3.81)	N/A
Mean Education of Censored Observations	7.07	7.66	7.70	8.42	N/A
	(3.72)	(3.75)	(3.78)	(3.54)	N/A
Mean Education of Full Time Wage Earners	8.10	8.62	7.94	8.60	N/A
	(4.19)	(4.09)	(4.17)	(4.10)	N/A
Censored	50.58	40.68	53.26	54.52	N/A
Employed	49.42	59.32	46.74	45.48	N/A
Mean Earnings/Month of Full Time Wage Earners	1723.46	1934.35	1632.10	2443.86	N/A
	(3464.60)	(2231.36)	(1734.08)	(3567.08)	N/A
Mean Log Earnings/Month of Full Time Wage Earners	6.87	7.08	6.93	7.28	N/A
	(1.12)	(1.04)	(1.03)	(1.04)	N/A
Median Earnings/Month of Full Time Wage Earners	1000.00	1268.00	1200.00	1500.00	N/A

Notes.

The ‘Actual EAP’ statistics are the average proportions by race, gender and location of the economically active population calculated by averaging these proportions over the 4 surveys. They therefore indicate the likely breakdown by race, gender, and location given no missing information. Standard deviations are in parentheses.

Table 6. Returns to Education (Ordinary Least Squares Estimates)

Variable	Equation 5 (Standard Mincer Model)							
	1993		1995		1997		2000	
Constant	-5.713 *	(0.32)	-5.751 *	(0.18)	-4.923 *	(0.20)	-7.546 *	(0.18)
Age	0.339 *	(0.02)	0.336 *	(0.01)	0.292 *	(0.01)	0.399 *	(0.01)
Age^2	-0.003 *	(0.00)	-0.003 *	(0.01)	-0.002 *	(0.00)	-0.003 *	(0.00)
Education	0.245 *	(0.01)	0.263 *	(0.01)	0.171 *	(0.01)	0.202 *	(0.01)
n	8487		31777		30956		29949	
R^2	0.162		0.180		0.121		0.192	

Table 7. Returns to Education (Tobit Estimates – Marginal Effects)

Variable	Equation 5 (Standard Mincer Equation)							
	1993		1995		1997		2000	
Constant	-9.750 *	(0.38)	-9.588 *	(0.22)	-9.190 *	(0.24)	-12.87 *	(0.22)
Age	0.407 *	(0.02)	0.409 *	(0.01)	0.366 *	(0.01)	0.517 *	(0.01)
Age^2	-0.004 *	(0.00)	-0.004 *	(0.00)	-0.003 *	(0.00)	-0.005 *	(0.00)
Education	0.232 *	(0.01)	0.265 *	(0.01)	0.152 *	(0.01)	0.182 *	(0.01)
n	8487		31777		30956		29949	
Log likelihood	-16353		-68045		-58284		-54712	

<u>Notes</u>

An asterisk indicates significance at the 1 percent level. Double and triples asterisks indicate 5 percent and 10 percent levels of significance respectively. The dependant variable is the natural log of earnings. The reported coefficients in table 7 are the marginal effects. The full set of estimated parameters, including the index values and associated standard errors are not reported here but are available on request. The technical details surrounding the estimates in table 7 are outline in appendix E. The reported estimates are marginal effects of the Tobit estimator, computed by writing the mathematical expectation as follows:

$$E(y|x) = \int_{-\infty}^{z} \phi(z)dz\left(-x'\beta + \sigma\left(\frac{\phi(z)}{\Phi(z)}\right)\right)$$

where ϕ and Φ are the probability density functions and cumulative distribution functions of the standard normal distribution respectively and the last term in square brackets is the Tobit correction. This model has the feature of being non-linear both in the variables (as is the case in equations (5), (6) and (9)) as well as in the parameters. In the case of a left-censored dependant variable, the marginal effect of the *j*th explanatory variable (of the vector *x*) is simply the Tobit index value multiplied by the cumulative distribution function of the standard normal distribution evaluated at the sample mean of *z* (which is simply the standardized value of the *j*th explanatory variable). Thus the coefficients reported in tables 7, 9, and 11 are to be interpreted in the same way as those reported in tables 6, 8, and 10, and are arrived at by calculating:

$$\frac{\partial E(y)}{\partial x_j} = \Phi(z)\beta_j$$

Table 8. Returns to Education (Ordinary Least Squares Estimates)

Variable	Equation 6 (Non-linear Model – Quadratic Education)			
	1993	1995	1997	2000
Constant	-4.524 * (0.32)	-4.591 * (0.18)	-4.16 * (0.20)	-6.291 * (0.18)
Age	0.340 * (0.02)	0.336 * (0.01)	0.292 * (0.01)	0.393 * (0.01)
Age^2	-0.003 * (0.00)	-0.003 * (0.00)	-0.002 * (0.00)	-0.003 * (0.00)
Education	-0.273 * (0.03)	-0.210 * (0.02)	-0.177 * (0.02)	-0.206 * (0.02)
$Education^2$	0.039 * (0.00)	0.034 * (0.00)	0.026 * (0.00)	0.028 * (0.00)
R^2	0.196	0.206	0.136	0.207
n	8495	31777	30956	29949

Table 9. Returns to Education (Tobit Estimates – Marginal Effects)

Variable	Equation 6 (Non-linear Model – Quadratic Education)			
	1993	1995	1997	2000
Constant	-8.573 * (0.38)	-8.390 * (0.22)	-8.449 * (0.24)	-11.727 * (0.22)
Age	0.409 * (0.02)	0.411 * (0.01)	0.367 * (0.01)	0.513 * (0.01)
Age^2	-0.004 * (0.00)	-0.004 * (0.00)	-0.003 * (0.00)	-0.005 * (0.00)
Education	-0.270 * (0.03)	-0.218 * (0.02)	-0.179 * (0.02)	-0.192 * (0.02)
$Education^2$	0.037 * (0.00)	0.034 * (0.00)	0.025 * (0.00)	0.025 * (0.00)
n	8495	31777	30956	29949
Log likelihood	-16241	-67672	-58087	-54502

