Returns to Schooling: Skills Accumulation or Information Revelation?

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RETURNS TO SCHOOLING: SKILLS ACCUMULATION OR INFORMATION REVELATION?

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Abstract. This paper explores the degree to which imperfect information in the labour market regarding worker quality is likely to impact employment opportunities, as well as the wages associated with those opportunities. The primary purpose of this paper is to provide preliminary empirical evidence that market imperfections exist in South Africa's labour market, that those imperfections could be based on asymmetric private information, and that market participants pursue information gathering and revelation strategies to help mitigate the negative effects of the information asymmetries.

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1. Introduction

The human capital (HC) theory postulates that schooling equips students with potential skills, which are usable at the work place Wolpin (1977). Theoretically, HC entails a proportionate correlation between the marginal returns and the marginal costs of schooling. The primary feature of HC is the fact that more educated workers should receive higher wages, i.e., there are positive returns to education, due to the belief that education is assumed to impart knowledge and skills, which are valued in the marketplace.

Screening and Signalling (SS) theories, on the other hand, assume that education is used to separate individuals from each other. SS theories are based upon productivity differences among workers, which are identified through actions that are correlated with the schooling outcome. The correlation is often modelled as a difference in the relative marginal cost of schooling. For example, an individual with more innate ability or a 'protestant work ethic' will find it easier to attend school, and, therefore, could invest in relatively more education. Again, the result of SS is a positive return to education, even if schooling itself provides no marketable skills to the students.

There are two basic types of SS theories. One of these categories of theories shows how one's innate qualities and abilities (good or bad private information) can be revealed by education attainment, or some other costly activity, such that education is perceived as a filter that reveals differences in workers' abilities, which, in turn, accounts for wage differences. Empirical tests of the information revelation mechanism assumed in these SS theories are characterized by the weak screening hypothesis, as generally developed within the screening and signalling models proposed by Spence (1973), Arrow (1973) and Stiglitz (1975). The empirical applications of these models hold that information on productivity may not be perfectly revealed by the screen, such that employer learning may also be necessary. The strong screening hypothesis, on the other hand, presumes that information is perfectly revealed by the screen, such that no employer learning is necessary. Berg (1970) and Thurow (1970) discuss a credentials based theory of education and employment, which fits within the broad category of strong SS theories, and is often used to explain recruitment into specific professions. In these SS theories based only upon credentials - a PhD is needed to become a professor - no relationship is assumed between schooling, wages or productivity.

Due to the fact that both HC and SS theories suggest a positive correlation between earnings and schooling, there is an empirical identification problem, when it comes to separating the importance of the two effects. Despite the difficulties, Layard & Psacharopoulos (1974) suggest three salient differences to examine. The first is that rates of return to completed courses ought to be different from rates of return to uncompleted courses. The second point they raise is that standardised education differentials should fall with age, due to employer learning of the worker's true ability. The third point they raise is that there ought to be less expensive ways to screen employees than forcing potential employees to invest in unproductive education.

Objections, however, can be raised against each point. For example, different rates of return to completed vs non-completed courses could be due to differences in education quality, i.e., a completed course would provide a more complete picture of a subject, which could raise productivity non-linearly. Furthermore, if employers were good screeners, as we might expect in equilibrium, then they would not make costly mistakes in their screening activities, i.e., although employer learning may be necessary, it is likely to be a small component. In other words, properly screened individuals would be very likely to maintain their earnings advantage over other employed individuals in the labour market. Finally, the comment that less costly screening programs are available partially violates the assumptions of the SS theory, in which it must be too costly to attempt to mimic workers of another type. If screening and signalling become less costly, then it is possible that the screening mechanism would become less accurate. As can be gathered from the preceding discussion, empirical identification of SS effects is often difficult.[1]

It is likely that education, by itself, has value in the labour market, but it is also likely that screening is used to separate applicants in the job hiring process. Arrow (1973) is in favour of such a complementary view of SS and HC, rather than an antagonistic view. Similarly, Weiss (1995) and Chatterji, Seaman & Singell, Jr.

[1]Weiss (1995) highlights many of these difficulties.

(2003) argue that screening theories augment the basis laid down in the human capital theory. Specifically, Weiss (1995) maintains that a consensus does not exist on whether or not returns to education are determined by education, because it is a screening device or because it has intrinsic value.

In this paper, we examine the screening device vs intrinsic value debate in the context of a middle income developing economy with a highly skewed distribution for both income and educational attainment. The analysis employed is both descriptive and empirical, based on sample differences; the empirical models take into account potential sample selection based upon the sector of the marketplace in which an individual is found - the individual could be unemployed, self-employed, employed in the public sector or employed in the private sector. Although it is likely that unemployment is not preferred over employment, it is not obvious that the other employment categories can be ranked. Furthermore, unobservable information may even cloud the ranking of employment over unemployment. Therefore, the empirical models include a selection equation based upon the multinomial logit to model unordered alternatives.[2]

The remainder of the paper is organized as follows. We continue, in Section 2, by more carefully addressing the literature that is relevant to our study. Section 3 discusses the primary features of the data, while Section 4 recounts the primary theoretical and empirical predictions expected from sorting models that might apply in a developing country with skewed income and educational attainment distributions. The primary analytical model is presented in Section 5, while the main empirical results are tabled in Section 6. We conclude by noting a few drawbacks and directions for improvement in the present analysis in Section 7.

2. Literature

Empirical tests of the strong and the weak screening hypotheses commonly employ screened and unscreened samples, Wolpin (1977) and Psacharopoulos (1974). Results from estimations involving these two screening hypotheses have tended to support the weak and not the strong,[3] while those attempting to differentiate

[2]It is possible that the multinomial logit model does not accurately reflect the outcomes, due to the underlying IIA assumption. That assumption is considered in the analysis, below.

[3]See, for example, Brown & Sessions (1998), Brown & Sessions (1999), Wolpin (1977) and Riley (1979).

between screening and human capital theories, have had difficulty identifying a screening effect separate from a human capital effect. In other words, past empirical tests of either screening hypothesis have yielded equivocal results, see Riley (1979).

Given the equivocal nature of previous estimates, more recent efforts to separate SS effects from HC effects have been based on extensions of Layard & Psacharopoulos's (1974) hypothesis. For example, Altonji & Pierret (2001) consider whether or not employer learning (of true productivity) can impact the estimated returns to education. Theoretically, they argue, the impact is, at best, minimal. In their analysis, the expected returns to years of schooling should register an independent or even decreasing relationship with a worker's experience in the labour market, but an increasing one with measures of natural ability, since firms are expected to learn actual ability. Bauer & Haisken-Denew (2001), using panel data, however, realise a positive relationship in both cases. Although no evidence of employer learning regarding a worker's productivity is realised for white-collar workers in Bauer & Haisken-Denew's (2001) analysis, there is employer learning for blue-collar workers, whose work efforts primarily yield tangible production, which is somewhat surprising. The surprise is due to the fact that tangible production should be easily observed, and, therefore, should not require much in the way of signalling or screening; for example, firms and workers could agree on a piecemeal payment contract that would be completely devoid of any informational asymmetries, although it would not be risk-free for the labourer.

Brown & Sessions (1998) and Brown & Sessions (1999),[4] however, postulate that learning might be affected by the nature of the institutions within a specified region, as well as with the indigenous cultures of the work force involved. To this effect, Sakamoto & Chen (1992) provide estimates for Japan, Ziderman (1992) undertakes an analysis of Israel, and Australia is considered by Miller & Volker (1984). The preceding studies have all registered some support for screening. Research by Oosterbeek (1992) for the Netherlands, on the other hand, did not register support for screening or signalling. Psacharopoulos (1974) and Layard & Psacharopoulos (1974) obtain mixed results for the UK and the USA.

[4]These Brown and Sessions papers were previously discussed in Bauer & Haisken-Denew (2001).

Chatterji et al. (2003) offer the most recent extension. In their model, they are able to control for the extent of the signal, as a function of firm, job and individual attributes derived in a first stage ordered-probit model. From the ordered-probit results they derive a continuous measure of the signal, via a hazard rate, which is then incorporated into the second stage Mincerian wage equations; see Mincer (1974). Their results entail a significant, positive return to an education signal; the signal being a measure of the difference between the required and necessary qualifications for a specified job. Although a promising result, the data available to us does not provide a direct measure of either the potential monitoring costs or the potential over-educated status of the workforce.[5] The empirical model that we employ does, however, take into account a selection mechanism that is similar in nature to that employed by Chatterji et al. (2003).