Notes

An asterisk indicates significance at the 1 percent level. Double and triples asterisks indicate 5 percent and 10 percent levels of significance respectively. The dependant variable is the natural log of earnings. The reported coefficients in table 9 are the marginal effects. The full set of estimated parameters, including the index values and associated standard errors are not reported here but are available on request. The technical details surrounding the estimates in table 9 are outline in appendix E. The reported estimates are marginal effects of the Tobit estimator, computed by writing the mathematical expectation as follows:

$$E(y|x) = \int_{-\infty}^{z} \phi(z)dz\left(-x'\beta + \sigma\left(\frac{\phi(z)}{\Phi(z)}\right)\right)$$

where ϕ and Φ are the probability density functions and cumulative distribution functions of the standard normal distribution respectively and the last term in square brackets is the Tobit correction. This model has the feature of being non-linear both in the variables (as is the case in equations (5), (6) and (9)) as well as in the parameters. In the case of a left-censored dependant variable, the marginal effect of the *j*th explanatory variable (of the vector *x*) is simply the Tobit index value multiplied by the cumulative distribution function of the standard normal distribution evaluated at the sample mean of *z* (which is simply the standardized value of the *j*th explanatory variable). Thus the coefficients reported in tables 7, 9, and 11 are to be interpreted in the same way as those reported in tables 6, 8, and 10, and are arrived at by calculating:

$$\frac{\partial E(y)}{\partial x_j} = \Phi(z)\beta_j$$

Table 10. Returns to Education (Ordinary Least Squares Estimates)

Variable	Equation 9 (Non-Linear Model – Cubic Education)							
	1993		1995		1997		2000	
Constant	1.091 *	(0.41)	0.56 **	(0.24)	1.019 *	(0.26)	-0.021	(0.29)
Age	0.208 *	(0.02)	0.25 *	(0.01)	0.174 *	(0.01)	0.238 *	(0.01)
Age^2	-0.002 *	(0.00)	-0.00 *	(0.00)	-0.002 *	(0.00)	-0.002 *	(0.00)
Female	-0.545 *	(0.06)	-1.36 *	(0.03)	-0.837 *	(0.03)	-0.682 *	(0.03)
African	-3.165 *	(0.11)	-2.50 *	(0.06)	-2.293 *	(0.08)	-2.597 *	(0.07)
Coloured	-2.117 *	(0.15)	-1.26 *	(0.07)	-1.186 *	(0.10)	-1.504 *	(0.09)
Indian	-0.894 *	(0.19)	-0.54 *	(0.09)	-0.206	(0.14)	-0.622 *	(0.13)
Education	0.220	(0.17)	0.84 *	(0.10)	0.547 *	(0.10)	0.485 *	(0.11)
$Education^2$	-0.089 *	(0.03)	-0.19 *	(0.02)	-0.130 *	(0.02)	-0.106 *	(0.02)
$Education^3$	0.006 *	(0.00)	0.01 *	(0.00)	0.007 *	(0.00)	0.005 *	(0.00)
Age* Education	-0.005	(0.00)	-0.02 *	(0.00)	-0.015 *	(0.00)	-0.011 *	(0.00)
Age* $Education^2$	0.002 *	(0.00)	0.00 *	(0.00)	0.003 *	(0.00)	0.002 *	(0.00)
Age* $Education^3$	0.000 *	(0.00)	0.00 *	(0.00)	0.000 *	(0.00)	0.000 *	(0.00)
Union Member	3.232 *	(0.09)	3.04 *	(0.04)	4.033 *	(0.04)	4.324 *	(0.04)
Western Cape Province	1.132 *	(0.14)	-0.04	(0.07)	0.920 *	(0.07)	0.408 *	(0.07)
Eastern Cape Province	-0.349 *	(0.11)	-1.07 *	(0.06)	-0.800 *	(0.06)	-0.924 *	(0.06)
Northern Cape Province	0.007	(0.26)	-0.59 *	(0.09)	0.416 *	(0.09)	-0.17 ***	(0.09)
Free State Province	-1.024 *	(0.17)	-0.24 *	(0.06)	0.437	(0.06)	-0.340 *	(0.07)
KwaZulu-Natal Province	0.009	(0.10)	-0.36 *	(0.06)	-0.493	(0.05)	-0.402 *	(0.05)
Northwest Province	1.038 *	(0.11)	-0.27 *	(0.07)	0.032	(0.06)	-0.388 *	(0.06)
Mpumulanga Province	1.181 *	(0.12)	-0.37 *	(0.06)	0.332 *	(0.06)	-0.520 *	(0.07)
Northern Province	0.101	(0.12)	-0.87 *	(0.07)	-0.096	(0.06)	-0.785 *	(0.06)
n	8487		31777		30956		29949	
R^2	0.45		0.44		0.43		0.47	

<u>Notes</u>

An asterisk indicates significance at the 1 percent level. Double and triples asterisks indicate 5 percent and 10 percent levels of significance respectively. The dependant variable is the natural log of earnings. All variables are binary except for age and education. Standard errors are in parentheses. Given the non-linearity of the schooling term, and its interaction with the age variable, the rate of return to education (as in the case of tables 8 and 9) are not obvious from the above parameter estimates. These are computed according to equation (9) and reported in the top panel of table 12.

Table 11. Returns to Education (Tobit Estimates- Marginal Effects)

	Equation 9 (Non-Linear Model – Cubic Education)							
	1993		1995		1997		2000	
Constant	-2.9270 *	(0.51)	-3.037 *	(0.32)	-3.060 *	(0.32)	-5.187 *	(0.36)
Age	0.2750 *	(0.02)	0.328 *	(0.01)	0.238 *	(0.01)	0.344 *	(0.01)
Age^2	-0.0030 *	(0.00)	-0.003 *	(0.00)	-0.002 *	(0.00)	-0.003 *	(0.00)
Female	-0.5770 *	(0.07)	-1.716 *	(0.04)	-0.918 *	(0.04)	-0.758 *	(0.03)
African	-2.8380 *	(0.13)	-2.571 *	(0.07)	-2.019 *	(0.09)	-2.243 *	(0.08)
Coloured	-1.6420 *	(0.17)	-1.079 *	(0.08)	-0.785 *	(0.10)	-1.048 *	(0.10)
Indian	-0.5390 **	(0.21)	-0.434 *	(0.11)	0.188	(0.15)	-0.365 *	(0.14)
Education	-0.0650	(0.21)	0.929 *	(0.13)	0.595 *	(0.12)	0.442 *	(0.13)
Education^2	-0.0500	(0.04)	-0.215 *	(0.02)	-0.150 *	(0.02)	-0.107 *	(0.02)
Education^3	0.0050 **	(0.00)	0.012 *	(0.00)	0.008 *	(0.00)	0.006 *	(0.00)
Age* Education	0.0010	(0.01)	-0.024	(0.00)	-0.017 *	(0.00)	-0.011 *	(0.00)
Age* Education^2	0.0010	(0.00)	0.005 *	(0.00)	0.004 *	(0.00)	0.002 *	(0.00)
Age* Education^3	0.0000 ***	(0.00)	0.000 *	(0.00)	0.000 *	(0.00)	0.000 *	(0.00)
Union Member	2.9060 *	(0.09)	3.140 *	(0.05)	3.436 *	(0.05)	3.545 *	(0.50)
Western Cape Province	1.1310 *	(0.16)	0.019	(0.08)	0.942 *	(0.08)	0.393 *	(0.08)
Eastern Cape Province	-0.5590 *	(0.14)	-1.281 *	(0.07)	-1.019 *	(0.08)	-1.115 *	(0.07)
Northern Cape Province	0.0480	(0.31)	-0.598 *	(0.11)	0.518 *	(0.10)	-0.083 *	(0.10)
Free State Province	-1.8790 *	(0.25)	-0.086	(0.08)	0.584 *	(0.07)	-0.292 *	(0.08)
KwaZulu-Natal Province	0.0570	(0.13)	-0.396	(0.07)	-0.672 *	(0.07)	-0.453 *	(0.06)
Northwest Province	1.2330 *	(0.14)	-0.258 *	(0.08)	0.066	(0.07)	-0.424 *	(0.07)
Mpumulanga Province	1.3760 *	(0.14)	-0.406 *	(0.08)	0.423 *	(0.07)	-0.597 *	(0.08)
Northern Province	0.1160	(0.14)	-1.075 *	(0.09)	-0.06	(0.08)	-0.947 *	(0.08)
n	8487		31777		30956		29949	
Log likelihood	-14985		-62975		-53247		-50255	

Notes

An asterisk indicates significance at the 1 percent level. Double and triples asterisks indicate 5 percent and 10 percent levels of significance respectively. The dependant variable is the natural log of earnings. All variables are binary except for age and education. Standard errors are in parentheses. The model is both non-linear in the variables (as in table 10), but also non-linear in the parameters. Thus, in order to arrive at estimates of the rate of return to education, we first find the marginal effects of the variables in the model as outlined in the note to table 9 (the full set of estimated parameters, including the index values and associated standard errors are not reported here but are available on request). This calculation gives the coefficients reported in table 11 and is to be interpreted in the same way as those reported in table 10. But given the non-linearity introduced through the schooling term and its interaction with the age variable, the rates of return to education are not obvious from the above marginal effects. In order to arrive at these estimates, we first apply equation (9) to the above coefficients. The results are reported in the bottom panel in table 12.

Table 12. Returns to Education (Non-Linear Models)

Years of Schooling	1993		1995		1997		2000	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit
Based on Equation 6 (Non-linear Model – Quadratic Education)								
7	0.27	0.25	0.27	0.26	0.19	0.17	0.19	0.16
10	0.51	0.47	0.47	0.46	0.34	0.32	0.35	0.31
12	0.66	0.62	0.61	0.60	0.45	0.42	0.47	0.41
15	0.90	0.84	0.81	0.80	0.60	0.57	0.63	0.56
1 – 7 (Average)	0.04	0.03	0.06	0.05	0.03	0.02	0.02	0.01
8 – 12 (Average)	0.51	0.47	0.47	0.46	0.34	0.32	0.35	0.31
13 – 15 (Average)	0.82	0.77	0.74	0.73	0.55	0.52	0.58	0.51
Based on Equation 9 (Non-linear Model – Cubic Education)								
7	0.09	0.08	0.06	0.06	0.04	0.03	-0.01	-0.02
10	0.28	0.27	0.27	0.29	0.20	0.19	0.15	0.14
12	0.46	0.46	0.46	0.53	0.35	0.36	0.32	0.32
15	0.80	0.89	0.85	1.05	0.65	0.76	0.54	0.61
3 – 7 (Average)	0.02	0.02	0.00	-0.01	-0.02	-0.03	-0.04	-0.06
8 – 12 (Average)	0.29	0.28	0.28	0.30	0.21	0.20	0.16	0.15
13 – 15 (Average)	0.68	0.73	0.71	0.86	0.54	0.61	0.54	0.61

Notes

The top panel shows the coefficients (marginal effects) of tables 8 and 9 evaluated at various levels of education, according to equation (7). The bottom panel does the same utilising the coefficients from tables 9 and 10, and the formula given by equation (9). The "average effects" in both panels are calculated by averaging the marginal effects for each year of the relevant education span. For example, the 8-12 average for the 2000 estimate based on the Tobit model given in the bottom panel is calculated by finding the rates of return to each year of education in the range, thus giving 4 estimates, which is then divided by 4 to give the reported estimate of 0.15.