2.1. **South African Empirical Analysis.** A considerable number of studies on returns to investments in human capital have been conducted for South Africa, and many different aspects of the relationship between wages and education have been researched. Importantly, most studies have emphasised, and thus included, arguments such as race, gender, union membership, physical location, and years of education (including education splines) as wage determinants. However, other missing variables are also likely to be important. Although some of the studies have addressed sample selection, which can be modelled as an omitted variable bias within the empirical analysis, issues such as education quality, family background, screening and signalling have not been addressed, as far as can be discerned, primarily due to difficulties in obtaining the appropriate data.[6]

Although informational aspects have not been explicitly modelled in the South African context, a considerable number of studies estimating the returns to investment in education have been conducted using South African data. The analyses

[5]Recent research in South Africa by Simkins (2007) has shown an increase in educational attainment. However, Burger & Von Fintel (2006) suggest that the increased educational attainment is not translating into job opportunities. These combined results suggest that informational problems exist across the labour market in South Africa.

[6]Hertz (2003) addresses the countervailing effects of omitted variables and measurement errors in OLS estimations of returns to schooling in South Africa. The biases associated with these two causes are known to be opposing, upward and downward, respectively. The impact of the former is expected to be greater in developing countries, thus yielding a net upward bias. After correcting for the two different problems, the estimated returns of 5 to 6 per cent are about half those yielded from OLS (11 and 13 per cent).

have mainly utilised the Mincerian logarithmic wage function,[7] although some recent analysis has considered other estimation strategies, such as quantile regression.[8] The most common dependent variables analysed include: average annual log earnings; gross monthly pay, including overtime and bonuses; gross weekly earnings and hourly wages.[9]

Keswell & Poswell (2004), utilising four data sources collected in different years, and gross monthly pay as the dependent variable, consistently confirm convexity in the structure of returns to human capital investment in South Africa; nearly zero marginal return is registered for primary education, although marginal returns rise quickly following the completion of secondary school. Moll (1996) provides one explanation for this observation, and it is likely to be relevant for our analysis of screening. Moll argues that the inferior inputs into primary and secondary education for the African population, who make up the majority of South Africans, beget inferior outputs; thus, there is a negligible impact of primary and secondary education on the market wages. In a related paper, Bhorat (2000), reports that an additional year of education for African workers with tertiary education yields a 16 per cent return, but only a 4 per cent return for holders of primary education.

The completed schooling rate of return to full time wage earners is estimated by Keswell and Poswell to range from 15 to 26 percent. However, their analysis, like many others, uses a highly aggregated description of human capital accumulation, and such a variable may miss the complexities surrounding the specific roles of education credentials towards the determination of wages, as argued by Blundell, Dearden, Meghir & Sianesi (1999).

In considering these complexities, the range realised by Hofmeyer (2001), who disentangles the schooling credentials further, is much wider.[10] Mwabu & Schultz (2001) also extend the complexity analysis; their estimates of the marginal rate of return to education in South Africa are shown to be sensitive to race and gender.

[7]See, for example, Moll (1996), Bhorat (2000), Michaud & Vencatachellum (2001), Hofmeyer (2001).

[8]Keswell & Poswell (2004) provide an excellent summary of the research.

[9]According to Keswell & Poswell (2004) the impact of differences in measures of earnings used (hourly, weekly, monthly or annually) is trivial. However, comparison requires conversion into a similar unit.

[10]Mwabu & Schultz (2001) also reported a 60 per cent return for African women; that estimated return was, however, challenged by Butcher & Rouse (2001).

Mwabu & Schultz (2001) estimates of the returns to workers belonging to the African population group, and those to men, exceed those of other races and sex, respectively. However, Bhorat's (2000) 26 and 16 per cent return to an additional year of tertiary education, for the whites and Africans respectively, contradicts the racial differences found by Mwabu & Schultz (2001). Bhorat (2000), like Moll (1996), attributes the higher returns for whites, as compared to that of Africans, to differences in education quality, perceived or actual. What is left unanswered, and not easily addressed, is the variation in returns based on school quality perceptions and other informational issues.

Mwabu & Schultz (1996), predicted a reverse in the racial pattern of South African returns to education, as the impact of education rationing implemented by the apartheid government is rectified by the new and democratically elected government. Unfortunately, recent research by Wittenberg (2007), Kingdon & Knight (2005) and Burger & Von Fintel (2006) challenge the view that increased education is leading to a convergence in employment opportunities across population groups, which is likely to have repercussions on the patterns of returns to education predicted by Mwabu & Schultz (1996). Michaud & Vencatachellum (2003) findings also contrast with Mwabu & Schultz's (1996) prediction of a reversal in the pattern of returns to education.[11]

Apart from Mwabu & Schultz (1996), who argue that screening may be an alternative explanation for the observed differences in returns to education by populations groups in South Africa, other studies have not attempted to disentangle returns to education that accrue to the skills acquired from those that accrue to innate differences in individuals. Using quartile regression, Mwabu and Schultz show that the impact of worker abilities on wages differs with population group and education splines. For whites with higher education, Mwabu and Schultz's results are similar to those expected by screening theories relating education achievement and ability. However, Mwabu and Schultz argue that the results are more consistent with the human capital theory for African males with primary credentials

[11]Michaud & Vencatachellum (2003) show that positive externalities related to increases in average education level within a population group tend to raise demand faster than supply; thus, convergence may not occur; they show the pervasiveness of the within-population externality effect.

and whites with secondary education. In the former case, education and ability are shown to be substitutes.

2.2. **The South African Labour Market and Education Policy.** From the preceding review, it is evident that little emphasis has been paid to disentangling the informational role of human capital accumulation from that which accrues to the skills bestowing role of education in estimating wage determinants. Yet, in South Africa's labour market, there are many labour market imperfections and information asymmetries likely to provoke the information revelation role of education, in an effort to counter the imperfections and information asymmetries.

The information asymmetries are potentially diverse. For example, there are differences in workers' mental and physical productivities. In addition to basic asymmetries, some labour market policies have raised the cost of hiring a poor quality worker, such as laws enforcing/addressing worker employment security and bargaining councils determining wages across entire sectors. Finally, other labour market policies meant to address previous imbalances have been imposed and those policies allow the government to interfere in employment practices, and these externalities, no matter how well intended, do raise the general cost of employment.

Historically, the apartheid legacy has heavily impacted the quality of labour in South Africa. Importantly, attempts at self-actualisation were racially controlled. Furthermore, The Bantu Education Act, implemented in 1953, restricted the education aspirations of non-whites. This education model was vertically integrated, culminating in racially demarcated: all white and all black universities.[12] The previous racially demarcated universities have now been amalgamated, and they issue the same certificates. However, pre-tertiary education institutions, a much larger component of the education system, continue to struggle under the weight of past oppression. Although a new education environment is being established, the desired changes will take time, Moll (1996).

[12]These are commonly referred to as historically white universities (HWU) and historically black universities (HBU), respectively. People of Indian or mixed heritage 'enjoyed' an intermediary education model.

One aspect of law likely to influence the labour market in South Africa is that of the newly enacted labour policy intended to address apartheid discrepancies. Examples include: extensive protection against unfair dismissal and the minimisation of retrenchments; the mandatory transfer of workers to a new business owner; and the extension of bargaining council agreements to non-parties/employers, so long as they fall within the scope of the bargaining council. These recent labour policies impose additional costs and reduced flexibility in the work place, and are, thus, likely to manifest in a heavy burden on investment and on the decision of whom to employ, Barker (1999).

With information asymmetries, employee protection laws, and other negative externalities in the labour market, a firm's profit maximisation efforts will be further constrained.[13] Therefore, employers are compelled to seek each potential worker's true innate abilities. Schooling may serve as such an information revealing device, although firms are also likely to undertake additional costly testing activities to measure worker potential. This study, thus, investigates whether, amid information asymmetries, accumulation of human capital may be used as an information recovery mechanism in South Africa's labour market.

3. The Data

3.1. **The LFS.** For this analysis, a single data source is utilised;[14] it is the September 2004 Labour Force Survey (LFS), conducted by Statistics South Africa. The LFS is a bi-annual 20% rotating panel household survey.[15] The primary purpose of the survey is to provide information on labour force participation, unemployment and employment, although many additional questions are included in the survey.

The survey is a two-stage stratified random sample of 3000 primary sampling units covering all households from the 2001 census enumeration areas with at least

[13]The HIV/AIDS pandemic is also fundamentally influencing the labour market. Employers are likely to be concerned about the future impact of the epidemic on worker productivity and absenteeism. However, anti-discrimination laws towards the HIV positive, or those that society assumes to be, as well as policies that oppose mandatory testing for HIV, perpetuate information asymmetry.

[14]However, similar analysis was conducted using the 2003 General Household Survey, with similar results as reported here.

[15]The panel has recently been released for use. However, due to issues regarding retention in the panel, which have not been adequately addressed, the panel has not yet been considered for the analysis reported here.

25 households, but not including workers' hostels, convents or monasteries.[16] Completed response rates for this survey vary from 79% to 94%, depending upon the province; refusals represent about 2% of non-responses, while vacant and unoccupied dwellings represented an additional 3%-4%, each. The data includes 73 797 working age adults out of 109 888 individuals interviewed in 28 494 households. The research reported below relies primarily upon data from working age adults, although household characteristics are also created from the individual data and match-merged to workers within each household.

3.2. **Summary Statistics.** Despite the fact that 79% to 94% of the surveys were deemed to be complete by StatsSA, responses to various questions were either not recorded or, more likely, not offered. Of primary concern is unavailable salary data. Although salaries for the unemployed and non-participants is not available for expected reasons, it is notable that within the survey, of the 25 506 working age adults, who are classified as working, only 17 372 offered an actual salary response; another 6 408 were prompted, and provided, salary range information.[17] In addition to the employed, a further 9 052, or 26.2% of the sample, were unemployed, according to the narrow definition, which requires active search. Using the broad definition, 18 547 individuals, or 42.1% of the sample, were unemployed according to the broad definition - an additional 9455 working age adults were not actively seeking employment. Non-participation in the labour force was 40.3% of the sample, when discouraged workers are part of the unemployed, and 53.2% according to the narrow definition. The remaining summary information from the data used in the analysis is available from the authors.

4. A Tabular Analysis

Given that no earlier study of returns to education for South Africa has addressed the possibility of the screening bias as its central focus, this paper aims at empirically contributing towards the debate between schooling's productivity boosting and ability revealing qualities, across the different education certificates.

[16]Weights are available to aggregate the data to national level, although they are not used here. However, primary sampling unit information is retained to control for variance effects of cluster surveys, within the uncorrected Mincerian regressions. The remaining results are bootstrapped

[17]Averages within the salary ranges, calculated from those who reported salaries, were used for those who did not report a salary, but did report a salary range.

It caters for the employed, in three sectors (private, public or self-employed) in South Africa, but adjusts for the sample selection bias, including selection into unemployment. The self-employed serve as the control group and reference sample, differences from this group are presumed to account for some of the informational aspects of education choices.

4.1. **Employment-Education Profile.** Consider a market in which there are v vacancies and u unemployed people. Given the fact that the unemployment rate is high in South Africa, we will assume $u \gg v$. Under such a scenario, all firms can be choosy and employ the best candidate(s) in the applicant pool. Furthermore, suppose each unemployed individual has private information concerning their contributory value to the firm,[18] which may be due to innate ability, work ethic or any other trait that is not costlessly observable. Furthermore, assume that the underlying unobservable trait makes education easier to pursue, and, finally, assume that the quality of education is not verifiable. Given private information on the part of the worker as well as non-verifiability of education quality, we would expect firms to glean as much information as possible from each applicant before extending an interview. In this labour market, job seekers are likely to have great difficulty obtaining an interview, and, therefore, they are likely to have difficulty garnering employment.[19]

As alluded to previously, one of the expected features of information asymmetries and other imperfections in the labour market is uneven unemployment rates across different levels of school completion, and such differences can be calculated from the numbers presented in Table 1, below. Table 1 shows the percentage of the working age population that has attained certain levels of schooling, and those percentages are split across labour force participation status, using both the narrow and broad definitions. The schooling level unemployment rate, not shown,[20]

[18]Realistically, the firms are also likely to have private information regarding the potential value of the vacancy to the worker, but we will ignore that, given the depth and breadth of unemployment and poverty in South Africa.
[19]Admittedly, those who do obtain an interview are likely to undergo another series of processes in order to obtain the job, as the hiring firm undertakes further 'screening', with a view towards measuring the quality of the individual's education credentials.
[20]The unemployment rate for each schooling level can be calculated by taking the percentage unemployed and dividing it by the sum of percentage unemployed and employed. Those rates for the narrow definition are 14.7%, 23.8%, 28.6%, 33.1%, 25.9%, 20%, 8.3% and less than 2%.

follows an inverted U-shape. However, simple unemployment rates do not capture the entire story, as non-participation is highest amongst those with lower levels of completed education. Employment rates, on the other hand, follow a general upward trend as schooling attainment increases, which would be expected in markets where either learned skill or innate ability, revealed by schooling completion, were valued.

4.2. **Wage-Education Profile.** Although employment is affected by education, as shown above, actual employment is only part of the potential effect of screening. Labour market sorting should also reveal itself through differences in returns to education by employment sector. Initially, we consider average wages by education level to determine whether there are differences in that average across employment sector. Those averages are available in Table 2. The average earnings presented in Table 2 suggest a relatively flat earnings structure within the public sector compared to the steeper earnings profiles within the self-employed and private sectors. Public sector employee average earnings exceed both privately employed and self-employed average earnings, until the completion of a secondary education; however, that relationship reverses for specialized training (national training certifications) and completed undergraduate and postgraduate education.

In a labour market with sorting (screening or signalling), where specific individual traits matter, it is possible that course completion will provide improved earnings over incomplete education, Weiss (1995) and Layard & Psacharopoulos (1974). Furthermore, the completion effect is likely to be stronger as schooling increases. We consider that possibility in two ways in this analysis.[21] Initially, we calculate the ratio of wages for completed primary to incomplete primary and for completed secondary compared to incomplete secondary.[22] We report those ratios by age category in Table 3 for everyone employed and for the three different employment sectors discussed above to see if different sectors reward completion differently. The reported data suggests that sorting may be rampant across the

[21]The regression version is considered below.
[22]This is computed as the wage for individuals who have completed grade 12 relative to individuals only completing grade 11, and the wage for those who have completed grade 7 to those who have only completed grade 6.

population and across employment sectors. In all but one case, although statistical comparisons are not drawn, the calculated ratio is higher for those who have completed more schooling. However, the data also suggests that completion of high school is relatively more valuable for self-employed workers than for other employees, while the results are less suggestive of a sectoral advantage for primary school completion. The relative gain to completion for self-employment does not square with expectations, if it can be assumed that self-employed people know their own abilities, and, therefore do not need to signal their innate abilities to themselves.[23]

Taubman & Wales (1973) offer the prediction from screening and signalling models that the education return should fall with experience, as true ability is learned. As can be expected, given the importance of general on-the-job learning by the employee, the preceding prediction is not likely to hold, exactly. However, an analysis of this effect is considered both via regression, below, and by means of a simple table. The ratio of earnings for various levels of education relative to completed secondary education for different age groups is presented in Table 4. Again, those ratios are available for all workers as well as for the workers in specific employment sectors. The data in Table 4 are broadly supportive of the screening model's learning predictions, as the wage ratios tend to fall over the age profiles presented, although wages in the public sector do not exactly follow the predicted pattern.

4.3. **Summary.** According to both HC and SS theories, we should expect to observe a positive relationship between earnings and schooling attainment. The earnings averages presented in Table 2 are consistent with that expectation. Furthermore, as argued by Wolpin (1977), employment sectors are likely to differ according to their inherent need to ascertain individual-specific asymmetric information. Given the nature of self-employment, it is expected that the employer-employee knows her own inherent abilities, such that there is no need for screening. The public sector is also less likely to screen than the private sector, given the fact that public sector employer preferences are less focussed on profitability. If, in fact,

[23]An anonymous referee worried that the self-employed, who often have to sell their wares and services in product markets (with potentially imperfect information), may also need to signal their ability. Our analysis, below, suggests that this concern is not warranted.

there is more screening in the private sector than in the other sectors, Wolpin suggests that more educational attainment will be seen within the private sector, and, generally, wages will be higher to compensate the worker for the cost of additional schooling. Although average wages are definitely higher in the private sector for the very well educated and the private sector employs more people than any other sector,[24] the private sector absorbs relatively fewer workers in the higher schooling categories; therefore, Wolpin's (1977) intuition is not directly observable in Table 2.

The strong screening hypothesis, which assumes that information is completely revealed by the signalling/screening mechanism, such that employer learning of employee productivity is not needed during the employee-employer relationship, has different empirical implications than the less strict weak screening hypothesis, which assumes that the screening and signalling mechanisms do not completely reveal the asymmetric information. Under the weak assumption, the employer is assumed to undertake additional learning during the employee tenure. Given the differences in presumed information revelation, constant career wage profiles ought to be observed under the strong screening hypothesis.