Appendix A: Summary of Recent South African Return to Schooling Literature

Study & Data	Sample	Dependent	Explanatory Variables	Estimator	Samples				
Mwabu and Schultz (2000) (PSLSD 1993) Source:Table 2 p214	Wage earners 16-65	Continuous: log gross hourly wage	rural dummy, experience, experience^2 Education variable: Spline Function	OLS (Separate equations for gender, race, location(not included here)	Sample / Education	African Male	African Female	White Male	White Female
					Primary	0.084 *	0.062 *	-0.012	-0.034
					Secondary	0.158 *	0.249 *	0.084 *	0.052 *
					Tertiary	0.294 *	0.396 *	0.151 *	0.139 *
					N	9325	10473	1447	1517
Rospabe (2001) (OHS 1999)	Formal & informal 16-65	Dichotomous: 0 = unemployed 1 = employed 2 = self – emp.	race dummies, age, age^2, no of kids, urban dummy, marital status dummy, family members' employment status dummies, household head dummy, distance from phone, province dummies Education variable: Spline Function	Multinomial logit	Sample / Education	Male employed	Male self-employed	Female employed	Female self-employed
					Primary	-0.022 *	0.031	-0.031 *	-0.052 *
					Secondary	0.039 *	0.032	0.086 *	-0.051 *
					Tertiary	0.446 *	0.422 *	0.764 *	0.636 *
					N	19920		18913	
				Interval regression	Primary	0.027 *	0.030 *		
					Secondary	0.091 *	0.111 *		
					Tertiary	0.176 *	0.153 *		
					N	9913	7651		
Bhorat (2000) (OHS 1995)	Formal & informal 16-64	Continuous: log monthly wage	gender, province ,sector, union (all dummies), experience, experience^2, urban dummy, log hours worked per month Education variable: Spline Function	OLS (Separate equations for race)	Sample / Education	African skilled	White skilled	African Semi-skilled	White Semi-skilled
					Primary	0.037 *	0.010	0.039 *	-0.074
					Secondary	0.122 *	-0.004	0.128 *	0.137 *
					Tertiary	0.159 *	0.256 *	0.017	-0.031
					N	2663	2536	7396	3179
Michaud and Vencatachellum (2001) (PSLSD 1993)	Wage earners	Continuous: log gross hourly wage	experience, experience^2, wealth proxy, skilled/semi-skilled dummy, manufacturing/ tertiary/ professional sector dummy, urban dummy, province dummies, union dummy Education variable: Spline Function	OLS	Sample / Education	African Male	African Female		
					Primary	0.046 *	0.013		
					Secondary	0.116 *	0.073 *		
					Tertiary	0.114 *	0.055		
					N	2361	1525		
		Binary: Union member Participation eq.		Modified Heckman 2-Step	Sample / Education	African Male Unionised	African Male Non-Unionised	African Female Non-Unionised	African Female Unionised
					Primary	0.042 *	-0.007	0.013	-0.066 *
					Secondary	0.114 *	0.055 *	0.052 *	0.092 *
					Tertiary	0.085 *	0.182 *	0.035	0.136 *
					n	1571	791	1208	317

Appendix A: Summary of Recent South African Return to Schooling Literature (Cont.)

Study & Data	Sample	Dependent	Explanatory Variables	Estimator	Samples				
Bhorat & Leibbrandt (2001) (OHS 1995)	Africans 16-65	participation	age dummies, urban dummy, household structure variables, household income Education variable: Spline Function	Probit (coefficients are marginal effects)	Sample / Education	Broad UE		Narrow UE	
						African male	African female	African male	African female
					Primary	0.003 *	0.003	0.004 *	0.003
					Secondary	0.005 *	0.052 *	0.016 *	0.057 *
					Tertiary	0.003	-0.023	0.016 *	0.011 *
					n	15658	19548	15658	19548
		employment	age dummies, urban dummy, province dummies Education variable: Spline Function	Probit (coefficients are marginal effects)	Primary	-0.012 *	-0.004 *	-0.009 *	-0.009 *
					Secondary	0.010	0.036 *	0.000	-0.021 *
					Tertiary	0.047 *	0.142 *	0.036 *	0.153 *
					n	14203	12810	11931	9426
	Formal & informal	Log gross monthly wage	Urban dummies, province dummies, industrial sector dummies, occupation dummies, experience, experience^2, log hours worked per month	Heckman Maximum likelihood	Primary	0.035 *	0.049 *	0.036 *	0.051 *
					Secondary	0.109 *	0.082 *	0.108 *	0.093 *
					Tertiary	0.037	0.023	0.031	0.032 *
					n	14124	12723	11886	9393
Lam (1999) (OHS 1995)	Males, all races 30-49	log gross monthly earnings	race dummies, age, age^2 Education variable: Dummies for each year	OLS	Education	Males	Education	Males	
					1-3 yrs	-0.010	8	0.571 *	
					4	0.090 *	9	0.733 *	
					5	0.150 *	10	0.968 *	
					6	0.269 *	11	1.041 *	
					7	0.397 *	12	1.484 *	
							>=15	1.970 *	
					n	10867			
Moll (1996) (CSS/HSRC1990)	Africans, urban, male, non-agricultural employees 18-59	log of gross annual cash Income	experience, experience^2, married, region dummies	OLS	Education	Males	Education	Males	
					0	-0.140 *	8	0.068 *	
					1-3 yrs	-0.170 *	9	0.120 *	
					4	-0.110 *	10	0.210 *	
					5	-0.075 *	11	0.340 *	
					6	-0.088 *	12	0.540 *	
					7_base	0	Diploma	0.330 *	
							Degree	0.480 *	
Moll (1998) PSLSD, 1993	African Males, regularly employed, subject to literacy test	Log of hourly wage	Urban dummy, gender dummy, experience, experience , experiance^2, test score index.	OLS	Sample / Education	African male			
					Primary	0.03 *			
					Secondary	0.09 *			
					Tertiary	0.63 *			
					n	133			

Appendix A: Summary of Recent South African Return to Schooling Literature (Cont.)