The results in Table 3 and 4 are broadly supportive of both of these hypotheses, if it can be assumed that the public sector is more likely to hire and promote due to credentials and experience than any other factor, while the public sector is likely to offer promotion based on credentials and experience. In this scenario, relative pay rates should rise with experience (although age is used as a proxy here) rather than fall, and pay should reflect those credentials. Within the private sector, however, the evidence is more supportive of the weak screening hypothesis. There does appear to be some employer learning of productivity over the employee's career cycle. The initial cut of the data suggests that the private sector rewards completed degrees better than incomplete degrees, and that those rewards are higher for higher levels of schooling. Interestingly, though, the data also suggests that the self-employment sector rewards completed degrees over incomplete degrees, and by a larger margin than any other sector. In other words, although the public sector data

[24]It is assumed that experiential effects are independent of schooling attainment, such that experience does not have a greater payoff for more educated workers than for less educated workers. Such an assumption is not likely to be realistic.

(and intuition) implies that credentials (and strong screening) are relevant and the private sector data implies that weak screening is plausible, the self-employment sector data provide a wrinkle. One of the predictions of the screening or signalling hypothesis is that self-employed workers need not signal their innate abilities, and, therefore, the preceding predictions should not necessarily apply to them. So far, the results are mixed for the self-employed workers.

Finally, the screening model implies that completed degree programs are likely to matter more than merely education, and that completed degrees will become more valuable for each level of additional education. Table 3 presents mid-career to early-career earnings ratios by educational attainment. The data in the table does not provide insurmountable evidence of the strong screening hypothesis, although the public sector data suggests the potential for the strong screening hypothesis. However, the public sector data is also consistent with a salary structure that is based on credentials and years of experience, such that salaries increase with credentials (as measured by schooling completion) and experience is rewarded according to a fixed formula, regardless of qualification. Within the private sector, there is some support for the weak screening hypothesis, although the data is also consistent with a strong screening hypothesis and an experience-earnings profile that is higher for more educated workers than for less educated workers.

5. Empirical Methodology

Although the potential for screening was examined in the preceding section, and the previously presented data was broadly supportive of that potential, the aforementioned analysis was tabular. The preceding analysis was completely non-parametric in the sense that no distributional assumptions were made; underlying test statistics, although non-parametrically available, were not calculated for the comparisons. Furthermore, controls based on additional variables cannot be included in a tabular analysis. Finally, no attempt was made to control for issues of sample selection that might arise in an analysis that compares results across multiple samples. Therefore, in this section, the preceding analyses are extended to allow for additional control variables, especially controls for sample selection.

5.1. **Multinomial Selection Corrected Mincerian Regressions.** In empirical models of signalling, identification of screening and signalling relies upon a comparison across different samples. For example, we expect that people who are self-employed have less need for signalling devices than those who are looking to be employed in the private sector; or, we expect that people who are easily monitored might have less need for signalling, since productivity can be determined with little cost. However, these various samples are likely to be selected. Those who are self-employed may choose to be, so they do not have to work for others; on the other hand, they may not have the opportunity to work for others, and, therefore, they are forced to work for themselves. Also, those who work in the public sector may do so, because they want to give something back to the community, or because there are excellent benefits associated with the job; on the other hand, they may do so, because no one in the private sector will give them employment.

In other words, individuals in the labour force survey are not randomly selected into different occupations (or unemployment status). Therefore, the empirical model must address the potential for sample selection. There are a number of ways to address sample selection, although the most common approach is to apply Heckman's (1979) method in its instrumental variables form, or under full information maximum likelihood.[25] However, Heckman's approach explicitly allows for binomial outcomes only. In the distinctions made above, there are at least three and as many as four outcomes: unemployed, self-employed, privately employed and publicly employed. Therefore, the model used here must account for multinomial selection effects.

Lee (1983) suggested a polychotomous selection correction model; however, the assumptions behind it were onerous, as shown by Schmertmann (1994) as well as Bourguignon, Fournier & Gurgand (2007). Almost at the same time, Dubin & McFadden (1984) proposed another correction based upon the multinomial logit. Their correction, although more robust than Lee's (1983), might be problematic, when

[25]In Heckman's IV formulation, the selection hazard is estimated from a probit regression on an employment dummy, and the estimated hazard is included in the second-stage wage regression; the FIML version results in improved efficiency. However, the model is heavily dependent on the underlying bivariate normal distribution used to derive the probit and the FIML estimators. If the underlying distribution is not bivariate normal, then the proposed estimates are inconsistent.

the IIA assumption inherent in the multinomial logit is violated.[26] More recently, Dahl (2002) proposed a non-parametric correction model. The real drawback in Dahl's (2002) model, compared to the others, is the difficulty in interpreting the correction parameters, which have no meaning. Monte Carlo comparisons of all of these models have been undertaken by Bourguignon et al. (2007). The Monte Carlo comparisons suggest that a modification of Dubin & McFadden (1984) performs well, even if the IIA assumption from the multinomial logit is incorrect, while the semi-parametric version performs well, when the conditional mean of the residual is either nonlinear or non-monotonic. As expected, if the IIA assumption is reasonable, then Dubin & McFadden's (1984) model provides consistent and efficient estimates; it is this version of the multinomial selection model we employ.[27]

5.2. **The Model.** In the LFS data, the econometrician can observe whether or not individuals are unemployed, employed in the private sector, employed in the public sector or self-employed; similarly, the econometrician can see their wages in the three employment sectors. Presumably, the employment, or lack thereof, outcome is partly determined by their preferences and market dictates, and the model must account for selection on preferences and market dictates.

Begin by defining the employment sectors as unemployed, u, public sector, g, private sector, f and self-employed sector, s, respectively. Participation in the market implies that the individual successfully cleared at least one hurdle, the employment hurdle. However, since the research is attempting to model screening and signalling across the markets, and not just in terms of actual employment. Therefore, we will also consider sectoral hurdles. Technically, we cannot observe the screening process across sectors, so we assume the screening is buried in the hurdle. Given the hurdle, which splits the sample into different sectors, Mincerian wage regressions are estimated, which take into account the endogenous sectors.

In order to anchor the discussion, consider the public sector, denoted by g. The goal is to estimate the expected public sector wage $E[w_g|x, z]$, where $x \subset z$ for parametric identification, while factors in the point that public sector wages are

[26]We consider that issue, below.

[27]Relaxing the IIA assumption was also considered, i.e., we employed Dahl's empirical technique as well. The results, available from the authors, are not substantively different, and, therefore, they are not discussed here.

only observed for people employed in the public sector. Therefore, specify:

$$w_g = x\beta_g + \epsilon_g \tag{1}$$

$$y_j^* = z\gamma_j + \eta_j, \qquad j = f, g, s, u. \tag{2}$$

In the preceding specification, w_g is observed if $y_g^* = \max_j y_j^*$, where y_j^* is a latent function meant to capture a discrete observation - either the individual participates in that sector or not. Assuming that $E[\eta_i \eta_k] = 0$, $\forall i \neq k$, while the cumulative density of the error terms follows a Gumbel distribution, $G(\eta_j) = \exp(-e^{-\eta_j})$, the discrete choice component can be consistently estimated with a multinomial logit, McFadden (1973). However, to consistently estimate β_g, one other factor must be taken into account, the fact that $E[\epsilon_g|x] \neq 0$.

Given that w_g is observed if and only if $y_g^* = \max_j y_j^*$,

$$\begin{aligned} E[w_g|x] =& E[x\beta_g + \epsilon_g | y_g^* = \max_j y_j^*] \\ =& x\beta_g + E[\epsilon_g | y_g^* > y_f^*, y_g^* > y_s^*, y_g^* > y_u^*] \\ =& x\beta_g + \mu(P). \end{aligned} \tag{3}$$

where $\mu(P)$ measures the bias in the error term, due to the fact that the error is taken from a truncated multinomial distribution, a Gumbel distribution in this case.[28]

The difficulty with applying estimators to control for various forms of endogeneity lies in the ability to identify that endogeneity, represented by $\mu(P)$ in this case. In general, identification requires an exclusion restriction, whereby a variable is included in the employment regression, but not in the salary regression. This research will consider four such variables, which are related to family structure. These controls include: size of the household, and the number of household dependents (children under the age of 5, children aged 5 to 15, and the number of retired persons). These variables, although they do not provide any obvious theoretical traction on the potential for signalling, they do provide some traction regarding

[28]In the binomial selection model, á la Heckman (1979), $\mu(P)$ measures the correlation between two binomially distributed errors and the inverse Mill's ratio, e.g., $\mu(P) = \sigma_{12} * \lambda$, where the numeric subscripts refer to the two potentially endogenous equations. In the multinomial selection model, there is potential for multiple correlations of this sort.

certain job characteristics that might be preferred by workers, and, furthermore, might be sector specific.[29]

6. Empirical Results

In this section, results from a wide series of regressions are discussed. The results are presented in a series of four tables, Table 5 through Table 8. The differences between the tables is based on possible combinations of two binary variables: unemployed (included or not) and tenure (included or not). Only a limited set of results are presented in each table, and those results are primarily focused on schooling, the effect of tenure and tenure interacted with schooling and the correlation between the error terms in the selection correction model.[30]

6.1. **The First Stage Regression.** Although the multinomial logit results are presented in each table for each sector, a detailed discussion will not be presented for each table, since the results are uniformly similar across all the tables.[31] In nearly all of the analyses, the multinomial results point to the importance of schooling on employment, as well as sectoral differences in employment probabilities. In each of the analyses, the private employment sector is the base category; therefore, the multinomial parameters are relative to the private sector, such that all probabilities will be discussed relative to the probability of private sector employment.[32]

Generally, years of schooling and completed secondary school result in the increased probability of self-employment; furthermore, with the exception of completed primary education, which has no discernable empirical effect, all reported schooling variables have a positive impact on public employment. Interestingly, completed years of school not only increases the probability of self-employment

[29]Because these variables may not be good sector identifiers, a new variable, similar to that suggested by Kroch & Sjoblom (1994), will be created in future, and used in the first stage multinomial regression. The variable is a numeric ranking of education completion. Current difficulties in creating the variable, and determining whether it should be cohort specific, cluster specific, or some combination, has delayed the implementation to this point.

[30]Additional results are available upon request. The extra variables used in each of the analyses are listed in each table.

[31]Recall that one of the underlying assumptions in the multinomial logit is that irrelevant alternatives do not effect the estimates. Although Hausman tests generally reject IIA, the economic interpretation of the results does not change, i.e., the signs stay the same, while the results are similar in magnitude. Therefore, we are not greatly concerned about any violation in the IIA assumption in this analysis.

[32]Although marginal effects are available for the multinomial regressions, they are not presented here, given the interest in the second stage regressions, which are linear in the parameters.

and employment in the public sector as before, it increases the probability of unemployment, too.[33] However, this result is not unexpected given the analysis of Burger & Von Fintel (2006). In their careful dissection of the South African labour market they point out that education levels have improved, but not necessarily resulted in better employment outcomes. The similarity of these results to Burger and von Fintel's is relaxed slightly, when we consider the schooling hurdle effect. Although completion of particular hurdles raises the likelihood of employment in the public sector, completing the same set of hurdles makes unemployment less likely.[34]

Employment in both the public sector and the private sector is more likely than unemployment or self-employment for people who have completed specific education hurdles. The results also show convexity in the returns to education in terms of employment opportunities in all sectors, decreasing at an increasing rate for the unemployed and self-employed, but rising at an increasing rate for the publicly employed. For the unemployed, we see that although schooling raises the probability of unemployment, that probability falls at an increasing rate, when additional schooling hurdles are included. In addition, schooling raises the initial probability of self-employment, but completed secondary schooling lowers the probability. Employment in the public sector, on the other hand, increases in probability with both years of schooling and each potential school hurdle.

Importantly, these results are not inconsistent with screening in the labour market, especially if screening is used to determine employment outcomes relative to unemployment. This interpretation is derived from the empirical importance associated with the completion of various schooling hurdles. Convexities in terms of employment opportunities, especially within the public sector, and convexities in

[33]Given spatial limitations, empirical effects related to the composition of the household on sectoral employment are not included in the tables. The unreported results show that having children under the age of 14 is not indicative of an individual working in the private sector. Rather workers with children are more likely to either be self-employed or working in the public sector. These household composition variables are used as identifiers in the second-stage regression. The observed results agree with selection that might be due to lower maternity/paternity benefits in the private sector, relative to the other sectors. For example, the public sector may offer more paid leave than the private sector, while being self-employed may offer the opportunity to both remain at home with the children and continue to earn an income.

[34]Each schooling completion hurdle is for people who completed that level only, i.e., someone who completed a postgraduate degree is not also given credit for completing every schooling hurdle before that, which affects the exact interpretation, although not the general conclusion.

terms of unemployment, suggests that the public sector, in particular, makes its employment decisions based upon completion, in addition to any skills that might have been learned in school. The screening effect on employment, which has not been generally considered in the literature before, is likely to be more important in a developing country than in a developed economy, due to: high levels of unemployment, highly skewed income distributions and large differences in educational attainment and school quality.

6.2. **Models not Accounting for Tenure.** One of the underlying expected features of a screening model is that returns to education are higher in the screened sector than in the unscreened sector. This idea has been espoused by Layard & Psacharopoulos (1974), Wolpin (1977), Weiss (1995) and others. Another expected feature, previously alluded to, is that returns should generally be higher for those who have completed their degree course, as compared to those workers who have not. These two features of screening models are examined in sections 6.2.1 and 6.2.2 through Mincerian wage regressions, using log annual earnings, as well as Dubin & McFadden's (1984) model of multinomial selection. The independent variables in the regressions included age and age-squared to proxy for potential experience and potential decreasing returns to experience, gender differences, population groups, provinces, tenure and tenure-squared to control for on-the-job experiential effects and firm size.[35]

6.2.1. *Self-employed, Privately Employed and Publicly Employed.* Initially, the analysis considers only people who are either self-employed, employed in the private sector, or employed in the public sector; neither unemployment nor tenure variables are considered. The focus of this analysis is on whether or not there are observable differences in returns across sectors, and whether or not those differences are related to completion status in the employment sector; observing the importance of completed hurdles lends credence to the view that education signals are important. The results are presented in Table 5, which includes each sector's uncorrected

[35]Although union membership is likely to matter, the self-employed are generally not part of a union; therefore, in order to maintain comparability across sectors, union membership is not included.

Mincerian regression, the multinomial logit first stage regression results and the selection corrected Mincerian regressions.

The Mincerian regression for self-employed individuals suggests strong returns to both years of completed schooling and specific school hurdles, namely completed secondary and tertiary education. However, once selection effects are controlled for, returns to completed education decrease, while the non-linearities associated with specific school hurdles lose significance. In other words, although educated self-employed individuals have an earnings advantage over their less educated counterparts, the advantage is small, in the neighbourhood of 2.5% per additional year of schooling; if the individual only completed primary school, the average salary is nearly 8% lower.

The empirical results for the private sector employees are rather similar to the results for those who are self-employed. In general, selection reduces both the returns to completed years of schooling and for the completion of specific education hurdles. As with self-employment, the returns to education in the private sector are reduced by nearly one-half, from 3.5% to 1.9%, after correcting for selection. More importantly, secondary qualifications no longer matter, once selection is taken into consideration. These results suggest that the returns to completed years of schooling are small for workers in the private sector; estimated private sector returns are not economically different than the estimated returns to schooling for those who are self-employed.[36] Also, if the potential for selection is not considered, screening effects, measured by the large returns to the completion of specific education hurdles, are likely to be overstated.

For public sector employees, however, the selection effects are reversed. Selection correction increases the returns to years of schooling and all schooling hurdles above primary education. Although the uncorrected Mincerian estimates were suggestive of screening, in that there were positive returns to completed degrees over and above each year of schooling, the selection corrections strengthen the case, because the estimated returns in the public sector exceed the estimated self-employment returns to education for all education categories, once selection is taken into account.

[36]At this stage, no attempt has been made to statistically compare the estimates; however, the reported estimates are higher for self-employed workers.

6.2.2. *Employment Status and Employment Sector.* The preceding discussion in section 6.2.1 does not include unemployed people. Therefore, the analysis was extended to see if including unemployment in the selection equation affected the results. With a few exceptions, the results were not strongly affected. A few estimates from this extension are presented in Table 6.

For the self-employed, the effect of selection is a reduction in the relevant schooling returns parameters. Returns to completed years of schooling decrease from 5.2% to 2.1%. Furthermore, all of the completed hurdle effects become insignificant, once employment sector selection has been accounted for in the regression. The effect of selection on the private sector estimates differs, when unemployment is included as a labour market outcome. Although correcting for selection effects results in, as before, a near halving of the returns to completed years of schooling, there are significant increases in the returns to specific schooling hurdles beyond the completion of primary education. The results do, despite the decrease in return to specific schooling hurdles (uncorrected Mincerian to corrected Mincerian), show a strong inclination in the private sector towards completed degrees. That inclination could be construed as screening by employers, especially when it is noted that self-employed workers do not receive a premium for specific education hurdles.