Study & Data	Sample	Dependent	Explanatory Variables	Estimator	Samples				
					Sample / Education	Formal non-union	Formal union		
Hofmeyer (2001) OHS (1999)	African Males, formal and informal sector workers	log gross hourly wage	urban, rural, industrial sector, occupation, single, not household head, experience, experience^2, job duration, (job duration)^2	weighted least squares (wage equation)	primary	0.175 *	0.140 *		
					std8	0.326 *	0.247 *		
					matric	0.507 *	0.470 *		
					dip (no mat)	0.486 *	0.623 *		
					dip (with mat)	0.957 *	0.841 *		
					degree	1.297 *	1.006 *		
					n	3039	2720		
					Sample / Education	1993 male	1995 male	1993 female	1995 female
Erichsen & Wakeford (2001) (OHS 1995, PSLSD 1993)	Regular wage earning employees 16-64 (excl. self-emp.)	log gross monthly wage	experience, experience^2,rural, union, industrial sector, occupation, province	OLS	Years	-0.004	-0.005	-0.01	0.026 *
					Years^2	0.007 *	0.007 *	0.005 *	0.004 *
					n	2223	11727	1570	6396
					Sample / Education	All races & genders			
Kingdon & Knight (1999) (PSLSD 1993)	wage earners 16-64	Log of gross hourly wage	experience, experience^2, race, gender, union, urban, province, married, occupation, public sector, tar road, broad unemp. Rate/cluster, dissatisfied, homeland	OLS	Years	0.004			
					Years^2	0.004*			
					n	6498			

Appendix B: Non-reporting of Income

A potential problem exists with regards the reliability of the reported income data in the October Household Surveys, especially in the most recent surveys, since respondents were given the option of reporting only their income bracket as opposed to their actual income. Percentage-wise, the number who reported their actual income in 1997, 1998 and 1999 is relatively low. However, if it could be established that those who reported actual earnings is a random sample of those who could have reported actual earnings, then using only the reported data even if the sample is relatively small, would be of no consequence to the question we address in this paper. If this were not to be the case however, such that the pattern of non-reporting was systematically related to some other observable characteristic of the data, then using only the actual data would result in biased estimates as the assumption that income is log normally distributed would be violated. Thus far, the only other approach to dealing with this problem in the literature is to use the midpoints of the intervals reported (see for example Hofmeyer (2001) and Rospabe (2001)). This approach is incorrect for technical reasons given the peculiar nature of censored data, but even if this were not the case, changes in the definition of income catagories, particularly between the 1995 survey and subsequent years complicates matters given that one of our objectives is to compare estimates across surveys. Rather, we adopt a different approach that makes use of both simulated and empirical versions of the earnings distributions under question. We explain and demonstrate below how we tested for randomness of reported earnings in each of the OHS datasets.

The samples of interest are all those classified as employed according to our definition, who have reported earnings, either as an actual amount or as falling into a specified earnings bracket. The first step was to create an earnings category variable that reflected the appropriate earnings interval for all individuals under consideration (including those who reported their actual data). Step two involved generating simulated earnings data for each earnings category. This was achieved by using a random number generator to sample numbers over a uniform distribution defined by the relevant intervals. Sampling was carried out with replacement so as to allow for the possibility of clustering. However, given that we know nothing about the actual clustering process, no further manipulations were made to the actual data generating process.

Using the simulated data, we then plotted the implied earnings distributions for each survey year using standard density curves that integrate to unity. We did the same for the actual earnings data that was reported and then super-imposed onto this, a plot of the distribution of these same individuals' simulated data. Finally, we plotted the densities of all midpoint data for the full set of earnings categories as well as for just those who reported actual earnings data. Figure 1 shows the results for each survey.

We start by comparing the density plots for those who reported actual earnings, with the simulated data from constructed earnings categories for this exact group of respondents. We do this to examine how well our simulation rule replicates the true distribution. We see that for 1995 and 1997 the simulated data (for those that reported actual data) has the identical shape to the simulated data of the entire sample. This suggests that if the data generating process is the same among the two catagories of respondents (meaning that any patterns of skewness of the true distribution of incomes within intervals (if they exist) is assumed to be the same across both groups of respondents), then the true distribution of actual earnings for the full sample is likely to be similar to that of the sample of individuals who actually did report their actual earnings. The reverse is true, however, for 1998 and 1999 – i.e., since there is an apparent increase in the divergence in the simulated earnings data of those who bothered to report their actual earnings data compared to the simulated earnings data for all individuals in the sample, the actual earnings data of the entire sample is likely to have a significantly different distribution that the actual earnings data of those who bothered to report such. This matches very closely with what is known about the changes in the frequency of non-reporting over time – indeed, the problem is especially acute in the later surveys. These findings suggests that if one were to treat only reported income data as valid earnings observations, then doing so for earlier years in the survey poses fewer problems from an econometric standpoint than the later years. For this reason, we use only the 1995 and 1997 samples from the October Household Surveys, along with the PSLSD of 1993 and labour force survey of 2000 (which of course are not plagued with these problems)

Finally, notice that across surveys, the density plot that diverges most from the plot of actual reported data is the graph constructed from interval midpoints for all individuals. This is most apparent for the 1995 OHS where we see the midpoint distribution is rather arbitrary with quite obvious over-representation of wealthier individuals in the process of assigning observations to the middle of each relevant category. The reason the OHS 1995 result is so pronounced is rooted in the questionnaire design for this year. As pointed out earlier, the choice of income categories in 1995 differs from the other years in that the lowest category was large (R1-R999 per week, month or year) compared to subsequent years where it was broken down into 3 smaller categories. It can be seen quite clearly from our graphs that using midpoint data will not yield unbiased results in all cases except for the 1997 survey.

Appendix C: Defining Employment and Earnings

The aim of the empirical analysis was to test the same earnings function specification across a number of datasets and thereby to verify whether increasing returns are a robust feature of the data. Working with a number of datasets required a careful study of each survey's representativeness. It also required definitions of variables to be precise and consistent across datasets.