The public sector Mincerian estimates do not, however, show the same pattern as they did in section 6.2.1. Although controlling for selection results in a general increase in the average returns to a completed year of school from 9.9% to 10.8% per annum, the selection controls, which include unemployment, result in a decrease in the returns to various schooling hurdles. Once again, the public sector rewards system is strongly tied to schooling completion, although school hurdles generally receive a smaller premium in the public sector than in the private sector. This change in the relative school hurdle premium between the private and public sector is the biggest difference between the models with and without the unemployment alternative.[37]

6.2.3. *Selection Correlations.* There are three highlights from sections 6.2.1 and 6.2.2. The first highlight is that, when unemployment is not included as a potential labour

[37]However, it should be kept in mind that the public sector receives, on average, nearly double the return the private sector receives for each completed year of schooling.

market outcome, convexities in the returns to education, as well as the actual returns to education become less prominent, and even non-existent, for those who are either self-employed or employed in the private sector; the public sector returns and returns convexity, on the other hand, becomes more striking. The second highlight is that, when unemployment is included, the returns and convexities become less prominent in all employment sectors. The third highlight is that the selection corrected returns to education are higher for public and private sector employees compared to the self-employed, as long as unemployment is included; without unemployment, however, the public sector returns far outstrip returns for the self-employed and privately employed.

These three results can be related back to the impact of the unobservable determinants of the labour market outcomes and the expected wages in those various labour market sectors. Although most signs are intuitive, there is one result that is surprising.[38] Intuitively, the unobserved determinants of private sector employment are negatively correlated to the unobserved determinants of wages for both the self-employed and the privately employed. People aware that they are in poor health, for example, may prefer to seek public sector employment, especially if they believe the public sector provides more health benefits; generally, we would expect that people in poorer health would receive lower wages in both the private sector and if they are working for themselves. The same argument can also be applied to the positive correlation observed between the unobserved determinants of private sector employment and self-employed earnings (as well as the probability of self-employment and the wages of those employed in the private sector); healthier people may be more willing to work in an environment with more health benefit uncertainty, since they do not expect to be unhealthy.

The surprising result, however, can be seen in Table 6; the unobserved determinants of unemployment are positively correlated with the unobserved determinants of public and private sector wages. If the correlation is due to the fact that health is not included in the regressions, then the (not entirely believable) implication is

[38]Importantly, the selection correlations in Tables 5 and 6 show that the sign of the correlations are maintained before and after unemployment is included as a labour market outcome, although the correlation between the probability of self-employment and the public sector wage loses significance.

that private information related to better health raises the probability of unemployment *and* the expected wage in both the public and private sectors.[39] It is quite likely, however, that there is a combination of control variables that are missing, and not just. For example, racial preferences, which cannot be easily included as a regressor, might result in generally higher unemployment and be associated with higher wages for enough individuals to raise the expected wage.

6.3. **Allowing for Tenure Interactions.** The preceding Mincerian regressions, reported in section 6.2, suggest that screening and signalling could be a feature in very specific areas within the labour market, but other interpretations are also reasonable. Therefore, we next consider an extension to the preceding models. In the screening or signalling equilibrium, firms offer workers a wage based on their expected productivity, as revealed within the equilibrium revelation mechanism. Through time on the job, an employer is able to observe the employee to see if productivity matches the equilibrium expectation. Therefore, tenure is expected to result in a narrowing of the gap between expectation and reality, if the screening mechanism is not perfect. That intuition was used in the analysis by Altonji & Pierret (2001), who suggest that schooling should be interacted with tenure, because tenure should be associated with employer learning of worker productivity. Furthermore, the interacted effect should be negative. However, such an analysis ignores survival effects, where only those, whose observed productivity does not disappoint, manage to continue with the firm for an extended period of time. Yet, if survival effects matter, the empirical observation of a narrowing in the gap between expected productivity and wages would be rather less likely, and, therefore, should lend credence to the original hypothesis, i.e., ignoring survival effects would tend to bias the learning effect towards zero.

Tables 7 and 8 contain the empirical results from the models that included tenure effects. As before, the estimates are further split. In Table 7 the estimates are determined without unemployment, while the Table 8 estimates include unemployment as a labour market outcome. The results reported in Tables 7 and 8 are very similar

[39]This counterintuitive result is partly driven by the model assumptions requiring the correlations to have a net zero effect in the model, i.e., if some of them are positive, then some of them must be negative to provide an offset.

to those reported in Tables 5 and 6. Years of school and completed school hurdles raise expected wages, while selection tends to reduce the estimated returns. The exception to this rule, as before, is within the public sector when unemployment is not included in the multinomial logit. In these public sector estimates (without unemployment), selection raises the estimated returns and increases the convexity of the estimates; in all other estimates selection lowers the returns to education and decreases the convexity of the returns. Given the negative and convex relationship between education (and school hurdles) and the probability of unemployment, the estimates suggest that the strong convexity in public sector wages results from selection bias.

It can be gleaned from the analysis that ignoring unemployment as a labour market outcome strongly impacts the returns to education. One interpretation of the importance of unemployment in the selection model is that if there is a reasonably constant pool of jobs within the public sector, and a specific group of people are competing for those jobs, an *arms race* may ensue. Signalling employability through educational attainment requires ever increasing levels of education in order to garner employment. Furthermore, the *arms race* effect is only visible in the public sector, since correction for selection tends to have the same effect in the other employment sectors regardless of whether or not unemployment is included as a labour market outcome.

7. Conclusions and Future Directions

The research presented in this paper was empirical, based on well-founded observations from screening and signalling models. The empirical models were nonparametric (tabular) and parametric; the latter relied upon regressions, which accounted for multinomial selection effects. The results show that labour markets are segmented, in the sense that different types of workers end up in different employment sectors; furthermore, the observed sorting (or selection) is an important determinant of wages in all of the employment sectors examined. Given the fact that the labour market in South Africa is operating well below capacity, such that a large number of potential workers are seeking employment within a limited number of vacancies, the existence of strong market sorting mechanisms was expected, despite the fact that the data is not necessarily the best data for answering the proposed question; specific controls for the determinants of education attainment, such as ability, distance from a school during childhood, or parental education are completely lacking in the data. The selection models, however, provide some control for these missing data.

The observed results imply that there is sorting in the labour market, i.e., that there are imperfections in the labour market. In the main, the data is consistent with the screening interpretation. It is possible that these imperfections are based on asymmetric information, due to the fact that people who are more able, have received their education at better schools or are healthier, are more likely to have completed more education. The information content of the years of schooling as well as the completed education hurdles, although imprecise, sends a strong signal to the labour market, especially the public and private sectors, that these people are potentially productive, and are, therefore, employable.

However, the results point to the need to investigate other explanatory avenues. Riley (1979), for example, has suggested a slightly different approach. Rather than considering employees from the private sector relative to employees from either the public or self-employment sector, it is appropriate to consider what types of workers might actually be screened. For example, workers who are under a direct supervisor can be observed, such that information problems can be controlled by direct supervision. If, instead, the worker is unsupervised, then the worker's productivity is likely to be difficult to measure, and, therefore, firms would prefer to hire someone who has exhibited specific traits, and, for example, completed their degree programs. Fortunately, the data does provide information on age and education, so it is possible to construct an index ranking of education by age group. Furthermore, the recent release of the LFS panel may provide other dimensions within which to address the preceding questions. Finally, the data does provide extensive information on the permanency of employment. Research is currently under way to determine whether or not contractual information and other data can provide additional empirical traction.

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Table 1. Schooling Completion and Employment Status

Narrow Participation Status

Schooling Level	Non-participant	Unemployed	Employed	Total	Employment Rate
None	7.9	0.5	2.9	11.3	25.7
Preprimary	10.9	1.9	6.1	18.8	32.4
Primary	4.8	1.0	2.5	8.2	30.5
Some Secondary	23.1	5.2	10.5	38.7	27.1
Secondary	6.2	3.7	10.6	20.4	52.0
National Training Certificate	0.2	0.1	0.4	0.6	66.7
Baccalaureate	0.2	0.1	1.1	1.4	78.6
Postgraduate	0.1	0.0	0.4	0.5	80.0
Total	53.3	12.3	34.4	100.0	34.4

Broad Participation Status

Schooling Level	Non-participant	Unemployed	Employed	Total	Employment Rate
None	6.9	1.5	2.9	11.3	25.7
Preprimary	8.1	4.6	6.1	18.8	32.4
Primary	3.7	2.1	2.5	8.2	30.5
Some Secondary	17.7	10.5	10.5	38.7	27.1
Secondary	3.6	6.3	10.6	20.4	52.0
National Training Certificate	0.1	0.1	0.4	0.6	66.7
Baccalaureate	0.2	0.1	1.1	1.4	78.6
Postgraduate	0.1	0.0	0.4	0.5	80.0
Total	40.4	25.1	34.4	100	34.4

Source: Author's calculations from September 2004 LFS

Values are rounded to nearest 0.1% (of 73 200 respondents)

Table 2. Average Earnings by Education Attainment Across Employment Sectors

		Employed Respondents		
Schooling Level	**All Respondents**	**Self-Employed**	**Public Sector**	**Private Sector**
None	10619	9341	24119	9864
Preprimary	12444	10379	25269	11676
Primary	14472	12021	28109	13483
Some Secondary	20032	17744	40016	17947
Secondary	44360	60320	62081	34274
National Training Certificate	57252	67563	47950	57744
Baccalaureate	97065	116400	90075	107975
Bac Honours	134436	123000	116423	171670
Masters and PhD	176705	191200	141073	236663
Postgraduate Average	150469	160889	124997	196262

Source: Author's calculations from September 2004 Labour Force Survey

Average annual wages by education qualification and employment sector.
Postgraduate Average includes Bac Honours as well as Masters and PhD degrees.