In the econometric exercise we wished to explore the total effect of education on individuals' economic outcomes. We therefore include the unemployed in the analysis in order to account for the impact of education on both the probability of finding full time employment and on earnings given that one is employed. As the unemployed are included, it was necessary to define the economically active population and therefore choose whether to use the broad or narrow definitions of unemployment. A growing literature on the extent of 'discouraged workers' and the greater suitability of using the expanded definition when examining the jobless in a South African context informed our choice here (see Kingdon and & Knight (1999, 2000); Natrass (2000); Wittenburg(1999); Dinkelman & Pirouz (2002)).

Although we use a broad classification for the unemployed, we use a 'narrow' definition for the employed. Income earners are restricted to full time wage employees from age 15. The main reason for using this restricted group is that full time wage employment should represent the least variable component in earnings. Apart from being inconsistently defined across surveys, and poorly measured and recorded, self-employment and casual labour is largely characterised by highly variable earnings that will often be subject to a large degree of seasonality. Inclusion of these groups has the consequence of confounding issues if large differences are found in rates of return between surveys. Limiting the effects of seasonality and inter-temporal fluctuations of incomes due to idiosyncratic shocks (both of which matter greatly in secondary labour markets) allows us to say with a greater level of precision whether such differences are due to structural features of primary labour markets.

All individuals who were not employed full time therefore did not fit our definition of employment and are excluded from the sample of interest. Our sample is therefore comprised of full time waged workers who have positive earnings, and those classified as unemployed, who have zero earnings. The latter do not have paid employment of any kind and includes those classified as discouraged work seekers. Individuals with part time paid employment were also excluded from the analysis, as are individuals who were self-employed.

Appendix D: The Consequences of Omitting the Unemployed

Simple Mincerian returns to education are generally calculated using ordinary least squares regressions run for all those with positive earnings in the relevant sample. This, however, can be problematic. Random samples of a population of interest are likely to include both earners and non-earners. Excluding non-earners from the regression implies that the sample is no longer randomly selected and OLS results will not be truly representative of the population. Furthermore, the results will be biased for technical reasons. Essentially we have a sample selection problem in that we have the right hand side variables for all individuals sampled, but either a zero for those who are unemployed or positive earnings for those who are employed. That is, one can only earn an income, given one is employed. Thus, our dependent variable is said to be left censored at zero.

Writing a standard OLS regression in condensed form:

$$y = x'\beta + u \tag{11}$$

the estimates of β are BLUE *iff*

$$\left.\begin{aligned} E(u_i) &= 0 \\ E(u_i u_j) &= 0 \end{aligned}\right\} \forall \quad i \neq j \tag{12}$$

.

If either of these assumptions are violated, then estimates of β will be biased.

When using OLS, one can exclude the unemployed (most studies summarised in appendix A for example adopt this approach). Leaving aside the lack of intuition in doing this in country with massive unemployment, there is the econometric issue of discarding information (the zero's are valid observations). Specifically, considering only those who report positive earnings leads to truncation in the sample under consideration. Thus y_i is observed if and only if $y_i > 0$. Formally:

$$y = x'\beta + u \qquad \textit{iff} \quad y > 0 \tag{13}$$

Estimating such a model requires one to take the mathematical expectation of (13), which we do by using the law of total probabilities, giving:

$$E(y|x) = pr(y > 0|x)E(y|y > 0, x) \tag{14}$$

Now $y_i > 0$ implies that

$$\begin{aligned} y &= x'\beta + u > 0 \\ &\rightarrow x'\beta + u > 0 \\ &\rightarrow u > -x'\beta \end{aligned} \tag{15}$$

Given the assumption of normality, $pr(y > 0|x)$ can then be written equivalently as

$$pr(u > -x'\beta) = pr(u < x'\beta) \tag{16}$$

which implies that (14) can be simplified as:

$$E(y|x) = pr(u < x'\beta)E(y|y > 0, x) \tag{17}$$

$$E(y|x) = pr(u < x'\beta)(x'\beta + E(u|u > x'\beta)) \tag{18}$$

To estimate equation (18), using ordinary least squares, it is required that

$$E(u_i|u_i > -x_i'\beta) = 0 \tag{19}$$

This cannot be true if (12) holds. Therefore, equation (18) is a biased estimator of the underlying relationship modelled in (13).

Appendix E: The Consequences of Including the Unemployed

A key challenge to estimating standard earnings functions based on household surveys is finding an appropriate method for dealing with zero earners. The econometric literature is divided on precisely how to deal with this issue (see Madalla (1983) and Deaton (1997) for opposing views). However, the practice of simply treating zeros as missing values (which all except one of reviewed studies does) results in biased estimates. Moreover including the zeros and not adjusting the estimator used can have consequences, especially if the goal is to compare estimates across surveys where the degree of censoring differs substantially. Since the degree of censoring in the 1995 OHS differs by a magnitude of 10-15% compared to the other surveys, the cross-sectional comparisons made in this paper depends crucially on a systematic treatment of this problem.

To correct for this potential bias, we utilize a *Tobit* regression framework. In condensed form, we can represent the model (whether we are dealing with equations (4), (5), (6) or (9)) equivalently as

$$y = x'\beta + u \tag{20}$$

If the dependant variable is left censored at zero (meaning a sizable fraction of the observations are zero values as is the case with our data), then the data structure can be represented as

$$\begin{aligned} & y^* = x'\beta + u \\ & if \quad y^* \leq 0, \quad then \quad y = 0 \\ & if \quad y^* > 0, \quad then \quad y = y^* \end{aligned} \tag{21}$$

Note that the dependent variable is latent (indicated by the star), since only reported earnings are observed.

Since the Tobit estimator is non-linear in the *parameters*, we use the technique of maximum likelihood estimation. In short, the approach approximates the most likely data generating process – i.e., the parameter values in (4), (5), (6), or (9) mostly likely to have generated the observed data. Thus, we write out the likelihood (denoted by *L*) of the observing the given data, as the product of the probabilities of observing the zero and non-zero observations, given by

$$L = \prod_0 (1 - \Phi_i) \prod_1 \Phi_i \tag{22}$$

Focusing on the second term of (22), the likelihood of sampling a non-zero observation can be represented as the joint density of the error terms. If the errors are characterised by the standard normal distribution, then the probability density of a single observation is

$$f(u) = \frac{1}{\sqrt{2\pi\sigma^2}} = \exp\left\{-\frac{u^2}{2\sigma^2}\right\} \tag{23}$$

The likelihood of observing the full set of non-zero outcomes is then the joint density of the errors, given by,

$$L = (2\pi)^{-\frac{n}{2}}\left(\sigma^2\right)^{-\frac{n}{2}}\exp\left\{-\frac{1}{2}\Sigma\frac{(y_i - x'\beta)}{\sigma^2}\right\} \tag{24}$$

Given the exponential term contained in (24), it is useful to take the natural logarithm. The problem of finding the parameter vector most likely to have generated the observed data, then reduces to a problem of maximising the log of the likelihood function which, utilising (24) and (22), can be written as:

$$\log L = \sum_0 \log(1 - \Phi_i) + \sum_1 \log \Phi_i \tag{25}$$

$$\log L = \sum_0 \log(1 - \Phi_i) + \sum_1 \log\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) - \sum_1 \frac{1}{2\sigma^2}(y - x'\beta)^2 \tag{26}$$

$$\log L = \sum_0 \log(1 - \Phi_i) - \frac{n_1}{2}(\ln\sigma + \ln 2\pi) - \frac{2}{2\sigma^2}\Sigma(y - x'\beta)^2 \tag{27}$$

As is well know, the normal equations corresponding to this problem do not have closed form solutions owing to the presence of the censored observations represented by the first part of the log-likelihood function. We therefore have to rely on numerical methods of finding the maximum of the log-likelihood function. In all cases, the algorithm used is that of Newton-Raphson, with the usual Olsen (1978) transformation.

What distinguishes the Tobit estimator from the OLS estimator is that in the case of the former, we account for the likely bias introduced by the zero observations. Taking the mathematical expectation of (21) produces

$$\begin{aligned}
E(y|x) &= \Pr(y > 0|x)E(y|y > 0, x) \\
&= \Pr(u > -x'\beta)E(y|y > 0, x) \\
&= \Phi(E(-x'\beta + u)) \\
&= \Phi(E(-x'\beta) + E(u|u > -x'\beta)) \\
&= \Phi\left(-x'\beta + \sigma\left(\frac{\phi(z)}{\Phi(z)}\right)\right) \\
&= \int_{-\infty}^{z} \phi(z)dz\left(-x'\beta + \sigma\left(\frac{\phi(z)}{\Phi(z)}\right)\right)
\end{aligned} \tag{28}$$

where ϕ and Φ are the probability density functions and cumulative distribution functions of the standard normal distribution respectively and the last term in square brackets is the Tobit correction factor. An intuitive approximation to Φ in many studies is one minus the fraction of the censored sample.

This model has feature of being non-linear both in the variables (as is the case in (5), (6) and (9)) as well as in the parameters. Estimating (28) gives the Tobit index values, but because the model is non-linear in the parameters, the parameter estimates recovered from (28) are not directly comparable to standard OLS estimates of the same relationship. To achieve this comparison, we have to find the marginal effects of the variables in the model. In the case of a left-censored dependant variable, the marginal effect of the *j*th explanatory variable of the vector x is simply the Tobit index value multiplied by the cumulative distribution function of the standard normal distribution evaluated at the sample mean of z (which is simply the standardized value of the *j*th explanatory variable). In other words,

$$\frac{\partial E(y)}{\partial x_j} = \Phi(z)\beta_j \tag{29}$$

The coefficient reported as the Tobit estimates of the returns to education are therefore calculated according to (29) and are comparable to the simple OLS estimates.