Table 3. Matric to Grade 11 and Grade 7 to Grade 6 Wage Ratios by Age

	All Employed	Public Sector	Private Sector	Self-Employed
Less than 30				
Grade12 to Grade 11	1.811	2.702	1.689	1.940
Grade7 to Grade 6	0.923	0.657	0.955	0.921
Age 30 to 40				
Grade12 to Grade 11	2.001	1.859	1.860	3.041
Grade7 to Grade 6	1.120	1.357	1.034	1.232
Age 40 to 50				
Grade12 to Grade 11	2.191	1.665	2.095	3.299
Grade7 to Grade 6	1.132	0.787	1.223	1.228
Age 50 to 60				
Grade12 to Grade 11	1.791	1.364	2.130	1.070
Grade7 to Grade 6	1.100	1.306	1.139	0.781
Age 60 and above				
Grade12 to Grade 11	4.165	2.159	0.851	9.682
Grade7 to Grade 6	1.391	0.907	1.206	1.806

Source: Author's calculations from September 2004 Labour Force Survey.

Ratio of wages for completing secondary or primary compared to completing one year less.

Table 4. Relative Wages by Schooling Level, Employment Sector and Career Profile

	Schooling Ratios					
	None/ Grade 12	Preprimary/ Grade 12	Primary/ Grade 12	Some Secondary/ Grade 12	University/ Grade 12	Postgraduate/ Grade 12
	All Employed					
Under 30	0.385	0.386	0.402	0.555	3.148	3.586
Age 30 to 40	0.276	0.300	0.331	0.477	2.866	4.338
Age 40 to 50	0.206	0.259	0.308	0.444	2.338	3.991
Age 50 to 60	0.163	0.198	0.246	0.408	1.329	2.348
Over 60	0.159	0.175	0.311	0.501	0.691	1.557
	Public Sector					
Under 30	0.164	0.277	0.204	0.591	1.418	2.929
Age 30 to 40	0.294	0.329	0.360	0.579	1.457	2.068
Age 40 to 50	0.333	0.332	0.404	0.607	1.325	1.730
Age 50 to 60	0.238	0.392	0.406	0.618	1.381	1.425
Over 60	0.440	0.495	0.847	0.601	1.377	3.135
	Private Sector					
Under 30	0.379	0.370	0.433	0.555	2.607	3.950
Age 30 to 40	0.287	0.306	0.341	0.478	3.411	4.847
Age 40 to 50	0.182	0.252	0.304	0.432	2.738	4.763
Age 50 to 60	0.133	0.167	0.222	0.341	1.571	2.886
Over 60	0.211	0.230	0.398	0.809	0.832	2.389
	Self-Employed					
Under 30	0.625	0.611	0.346	0.518	8.780	1.406
Age 30 to 40	0.183	0.214	0.230	0.310	1.979	5.036
Age 40 to 50	0.135	0.188	0.186	0.269	2.071	3.888
Age 50 to 60	0.113	0.119	0.178	0.439	0.488	1.427
Over 60	0.016	0.018	0.054	0.067	0.322	0.040

Source: Authors' calculations from September 2004 LFS

Wage ratios relative to wage for Grade 12 completion by sector.

Table 5. Mincerian Wage Regressions with and without Multinomial Selection Model Results: No Unemployment or Tenure Effects

VARIABLE	Self-Employed			Publicly Employed			Privately Employed#	
	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	Corrected Mincer (ac)
Continuous School	0.0518 ***	0.0345 ***	0.0247 ***	0.0667 ***	0.1633 ***	0.0834 ***	0.0354 ***	0.0189 ***
	(0.008)	(0.007)	(0.012)	(0.008)	(0.010)	(0.018)	(0.003)	(0.018)
Completed Primary	-0.0014 *	-0.0450	-0.0798 **	-0.0032	-0.1812	-0.0258	-0.0448 **	-0.0293
	(0.061)	(0.078)	(0.066)	(0.054)	(0.096)	(0.058)	(0.018)	(0.058)
Completed Secondary	0.1998 ***	-0.2143 ***	-0.1125	0.1691 ***	0.9689 ***	0.2531 ***	0.1360 ***	-0.0588 *
	(0.069)	(0.068)	(0.116)	(0.045)	(0.071)	(0.100)	(0.020)	(0.100)
Completed Baccalaureate Degree	0.5221 ***	0.0856	-0.0975	0.3250 ***	1.9157 ***	0.5174 ***	0.4334 ***	0.0733
	(0.177)	(0.159)	(0.262)	(0.075)	(0.122)	(0.168)	(0.063)	(0.168)
Completed Postgraduate Degree	0.3852	-0.0345	-0.1745	0.3312 ***	1.4623	0.4796 ***	0.4710 ***	0.1508
	(0.298)	(0.243)	(0.362)	(0.097)	(0.182)	(0.154)	(0.102)	(0.154)
SELECTION CORRELATIONS								
Public Correlation			-0.8985 ***					-0.7849 ***
			(0.273)					(0.111)
Private Correlation			0.7044 *			-0.5066 **		
			(0.267)			(0.201)		
Self-Employed Correlation						0.4143 **		0.7624 ***
						(0.188)		(0.122)

Source: 'selmlog' applied in STATA SE 9.2; see Bourguignon et al (2004). # Sector is comparison sector in multinomial logit, i.e., all mnl parameters normalised to zero for this sector.
Bootstrapped (200 repititions) Standard Errors in Parenthesis. *** - 1% Significance. ** - 5% Significance. * - 10% Significance. Complete results are available from authors, upon request.
a: Regression also includes: age, age squared, gender dummies, provincial dummies, race dummies and an English language dummy.
b: Regression also includes: size of household (hh), number of children under 5 in hh, number of children 5 to 15 in hh and number of retired persons in household.
c: Regression also includes: dummies for firm size categories by employees.

Table 6. Mincerian Wage Regressions with and without Multinomial Selection Model Results: Unemployment Included, but no Tenure Effects

	Unemployed	Self-Employed			Publicly Employed			Privately Employed#	
VARIABLE	MNL (ab)	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	Corrected Mincer (ac)
Continuous School	0.0519 ***	0.0645 ***	0.0305 ***	0.0218	0.0987 ***	0.1708 ***	0.1081 ***	0.0680 ***	0.0676 ***
	(0.005)	(0.009)	(0.012)	(0.015)	(0.008)	(0.009)	(0.008)	(0.003)	(0.015)
Completed Primary	-0.0015	-0.1282 **	-0.0801	-0.0666	-0.0626	-0.2247 **	-0.0643	-0.0786 ***	-0.0748 ***
	(0.054)	(0.064)	(0.066)	(0.070)	(0.067)	(0.093)	(0.071)	(0.021)	(0.027)
Completed Secondary	-0.2469 ***	0.2764 ***	-0.2325 ***	0.0737	0.2664 ***	0.9212 ***	0.2376 ***	0.2404 ***	0.1297
	(0.044)	(0.073)	(0.116)	(0.100)	(0.051)	(0.066)	(0.050)	(0.023)	(0.100)
Completed Baccalaureate	-1.0299 ***	0.7821 ***	0.0678	0.0775	0.4708 ***	1.7287 ***	0.3655 ***	0.8032 ***	0.5069 ***
	(0.1773)	(0.183)	(0.262)	(0.243)	(0.070)	(0.113)	(0.096)	(0.068)	(0.158)
Completed Postgraduate	-1.7480 ***	0.5557 **	0.2468	-0.0165	0.4250 ***	1.2425 ***	0.2530 *	0.7107 ***	0.4470 ***
	(0.429)	(0.261)	(0.362)	(0.292)	(0.092)	(0.165)	(0.133)	(0.103)	(0.113)
SELECTION CORRELATIONS									
Unemployed Correlation				-0.146			0.5288 ***		0.4963 ***
				(0.346)			(0.165)		(0.156)
Public Correlation				-2.1325 ***					-0.9454 ***
				(0.519)					(0.116)
Private Correlation				3.6702 ***			-0.5408 **		
				(1.257)			(0.196)		
Self-employed Correlation							-0.0262		0.3445 *
							(0.244)		(0.299)

Source: 'selmlog' applied in STATA SE 9.2; see Bourguignon et al (2004). # Sector is comparison sector in multinomial logit, i.e., all mnl parameters normalised to zero for this sector
Bootstrapped (200 repititions) Standard Errors in Parenthesis. *** - 1% Significance. ** - 5% Significance. * - 10% Significance. Complete results are available from authors, upon request
a: Regression also includes: age, age squared, gender dummies, provincial dummies, race dummies and an English language dummy.
b: Regression also includes: size of household (hh), number of children under 5 in hh, number of children 5 to 15 in hh and number of retired persons in household
c: Regression also includes: dummies for firm size categories by employees.

Table 7. Minecerian Wage Regressions with and without Multinomial Selection Model Results: Tenure Effects Included, but not the Unemployed

VARIABLE	Self-Employed Mincer (ac)	Self-Employed MNL (ab)	Self-Employed Corrected Mincer (ac)	Publicly Employed Mincer (ac)	Publicly Employed MNL (ab)	Publicly Employed Corrected Mincer (ac)	Privately Employed Mincer (ac)	Privately Employed Corrected Mincer (ac)
Continuous School	0.0639 ***	0.0294 ***	0.0315 **	0.1368 ***	0.1654 ***	0.1732 ***	0.0626 ***	0.0426 ***
	(0.009)	(0.006)	(0.013)	(0.009)	(0.009)	(0.023)	(0.003)	(0.005)
Completed Primary	-0.1381 **	-0.0676	-0.0934	-0.0387	-0.2104 **	-0.0853	-0.0791 ***	-0.0579 **
	(0.064)	(0.073)	(0.063)	(0.056)	(0.093)	(0.063)	(0.019)	(0.026)
Completed Secondary	0.2659 ***	-0.2163 ***	-0.0705	0.2220 ***	0.9300 ***	0.4117 ***	0.2246 ***	0.0033
	(0.073)	(0.063)	(0.123)	(0.047)	(0.067)	(0.113)	(0.021)	(0.035)
Completed Baccalaureate	0.8200 ***	0.0798	0.1844	0.4329 ***	1.7560 ***	0.7581 ***	0.7918 ***	0.3866 ***
	(0.184)	(0.139)	(0.262)	(0.065)	(0.113)	(0.176)	(0.063)	(0.084)
Completed Postgraduate	0.4981 **	0.2597	-0.0133	0.3875 **	1.2769 ***	0.6237 ***	0.7174 ***	0.4251 ***
	(0.258)	(0.190)	(0.284)	(0.086)	(0.165)	(0.139)	(0.101)	(0.107)
Months on the Job	-0.0001		0.0001	0.0072 ***		0.0072 ***	0.0033 ***	0.0035 ***
	(0.003)		(0.003)	(0.0005)		(0.0005)	(0.0003)	(0.0002)
Months on the Job (Squared)	-0.000002		0.000001	-0.000007 ***		-0.000008 ***	-0.000006 ***	-0.000006 ***
	(0.000006)		(0.00001)	(0.0000009)		(0.0000008)	(0.0000006)	(0.0000006)
Months on the Job * Schooling	0.0003 **		0.0003 *	-0.0002 ***		-0.0002 **	0.00002	0.0000
	(0.0001)		(0.0002)	(0.00003)		(0.00003)	(0.00002)	(0.00002)
SELCTION CORRELATIONS								
Public Correlation			-1.0424 ***					-0.8708 ***
			(0.310)					(0.111)
Private Correlation			0.8646 ***			-0.4135 **		
			(0.293)			(0.200)		
Self-employed Correlation						0.1729		0.7835 ***
						(0.181)		(0.120)

Source: 'selmlog' applied in STATA SE 9.2; see Bourguignon et al (2004). # Sector is comparison sector in multinomial logit, i.e., all mnl parameters normalised to zero for this sector
Bootstrapped (200 repititions) Standard Errors in Parenthesis. *** - 1% Significance. ** - 5% Significance. * - 10% Significance. Complete results are available from authors, upon request
a: Regression also includes: age, age squared, gender dummies, provincial dummies, race dummies and an English language dummy.
b: Regression also includes: size of household (hh), number of children under 5 in hh, number of children 5 to 15 in hh and number of retired persons in household
c: Regression also includes: dummies for firm size categories by employees.

Table 8. Minciberian Wage Regressions with and without Multinomial Selection Model Results: Tenure Effects and the Unemployed Included

	Unemployed	Self-Employed			Publicly Employed			Privately Employed#	
VARIABLE	MNL (ab)	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	MNL (ab)	Corrected Mincer (ac)	Mincer (ac)	Corrected Mincer (ac)
Continuous School	0.0519 ***	0.0639 ***	0.1708 ***	0.0220 *	0.1368 ***	0.1708 ***	0.1415 ***	0.0626 ***	0.0634 ***
	(0.005)	(0.009)	(0.009)	(0.013)	(0.009)	(0.009)	(0.012)	(0.003)	(0.012)
Completed Primary	-0.0015	-0.1381 **	-0.2247	-0.0778	-0.0387	-0.2247 **	-0.0360	-0.0791 ***	-0.0756 ***
	(0.054)	(0.064)	(0.0093)	(0.066)	(0.056)	(0.093)	(0.111)	(0.019)	(0.027)
Completed Secondary	-0.2469 ***	0.2659 ***	0.9212 ***	-0.0777	0.2220 ***	0.9211 ***	0.1726 ***	0.2246 ***	0.1273 **
	(0.044)	(0.073)	(0.066)	(0.109)	(0.047)	(0.066)	(0.080)	(0.021)	(0.078)
Completed Baccalaureate	-1.0299 ***	0.8200 ***	1.7287	0.1312	0.4329 ***	1.7287 ***	0.2409 ***	0.7918 ***	0.5428 ***
	(0.1773)	(0.184)	(0.113)	(0.242)	(0.065)	(0.113)	(0.111)	(0.063)	(0.126)
Completed Postgraduate	-1.7480 ***	0.4981 *	1.2425	-0.0594	0.3875 ***	1.2425 ***	0.1063	0.7174 ***	0.4995 ***
	(0.429)	(0.258)	(0.165)	(0.291)	(0.086)	(0.165)	(0.145)	(0.101)	(0.111)
Months on the Job		-0.0001		0.0001	0.0072 ***		0.0071 ***	0.0033 ***	0.0035 ***
		(0.003)		(0.004)	(0.0005)		(0.0006)	(0.0003)	(0.0002)
Months on the Job (Squared)		-0.000002		0.000002	-0.000007 ***		-0.000007 ***	-0.000006 ***	-0.000006 ***
		(0.000006)		(0.00001)	(0.0000009)		(0.0000009)	(0.0000006)	(0.0000006)
Months on the Job * Schooling		0.0003 **		0.0003	-0.0002 ***		-0.0002 ***	0.00002	-0.000003
		(0.00001)		(0.0002)	(0.00003)		(0.00005)	(0.00002)	(0.00001)
SELECTION CORR.									
Unemployed Correlation				-0.1632			0.2057		0.3801 ***
				(0.354)			(0.149)		(0.107)
Public Correlation				-2.1098 ***					-0.7888 ***
				(.466)					(0.116)
Private Correlation				3.6789 ***			-0.3302 **		
				(1.208)			(0.162)		
Self-employed Correlation							0.0047		0.3252
							(0.216)		(0.231)

Source: 'selmlog' applied in STATA SE 9.2; see Bourguignon et al (2004). # Sector is comparison sector in multinomial logit, i.e., all mnl parameters normalised to zero for this sector
Bootstrapped (200 repititions) Standard Errors in Parenthesis. *** - 1% Significance. ** - 5% Significance. * - 10% Significance. Complete results are available from authors, upon request
a: Regression also includes: age, age squared, gender dummies, provincial dummies, race dummies and an English language dummy.
b: Regression also includes: size of household (hh), number of children under 5 in hh, number of children 5 to 15 in hh and number of retired persons in household
c: Regression also includes: dummies for firm size categories by employees.