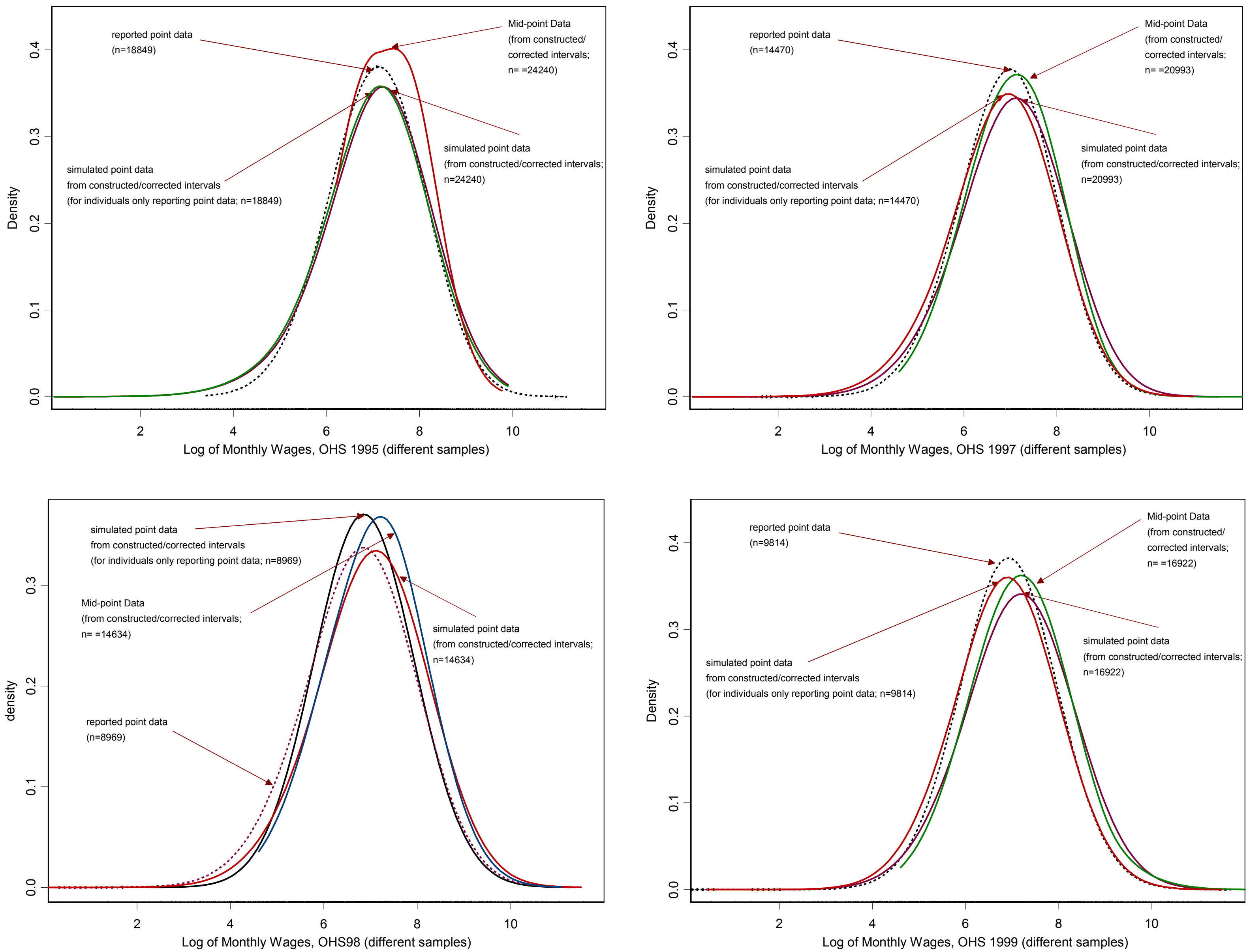


Figure 1: Simulated and Actual Earnings Distributions based on the October Household Surveys (see Appendix B)

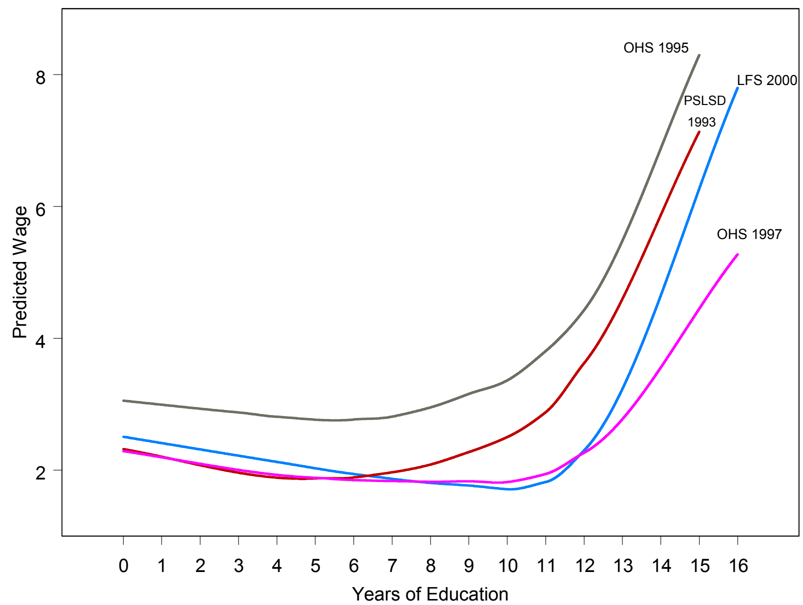
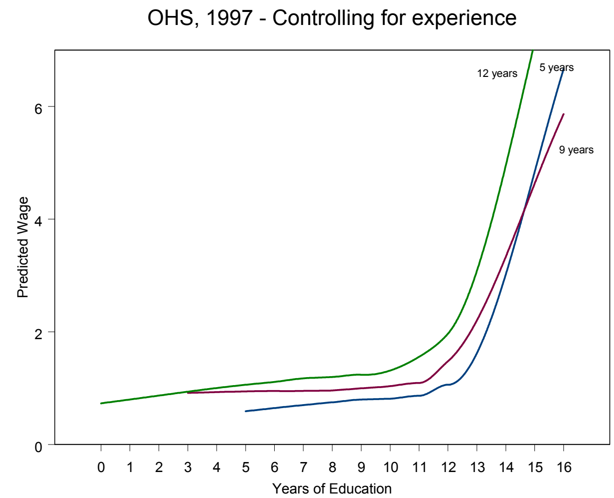


Figure 2. Convex Returns to Education

Notes

The vertical axis is log of predicted earnings, controlling for age (quadratic), gender, race, years of education (cubic), location, age-education interactions, remoteness, and regional fixed effects. The fitted values were generated using the Tobit estimator, to control for bias introduced through conditioning on whether an individual reported non-zero earnings. The pictures show a locally weighted fit from the underlying regression (as opposed to the average fit) against years of reported education, in order purge the influence of outliers.



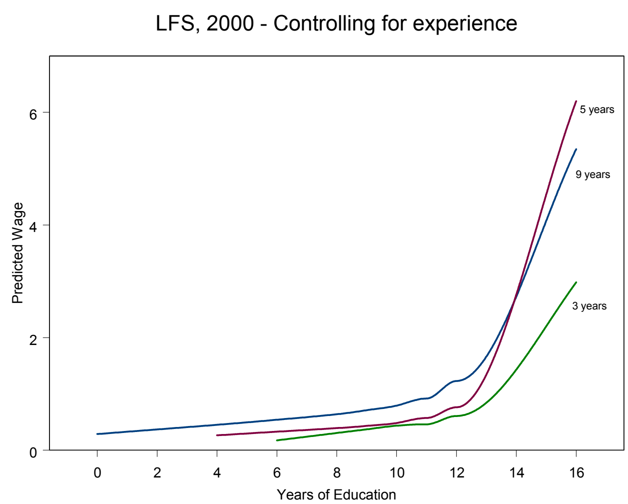


Figure 3. Convex Returns to Education (adjusted for experience)

Notes

The figures show each individual's predicted earnings plotted against their corresponding educational attainment (as in figure 2) but conditioned further on "potential experience" which is calculated according to the formula: age – years of education – 6 (Mincer's (1974)). The same patterns shown above also hold for the PSLSD and OHS (1995) data.